CONTEXT, LATENCY AND THE VALUE OF PREVENTING A STATISTICAL CANCER FATALITY

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Abstract

This thesis contributes to the state of understanding about the value of latent health and fatality risk reductions, focussing on the effects of context and latency on the Value of Preventing a Statistical Cancer Fatality (VSL_{CAN}) relative to road accident fatalities. The conceptual, methodological and empirical contributions are derived from two stated preference studies. The studies are designed to explore how the VSL_{CAN} is driven by the context effect, which includes dread of the cause 'cancer' and the effects of illness prior to fatality; and the latency (delay) effect which depends upon time preferences and risk preferences.

Study 1 develops a Risk-Risk survey protocol, and the resulting central tendency and regression analysis verify that the context of cancer increases the VSL and that latency decreases it. The relativity between VSL_{CAN} and the road accident VSL is then summarised into a simple relationship where the offsetting influences of context and latency are parameterised. This novel tool has the potential to enhance the comparability and evaluation of a wide range of existing and future VSL studies involving context and latency effects through the elicitation of key underlying parameters such as the context premium and effective discount rate. As such it represents a significant methodological contribution.

Study 2 focusses directly on two aspects of the latency effect. These relate to risk and time preferences, explored in Studies 2a and 2b respectively. Delayed outcomes are inherently risky, so the exploration of latent outcomes requires controlling for risk preferences. Study 2a develops a theoretical and empirical framework for eliciting risk aversion proxies in the domain of health, which have not previously been fully developed in the literature. The method extends the classic Holt-Laury risk preference elicitation framework into a new domain- health risks- and the method is implemented successfully in Study 2. This chapter therefore makes both conceptual and methodological contributions through clarifying the utility theoretic basis of a health risk aversion measure and then developing a way to elicit such a measure in surveys. Study 2b uses the novel VSL_{CAN}:VSL relationship developed in Study 1 to elicit exponential discount rates from Risk-Risk data comparing latent cancer and road accident risks. Regression analysis performed on these rates on a sample and individual level, provides strong evidence to suggest that a non-standard (sub-additive) discounting model is the most descriptively accurate discounting assumption for this sample. It provides the first evidence regarding sub-additive discounting in the domain of health and fatality risk.

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Declaration

Overview

The majority of the work in this thesis is my own. Where I have used the ideas or contributions of others, I have acknowledged them fully in the text. The studies reported were externally funded and were conducted in collaboration with my supervisors (Dr Hugh Metcalf, Prof Susan Chilton and Prof Mike Jones-Lee). My contribution to each chapter is outlined below, along with the contribution of my supervisors.

Part	Chapter	Content	Description of my contribution
Part I	Chapters 1-2	Intro and literature review	These chapters were entirely my own work.
Part II: study 1	Chapter 3	Background, methodology and preliminary analysis	The overall survey structure was my own design and the majority of the specific wording of the protocol was my own, but my supervisors had some input into the specifics of the survey protocol (e.g. use of risk communication tools, training sessions etc.). The implementation of the survey was a combined effort, with Dr Metcalf or Prof Chilton reading the protocol while I handled respondents' queries and managed the logistics.
	Chapter 4	Analysis and conclusions	All of the analysis and conclusions were my own work.
Part III: Study 2	Chapter 5	Intro methods and preliminary analysis	I made the modifications to study 1 that were necessary for study 2. Dr Metcalf read the protocol while I handled queries and logistics. The analysis was my own work.
	Chapter 6	Risk preferences in health	This chapter was entirely my own work.
	Chapter 7	Eliciting effective discount rates from survey data	This chapter was entirely my own work.
Part IV	Chapter 8	Conclusions and policy implications	This chapter was entirely my own work.

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Table of Contents

List of Tables

List of Figures

Executive Summary

Background

This thesis examines the underpinnings of the value of preventing a statistical cancer fatality (VSL_{CAN}) relative to the value of preventing a statistical road accident fatality (VSL). Cancer fatalities differ from road accident fatalities along two key dimensions. The first is the context of the fatality itself. While road accident fatality is typically near-instant, cancer fatality usually follows a period of illness or 'morbidity' prior to fatality, and is often described as engendering a particular 'dread' or horror. The second dimension is timing. Exposure to a cancer risk today will not typically lead to morbidity and death until a number of years or even decades have passed. This delay from exposure until fatality is known as latency. These attributes of the cancer fatality scenario are hypothesised to influence the VSL_{CAN} in two ways:

1) The main effect of the cancer context is to increase the VSL_{CAN}. This is through the influence of morbidity and dread effects.
2) The main effect of latency is to reduce the VSL_{CAN}. This can be expressed through an effective discount rate.

However, there is little consensus in the existing literature as to whether these hypotheses are correct, particularly because up to now efforts to disentangle context and latency effects have not been commonplace.

Two stated preference studies are conducted to validate these hypotheses and to provide further insights about the effects of latency on the VSL_{CAN}. Alongside the empirical insights that are generated, the studies make significant methodological and theoretical contributions. Future research related to latent fatality risks could benefit significantly from these developments.

The thesis is structured in four parts. Part I outlines the background and situates this research in the wider literature. Part II reports study 1, which explores the VSL_{CAN}:VSL comparison in a broad sense, considering context, morbidity and latency effects. Part III reports the results of study 2, which provides more in-depth investigation into latency. Study 2 is presented in two distinct chapters, each of which explores a distinct aspect of latency. Recognising that delayed outcomes are inherently risky, study 2a develops the theoretical and empirical frameworks for eliciting risk aversion coefficients in the domain of health. Study 2b investigates the appropriate rate and

functional form at which latent cancers are discounted. Finally, part IV provides overall discussion and conclusions, with a particular focus on the relevant messages for policy analysis.

Study 1

Study 1 had the broad focus of considering the overall VSL_{CAN}:VSL relationship and attempting to understand its underpinnings. Specifically it aimed to test the hypotheses on pg.52, and to elicit information about the magnitude of these context and latency effects.

Study 1 Methods

Study 1 took place in Newcastle upon Tyne in Jan-Feb 2012. The sample consisted of 159 members of the public (plus further respondents interviewed during piloting), and all respondents were aged between 30 and 50 at the time of the study. The study was administered to groups of around 10 people at a time, but the questions were answered on an individual basis. The protocol for Study 1 is provided in Appendix A. The study consisted of three sections, the learning rounds, the Risk-Risk survey and the supplementary questions.

Learning rounds

The sessions began with learning and teaching rounds. Respondents were familiarised with the concepts of fatality risk and risk increases, risk trading mechanisms and the influence of timing. These concepts were conveyed through examples and informal questioning. Respondents practiced with the Risk-Risk trade-off mechanism using 'practice' fatality contexts to learn the mechanism. Finally, the cancer and road accident fatality scenarios were introduced and the key scenario assumptions were set out (for example, that the cancers are not behaviour-related and that the road accidents would involve fatality after minutes or hours of suffering). Throughout the learning rounds, respondents had the opportunity to ask questions and clarify concepts.

Risk-Risk survey

In the Risk-Risk (R-R) survey section, Respondents expressed their relative strength of preference for avoiding risks of certain fatality scenarios by trading-off risks. Pairs of scenarios were presented to the respondent and their willingness to accept risk increases in one cause of fatality indicates their strength of preference for avoiding risk increases

in the other. For example, indifference between an x in 60 million increase in the risk of fatality by some cause A and a 2x in 60 million increase in the risk of fatality by some other cause B would imply that the respondent perceives fatality risk increases in cause A to be twice as bad as in cause B.

The ten scenario pairs can be summarised in four blocks. The first is the 'overall' block (Q1-3) where latent cancer fatality risks are compared with current road accident fatality risks, incorporating both context and latency effects together. The second block (Q4-5) captures 'context' effects, because the fatalities in the scenarios would occur at the same time but one is death by cancer (with associated morbidity) and the other is death in a road accident. The third block (Q6-7) considers latency, comparing cancer risk increases sooner with cancer risk increases later, *ceteris paribus*. The fourth block (Q8-10) covers the underpinnings of the context effect. In Q8-9 the scenarios are all cancer, but the morbidity period varies between scenarios. Q10 tests for 'label dread' by holding everything but the scenario label (cancer or roads) identical between the two scenarios being compared.

Supplementary questions

After the R-R survey had been completed, three supplementary questions were posed. First, respondents' risk preferences were elicited using hypothetical financial lottery choices following the Holt and Laury (2002) elicitation mechanism. Second, their time preferences were elicited using hypothetical money amounts, but this time comparing a smaller payoff to be received sooner with increasingly large payoffs to be received later following the Coller and Williams (1999) framework. This allowed the exponential discount rate to be elicited. Finally, the Holt and Laury (2002) framework was adapted for the domain of health, and the switching point used as a proxy for risk aversion in health. This is explored in detail in Chapter 6. Respondents then answered demographic questions. The information in the supplementary questions would provide explanatory variables for subsequent statistical analysis.

Study 1 Analytical Methods

Basic analysis of the central tendencies is presented. This involves examining the size of the relativity and observing whether the difference in responses between questions is in line with the expected movement (for example, does a longer latency period generate a lower VSL_{CAN}:VSL relativity?). Regression analysis is used to complement the

analysis of central tendencies and to control for demographic effects. All of this is standard analysis.

However, the second part of analysis of the relativities in study 1 is novel. The VSL_{CAN}:VSL relationship is proposed to be well approximated by a simple equation referred to as C_TR_t. This equation suggests that VSL_{CAN} for a cancer at time T is equivalent to the VSL for a road accident at time t, adjusted upwards for the context effect (captured by a multiplier (1+x)), but deflated for latency effects through an effective discount rate r which is assumed to apply exponentially. This generates the relationship in equation (i).

$$VSL_{CAN}:VSL = \frac{C_T}{R_t} = \frac{(1+x)}{(1+r)^{T-t}} \qquad (i)$$

From this basis, using simple simultaneous equation techniques, it is possible to use combinations of questions to elicit the underlying parameters r (the effective discount rate) and (1+x) (the context premium). This is a key contribution from Part II of this thesis, and could be used in future with any relativities data for scenarios with different contexts and timescales.

Study 1 Findings

The main empirical finding from a policy perspective is that there is a 1:1 relationship between the VSL_{CAN}:VSL for latency periods of 10 years. This is evidence against the imposition of a 'cancer premium' in policy settings and contradicts the practice of applying a multiplier of 2 to the VSL for cancer which is advised in UK government bodies including the Health and Safety Executive (HSE).

In addition, the results of the central tendency and regression analyses confirm hypotheses (1) and (2) so provide evidence that the cancer context (including a morbidity period prior to fatality) increases the VSL *ceteris paribus* while latency reduces the VSL *ceteris paribus.* This provides support for the C_TR_t relationship in equation (i).

The simultaneous equation analysis using this relationship estimates the context premium to be 1.4 so cancer with a year of morbidity is perceived to be 40% worse than a road accident fatality at the same time. It estimates the effective exponential discount rate to be 7.37%p.a. This value is in line with typical estimates in the domain of health and physical risk outlined in the literature review.

Somewhat surprisingly, the 'label dread' of cancer appears to be very weak. That is, there is no evidence on the basis of these results that cancer *per se* is perceived to be worse than road accidents. Instead, the context premium appears to be driven by the preference for avoiding the associated morbidity. This result would benefit from further investigation in future, particularly extending the analysis to consider severity effects.

Study 2

Consideration of latency in Study 1 was limited because dread, morbidity and context were to be investigated as well, so only a subset of the questions could focus on latency. Study 2 addresses this by focussing specifically on the effects of latency in determining the VSL_{CAN}:VSL relativity.

Study 2: design and implementation

Study 2 was conducted in Newcastle upon Tyne in February 2013. The sample (n=112) consisted of students aged between 18 and 25 enrolled at Newcastle University. Again, the study was administered to groups of respondents but questions were answered on an individual basis. The protocol for Study 2 is identical to that for Study 1, with one exception: the scenarios being compared in the R-R survey were different. Q1-3 was identical to Study 1. Q10 replicated a 'context' question by comparing cancer and road accident risk increases when both would occur ten years from now. However, Q4-9 all compared latent cancer risk increases with road accident risk increases sooner. This allows greater variation in timing than Study 1 and so allows greater confidence in the inference of discounting rates and functions.

Study 2 is reported in two chapters, with Study 2a considering risk aversion elicitation and Study 2b using the R-R survey answers to draw inferences about discounting rates and functional forms.

Study 2a

Study 2a is motivated by the observation that delayed outcomes inherently incorporate more risk than immediate outcomes. As such, risk preferences are expected to influence preferences over latent outcomes. The current literature lacks appropriate theoretical and empirical frameworks within which to elicit estimates of the coefficients of relative risk aversion in the domain of health. These frameworks are developed and implemented in Study 2a.

The structure of the argument in 2a is as follows. First the utility theoretic underpinnings of the Holt and Laury (2002) (H-L) procedure for eliciting financial risk aversion are set out and explained. This framework is converted to handle utility of health by assuming that health can enter directly into the utility function. With this assumption, it is straightforward to demonstrate that the theoretical framework and the associated risk aversion elicitation procedures will transfer between these domains.

Next the analysis considers how the new framework can be implemented in practice. To operationalize it requires a measure of health that increases in severity. The author sets out a range of possible health state communication tools and selects the EQ-5D description system as the most appropriate of the currently available options. As such, the elicitation procedure faced by respondents in Study 2 included an H-L elicitation table containing lotteries between financial outcomes and a second H-L elicitation table where the outcomes in the lotteries were health states of increasing severity described using the EQ-5D system.

The interpretation of the health-state H-L data is not entirely straightforward. There are two major sources of contention. The first is the choice of input value for the EQ-5D health states. There are two options, one is to use pre-existing population estimates of the value of these health states which were derived by the EuroQoL group. However, the UK-specific values were elicited using a Time-Trade-Off method which is subject to problems with bias from time preferences. A correction procedure is developed and presented. The second option is to use Visual Analogue Scale values of the health states. These are a visual representation of the loss from full health that each respondent considers to be associated with the health state description. In Study 2 both the VAS and the TTO approaches are used.

The second contentious point derives from what the VAS and TTO scores actually represent. While the theory requires a measure of health severity (preferably on a ratio scale), the VAS and TTO scores in fact represent a value of health. As such, the TTO and VAS scores will incorporate the effects of diminishing utility in health, which is of course a key aspect of risk aversion. Algebraic manipulation is used to demonstrate that the interpretation of the risk aversion parameter in study 2 is limited to capturing the gambling aversion component of risk aversion. While this is clearly a limitation, chapter 7 argues that the limitation would be resolved if a ratio scale measure of increasing health severity could be developed. In addition, the theoretical work in this

chapter means that the interpretation of the measure is unambiguous. The procedure is therefore argued to represent an improvement upon existing risk aversion proxies in the domain of health.

Findings

The main contributions of Study 2a are methodological or theoretical. These have been mentioned in the chapter summary above, but are highlighted here for clarity.

The key methodological contribution is the development of the empirical framework for eliciting risk aversion coefficients over health states. Achieving this requires two innovative theoretical contributions as follows.

The theoretical framework for eliciting financial coefficients of relative risk aversion is translated into the domain of health states. Additionally, the theoretical link is formalised between the elicitation of risk aversion parameters (which are elicited when a direct measure of health severity is used) and the elicitation of gambling aversion (based on the currently available health values). This lends additional clarity to the interpretation of the health risk aversion proxy.

The empirical results from this chapter are a secondary concern compared to the methodological and theoretical contributions, but for completeness they will be summarised here. Firstly, risks preferences defined over financial outcomes are found not to be highly correlated with the health risk aversion proxies generated by this new methodology. This adds to the growing evidence that suggests risk preferences are domain-specific. In terms of the levels of risk aversion, the tentative conclusion is drawn that risk aversion is lower in health than in finance, although acknowledging that this could be an artefact of the interpretation of the coefficient as a measure of gambling aversion as opposed to a measure of 'full' risk aversion.

Study 2b

The health risk aversion proxies elicited in Study 2a are taken forward into Study 2b which focusses on establishing the most descriptively appropriate discount rates and discounting functional forms. This is to test the well-established finding in the financial experimental literature that exponential discounting is not descriptively accurate for the majority of individuals.

Study 2b: analytical methods

First the VSL_{CAN}:VSL relativities are plotted as a function of latency in order to make initial inferences about the effects of timing. Next, the C_TR_t relationship at the heart of Study 1 (equation i) is used to elicit exponential discount rates for every individual in the sample, and these are tested for significant correlation with underlying time-related aspects of the fatality scenarios. Specifically, the exponential discount rates are regressed on the average delay until the risk outcome, which tests for hyperbolic discounting, and on the difference between the time of the road accident and cancer fatalities (known as the latency differential) which tests for sub-additive discounting. Probit analysis is run to explore whether discounting behaviour is predicted by demographic characteristics. Finally, the C_TR_t relationship is adapted for the different discounting hypotheses (hyperbolic and sub-additive discounting) and the discount rates are elicited and compared in each case.

Findings

The theoretical contributions in Study 2b relate to clarification of the way each discounting assumption would relate to, and be elicited from, the VSL_{CAN}:VSL relativity. The main methodological contribution is the procedure for categorising individual respondents by discounting type using basic OLS regression techniques. However, in this chapter the main contributions are the empirical results.

The key finding is that based on the sample averages and on the individual classification, exponential discounting is not the most suitable discounting assumption for this sample. Only 35% of respondents had discount rates that did not depend on the time parameters tested in this chapter. Sub-additive discounting appears to best categorise the sample as a whole, and hyperbolic discounting is not well supported by these data.

Finally, the levels that the effective exponential discount rates take (between 1 and 20%p.a. based on sample averages) align well with the existing evidence about discounting. However, eliciting rates and functional forms on the level of the individual highlights just how diverse and varied discounting is between individuals and domains, and the rates elicited on an individual level span from the strongly negative to high positive rates. Dealing with such heterogeneity in time preferences is not

straightforward, but is a question that needs to be considered. The procedure used here that allows the inference of discounting type on the individual level is arguably an important step towards allowing this debate to proceed.

Policy implications

The thesis as a whole has a number of implications for policy. These categorise into two main areas: empirical and normative.

The empirical or descriptive implications relate to the size of the VSL_{CAN}:VSL relativity (shown to be 1:1, rejecting the 2:1 cancer multiplier recommended by the HSE). Alternatively, instead of applying a constant VSL_{CAN}, policymakers could use a context premium to adjust for the disutility from the cancer context including morbidity effects. Then a discount rate could be applied to find the present for cancers with different latency periods. Study 1 provides estimates of 1.4 for the context premium and a discount rate of 7.37%p.a. to be applied exponentially.

However, this is called into question by the finding that the majority of the sample appears to consist of non-exponential discounters. This is particularly important because the implications for policy values are shown to be large based on a simulation reported in Part IV. While of course findings from the student sample in study 2 might not generalise to the population, comparing the two samples in terms of the questions common to both studies generates surprising similarities. This gives the validity of the empirical policy results tentative support.

However, arguably the more important policy implications fall into the normative category and relate to the appropriateness of reflecting public opinion over intertemporal choices in policy decisions.

The inferred discount rate of 7.37%p.a. exceeds the policy rate typically used for fatality risks (the social rate of time preference (STPR)), which is 1.5%p.a. However, because x and r are elicited jointly, use of the 1.43 context multiplier in combination with an alternative discount rate would imply overriding the overall relativity elicited in Study 1. This highlights the complexity of the policy interpretation of the results of this study. Bringing non-exponential discounting into the picture intensifies the conundrum. This is because exponential discounting in policymaking is normatively appealing because it does not imply time inconsistency. However, imposing exponential discounting would mean overriding public preferences. For a policy maker that wishes to respect the

preferences of the public, while maintaining normatively appealing policies that are not time inconsistent and which reflect wider concerns such as intra-generational equity, the interpretation of the evidence in this thesis is clearly not straightforward. Nonetheless, good policymaking can only be enhanced by better and more comprehensive information about the way that individuals approach intertemporal fatality risk considerations in practice. This thesis adds substantially to that body of information, as well as to the tool kit for researchers that would contribute further in the future.

Future research

Part IV concludes with a set of questions for further research. These include questions of clarification, for example research to clarify the influence of morbidity upon the context premium, and validation of the method employed to correct the TTO health scores for time preference effects. However, a large scale question that is also raised is whether it would be feasible to develop a scale for health state measurement that does not draw on respondents' value functions for health. These areas for future consideration demonstrate the potential for this thesis to lead to further research and publications.

PART I.

INTRODUCTION, LITERATURE AND MODELS

Chapter 1. Introduction

1.1 Background and Scope

Since the seminal work of Drèze (1962), Schelling (1968) , and Mishan (1971) on the valuation of a change in probability of dying, (elaborated in Jones-Lee (1969) (Jones-Lee (1974)) Jones-Lee (1976) and Jones-Lee (1979)), there has been continued academic and policy interest in developing and refining an estimate of the value of reducing fatality risks. This has resulted in an indicator referred to as the Value of Preventing a Fatality (VPF) or Value of Statistical Life (VSL) which is, in simple terms, the aggregated willingness to pay for small risk reductions for a population such that the mathematical expectation of the number of fatalities to be prevented is exactly equal to one[1].

There is much debate about whether applying a uniform VSL across all policy areas is appropriate, or whether different values ought to be used for fatality risks in different contexts, for different sections of the population, and at different times. While this normative debate is on-going, in terms of a descriptive account of public preferences existing evidence suggests that different risks are perceived differently- and more specifically that their reduction is valued differently- by members of the public. Invoking the claim that good policymaking must utilise a firm base of evidence and understanding about public preferences, the overarching aim of this thesis is to contribute to knowledge about what drives the differences between public preferences for reductions in the risk of fatality in specific contextual and temporal circumstances.

The specific focus of this work is a special case of fatality risk: cancer fatality[2]. Since Kneese and Schulze (1977), economics has recognised its role in evaluating the impacts of cancer on the wellbeing of society. UK policy guidance (from the Health and Safety Executive and other departments) suggests applying a multiplier of two to the VSL for cancer, while the OECD does not recognise such a cancer premium. This lack of

[1] Note that the US literature uses the concept of VSL slightly differently, to mean an individual's marginal rate of substitution of wealth for fatality risk. This is an important distinction, and wherever the term VSL is used in this thesis it means the aggregation over the population.

[2] More specifically, the study considers cancer fatality that is not linked to behaviour traits such as smoking, and which have characteristics that approximate those of typical occupational and environmental cancer fatalities. The HSE will use insights from the work in application to occupational cancer risks.

consensus reflects wider disparity in the underlying theoretical, ethical and empirical evidence bases that support these policy positions.

Reflection on the nature of cancer fatalities leads to the conclusion that they differ from accidental fatalities in two main ways. Firstly, cancer fatality is usually preceded by a protracted period of pain, suffering and illness prior to death, and is often considered a particularly bad way to die as accounted for by the so-called cancer multiplier (see Jones-Lee *et al.* (1985a), Slovic (1987), Sunstein (1997) and Revesz (1999)). Secondly, cancer fatality usually occurs many years after exposure to the carcinogenic (cancer-causing) influence that triggered it; in other words cancers are latent fatalities (Rushton *et al.*, 2010). Heterogeneity in the cancer scenarios under consideration in valuation studies is likely to contribute to the lack of consensus in VSL estimates.

A key question is then whether the prospect of fatality in the context of cancer does engender special "dread" or fear, perhaps because of the preceding illness (morbidity) period or for some particular psychological aversion to the 'cancer' label. If so, does this context effect result in a higher VSL for cancer? A second question is whether latency tends to diminish the VSL for cancer. If this is so, to what extent does this occur?

In light of this, this thesis will examine the roles of morbidity, dread, latency and discounting in determining the value of preventing statistical cancer fatalities. The first study (study 1)[3]conducted to this end employs quantitative survey methods to establish the existence and magnitude of the effects of context and delay on the relative valuation of cancer risk changes for a subset of the general population. This provides the first dedicated and specific UK evidence in support of the hypothesis that context and latency act in opposing directions on the VSL for cancer, and provides a firm base of evidence upon which to build a framework for the elicitation of key underlying parameters in the cancer VSL, which are the premium placed on the context of cancer and the effective discount rate at which latent cancers are evaluated.

A further study (study 2) adopts a narrower focus, investigating the implications of latency for the VSL. This study provides a methodology for eliciting discount rates from Risk-Risk trade-off relativities data. In addition, it allows the categorisation of respondents into discounting 'types' and allows an analysis of what drives the differences in discounting behaviour. In order to fully understand discounting in the

[3] Study 1 is funded by the HSE and ONR (contract ND2484)

domain of health and physical risk, arguably a health-related measure of risk preferences is necessary. This is provided in part III of this thesis, which uses novel estimation techniques grounded in newly formalised theory to provide a health-related measure of risk preference which is then used in the estimation of discount rates in the full analysis of study 2.

Taken together, the results provide an array of insight into public preferences regarding the evaluation of latent fatality risk in general and cancer fatality risks in particular. In addition, new methodological procedures and tools are generated to allow the elicitation of risk, time and context preferences from survey data. As such, this thesis provides tools for future research alongside empirical evidence about existing public preferences over fatality risks.

The thesis is structured in four parts. Part I situates it in the literature. Part II reports study I, which considers the overall relativity between latent cancers and current period road accidents. Part III reports study 2 which explores latency effects (specifically risk preferences and discounting), and part IV provides discussion and conclusions, with reference to the policy implications of this work.

Chapter 2. Literature Review

2.1 Introduction

This literature review first outlines the background and history of the value of statistical life (VSL), and then presents the one-period model of valuing a change in risk. Next, the multi-period life cycle consumption model is presented and its relation to the VSL explained. Empirical evidence about the level of the VSL for road accidents is presented in brief, highlighting UK policy values. Attention is then turned to the specific case of cancer. As set out in the introduction, cancer differs from road accidents in terms of the context (incorporating a period of morbidity prior to fatality) and because there is typically a lengthy latency period between exposure and fatality. The theory and the empirical evidence surrounding both of these aspects is presented and discussed. The insights are combined in a multi-period model (Van Houtven *et al.*, 2008) and then a new, simple relationship is presented which links the VSL for cancer (hereafter VSL_{CAN}) to the VSL for road accidents (VSL) incorporating both the proposed context premium and discounting for latency.

2.2 Background and History of the VSL

Policies that save lives are typically associated with costs of implementation, be they directly incurred monetary costs or foregone benefits in other domains. In this respect, fatality risk reductions can be viewed as just one item upon an almost inexhaustible list of beneficial policy outcomes competing for the scarce resources available to society. Where markets exist and function well, individual agents acting in their own self-interest will generate optimal allocations of goods and services. However, in the case of publicly implemented fatality risk reductions there is no obvious market within which these self-interested interactions can take place, and as such prioritisation must rely on more structured information.

Jones-Lee (1982) discusses the options for societal decision making with the conclusion that the most promising approach is to base policy decisions on information about the value of fatality risk reduction as perceived by members of the public[4]. The monetisation of these life-saving benefits allows the beneficial policy outcomes to be

[4] A recent study by Roman et al. (2012) investigates the extent to which expert judgement can be relied upon to inform allocative policy decisions. While the results are favourable, this author advocates reliance on preferences of members of the public where this is viable to avoid problems such as motivational bias in expert evaluations.

compared to the costs of achieving them, or to the benefits of alternative projects, and as such facilitates decisions surrounding legislation, regulation and public spending. Drummond and Torrance (2005) provide additional arguments to support using public opinion as the basis for policymaking, although caveat the economic evaluation approach, noting "none of these approaches is intended to be a magic formula for removal of judgement, responsibility or risk from decision-making activities". Nonetheless, the book advocates the use of explicit valuation techniques as part of the decision maker's toolkit.

Of course, for the majority of people, the concept of placing a finite sum on money on the value of their life is inconceivable. However, as first formally noted in Mishan (1971) and Schelling (1968), the good in question is not a life saved or a death prevented: it is a reduction in fatality risk. It is a much less controversial statement that there is some monetary sum which a person would be willing to pay in return for a small reduction in their personal risk of fatality. This is exemplified by the markets for seatbelts, smoke alarms and other risk-reducing devices which are readily available to purchase. Although it might seem more difficult to imagine a monetary amount that would compensate for an *increase* in fatality risks, market based evidence again suggests the contrary: the labour market provides countless examples of jobs with a risk premium, for example. As such, the concept of individuals making trade-offs between their personal income or wealth against their personal fatality risk does not seem to be implausible.

Based on these foundations, Drèze (1962) formalised the expected utility framework that captures changes in the probability of fatality. This framework has been elaborated upon and formalised through the work of Jones-Lee, including Jones-Lee (1969) Jones-Lee (1974) and Jones-Lee (1989). This body of work provides the basis for what has become the standard model of the valuation of a single period risk reduction. The model is presented in the next section (2.3), and will be referred to and elaborated upon where appropriate through this theory and literature review (chapter 2).

It should be noted at this stage that the model and its implementation takes as its basis the Von-Neumann and Morgenstern (1947) axioms underpinning standard expected utility theory. There has of course been substantial and convincing criticism of standard expected utility theory with notable contributions from Schoemaker (1982) Kahneman and Tversky (1979) and Starmer (2000), the latter of which highlights the diversity of

attempts to find an alternative to EUT. The decision in this thesis to base the analysis within the expected utility framework was not taken lightly, but was taken in the interests of analytical tractability in the absence of a clearly superior alternative framework within which to consider the questions at hand.

Theoretical models of willingness to pay for risk changes are presented next, beginning with the generic one-period model from Jones-Lee (1974) and then moving to the generic life cycle consumption models using Cropper and Sussman (1990) as an example. These models are presented here because the framework they capture underpins the majority of empirical work estimating the value of a statistical life. As such, the models provide a firm basis for understanding the existing literature about the VSL, and provide a platform for the development of the utility model at the core of this thesis and its analysis. The Van Houtven *et al.* (2008) model is the most relevant existing framework for considering fatality risks from latent cancer. It will be presented later, in section 2.11.1, after the different empirical and theoretical features that motivate it have been discussed. The key insights from the Van Houtven model and additional insights from the theoretical and empirical literature will then be distilled into a very simple relationship (pg.53) which will underpin the analysis in subsequent parts of this thesis.

2.3 The Basic Model of a Single Period Risk Reduction in Discrete Time

This model is taken largely from Jones-Lee (1974), replicated here for reference and to provide a basis for the discussion of the likely effects of baseline risk and income on the VSL. Consider an individual with initial wealth $\bar{w}$ with a subjective risk of fatality initially at probability $\bar{p}$. That is, the individual places a probability $\bar{p}$ on the likelihood of their own fatality during the current period. Defining utility conditional on survival as $U(w)$ and utility conditional on dying as $D(w)$, the individual's expected utility for the coming period is

$$E(U) = (1 - \bar{p})U(\bar{w}) + \bar{p}D(\bar{w}) \qquad (1)$$

Further, assume that utility over wealth conditional on survival is strictly increasing and strictly concave, and that utility over wealth conditional on death is non-decreasing and concave. Utility of wealth greater than zero conditional on dying would reflect some bequest motive, and the bequest motive is allowed to be zero. Given the concavity of

the utility of wealth functions, the individual is assumed to display risk aversion over wealth at least given survival.

$$\frac{dU}{dw} > 0 \text{ and } \frac{d^2U}{dw^2} < 0 \qquad (2)$$

$$\frac{dD}{dw} \geq 0 \text{ and } \frac{d^2D}{dw^2} \leq 0 \qquad (3)$$

In addition, assume that utility of wealth conditional upon living is greater than utility of wealth conditional on dying. That is, the individual prefers life to death at any given level of wealth.

$$U(w) > D(w) \qquad (4)$$

Finally, it is assumed that utility is more responsive to changes in risk conditional on survival than conditional upon death which is reflected in the higher marginal utility of wealth conditional on survival than on death.

$$\frac{dU(w)}{dw} > \frac{dD(w)}{dw} \qquad (5)$$

2.3.1 *Introducing a risk reduction*

Consider a potential risk reduction which would reduce the subjective fatality risk from $\bar{p}$ to p. This clearly reflects a welfare gain for the individual because of the assumption that life is preferred to death. As such, there can be some reduction in wealth, V, which when received along with the risk reduction $\bar{p}$ to p, leaves the overall expected utility unchanged. That is,

$$(1-\bar{p})U(\overline{w}) + \bar{p}D(\overline{w}) = (1-p)U(\overline{w}-V) + pD(\overline{w}-V) \qquad (6)$$

To understand the significance of the value V, which Jones-Lee refers to as the Hicksian compensating variation in wealth for the risk change under consideration[5], it is useful to consider how V changes with respect to changes in the probability.

2.3.2 Willingness to pay for a marginal risk change

Differentiating *(6)* with respect to p gives the following relationship

[5] An alternative definition for V, provided in Schmalensee (1972) and applied to the VSL definition by Smith and Desvousges (1987), is as an option price.

$$\frac{\partial V}{\partial p} = \frac{U-D}{U'(1-p)+pD'} \quad (7)$$

Where

$$U = U(\bar{w} - V),\ D = D(\bar{w} - V), U' = \frac{\partial U(\bar{w}-V)}{\partial V}, D' = \frac{\partial D(\bar{w}-V)}{\partial V}$$

$\frac{\partial V}{\partial p}$ then represents willingness to pay (WTP), defined ex-ante, for a marginal change in subjective fatality risk p. It depends on both the difference between utility under full health and death, and on the probability-weighted marginal utilities under full health and death. Some properties of this willingness to pay can be noted based simply on the assumptions provided above, in equations (2) to (5).

First, the numerator of the WTP formula is always positive, because utility is always higher in full health than in death for a given level of wealth, as assumed in equation (4). In addition, it is assumed that the marginal utility of wealth in full health is strictly positive, and as such, given that V is taken from wealth the partial derivative of the utility of wealth with respect to V (wealth loss) will always be negative. This is strictly true for the condition of full health, and weakly true in death, so

$$U' = \frac{\partial U(\bar{w}-V)}{\partial V} < 0 \text{ and } D' = \frac{\partial D(\bar{w}-V)}{\partial V} \leq 0 \quad (8)$$

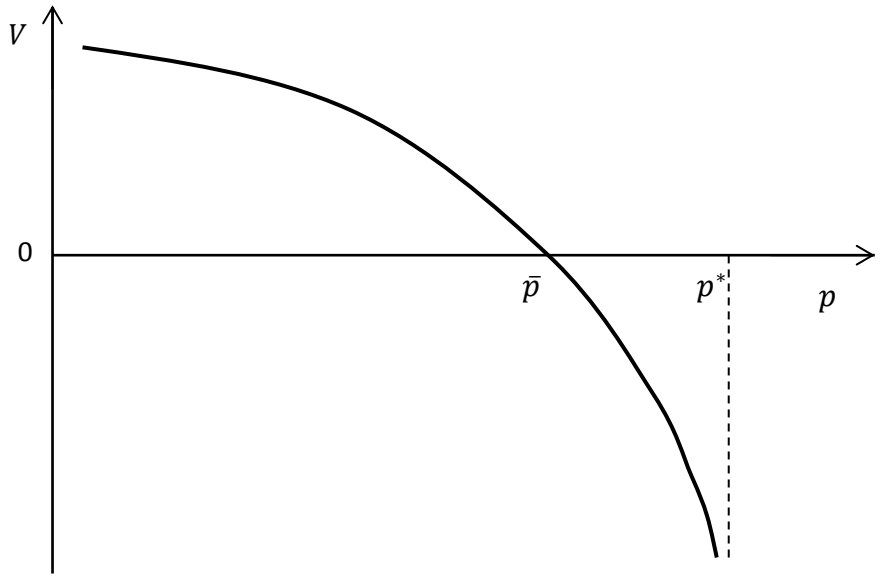
Given that equation (5) stated that utility is more sensitive to changes in wealth under full health than in death, it is natural to conclude that

$$\frac{\partial U(\bar{w}-V)}{\partial V} < \frac{\partial D(\bar{w}-V)}{\partial V} \leq 0 \quad (9)$$

From this, the denominator of the willingness to pay equation is negative, and as such $\frac{\partial V}{\partial p} < 0$.

Jones-Lee (1974) derives that $\frac{\partial^2 V}{\partial p^2} < 0$ which allows the relationship between willingness to pay for a change in risk (V) to be plotted as a function of the new risk level (p) as is shown in figure 2.1, which is adapted from Jones-Lee (1974, p.95).

Figure 2.1: Willingness to pay and willingness to accept for changes in fatality risk



The diagram in figure 2.1 demonstrates that V (WTP for a change in risk) is positive for reductions in risk ($p < \bar{p}$) and negative for increases in fatality risk ($p > \bar{p}$) reflecting willingness to accept (WTA) compensation. The limit p^* represents the maximum acceptable increase in risk, for which no finite sum would be sufficient to compensate the individual for accepting the risk increase, which would *ceteris paribus* cause a reduction in their expected utility, according to equation (2).

2.3.3 *Willingness to pay for a change from baseline risk*

Typically, policies that address risks are concerned with the effects of small changes in the probability of fatality. That is, the willingness to pay for marginal changes in fatality risk evaluated from the perspective of the current risk level $\bar{p}$. Given that where the risk change is zero (i.e. $p = \bar{p}$) WTP for the change in p is zero, then

$$\left(\frac{\partial V}{\partial p}\right)_{\bar{p}} = \frac{U(\bar{w}) - D(\bar{w})}{(1-\bar{p})U'(\bar{w}) + \bar{p}D'(\bar{w})} \qquad (10)$$

For the risk reduction case, $-\left(\frac{\partial V}{\partial p}\right)_{\bar{p}}$ is then the marginal value of a risk reduction from the baseline fatality risk, $\bar{p}$.

2.3.4 *Aggregation to the VSL*

The elicited private values for an individual's marginal risk reduction are typically aggregated in order to provide a useful and easily interpreted unit of measurement for

use in policy making. Traditionally this has been through aggregation into the Value of Statistical Life (VSL) also known in the UK as the Value of Preventing a Statistical Fatality (VPF)[6]. The aggregation procedure is to take the mean of the marginal rates of substitution of wealth for fatality risk amongst a population. This is explored in Jones-Lee (1991). The elicitation of marginal rates of substitution, however, is not straightforward in practice and instead what is typically measured is Willingness to Pay (or Willingness to Accept) for a small but defined change in probability of fatality. These WTP values are then aggregated over a population such that the expected change in the number of fatalities is precisely equal to one, hence the term VSL. To illustrate, consider a population of size 10,000 which is offered a reduction in fatality risk equal to 1/10,000. The summation of the individuals' WTP values for this risk reduction will provide an estimate of the VSL.

2.3.5 A note on the interpretation of 'VSL'

It should be noted that in the US, there has been a recent trend towards two alternative interpretations of WTP values for dissemination. The approach taken by Hammitt and others (see for example Hammitt and Liu (2004b), Cropper and Sussman (1990)) is to define the VSL as an individual's marginal rate of substitution between wealth and fatality risk. Under this interpretation, unlike under the standard interpretation described above, it is meaningful to talk about an individuals' own VSL. It is important to recognise the difference in interpretation of the VSL concept in these different literatures, because the implications on a population level are only the same if the population is homogeneous in its preferences.

The second approach, which is less easily confused with the standard VSL, is to disseminate the information in the form of a micro-risk reduction. This approach, defined by Cameron and DeShazo in multiple works (see for example Cameron *et al.* (2009) or Cameron and DeShazo (2012)) is an attempt to avoid the public outrage that is sometimes associated with the misinterpretation of the VSL as a value to be placed on a particular fatality. However while at face value the micro-risk reduction approach appears very different, in essence it is equivalent to the standard VSL as applied by

[6] The term 'VPF' is arguably more intuitively appealing than the term 'VSL' because it is less open to misinterpretation as being the value of a particular or identified life, which as discussed and as shown in figure 2.1 is arguably beyond value. The VPF definition was recommended in a report to the World Health Organisation (Sommer et al. 1999) but for the sake of comparability with the majority of published literature on the valuation of fatality risks, will not be used here.

Jones-Lee and others in the UK and Europe, with the exception that the VSL estimate is divided by one million. However, the author of this thesis is of the opinion that with due care of explanation, the VSL concept is a useful and intuitively appealing unit of measurement, and the standard definition Jones-Lee (1991)will be employed throughout the rest of this work.

2.3.6 *Factors predicted to influence the single-period VSL*

The VSL as defined over single period one-off fatality risks is theoretically predicted to respond to both baseline risk and wealth. These predictions are discussed below, and will inform the treatment of baseline risk and wealth in the survey reported in part II (pg.63). Existing empirical evidence about the influence of baseline risk and wealth on the VSL is provided later in this literature review, while this section focuses on predictions from theory.

2.3.6.i *Predicted influence of the baseline risk level*

Equation (10) defined the marginal rate of substitution between wealth and fatality risk viewed from the baseline level of risk $\bar{p}$. Taking the derivative of this function with respect to $\bar{p}$ allows predictions to be made about the way that the marginal rate of substitution between wealth and risk- and hence the VSL- is expected to depend upon the baseline risk. Using the product rule it is possible to show that

$$\frac{\partial\left(\frac{\partial V}{\partial p}\right)_{\bar{p}}}{\partial \bar{p}} = \frac{(D-U)(D'-U')}{[(1-\bar{p})U'+\bar{p}D]^2} \qquad (11)$$

and given that $(D-U) < 0$ and $(D'-U') \geq 0$, then the expression in equation (11) is not greater than zero. Recasting this in terms of willingness to pay for risk reductions generates equation (12).

$$\frac{\partial\left(-\left(\frac{\partial V}{\partial p}\right)_{\bar{p}}\right)}{\partial \bar{p}} = -\frac{(D-U)(D'-U')}{[(1-\bar{p})U'+\bar{p}D]^2} > 0 \qquad (12)$$

As such, the marginal rate of substitution of wealth for a reduction in risk, defined at current risk level p, is increasing in baseline risk.

2.3.6.ii *Predicted influence of initial wealth*

Similar analysis allows the investigation of the impact of initial wealth on the VSL. Differentiating equation (10) with respect to the wealth parameter W gives

$$\frac{\partial\left(\frac{\partial V}{\partial p}\right)_{\bar{p}}}{\partial \overline{w}} = \frac{[(1-\bar{p})U'+\bar{p}D](D'-U')+(U-D)[(1-\bar{p})U''+\bar{p}D'']}{[(1-\bar{p})U'+\bar{p}D']^2} \quad (13)$$

Again using the assumptions from equations (2)-(5), and the observations that $U' < D' \leq 0$ and $U'' < D'' \leq 0$, it is possible to show that equation (13) is negative, and as such that the counterpart for a risk reduction is increasing in initial wealth $\overline{w}$.

2.4 Multi-period Models of Utility Maximisation

The model described and analysed in section 2.3 is restricted to consider a single time period which is a limitation that will become particularly pertinent when this analysis turns to consider cancer fatality risks. In reality, it seems clear that an individual would have some preferences over the timing of risk changes. There are two main classes of models that look at utility over multiple periods of time. These are the life cycle consumption models (LCM), which originated with the work of Yaari (1965), and simpler extensions of the single period model as discussed in Jones-Lee (1982). The life cycle consumption models involve restrictive assumptions, but they are more commonly used than the Jones-Lee models to explore willingness to pay for fatality risks over time under different assumptions. As such, this review considers just the LCM to provide a basis for understanding the existing empirical literature and for the development of the van Houtven (2008) model which underpins the cancer VSL to be examined in this thesis.

2.4.1 *Set-up of the Life cycle consumption model- Cropper (1990)*

The life cycle consumption model is presented because it is commonly used in the literature as a basis for the theoretical exploration and survey design in studies investigating different influences upon the VSL where timing is important. Examples are the work of Ehrlich and Chuma (1990) in combining the Grossman model of investment in health (Grossman, 1972) with the LCM; and the work of Bleichrodt and Quiggin (1999) in combining the QALY[7] model insights with the LCM. Perhaps most relevant is the use of the LCM by Van Houtven *et al.* (2008) in setting up a risk-risk model of cancer risk reductions, which will be presented and discussed on pg.49 as a basis upon which the empirical work in this thesis builds.

For a working example of an LCM see Cropper and Sussman (1990), from which the following exposition is adapted. The pattern typically seen in these life cycle

[7] Quality Adjusted Life Year

consumption models is that utility over wealth is weighted by the probability of surviving, and as such they are comparable with the single period model- but these weighted utilities are modelled over multiple periods of time. A simple basic model assumes additive periods of discrete time, such that the lifetime expected utility is given as

$$Z_j = \sum_{t=j}^{T}(1+\rho)^{j-t} q_{j,t} U(c_t) \qquad (14)$$

Where expected utility as perceived at current age j is the sum of instantaneous utility of consumption $U(c_t)$ in each future period at age t up to the maximum age T.

The instantaneous utility is weighted by $q_{j,t}$ which is the probability, given that the individual survives to j, of being alive during period t; and also weighted by the discount factor $(1+\rho)^{j-t}$ which assumes exponential discounting is applied by the individual at rate ρ over the $t-j$ periods until the time period in question. The probability of surviving to age $t+1$, given survival to age t, is $\frac{q_{j,t+1}}{q_{j,t}}$. Let this be denoted by the probability $1-D_t$, where D_t is the probability of dying at age t conditional upon survival until the t^{th} birthday.

The next ingredient for the optimisation problem is the wealth constraint. Cropper and Sussman (1990) demonstrate that this can be reduced to the assumption that the present value of expected consumption is equal to the present value of lifetime earnings plus initial wealth, i.e.

$$\sum_{t=j}^{T} q_{j,t}(1+r)^{j-t} c_t = \sum_{t=j}^{T} q_{j,t}(1+r)^{j-t} y_t + W_j \qquad (15)$$

where r is the riskless rate of return on savings and interest on borrowings.

The individual therefore faces a maximisation problem, where expected utility from lifetime consumption (given in equation (14)) is maximised subject to the wealth constraint in equation (15) resulting in an optimal consumption stream.

2.4.2 *Eliciting willingness to pay from the life cycle consumption model*

As for the single period model, differentiation is used to establish the willingness to pay (WTP) for a reduction in risk. Consider a regulation to reduce the probability of fatality during a given year, conditional on being alive at the beginning of that year.

Specifically, the regulation will reduce D_k, which as discussed is the probability of dying at age k conditional on having reached age k.

The result was reached earlier that WTP for a risk change is the amount of wealth that an individual is just willing to give up in exchange for the change in probability of fatality. Placed within an intertemporal frame, this becomes the amount of wealth that an individual will give up at age j for a reduction in D_k. That is, the payment happens at present while the risk change may occur in the future. This demonstrates the flexibility of the model. To formalise, willingness to pay at age j for a reduction in D_k is as follows

$$WTP_{j,k} = -\frac{\partial V_j / \partial D_k}{\partial V_j / \partial W_j} dD_k \qquad (16)$$

Cropper et al state that applying the Envelope Theorem to the Lagrangean function that represents the maximisation of the objective function in equation (14) with respect to the constraint in (15) allows the $WTP_{j,k}$ to be written as

$$WTP_{j,k} = \left[(1 - D_k)^{-1} \sum_{t=k+1}^{T} \left[(1+\rho)^{j-t} U(c_t) \lambda_j^{-1} + (1+r)^{j-t}(y_t - c_t)\right]\right] dD_k \qquad (17)$$

where λ_j is the marginal utility of income in year j. Cropper and Sussman (1990) provide an intuitive interpretation of this result. Willingness to pay is equal to the loss of discounted utility from age $k+1$ and all subsequent periods, which is converted into a monetary amount by dividing by the marginal utility of income λ_j. This is augmented by the impact of the change in D_k on the budget constraint, in that an increased survival probability will decrease the affordable consumption opportunities while increasing earnings potential. The resulting influence is therefore ambiguous. WTP for a risk reduction therefore depends on a combination of utility and budget effects. Cropper and Sussman (1990) note that in abstracting from any value of longevity or survival *per se*, this framework likely provides a lower bound for the WTP for a given change in the conditional probability of fatality.

2.4.3 *Age and the VSL*

In addition to the theoretical predictions about wealth and baseline risk, which were explored in section 2.3.6, introducing a lifetime frame provides a framework for considering two further influences upon the VSL. These are latency of a risk, the treatment of which is postponed until section 2.10, and age. Based on the life cycle consumption model, the effect of age on the VSL is ambiguous, as described by Hammitt (2000):

> "Two factors influence the life-cycle pattern of VSL. First, the number of future life years at risk declines as age increases, so the benefit of a unit decrease in current-period mortality risk declines. Second, the opportunity cost of spending on risk reduction also declines with age as savings accumulate and the investment horizon approaches. The net effect may cause VSL to fall or rise with age." (Hammitt, 2000)

2.4.4 *Assumptions in the Cropper (1990) model of life cycle consumption*

The Cropper model of life cycle consumption presented above requires a number of assumptions, some of which have been discussed. They are summarised below.

- The analysis depends upon the von Neumann and Morgenstern axioms (von Neumann and Morgenstern, 1947) and is therefore constrained by the same criticisms as the single period model regarding the realism of the underlying assumptions and the appropriateness of their application. As stated previously, it is in this author's opinion the most appropriate framework within which to work in the absence of clearly superior alternatives.
- An individual's utility is assumed to depend only on consumption, which is weighted only by discounting and survival probability. This is a restrictive assumption but simplifies the analysis to the factors that are to be investigated in a wealth-risk trade-off.
- Utility received if one dies is assumed to be zero. This precludes the bequest motive for positive utility under fatality that was accommodated by the single period model, although this assumption can be relaxed if necessary.
- Survival probabilities are assumed to be exogenous, as in the single period model.

- Utility over different life spans is represented by the additional consumption possibilities in those periods, weighted as discussed. No utility is derived from survival *per se*, only from the consumption possibilities that survival presents.
- Utility of consumption in any given period is independent of the other periods' consumption and utility. This additive separability assumption is arguably the most problematic assumption within these models, but its relaxation results in a loss of analytical tractability.
- The assumption of perfect capital markets is be imposed (see Cropper and Sussman (1990) for a discussion).

2.5 Insights Taken from the Jones-Lee (1974) and Cropper (1990) Models

The influences taken from Cropper and Sussman (1990) and Jones-Lee (1974) are the weighting of utility of wealth by survival probabilities in forming an expected utility maximisation problem for the individual responding to risk trade-off scenarios. These models have provided the theoretical basis for the assumed relationship between wealth, risk and utility that forms the basis of the mechanism of the Risk-Risk trade-off mechanism that will be discussed in section 3.2. In addition, the insights about the importance of baseline risk and wealth in determining the VSL will inform the design of the survey and the analysis in parts II and III of this thesis.

2.6 Existing VSL Estimates

Having outlined the theory underpinning the elicitation of estimates of the VSL, this section now presents a summary of existing empirical work aimed at estimating the appropriate value for the VSL as defined over instantaneous accidental fatality. This section is to be kept intentionally brief, because the main focus of this research is to consider the VSL for cancer. Nonetheless, understanding the VSL defined over instantaneous accidental fatality will be important because road accident fatalities (a subset of instant accidental fatalities) are to be the comparator case in the theoretical analysis reported in section 2.11.1 and the empirical work in part II.

2.6.1 *Meta-analyses of worldwide instantaneous fatality VSL estimates*

There exists substantial literature dedicated to establishing the appropriate value of preventing a statistical instantaneous fatality (VSL). For example, the meta-analyses by Viscusi and Aldy (2003) or Mrozek and Taylor (2002) each provide a summary of

hedonic wage estimates of the VSL worldwide. Alternatively, for meta-analysis of both contingent and revealed preference studies see Miller (2000) or Bellavance *et al.* (2009). A comprehensive review of elicitation techniques and estimates can be found in the report "Health of Nations" prepared for the Australian Safety and Compensation Council (ASACC, 2008), comprising over 200 estimates of the VSL, while the global meta-analysis of stated preference studies conducted by Lindhjem *et al.* (2011) is perhaps the most comprehensive in considering the factors that affect the VSL.

Given this wealth of secondary analysis on the level of the VSL worldwide, further evaluation of individual VSL studies will not add value to the present discussion or to knowledge in general. However, a key message from the meta-analyses is that estimates of the VSL vary substantially both within and between studies.

2.6.2 *Factors explaining the variation in VSL estimates*

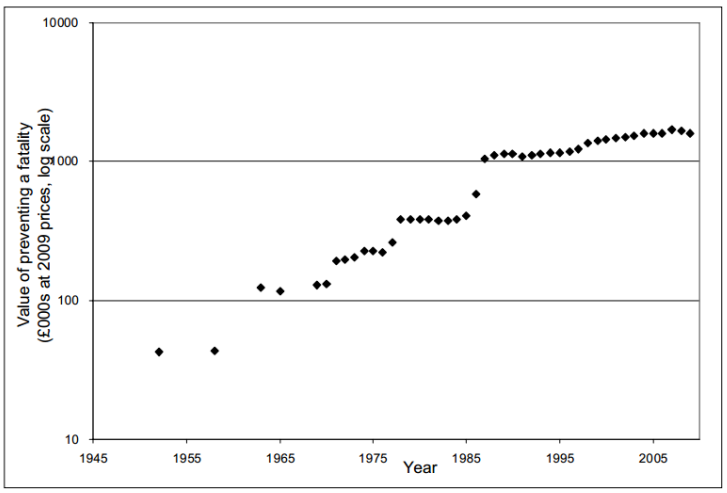
The variation between studies is often due to differences in the exact scenario presented to respondents (see Chilton *et al.* (2006a) which shows the variation in strength of preference for avoiding instantaneous fatalities in different contexts) or in the elicitation mechanism (revealed preferences have repeatedly been shown to generate higher estimates of the VSL than stated preference studies (de Blaeij *et al.*, 2003)). These issues will be taken into consideration when designing the survey instrument for the empirical investigation in parts II and III. In addition to the between-study variation, respondent characteristics have been shown to generate different VSL levels within studies. This includes the theoretically predicted influences of wealth and baseline risk (identified by Lindhjem *et al.* (2011) as the most robustly and consistently important factors influencing the VSL) but in addition age, gender and other demographic effects have been repeatedly shown to influence the VSL. In depth discussion of these influences is provided in the meta-analyses mentioned above and will not be repeated here, but this observation will be taken forward to inform the regression models in the later analyses (see part II).

2.6.3 UK policy VSL

Since 1987 the UK's Department for Transport (DfT) has based its value of safety on what it refers to as the VPF (Value of Preventing a Statistical Fatality- synonymous with the VSL as defined on pg.20) on stated preferences, with additional value included to account for the avoided lost output and ambulance and safety costs which would not

necessarily be incorporated into an individual's WTP value. The value has been updated for inflation and methodological advances (see Carthy *et al.* (1999)) with the progression of the VPF in 2009 prices shown in figure 2.2. The leap in the value in 1987 reflects the change (implemented in 1988) to using the Stated Preference values as opposed to the previous 'gross output' method where the VSL was based on the value of lost economic output that would be avoided by the prevention of a premature fatality as opposed to capturing the intrinsic value of survival. The currently utilised VSL is around £1.6million in 2009 prices for all fatalities except cancer. As such, the current UK 'roads VSL' is £1.6million. The interested reader should consult Jones-Lee and Spackman (2013) for an up-to-date account of the development of the value of road safety in the UK.

Figure 2.2: Value of preventing a UK road fatality: 1952-2009



Source, Department for Transport, (2011), p.2

2.7 Variation in the VSL Across Contexts

So far in this review, the focus has been restricted to consider the value of changes in the risk of instantaneous accidental fatalities, with a particular focus on road accident risk changes. However, in reality fatality risks are diverse in their characteristics. It is beyond the scope of this literature review to discuss the arguments- which are on-going in the literature[8]- pertinent to the appropriateness of applying differentiated VSLs in policy. Whilst acknowledging the importance of this debate, this thesis adopts the

[8] The discussion of how far policy ought to reflect public preferences has been considered explicitly in McDaniels et al. (1992), Sunstein (1997) and Savage (1993). The pragmatic and ethical desires for a single VSL for policymaking must be weighed against the importance of consumer sovereignty principles.

viewpoint taken by the HSE that policy decisions ought to reflect the preferences of members of the public as far as is practical. To that end, it aims to provide information about the appropriate level of the cancer VSL, relative to the value of preventing a statistical fatality in the context of road accidents (which, as discussed on pg.28, is currently £1.6million). A number of studies discuss the variation in VSL across contexts, with a notable recent meta-analysis by Dekker *et al.* (2011) which evaluates the possibility of conducting Benefits Transfer of VSLs across contexts. Dekker et al. conclude that the procedure is not straightforward due to the importance of context to the VSL. They do not, however, consider the case of cancer.

There are certain elements of the prospect of cancer fatality which lead to the assumption that these risk changes will be valued differently than road accident fatality risk changes. This is the focus of the next section of this literature review.

2.8 Existing Evidence About the VSL for Cancer

Based on the existing empirical literature on cancer, there is little consensus about the magnitude, or even the existence, of any cancer premium. Like for the roads VSL, the broad range of values is likely to be due to differences between the studies eliciting them; particularly the specific context, the country in which the study was performed, the typical age, wealth and other characteristics of the sample and so on. However, there are two additional features of the prospect of cancer fatality that set it apart from road accident fatality, and which may well contribute to the very broad spread of results. These are the effect that the context "cancer" has on the prospect of fatality and the fact that typically cancer fatality occurs after a delay of some years after the change in underlying exposure risk. This review will argue that the context of cancer engenders specific or additional disutility for two main reasons: a dread of the particular label "cancer", and the additional disutility that is associated with a period of illness prior to fatality. For the delay- referred to as latency- this is likely to reflect discounting but also some additional timing effects reflecting age, life stage and susceptibility to risks. These will be discussed in turn in section 2.10, along with the existing empirical evidence. To maintain clarity throughout this thesis, the key terms are defined in figure 2.3.

These definitions are used throughout this thesis. At times, they differ from definitions used in the literature, because there is little consensus in the stated preference literature about how cancer fatality risks ought to be explained and presented to respondents.

This is arguably a key explanation for the differences in VSL between studies but so far studies are too few to conduct a full meta-analysis of these effects, and they have insufficient detail regarding the way that cancer fatality scenarios are explained. Instead, this review takes a more general approach and considers the evidence for the influence of these context and latency effects, concluding that the label 'cancer', morbidity preceding cancer fatality, and latency can all be shown at least by some studies to influence the perceived value of cancer risk reductions. This will inform the survey design in part II which will explore these effects directly and explicitly.

Figure 2.3: Key definitions

OVERALL PREMIUM	the relative size of the cancer VSL incorporating all relevant effects (morbidity, label dread and latency) compared to the road accident VSL defined as an instant near-term fatality.
CONTEXT PREMIUM	the effect on the VSL of the specific cause of fatality, cancer as opposed to road accidents. Context is defined as being independent of time, but incorporating the influence of the illness associated with cancer.
LABEL DREAD	a component of the context premium, 'label dread' is the particular influence of the term "cancer" on the VSL controlling for both timing and morbidity.
MORBIDITY	the time spent ill prior to fatality from cancer
LATENCY	the time from exposure to the cancer-causing substance until fatality. As such, the latency period includes the morbidity period within it.

2.9 Context, Morbidity and Labelling Dread Literature

2.9.1 *Different valuation for different contexts: psychological underpinnings*

This literature review has made the assumption that there is likely to be differences of valuation of risks in different contexts. Recall figure 2.3 which defined context effects as encompassing all of the differences between the prospect of a cancer fatality compared to the prospect of a road accident fatality, while holding the time of fatality constant. In the lifetime consumption model by Cropper and Sussman (1990) which was presented on pg.23, utility of a change in the probability of dying is dependent upon

the risk change, wealth level, initial risk and timing. In the assumptions on pg.26 it was discussed that lifetime utility depends on the utility of consumption in each period. Any direct utility from a change in risk itself was assumed away. However, there is evidence to suggest that individuals may value survival and survival probability for its own sake. As Slovic (1987) has it, "In short, "riskiness" means more to people than "expected number of fatalities."”

This concept of valuing a risk change for more than the utility from the additional expected consumption is particularly pertinent when considering risk changes that are considered particularly "dreadful" ways to die. Sunstein's seminal work (Sunstein, 1997)introduces the idea that deaths are not considered the same as one another, because "Some deaths are taken to be part of life, whereas others seem disruptive and terrifying." This idea is expanded upon in an extensive literature surrounding the practical and psychological differences between fatalities by different causes.

2.9.2 *Different valuation for different contexts: empirical evidence*

Slovic (1987) provides a seminal review of early studies into the influences of psychometric factors like voluntariness, dread, knowledge, and controllability of the risk; baseline risks; and benefits which combine to provide an individual's perception of a risk scenario. Slovic suggests collapsing the wide range of psychometric factors into just two dimensions, 'dread risk' and 'unknown risk'. The former captures (on a scale of increasing severity) perceived lack of control, pure dread, catastrophic potential, likelihood of fatal consequences, and the inequitable distribution of risks and benefits. Each of these is argued to increase how severe the risk would seem, even if the respondent was fully informed about the risk and what it would be like. The second dimension, "unknown risk" captures to what extent the risk is judged to be unobservable, unknown, new to society or to science, and delayed in the manifestation of the harm. As such, they are more to do with the uncertainty of the risk occurring and being detected, than to do with the severity of the scenario itself. These definitions are adapted from Slovic (1987).

A similar categorisation was provided earlier by Fischhoff *et al.* (1978). Risk perception was described as depending upon a range of factors, sharing a number of common features with the Slovic factors, but with some differences. Fischhoff's factors are listed as the immediacy of the risk, the voluntariness of undertaking the risk, the knowledge of both those exposed and those in a position to deal with the risk (Fischhoff

cites the scientific community in this role), the controllability of the risk, its novelty, its potential to be catastrophic, its associated dread, and the perceived severity of the risk. In contrast to Slovic, Fischoff simplifies the factors by the level of technology (high to low tech) and the certainty of fatality if the risk materialises.

Mcdaniels *et al.* (1992) is a more recent example of a study that discusses the perception of risk in terms of the characteristics of that risk. In this study, the authors find that the characteristics of a hazard influence WTP to reduce the risk. They define "dread risks" as being severe, uncontrollable and catastrophic, but also note the importance of knowledge, controllability and voluntariness on the way that the risk is perceived. The *a priori* discussion of these factors is confirmed using a contingent valuation and risk perception study. This is replicated in Jones-Lee and Loomes (1995) who show that controllability, voluntariness and responsibility are more influential to the way a risk is perceived than its potential to be catastrophic (i.e. involve multiple fatalities). This study provides further support to the emerging factors from previous work.

Chilton *et al.* (2006a) conducted a study to consider whether the context of the fatality influences decisions in a risk-risk framework. This study is an important complement to the above because it explicitly controls for baseline risk, which could arguably be driving the apparent preference for avoiding risks in certain contexts (see pg.22 for a discussion about the influence of baseline on the WTP for changes in risk). The Chilton et al. study provides further evidence that differences in context generate different strengths of preference, even when all risks are instantaneous and when baseline risk is controlled for. In contrast, Carlsson *et al.* (2010a) consider age and context effects on VSL in a choice experiment, and find that while age significantly influences the VSL, the context of the fatality does not. However, the authors note that their study is framed in terms of risks to other people. This may explain why the more emotive or affective factors described in the work of Slovic, Fischhoff and others may not have applied.

To summarise this section, a range of factors has been considered in a literature spanning over three decades. These factors are presented in figure 2.4. These factors allow a vast array of risk scenarios to be considered, and provide a rationale that is missing in the standard WTP models like the Cropper and Sussman (1990) model, for the difference between WTP for risks across different contexts.

Figure 2.4: Factors driving the context premium for general risks

Voluntariness of undertaking the risk: WTP more to avoid risk that is not voluntarily undertaken

Controllability of the risk: WTP more to reduce a risk that is perceived to be outside of individual's control

Knowledge: WTP more to reduce the risk of something that is poorly understood, either by those exposed or by science

Novelty: If a technology or hazard is new, WTP more to avoid the associated risk. This links to knowledge.

Associated **dread:** WTP more to reduce the risk of something perceived to be particularly dreadful. This is related to the perceived severity of the risk scenario.

Potential to be **catastrophic** (kill multiple people at once): some evidence that WTP more to reduce catastrophe risks

Benefits: Willing to accept a higher level of risk in an activity when the perceived benefit is higher

Immediacy of the risk: WTP more to avoid immediate risk (links to time preference and latency)

The above discussion has confirmed that there are psychological reasons, supported empirically, for different fatality causes to be valued differently because of the affective or emotional considerations that they generate in individuals' conceptualisation of the fatality and the risk. However, up to now, the specific case under consideration in this thesis has been left aside. The next section addresses this, relating each of the causes listed in figure 2.4 to cancer, and then exploring whether the existing empirical literature supports the hypothesis that cancer is considered worse than other fatality causes. Notice that in this section, the influence of timing is set aside because the focus here is on the causes. The timing element will be returned to in section 2.10, pg.42.

2.9.3 *Cancer context premium: predictions*

Figure 2.5 summarises the way that cancer is likely to be perceived on each of the dimensions discussed in section 2.9.2 and summarised in figure 2.4. The direction and comments are speculative, but generate an overall summary of the likely implications.

Figure 2.5: Applying the context factors to the case of cancer

Characteristic	Cancer on this scale	Implication for cancer VSL	Comments
Voluntariness	Ambiguous	Ambiguous	Behavioural or occupational cancer risks may be perceived more voluntarily undertaken than genetic cancer risks.
Controllability	Low (with exceptions)	Decrease (with exceptions)	Behavioural or occupational cancers may be perceived more controllable than genetic cancers
Knowledge	Low but increasing	Increase (but at a decreasing rate?)	Knowledge of cancer from a scientific perspective is improving.
Novelty	Low	Decrease	Perhaps depends on cancer cause- if occupational, what industry etc.?
Dread	High	Increase	See section 2.9
Catastrophic	Low	Decrease	Except in large scale occupational/environmental accident scenarios.
Benefits	Ambiguous	Ambiguous	Depends on cancer cause- if occupational, what industry etc.?
Immediacy	Low	Decrease	See section 2.10

Figure 2.5 shows that there is not an unambiguous consensus between the factors with respect to whether they are likely to have an upward or downward influence on the VSL for cancer. However, there are some clear results, for example that cancer is typically considered a 'dreaded' fatality and that it is typically difficult to control, but that it is usually not immediate.

To build upon this speculation, the next section of this review considers the empirical evidence that exists surrounding the characterisation of cancer as a "bad death"(Sunstein, 1997), *ceteris paribus.*

2.9.4 *Cancer context premium: empirical evidence*

Early empirical work which considered the cancer and road accident risk comparison was Jones-Lee *et al.* (1985a). This Person Trade Off matching study did not explicitly describe the latency period involved in the cancer case, which means that the interpretation of the premium that they find is slightly problematic. Under the assumption that respondents assumed that the risks would manifest at the same time, the cancer context premium is above 3 based on the cancer VSL at £23m and the road accident VSL at £7m. Of course, as with all matching studies there is an element of other-regarding preferences which could have affected the values, but this ought not to dramatically affect the relativity between the two VSLs, if the effects of the other-regarding preferences are similar in the cancer and road accident cases.

The next notable study to provide empirical evidence about the cancer to roads relativity is Savage (1993). This study addresses the comparison from a psychological perspective, eliciting information about public perceptions of the hazards in terms of the psychological factors presented in figure 2.4. The results show that cancer (specifically stomach cancer) is "in a league apart from the other risks", with a very high WTP for cancer compared to the other risks. Magat *et al.* (1996) find contrasting results to the earlier two studies. They find no premium for cancer compared to road accidents, even contemporaneously. This difference may be a result of the Risk-Risk trade-off methodology or of the particular cancer specified (lymphoma), but as discussed the heterogeneity in survey mechanisms makes the results difficult to compare.

At this stage chronologically, Revesz (1999) produced a report with a legal focus which considered the value of cancer risk reductions. This article provides no new empirical evidence but is a comprehensive summary of thought and empirics up until that stage. The focus is largely on the latent nature of cancer risks, and this will be returned to in section 2.10. Nonetheless, Revesz argues that discounting latent harms ought to be "accompanied by countervailing upward adjustments" and cites the dread of cancer and involuntary nature of the cancer harm.

After the Revesz study, the empirical work is noticeably more rigorous in its treatment of the characteristics of the cancer cases under consideration. Hammitt and Liu (2004b) find no premium for cancer, but this is after controlling for the latency. They report a preference for avoiding cancer *ceteris paribus* and discuss that this is due to the protracted suffering but also because of the knowledge of impending death. It ought to be noted that they did not include an instantaneous accidental fatality as a comparator, instead considering different latent diseases. In a study conducted for the UK's Health and Safety Executive (HSE), Chilton *et al.* (2007) conduct a choice experiment (also referred to as conjoint analysis) which includes a direct cancer to road accident comparison. They find a premium for cancer, and discuss that this is likely due to effects including blame and responsibility especially when comparing behavioural cancers like smoking-attributable cancers to work-related cancers like occupational mesothelioma, which is related to asbestos. Their qualitative evidence does not suggest a particular dread of the label 'cancer', because "no specific or emotive comments were made about the fact that the deaths were labelled as 'cancer' death" (Chilton *et al.*, 2007). This suggests that other features may have played more of a role.

The HSE study had a broad focus ranging from rail accidents to occupational cancers and considering aspects from illness through to blame and responsibility, while the Hammitt and Liu (2004b) study had a narrow focus to the extent that the instantaneous roads comparison was excluded. A study which arguably fits between these extremes is Cameron *et al.* (2009), which considers mainly latent diseases (like Hammitt and Liu (2004)) but in addition includes the road accident case for comparison (like the HSE study). Using conjoint analysis, the authors find mixed evidence for cancer context premia, with some cancers at a premium compared to the base case and some at a discount. The cancers particularly feared are breast, prostate and colon cancers while lung and skin cancer generate lower WTP. This may reflect elements of blame and responsibility because lung and skin cancers are often linked to behaviours such as smoking and carelessness about UV rays from the sun or sunbeds. As such, the "dread" of cancer appears again to be offset by the ability to blame the cancer on actions of the victim. This mirrors the HSE result as well as the early results in Jones-Lee *et al.* (1985a).

2.9.5 *Cancer morbidity premium: predictions*

So far, the theoretical discussion has mostly focussed on the label dread of cancer that was presented in the definitions in figure 2.4. That is, the way that the label 'cancer' is enough to evoke a particular aversion to the risk increase, perhaps because of the associated perceptions about responsibility, unfamiliarity, uncontrollability and so on that the label engenders. However, the empirical evidence presented was largely unable to distinguish this effect from a more general 'context premium' which captures more than this label dread. The other main component which is hypothesised to generate the 'context premium' for cancer is referred to here as the 'morbidity premium' which captures the effect of the protracted period of pain and suffering prior to eventual fatality which characterises the typical cancer case.

While the morbidity and mortality aspects of cancer fatality are conceptualised separately in this literature review, in practice they are almost impossible to separate. The suggestion of cancer fatality with no prior morbidity is deemed unrealistic (although it has been used in previous studies including Cameron *et al.* (2009)), a consideration which influences the choice of scenarios in the survey design in part II.

Again, Sunstein (1997) provides a strong hypothesis about the influence of morbidity on the VSL based on psychology. For cancer morbidity, the author suggests that the frame 'cancer death' may induce fears beyond what would be considered reasonable in a VSL study "people call to mind especially stressful periods of pain and suffering that are not representative, or because those incidents may assume undue salience (dwarfing the very fact of death itself)". Goddeeris (1983) provides a theoretical exposition on WTP for illness *ex ante* which corresponds to Sunstein's concerns, stating "aggregate willingness to pay ex ante to reduce the probability of illness to zero exceeds the ex post consumer surplus gained". This review, and indeed this thesis takes the view that strong preferences amongst members of the public ought to be reflected in policy, and in this respect contradicts Sunstein's argument in advising that the morbidity preference legitimately drives the cancer premium. However, it is nonetheless the case that if *excessive* salience is placed on the morbidity attribute this might distort the elicited relativities. This will be considered when designing the survey instrument in part II. In any case, Sunstein provides evidence that morbidity is an important driver of the preference for avoiding cancer fatality, and he concludes (with caveats that the preference ought to be able to "survive a process of reflection") that "when a death is

preceded by a period of pain and suffering, it is appropriate to make special efforts to guard against it" (Sunstein, 1997).

2.9.6 *Cancer morbidity: empirical evidence*

Again, the earliest to provide empirical evidence is the Jones-Lee *et al.* (1985a) study. It does not explicitly provide information about illness but recognises the importance of the cause of latent fatality. The results provide evidence that cancer is considered more dreadful a way to die than road accidents as discussed above on pg.34. However, heart disease fatality is also shown to generate a higher WTP than road accident fatalities. As such, it is clearly not only the label dread of cancer that distinguishes it from road accident fatalities, and morbidity is likely to explain some of the additional preference.

Magat *et al.* (1996) put Sunstein's arguments (outlined on pg.35 above) to an empirical test by including morbidity explicitly in their risk-risk trade-off study mentioned previously. The result is striking: of a fatality preceded by morbidity, 58.3% of the utility loss from the scenario is shown to be attributable to the illness while only 41.7% is attributable to the fatality itself. This reflects Sunstein's argument that considerations about illness might overshadow the fatality aspect, which leads to the essentially unanswerable question about whether the 58.3% value would survive the reflection that would be required to make it a legitimate feature for inclusion in a policy VSL. Nonetheless, if the present agenda is to understand the factors influencing preferences for avoiding cancer risk increases, then this is surely strong evidence that morbidity matters.

A number of more recent studies have included morbidity explicitly in the analysis of the cancer VSL, and find it to be significant in driving the preferences over cancer fatality risks. These are DeShazo and Cameron (2004), Chilton *et al.* (2007) and Cameron and DeShazo (2012). All three find evidence that a longer period of illness increases WTP to avoid the latent fatality risk. However, they each have different contributions. DeShazo and Cameron (2004) illustrate how the lifetime consumption model can be adapted for illness. They introduce the VSI (value of statistical illness) and show that the longer the illness, the higher is WTP. Chilton *et al.* (2007) use length of illness and also find increasing WTP. However, they additionally consider the concept of illness severity, which is not the case in the other studies considered. While quality of life is a harder concept to convey than simply length of an illness period (see chapter 6 for a full discussion of this issue), arguably severity is at least as relevant as

duration when it comes to the effect of illness on the VSL. As such, this study can be seen to make an important contribution. Finally, the Cameron and DeShazo (2012) study is interesting in that while it builds on the framework in the DeSchazo and Cameron (2004) study, its findings are slightly different. While willingness to pay does increase with length of illness, the difference in willingness to pay between the zero illness, 1 year of illness and 5 years of illness scenarios is insignificant. This result is surprising given the other findings discussed.

Hammitt and Liu (2004b) provide a possible explanation for this finding: while morbidity itself is perhaps perceived as a 'bad', and would therefore be expected to increase the willingness to pay to avoid risks of a scenario with long illness, it might be the case that an extensive morbidity period is seen as an extension of length of life. This is the set-up in Van Houtven *et al.* (2008) amongst other studies, and the implications of this description are that the respondent might perceive the illness to be a trade-off between length of life and quality of life. In addition, even if the illness period is not presented as an extension to life, a longer illness period may still be perceived as a good thing if it presents a chance to come to terms with the fatality. Similarly, some respondents may value the opportunity to put their lives in order and perhaps to say goodbye to loved ones. This would mean that a longer period of illness might be perceived to be a good thing, despite the associated pain and suffering. These possible effects will be considered when designing the survey instrument in part II of this thesis. It should be noted that in this study, Hammitt and Liu are unable to test the significance of the morbidity because it is held constant (at 2-3 years) for all scenarios, and the language is "identical for symptoms and prognosis" for all scenarios that they present.

Overall, it appears that the majority of evidence suggests that morbidity matters to respondents when considering cancer fatality risks. While some evidence suggests that the influence is insignificant, in other studies morbidity was the dominant effect driving a preference for avoiding cancer risks. This suggests that morbidity is an area ripe for further empirical investigation which will be performed in part II of this thesis.

It will be noted that this discussion about morbidity has not touched on the literature surrounding the valuation of a QALY. This is because the current analysis is based upon the VSL literature, and considers morbidity as a component of the prospect of cancer fatality. The QALY literature is not rooted in expected utility theory in the same way as the VSL literature, and as such an exposition on the methods and evidence

surrounding the value of a QALY is considered largely irrelevant for this part of the thesis. In part III, where some aspects of the QALY framework will be used, this literature will receive some attention.

2.9.7 *Summary: dread and morbidity components of the cancer context premium*

While the evidence surveyed so far is not without contradiction, it appears that cancer is held at a premium compared to contemporaneous instantaneous fatalities such as road accidents, and that the morbidity prior to fatality is a substantial component of this preference. Speaking normatively, as long as these dread and morbidity effects reflect genuine well-thought-out preferences of members of the public and are not the result of mistakes or misguided decision heuristics, then arguably both label dread and morbidity should be reflected in the VSL for cancer (although the reader is invited to consider the work of Mcdaniels *et al.* (1992), Sunstein (1997) and Savage (1993) for a full discussion of the underlying ethical and theoretical issues that surround the inclusion of dread and morbidity in the value of preventing a statistical fatality). From a more practical sense, descriptively the evidence is convincingly in favour of a cancer context premium, although its magnitude and underpinnings are less clear.

A number of observations will be taken forward and will shape both the theoretical framework and empirical investigation to follow in this thesis. These include the range of factors that might be expected to influence the dread of cancer (see figure 2.5, pg.35) which will be controlled for where possible in the survey design; the potential to confound the morbidity period with length of life; the possibility that morbidity concerns are exaggerated *a priori*; and the need for explicit description of morbidity and latency periods, not least for the analysis of the results by future researchers. If the context premium can be verified and understood, this will provide a firm basis upon which to model the link between the standard roads VSL and the VSL for cancer, and as such will provide a platform for empirical analysis in part II.

2.10 Latency Literature

2.10.1 *Informal intuition about latency*

In figure 2.3 (pg.31), latency was defined as "the time from exposure to the cancer-causing substance until fatality. As such, the latency period includes the morbidity period within it". As such, a longer latency period can be thought of simply as implying a more distant fatality, viewed from the present.

Initial consideration of the likely effects of latency on the perception of fatality risks in general would suggest two main effects. Firstly, viewed from the present, fatality after 30 years entails more life and fewer lost life years than fatality after 20 years making fatality further in the future preferable to fatality sooner. Secondly, given that generally people prefer good things sooner and bad things later, risk reductions are likely to be preferred now and risk increases preferred later. All of these effects would translate into lower willingness to pay for risk reductions in the future, and hence a declining VSL with latency.

2.10.2 *Latency formalised in the Life cycle Consumption Model*

These influences can be formalised in the Lifecycle Consumption Model (Cropper and Sussman, 1990) as discussed in detail in section 2.10 above. Equation (17) (pg.25) is replicated here for convenience:

$$WTP_{j,k} = \left[(1 - D_k)^{-1} \sum_{t=k+1}^{T} \left[(1+\rho)^{j-t} U(c_t) \lambda_j^{-1} + (1+r)^{j-t}(y_t - c_t)\right]\right] dD_k \qquad (17')$$

Where $WTP_{j,k}$ is the willingness to pay at age j for a risk reduction at age k; D_k is the probability of dying at age k given survival to age k; ρ is the rate of time preference; $U(c_t)$ is the instantaneous utility of consumption at time t; λ_j is the marginal utility of wealth at age j; r is the market rate of interest on saving and borrowing; and $y_t - c_t$ is income at time t less consumption at time t.

Using this equation, it is clear to see that the later is k, the lower is willingness to pay, because there are fewer remaining years of consumption to be evaluated. In addition, later life years are subject to more discounting than life years sooner, as evidenced by $(1+\rho)^{j-t}$. One caveat, however, is that the sooner the risk reduction is taken, the more impact it will have over time because D_k is the probability of fatality in a given year *conditional* on surviving to that age. Survival to a given age will be higher if the risk reduction is taken earlier. This is clearly shown in Jones-Lee (1982) and the reader is invited to see Nielsen *et al.* (2010) for a discussion. This result is the first that has indicated that a risk reduction to be taken sooner might be more valuable than a risk reduction that would manifest later.

In addition to the effects considered in the previous section, which were all rooted in the Lifetime Consumption Model, there are classes of effect that are likely to influence

preferences for the timing of fatality risks. There are three main classes of effect: straightforward delay effects, stage-of-life effects and state-of-the-world effects. These are outlined in the next section with reference to the relevant literature.

2.10.3 *Delay effects: dread, context and discounting*

The dread, context and morbidity effects outlined in section 2.9 above concluded that, although not unanimous, there are significant psychological and empirical grounds on which to suspect that cancer fatality risks would be considered worse than contemporaneous road accident fatality risks. The implication of this is that if the cancer fatality is latent while the road accident is not, then the effect of discounting would work to give the dread and morbidity associated with cancer risks less weight, and hence generate a decline in the VSL_{CAN}:VSL relativity because the cancer scenario would be ameliorated by the delay.

Typically discount rates are applied to the VSL itself, as opposed to the underlying consumption. This is a simplification when considering the on-going discounting in the LCM, but it does provide the basis for tractable models and estimation procedures. In addition, the discounting of the risk change itself allows the dread and morbidity effects to be discounted together, which again simplifies the analysis and interpretation.

However, there is debate in the literature about exactly how to deal with discounting. Some key studies considering cancer fatality risk valuation neglect to mention latency or discounting at all- these include early studies by Jones-Lee *et al.* (1985a) and Magat *et al.* (1996), perhaps before the importance of the discounting issue was fully recognised but also Chestnut *et al.* (2012). The approaches taken in a number of studies that do consider latency are provided in table 2.1 in chronological order. Although some of these values are not based on cancer, all are within the health or physical risk domains. Some studies are included despite not eliciting a discount rate, if they consider the concept of latency explicitly.

Table 2.1: Discount rates in the existing health literature

Study	Study type	Approach	Rate
Viscusi and Moore (1989)	Revealed preference	Derive a discount rate	11%.
Horowitz and Carson (1990)	Person trade off	Derive a discount rate	4.54%
Cropper *et al.* (1992)	Dichotomous choice	Derive a discount rate	3.8-16.8%
Ganiats *et al.* (2000)	Dichotomous choice	Derive a discount rate	6.4%
Gayer *et al.* (2000)	Revealed preference	Assume a discount rate	3%
Lazaro *et al.* (2001)	Multiple list health choices	Derive a discount rate	14-22%
Gayer *et al.* (2002)	Revealed preference	Assume a discount rate	3%
Davis (2004)	Revealed preference	Assume a discount rate	3%
Hammitt and Liu (2004b)	Stated preference	Derive a discount rate	1.5%
Alberini *et al.* (2006)	Contingent valuation	Derive a discount rate	1.3-8.6%
Chilton et al (2007)	Ethical discussion about treatment of future generations	Do not explicitly derive or assume a discount rate	n/a
Khwaja *et al.* (2007)	Analysis of smoking data	Derive but do not report discount rate	n/a
Van Houtven (2008)	Risk-Risk trade-off	Do not explicitly derive or assume a discount rate	n/a
Cameron et al (2009)	Conjoint analysis	Assume a discount rate	5% p.a. (also1%, 3%, 8%)
Hammitt and Haninger (2010)	Contingent valuation	Derive a discount rate	Insig. diff. than zero.
Alberini and Scasny (2010)	Conjoint analysis	Derive a discount rate	0%
Alberini and Ščasný (2011)	Conjoint analysis	Derive a discount rate	0%
Adamowicz *et al.* (2011)	Conjoint analysis and contingent valuation	Assume a discount rate	5%

Reflecting on table 2.1, there appears to be minimal consensus on how to treat latency and discounting in stated preference studies. The majority of the studies considered derive a discount rate from responses, but the inferred rates have a very broad range both within studies and between them. A considerable minority of studies assume a discount rate, typically 3-5%, and use this to make inferences about other aspects of the cancer VSL. Finally, three studies choose not to report derived discount rates, instead including dummy variables for latency periods (van Houtven et al. 2008) or in terms of "extra days needed" to offset timing elements (Khwaja *et al.*, 2007) .

Despite a wealth of evidence in the financial domain that discounting is likely not to be constant across time periods and intervals (Frederick *et al.*, 2002), in the existing stated preference literature for health alternative discounting models are almost never considered. In some cases exponential rates are elicited but subsequently described as reflecting hyperbolic or sub-additive patterns (Khwaja et al 2007). However, typically this is not extended to an investigation of the alternative hypotheses. This observation motivates the research conducted in chapter 7 of this thesis, which dedicated to exploring the theoretical and empirical evidence surrounding both the level of the discount rate for health but also to the functional form that is most appropriate. In this part, the debate is intentionally simplified by referring only to the exponential discount rate. As such, the assumption taken forward is that some rate of time preference underpins the effective discount rate for health, and that on the basis of existing studies, this rate is likely to be below 10% p.a on average. The insight to be taken forward is that the elicitation of this rate is not always straightforward from survey data and that the literature would benefit from a simple mechanism by which this could be achieved. This will be developed in section 2.11.2.

Aside from discounting, there is another effect that results exclusively from the delay until the risk change. This is what Loewenstein (2006) refers to as 'anticipatory utility', and encompasses the idea that the knowledge of something impending carries its own utility or disutility. If this is so, then provided an individual is aware of having been exposed, then with a longer latency illness they experience the anticipatory disutility of premature fatality. As such, the WTP is not just to avoid the illness, fatality and loss of future years of life, but also to avoid the disutility from the anticipation or knowledge of the possibility of these losses. This would be likely to increase WTP, *ceteris paribus*, for the latent illness over the instantaneous illness with no chance for anticipation.

Of course, latency is likely to influence the VSL for cancer (VSL_{CAN}) for reasons beyond basic delay effects. Two key channels of the influence of latency are set out in the next sections.

2.10.4 *Stage-of-life effects: ambiguous influence of latency on the VSL*

It is commonly acknowledged that the VSL is not constant with age. While the shape of the relationship between VSL and age is not beyond debate (see section 2.4.3 which discussed this in more detail) it is typically acknowledged that there might be a peak around middle age. This, as argued in Shepard and Zeckhauser (1984) and Jones-Lee (1989) can be modelled to reflect patterns of consumption over the life cycle. In addition, Moore and Viscusi (1988) discuss how fewer remaining life years are lost such that older people might be expected to have lower is likely to reflect a combination of effects including consumption over the life cycle. As such, WTP for risk reductions with different latencies- and which would hence impact at different ages- might be expected to vary.

This variation might be expected to be exaggerated or dampened by other life stage effects, for example the likelihood of having dependent children might increase WTP to reduce risks at that age, because of the additional negative consequences of fatality for the dependents. Consider an example which illustrates that the interaction of latency and age effects might therefore be confounding:

- Person A is aged 20, and person B is aged 30.
- Suppose there is additional value of a risk reduction at age 40, perhaps because both person A and B expect to have young children at that age.
- Two risk reductions are offered: one with latency of 20 years, and the other with latency of 10 years.
- Clearly then, *ceteris* paribus person A would be WTP more than person B for the 20 year latent risk reduction (because it would manifest at age 40) while *ceteris paribus* person B would be WTP more than person A for the 10 year latent risk reduction (because for her this would manifest at age 40).
- A naïve researcher might infer a negative age effect for the 20 year latent risk reduction (because the 20 year old is WTP more for it) and a positive age effect for the 10 year risk reduction (because the 30 year old is WTP more for it) or perhaps to infer no aggregate effect of age, when in fact we

have discussed that the driving force in this scenario is age at the time of the risk change itself.

A second strand of the stage-of-life effect refers to the perceived likelihood of succumbing to a risk at different ages. A risk change when elderly may be perceived to be more of a threat than one while young, which might have the effect of increasing WTP to avoid latent risks. Of course, in the VSL framework laid out above, the marginal rate of substitution is between subjective fatality risk and wealth, and as such the effect of susceptibility to risk ought not to influence the WTP, as long as the question scenario properly reflects the individual's true baseline risk and explains that the risk change being valued already takes into account the individual's frailty, level of exposure and so on. However, it is very conceivable that when risk changes are presented as an "n in 10,000" frame, respondents might perceive that their likelihood of being one of those n individuals becomes higher with age. This is a fairly subtle effect which requires either careful tailoring of risk scenarios and changes, or at least a strong a priori reason to suspect that respondents 'buy in' to the baseline risks and risk changes presented to them.

2.10.5 *State-of-the-world effects*

The effects here relate, as the name suggests, to the anticipated state of the world at the time that the risk would manifest. This might include anticipated developments in technology and productivity such that a risk is either increased, for example with the development of more hi-tech solutions to problems which might be seen as carrying higher risks of catastrophic or carcinogenic outcomes. On the other hand, technological advancement might be expected to generate risk mitigation such as developments in cancer screening and treatment. As such, the influence of the future state of the world on the likely influence of a risk change is very subjective and will be difficult to control for in any analysis.

2.10.6 *Future generations*

An extreme interpretation of the state-of-the-world effects is that the world may not in fact include the individual making the wealth-risk trade-off. This requires the consideration of intra-generational time preference and discounting. These arguments are fascinating from a normative, ethical perspective but difficult to tackle empirically. As such, the majority of the work has been conducted in a theoretical perspective, dating back to Ramsey (1928). The good in question- risks to future generations- does

not easily slot into the life cycle consumption frameworks used in section 2.11 and in addition will be abstracted away from in the rest of the thesis. As such, this review will not go into any detail, but instead directs the reader to the arguments of Michael Spackman in Chilton *et al.* (2007), Cropper and Portney (1990) and Revesz (1999) amongst others.

2.10.7 *Summary: latency and the VSL*

Using straightforward intuition about discounting and the number of life years lost, it would seem that a latent fatality risk is unambiguously better than a fatality risk sooner. This is formalised in Jones-Lee and Loomes (2010). Given the potential for improvement in life-saving technologies over the coming decades and the typically lower VSL estimates empirically based on the wealth-risk trade-offs of people over 60, the argument for diminishing of the VSL with latency is fairly comprehensive. However, there are a number of reasons that this may not be the case. Firstly, any fatality risk reduction achieved now will improve conditional survival probabilities in all later periods, so a risk reduction of a certain magnitude (say, x in 10,000) would give a greater overall risk reduction benefit if it is taken now than later. Secondly, and perhaps more informally, it is possible to think about stage-of-life effects such as the likelihood of having dependents at a certain age which could make survival seem more important at some ages than at others, generating WTP for risk reductions that does not diminish monotonically with latency. In addition, perceptions of increased vulnerability to risk changes at old age could lead an individual to prefer an earlier risk reduction to one later.

This discussion leads to the conclusion that while the evidence and theory is in favour of a negative relationship between latency and the VSL, there are some factors that may drive it in the opposite direction. As such, like for the positive effect of the cancer context on the VSL, it will be necessary to verify the latency-VSL relationship empirically before any further theoretical or empirical frameworks can be based upon this assumption.

2.11 Modelling Using these Insights

As discussed Cropper and Sussman (1990) et al. reduces the utility maximisation problem to conditional survival probabilities and the utility of consumption in future years. Two major works have adjusted this framework to account for the kinds of

effects considered in this literature review. Magat *et al.* (1996) and subsequently Van Houtven *et al.* (2008) show how a multi-period utility framework can capture different utilities conditional on different fatalities. The Van Houtven framework is outlined in this section.

2.11.1 *Van Houtven et al. (2008)*

Van Houtven *et al.* (2008) takes as a starting point Magat *et al.* (1996) in defining the respondent's problem in considering fatality risks. As in the Cropper and Sussman (1990) model, the respondent is considering lifetime utility from consumption (Y), but in this framework the utility depends on the state of the world, which is healthy life, death in a road accident or death by cancer. Each potential lifetime utility stream is weighted by the probability of that fatality.

So, Van Houtven et al. assume that respondents make choices to maximise Expected Utility defined as:

$$E(U) = P_D U(D,Y) + P_C U(C,Y) + (1 - P_D - P_C)U(H,Y). \qquad (18)$$

where the outcomes are D (die very soon in car crash, with associated utility normalised to zero), C (contract cancer which will eventually be fatal) and H (live in normal health, which can be thought of as any other health outcome that could occur (including death by another cause)). Both Magat et al. and Van Houtven et al. assume that these are mutually exclusive lifetime profiles.

Differentiating (18) and normalising such that the utility of near-immediate road accident fatality is zero ($U(D) = 0$), Magat et al. express the relationship between the road accident VSL and the VSL for cancer (VSL_{CAN}) as a so-called "mortality equivalence ratio" (MER), which expresses the number of avoided cancer fatality risks in terms of the number of avoided road accident fatality risks that would leave the respondent indifferent. They show that this is equivalent to the proportional utility loss from cancer fatality when starting from full health $U(H,Y)$:

$$MER = \frac{VSL_{CAN}}{VSL} = \left(1 - \frac{U(C,Y)}{U(H,Y)}\right) \qquad (19)$$

A major contribution from Van Houtven et al. is to frame the problem to explicitly account for timing. The mortality equivalence ratio is then indexed on time. Notice that the healthy profile does not depend upon time because there is no set fatality time

for that eventuality (time of fatality would depend upon the underlying survival function).

$$MER(t) = (1 - \frac{U(C(t),Y)}{U(H,Y)}) \quad (20)$$

Van Houtven et al. also allow the utility function to have more detail. The lifetime utility function for fatality from cancer at time t is

$$U(C(t),Y) = (\sum_{j=0}^{t-1}(s_j)(d_j)u^h(y_j)) + (s_t)(d_t)u^c(y_t) \quad (21)$$

Where:

- s_j is the subjective probability of surviving j periods into the future as evaluated from the present ($j = 0$)
- d_j is the time preference factor by which utility in period j is discounted to its present value (see part III for a full discussion)
- y_j is consumption in period j
- $u^k(y_j)$ is the state dependent utility of consumption in period j with $k = c$ for the period of fatality from cancer and $k = h$ for periods of consumption in full health.

Notice that the cancer is modelled as a single period incorporating both illness and fatality. This assumption neglects the anticipatory utility models discussed in the literature review, and might be implausible for long morbidity periods. The model could be adjusted for this by extending the three possible health states to four, with $u^m(y_j)$ referring to the utility of consumption conditional on being in a state of cancer morbidity. Newbold (2011) demonstrates how the Lifetime Consumption Model can be adapted to include morbidity prior to fatality, which allows the morbidity to be included explicitly and avoids the traditional way that morbidity is handled in VSL studies, which Newbold calls "separately and… in an ad hoc fashion".

However, returning to the Van Houtven model, similarly to equation (21), the lifetime profile without cancer can be represented by:

$$U(H,Y) = \left(\sum_{j=0}^{\infty}(s_j)\,(d_j)u^h(y_j)\right) \quad (22)$$

As mentioned, this does not depend on any specific time of fatality. For tractability, the survival function s can be truncated if after some j, probability of survival is zero.

This framework allows Van Houtven et al to generate some specific predictions for the MER (which reflects the relative size of the VSL_{CAN}). They show that an increase in latency usually has a negative effect on MER, so that the preference for avoiding cancer risks declines. In addition, they show that increased survival probability up until the time of the cancer fatality time (t) is expected to positively influence the MER.

This framework allows the theoretical investigation of the likely effects of latency and survival probability on the relative value of fatalities at two different times, and as such enriches the standard LCM substantially as a basis for the investigation of the VSL_{CAN}. However, it relies on the assumption that cancer fatality engenders a different utility than road accident fatalities, but does not provide an explicit parameter through which this occurs (instead simply implying that $u^h \neq u^c$). Given that this body of work is intended to explicitly test whether a premium is placed on contemporaneous cancer fatalities compared to road accident fatalities, it would be preferable to model this more explicitly through a context parameter.

In addition, as discussed, it restricts the influence of the dread and morbidity effects from cancer to occur only in the final fatality period. This assumption, as well as the additive separability assumption, and many others reported in on pg.26, are problematic. For the purposes of this research, it will be enough to assume that latency has a per-period discounting effect. This is, as argued in Hammitt (2000), is the state-of-the-art in current research:

> "The appropriate procedure to account for latency is to value the risk change using the VSL representing the individual's value when the risk change occurs and to adjust for the time-value of money and the chance that the individual will die before then. The adjustment is made by discounting the future value of the risk reduction back to the time when the expenditure must be incurred" Hammitt (2000)

Having said this, the validity of the discounting assumption will be tested alongside the validity of the context premium in the coming analyses.

2.11.2 *The proposed $C_T R_t$ relationship*

The major insights taken from this literature review are twofold. These are that there is limited consensus in the literature about the effect of context on the VSL_{CAN}, and that

there is more, but still not overwhelming, consensus as to the effect of latency on this value. On the basis of current evidence, however, two hypotheses can be made:

1) *Ceteris paribus*, there is a preference for avoiding cancer fatality risks as compared to road accident fatality risks.
2) *Ceteris paribus*, a longer latency period until the manifestation of a risk reduces the willingness to pay to reduce that risk.

These insights lead to a concise yet powerful relationship between the typical cancer and road accident VSL. For a cancer fatality and a road accident fatality which would *both* occur at time t, the relationship can be expressed as:

$$C_t = R_t(1 + x) \qquad (A1)$$

The VSL_{CAN} with cancer fatality at time t (C_t) is assumed to be equivalent to the road accident VSL at time t (R_t) once it is augmented by $(1 + x)$ (A1). $(1 + x)$ is referred to as the "context premium" and captures all of the perceived difference in value of preventing a risk of cancer fatality compared to road accident fatality at the same time, and as such will encompass morbidity (which could be long term), psychological effects and dread. To claim that a time-invariant multiplier is sufficient to capture all context effects is of course a strong assumption, which can in theory be relaxed to better reflect reality. However, for the purposes of this exposition it will suffice.

The effects of latency are captured in assumption (A2). If latency can be expressed in terms of an effective discount rate, which is, for the moment, applied exponentially:

$$X_{t+\varphi} = \frac{X_t}{(1+r)^{\varphi}}, \; X = \{C, R\} \qquad (A2)$$

Where an outcome X_t has a value at $t + \varphi$ equivalent to its value at t (i.e. sooner) diminished by the effective discount factor $\frac{1}{(1+r)^{\varphi}}$ which captures discounting over the interval φ at an effective discount rate r.

(A1) and *(A2)* allow the VSL_{CAN} with fatality T years from now to be expressed in terms of the standard VSL ($t = 0$) as follows

$$C_T = \frac{R_0(1+x)}{(1+r)^T} \qquad (23)$$

From this, the relativity between VSL_{CAN} and the VSL for roads $C_T R_t$, with cancer fatality at time T and road accident fatality at time t (typically $t < T$) can be expressed as follows:

$$C_T R_t = \frac{(1+x)}{(1+r)^{(T-t)}} \qquad (24)$$

This $C_T R_t$ relationship will form the core of much of the analysis throughout this thesis.

The framework distils the main insights from the literature into a relationship which is both comprehensive and simplistic, avoiding the complex assumptions of the lifetime consumption model. It has an immediate and obvious counterpart in survey data because the relativity between latent cancer and current period road accident values is readily available in the literature as a survey output. Also, as will be shown in chapter 4, it can be easily used to elicit the parameters for the context premium and effective discount rate.

However, to use the method with confidence will first require the validation of the underlying hypotheses. That is, it will need to be shown that cancer is held at a (possibly time-invariant) premium compared to road accidents at the same time. In addition, it will need to be verified that the VSL reacts to latency, in that longer latency diminishes the VSL. If this is so, then it will be possible to have the confidence in the framework to use it to elicit the underlying parameters for the context premium and effective discount rate. When this basis is established, then the relationship will be used to form the basis of detailed work looking at latency effects on the cancer VSL, reported in part II of this thesis.

2.13 Summary

This review has set out the theoretical frameworks that underpin the concept of the VSL in both a static and a multi-period framework. It was noted that these models do not allow for VSLs that vary across contexts. However, there is a plethora of evidence to suggest that contextual differences in general- and cancer in particular- engender very different levels of willingness to pay for risk reductions than for reductions in the risk of instantaneous fatality. Empirical evidence to date appears to suggest that a context premium applies, at least for cancer fatalities compared to road accident fatalities at the

same time. However, this evidence is not unanimous. Similarly, strong evidence was presented in support of a negative relationship between the latency of a risk scenario and the VSL. This evidence again is not without contradiction. However, from this base of theoretical and empirical evidence, two hypotheses can be constructed:

1) *Ceteris paribus*, there is a preference for avoiding cancer fatality risks as compared to road accident fatality risks.
2) *Ceteris paribus*, a longer latency period until the manifestation of a risk reduces the willingness to pay to reduce that risk.

These hypotheses were intrinsic to the work of Van Houtven (2008) whose model was used to summarise the key insights of the literature. However, for the present purposes that model is lacking on two fronts: first, it assumes cancer affects only the final period in the lifetime consumption model (precluding long morbidity periods); second, it lacks of a specific parameter to capture the context premium.

This motivated the construction of a new formulation of the relationship between the cancer VSL and roads VSL. This formulation is stripped of any explicit reference to the LCM, although it is not incompatible. This new relationship will form the basis of future analysis in this thesis, but for this to be robust the hypotheses need to be verified.

Part II of this thesis addresses this by verifying these hypotheses, meanwhile allowing insights into what other preferences and considerations might be relevant to the VSL_{CAN}, through a stated preference R-R trade-off study. Results from the survey are used to demonstrate the potential for the use of the formulation in allowing the underlying context premium and effective discount rate to be inferred.

However, up to this point in the analysis, an exponential discounting function has been assumed. However, as will be discussed in more detail in the review of literature in part III, exponential discounting is unlikely to characterise the majority of people's preferences over the timing of outcomes. The C_TR_t framework will be used in part III to elicit and analyse discount rates under different hypotheses. For this analysis, it is arguably useful to have a measure of risk preference elicited in the domain of health. part III of this thesis provides such a measure of health risk aversion, clarifying the relevant theory and providing a novel estimation technique. This measure is then taken forward into the analysis of discount rates. part III therefore provides further insight into the results from part II as well as contributing theoretical and empirical insights that could benefit a range of future VSL and health valuation studies.

PART II.

STUDY 1: VERIFYING THE RELATIONSHIP BETWEEN THE VALUE OF STATISTICAL LIFE FOR CANCER AND ROAD ACCIDENT FATALITIES

Chapter 3. Background, Methodology and Preliminary Analysis

3.1 Background

When considering the value of preventing latent cancer fatalities, it is typically assumed that the context of cancer increases the willingness to pay for a fatality risk reduction while the length of the latency or delay until the fatality decreases it. However, these hypotheses have not been formally and directly tested in the UK. In addition, VSL studies considering latent fatality risks across contexts would benefit from a simple methodology to allow the direct elicitation of the cancer context premium and the effective discount rate from survey data. This would clarify the explanation of the findings of different studies.

This chapter presents a stated preference study[9] which was commissioned by the UK's Health and Safety Executive to explore the influence of dread and latency on the overall cancer premium. Specifically, the study tests hypotheses about the influence of context (including illness and dread of cancer) and latency (delay) on the Value of Preventing a Statistical Cancer Fatality (VSL_{CAN}). On the basis of these hypotheses, a simple model is developed which links the VSL_{CAN} and the standard (road accidents) VSL, and from which key underlying parameters can be elicited.

3.1.1 *Headline results*

Cancer is perceived to be worse than road accidents as a cause of fatality if the fatalities were to be at the same time. Latency (delay) decreases the preference for avoiding a fatality, *ceteris paribus*. This suggests a relationship by which the VSL for roads is inflated to account for the cancer context, but this inflated value is discounted to the present. Using this model and data collected in the study, an effective discount rate of 7% p.a. and a context premium of 40% are elicited.

3.1.2 *Definitions*

To avoid adding to the lack of clarity typically found in the literature surrounding the VSL_{CAN}, this study uses the following definitions. These relate to the definitions initially introduced on pg.31 (figure 2.3), but refer now to the implications of context, morbidity, latency and label dread for the strength of preference for avoiding cancer fatality risk increases:

[9] The author would like to gratefully acknowledge funding from the HSE and the OND

Figure 3.1: Preference definitions

- **The overall cancer premium:** the premium placed on avoiding a latent cancer fatality risk compared to a current period risk of accidental fatality on the roads.
- **Latency effect:** the reducing effect on the value of preventing a latent fatality of the delay between exposure to a cancer-causing substance and death from cancer.
- **Context premium:** the premium placed on avoiding a cancer risk increase as opposed to a road accident fatality risk increase when the risks would occur at the same time.

  The context premium is assumed to account for

  - **Morbidity premium:** the premium placed on avoiding the period of illness preceding cancer fatality, with symptoms getting increasingly severe until death.
  - **Label dread:** the preference for avoiding a risk increase in cancer as opposed to road accident fatality when the illness and fatality description is otherwise identical (i.e. holding both the period and description of morbidity constant, with fatality at the same time).

As outlined in the literature review, the evidence regarding the context premium and latency effect is not in total agreement. To that end, the preliminary aim of Study 1 is to verify two hypotheses:

1) *Ceteris paribus*, there is a preference for avoiding cancer fatality risks as compared to road accident fatality risks.
2) *Ceteris paribus*, a longer latency period until the manifestation of a risk reduces the willingness to pay to reduce that risk.

If these hypotheses can be verified, this will suggest that the cancer VSL is equivalent to the standard roads VSL, inflated for the context premium (which may incorporate either or both of morbidity and label dread effects) and then reduced by the latency that applies in the cancer case. This generates the C_TR_t relationship equation developed in section 2.11.2, pg.53, which is replicated here for convenience.

$$\frac{C_T}{R_t} = \frac{(1+x)}{(1+r)^{T-t}} \qquad (24')$$

Where C_T is the VSL_{CAN} at time T, R_t is the VSL for road accidents at time t, $(1 + x)$ is the context multiplier and r is the effective discount rate[10].

3.1.3 *Research questions*

Given this standpoint, the research questions are as follows:

1) To what extent can the hypotheses be confirmed?
2) How is the context premium related to labelling dread and morbidity?
3) Can a method be developed to derive effective discount rates and context premia from survey data?

The rest of this part of the thesis is structured in two chapters. The rest of this chapter describes the choice of methodology and the protocol and survey instrument used to validate the hypotheses about context and latency effects. It also provides a plan for the analysis of the resulting data and discusses the necessary preliminary work including presentation of the sample statistics and a brief discussion of how the data will be handled. Chapter 4 provides the results of the R-R study in verifying the hypotheses from pg.52, initially analysing the context premium, morbidity and labelling dread effects, followed by discussion of latency. Some sensitivity analyses, economic consistency checks and face validity checks are reported which in general lend support to the robustness of the methodology and to the reliability of the responses and hence the results. This analysis supports the hypotheses presented above (pg.52). On this basis, the methodology for eliciting the effective discount rate and context premium is presented and implemented, and then conclusions are drawn.

3.2 Methodology for Study 1

As discussed, the preliminary aim of this study is to test the hypotheses from pg.52. These hypotheses relate to the way that specific attributes of the typical cancer case will influence the VSL_{CAN}. This influences the design of the Risk-Risk trade-off methodology used in the stated preference study, study 1.

Section 3.2 explains the Risk-Risk methodology in generic terms, beginning with the utility theoretic underpinnings, and culminating in a discussion of its merits and drawbacks. A set of ten risk-risk scenario pairs is drawn up. Next the specifics are discussed; firstly with an explanation of the question design and secondly with a

[10] Notice that an exponential functional form is assumed. See part III of this thesis for fuller discussion about the discount rate.

discussion about how the protocol more broadly is designed and implemented to maximise respondents' understanding. There follows a discussion about the way that some specific potential issues with this particular survey design have been mitigated.

3.2.1 *Selection of methodology*

Options for this survey were threefold: conjoint analysis (see for example Alberini and Ščasný (2011)), direct willingness to pay (such as in Hammitt and Liu (2004a)) or Risk-Risk (as in Van Houtven *et al.* (2008)).

3.2.1.i *Conjoint analysis*

The conjoint analysis technique was disregarded for this study for two main reasons. The first was a resource constraint. The latency and risk aspects of the study were revealed in piloting to need careful explanation and face-to-face training, which ruled out any large scale or internet application. Because conjoint analysis involves asking one-shot comparisons between options that vary along different dimensions, it does not allow for the elicitation of indifference points for each respondent and for each attribute. Even without this constraint, however, given the exploratory nature of this study and the variety of research questions it intends to address, the more directed and focussed approach that the Risk-Risk methodology allows was judged to be more appropriate. Finally, given the attribute non-attendance issues (DeShazo and Fermo, 2002; 2004), (Carlsson *et al.*, 2010b), that relate to the conjoint analysis technique it seems inappropriate for this study whose primary aim is to judge the importance of context effects (including labelling and morbidity) and of latency, which are of course key attributes of the cancer scenario.

3.2.1.ii *Direct Willingness to Pay*

Direct willingness to pay (WTP) avoids these problems by eliciting a point estimate of WTP for each respondent and ensuring that they focus on each of the attributes under consideration. However, during the late 1980s, some serious problems started to be observed in responses to the traditional direct WTP questions. These include problems with protests and refusal to respond; for many people the first reaction to the task of placing a monetary value on their personal safety seems at best distasteful and at worst impossible. While it is true that anyone who has ever paid for- or perhaps refused to pay for- any sort of safety equipment has made an implicit trade-off between wealth and safety, this has not always translated well into the survey domain. The direct WTP

approach generates problems in data even from respondents who had apparently been willing to engage with the questions. Direct WTP questions have been shown to generate some 40% of respondents offering exactly the same willingness-to-pay value for risk reductions of different sizes (see for example Jones-Lee *et al.* (1985b) and Beattie *et al.* (1998)), a phenomenon referred to as 'scope insensitivity'. This has very serious issues for application: when aggregated, the implied population VSL figures differ substantially[11]. In addition, it suggests a response mechanism within which respondents are largely unwilling or unable to work.

3.2.1.iii *Risk-Risk trade-off*

The risk-risk trade-off methodology (R-R) was first introduced in Viscusi *et al.* (1991) and was developed in Jones-Lee and Loomes (1995). Its major advantage is its ability to avoid some of the conceptual and other biases that plague the direct WTP approach. This is not least because the respondent is not required to juggle the comparison of wealth with fatality risks. As such, protest and refusal answers are typically fewer in comparison with direct WTP surveys. In addition the two commodities Risk A and Risk B are inherently more comparable than wealth and risk, simply because there are many more attributes along which they can be compared. Given the emotive nature of the subject matter and the conceptually challenging issues of latency and future morbidity to be addressed in this study, the decision was taken to use the risk-risk methodology so as to maximise respondents' engagement and their ability to communicate their underlying values effectively.

3.2.2 *Utility theory underpinnings of the risk-risk methodology*

The problem facing the respondent in a risk-risk trade-off scenario can be captured in a utility framework similar to the one used by Viscusi *et al.* (1991) and Van Houtven *et al.* (2008).

3.2.2.i *Basic framework*

The framework incorporates three possibilities: some years of life followed by death in a fatal car accident (D), some years of life followed by illness and death from cancer (C) and years of life with neither a fatal road accident nor cancer (H). Each of these

[11] For example, £50 average WTP for a 1/100,000 risk reduction implies a VSL of £5,000,000. If respondents also state a WTP of £50 for a 2/100,000 risk reduction, the implied VSL is just £2,500,000.

possibilities has an associated lifetime utility[12] that depends on the cause of death (which can be extended to include the impacts of different timings and of illness as well as the context of the fatality: for now these impacts are bundled into an overall prospect in each case) and also upon wealth, w. These lifetime utilities are denoted $U(D,w)$, $U(C,w)$ and $U(H,w)$. The lifetime profiles are assumed to be mutually exclusive, and will be occur with probabilities π_D, π_C, and $(1-\pi_D-\pi_C)$ which correspond to road accident fatality, cancer fatality, and neither road accident nor cancer fatality. As such, expected lifetime utility as evaluated from the present by the respondent answering the survey can be written as

$$E(U) = \pi_D U(D,w) + \pi_C U(C,w) + (1-\pi_D-\pi_C)U(H,w) \qquad (25)$$

This equation is equivalent to equation (18) from pg.49.

3.2.2.ii *Introducing differentiated risks*

The respondent is asked to consider a choice between two options: in option A, the probability of the lifetime that culminates in a fatal road accident is π_D^A, and the probability of the lifetime that ends with cancer fatality is π_C^A; while in option B these probabilities are π_D^B, π_C^B. As such, option A gives the expected lifetime utility in equation *(25a)*, while option B gives the expected lifetime utility in equation *(25b)*.

$$E(U)^A = \pi_D^A U(D,w) + \pi_C^A U(C,w) + (1-\pi_D^A-\pi_C^A)U(H,w) \qquad (25a)$$

$$E(U)^B = \pi_D^B U(D,w) + \pi_C^B U(C,w) + (1-\pi_D^B-\pi_C^B)U(H,w) \qquad (25b)$$

If an expected utility maximiser indicates indifference between options A and B, this suggests that

$$\pi_D^A\, U(D,w) + \pi_C^A\, U(C,w) + (1-\pi_D^A-\pi_C^A)U(H,w) = \pi_D^B\, U(D,w) + \pi_C^B\, U(C,w) + (1-\pi_D^B-\pi_C^B)U(H,w) \qquad (26)$$

Rearranging equation (26) allows the lifetime utility in the case with cancer fatality to be reduced to the following lottery equivalent between the road accident fatality and the lifetime with neither of the specified fatalities:

[12] see section 2.4, pg.23 for a discussion of the lifetime utility models including Cropper (1990) that could underpin these utilities

$$U(C,w) = \pi^* U(D,w) + (1-\pi^*)U(H,w) \quad (27)$$

where $\pi^* = \frac{\pi_D^B - \pi_D^A}{\pi_C^B - \pi_C^A}$ (28)

3.2.2.iii *Introducing risk timing*

Up to now, time has been left unspecified in the background of the model, but it can be explicitly included in the equation in the manner proposed by Van Houtven et al. Death is assumed to occur at time t_D for the road accident fatality and at time t_C for cancer, giving:

$$U(C(t_C),w) = \pi^* U(D(t_D),w) + (1-\pi^*)U(H,w) \quad (29)$$

A full discussion of potential lifetime utility models that could underpin $U(C(t_C),w)$ and $U(D(t_D),w)$ is provided in Van Houtven *et* al. (2008). However, for the purposes of the Risk-Risk trade-off there is no need to specify the utility function in any detail.

3.2.2.iv *From model to VSL*

As with most stated preference studies that consider risks to life, the aim of this methodology is to give insights into the VSL (value of statistical life). As such, the utility framework developed so far must be recast in terms of the wealth-risk trade-off that underpins the VSL. As discussed fully in part I of this thesis (pg.20) the VSL for roads is defined as the aggregate marginal rate of substitution of wealth for risk of fatality in road accidents. Similarly, for the cancer VSL (VSL_{CAN}) is defined as the aggregate marginal rate of substitution of wealth for risk of cancer fatality. Notice that Van Houtven et al. follow the convention, common in the US, of defining the VSL simply as the individual's marginal rate of substitution of wealth for risk, with no aggregation. This is only equivalent to the population aggregate if members of the population can be assumed to be homogeneous in this respect. However, given this assumption, and by differentiating equation (25) with respect to π_D, π_C, and wealth, letting $U(D,w) = 0$, van Houtven et al show that the relativity VSL_{CAN}:VSL is equivalent to proportion of full-health utility lost given the cancer case.

$$\frac{VSL_{CAN}}{VSL} = 1 - \frac{U(C,w)}{U(H,w)} \quad (30)$$

Of course, an individual's responses do not allow the direct observation of utilities, but instead show the relative sizes of the risk changes that generate indifference between the two options A and B. Recalling equation (27) and, with no loss of generality, letting $U(D,w) = 0$ gives

$$U(C,w) = \left(1 - \left(\frac{\pi_D^B - \pi_D^A}{\pi_C^B - \pi_C^A}\right)\right) U(H,w) \qquad (31)$$

Rearranging, and in combination with equation *(29)*,

$$\frac{VSL_{CAN}}{VSL} = 1 - \frac{U(C,w)}{U(H,w)} = \frac{\pi_D^B - \pi_D^A}{\pi_C^B - \pi_C^A} \qquad (32)$$

As such, analysing the relative sizes of π_D and π_C that generate indifference between options A and B allows the relative size of the value of statistical life for one cause compared to another to be established. If the underlying VSL_{CAN}:VSL is 2, the above analysis implies indifference between an increase (decrease) in road accident fatality risk that is twice as large as the increase (decrease) in cancer fatality risk. This is intuitively appealing.

3.2.3 *Design of survey in Study 1*

Up to now, the discussion of the methodology has been generic but this section sets out the risk scenarios used in the present survey. The survey is structured to allow each of the previously identified key attributes (context- to include morbidity and label dread- and latency, refer to figure 3.1 on pg.57 for definitions) to be analysed in isolation and in combination.

3.2.3.i *Notation: explanatory codes for comparisons*

To clarify the exposition both in this section and the results chapter, a notational simplification will be used throughout. Comparisons (or relativities) are denoted by C_TR_t where C stands for cancer fatality and R for road accident fatality. T and t denote the latency for each cause, which is the number of years between the present and the fatality. T refers to the later fatality and t to the sooner fatality. For example, when comparing cancer 15 years from now with road accidents two years from now, the code is $C_{15}R_2$. When morbidity periods differ from standard (i.e. minutes or hours in the road accidents and 12 months in the cancer case) they are included in square brackets e.g. C_{10}[36m]:C_{10}[6m].

3.2.3.ii *Risk-risk survey questions*

The survey questions are presented in table 3.1. The table provides the effect under examination, the question number, a summary description of the scenarios and the explanatory code as discussed above.

Table 3.1: Risk-Risk questions

Purpose	Question	Explanation	Code
Overall premium*	Q1	Road death in the coming year vs. cancer death in 10 years	C_{10} :R_1
	Q2	Road death the year after next vs. cancer death in 10 years	C_{10}:R_2
	Q3	Road death the year after next vs. cancer death in 25 years	C_{25}:R_2
Context	Q4	Road death the year after next vs. cancer death year after next	C_2:R_2
	Q5	Road death in 10 years vs. cancer death in 10 years	C_{10}:R_{10}
Latency	Q6	Cancer death year after next vs. cancer death in 10 years	C_2:C_{10}
	Q7	Cancer death year after next vs. cancer death in 25 years	C_2:C_{25}
Morbidity	Q8	Cancer death in 10 years (6 months' illness prior to death) vs. Cancer death in 10 years (1 year's illness prior to death)	C_{10}[12m] :C_{10}[6m]
	Q9	Cancer death in 10 years (6 months' illness prior to death) vs. Cancer death in 10 years (3 years' illness prior to death)	C_{10}[36m] :C_{10}[6m]
Labelling	Q10	Road death in 10 years (1-2weeks' illness prior to death) vs. Cancer death in 10 years (1-2 weeks' illness prior to death)	C_{10}[2w] :R_{10}[2w]

*including context/morbidity effects and latency/discounting effects combined in people's preferences.

In Q1-3 ($C_{10}R_1$, $C_{10}R_2$, $C_{25}R_2$) the questions vary in context but also in timing. This allows the overall cancer premium to be elicited. In Q4-5 (C_2R_2 and $C_{10}R_{10}$) the timing was held constant in each question but the context differs, allowing direct observation of the effect of context. Comparison of Q4 to Q5 allows the researcher to identify whether and how the context premium changes when it relates to fatalities further into

the future. Q8-10 allow insight into what drives any context premium, because Q10 (C_{10}[2w]R_{10}[2w]) holds morbidity and timing constant, and as such tests for label dread while Q8 (C_{10}[12m]R_{10}[6m]) and Q9 (C_{10}[36m]:R_{10}[6m]) vary the length of the morbidity period prior to fatality. These questions therefore highlight the likely drivers of the context premium. Latency is considered indirectly in Q1-3, but also directly in Q6 (C_2:C_{10}) and Q7 (C_2C_{25}) where the scenarios alter only in terms of the latency period.

Questions 1-3 ($C_{10}R_1$, $C_{10}R_2$ and $C_{25}R_2$) allow a multi-attribute comparison because they vary both the cause of death and the time of fatality. This is designed to avoid the focussing problems that can occur when a single attribute is isolated (see section 4.4.3 pg.101 for a discussion). The remaining questions isolate a single domain for comparison, with respondents focussing on each attribute in turn and explicitly expressing preferences over each of these. In addition, two of each 'single attribute' question are included (e.g. two latency differentials, two morbidity differentials) in order to investigate the functional form of the relationship between the elicited relativity and the attribute in question.

Notice that for this study the morbidity is varied only in terms of the length of time spent ill. While severity and particular symptoms are also likely to influence how morbidity is perceived by the individual, these are not easy to communicate objectively. There is extensive literature surrounding the likely non-linear relationship between duration of illness and disutility, but for the purposes of this exploratory analysis, it was important to have an objective measure to indicate whether the morbidity component of cancer fatality was an important aspect of the prospect at all. As such, time spent ill provided a simple and easily interpreted measure of illness, and severity issues were controlled as far as possible using a generic description of cancer symptoms. The methodology could usefully be extended to investigate the influence of severity and particular type of morbidity in future work.

3.2.4 *Predictions*

Using a combination of economic theory, especially prior evidence about cancer dread, discounting, and general logic, some prior hypotheses can be drawn about the resulting relativities. For some of the questions, there is a clear prior expectation of whether the relativity is greater than one, though for other questions it is less clear because of some potentially offsetting effects. For each question set ('overall premium', 'context',

'latency' and 'morbidity') the movement in the relativity between questions is predicted.

Any evidence to suggest that the relativities do not behave in the hypothesised way will necessarily lead to doubt about the underlying hypotheses about perceptions of context, timing and morbidity when considering fatality risks.

The underlying statements that drive the predicted movements in the relativities are:

1) Cancer fatality is, *ceteris paribus*, perceived to be worse than road accident fatality.
2) Delaying the fatality lessens the present disutility from the prospect of an increase in the risk of that fatality.
3) Less morbidity is preferred to more.

The predicted movement (increase or decrease) of the relativity between questions is discussed in detail in each section, but the overall pattern is summarised in table 3.2. The prediction, in each case, reflects the three statements above.

Table 3.2 Relativity movement predictions

Set	Question	Code	Prediction
Premium*	Q1	$C_{10}R_1$	Increase
	Q2	$C_{10}R_2$	Q1-Q2 Decrease
	Q3	$C_{25}R_2$	Q2-Q3
Context	Q4	C_2R_2	No prior hypothesis
	Q5	$C_{10}R_{10}$	
Latency	Q6	C_2C_{10}	Increase Q6-Q7
	Q7	C_2C_{25}	
Morbidity	Q8	$C_{10}[12]C_{10}[6]$	IncreaseQ8-Q9
	Q9	$C_{10}[36]C_{10}[6]$	
Labelling	Q10	$C_{10}[2w]R_{10}[2w]$	-

*including context/morbidity effects and latency/discounting effects combined in people's preferences.

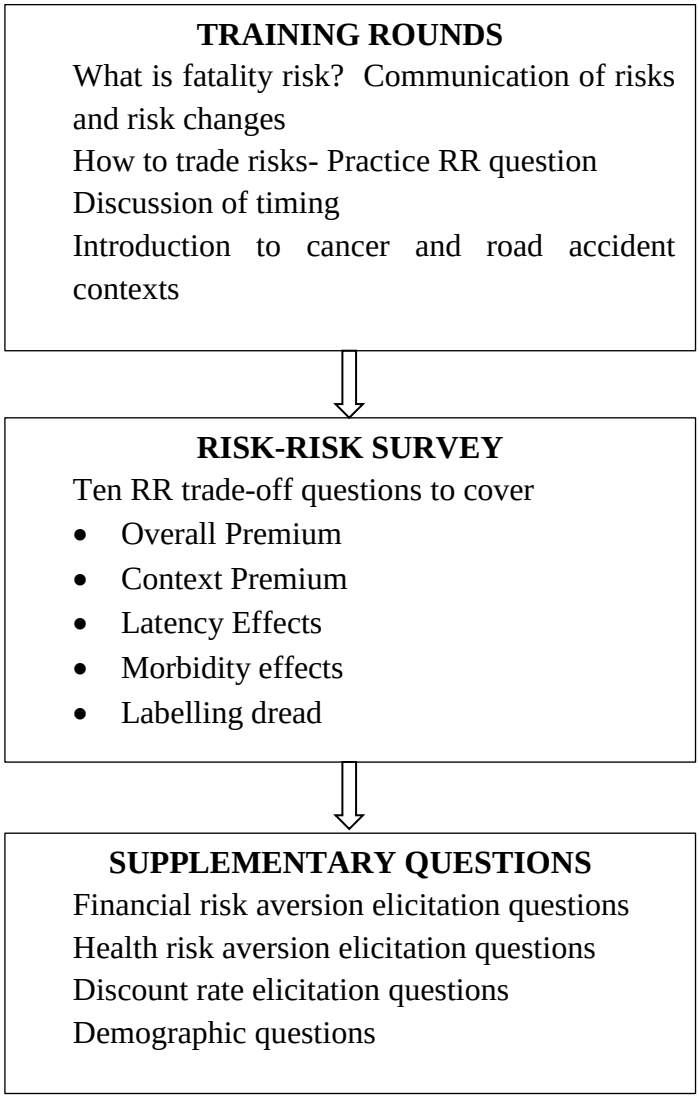
This section outlined what question scenarios were compared during the survey. The next section explains how this was carried out within the wider protocol.

3.2.5 *Implementation of Study 1*

Responses were collected face-to-face as opposed to over the internet or by telephone. The reasons are twofold: the subject matter of the survey is necessarily somewhat difficult and emotive, and the questions themselves are cognitively difficult. To ensure

that all respondents paid full attention and had the opportunity to ask questions to clarify their understanding during the precursory training rounds (see figure 3.2 and section 3.2.6), it was important that the sessions were conducted in-house[13]. In addition, respondents were deemed more likely to have been focussed and engaged during the R-R questions than would have been the case if they had answered over the internet, because no distractions were present during the session.

Figure 3.2: Structure of the sessions



The survey was administered to groups of 10 respondents although all questions were deliberately designed and implemented such that the responses were private and individual. The groups were held during January and February 2012. The total sample

[13] The sessions were manned by the principal researcher and at least one additional staff member to ensure that respondents had adequate support where necessary

size was 216, of which 57 formed the pre-pilot and 159 people formed the final sample for analysis[14]. Respondents were recruited by a professional market research firm.

The next subsections describe in detail the procedures that respondents encountered during the survey groups. This is summarised in the flow diagram in figure 3.2.

3.2.6 *Training rounds*

After respondents were welcomed and informed about the broad aims and the structure of the session, they were introduced to some key ideas and concepts that would be useful to them throughout the RR survey. This consisted of a 45 minute preliminary session involving practice rounds, explanation and discussion. The training rounds were included because while everybody makes implicit risk-risk trade-offs in day-to-day life, some of which may even incorporate attributes and features that are the focus of the study at hand, it is certainly not a simple task for most people to explicitly consider them and to answer these structured R-R trade-off questions about such difficult and emotive issues.

3.2.6.i *Fatality risks, risk increases and RR trade-offs*

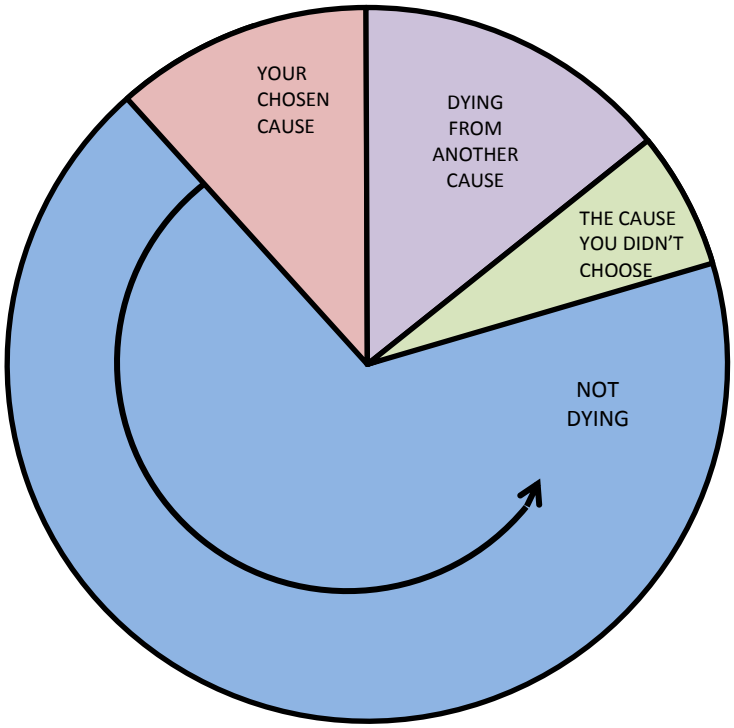
Respondents were first asked to consider abstract risks of fatality, simply as a chance of dying, as a clean and straightforward introduction to the idea of fatality risk and the 60 million baseline[15] that would be used throughout the survey. It also allowed a discussion of the concept of risk exposure, in particular highlighting that an exposed individual might *or might not* be one of the x in 60 million that would die from this cause in the specified time period. The next concept introduced was comparing risks, so context was required to allow for comparisons. Fire in the home and influenza were selected as the example causes because they share some of the properties of road accident and cancer risks (one being accidental, one being illness-related, one being more common for the elderly) while being far enough removed, and with very different baseline risks, that the likelihood of anchoring on these responses was minimal. Respondents used these contexts to practice a risk-risk trade-off question, providing an opportunity to ask questions and to ensure full understanding of the multiple list mechanism employed here (for a detailed discussion, see section 3.2.2 on pg.60).

[14] The pilot responses were excluded from the quantitative analysis reported later in this part of the thesis to ensure that all responses were from respondents that experienced identical stimuli.

[15] 60 million is approximately the population of the United Kingdom

3.2.6.ii *Communicating a risk change*

Figure 3.3: Risk-risk teaching tool



At this stage of the sessions, the risk-risk teaching tool was introduced. This was a pie chart with four segments: the risk of dying by the cause selected for the risk increase, the risk of dying by the cause they did not select, the risk of dying from some other cause, and the chance of none of these fatalities occurring, as shown in figure 3.3[16]. The pie chart was included because in early piloting, respondents appeared to ignore two important facts: firstly that the other risk is not reduced when they take a risk increase in their least feared cause; and secondly that taking an increase in their least feared cause of dying means reducing their survival probability overall. The pie chart allowed the moderator to show the implications of an increased risk of the least feared cause in a non-technical way, by simply showing the 'pink area' (least feared cause) getting larger, the 'blue area' (chance of not dying) getting smaller, and the 'green area' (the most feared cause) and 'purple area' (all other causes) staying the same size.

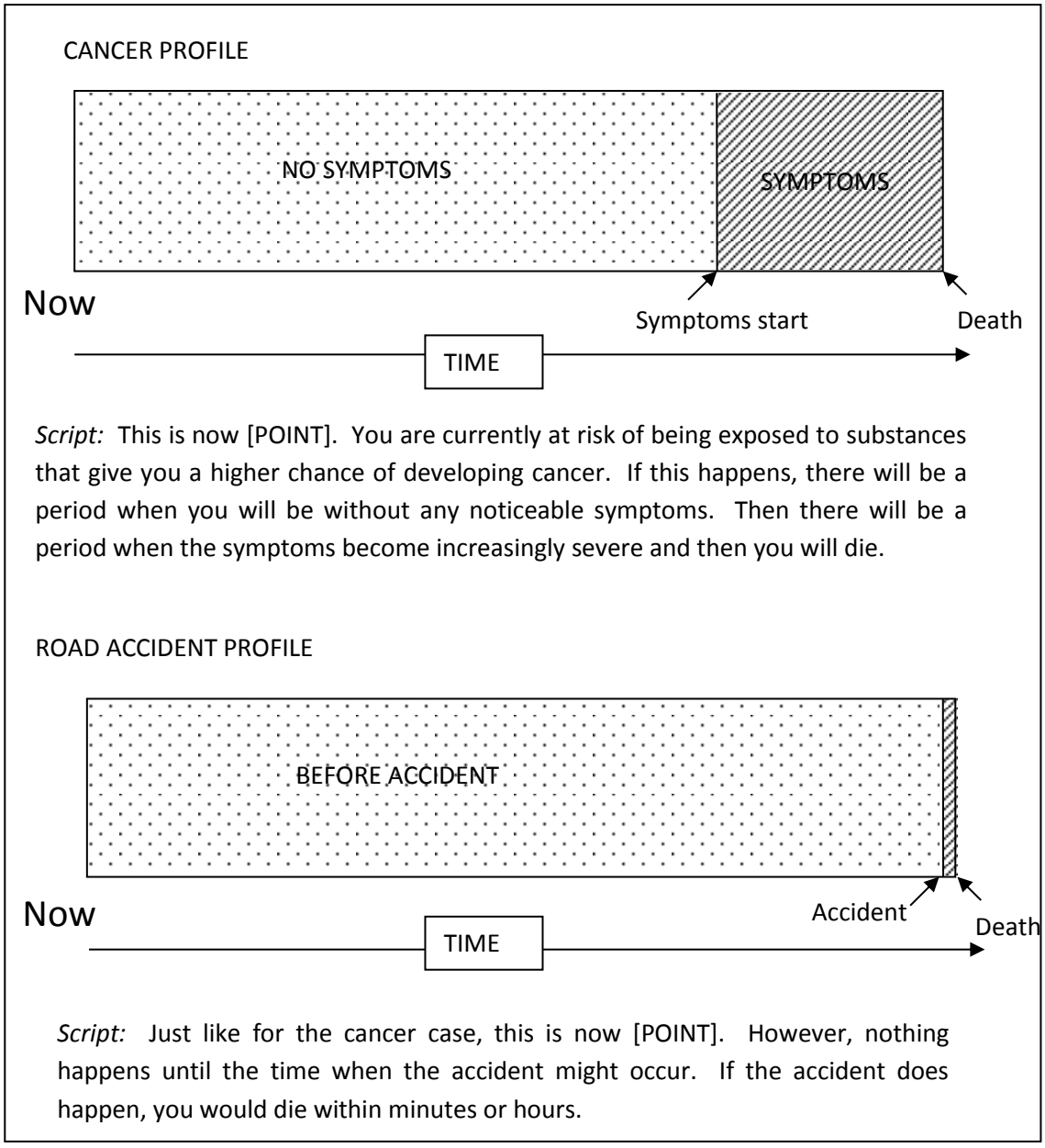
3.2.6.iii *Introduction to timing and contexts*

After this, respondents were asked about the way their answers might have differed if the timing of the fatality was different. They were prompted to consider whether and how their life would be different in the future and the way that they feel about risks in

[16] Given the small baseline risks, the pie chart was not drawn to scale. Respondents were informed of this and were asked to treat it as an illustration.

the future compared to the present. There were no formal questions at this stage; instead this was treated as an ideas initiation exercise.

Figure 3.4: Cancer and road accident profiles



Finally, the contexts of cancer and road accidents were introduced. Respondents were given the opportunity to bring their own conceptualisation of the two scenarios to the forefront of their minds by writing down what they considered to be the most salient attributes. After this, the moderator set some boundaries on the scenarios. Importantly, this included that the road accidents would be driver/passenger car accidents, and would exclude pedestrian and cyclist fatalities and death in public transport. For the cancers, it was specified that the cancers were not behaviour-related or exclusively related to genetics. This was to minimise the chance that respondents would conceptualise their

own risk to be lower, because they do not smoke, drink or have family history of cancer. In addition, it allows the results to be interpreted as applying to the average member of the public, because the baselines presented were, as far as possible, population averages (see section 2.3.3 pg.20 for a fuller discussion). Respondents were encouraged to think only about how the risk would affect them, not how other people might be impacted. Respondents were introduced to the communication tool or 'profiles' that would be used to describe each cancer and road accident scenario. See figure 3.4 for an example.

As a result of this training, respondents had been introduced to the concepts of fatality risk, risk trading, latency and timing, cancer and road accident contexts. They were deemed to be better prepared to approach the subsequent risk-risk questions.

3.2.7 *Risk-Risk (R-R) survey*

This section describes the procedures in the R-R survey section of the protocol. The procedure was the same for all ten questions, so the explanation here will be kept generic. For the full list of scenarios compared, the reader can revisit table 3.1 from pg.64.

The main risk-risk questions were designed with the aim of maximising respondents' understanding. As such, respondents were encouraged to ask the assistant if they required any clarification of the response mechanism or the scenarios, and the moderator slowly explained the procedure in each question. The key messages about avoiding altruistic concern, about the possible differences in timing, and about the implications of taking very high risks of the least feared cause of fatality were reiterated in every question, and respondents were guided to their information sheets which contained the key pieces of information about the cancer and road accident scenarios.

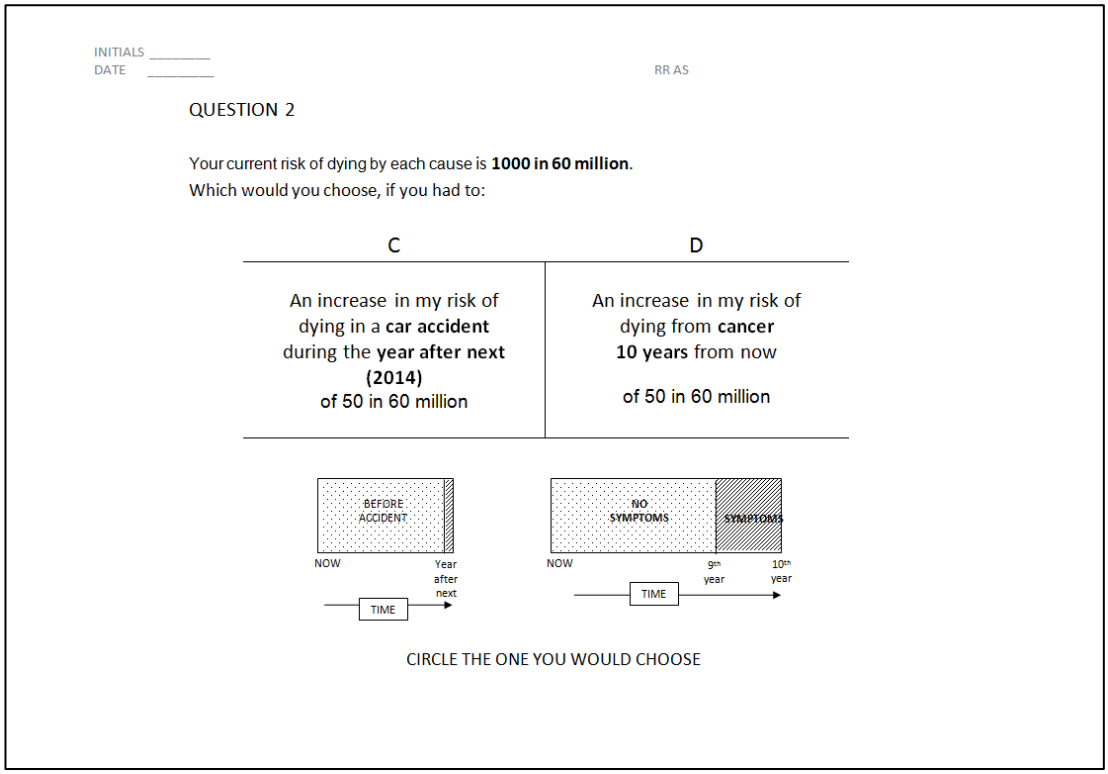
3.2.7.i *Initial choice*

In each question, respondents were presented with an initial choice between risk increases in the two scenarios under consideration. In every case, the baseline was given as 1000 in 60 million. This is approximately the baseline risk of road accidents in the UK for the average individual[17], and groups of cancers can be found with the described properties such that the baseline for the cancer group is also equal to 1000 in 60 million. The equalisation of the baseline was included early in piloting when it

[17] The level for road accident fatalities for car users was 845 in 2010. Source: *Reported road casualties Great Britain 2010*

became apparent that baseline effects would swamp any latency, dread and morbidity effects of the kind that are the focus of this study[18]. The respondent's initial response sheet included a table containing the key information (context, timing, baseline risk and risk increment), a visual profile to illustrate the cause, and a prompt to circle the risk increase they would choose to take, if they had to. An example initial response sheet is given in figure 3.5.

Figure 3.5: Initial response sheet



3.2.7.ii *Multiple list table*

After the initial choice, which would be to circle C or D in this example, the respondent received the appropriate follow up table. The table they received had a standard multiple list format, with the risk increase they had chosen in the first column, which increased down the table, and the alternative, fixed risk increase that they had avoided in the second column. An example is provided in figure 3.6. Alternatively, the respondent could indicate indifference by drawing an equals sign between the options on the initial response sheet. In this case, the respondent did not receive a second answer sheet.

[18]See Chilton et al (2006) for further discussion of baseline effects.

Figure 3.6: Multiple list table for a respondent that originally chose the increase in road accident risks

INITIALS _____
DATE _____ RR AS

ANSWER SHEET 2A

C *Dying in a car accident during the year after next* *1000 in 60 million* RISK INCREASE :		D *Dying from cancer 10 years from now* *1000 in 60 million* RISK INCREASE :	CHOICE:
50 in 60 million	OR	50 in 60 million	*C*
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	*D*

Respondents were encouraged to treat each row in the multiple list table as a dichotomous choice between the (larger) risk increase in their least feared cause (i.e. road accidents in figure 3.6) and the (smaller) risk increase in the most feared cause (i.e. cancer in figure 3.6). The point at which the respondent switches their decision (in this example from choosing roads to choosing cancer risk increases) indicates an indifference range, and given the relatively small intervals between each row, the mid-point was assumed to adequately approximate the indifference point. If the respondent was not willing to switch to the smaller risk increase at any point within the table, they were prompted to indicate the risk increase that would be just large enough to make them switch, and to indicate this in the bottom row of the table in figure 3.6. This mirrors the open ended bid in Willingness to Pay based approaches, and ensures that the respondent is not constrained by options selected by the researcher. This procedure was repeated for all ten risk-risk questions.

3.2.8 *Supplementary information*

Having completed the ten RR questions in the survey, respondents provided information about their risk and time preferences. Risk preferences were captured in the financial domain using standard Holt-Laury (H-L) procedures through comparing financial lotteries with different probabilities of success (Holt and Laury, 2002). From the decisions made in these questions, the respondents' relative risk aversion could be inferred (Arrow, 1971). Time preferences in the financial domain were captured using 'smaller sooner or larger later' procedures based on Coller and Williams (1999). This involves comparing a small payoff to be received in the near future with larger amounts to be received in seven months' time. The choices allow discount rates to be inferred. There followed elicitation of health-state risk aversion using the Holt-Laury (H-L) procedure adapted to use health states described in terms of the EQ-5D-5L descriptions of illness in place of the usual monetary outcomes.[19]

Finally, standard demographic information was collected, alongside some information about the respondents' familiarity with road accidents and cancer, and their health state and perceived road accident risks. These demographics will be analysed to explore to what extent preferences over different fatality risks are driven by demographic influences.

3.2.9 *Multiple List or Dichotomous Choice*

When asking R-R questions, there are two main methods for recording responses: the multiple list (ML) format and the dichotomous choice (DC) format. This study uses the ML format, because it provides more information per respondent than the DC format. However, there are well documented problems with using the ML format, and so this section sets out the benefits and drawbacks of both options, and the reasons for choosing the multiple list in this study.

3.2.9.i *Multiple List (ML)*

The multiple list format involves presenting respondents with a table or series of binary choice questions where the option or options vary incrementally. For willingness to pay (WTP) studies, this might be a series of potential WTP values, or for risk-risk studies like the one reported here, it will be a series of risk profiles that are incrementally

[19] This is discussed in more detail in part III of this thesis, because risk and time preferences in health and safety are the main focus of those analyses.

improved or worsened (see figure 3.7). The respondent works their way through the series of decisions until they reach their 'switch-point', i.e. the decision that makes them change their mind from their initially chosen option to the alternative. This allows the researcher to establish where the respondent is indifferent between options A and B, within a defined range.

In figure 3.7, the risk reductions in option B are held constant, while the risk reductions in cause X are improved down the table. This is the simplest form of risk-risk ML format because only one column varies. In this case, the respondent will have made an initial choice suggesting a preference for reductions in risk Y over risk X, and this table makes the cause X risk reduction more attractive until the respondent feels she would choose it even though it is in her less preferred cause. Should the respondent feel that her preferences are not captured within the table, she would be required to state the risk reduction in cause X that would be just big enough to be equally good as a 5/1000 reduction in her risk of cause Y.

Figure 3.7: Risk-risk multiple list stylised example

A		B		
Risk reduction in cause X	Risk reduction in cause Y	Risk reduction in cause X	Risk reduction in cause Y	My Choice Is
5/1000	0/1000	0/1000	5/1000	B
10/1000	0/1000	0/1000	5/1000	B
15/1000	0/1000	0/1000	5/1000	A
20/1000	0/1000	0/1000	5/1000	A
25/1000	0/1000	0/1000	5/1000	A
___/1000	0/1000	0/1000	5/1000	A

In this example, the respondent's indifference point lies between 10 and 15 in 1000. Using the simplifying assumption that the midpoint is an adequate proxy for the point of indifference, the respondent would be allocated a value of 12.5/1000, i.e. a relativity of 2.5:1 reflecting how much worse the risk of cause Y is relative to cause X. If the respondent writes in their own value in the bottom of the table, their stated amount is assumed to indicate their exact indifference point.

3.2.9.ii *Dichotomous Choice (DC)*

The dichotomous choice format involves asking respondents a single binary choice question, for example "option A or option B" in a risk comparison exercise.

Figure 3.8: Risk-risk dichotomous choice stylised example

A		B		
Risk reduction in cause X	Risk reduction in cause Y	Risk reduction in cause X	Risk reduction in cause Y	My choice is
25/1000	0/1000	0/1000	5/1000	

3.2.9.iii *Benefits and drawbacks of the Multiple List format*

The ML format has been evaluated by Andersen *et al.* (2007) and Andersen *et al.* (2006). They consider incentivised multiple price list formats, which is slightly different to the hypothetical risk formats used here, but they discuss some applicable benefits and drawbacks of the ML format generally. The benefits include ease of explanation; ease of implementation; and the inclusion of a simple truth telling mechanism (when subjects are told that one row at random will be chosen for payoff). While the last is irrelevant to the current hypothetical scenarios, the former two are relevant benefits. In addition, using a multiple list allows the estimation of indifference for every individual within the sample as opposed to just the sample average that is obtained using dichotomous choice.

The drawbacks suggested by Andersen *et al.* (2007) are threefold. Firstly the technique only allows interval estimation of indifference values and although some statistical techniques exist to isolate the actual values, this is always based on assumption. Secondly, Andersen *et al.* (2007) suggest that there can be multiple switch-points indicating inconsistent valuations, or otherwise a very wide interval value for indifference. Finally, and possibly most importantly, they highlight potential framing effects whereby subjects might be drawn to the middle of the table. In addition, they highlight that valuations might be influenced by the answer to previous questions. These latter effects fall under the umbrella of framing effects. Having said this, they find in their empirical work that order and framing effects *"*are not likely to be severe or pervasive*"* (Andersen *et al.*, 2007).

3.2.9.iv *Benefits and drawbacks of the Dichotomous format*

Dichotomous choice questions have the major benefit that they will be less susceptible to anchoring or framing bias, with the possible exception of the yea-saying tendency and starting point bias noted in Holmes and Kramer (1995). They will be completely free of the bias generated when respondents are drawn to the middle of the list of values. However, they provide less information than ML because it is impossible to infer each respondent's indifference point, instead generating sample averages. This means that there is less information for a given sample size, and it precludes any within-individual analysis.

On balance, given the sample size constraint under which this study was conducted, and given the potential for useful within-individual insights, it was decided to use the ML format for the study. Further steps were taken to mitigate against the specific problems that might occur when employing an ML methodology for preference elicitation,

3.2.10 *Design issues with the ML format*

The questions that this study addresses are by their nature complex and difficult, and to capture the preferences of all respondents is complicated, especially when these preferences may not be well understood by the respondents themselves. Although employing the RR methodology addresses some of the common problems with direct WTP approaches (see section 3.2.1 for a discussion), it suffers from some of its own, some of which are particularly pertinent to Study 1 and were touched upon in the preceding section. These include anchoring; the influence of lexicographic preferences for avoiding certain risks; the impact of the chosen risk increment; and herding. Some of the problems have been suggested to the researcher by independent commentators on this study[20], while others arose organically through piloting. The potential pitfalls are presented in section 3.2.10. Having said this, mitigating steps have been taken throughout the design of this protocol and survey to minimise the likely problems that might be expected to arise. Analysis of how pervasive they are in the current study postponed until section 4.9.

3.2.10.i *Anchoring*

Anchoring refers to the tendency for respondents to infer information about the 'right' answer from the first option that they are shown. For example, in direct WTP studies,

[20] Particular thanks are due to Professor J Hammitt for his insightful comments.

responses tend to be lower when the initial value is low and higher when the initial value is higher (see Boyle *et al.* (1985) for a review of early evidence about anchoring). Similarly, when a ML format is used, the range of options in the table might be perceived to represent a 'reasonable' or even 'endorsed' range of values, and this can sometimes lead to an artificial spike in the data around the midpoint of the table. In this study, the variations on the ML in figure 3.6 (pg.73) were used to infer indifference. The lists were varied between the question sets as outlined in table 3.3. This was to ensure that a single starting point was not reinforced throughout, in order to minimise the effect of range-related bias.

Table 3.3: Risk increments and initial values

Questions	Initial value	Increment	Final value	Implicit range within table
1-3	100	+40/60 million	420	1.5:1 to 8:1
4-5	90	+40/60 million	410	1.4:1 to 7.8:1
6-7	80	+40/60 million	400	1.3:1 to 7.6:1
8-9	85	+40/60 million	405	1.35:1 to 7.7:1
10	90	+40/60 million	410	1.4:1 to 7.8:1

In addition, the option to fill in the respondent's own risk increase was intended to signal that there are 'no right or wrong answers', a message repeated explicitly throughout the protocol. These measures ought to go some way to mitigate anchoring bias, and results of validity checks are reported in section 4.9 (pg.113).

3.2.10.ii *Risk reductions and lexicographic preferences*

Early iterations of the protocol described risk reductions, with the RR multiple list tables offering increasingly small reductions in the risk of the most feared cause, compared to constant, fairly substantial reductions in the risk of their least feared cause. The utility underpinnings would therefore suggest that the respondent would prefer the risk reduction in their most feared cause, given that the risk reductions are the same size from the same baseline. At some point in the table, however, the risk reduction ought to be small enough that the respondent would prefer the large reduction in their less feared risk.

However, early piloting revealed that respondents were unwilling to switch, even when the risk reduction in their most feared risk became very small. This suggests an almost

lexicographic preference for taking the risk reduction in their most feared cause. Discussion with pilot groups led to the conclusion that for some people, the baseline risk of their least feared cause (for example, road accidents) was acceptable to them, and as such, they did not value a risk reduction in that cause at all. As such, even minute reductions in their most feared cause (for example, cancer) were always preferable, because this risk was not deemed to be at an already acceptable level. This effect has been previously noted in the choice experiment literature in environmental economics, in which an attribute might be considered so important that the payment attribute does not present enough of a cost to generate a trade-off (see Rosenberger *et al.* (2003) for a discussion).

To counter this, the protocol was redesigned to incorporate risk *increases* (as opposed to risk reductions) as shown in figure 3.6 on pg. 73. The reasoning is that even an acceptable baseline risk will become unacceptable given a large enough increase in that risk.

3.2.10.iii *Increments (the step range of the risk increase)*

In every question, the risk increase step was 40 in 60 million on top of an initial step of between 30 and 50 in 60 million (see table 3.3 for details). It might therefore be the case that individuals with a marginal preference for one cause or the other are unable to accurately express their preference, because these intervals are fairly large.

In terms of the very first interval, this would be expected to manifest in one of two ways, either;

a) Understatement (respondents are unable to indicate less than 1.5:1 so instead express indifference in their initial choice)
b) Overstatement (respondents are unable to indicate less than 1.5:1 so instead switch in row 1)

In addition, respondents were offered a similar range for every question, which could be expected to condense the range of responses artificially. However, to use smaller increments would mean reducing the range of switch-points on offer in the table, and this would mean losing the ability to capture strong preferences for one cause over the other. The trade-off between range and accuracy was not taken lightly, and piloting suggested that the structure used would be the best compromise. A '*skew low, skew high'* procedure as mentioned in Andersen *et al.* (2007) could have been employed to

allow the responses to be tested for range biases, but given the small sample size it was decided that this would be counterproductive. Analysis of the choice patterns is reported in section 4.9

3.2.10.iv *Herding*

If respondents are able to see what decisions were made by others in the group, their responses might reflect herding or copying behaviour as opposed to their true preferences (see Haley and Fessler (2005) for an interesting experimental approach where the presence of stylised impressions of eyes facing the respondents increased pro-social behaviour in an otherwise anonymous experiment). It is not feasible that any respondent could observe the exact response of another respondent in the session, because respondents were well spaced out and working individually. However, the initial decision (e.g. A, B, or Indifference) might be observable. As such, checks for convergence of decisions through the survey are reported in section 4.9.

In summary, while there are of course issues and imperfections in any survey instrument designed to elicit information about respondents' preferences over complex scenarios, the methodology has been carefully developed to minimise the issues. Where these issues are considered likely to have persisted, post-estimation tests and checks are run, which allow some reassurance that the results appear robust to these issues. The results of these checks are reported in section 4.9 (pg.113).

3.3 Proposed Analysis and Preliminary Work

The methodology has now been explained in some detail, with particular focus on the ways in which respondents' engagement and understanding were maximised. This subsection moves on to explain aspects of the analytical methodology which will be employed to generate insights from the data; in section 3.3 the sample characteristics and central tendencies are presented. After this analytical basis has been established, chapter 4 will provide the main analysis and results.

Initially the choice of central tendency measures is considered, because these will underpin a substantial proportion of the analysis, rendering the choice of measurement important. Next, the proposed regression analysis techniques are outlined. The reason for including this discussion at this stage is rooted in the broad scope of the research: the study aims to consider context, morbidity and latency individually and in combination, and as such the analysis of the central tendencies will be repeated on each

subset of the data- for latency, morbidity, and context- and giving the explanation up front avoids the need to repeat the explanation through the text, which would detract from the key messages from the data.

3.3.1 *Central tendencies*

There are four potential measures of central tendency to be considered for use in the main analysis. The relative strengths and weaknesses of each of these measures are discussed in this section, particularly in terms of describing the current survey data, and in conclusion the geometric mean is found to be the most suitable measure.

3.3.1.i *Arithmetic mean*

The arithmetic mean is perhaps the easiest to calculate and to interpret, but it is a seriously flawed measure for dealing with ratio data. To illustrate, take the example of a two-person society where person A has a relativity for cause X to cause Y of 3:1, while person B has a relativity for cause X to cause Y of 1:3. Logically, any central tendency measure should suggest these preferences cancel to provide an average of 1:1. However, taking the arithmetic mean suggests otherwise: the average X:Y relativity is 1.67. Perhaps even more strikingly, if the ratio is instead defined as Y:X, the relativity for person 1 is now 1/3 and for person 2 is 3/1. Now, the average Y:X relativity is 1.67. Logically, Y:X and X:Y clearly cannot both be 1.67. This effect will hereafter be referred to as 'numerator bias' because it automatically over-weights the cause that is arbitrarily designated as the numerator. In addition to this numerator bias, the arithmetic mean is always problematic in datasets like this one with high end outliers.

3.3.1.ii *Median*

The median is the mid-point of the data when ranked from highest to lowest. It is simple to interpret and percentiles can be chosen for use as confidence intervals. By definition, the median is free from numerator bias and from the undue influence of high-end outliers. However, this measure is insensitive to small variations in response data, and often fails to capture some of the more subtle differences that are picked up by alternative central tendency measures. Nevertheless, the median will be included as a supplementary central tendency measure where appropriate. For these analyses the quartiles (25% and 75%) are used as a measure of similarity for comparing between relativities.

3.3.1.iii *Geometric mean*

Taking the geometric mean involves finding the product of the relativities, and then taking the n^{th} root. It is therefore equivalent to the anti-log of the average logged relativity. Taking logs of the relativities is appropriate because it neutralises the numerator bias problem discussed above, and as such the geometric mean is usually considered the most appropriate measure of central tendencies for ratios. The geometric mean is sensitive to low end outliers and collapses with any zero observations, because it involves taking the product of the observations as opposed to the sum. However, in this dataset there are no zero observations, and as such the geometric mean will be used as the main central tendency measure throughout the subsequent analysis. It has associated 95% confidence intervals that are easily interpreted.

3.3.1.iv *Context Indexing*

The context index approach was developed in Chilton *et al.* (2002) to overcome the problem of numerator bias in the analysis of matching data, i.e. relativities. A value of 1 is assigned to each respondent's most feared cause (i.e. the cause in which they avoided taking the risk increase). The appropriate fraction is then assigned to the other cause, for example using the two-person society described above, person 1 would have a score for cause X of 1/3 and for cause Y of 1. Person 2 would have an X score of 1 and a Y score of 1/3. The arithmetic mean of the scores for each cause is calculated, and the ratio between these scores gives the overall central tendency measure for the sample. This collapses to the sum of the scores for each cause as shown:

$$ratio = \frac{\frac{1}{n}\sum_1^n cancer\ scores}{\frac{1}{n}\sum_1^n roads\ scores} = \frac{\sum_1^n cancer\ scores}{\sum_1^n roads\ scores} \qquad (33)$$

In the current 'two person society' example, the resulting context index ratio is 1:1, as logic would predict.

The main benefit is that the context index is, by design, immune to the problem of numerator bias. It is more sensitive than the median, and lacks the sensitivity to zero responses which plagues the geometric mean. In addition, if every member of the population placed the same monetary value on a change in their risk of their most feared cause, then the context index approach can be shown to give exactly the correct willingness-to-pay (WTP) based relativity. However, this latter strength could also be framed as the weakness of the approach: it imposes the assumption that the same weight

ought to be placed on the most feared cause for each individual. While this is arguably the most equitable assumption in the lack of better evidence, it is nonetheless one that lacks empirical underpinnings.

A second and probably more practically awkward problem with the context index is the lack of associated confidence intervals. Covey *et al.* (2010) developed a method for calculating pseudo-confidence intervals around the context index. This method is summarised in figure 3.9. The numerator and denominator of the confidence interval formula displayed above both have associated 95% confidence intervals, and these are used to form a "worst case" confidence interval. That is, the ratio of upper limit of the confidence interval for the numerator to the lower limit of the confidence interval for the denominator is used as the upper bound of the pseudo confidence interval. Correspondingly, the lower limit of the numerator confidence interval and the upper limit of the denominator confidence interval are used to give the lower bound of the pseudo confidence interval. This generates the broadest combination of values for inclusion within the confidence interval, and can account for the extreme case where the numerators and denominators display perfect negative correlation.

Figure 3.9 Pseudo confidence interval calculation for Q2

$C_{10}R_2$	Arithmetic mean	Lower bound of 95% C.I	Upper bound of 95% C.I
C_{10} index number	0.961	0.916	1.006
R_2 index number	0.190	0.116	0.264
	Context index = 0.198	0.115	0.288

The geometric mean will be supplemented by the context index as well as the median in the discussion of central tendency results in chapter 4.

3.3.1.v *Summary of central tendency discussion*

To summarise, the arithmetic mean will be disregarded because of its sensitivity to high end outliers and also because of its unsuitability for the analysis of ratio data. The other three central tendency measures- the geometric mean, median and context index - will be used in combination, allowing the inclusion of high end outliers (within reason, see

section 3.3.1.v for a fuller discussion of trimming) without allowing them undue influence over the population average.

As discussed, the central tendency decision will be especially necessary for this chapter because, subject to the verification of hypotheses1 and 2 above (pg.52), a substantial proportion of the analysis will be based on these central tendencies. Manipulation of the central tendencies of the relativities data from the RR survey will allow the elicitation of underlying parameters including the context premium and the discount rate. See section 4.11 for this analysis.

3.3.2 Planned regression analysis

Analysis of the central tendency figures can provide a rich set of information about a variety of population average effects. However, it is unable to take account of any demographic influences, nor to give a good insight into the strength of preference over the different attributes of the scenarios. As such, regression analysis will be conducted.

For each attribute in turn, regressions will be run of the relativities for each question on the underlying personal characteristics. In this way, it will be possible to investigate whether demographic characteristics are well equipped to explain the relativity in each question, and hence to identify whether the response to differences in context, timing and morbidity are related to personal characteristics.

In addition, the data can be pooled and regressions run of all relativities on characteristics of the scenarios (difference in timing, context, and illness) and characteristics of the respondent. This pooled regression will provide a final summation of the results and will form a holistic analysis of the available information.

On the basis of these regressions, supplemented by the analysis of central tendency movements between questions, the validity of hypotheses 1 and 2 from pg.52 will be determined. However, prior to this, some preliminary work is required to ready the data for analysis.

3.3.3 Preliminary work

3.3.3.i *Introduction*

Initially the demographic characteristics of the sample are presented and discussed. There follows discussion of the information that was collected about experience with

and preferences for risky and intertemporal decisions as well as familiarity with cancer and road accident risks. This information, along with the demographics, will form the basis of regression models, so a brief discussion is provided about the way that these models are built. Finally attention is turned to the data produced in the R-R survey part of the study, including discussion of the most appropriate trimming levels for use. The central tendencies are presented, and this provides the basis for the analysis in chapter 4.

3.3.3.ii *Sample Statistics*

Table 3.4: Demographics

Variable	**Full Sample**
Gender (% female)	52.6%
Age (mean (s. dev.))	39 (5.76)
Household size (mean (s. dev.))	3.27 (1.36)
No. children in household (mean (s. dev.))	1.38 (1.19)
Child under 18	58.7%
Child under 6	23.2%
Rental (% rent)	39.7%
Further education (% furthered)	47.7%
Own social class based on ISCO-88 (mean (s. dev.))	6.23 (6.47)
Spouse social class based on ISCO-88 (mean (s. dev.))	4.86 (3.03)
Personal income (monthly mean (s. dev.))	£1784.92 (£1879.01)
Household income (monthly mean (s. dev.))	£2685.52 (£2074.88)

The respondents (n=157) were all between the ages of 30 and 50, resident in the Newcastle-upon-Tyne area of the UK. The demographics for the sample are given in table 3.4, with mean and standard deviations provided where appropriate.

The sample was recruited by a market research agency. Although not formally stratified to reflect 30-50year olds in the North East, the comparison to census data suggests that the sample is reasonably representative. For example, the ratio of females to males in the North East[21], is 51.1% and in our sample it was 52.6%. However, there is a higher than average proportion of unemployed people (reflected in own class and a peak at very low income levels), which may be an artefact of holding some survey group sessions during the working week.

3.3.3.iii *Preference related characteristics*

In addition to the observable demographic characteristics, information was gathered about the experience that respondents had with cancer and road accidents, as well as their perceived existing levels of health and of road accident risks. The majority of the sample had had experience of road accidents and of cancer, either personal experience or having a close friend or family member affected (50.3% for road accidents and 73.5% for cancer). The proportion is higher for cancer than for road accidents, which could contradict the assertion in the literature review that cancer is dreaded partly because it is unknown. Respondents typically judged their current health to be at or slightly above the population average and judged their relative likelihood of dying in a road accident as slightly lower than the population average.

3.3.3.iv *Variable selection for regression analysis*

The demographic information will be used in regression analysis to explore the influence of underlying personal characteristics on the relativities elicited in the RR survey.

It will typically be useful to keep the same demographic explanatory variables in each regression to facilitate comparison. As such, and acknowledging the risk of over fitting the model, a full set of predictor variables is developed. Given that this is exploratory analysis, there is no clearly defined set of explanatory variables that ought to be included. This is addressed using a combination of variable selection techniques. Initially, correlation is assessed with the aim of removing any extremely correlated

[21] Census data release (2013) http://www.ons.gov.uk/ons/publications/re-reference-tables.html?edition=tcm%3A77-300560 was used to make comparisons where possible. Notice that this information refers to the whole North East population as opposed to the 30-50 year old demographic, so comparisons are not intended to be extremely close.

variables. With the exception of some income variables, high correlation is not found. Table B1 in Appendix B gives the correlation coefficients above 0.3 for this dataset. The variance inflation factors (VIFs) for each variable are given in Appendix B, and because none is over 10 there is no evidence of serious multicollinearity. The mean VIF is 0.37, which can be considered lower than the threshold for problematic collinearity.

Using previous literature a range of potential explanatory variables was decided upon. These included the variables used in Hammitt and Haninger (2010) and Van Houtven *et al.* (2008) because these papers explicitly considered similar issues to those under investigation here. Specifically, the former paper used gender, age, income, education, health risk perception and a proxy for risk preferences (insurance). The latter used some of these variables and additionally used health status, household size, having experience of cancer and road accidents and subjective road accident risk. These variables formed the basis of the variable set used in studies 1 and 2. In addition, a variable was included to capture having children in the household, because piloting suggested that this might influence the perceived optimal time to take a risk increase. Where two variables are likely to be picking up the same influence (e.g. having children under 18 and having children under 6), the *vselect* tool for model selection in Lindsey and Sheather (2010) is used to choose the variable set that will maximise the fit of the model.

Vselect allows the user to perform stepwise regressions forwards or backwards using any of the major information criteria C (Mallow's Cp), AIC (Akaike's information criteria), AICc (Akaike's corrected information criteria), BIC (Bayes information criteria) and R^2adj (Adjusted R-squared). See Lindsey and Sheather (2010) for a discussion and Stata software examples. It also allows the user to perform leap and bound selection which is arguably more robust than the stepwise versions. This analysis uses the leap and bound approach, and compares Mallow's C_p r^2adj, AIC, AICc and BIC to maximise the chance of choosing the right variable set. In addition to selecting specific variables to choose the full analysis model this command is also used to select best-fit models for the regressions of relativities on observable characteristics. These models are presented as appropriate throughout the analysis.

The full predictor model is as follows:

$$Relativity = \alpha + \beta_1 age + \beta_2 age^{*} hhinc + \beta_3 loghhinc + \beta_4 female + \beta_5 under6 + \beta_6 mother + \beta_7 educ + \beta_8 canexp + \beta_9 roadexp + \beta_{10} health + \beta_{11} carrisk + \beta_{12} finRA + \beta_{13} finTP + \beta_{14} healthRA + \mu \quad (34)$$

The variables are described in table 3.5. This variable list incorporates standard relevant demographics from the literature, some cancer-specific characteristics, and some interacted variables.

While the *vselect* tool suggests that rent generates better fit than household income as a proxy for income level, in order to run regression with the interaction between age and income it is necessary to include household income as a level variable.

Table 3.5: Full list of predictor variables

Variable name	Description
age	Age (years)
age*hhinc	log of household income interacted with age
loghhinc	log of household income
female	gender (female =1)
under6	children under 6 in the household
mother	being female and having children under 6
educ	further education
canexp	Having experience of cancer (self or close friend or family member)
roadexp	experience of road accidents (self or close friend or family member)
health	self-reported health state (1-3 increasing scale of health)
carrisk	perceived road accident risk (1-5 increasing scale of road accident risk)
finRA	financial risk aversion
finTP	financial time preference
healthRA	health state risk aversion

Interaction terms are included for variables that could matter in combination. The interaction between gender and having children captures a 'motherhood' effect[22] which was justified by the short written explanations in which women frequently mentioned having young children. The interaction between age and household income captures the effects of different levels of wealth over a lifetime.

Risk and time preferences were also elicited. These are discussed in more detail in part III where the analysis considers the implications of latency on the relativity in more detail.

[22] The effect of fatherhood was also tested and found to be insignificant.

3.3.3.v *Risk-risk relativities data*

This section describes the preference-based data that was elicited in the RR survey section of the protocol, as well as the way that it will be cleaned and organised in advance of the analysis which will be reported in chapter 4. As discussed, in addition to the demographic information explored in sections 3.3.3.ii-iii, data was collected for ten risk-risk trade-off questions. The scenarios to be compared were summarised in table 3.1 on pg.64.

As discussed in detail in the methodology section, the questions categorise as 'overall', 'context', 'latency', 'morbidity' and 'labelling'. The resulting relativities are formed of the risk increase in the respondent's least feared cause that would make them just indifferent, and a 50 in 60 million increase in their most feared cause, expressed as a ratio between the two risk levels. As an example, the data for question 2 is the ratio between the increase in risk of cancer ten years from now divided by the increase in risk of road accidents during the year after next, and this ratio could be greater than or less than 1 depending whether the respondent's initial choice was to take the cancer or the road accident risk, because this determines which of the two risks is held at 50 in 60 million.

The central tendency measures for these relativities are given in tables 4.1 to 4.3 on pg.94-95.

3.3.3.vi *Extreme outliers and trimming*

Section 3.3.1 on pg. 81 discussed the possible measures of central tendency for use in subsequent analysis and concluded that the geometric mean presents the best option, supplemented by the median and context index. One reason for the use of the geometric mean is that it allows outliers to be included but does not give them excessive weight, especially compared with the arithmetic mean. Despite this, and despite that the survey and preceding teaching sessions were designed to maximise respondents' understanding, given the complexity of the issues and the emotive nature of the issues discussed it is perhaps unsurprising that extreme answers were given by a small proportion of respondents. However, there is no failsafe way to know whether a high response is a protest, an exaggeration, or a true reflection of a very strong preference. As such, dealing with outliers is not straightforward.

The approach employed here is to clean the data on two levels:

- The ‘untrimmed’ sample excludes responses where the respondent refused to provide an answer, wrote an answer greater than 60million (which indicates a probability greater than 1, an impossibility), or switched backwards and forwards between causes multiple times. All usable responses are retained.
- The ’30 million level’ excludes any answer greater than or equal to 30 million in 60 million. 30 million in 60 million indicates indifference between taking a risk of fatality in their least feared cause that is essentially the same as the toss of a coin, and taking a very small (50 in 60 million) increase in their risk of fatality in their most feared cause. While this could suggest very strong preferences, at least some of these respondents are likely to have been indicating protests, or failing to fully understand the response mechanism and the implication of their answers. Relativities are restricted to be below 600 000:1.

Trimming on each of these levels generates the per-question sample sizes in table 3.6.

Table 3.6: Sample sizes by trimming level

Question		**Cleaning (untrimmed) n**	**Trimming (30million +) n**
1	C_{10} :R_1	146	133
2	C_{10}:R_2	144	128
3	C_{25}:R_2	140	127
4	C_2:R_2	136	126
5	C_{10}:R_{10}	139	129
6	C_2:C_{10}	139	125
7	C_2:C_{25}	133	119
8	C_{10}[12] :C_{10}[6]	140	133
9	C_{10}[36] :C_{10}[6]	132	124
10	C_{10}[2w] :R_{10}[2w]	142	140

An important distinction to make at this stage is that the trimming applies to the responses themselves, and not to the respondent. That is, if a respondent generates a

mixture of relativities across questions, some of which fall above the trim level, then their acceptable responses will be retained for the analysis while their outlying responses will dropped. This avoids the loss of apparently usable information, and is in the interests of maintaining a reasonable sample size, as well as for the ethical purpose of allowing the preferences of respondents as expressed in some questions to be included in the overall analysis regardless of the respondent's performance on other questions. Sample sizes may therefore vary between questions depending on the number of responses dropped.

For the untrimmed sample, per-question sample sizes lie between 132 and 146. For the 30 million trim this falls to the range 119 to 140. Both trim levels are presented for reference in tables 4.1-4.2 on pg. 94, although the subsequent analysis will use the 30 million trim because it is judged to present the optimal trade-off between retaining as much information as possible while maintaining the integrity of the data and eliminating obvious protests and misunderstandings.

3.3.1.vii *Summary*

Having dealt with the preliminary issues of the sample size and selection, the structure of the available data, variable selection techniques and trimming, the next stage is to report the results of study 1. The verification of hypotheses 1 and 2 from pg.52 lends support to the C_TR_t relationship developed in section 2.11.2, and on this basis the relationship is used in conjunction with the relativities data elicited in study 1 to elicit estimates of the underlying parameters that define the VSL_{CAN}:VSL relativity. These are the context premium (1+x) and the effective discount rate (r). However, first the results are presented in support of these hypotheses

Chapter 4. Study 1 Analysis and Conclusions

4.1 Introduction

As described in detail in chapter 3, the survey in study 1 was designed to elicit information on the way in which context, morbidity and timing influence the preference for avoiding fatality risk increases. The questions included these attributes both jointly and separately and the analysis will follow a similar philosophy. Initially, the 'overall' comparisons are analysed with the conclusion that context and timing both influence the overall relativities elicited. Having established the existence of both context and latency effects in the overall questions, the analysis moves on to separately consider the cancer context premium; its hypothesised components morbidity and dread of the cancer label; and then latency. Regressions are run to explore what demographics influence the relativities in each set of questions. These find little of significance, which supports the assumption that the effects in question (context effects, discounting) are largely intrinsic to the individual, and do not arise as a result of personal characteristics.

Insights from these subsections are combined and supplemented by a final overall pooled regression which uses information from all ten questions simultaneously to explore the way that context, time and morbidity influence the overall relativities, controlling for any influence of demographics.

On this basis, the hypotheses that the cancer context increases the VSL and that latency decreases it, *ceteris paribus*, are verified.

After this, sensitivity analysis and some economic consistency checks and tests of face validity are presented, whereby evidence is utilised to lend support to- and highlight areas of conflict with- the results from the main analysis.

With the hypotheses validated, the C_TR_t relationship from section 2.11.2 can be assumed to hold, and novel analysis is conducted to elicit the key underlying parameters including the context premium and effective discount rate. Results of this analysis are postponed to pg.123.

The analysis that will be reported is outlined in figure 4.1.

Figure 4.1: Analysis of RR relativities data

- Overall premium (Q1-Q3, C_TR_t)
    - Central tendencies: predicted movement and discussion
    - Regression on demographics
- Context Premium(Q4-Q5, C_TR_T)
    - Central tendencies: predicted movement and discussion
    - Regression on demographics
- Morbidity premium and labelling dread(Q8-Q10, $C_T[m]X_t[m]$)
    - Central tendencies: predicted movement and discussion
    - Regression on demographics
- Latency effects (Q6-Q7, C_TC_t)
    - Central tendencies: predicted movement and discussion
    - Regression on demographics
- Pooled analysis (all questions)
    - Regression on scenario attributes only
    - Regression on scenario attributes and demographics
- Validity and consistency checks
    - Results of methodology tests
    - Regression upon residuals
- Elicitation of underlying parameters
    - Elicitation of estimates for r and x from Q1-3
    - Elicitation of estimates for x from Q4-5
    - Elicitation of estimates for m from various questions
    - Elicitation of estimates for r from Q6-7

4.2 Central Tendencies

Tables 4.1 and 4.2 summarise the central tendency measures for each trim. More detail at the 30 million trim is provided in table 4.3.

Table 4.1: Central tendencies: untrimmed

	Q1 $C_{10}R_1$	Q2 $C_{10}R_2$	Q3 $C_{25}R_2$	Q4 C_2R_2	Q5 $C_{10}R_{10}$	Q6 C_2C_{10}	Q7 C_2C_{25}	Q8 C[12m]C[6m]	Q9 C[36m]C[6m]	Q10 C[2w]R[2w]
Arithmetic mean	60703	55843	38147	59042	57311	98817	112861	35239	60899	18597
Median	1.01	1.00	0.179	9.50	10.0	10.0	20.0	6.10	7.70	1.00
Geometric mean	**1.473**	**0.698**	**0.238**	**14.50**	**12.28**	**61.64**	**94.14**	**9.919**	**36.62**	**1.233**
Context index	1.121	1.013	0.597	2.591	2.452	4.415	5.106	2.440	3.321	1.044

Table 4.2: Central tendencies: 30 million trim

	Q1 $C_{10}R_1$	Q2 $C_{10}R_2$	Q3 $C_{25}R_2$	Q4 C_2R_2	Q5 $C_{10}R_{10}$	Q6 C_2C_{10}	Q7 C_2C_{25}	Q8 C[12m]C[6m]	Q9 C[36m]C[6m]	Q10 C[2w]R[2w]
Arithmetic mean	3629	2042	1265	8172	9040	12125	6128	7018	13215	1720
Median	1.00	1.00	0.179	7.80	7.80	10.0	5.20	6.10	7.70	1.10
Geometric mean	**1.116**	**0.814**	**0.280**	**9.319**	**9.647**	**21.235**	**25.73**	**8.215**	**17.05**	**1.012**
Context index	1.089	1.041	0.595	2.526	2.460	3.995	4.451	2.437	3.103	1.026

Table 4.3: 30 million trim central tendencies

Question	Arithmetic Mean [confidence interval] (*standard deviation)*	Median (percentiles)	Geometric mean [confidence interval]	Index [confidence interval]
1 ($C_{10}R_1$) N= 133	**3629** [-2340, 9598] *(34799)*	**1** *(25% = 0.111)* *(75% = 7.2)*	1.116 [0.576, 2.161]	**1.089** [0.847, 1.406]
2 ($C_{10}R_2$) N= 128	**2042** [-1088, 5172] *(17894)*	**1** *(25% = 0.108)* *(75% = 7.2)*	0.814 [0.429, 1.643]	**1.041** [0.805, 1.347]
3 ($C_{25}R_2$) N= 127	**1265** [-376, 2905] *(9342)*	**0.179** *(25% = 0.05)* *(75% = 4.8)*	0.280 [0.139, 0.566]	**0.595** [0.446, 0.7766]
4 (C_2R_2) N= 126	**8172.216** [-232, 16576] *(47665)*	**7.8** *(25% = 1)* *(75% = 40)*	9.319 [4.821, 18.01]	**2.526** [1.944, 3.426]
5 ($C_{10}R_{10}$) N= 129	**9040.34** [1000, 17081] *(46154)*	**7.8** *(25% = 1)* *(75% = 40)*	9.647 [4.841, 19.22]	**2.460** [1.904, 3.308]
6 (C_2C_{10}) N= 125	**12125.26** [2537.2, 21713] *(54159.78)*	**10** *(25% = 5.25)* *(75% = 40)*	21.235 [12.15, 37.12]	**3.995** [3.060, 5.448]
7 (C_2C_{25}) N= 119	**6127.82** [1027.69, 11227.95] *(28095)*	**5.2** *(25% = 10)* *(75% = 100)*	25.73 [14.86, 44.54]	**4.451** [3.396, 6.298]
8 ($C_{10}[6]C_{10}[12]$) N=133	**7018** [1518, 12519] *(32069)*	**6.1** *(25% = 1.35)* *(75% = 10)*	8.215 [4.534, 14.89]	**2.437** [1.961, 3.122]
9 ($C_{10}[6]C_{10}[36]$) N= 124	**13215** [3973, 22456] *(51990)*	**7.7** *(25% = 2.7)* *(75% = 35)*	17.05 [8.55, 34.00]	**3.103** [2.419, 4.174]
10 ($C_{10}[2w]R_{10}[2w]$) N= 140	**1720** [-1397, 4838] *(18657)*	**1** *(25% = 1)* *(75% = 1.8)*	1.012 [0.647, 1.584]	**1.026** [0.880, 1.197]

4.3 Overall Results: Questions 1-3

This section presents analysis of the relativities which compare latent cancer risks and current period road accident risks. The analysis uses questions 1-3, ($C_{10}R_1$, $C_{10}R_2$ and $C_{25}R_2$). The cancer scenarios include 12 months' morbidity prior to fatality, and the relativities can therefore be interpreted as including the combined impacts of context, morbidity and latency.

4.3.1 *Predictions: questions 1-3*

Initially consider Q1-Q2 ($C_{10}R_2$ to $C_{25}R_2$). Statements 1 and 3 from pg.65 section 3.2.4 (cancer fatality is, *ceteris paribus*, perceived to be worse than road accident fatality; and less morbidity is preferred to more) suggest that the cancer risk increase will be avoided, while statement 2 (that delaying the fatality lessens the present disutility from the prospect of an increase in the risk of that fatality) suggests the opposite. As such, it is impossible *a priori* to predict whether the relativity is greater or less than 1. Comparing Q1 to Q2, the road accident is later in Q2 than in Q1 and so better by comparison. Because the cancer case stays the same, the overall relativity (C_TR_t) is expected to increase from Q1-Q2.

Moving from Q2-Q3 ($C_{10}R_2$ to $C_{25}R_2$) the cancer fatality risk is delayed from 10 to 25 years from now and hence ameliorated. This is expected to manifest as a smaller overall relativity for Q3 than for Q2.

The relativity is therefore expected to increase from Q1-Q2 then decrease from Q2-Q3. The central tendency results are and discussed below.

4.3.2 *Central tendencies: questions 1-3*

For Q1 ($C_{10}R_1$) and Q2 ($C_{10}R_2$) the relativity is insignificantly different to 1 for the context index and for the geometric mean, and the median is equal to 1. The relativity becomes significantly lower than one when the cancer fatality is delayed until 25 years, in Q3 ($C_{25}R_2$).

Although in absolute terms the relativity appears to decrease between Q1 and Q2 as opposed to the anticipated increase, in fact the relativities are insignificantly different than one another. This result, which replicates the finding of Meyer (2013) suggests that respondents did not perceive a significant difference between the road accident during the coming year and during the year after next, which suggests that a strong

'passion for the present'[23] does not appear to be driving preferences for road accident risks as compared to cancer risks in the future. Given this insight, the analysis will proceed with using Q2 and Q3, because these questions were designed for comparability with the later questions in the survey[24].

The predicted decline in the relativity from Q2 to Q3 is evident, and the difference is significant. This suggests that respondents were significantly less averse to the prospect of cancer fatality risks 25 years from the present than 10 years from the present. This is significant for the geometric mean at the 95% level, and holds for the median and context index according to the calculated confidence intervals.

4.3.3 Regression: questions 1-3

Section 3.3.3 discussed the choice of models for regression. The full model is used to run regressions of each question in this section in order to explore the influence of demographics on the overall cancer:roads relativity. If demographics are found to be insignificant, this suggests that the preferences expressed in the overall relativity are largely intrinsic. Having said this, as discussed in earlier chapters age, income and current risk levels might all be expected to influence the perceived benefit of a risk reduction, and both age and risk level will be expected to have a different effects for latent cancer than for roads risks sooner (and hence to influence the relativity). A brief discussion of the results is provided next. Table 4.4 demonstrates that some demographic characteristics are able to explain the relativity for the "overall" questions. These are explained in turn.

4.3.3.i *Age*

Age at the time of the study is negatively correlated with the relativity (Q2). Being older at the time of the survey might mean that the respondent is less willing to accept a higher roads risk to avoid the cancer risk increase (perhaps the older population feel like they would be strongly affected by a risk increase now) or perhaps it reflects that there is a smaller chance that the individual would be alive to experience the increased risk of the latent cancer fatality.

[23] See Laibson (1997) for discussion of quasi hyperbolic discounting models which incorporate these sorts of preferences

[24] This is because 'during the year after next' was deemed to be the earliest plausible fatality date for cancer risks (relevant for Q4 (C_2R_2) Q6 (C_2C_{10}) and Q7 (C_2C_{25})).

Table 4.4: Overall relativity regressions

	Q1, $C_{10}R_1$ n=99, r2=0.1990 Coef. (Robust Standard Error)	Q2, $C_{10}R_2$ n=94, r2=0.2040 Coef. (Robust Standard Error)	Q3, $C_{25}R_2$ n=92, r2=0.3257 Coef. (Robust Standard Error)
Age	2.92**	2.82*	2.05
	(1.43)	(1.57)	(1.40)
log of household income interacted with age	-111.35**	-113.49*	-85.5
	(55.77)	(62.05)	(55.23)
log of household income	111.26**	113.4*	85.14
	(55.68)	(61.86)	(55.99)
gender (female =1)	-0.401	-0.67	-1.56**
	(0.90)	(0.89)	(0.76)
children under 6 in the household	1.05	1.01	0.67
	(1.18)	(1.23)	(1.41)
being female and having children under 6	-2.93	-4.11*	-3.78*
	(2.09)	(2.16)	(1.95)
further education	1.64**	1.31	1.24
	(0.81)	(0.90)	(0.79)
experience of cancer (self or close friend or family member)	2.18**	1.88	1.77*
	(0.89)	(1.00)	(0.99)
experience of road accidents (self or close friend or family member)	-0.47	-1.12	-1.89**
	(0.77)	(0.86)	(0.78)
self-reported health state	0.33	0.06	-0.87
	(0.73)	(0.70)	(0.63)
perceived road accident risk	-0.28	-0.12	0.18
	(0.40)	(0.48)	(0.42)
financial risk aversion	-0.03	-0.69	-0.09
	(0.53)	(0.65)	(0.59)
financial time preference	-0.24	1.4	2.23*
	(1.28)	(1.29)	(1.33)
health state risk aversion	-0.45*	-0.32	-0.40**
	(0.23)	(0.22)	(0.18)
Constant	294.91*	305.89*	235.87
	(149.39)	(167.79)	(149.28)

4.3.3.ii *Income*

Two significant explanatory variables in Q1 might proxy for income. Having had further education increases the relativity. Having a higher monthly household income also increases the relativity. Combined, these suggest that higher income levels might be correlated with larger VSL_{CAN}:VSL relativities. However, neither is significant for Q3.

4.3.3.iii *Experience*

In Q1, experience of cancer is significantly and positively related to the overall relativity. In Q3, experience of road accident risks is significantly and negatively related to the overall relativity. This suggests that familiarity with a certain scenario reduces the willingness to accept additional risk of fatality by that cause.

4.3.3.iv *Motherhood*

In Q2-3, the combined impact of being female and having children is negative, suggesting that mothers are more willing to accept increased future cancer risks, plausibly so as to be around for their young children.

4.3.3.v *Time preference*

Financial time preference is significant in Q3, with a higher financial discount rate appearing to increase the relativity (i.e. people are willing to take a higher road accident risk now to avoid the future cancer if they have previously indicated high levels of discounting). It is unsurprising that time preferences only appear to matter over longer time periods, although the sign of the coefficient is counterintuitive.

4.3.3.vi *Risk preference*

Being risk averse over health states reduces the average respondent's willingness to accept higher road accident risks, resulting in a lower relativity for Q1 and Q3. Risk preferences are discussed in more detail in part III of this thesis.

4.3.4 *Summary: questions 1-3*

Having considered the overall relativities, it appeared that both timing and context influenced respondents' relative valuation of cancer and roads risk increases. These insights can be explored in more detail by analysing the responses to questions specifically designed to investigate these attributes. This is done first by looking at context holding timing constant in Q4-5. Then, to further explore what drives this context related preferences, questions that varied in terms of morbidity and in terms of the label of the context will be analysed. After this, attention will turn to the other aspect of the comparison: timing of the risk increase.

4.4 Context Premium Results: Questions 4-5

This section discusses the evidence surrounding the relative aversion to risks of cancer and road accidents, allowing for one year of morbidity prior to the cancer fatality, but when the two fatalities would occur at the same time. As such, the relativity reflects the difference between cancer and road accident fatality risks when controlling for any influence of timing. The relativity captured in this section is the 'context premium'.

4.4.1 *Predictions: questions 4-5*

In Q4 (C_2R_2) and Q5 ($C_{10}R_{10}$) the timing of fatality is the same for both causes in each question. However, the context is different between the options, and the cancer case includes 12 months' morbidity. As such statements 1 and 3 (cancer fatality is, *ceteris paribus*, perceived to be worse than road accident fatality; and less morbidity is preferred to more) lead to the prediction that the relativity in both cases is greater than 1. Comparing Q5 to Q4, both the cancer and road accident risk increases are ameliorated in Q5 by the additional 8 years until the risk would manifest. Assuming that the impact of latency is the same for road and cancer fatality risks[25], the overall relativity is expected to remain the same between Q4-Q5.

4.4.2 *Central tendencies: questions 4-5*

A strong preference for avoiding cancer risk increases compared to road accident risk increases can be observed for both questions 4 (C_2:R_2) and 5 (C_{10}:R_{10}). The 'context premium' that this implies is about 9.5 based on the geometric mean while the context index approach places the relativity lower, at 2.5:1. The median is within this range, at 7.8:1.

Q4 and 5 are statistically indistinguishable from one another according to the geometric mean, and the percentiles overlap for the median. Similarly, the context index cannot distinguish between the relativities. This accords with the prior hypothesis and adds evidence in support of the assumption (pg.52) that risks of both cancer and road accident fatality are discounted by the individual at the same rate, and that morbidity and death are combined for discounting[26]. More generally, the results suggest that the

[25] This is a strong assumption which is used here for analytical tractability. Future research into the validity of this assumption would be beneficial.

[26] This is another assumption that is employed for analytical tractability. Again, dedicated future research could explain whether this is a realistic characterisation of preferences.

timing of fatality does not appear to affect the relativity between contemporaneous road and cancer fatality.

4.4.3 *The focussing illusion*

The 9.5 context premium derived from these questions appears high, especially when compared to the premium implied by Q1-3 and by regression on all questions, as will be discussed in sections 4.9 and 4.12. An explanation for this could lie in the fact that when a single attribute is isolated, in this case context, respondents find this attribute to be excessively, perhaps exaggeratedly important. This is explained in Schkade and Kahneman (1998) who coin the term 'focusing illusion', which they describe as follows:

"When a judgment about an entire object or category is made with attention focused on a subset of that category, a focusing illusion is likely to occur, whereby the attended subset is over-weighted relative to the unattended subset." (Schkade and Kahneman, 1998)

Or, as Kahneman and Thaler (2006) have it, "Nothing matters as much as you think it does when you are thinking about it".

The prevalence of this effect in the present dataset is supported by the apparently high relativities for the latency questions and morbidity questions, in which the single attribute focus is a feature as well. See sections 4.6 and 4.7 for details.

4.4.4 *Regression: questions 4-5*

Fewer variables are able to explain the relativity in Q4-5 than was the case for Q1-3. However, the variables which are significant are economically sensible. The demographics explaining the dread question relativities are similar to those important in explaining the overall relativity, which suggests that the "overall" and "context" questions were approached in a similar manner.

4.4.4.i *Age*

In Q4 (C_2R_2), age no longer significantly influences the relativity.

4.4.4.ii *Experience*

For both Q4 and Q5 having had experience of cancer significantly increases aversion to it. This mirrors the answers from Q1-3.

Table 4.5: context relativity regressions

	Q4 C2R2 n=92, r2=0.1491 Coef. (Robust Standard Error)	Q5 C10R10 n=94, r2=0.1266 Coef. (Robust Standard Error)
age	0.9	1.73
	(1.28)	(1.49)
log of household income interacted with age	-36.17	-65.68
	(50.22)	(58.21)
log of household income	36.25	65.66
	(50.19)	(58.10)
gender (female =1)	-1.57*	-0.6
	(0.89)	(0.99)
children under 6 in the household	-1.66	-0.23
	(1.02)	(1.47)
being female and having children under 6	1.82	-0.42
	(1.71)	(2.15)
further education	-0.16	0.86
	(0.80)	(0.88)
experience of cancer (self or close friend or family member)	2.02**	2.79**
	(0.87)	(1.06)
experience of road accidents (self or close friend or family member)	0.04	-0.57
	(0.84)	(0.95)
self-reported health state	-0.55	-0.16
	(0.69)	(0.79)
perceived road accident risk	0.39	0.35
	(0.56)	(0.61)
financial risk aversion	-0.12	-0.22
	(0.26)	(0.60)
financial time preference	0.21	0.96
	(1.33)	(1.43)
health state risk aversion	0.12	-0.06
	(0.26)	(0.29)
constant	97.3	173.05
	(134.81)	(156.00)

4.4.4.iii *Motherhood*

While the motherhood variable is not significant in these regressions, being female is significant and negative in Q4. This may be picking up a similar effect to the motherhood variable.

4.4.5 *Summary: questions 4-5*

Age, Time preference, Risk preference and Income, all of which were significant for Q1-3, are insignificant in Q4-5. This might reflect that there is no 25 year latent scenario in Q4-5.

Having found a significant and positive premium for the context of cancer when compared to contemporaneous road accidents, it will be interesting to consider what drives this preference. It has been well documented that the cause "cancer" engenders a particular dread. This is tested in our survey using Q10 (C_{10}[2w]R_{10}[2w]), where the two fatality causes are given descriptions that are identical in every way except for the label: one is referred to as "cancer" and the other as "road accidents". An alternative explanation for the preference for avoiding cancer risks is that they tend to include a period of morbidity prior to the fatality. This is explored using Q8 (C_{10}[12m]C_{10}[6m]) and Q9 (C_{10}[36m]C_{10}[6m]) which vary the scenarios only in terms of the length of time that the person would be ill before they died. Through these three questions, it is possible to draw conclusions about the underpinnings of the context premium identified in the previous section.

4.5 Morbidity Results: Questions 8-10

First, the analysis will consider the effect of illness preceding fatality on the relativity. In this study, morbidity has been explored through questions that vary the length of time that the person is ill prior to fatality. For the cancer it is typically one year of illness. However, questions 8 and 9 explicitly vary the length of time spent ill with cancer prior to fatality, and the lengths of time are 6 months, 12 months or 3 years. For the road accident the illness lasts for "minutes or hours". The exception is in question 10, where both the road accident and cancer fatalities are described as occurring after "one or two weeks' pain and suffering". Of course, as described in section 2.9.6 (pg.39), duration is not the only aspect of morbidity that is likely to influence the overall relativities, but duration was chosen for simplicity of explanation. Further research considering

severity of illness would allow a more thorough examination of how illness influences the VSL.

4.5.1 *Predictions: questions 8-10*

Q8 (C_{10}[12m]C_{10}[6m]) and Q9 (C_{10}[36m]C_{10}[6m]) ask respondents to compare fatal cancer risks ten years from now but with differing lengths of time spent ill prior to fatality. The fatality preceded by 6 months of illness, is compared with fatality after 12 months' illness in Q8 and fatality after 36 months illness in Q9. Using statement 3 (less morbidity is preferred to more), the relativity will be expected to increase[27]. In both cases, the relativity is hypothesised to be greater than 1.

The labelling dread question, Q10 (C_{10}[2w]R_{10}[2w]) holds both time and morbidity constant, allowing an insight into the influence of label dread, to distinguish it from the influence of context in general. The relativity is predicted to be greater than one if statement 1 holds (that is if, *ceteris paribus*, cancer risks increases are considered to be worse than road accident risk increases).

4.5.2 *Central tendencies: questions 8-10*

As anticipated, the relativities for Q8- 9 shows that less illness is preferred to more. In addition, the relativity increases at a decreasing rate as the morbidity differential increases. It is possible to use Q8 and Q9 in conjunction with other questions in the survey to obtain more information about morbidity. Each question is assigned a 'morbidity differential', so for Q8 this is 6 months and for Q9 it is 30 months, but for Q4 (C_2R_2) and Q5 ($C_{10}R_{10}$) it is 12 months (from no morbidity in roads to a year of morbidity in cancer). If the prediction that the relativity is increasing in morbidity is correct, then the relativity should be larger for Q9 than Q4 or 5, and smaller for Q8. The geometric mean confirms this, with relativities of 8 (Q8), 9.5 (Q4 and Q5) and 17 (in Q9). The pattern is replicated in the context index.

The premia in Q8 and 9 are significantly different when considering the geometric mean and the median. However, the context index does not significantly differ between the two, according to the pseudo confidence intervals. It certainly seems that the jump from no morbidity to some morbidity is considered to be worse than an extension of an existing morbidity period. This may simply be an artefact of the label of cancer,

[27] As described in section 2.8, the morbidity period is included prior to fatality so there is no confounding trade-off between length of life and time spent in illness.

however, because it was not considered plausible to describe a cancer fatality that did not include prior morbidity. However, the test of label dread, Q10 (C_{10}[2w]R_{10}[2w]), found that for every measure of central tendency and at both levels of trimming, the ratio is insignificantly different to one. Taken at face value, this implies that the label 'cancer' is not sufficient to give rise to a context premium. There is, of course, a possibility that respondents recognised the identical description of the scenarios and concluded that indifference was the 'correct' answer to question 10; a concern which justified its inclusion after all of the other questions had been answered. Regression analysis reported below highlights the importance of morbidity in explaining choice. A final point to note is the breadth of the confidence intervals. They appear to be very wide, suggesting that different people view morbidity quite differently.

4.5.3 *Regression: questions 8-10*

To explore morbidity in more detail, regression is run on the full predictor model. The results for each of questions 8, 9 and 10 are presented in table 4.6 and followed by a discussion.

In comparison with the earlier regressions (Q1-5) the demographics are much less significant. The income proxy, rental, is significant and negative but only for Q8. Otherwise, none of the previously significant variables matters in explaining the morbidity or label dread preferences.

4.5.4 *Summary: questions 8-10*

Taken together, these results suggest that morbidity preferences as well as specific context labelling preferences are intrinsic and not influenced by demographics. The puzzle here is that some aspects of the demographic model were significant when considering the context premium Q4-5. The analysis of central tendencies, as well as the prior hypotheses, suggested that a preference for avoiding cancer over contemporaneous road accidents would be driven by one or both of a preference for avoiding morbidity and the dread that comes from the label of cancer. If this was the case, then the same pattern of significance ought to be observed for the regression of dread as for the regressions of the labelling and/or morbidity questions, but this is clearly not the case. As such, it appears that there may be some additional effect that is unaccounted for in the framework used here.

Table 4.6: Morbidity regressions

	Q8 C_12C_6 n=95, r2=0.1337 Coef. (Robust Standard Error)	Q9 C_36C_6 n=88, r2=0.1430 Coef. (Robust Standard Error)	Q10 C2wR2w n=101, r2=0.1226 Coef. (Robust Standard Error)
age	-1.79 (1.20)	-0.48 (1.40)	0.83 (0.96)
log of household income interacted with age	72.08 (46.76)	19.68 (54.22)	-33.27 (37.77)
Log of household income	-72.02 (46.71)	-19.99 (54.08)	33.39 (37.70)
gender (female =1)	0.27 (0.80)	1.41 (0.97)	-0.54 (0.68)
children under 6 in the household	0.41 (1.18)	0.99 (1.78)	-0.27 (0.74)
being female and having children under 6	-0.66 (1.40)	-1.86 (2.07)	0.59 (1.02)
further education	0.71 (0.68)	0.11 (0.84)	-0.64 (0.51)
experience of cancer (self or close friend or family member)	0.16 (0.85)	0.31 (1.05)	0.99 (0.80)
experience of road accidents (self or close friend or family member)	1.00 (0.74)	0.31 (0.89)	0.00 (0.55)
self-reported health state	-0.01 (0.64)	0.44 (0.85)	-0.46 (0.55)
perceived road accident risk	-0.14 (0.36)	-0.42 (0.45)	-0.29 (0.29)
financial risk aversion	0.60 (0.51)	0.67 (0.59)	-0.43 (0.37)
financial time preference	-1.28 (1.22)	-1.3 (1.59)	1.5 (1.00)
health state risk aversion	-0.02 (0.19)	0.30 (0.26)	-0.10 (0.15)
constant	-192.29 (124.7)	-50.36 (144.46)	89.44 (100.76)

Having established that a context premium exists- and having made the somewhat surprising discovery that for this sample it appears to be driven by the morbidity prior to fatality as opposed to any particular dread of cancer *per se*- this analysis turns to the second part of the relationship: the effects of latency. This effect is modelled as offsetting the context premium in the 'overall' comparisons between latent cancer and current period road accidents (see the C_TR_t relationship presented in section 2.11.2) and this section provides the empirical evidence in support of the hypothesised relationship.

4.6 Latency Results: Questions 6-7

The concepts of latency and discounting are distinct but related: latency is a descriptive concept reflecting the timing of the risks under consideration, and discounting is one way of formalising the effect that this latency has on valuations and hence on the VSL_{CAN}:VSL relativity. This distinction is important to bear in mind throughout this section.

In this study, latency can be addressed only through a limited array of questions, and the timing of fatality is restricted to 2 years, 10 years and 25 years. As such, while this section allows preliminary insight into the effects of timing and allows estimation of possible discount rates, for a fuller investigation of timing on the relativity, extended analysis has been performed on an in depth follow-up study (study 2) reported in part III of this thesis. Nonetheless, this section demonstrates how even in a survey constrained to be relatively short, inferences can be made about latency and discounting that illuminate aspects of the effect of timing on the relativity.

Five questions are relevant for this analysis: Q1-3 (C_TR_t) where the latent cancer fatality is compared to a road accident fatality sooner and Q6-7 (C_TC_t) where the latent cancer fatality is compared to short latency cancer fatality during the year after next. Morbidity is assumed to last for 12 months prior to fatality every cancer case. While the time of symptom onset and time of fatality differed between the scenarios and the questions, the time of exposure was always described as during the coming year.

4.6.1 Predictions: questions 6-7

The predictions for Q1-3 (C_TR_t) were discussed in detail on pg.97 and for these questions latency did appear to reduce the relativity between cancer and road accident risks. However, Q6-7 explicitly address the issue of latency by holding the context and morbidity constant and so arguably providing a clearer account of the influence of latency. Invoking statement 2 (that risk increases later are, *ceteris paribus*, preferred to risk increases sooner), the sooner cancer is expected to be considered worse than the later, and so the relativity is expected to be greater than one for both Q6-7. Q7 (C_2C_{25}) is identical to Q6 (C_2C_{10}) except that the later fatality is delayed until 25 years from now. This leads to the prediction that the relativity will increase from Q6-Q7 because the longer latency option is ameliorated.

4.6.2 *Central tendencies: questions 6-7*

The relativities are both large, with C_2:C_{10} at 21.24, and C_2:C_{25} at 25.73. This suggests that cancer sooner is over twenty times as bad as cancer after 10 years' delay, and over twenty five times as bad as the 25 year latent cancer. These high values may again be a result of the focusing illusion referred to in section 4.4.3.

The two relativities are insignificantly different for the geometric mean and context index, although the medians fall just outside the 25^{th}-75^{th} percentile range of one another. This insignificant difference is unexpected, and contradicts both the prior hypothesis and the evidence from Q2 and 3. Like in Q2-Q3, the only difference between Q6 and Q7 is the timing of the latent cancer fatality, and so it would be expected that the difference observed should be similar, but this is not the case. The two question pairs differ only in the context of the near-term fatality: in Q2-3 it is road accidents and in Q6-7 it is cancer.

Speculatively, the puzzling result might be because of the particular dread of cancer that is assumed to hold. If cancer is considered much worse than road accidents (and Q4-5 suggest that this is the case) then perhaps the near-term cancer risk increase is considered particularly abhorrent. If so, respondents may have focussed on this near term case to the detriment of consideration of the impact on their future cancer, resulting in the observed apparent indifference between the 10 and 25 year latent case. This relates to the argument in chapter 3 which discussed lexicographic preferences in the RR framework. It could also be helpful to consider the insights of some alternative discounting models such as those outlined in Frederick (2003). For example, Frederick et al discuss combining different psychology insights in explaining intertemporal choice, mentioning models such as reference dependence (Tversky and Kahneman, 1991). If cancer is viewed as a loss compared to the road accident risk reference point, it could receive higher weight than road accidents in decision making.

4.6.3 *Regression: questions 6-7*

Three effects in the demographics are significant in explaining preferences for the later cancer risk increases as compared to earlier ones in Q6 - Q7, but the significance is only significant at the 10% level. This implies that the preference for avoiding fatality risks at different times is largely exogenous. This contrasts with the result for both the context and the overall relativity regressions, both of which generated significance for

some of the explanatory variables, but coincides with the result for label dread and morbidity where demographics were unable to explain the relativities. The variables of significance are as follows: being female, having better self-reported health and having greater aversion to health risks all increase the relativity, indicating higher discounting or a greater aversion to taking the risk increase the year after next.

Table 4.7: Latency regressions

	Q6 C2C10 n=94, r2=0.1476 Coef. (Robust Standard Error)	Q7 C2C25 n=87, r2=0.1686 Coef. (Robust Standard Error)
age	-1.43 (1.03)	-0.43 (1.07)
log of household income interacted with age	58.71 (40.08)	19.03 (41.51)
Log of household income	-59.21 (40.02)	-19.37 (41.64)
gender (female =1)	1.31* (0.71)	1.54* (0.82)
children under 6 in the household	0.15 (1.41)	-0.84 (0.97)
being female and having children under 6	0.41 (1.56)	0.96 (1.50)
further education	-0.8 (0.65)	-0.25 (0.66)
experience of cancer (self or close friend or family member)	-0.57 (0.61)	-0.09 (0.68)
experience of road accidents (self or close friend or family member)	0.82 (0.71)	0.8 (0.67)
self-reported health state	1.04* (0.51)	0.71 (0.68)
perceived road accident risk	-0.14 (0.34)	0.26 (0.30)
financial risk aversion	0.59 (0.60)	0.22 (0.55)
financial time preference	-0.62 (0.99)	-1.17 (1.13)
health state risk aversion	0.29* (0.16)	0.31 (0.21)
constant	-154.96 (107.05)	-50.67 (109.62)

4.7 Interim Summary Of Results

So far, the analysis has considered the 'overall' relativities, concluding that there appeared to be a preference for avoiding cancer fatality, but that this preference (or 'context premium') is offset to some degree by latency. The 'context premium' questions 4-5 verified that there is a significant preference for avoiding cancer compared to contemporaneous road accident risks. The analysis of Q8-10 explored what drives this preference, with the conclusion that morbidity, as opposed to label dread, is the main driver of the preference for avoiding cancer risks compared to road accident risks. This is a novel result, although perhaps unsurprising. The analysis then moved on to consider latency. Latency was shown to reduce the VSL_{CAN}

However, so far the analysis has not addressed how the different attributes affect the overall relativity. That is, how do the relativities depend on the objective aspects of the scenarios (i.e. the context of the comparison, morbidity prior to fatality and the timing of the fatality risks)? This is addressed in the subsequent pooled regression analysis.

4.8 Pooled Analysis: All Questions

The insights from the central tendency analysis and the regression on demographics can be verified using a single regression, which takes all of the information from each question in the survey and pooling all of the relativities. The effects of context, latency, and morbidity are included as explanatory variables by generating variables for the differential along these dimensions, so for example $C_{10}R_2$ has a context differential (dummy) of 1, a latency differential of 8 years and a morbidity differential of 12 months. The results for five regression models are included in table 4.8. The regressions include information from each respondent to multiple questions, so the standard errors are clustered on the individual.

4.8.1 *Regression of relativities on attributes and demographics*

Model (1) displays the regression of the relativity on all three attributes of the scenarios to assess their overall impacts without controlling for the influence of demographics and other characteristics. Models (2) and (3) are included to allow comparison between context and morbidity in explaining the relativities. Finally, models (4) and (5) include respondent characteristics, initially using the best fit with observable demographics (model 4) and then using the full predictor list (model 5).

Table 4.8: Regression of relativities on attributes and demographics

log ratio	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
	N=1410	N=1410	N=1410	N=988	N=945
	R2= 0.1826	R2=0.1377	R2= 0.1815	R2=0.2708	R2= 0.2881
Cancer context (dummy 1= cancer:roads)	0.299	0.407	-	0.34	0.47
	(0.321)	(0.323)		(0.31)	(0.29)
Latency (differential in years)	-0.158***	-0.184***	-0.159***	-0.16***	-0.17***
	(0.015)	(0.016)	(0.014)	(0.01)	(0.02)
Morbidity (differential in months)	0.112***	-	0.113***	0.12***	0.12***
	(0.013)		(0.013)	(0.01)	(0.01)
Age	-	-	-	0.90	1.04*
				(0.57)	(0.58)
Log of household income	-	-	-	36.35	41.63*
				(22.29)	(22.84)
Log of hh income interacted with age	-	-	-	-36.32	-41.57*
				(22.34)	(22.88)
Female	-	-	-	-0.67**	-0.63*
				(0.33)	(0.33)
Child under 6	-	-	-	0.23	0.27
				(0.50)	(0.49)
Mother to child under 6	-	-	-	-1.20	-1.19
				(0.81)	(0.82)
Having had further education	-	-	-	0.63**	0.59*
				(0.31)	(0.31)
Cancer experience	-	-	-	1.20***	1.35***
				(0.43)	(0.44)
Road accident experience	-	-	-	-0.51	-0.43
				(0.31)	(0.34)
Self-reported health state	-	-	-	-0.41	-0.32
				(0.27)	(0.24)
Health risk aversion	-	-	-	-0.17*	-0.16*
				(0.09)	(0.09)
Self-reported road accident risk	-	-	-	-	-0.06
					(0.20)
Financial risk preference	-	-	-	-	-0.12
					(0.21)
Financial time preference	-	-	-	-	0.50
					(0.57)
Constant	-0.099	1.102***	0.086	98.18	111.32*
	(0.200)	(0.205)	(0.153)	(60.07)	(61.60)

In model (1), latency and morbidity appear to be the main drivers of the relativity, because the cancer context dummy is insignificant, although it is positive as would be expected. The central tendency analysis in section 4.5 suggested that morbidity

explains the majority of the dread of cancer, so including both context and morbidity could be over-fitting the data. As such, regressions 2 and 3 are run, each to include only one of these. The fit of the model with context included and morbidity excluded (model 2) is lower than the fit with morbidity included and context excluded (model 3), perhaps simply reflecting the dummy nature of the data for the context variable, but perhaps also suggesting that the morbidity is driving the overall relativities. Whichever case holds, it appears that one additional year of latency between the options compared in a questions will reduce the relativity by 15 to 20%. Model (2) suggests that for questions that compare roads to cancer risk increases across, the relativities are 40% larger than for the within-cancer comparisons, *ceteris paribus*. This links well to the 1.4 context premium that will be derived in section 4.11.2 from the relativities for questions 2-3. Model (3) considers the influence of an additional month of morbidity difference separating the two scenarios, which tends to increase the relativity by 10 to 15%.

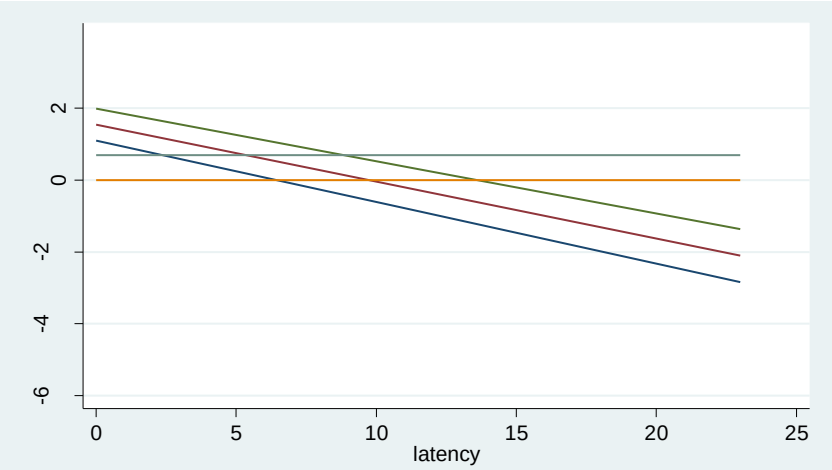
To test the robustness of these conclusions, models (4) and (5) include demographic and preference-based characteristics. Model (4) includes only the best fit predictors while model (5) uses the full set of predictors. In these models, the coefficients on the demographics are interpreted as picking up the factors underlying the respondents' willingness to accept larger risks in their least feared cause generally, i.e. their willingness to move down the multiple list. There are a number of significant coefficients in the models, with being older, being on higher income and having further education all reducing willingness to accept higher risks of the second cause[28]. Similarly those who display aversion to health state risks and those with experience of cancer are less willing to accept a larger risk increase in the second cause. Being female appears to increase the willingness to accept risk increases in the second cause, however. While the results are interesting from a methodological perspective, for the current analysis it is sufficient to state that regression on demographics improves the fit of the model, and that it allows a cleaner interpretation of the latency and morbidity attribute coefficients. In terms of the stability of the coefficients on the attributes, including these additional predictors does not destabilise the coefficients: it is still the case that an additional year of latency will decrease the relativity by 15 to 20 per cent, and an additional month of morbidity will increase the relativity by 10 to 12 per cent.

[28] The "second cause" forms the dominator of the relativity. It is R_t in C_TR_t, Ct in C_TC_t and C_T[xm] in C_T[6m]C_T[xm].

4.8.2 *Confidence intervals*

It is possible to construct confidence intervals around the relativity by predicting the relativity as a function of some variable of interest, and plotting it with associated 95% confidence intervals. Using model (1) to predict the relativity and plotting against latency, it is possible to observe a relativity that decreases with the length of the latency delay, as in figure 4.2. The context dummy is switched on, and the morbidity period is set equal to 12 months. This will be given more treatment in part IV which considers the policy implications of this research.

Figure 4.2: Re-constructed relativity as a function of latency



However, this analysis is based only on information about latency differentials of 0, 8, 9, and 23 years and as such there is a lot of uncertainty about latency periods between these points: more information on more data is provided in study 2b reported in part III of this thesis.

In summary, this analysis suggests that the relativity decreases with the length of the latency differential, verifying the assumption that latency decreases the VSL; and that with no latency, the average VSL_{CAN}:VSL relativity is between 1:1 and 2:1, verifying the assumption that some context premium exists. The assumption of 1:1 for the overall relativity is valid for latency differentials between around 7 and 14 years.

4.9 Economic Consistency and Face Validity

This section is included to add robustness to the results. The first necessary condition for the reliability of the results is that the methodology is robust, with respondents able to respond well to the mechanism. This is explored below in two ways: initially, the results of the validity checks for the methodology are reported.

The next condition is that the results themselves are consistent in economic terms. Throughout the results section, the correspondence between the results and the predictions was shown to be strong in most cases. This suggests that the results are interpretable in an economic sense. In addition on pg.120 regression upon some proxies for the strength of preference displayed over the attributes context, latency and morbidity are conducted. The significance of these parameters in explaining the preferences for the overall comparisons are as anticipated *a priori*, and as such the results are given an extra degree of credibility.

4.9.1 *Results of validity checks for the methodology*

In order to be confident in using the results above in validating hypotheses 1 and 2 from pg. 52, and hence in supporting the simple modelled relationship between the VSL for cancer and for road accidents, it is necessary to establish the robustness of the elicitation procedures.

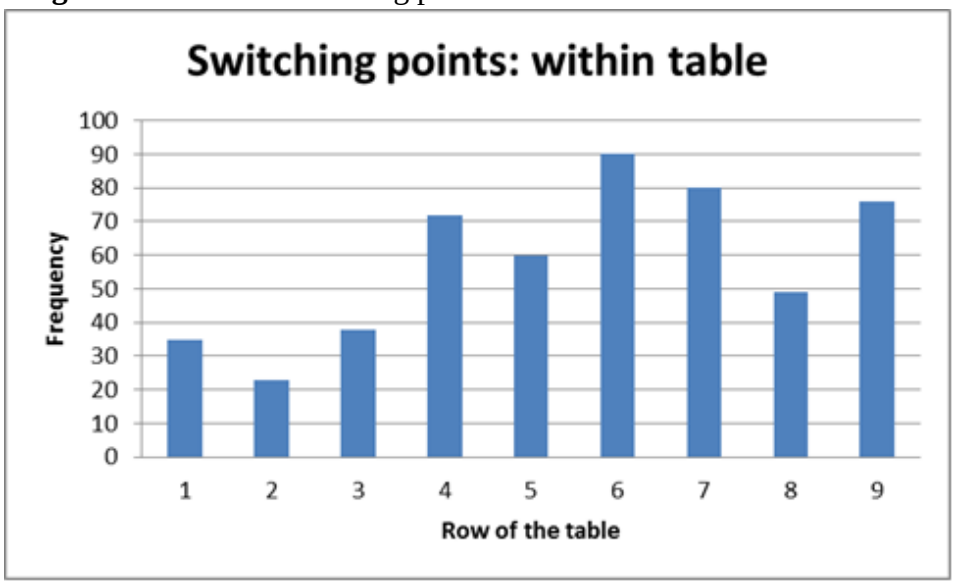
As set out in section 3.2.10 (pg.77), a number of checks can be made on the data to explore whether there are obvious problems with anchoring or framing. The data used here simply capture the row in which the respondents switched between their initial choice and the other option. Potentially problematic signs include a peak in the centre of the data (suggesting respondents anchored on the range provided to generate their response), and a peak at indifference or in row 1 (suggesting respondents were constrained by the fairly large initial step interval).

Bias towards the middle of the table would manifest itself as a cluster of responses around the middle of the distribution. However, looking at the frequency distribution by row this does not appear to be the case. The distribution of answers within the table is given in figure 4.3

If respondents felt constrained by the jump from 50 to 100 (or 85, 90, etc. for the later questions) they might have been obliged to choose row 1 when they really would have preferred to switch slightly earlier. If so, responses would be clustered in row 1. Again, this does not appear to be the case, with only 7% of within-table switching occurring in row 1. Disentangling understatement is a little more complex. If respondents were artificially indicating indifference because the initial step is too big for them, this would manifest as a higher than expected proportion of indifference indicated in the first place. However, given that indifference is both a protest mechanism and also the response of

anyone for whom context and timing do not affect preferences over risk changes, a higher proportion of people might be expected to indicate indifference than to switch in other rows even without any bias resulting from the steps in the risk options.

Figure 4.3: Overall switching points: within table



A high proportion of responses indicate indifference, at 10% of all responses (see figure 4.4) but as discussed, it is difficult to interpret whether this is genuine preference, protest, or understatement bias.

The final source of bias discussed relates to the signal, from the setup of the multiple list, that the start and end points are somehow legitimate bounds for the decision. This appears not to be the case for the majority of respondents, since in fact 56% of switching happened below the lowest suggested point on the table (see figure 4.4).

4.10.1.i *Switching below the table*

The high proportion switching below the table is an interesting result in itself. In many ways, the result is heartening because respondents do not seem to have felt constrained by the table bounds. However, it would be preferable if the survey instrument captured indifference within the table for most respondents. Considering the balance between the desire for detail within the table (which would suggest having small intervals) against the desire to capture the indifference points of the majority of the sample (which would suggest having large intervals, or more of them) the levels selected were judged to provide the best compromise. Transferring the RR survey section onto computers and employing an iterative mechanism would allow this issue to be addressed in future versions of this survey and protocol. Nonetheless, in the author's opinion, this survey

design presents the best compromise given the resource constraints under which the study was conducted.

Figure 4.4: Overall switching points 1

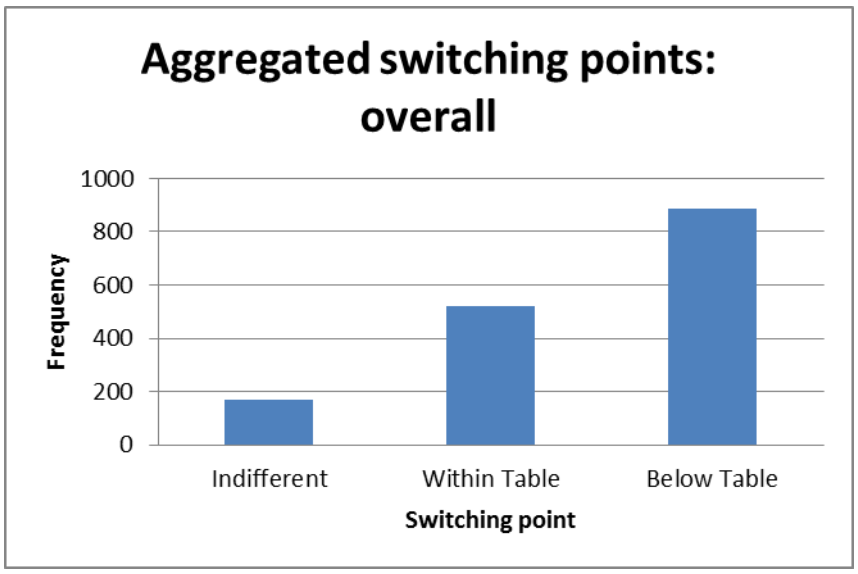
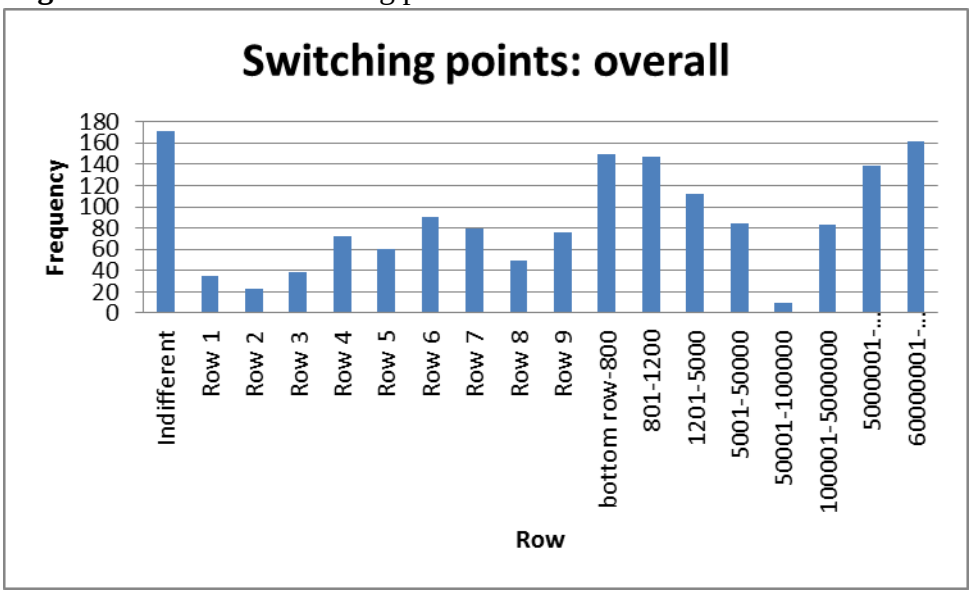


Figure 4.5: Overall switching points 2



In summary, while not without its problems, the multiple list format with the range of risk levels employed in this study was shown to deliver reasonably reliable responses. There is no strong evidence that respondents were constrained by the values in the table, because a majority actually chose to state values larger than were offered in the table. In addition, there is limited evidence that respondents were pushed towards stating indifference or switching in row one, (a concern raised as a result of the fairly large jump in values between 50 to 100 in questions 1-3).

4.9.1.ii *Herding*

As discussed in section 3.2.10 it is possible that a respondent could observe or infer the initial choice of others in the group because the individuals were interviewed in groups of 10 using paper answer sheets.

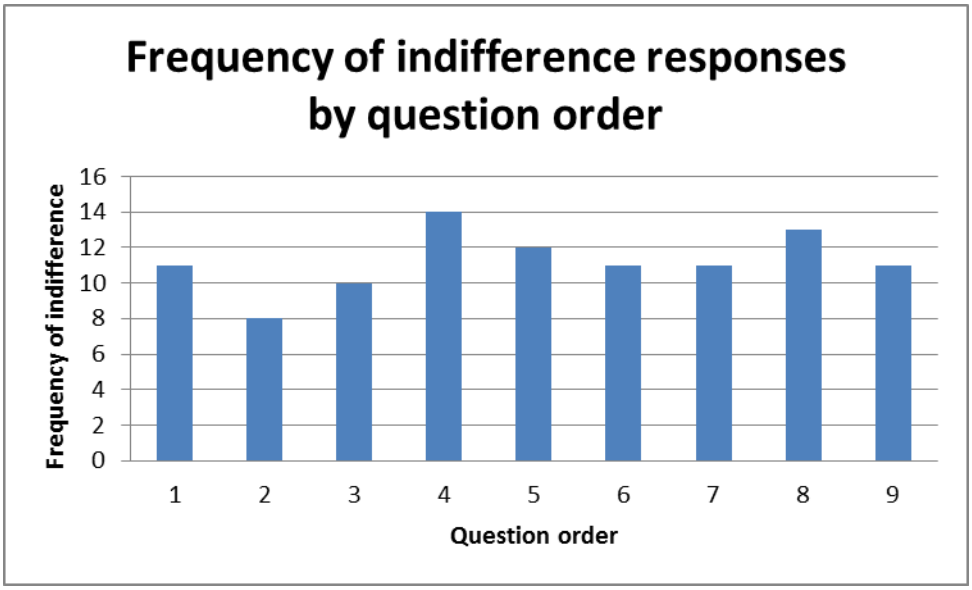
There is only a very limited chance that a respondent would know which of the two options (e.g. A or B) had been chosen by anyone else because the answer sheets that the respondents received were all but identical in either case and 'option As' and 'option Bs' were deliberately not handed out separately. In addition, questions were all answered on an individual basis, and respondents were spaced apart in the room. The data suggest that this procedure was sufficient: when examining responses to Q1-3, in only one group (there were 21 groups in total), and only in question 1, did every respondent make the same initial choice. In the other 20 groups (and hence in the other 62 questions) there was at least one different selection, and in 17 groups at least 2 people contradicted the majority on the initial choices for Q1-3. This suggests that people did not feel constrained to follow the crowd and choose along with the majority, probably in part because the decisions of others were not clearly apparent.

However, it would be noticeable to the observant respondent when someone had indicated indifference, because they would not receive the second answer sheet. As such, it is appropriate to check whether this appears to have influenced subsequent decisions.

Firstly, notice that indifference was indicated by a minority of respondents. For questions 1-9 (where there is a potential to influence the following question), indifference was recorded in only 7.14% of decisions. For the final question, C10[2w]R10[2w], there is a much higher indifference response rate (70 out of 157), which is likely to be because the respondents felt genuine indifference between the two risk increases on offer (after all the scenarios were deliberately explained using identical language, except for the context label).

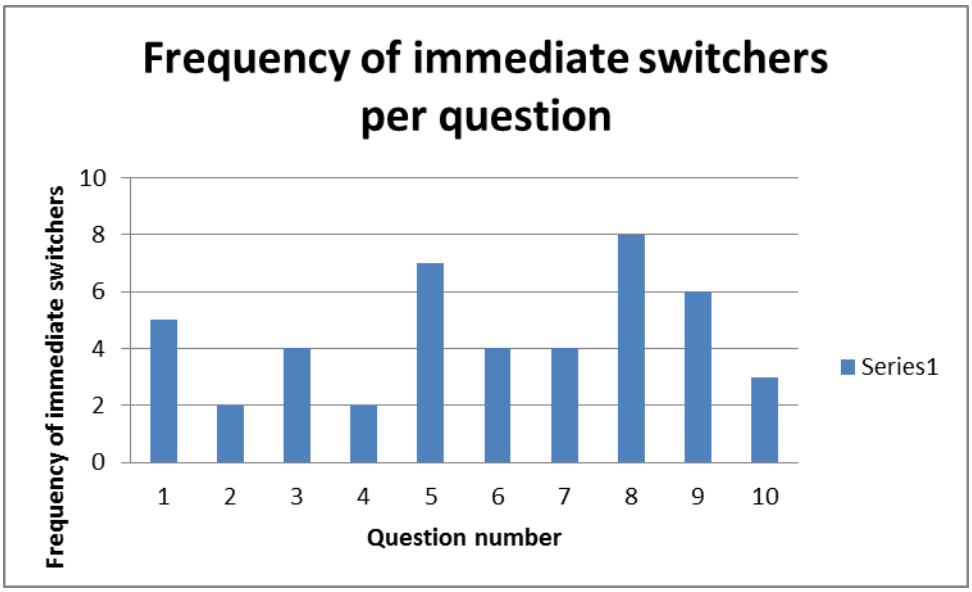
While 7.14% is a small proportion of the sample, it is possible that respondents were influenced by the indifference displayed by others in previous questions. If this is so, an increasing (or decreasing) rate of indifference responses would be observed along the 10 questions. Taking into account the order in which different respondents faced the different questions, the pattern in figure 4.6 emerges.

Figure 4.6: Switching points by question order



It does not appear that the frequency of indifference responses increased or decreased through the course of the survey, which indicates that these sorts of potential public or social pressures do not appear to have caused much trouble here.

Figure 4.7: Frequency of people who switch immediately



Of course, there may be some underlying unwillingness to state indifference but this would be revealed by people making early switches in the table. However, for Q1-3 there were 5, 2 and 4 people respectively out of 157 that chose to switch in the first row. This is between 1.2% and 3.2% of the sample.

In summary, there is potential for respondents to have noticed when others indicated indifference between two risk scenarios because those respondents would not receive the follow-up, multiple list answer sheet. As such, checks were run on the number of 'indifference' answers per question, and no evidence was found that the number or proportion of 'indifference' responses increased or decreased as the survey progressed. Checks were also run for a peak at the first row of switching which could indicate reluctance to publicly admit indifference between the two risks. This was not the case. There was a small minority of indifference responses, and for Q1-9 they made up just 7.14% of the total responses.

4.9.2 *Consistency within the survey: regression upon residuals*

This section aims to investigate whether respondents approached the RR questions in a consistent manner. For example, if an individual expressed a high relativity in the context questions then they would be expected to express a high relativity in the overall premium questions. Similarly, if they expressed a strong preference for avoiding the sooner illness in the latency questions then a lower overall relativity would be anticipated because they would be expected to discount the latent cancer. These can be verified using 'regression upon residuals'. Regressions are run of each of the overall relativities (Q2 ($C_{10}R_2$) and Q3 ($C_{25}R_2$)) on proxies for the strength of preference over the attributes of context, latency and morbidity from the later questions (3-10).

The strength of preference proxies used in this analysis are the residuals from the regressions of each of the later question relativities on a best fit model of observable characteristics. These residuals therefore capture the strength of preference that an individual has over the attribute in question, above that predicted by demographics. Formally, they capture the difference between the actual strength of preference expressed in Q4-10 and the level predicted by the demographics.

The reason for choosing regression upon residuals, as opposed to simple correlation analysis, is because the correlation analysis would be influenced by any demographic characteristics which would act to drive both the overall and the explanatory relativities in a particular direction. As a hypothetical example, if being female always tends to result in a larger relativity, then this would manifest in the explanatory relativities from Q4-10 as well as in the overall relativities from Q2-3. As such, simple correlation would potentially result in an overestimation of the relationship. Regression on

residuals provides a more robust test of the relationship between preferences expressed over the individual attributes of context, latency and morbidity and the overall relativity.

4.9.2.i *Hypotheses: regression upon residuals*

The coefficient on the latency residuals is expected to be negative, and the coefficients on the context-related residuals (morbidity, dread and labelling) are expected to be positive.

4.9.2.ii *Results: regression upon residuals*

Table 4.9: Regression on residuals

	Q2 residuals C10R2 n=74 r2=0.4585 Coef. (Robust standard error)	Q3 residuals C25R2 n=70 r2=0.3300 Coef. (Robust standard error)
Context residuals (C10R10)	**0.59*** **	**0.27***
	(0.09)	(0.14)
Latency residuals (C2C25)	**-0.35** **	**-0.67*** **
	(0.15)	(0.21)
Morbidity residuals (C[36]C[6])	-0.08	0.03
	(0.18)	(0.24)
Labelling residuals (C[2w]R[2w])	**0.29** **	0.06
	(0.14)	(0.18)
Experience of cancer (self or close friend or family member)	0.16	0.95
	(0.70)	(0.84)
Experience of road accidents (self or close friend or family member)	**-1.14***	-0.92
	(0.66)	(0.87)
Self-reported health state	-0.13	-0.50
	(0.56)	(0.70)
Financial risk aversion	0.08	-0.12
	(0.38)	(0.53)
Financial time preference	-0.30	0.93
	(1.25)	(1.45)
Health state risk aversion	-0.04	-0.02
	(0.20)	(0.28)
Perceived road accident risk	0.22	0.38
	(0.36)	(0.40)
Constant	0.47	-0.70
	(1.56)	(2.12)

Initially a stylised regression upon dread, latency, morbidity and labelling residuals and all the preference related characteristics is reported in table 4.9. This ensures that the effects of each of the later questions can be compared, although it does risk over fitting the model.

The results suggest that high relativities expressed in the context premium and latency questions are related in the anticipated way to the overall relativity. Morbidity and labelling are less clearly significant. This may be due to the fact that the context coefficient is already picking up the influence of these variables. In addition, there is limited variation in the 'labelling' relativity with a large proportion of respondents indicating no preference, which would reduce the ability for it to explain the overall relativities. The preference related characteristics are largely insignificant.

This model may have over fit the data, so regressions are run on the best fit, again using the *vselect* command in Stata (see pg.86 for an explanation) to guide the variable selection. The best fit regressions, for each of Q2 and Q3, are reported in tables 4.14 and 4.15.

Table 4.10: Best fit (for Q2) regression on residuals

	Q2 residuals C10R2 n=91 r2=0.2972 Coef. (robust standard error)	Q3 residuals C25R2 n=90 r2=0.1912 Coef. (robust standard error)
Context residuals (C10R10)	0.54***	0.29**
	(0.11)	(0.14)
Latency residuals (C2C25)	-0.38**	-0.55***
	(0.15)	(0.16)
Labelling residuals	0.25*	0.07
(C[2w]R[2w])	(0.14)	(0.16)
experience of road accidents		
(self or close friend or	-0.74	-0.32
family member)	(0.62)	(0.68)
constant	0.41	0.30
	(0.42)	(0.41)

Table 4.11: Best fit (for Q3) regression on residuals

	Q2 residuals C10R2 n=99 r2=0.2550 Coef. (robust standard error)	Q3 residuals C25R2 n=96 r2=0.1401 Coef. (robust standard error)
Context residuals (C10R10)	0.53***	0.32**
	(0.10)	(0.13)
Latency residuals (C2C25)	-0.36***	-0.47***
	(0.13)	(0.16)
constant	0.14	0.26
	(0.28)	(0.32)

The model in table 4.10 has best goodness of fit, but the model in table 4.11 shows higher significance of the residuals of the dread and latency questions, which matter significantly in all models.

In summary, the coefficients on the context and latency residuals have the sign and significance that would be expected in explaining the 'overall' relativities. It appears that those with high levels of aversion to cancer risks generally tend to produce higher 'overall' relativities, and those who discount the future substantially have lower 'overall' relativities. The coefficients on labelling and morbidity are not significant, but this is likely due to the role of the context residuals which are picking up the same influences.

At this stage, the results have been analysed to explore whether the respondents appeared to understand, to check for typical signs of anchoring and framing effects, and to explore whether the results accord with what would be expected *a priori* in terms of the underlying psychology of the tasks. In all dimensions, the data supports the overall conclusion that the survey instrument was reasonably well understood, and that respondents appeared to approach it in a consistent way.

4.9.3 *Summary of validity tests*

The tests and checks reported in section 4.9 are all designed to explore whether the methodological design and implementation were able to generate results which reflect well thought out preferences of the respondents, free from extreme levels of bias. This

was confirmed to a large extent as the tests demonstrate the consistency of the responses within the survey, and an absence of some typical symptoms of potential methodological problems. In summary, the methodology and results appear to suggest that the survey and its implementation were successful.

4.10 Discussion of RR results

A Risk-Risk stated preference study was designed and implemented to investigate the influence of context and latency on the relativity between increases in latent cancer fatality risks and in current period road accident fatality risks. In doing so, it provides the first dedicated UK evidence into these effects and adds to the stock of evidence in the debate about the appropriate level for a policy-based cancer premium. While the policy implications of this research will be considered in part IV, chapter 9, the key empirical results of this study have been reported here.

The analysis shows that there is a context premium for cancer *ceteris paribus* and that the effect of latency is to decrease the VSL_{CAN}. These results verify the hypotheses from pg.52.

A second result relates to what drives the context premium. The key driver of the context premium appears to be the morbidity period typically assumed to apply prior to fatality from cancer, as opposed to any dread of the label "cancer" *per se.*

The methodology and results are subject to scrutiny throughout this part of the thesis, with a dedicated section (pg.113) which specifically considers the reliability of the methods and results. The results of these supplementary analyses are encouraging, suggesting that the respondents were able and willing to provide thoughtful answers which can largely be interpreted in an economically intuitive manner.

As such, the analysis reported in this chapter so far appears to support the C_TR_t model proposed in section 2.11.2 (pg.51). The usefulness of the C_TR_t relationship in eliciting underlying parameters relevant to the VSL for cancer will be established through the subsequent analysis in section 4.11.

4.11 Eliciting Underlying Parameters: a New Methodology

As discussed in the literature review and motivation, studies investigating the VSL_{CAN} have typically been unable to disentangle the effects of context (including label dread and morbidity) and latency. This has been addressed in study 1, which addresses this

directly. As discussed, the preliminary evidence suggests that there is aversion to cancer *ceteris paribus*, but that this context premium appears to be offset by latency. This is in line with existing empirical evidence. This evidence can be made useful in future VSL studies, because it allows confidence in the model proposed in chapter 2 which links the VSL_{CAN} to the standard VSL. This relationship is powerful because it allows the elicitation of values for the context premium, effective discount rate and morbidity premium. This can be achieved on the sample or individual level using combinations of relativities. The procedure is explained in full in the next section.

4.11.1 *Elicitation procedure*

The procedure for eliciting r and x, using Q2 and Q3 to exemplify, is as follows:

Recall the simplified model introduced in part I of this thesis (pg.53)

$$C_t = R_t(1 + x) \qquad (A1')$$

Equation (A1) implies that cancer risks are equivalent to contemporaneous road accident risks, augmented by $(1 + x)$, an overview parameter which captures the combined effects of labelling dread and morbidity, and which is referred to as the context premium (see figure 2.3 in part I (pg.31) where these terms were defined).

$$X_{t+\varphi} = \frac{X_t}{(1+r)^{\varphi}},\ X = \{C, R\}\ \ 0 < r < 1 \qquad (A2')$$

Equation (A2) implies that any cause X in a time period after a delay φ is discounted exponentially at a constant effective discount rate r, where r captures the effects of diminishing remaining life expectancy and diminishing survival probability in addition to the pure rate of time preference.

4.11.1.i *To elicit the effective discount rate, r:*

From *(A1)* and *(A2)*, using Q2 ($C_{10}R_2$):

$$C_{10} = \frac{R_2(1+x)}{(1+r)^8} \qquad (35)$$

$$\frac{C_{10}}{R_2} = \frac{(1+x)}{(1+r)^8} \qquad (36)$$

From Q3 (C_{25}:R_2):

$$C_{25} = \frac{R_2(1+x)}{(1+r)^{23}} \qquad (37)$$

$$\frac{C_{25}}{R_2} = \frac{(1+x)}{(1+r)^{23}} \quad (38)$$

Q2 implies

$$\frac{C_{10}}{R_2} = \frac{(1+x)}{(1+r)^{8}} = (observed\ C_{10}R_2\ relativity) \quad (39)$$

Rearranging,

$$(1+x) = C_{10}R_2(1+r)^8 \quad (40)$$

Q3 implies

$$\frac{C_{25}}{R_2} = \frac{(1+x)}{(1+r)^{23}} = C_{25}R_2 \quad (41)$$

Rearranging,

$$(1+x) = C_{25}R_2(1+r)^{23} \quad (42)$$

(40) and *(42)* imply

$$(1+x) = C_{10}R_2(1+r)^8 = C_{25}R_2(1+r)^{23} \quad (43)$$

Solving,

$$\frac{C_{10}R_2}{C_{25}R_2} = \frac{(1+r)^{23}}{(1+r)^{8}} \quad (44)$$

$$\frac{C_{10}R_2}{C_{25}R_2} = (1+r)^{15} \quad (45)$$

So from the ratio of results of two questions, the effective discount rate can be inferred. The results will be provided on pg.130.

4.11.1.ii *To elicit the context premium, x.*

To find x, r is simply substituted into *(36) or (38).* The results will be provided on pg.129.

This section has outlined the novel approach that will be taken using the central tendency measures and a limited number of assumptions about the relationship between the cancer VSL and roads VSL, to elicit underlying preference parameters for the respondents in the study. This technique will be repeated for different question pairs, with the results provided as appropriate throughout section 4.11.

4.11.2 *Inferred r and x values: questions 1-3*

Using the sample geometric means for Q2 and Q3 to derive values for r and x gives:

$$r = 0.0737 \quad (46)$$

$$x = 0.434 \quad (47)$$

The implied effective discount rate is 7.37% per year and the context premium is 1.43, implying that cancer fatality risk increases are perceived to be 1.43 times as bad as road accident risk increases which occur at the same time. It should be noted that these parameters are elicited based on the assumptions in the C_TR_t relationship, and are interdependent. That is, because the estimate of the effective discount rate is elicited alongside the context premium, they ought to be applied together. This is an idea which will be returned to in part IV where the policy implications of these results are explored.

4.11.3 *Inferred x values: questions 2-5*

Again, using the simultaneous equation method described in section 4.11.1 or the simple comparisons in Q4-5, the context premia can be elicited for a range of questions. The resulting values for $(1 + x)$ are summarised in table 4.12.

Clearly, the resulting estimates using Q4-5 (C_TR_T) are much higher than those obtained from Q2-3 (C_TR_t). As discussed on pg.101, the excessive salience and possible focussing illusion apparent in Q4 and Q5 cast some doubt upon the context premium implied by these questions. On this basis, the 1.44 implied by questions 2 and 3 is perhaps the more solid foundation on which to base the context premium. This result is given support by the context coefficient of 0.407 from the pooled regression analysis results reported in section 4.8.

Table 4.12: Summary of implicit context premia

Measure	Symbol	Question(s)	Timescale	Level
Context premium	(1+x)	2	n/a	1.434
Context premium	(1+x)	3	n/a	1.437
Context premium	(1+x)	4	n/a	9.319
Context premium	(1+x)	5	n/a	9.647

4.11.4 *Inferred m values (morbidity premium): questions 4-5 & 8-9*

As discussed, morbidity appears to be a significant driver of the preference for avoiding cancer risks as opposed to road accident risks, *ceteris paribus*, especially since the relativity in Q10 (C_{10}[2w]:R_{10}[2w]) is indistinguishable from unity. As such, better understanding of morbidity preferences will be beneficial to evaluating the overall relativity. It is possible to infer the impact of an additional month of morbidity using questions 8 and 9, and a procedure similar to that employed for the elicitation of the context premium x and the effective discount rate r as described above. The assumption made in the derivation is that each month of morbidity has equal weight, although as this analysis will show, this may not reflect reality.

Initially the assumption (A1) above is adapted to account for the length of time spent in illness:

$$C_t = R_t(1 + xm) \qquad \textit{(A1*)}$$

x again captures dread and morbidity effects, but is now a multiplier on m, which is illness in months.

From Q4:

$$C_2 = R_2(1 + m12) \qquad \textit{(48)}$$

From Q5:

$$C_{10} = \frac{R_2(1+m12)}{(1+r)^8} \qquad \textit{(49)}$$

From Q8:

$$C_{10}[6] = \frac{R_2(1+m6)}{(1+r)^8} \qquad \textit{(50)}$$

$$C_{10}[12] = \frac{R_2(1+m12)}{(1+r)^8} \qquad \textit{(51)}$$

From Q9:

$$C_{10}[36] = \frac{R_2(1+m36)}{(1+r)^8} \qquad \textit{(52)}$$

From Q4:

$$\frac{C_2}{R_2} = \frac{R_2(1+m12)}{R_2} = (1 + m12) = C_2 R_2 \quad (53)$$

From Q5:

$$\frac{C_{10}}{R_{10}} = \frac{R_2(1+m12)/(1+r)^8}{R_2/(1+r)^8} = (1 + m12) = C_{10} R_{10} \quad (54)$$

From Q8:

$$\frac{C_{10}[12]}{C_{10}[6]} = \frac{\frac{R_2(1+m12)}{(1+r)^8}}{\frac{R_2(1+m6)}{(1+r)^8}} = \frac{(1+m12)}{(1+m6)} = C_{10}[12] C_{10}[6] \quad (55)$$

From Q9:

$$\frac{C_{10}[36]}{C_{10}[6]} = \frac{\frac{R_2(1+m36)}{(1+r)^8}}{\frac{R_2(1+m6)}{(1+r)^8}} = \frac{(1+m36)}{(1+m6)} = C_{10}[12] C_{10}[6] \quad (56)$$

which can easily be simplified to an expression for m. The results are provided in table 4.13.

The premium for avoiding an additional month of illness is much larger using information from Q4 and Q5 (the context premium questions) than from Q8 and Q9 (the morbidity premium questions). Intuitively, this might be because the difference between no morbidity (in the roads scenario in Q4-5) and morbidity (in the cancer scenario in Q4-5) is larger than the difference between an existing six months' illness and a longer illness period (in the comparisons in questions 8 and 9). It might indicate some "dread of morbidity" *per se*, and in fact that the length of time spent ill is not the most important aspect of the prospect of morbidity. This explanation appears to be supported by the data, because there is no context premium when there is no morbidity differential, a large premium for the difference between no morbidity and some morbidity (with roads compared to cancer) and a barely significant difference between the premium for the 12 and 30 months differential from a 6 month baseline (i.e. Q8 and Q9). The exception is that the relativities for Q8 and Q9 are both large, but this might again be attributable to the focusing illusion discussed above in relation to the discounting function. This interpretation, by necessity, has been speculative, and as such should be considered alongside the insights from regression analysis for morbidity

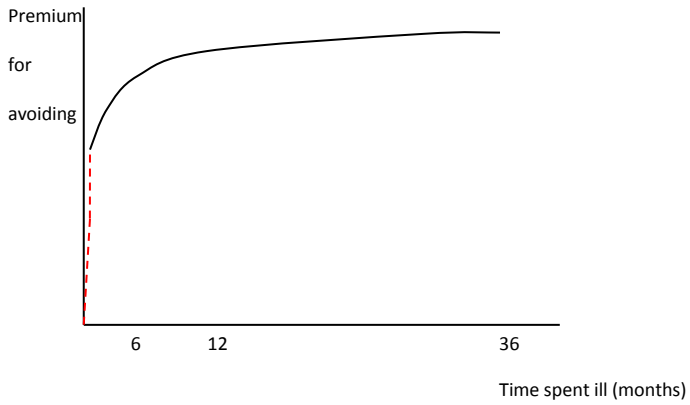
reported on pg.108, which ultimately provides more substantive conclusions surrounding morbidity.

Table 4.13: Summary of implicit morbidity premia.

Measure	Symbol	Question(s)	Timescale	Level
Morbidity premium (month)	m	4	n/a	0.69
Morbidity premium (month)	m	5	n/a	0.72
Morbidity premium (month)	m	8,9	n/a	0.097

The one-month morbidity premium can be displayed as a function of the morbidity differential that elicits it, and a stylised version of this is given in figure 4.8.

Figure 4.8: Morbidity



4.11.5 *Inferred r values: questions 2-4 & 6-7*

The effective discount rates discussed here are derived from responses to the risk-risk trade questions and as such ought to be treated as descriptive, not normative. A normative discussion of the implications of different discount rate choices in policymaking is provided in the policy implications section in part IV.

As with the context premium, there is more than one way to calculate the effective discount rate from these data. The implied rates differ substantially depending on the choice of questions. As highlighted previously, the highest estimates occur when the questions used considered risks of contexts that differed along a single dimension and

more modest estimates exist for the multi-dimensional Q2 and Q3, again perhaps because of the potential focusing illusion. The range of estimates is from 1.25% p.a. for data between the 10 and 25 year time periods, up to 46.6% p.a. for Q6 which compares 2 and 10 years. The rate from questions Q2-3, which incorporates all three time points, is within this range, at 7.37% p.a.

Table 4.14: Summary of implicit effective discount rates

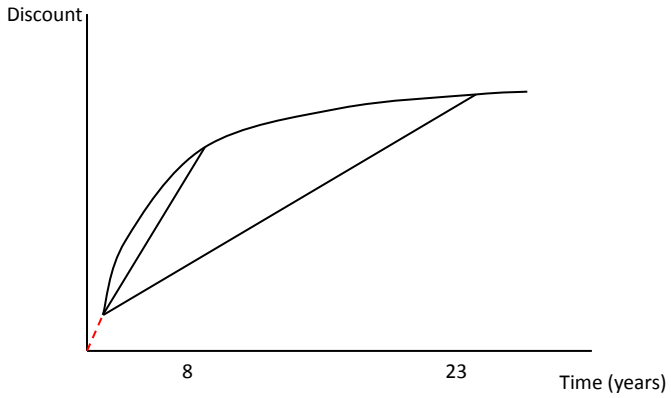
Measure	Symbol	Question(s)	Timescale	Level
Effective discount rate	r	2, 3	25:10:2 years	7.37% p.a.
Effective discount rate	r	6	10:2 years	46.6% p.a.
Effective discount rate	r	2,4	10:2 years	28% p.a.
Effective discount rate	r	7	25:2 years	15.1% p.a.
Effective discount rate	r	3,4	25:2 years	15.5% p.a.
Effective discount rate	r	6,7	25:10 years	1.25%p.a.

Jones-Lee and Loomes (2010) note that an effective discount rate applied to fatality risks will incorporate more than simply pure time preference. They highlight the effects of the diminishing VSL[29] with age and the chance of not surviving until the risk increase as additional effects, and the current study has picked up some additional effects that might have a role to play. Jones-Lee and Loomes (2010) estimate the combined effects of the diminishing life expectancy and diminishing survival probability (excluding pure time preference) to be in the range of 2 - 3% for a 15 year time frame, based on epidemiological evidence and some standard assumptions about the utility of remaining life expectancy function. This implies that the observed 7.37% effective discount rate from the analysis of Q2 and Q3 might imply a pure time preference rate in the region of 4-5%. This range aligns well with the rates presented in table 2.1 (pg. 44) which summarised existing estimates for the discount rate in the health and safety literature.

The effective discount rates can be plotted against the length of delay, as shown in figure 4.9.

[29] Value of Preventing a Statistical Fatality- see section 2.2

Figure 4.9: Discounting



4.11.6 *Summary of elicited parameters*

The context premium from Q2-3 is estimated to be 1.4, which implies that cancer fatality risk increases are considered to be 40% worse than road accident risk increases that would occur at the same time. The effective discount rate, estimated in conjunction with the context premium, is 7.37% per year under the assumption of exponential discounting. The overall conclusion is that the effects offset to generate a premium in the region of 1:1 or less for latency periods of 10 years or more.

4.12 Conclusions from Study 1

Study 1 provided evidence to support the hypotheses that the context of cancer increases WTP for risk reductions (and hence increases the VSL) while latency or delay reduces WTP. The evidence from the RR study therefore supports a model linking the cancer and roads VSLs according to a context premium (1+x) and an effective discount rate (r). This was further validated using robustness checks. The second part of the analysis used this relationship along with survey relativities data to elicit some underlying parameters including the effective discount rate and the context premium.

As such, this new methodology appears to be a simple, practical approach that could help to clarify the output of future VSL studies involving different contexts and risks.

4.12.1 *Policy implications from Study 1*

The results have some implications for policy making. For example, the effective discount rate of 7.37% is shown to be enough to offset the context premium for latency periods of ten years or more, implying an overall relativity for a ten year latent cancer compared to a road accident now that is insignificantly different than 1:1. When the

latency is increased, this overall relativity falls to be less than one. In addition, that the context premium appears to be driven largely by morbidity is a novel result which would benefit from dedicated research in the future, particularly to establish what besides duration of morbidity influences the premium. The policy implications of this study are considered in much more detail alongside the implications from study 2 in part IV.

4.12.2 *Further research requirements*

This study has provided insight into a broad range of factors influencing the relative size of the VSL_{CAN} and the standard roads VSL. However, there are unanswered questions that arise from it. The study was able to provide some initial insight into the importance of latency in influencing the cancer VSL, but a lack of data-points means that estimating the functional form of the relationship is beyond the scope of study 1. A related feature of latent fatality risk is the influence of risk preferences, which are intrinsically important to the valuation of any delayed outcome but particularly pertinent in a survey design which employs risk trading as its elicitation mechanism. As such, these two areas- risk preference and latency- are explored further in this thesis through a dedicated follow up study. This is reported in part III of the thesis. Beyond this, dedicated investigation of the drivers of the morbidity premium would be recommended for further investigation.

PART III.

STUDY 2: ON THE INFLUENCE OF LATENCY

Chapter 5: Introduction, Literature Review and Methodology

5.1 Background

The analysis of Study 1 reported in Part II of this thesis allowed insight into the influence of context, morbidity, labelling and timing on the VSL_{CAN} and the VSL_{CAN}:VSL relativities. Given this broad scope, it was successful in providing a comprehensive overview of the preferences underpinning the main relativities. It also demonstrated the tractability of the 'latent cancer to current roads' comparisons in the Risk-Risk framework, especially given the extensive training and learning session that preceded the main survey. Arguably its main contribution was the formulation of the simple C_TR_t relationship which is based on two assumptions: first that the context of cancer (incorporating morbidity and label dread effects) acts to increase the VSL_{CAN}, and second that longer latency reduces the VSL_{CAN}. These insights were both verified in the R-R study, and the relationship was used alongside survey data to infer both the context premium and discount rate from the survey data in relativities form.

It is the latter assumption, that latency reduces willingness to pay to avoid cancer risks that provides the motivation for the studies reported in this Part. The drawback of Study 1 was that it allowed only a limited investigation of the influence of timing. This is because in order to cover all of the research areas (examining dread, morbidity and latency), it was possible to vary the timing of outcomes in only a subset of the questions. Because the aim of the latency Section in Study 1 was simply to verify that longer delays prior to a risk outcome reduce the VSL, the survey was not designed with enough time intervals to reliably allow the inference of the functional form of the discount rate for the sample in aggregate, let alone on an individual level, so for simplicity an exponential discount function was assumed throughout. However, it is well established in the literature that exponential discounting is a poor predictor of behaviour in a range of domains. The Study reported in the following Sections will address this by allowing assumptions about the functional form for discounting to be varied and tested.

However, before any analysis of discount rates can be accomplished, the extent of risk aversion for members of the sample must be established. Any latent outcome is inherently risky, and to fully understand the choices and preferences made over latent outcomes requires controlling for the effects of risk preference. This insight motivates the analysis, reported in Chapter 6, which formalises the theoretical link between risk

preference elicitation in finance and in health, and then provides and implements a novel mechanism for the elicitation of risk preferences in the health domain.

These risk preference measures are taken forward into the analysis in Chapter 7 which aims to establish to what extent exponential discounting can characterise responses to R-R questions that compare fatalities with different latency periods, and to establish the likely alternative discount functions and rates that apply for this sample.

The rest of Part III of this thesis is structured as follows. First, some key works in the discounting literature are presented and discussed, with a particular focus on studies that have explored discounting in the domains of health and physical risk, and discount rate elicitation. Next, attention is given to the link between risk and time preferences, and to the extent to which risk preferences can be expected to vary between finance and health. From this basis, the research questions for Part III are set out, and then the methodology is outlined. The analysis follows. Risk preferences in health are elicited in Study 2a, reported in Chapter 6 and are taken forward to Chapter 7, which reports Study 2b and resolves some of the issues that motivated this Part of the thesis, focussing in particular on discounting.

5.2 Introduction to Literature Review

This literature review will first outline the key papers in the discounting literature, discussing discounting as a concept and its origins in economics and psychology literature. A brief summary of the development of classic discounting models is presented. The evidence is presented surrounding whether discounting is likely to differ by domain. The link is then made to the specific focus of this thesis: latent fatality risks. This motivates a re-cap of the evidence surrounding the discount rate in the domain of health and physical risk which was previously discussed in Chapter 2. Finally, the link is drawn between time and risk preferences, along with a brief discussion of the evidence for risk preferences that differ by domain. The review culminates in a series of research questions which, when addressed, will add to the state of understanding about the implications of latency on the VSL as well as to the toolkit available to the researcher exploring these questions.

5.3 Time Preference and Discounting

To start, consider the general intuition behind the concept of discounting latent outcomes. As discussed in Section 2.10, when an outcome occurs in the future, it is

assumed to receive less weight than an otherwise identical outcome that occurs in the present. This observation has been made across a wide range of sub-disciplines in economics and psychology, and is generally considered to be a key element characterising the preferences of economic agents. Indeed, in the extreme, it can be argued that without a preference for present gratification of wants and needs over future gratification of future wants and needs, there would be infinite deferral of action (in order to take advantage of increased productivity of resources in the future). See Frederick *et al.* (2002) for a brief discussion. This general intuition has been formalised in an extensive body of literature since the 19th century.

5.3.1 Early insight

Early thought- defined here as publications up to 1930- on the trade-off between present and future consumption focussed on psychological motivations for preferring immediate consumption including disutility from having to wait and the animal desire for present over future outcomes. The interested reader should consult Frederick *et al.* (2002) for a general review of early thought on time preference. The comprehensiveness of that analysis renders extensive discussion of the origins of discounting theory redundant in this review, although the most significant contributions will be outlined for completeness.

Key contributions include those from Rae (1834), Jevons (1888) Jevons (1905) and Senior (1836). The work of these early thinkers focused almost exclusively on present emotions, with some reference to the bequest motive for the accumulation of resources for future consumption. The first clear consideration of time preference as a trade-off decision between present and future consumption is presented in the work of von Böhm-Bawerk (1890), which highlighted a systematic tendency to underestimate future wants. These early insights were formalised with reference to a marginal rate of time preference by Fisher (1930). The problem was formalised diagrammatically, with the marginal rate of time preference dependent upon both time preference and diminishing marginal utility. Fisher summarises thought up to that point, and elucidates his contribution of the concept of time preference as follows:

> "Time preference, or impatience, plays a central role in the theory of interest. It is essentially what Rae calls the "effective desire for accumulation," and what Böhm-Bawerk calls the "perspective undervaluation of the future." It is the (percentage) excess of the present marginal want for one more unit of present

goods over the present marginal want for one more unit of future goods. Thus the rate of time preference, or degree of impatience, for present over future goods of like kind is readily derived from the marginal desirabilities of, or wants for, those present and future goods respectively" Fisher (1930)

So the Fisher model substantially developed understanding about the relative importance of present and future, and developed a tractable framework for its consideration. However, the Fisher model only gives insight into two periods, now and later, whereas in reality a future stream of income and consumption will influence utility. This was recognised by Samuelson (1937), whose Discounted Utility model (DU) was developed as a tractable model of preferences over multiple future periods.

5.3.2 *Discounted Utility (DU) Samuelson (1937)*

Samuelson's DU model is based on an additive multi-period utility model (equation (57)) with present value of lifetime utility $U(.)$ defined as the sum of instantaneous utility $u(.)$ which is dependent on consumption (c) in each period, discounted exponentially as described in equation (58). The discount factor $D(k)$ captures the previously described psychological influences in a single parameter, ρ.

$$U^t(c_t, \dots, c_T) = \sum_{k=0}^{T-1} D(k)u(c_{t+k}) \qquad (57)$$

$$D(k) = \left(\frac{1}{1+\rho}\right)^k \qquad (58)$$

The DU model, as in the Cropper (1990) model presented in Chapter 2, assumes that utility in each period is independent of utility in any other period. In addition, it assumes that the instantaneous utility function $u(.)$ and the discount rate ρ are both time-invariant. Finally, ρ is assumed constant for all domains. These assumptions are not, and were not, intended to reflect reality and are retained for analytical tractability. However, the DU model was long held to be the best available reflection of time preference.

5.3.3 *Non-standard discounting evidence*

However, there has been a plethora of evidence to suggest that the standard discounting models are not well equipped to describe the choices that people make in reality. Indeed, as stated, the standard DU model was never intended to reflect the reality of intertemporal decision making. Many of the alternative theories and models are

grounded in the observation that decisions over time often reveal inconsistent preferences. That is, when considering future outcomes from the standpoint of the present some course of action or decision maximises the present value of the future utility, but upon reaching the future point the agent will act differently. This is commonly and accessibly illustrated with examples of self-control and planning, such as the intention to attend an exercise class in a week's time never becoming a reality. Further, costly commitment devices, from formal devices such as pre-paid gym memberships to informal actions like moving the alarm clock out of arm's reach, would not persist if people's preferences were consistent over time.

5.3.4 *Common discounting assumptions*

This Section outlines the motivation and evidence surrounding five common alternative discounting assumptions. The technicalities underpinning the models are presented very briefly here, with full treatment being provided in the text of Study 2b in Chapter 7. Instead this review aims to highlight what is already known about these models, what motivated them, and which if any is expected *a priori* to explain the discounting behaviour in the VSL for cancer.

5.3.4.i *Exponential discounting*

The exponential discounting models are perhaps the most simple and tractable models that account for positive rates of time preference. They are based on the assumptions of the DU model, and impose a constant rate of time preference. Of course, this means that they are susceptible to the criticisms of the DU model especially in terms of the realism of the assumptions. Nonetheless they are the most commonly used in studies where the issue of time preference is important but not the sole focus, just like study 1 reported in Part II of this thesis.

The algebraic formulation of the discount factor is $\frac{1}{e^{\delta\tau}}$ (for continuous discounting) or $\frac{1}{(1+\delta)^{\tau}}$ (for discrete discounting). δ is the discount rate and τ is the delay until the outcome.

5.3.4.ii *Hyperbolic discounting*

Hyperbolic discounting is an alternative discounting model which accounts for the observation in much of the available evidence that the rate of time preference ρ is not constant, but declines over the time horizon. Evidence for this can be found in Cropper *et al.* (1994) amongst others. An early, specific study testing for this effect is reported

in Thaler (1981). 'Smaller payoff sooner' versus 'Larger payoff later' (hereafter 'smaller-sooner, larger-later') studies were conducted, with the result that implicit annual discount rates declined from 345% when the outcomes were delayed by one month to just 19% when they were delayed by 10 years. This result has been replicated in other studies, for example in Ainslie and Herrnstein (1981). In addition, Frederick (2003) describes a cross-study comparison which finds that the implied discount rates decline with the length of time involved in the underlying comparisons.

Having said this, Cameron and Gerdes (2003) conduct a study to distinguish between exponential and hyperbolic models in fitting their large dataset. They find it impossible to distinguish which is more appropriate. As such, although the evidence in support of it is strong, the superiority of the hyperbolic function compared to the exponential is not confirmed beyond doubt.

The algebraic formulation of the discount factor is either generalised as $\frac{1}{(1+\delta\tau)^{\gamma/\delta}}$ or simplified (assuming $\gamma = \delta$) to $\frac{1}{(1+\delta\tau)}$ where δ is the discount rate and τ is the delay until the outcome, and γ captures how far the function differs from standard exponential discounting.

5.3.4.iii *Quasi-hyperbolic discounting*

An alternative formulation to the hyperbolic discount model has been provided by Laibson (1997). It combines the qualitative findings of the hyperbolic model (a 'passion for the present' and declining discount rates) with the analytical tractability of the exponential discounting model. As such, this model is arguably the most tractable yet descriptively realistic of those commonly cited in the literature.

The algebraic formulation for the discount factor is $\beta\left(\frac{1}{e^{\delta\tau}}\right)$ where $0 < \beta < 1$ for $\tau > 0$ and $\beta = 1$ for $\tau = 0$. This means that the period 0 (the present) receives higher weight than future time periods, and these future periods are discounted exponentially, hence retaining analytical tractability in the model.

However, there are many reasons for a 'right now' bias, and these may not be to do with intrinsic time preference. For example, transaction costs and uncertainty effects both appear as soon as an outcome is non-immediate. This might have the effect of placing a premium on the present which is not due to any underlying psychological 'passion for

the present'. This confounds the existing evidence into the appropriateness of the quasi-hyperbolic discounting model.

5.3.4.iv *Sub-additive discounting*

An alternative explanation to the evidence supporting hyperbolic discounting models is the concept of sub-additive discounting. This theory, introduced in the finance literature by Rambaud and Ventre (1998) and in psychology by Read (2001), suggests that the discount rate might decline with the length of interval between two outcomes, rather than with the delay from the present. Read cites Rubinstein (2003) and Leland (2002) in suggesting that discounting "diminishes as a function of the judged similarity of the time-points marking the beginning and the end of an interval." As such, for any given interval, if it is subdivided, the overall discount rates will be lower than if it was not, suggesting that the discount factor (and hence present value of the outcome) will be higher for a more subdivided interval. Rambaud and Torrecillas (2010) provide the example that "the discounting function for one year will be greater than the product of the corresponding discounting function values for each month." A review of the literature and underlying theory of the delay versus interval concept is provided in Rambaud and Torrecillas (2010).

It is not possible to provide an algebraic formulation of the discount factor for sub-additive discounting because it relies inherently on a comparison between outcomes at different times.

5.3.5 *Other anomalies*

Other time-related anomalies have been documented in the literature. Some of these anomalies have sparked potential alternative utility models while others are, to date, curiosities that require further explanation. It is beyond the scope of this research to analyse the majority of the anomalies, and the reader is again invited to consult the review by Frederick *et al.* (2002) in which these models are given substantial treatment.

However, these effects may be able to explain particular observed preferences regarding the latent cancer VSL, and where this is the case it will be worth keeping these discounting models in mind. As such, the anomalies are briefly outlined in Sections 9.3.5.i-v, along with discussion of how the anomaly might influence a latent VSL.

5.3.5.i *The magnitude effect (Thaler, 1981)*

Small outcomes are shown to be discounted more than large ones, with illustration from Thaler (1981) for money amounts. If this is a persistent effect, it is evidence against the application of a constant discount rate across all domains. In terms of VSL studies, this effect could mean that different risk changes are discounted differently, which has implications for the interpretation of the risk-risk relativities, with potential overestimation of the VSL based on the (incorrect) assumption that disutility increases linearly with the size of the risk increase.

5.3.5.ii *The sign effect (Thaler, 1981)*

Thaler (1981) finds that gains are discounted at a higher rate than losses. This relates to the willingness to accept/willingness to pay disparity[30] and could be explained by reference point theories that have been proposed in behavioural economics, for example the classic prospect theory developed in Kahneman and Tversky (1979). If a loss is given more weight than a gain, then it will appear not to receive as high a discount rate if the elicitation does not account for the difference in weighting. In terms of the VSL framework, the elicited discount rates might differ between studies employing risk increases from the status quo and those employing risk reductions.

5.3.5.iii *Preference for improving sequences (Loewenstein and Sicherman, 1991)*

This anomaly might reflect a preference for 'getting the bad part out of the way', or perhaps a recognition of the fact that the later years will be experienced with the preceding years as a reference point: if the best outcome is latest, then it will not suffer by comparison to the periods that went before. This observation and tentative explanation link to another common anomaly: violations of independence (Loewenstein and Prelec, 1992). They show, through a very accessible thought experiment about choosing when to enjoy a sequence of fancy dinners, that their respondents have a preference for spreading consumption over time. Specifically, most people would choose to have a delicious meal last out of a selection of meals if it is the only chance to have it, but first if there is more than one occasion on which to have the dinner. This contradicts the standard discounting model's assumption that the different periods' utility ought to be independent. In terms of the VSL, this might result in a

[30] Although this anomaly is not irrefutable, see for example Chilton et al. (2012)

preference for taking a risk increase sooner rather than later, which contradicts the assumptions made about latency decreasing the VSL.

5.3.5.iv *'Date vs. delay' framing effect (Read et al., 2005)*

Most discounting theories predict no difference in the discount rate between outcomes described as being "four weeks from now" or "on the 15th April", as long as the delay is the same in each case. However, the framing of the scenario is shown in the work of Read et al. (2005) to be systematically and significantly related to the discount rate, with a strong positive effect on the elicited discount rate when the date is used as opposed to the delay. In addition, the phenomenon of hyperbolic discounting is shown to be much less evident where the date is used than when delay is described. Read et al. provide psychological explanations involving focusing effects and different salient aspects of the two types of framing. Sensitivity to framing is a common feature of stated preference studies, even when the incentives are made real. In terms of the VSL, this has implications for the way in which the latent outcome is described.

5.3.5.v *Summary of discounting anomalies*

To summarise, there are many accounts of anomalies in discounting behaviour that do not fit with the traditional DU model. However, the model was not intended to be a descriptive model of preferences, and the hyperbolic discounting model is able to cater for at least some of the effects described. The reference point model will account for some of the others. A range of additional discounting anomalies has been discussed with particular focus on the way that they might be expected to influence a latent VSL study. While it is beyond the scope of this research to explicitly address them all, they will be borne in mind for the design and implementation of the VSL study.

5.4 Discounting and Health

There is a range of evidence connecting time preferences and discounting to health outcomes, for example the well-established link between smoking and time preference. A survey of the recent evidence (since 2002) was conducted by Lawless *et al.* (2013) while a more general investigation of time preference and lifetime outcomes is presented by Golsteyn *et al.* (2013). Links are made between time preference, self-control and inconsistent preferences, especially in explaining apparently irrational health behaviours that are suboptimal, such as drug abuse or engaging in risky sexual behaviours. Chapman (2005) presents a meta-analysis which highlights a link between

'hot' behaviours like these and the discount rate but no link between time preference and 'cold' health behaviours like taking medicines and preventative health care. This might suggest that impulsivity has more to do with the link than pure time preference, although this is not confirmed.

However, while this literature is interesting and relevant to policymakers that wish to understand and then alter health behaviours with intertemporal consequences, it is not the main concern of this analysis. Instead of investigating the link between the (typically financial) time preference rate and health behaviours or outcomes, the present thesis is more interested in a more technical question. That is, is it appropriate to use the same discount rate for finance as for the domains of health and physical risk? The appropriateness of applying or assuming a constant discount rate across domains is a matter of debate in the literature both from a normative, policy perspective and from an individual perspective. The traditional view is that a single rate should be used, and these arguments are set out first. Criticism of this perspective is summarised afterwards, followed by empirical evidence.

5.4.1 *Normative arguments for constant discounting in policymaking*

In effect, health policy evaluation weighs financial costs against health benefits. Either or both costs or benefits could occur in the future, and as such, decisions need to be made about the suitable rate at which to discount them. The costs are clearly to be discounted at a financial discount rate, but for the benefits it is less clear. Traditional arguments suggest that the same rate ought to be used, because this ensures consistency of decision making over time. The consistency argument suggests that it should make no difference to overall allocation whether the future benefit is discounted to its present value, or a present cost is inflated to its future cost. This can only be the case when benefits are discounted at the same rate as costs, as shown in Weinstein and Stason (1977). An additional and commonly cited argument in favour of constant discount rates across domains is the Keeler and Cretin (1983) paradox of infinite deferral. This captures that for a set 'cost per unit' of health benefit (e.g. £1m per 10 lives saved) and for a given interest rate (e.g. 10%p.a.) then investing a health budget for financial return today will allow more lives saved in the future (in the present example, the value of £1m invested today will be £1.1m in one year's time, allowing 11 lives to be saved as opposed to 10). This generates an incentive for society to postpone health spending

indefinitely. On the basis of these two arguments, policymakers have increasingly ruled for the use of a constant discount rate for costs and benefits.

5.4.2 *Normative arguments for constant discounting in private decision-making*

Private decision making, according to the life cycle consumption models with discounted utility at their heart (see (Cropper and Sussman (1990); Cropper and Portney (1990)) and Alberini and Chiabai (2007b)) also suggests a domain-independent discount rate, which will be equivalent to the consumption discount rate in the case of perfect capital markets, or perhaps higher if there is imperfect access to capital markets.

Standard economic theory suggests that the discount rate for all production and consumption decisions is intrinsically related to the financial interest rate, and relates to the ability to smooth consumption optimally over the lifetime. Personal, subjective time preference has been shown to drive positive real rates of interest, at least in theory, and in the majority of the theoretical literature a single value is assumed to hold no matter the good or service under consideration.

5.4.3 *Critiques of the normative assumptions of domain-independent discounting*

The challenges to the domain independence hypothesis are twofold: theoretical and empirical. The theoretical support for applying a constant discount rate across policy domains has been criticised because the proofs offered (the consistency argument and the Keeler and Cretin paradox of infinite deferral) have at their heart a fundamental and problematic assumption. To take this assumption directly from Weinstein and Stason (the proponents of the consistency argument),

> "It is the discounting of dollar costs, and the assumed steady-state relationship between dollars and health benefits, that mandates the discounting of health benefits as well as costs" (Weinstein and Stason, 1977, p. 720) p720

This assumption of a steady-state relationship between monetary costs and health benefits is a problematic assumption: quite plausibly the value of health might increase over time. The debate is summarised in Cairns (1992), and Van Hout (1998) gives the debate surrounding domain independence full treatment in his paper arguing for a reconsideration of the standard approach of using a single rate. He clarifies that

> "costs need to be discounted on the basis of the expected increase in income and the marginal utility of consumption, and that effects need to be discounted on

> the basis of the expected increase in health and the marginal utility of health" (Van Hout, 1998)

and demonstrates that this only requires a constant discount rate across the domains under the "heroic" assumption that growth rates are generated by a social utility function with perfect market function. The paradox of infinite deferral is shown to hold only for benefits that are single period, which is unrealistic. The consistency argument is shown to hold only when a growth equilibrium is assumed. This is again a theoretical construct which may not hold in reality. As such, Van Hout argues strongly in favour of differentiated approaches to discounting across domains. If the value of health over time can be expected to grow, then the discount rate that ought to be applied should be lower than that over finance.

Despite this, the arguments are ongoing in the literature, with a real-world example being the decision of the UK's NICE (National Institute for Health and Clinical Excellence) ruling to adopt constant discount rates for costs and benefits as recently as 2005[31], prompting responses to the contrary from Brouwer *et al.* (2005) and Gravelle *et al.* (2007).

As with the social arguments, the private arguments for discount rates that differ across domains rest on the inability to trade wealth for money at a constant rate over time. This is not necessarily a valid assumption due to changing wealth over the lifetime, and due to the lack of direct transferability from wealth to health on an individual level (it is of course an easier assumption on a societal level).

As such, it appears on a theoretical level that while there are normative and ethical reasons to prefer a single rate of discounting across all domains, particularly costs and benefits, further scrutiny of these assumptions and application to the real world makes these less attractive. On an individual level, the argument for domain-independent discount rates appears even less convincing. Nonetheless, the debate is ongoing in the literature.

Whether or not a single discount rate across domains is normatively superior to a differential rate, it will nonetheless be important to discover whether these rates differ in

[31] The debate is on-going, as can be seen at http://www.nice.org.uk/newsroom/features/HowShouldNICEAssessFutureCostsAndHealthBenefits.jsp

reality. That is, do people apply different discount rates when considering future health or physical risk outcomes compared to future financial outcomes? If this can be resolved, it will add substance to one or other of the sides of the normative argument. Substantial empirical work has already been carried out to infer discount rates in different domains, with some emerging consensus but also with some emerging points of controversy. The key evidence comparing discounting in health (and sometimes physical risk) and discounting in finance will be presented in the next Section (9.4.4) with the conclusion the domains engender different discounting behaviour, but that there is no clear signal that one domain is more highly discounted than another.

5.4.4 *Empirical evidence on discounting across domains*

As discussed, there is strong evidence to suggest that discount rates differ by domain (see Frederick *et al.* (2002) and Lawless *et al.* (2013)) and even within the health domain across specific health contexts (Ganiats *et al.*, 2000). Typically, environmental and financial discount rates are shown to be similar, with the conclusion that financial discount rates are reasonable proxies for environmental time preference (Hardisty and Weber, 2009). However, the case for health is not so clear cut. This may of course relate to the difficulty in transferring between health and money.

Studies which appear to support the (admittedly controversial) theoretical prediction that health is likely to be discounted at a lower rate than money are not uncommon. An early example is the Cairns (1992) study which explicitly considers this issue. However, it is a small (n=27) pilot study based on students' preferences and as such it cannot be assumed to be generalizable to the population. Alberini and Chiabai (2007a) conduct a much larger (n=801) and more representative study in Italy and find that the discount rate for fatality risk is significantly lower than for money. However, given that their investigation involves fatality risks as opposed to health per se, it is not directly comparable to the health studies considered here. Finally, Meerding *et al.* (2010) conducted a study aimed directly at comparing health and money discount rates. They again find rates for health discounting that are lower than for finance, and in addition confirm the received wisdom that financial and environmental discounting behaviour is similar. This lends further confidence in their conclusions. However, the study exclusively considers a social decision frame as opposed to private discounting.

As such, none of the presented studies provides robust evidence on the comparison between private discount rates over health compared to finance, although all of them

support that the health (or fatality risk) domain generates lower rates of time preference than financial. However, there are two key studies by Lazaro (Lazaro *et al.*, 2001; Lazaro *et al.*, 2002) that contradict this finding.

Both of these studies explicitly estimate health and financial discount rates and both find that health is discounted more than money. The first of the studies is essentially a pilot on a student sample, which could of course be used to explain the apparently anomalous result, but it is replicated in the second which used a representative sample. The set up and design is careful, with EQ-5D descriptions of health and controls for private as compared to social frames. The result is, nonetheless, surprising and cannot easily be explained.

Given this mixed evidence, it is perhaps unsurprising that there are a variety of studies in which it is unclear which of health and financial discount rates are the highest. Both Chapman (1996) and Khwaja *et al.* (2007) find that domain independence is violated in their studies, but neither clearly shows one domain generating higher discount rates than the other.

As such, the evidence is clearly mixed about how the sign of the difference between time preference estimates in money and in health, but it appears to be true, empirically at least, that the two domains generate discount rates that differ from one another. On this basis, and taking into account arguments from Cubitt and Read (2007) which caution against experimentally elicited financial discount rates being applied to real decisions, it is deemed necessary to elicit and examine preferences over health and physical risk, particularly when health outcomes such as cancer fatality are of interest to the researcher as is the case in this thesis.

5.4.5 *The functional form of the health discount rate*

Having concluded that discounting behaviour is likely to differ between domains, the question is then what functional form can be expected to apply in the case of health and physical risk discount rates. Section 5.3.4 discussed the different discounting hypotheses in some detail, but the majority of the studies considered were developed with financial scenarios in mind and tested in experiments over financial outcomes.

There is limited evidence regarding whether discounting in health is exponential, hyperbolic or sub-additive. This may be because until the techniques for elicitation have been refined in finance, it might be considered overly ambitious to attempt to infer

this information in other domains. Similarly, it might be because the methods for directly eliciting discounting in health are underdeveloped. Nonetheless, the implications of different discounting functions for policy decisions are considerable (see Part IV for a discussion) and as such this thesis will not attempt to sidestep the issue as others have typically done.

Two key studies that explicitly consider the functional form for discounting in health are Chapman (1996) and Khwaja *et al.* (2007). Both studies find evidence for hyperbolic discounting. Two further studies are of note in eliciting discount rates outside of the financial domain, but both are environmental in focus. Each of the studies finds evidence in support of positive discounting of the environment but the discounting functional form conclusions are different. Viscusi *et al.* (2008) find evidence of quasi-hyperbolic discounting in a stated preference study which considers water quality over time. In contrast, Meyer (2013) finds no evidence to dismiss exponential discounting when the scenario is the clean-up of a lake. The two studies are comparable in context, although the Meyer study is arguably more robust in controlling for potential confounds in the elicitation of the discount rate. Nonetheless, it is an interesting and somewhat surprising result that such different conclusions have been drawn from studies in a similar area. This cautions against placing a firm emphasis on the hyperbolic result in the two health studies considered above.

This discussion has outlined the studies that elicit the functional form of discounting outside of finance. Clearly no firm consensus has been found and further evidence would be valuable in this area. Given the disparity of findings between studies and domains, there is a chance that the discount rate and functional form might differ even within an individual and within domains. This suggests a gap in the researchers' toolkit which needs to be filled with a method for eliciting information about discounting from survey responses to questions in the specific area of interest. This motivates the Study 2b in Chapter 7 which aims to demonstrate just such a method.

5.5 The Confound of Risk and Time Preferences

However, before time preference elicitation can be considered, it will be important to recognise an often neglected confound: the link between risk and time preferences. A future outcome is inherently more risky than an outcome at the present, because of the probability of non-survival until the date at which the future outcome would occur and also because of the uncertainty about the existence or delivery of the outcome.

Intuitively, it is clear that this uncertainty could render the prospect of the latent outcome less valuable. This has motivated substantial discussion in the financial literature, where methods have been developed to jointly elicit risk and time preferences (Andersen *et al.*, 2008). Andersen et al. note that this confound biases the estimate for time preference because the typical discounting elicitation procedures (for example the Coller and Williams (1999) technique) simply discount the money value, not the utility derived from the money value. Their method corrects for this by assuming a utility function for the money amount and applying the discount function to this utility. An example of jointly estimated (financial) risk and time preferences applied to health behaviours is Ida and Goto (2009). An alternative approach in the financial literature which controls for the risk and time preference confound is in the recent study by Laury *et al.* (2012) which elicits discount rates from risky outcomes thereby side-stepping the risk preference issue.

Happily, in the method of discount rate elicitation used in Study 1 (Section 4.11) which will be used again in Chapter 7, the risk and time preference confound is not problematic. This is because the discount rate is inferred from the relativities between (unspecified) VSL values. These values already incorporate the effect of utility function curvature, and because no explicit value needs to be placed on the VSL or the VSL_{CAN} in the elicitation of the discounting parameter, risk preferences are effectively dealt with in an implicit fashion. As such, the elicited discount rates are free from the confound of risk preferences.

However, this is not to say that risk preferences are irrelevant in the analysis of Risk-Risk relativities. In fact, quite the opposite is true. The underlying VSL estimates depend on the rate of substitution between wealth and risk, and the Risk-Risk methodology- which was used in Study 1 and will be used again in Study 2b- employs risk increases as the currency for expressing preference. As such, an understanding of risk preferences as they relate to health outcomes will be vital to the analysis presented here and also to VSL studies more broadly. This is the focus of Section 6.1.

There is debate as to whether risk preferences derived over financial outcomes are adequate proxies for health related risk preferences. If so, then the use of financially derived risk aversion coefficients (see Section 6.2 in Chapter 6) is likely to suffice to control for the risk preference effect. If not, then a reliable method for eliciting these

preferences needs to be developed. This latter issue is the focus of Chapter 6, and as such will not be addressed here. However, the former deserves some treatment.

5.6 Financial and Health Risk Preferences?

Risk preferences derived over financial lottery choices are commonly used in explaining behaviour in a variety of contexts, especially those that are intrinsically risky such as decisions over physical risk or intertemporal choice decisions. However, there is little consensus over the relevance of risk preferences derived over financial decisions (hereafter 'financial risk preferences') to situations where the risk is related to health or to physical risk. While it may be the case that preference for risk and its avoidance *per se* is similar across domains, there is no reason *a priori* to suppose that the underlying utility function displays the same concavity across domains.

Empirical evidence regarding this domain dependence of risk preferences is mixed. Weber *et al.* (2002) use stated risk attitudes and find low correlation between risk attitude across domains, while Einav *et al.* (2010) use insurance scenarios and find that domain-generality is present, to varying extents. Anderson and Mellor (2008) compare experimentally-elicited financial risk aversion coefficients with risky behaviours like smoking and drinking to excess, and find significant correlation. The confusion is compounded in Soane and Chmiel (2005) who take a psychological perspective and find that the degree of domain dependence of risk preference actually varies between people , such that while some individuals display a high degree of consistency in risk attitudes, others display large variation. In summary, the evidence is mixed. This may, in part, be due to the heterogeneity in the ways that health risk aversion is defined in these studies, be it stated risk attitude, risk attitude inferred from behaviours like smoking, or psychological definitions of risk attitude.

Contrast to this the financial domain. The seminal work of Holt and Laury (2002) has given economists a tool for eliciting financial risk aversion (specifically the coefficient of relative risk aversion (CRRA)) through a simple experimental procedure. By contrast, the standard approach of researchers wishing to control for risk aversion in health typically use stated risky behaviours such as seatbelt non-use or smoking. This is validated by the finding in Anderson and Mellor (2008) that the correlation between these and other risk preference measures is high, but nonetheless these behavioural measures are not as informative nor as comparable as the coefficient of relative risk aversion (CRRA) in financial decisions.

However, attempts to measure risk aversion more thoroughly in the domains of health and physical risk have been relatively few, and in these attempts only minimal attention has been paid to understanding what exactly is being captured or measured. This is a clear gap in the literature. The analysis in Chapter 6 addresses these issues first by formalising the theoretical framework for considering risk aversion in the domain of health, then by developing a method, firmly grounded in utility theory, for eliciting a proxy for risk aversion in health.

5.7 Summary

This review has considered time preference in general terms and in the domain of health. Different discounting assumptions were considered, and the lack of consensus was highlighted on two fronts. First, whether health and financial discount rates are good proxies for one another, and second what the likely functional form for discounting in the domain of physical risks might be. On this basis, there is a considerable role for developing a methodology to reliably elicit discount rates from choices related to physical risk.

The elicitation of time preferences is closely linked to risk and risk preference, and as such the review turned to consider risk preferences in health. Relatively little work to date has explored the elicitation of coefficients of risk aversion in the domain of health and this was highlighted as an area ripe for further exploration.

Study 2 will address both of these issues. Chapter 6 will report Study 2a which considers the health risk aversion issue and Chapter 7 will report Study 2b which considers the time preference issue. Both Study 2a and Study 2b are based on the same survey, however. The methodology is presented in the next Sections.

5.8 Methodology for Study 2

The protocol for Study 2 closely follows that of Study 1, which was reported in detail in Section 3.2 in Part II. The preliminary learning rounds are identical, and the reader is directed to the discussion in Section 3.2.6 for details. The R-R survey follows the same structure as for Study 1, with the elicitation mechanism and explanations unchanged. Q1-3 are identical in studies 1 and 2. However, the scenarios in Q4-9 are slightly different. The supplementary questions are the same as in Study 1. It should be noted that while the R-R questions are outlined here, their analysis will not be conducted until

Chapter 7, because Chapter 6 deals with the preliminary issue of eliciting risk preferences in the domain of health.

5.8.1 Risk-Risk (R-R) Questions

All ten questions compare cancer risks (with one year of morbidity prior to fatality) with road accident risks. Question 10 replicates a "context" question from Study 1, in that both fatalities would be ten years from now. Questions 1-9 all compare a latent cancer risks with road accident risks sooner. The range of timing and questions is provided in Table 5.1.

Table 5.1: Latency differentials and delays

Question	Code	Cancer	Roads	Latency differential (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_5R_2	5	2	3	3.5
5	C_7R_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

The questions are designed to elicit preferences over a range of delays from the present to the time of the risk, and latency intervals between the cancer and road accident risks. This will allow sub-additive and hyperbolic discounting to be considered.

Subsequent to the ten R-R trade questions respondents were asked to make a series of additional choices. These allowed the elicitation of risk and time preferences in the domains of health and physical risk.

5.8.2 *Financial risk preference elicitation*

The first set of choices implemented a financial Holt and Laury (H-L) style experiment where respondents chose between lotteries with changing probabilities of the good outcome. The decision table is presented in Table 5.2.

Table 5.2: Holt-Laury style financial lottery comparisons

Decision number	A		B	Your choice
1	10% chance of £6 90% chance of £5	OR	10% chance of £12 90% chance of £1	
2	20% chance of £6 80% chance of £5	OR	20% chance of £12 80% chance of £1	
3	30% chance of £6 70% chance of £5	OR	30% chance of £12 70% chance of £1	
4	40% chance of £6 60% chance of £5	OR	40% chance of £12 60% chance of £1	
5	50% chance of £6 50% chance of £5	OR	50% chance of £12 50% chance of £1	
6	60% chance of £6 40% chance of £5	OR	60% chance of £12 40% chance of £1	
7	70% chance of £6 30% chance of £5	OR	70% chance of £12 30% chance of £1	
8	80% chance of £6 20% chance of £5	OR	80% chance of £12 20% chance of £1	
9	90% chance of £6 10% chance of £5	OR	90% chance of £12 10% chance of £1	
10	100% chance of £6	OR	100% chance of £12	

The money amounts stay the same down the table but differ between the choices A and B. Option A represents the 'safe' lottery because the spread between the prizes is low. Option B presents the 'risky' lottery because the spread is much higher- there is a chance of a very high payoff (£12) but also a chance of a very low payoff (£1). The probability of "winning" increases down the table, making the 'risky' option B more attractive. See Chapter 6 for more detail about the utility theory underpinning the HL elicitation procedure. The payoffs were deliberately hypothetical to facilitate comparison with the health related risk aversion coefficients, which were necessarily hypothetical.

5.8.3 *Health risk preference elicitation*

Respondents also completed a variation of the H-L procedure adapted for health states. This is a novel empirical device developed in this thesis. Its explanation and description are the focus of Chapter 6 and as such the procedure will not be described here.

5.8.4 *Financial time preference elicitation*

The penultimate task consisted of "larger later or smaller sooner" choices between financial outcomes in order to generate financial time preference parameters. The methodology is based on the work of Coller and Williams (1999) which is widely applied in the literature, for example by Andersen *et al.* (2008). Respondents filled in a decision table as shown in Table 5.3, choosing (hypothetically) between £350 to be received in one month's time and some larger amount to be received in seven months' time.

The 1 month delay is included before the earlier outcome would be received. This front end delay (FED) avoids the potentially confounding influence of an immediate outcome, because preference for this might reflect reduced transaction costs as opposed to pure time preference, and may artificially inflate the perceived discount rate over the very short term. In addition, given that one year is the shortest delay for a risk outcome in the main questions, it was decided to avoid having immediacy in the financial time preference questions in order to maximise the comparability of the discount rates elicited in finance and in the domain of physical risks.

The choices were hypothetical, mirroring the main questions and the risk preference questions. Frederick et al (2002) summarise this issue and conclude that there is no strong evidence base to suggest that hypothetical and real outcomes are discounted differently. However, a second and possibly more fundamental criticism of the elicitation of discount rates from these sorts of questions is addressed by Krupka and Stephens (2013). They reference an earlier debate ((Fuchs, 1982); (Loewenstein, 1987); (Pender, 1996)) about whether the responses to these questions reveal personal discount rates, or whether they simply reflect market interest rates faced by respondents. If respondents have access to perfect capital markets, in theory they can use these markets in such a way as to arbitrage the choices presented to them. Krupka and Stephens (2013) test this idea and find that the results are significantly related to the degree of

access to capital markets, concluding that the elicited discount rates capture more than simply personal time preference rates.

Table 5.3: Time preference elicitation

Decision number	Option A Sooner: Receive the money **1 month from today**	Option B Later: Receive the money **7 months from today**	Your choice
1	£350 sooner	£354 later	
2	£350 sooner	£359 later	
3	£350 sooner	£363 later	
4	£350 sooner	£368 later	
5	£350 sooner	£372 later	
6	£350 sooner	£377 later	
7	£350 sooner	£381 later	
8	£350 sooner	£386 later	
9	£350 sooner	£390 later	
10	£350 sooner	£395 later	
11	£350 sooner	£404 later	
12	£350 sooner	£414 later	
13	£350 sooner	£423 later	
14	£350 sooner	£433 later	
15	£350 sooner	£443 later	

However, given that the main questions relate to fatality risk in which arbitrage is not a possibility, and given that the "smaller-sooner or larger-later" methodology is the prevalent method in the literature for estimating time preference, it was used in spite of the potential problems discussed. The problems provide further motivation for eliciting domain-specific discount rates from survey data. This is conducted in Chapter 7.

5.8.5 *Final procedures*

The final task was to complete a questionnaire about standard personal demographics as well as basic questions to elicit familiarity of cancer and road accidents (specifically whether the respondent or a close friend had experienced cancer or a serious road

accident). These will be used to explain the observed preferences where appropriate through the analysis.

5.8.6 *Implementation*

Implementation procedures follow those in Study 1 reported in Part II.

5.8.7 *Sample statistics*

The sample size is 112, and all respondents are aged between 18 and 25, enrolled as undergraduate and postgraduate students at Newcastle University in the UK. The demographics for this sample are provided in Table 5.4. Given the demographic differences between this group and the older sample from Study 1, the insights from this Part will not necessarily generalise to the overall population. However, this Study provides theoretical, methodological and empirical contributions with respect to the elicitation of risk and time preferences, and acts as a pilot for further investigation using a more representative sample.

Table 5.4: Sample statistics

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%
Self-reported car accident risk	1.04 (1.09)
Self-reported health status	1.48 (0.57)

The sample has a mean age of almost 21 as would be expected for a sample dominated by undergraduates. Unsurprisingly, personal income is low and the proportion renting is high. However, household income is high at £3000 per month which is likely to reflect high parental incomes. Females are underrepresented compared to the general population, at 45%. In terms of characteristics likely to relate to the preference for cancer and road accident risk avoidance, experience of cancer and road accidents is similar to that reported in Study 1 (69% and 48% in Study 2 compared to 75% and 64% for Study 1). Respondents tended to report "better than average" health, and "lower than average" car accident risks, although the variance in the latter is high.

5.8.8 *Summary*

This Section has set out the methodology for Study 2, focusing on the way that it differs from Study 1 and presenting the main methods for the elicitation of risk and time preferences in finance, because these will be key comparators to the risk and time preferences to be elicited over health in the coming Chapters. Study 2 will be analysed in two ways. Chapter 6 will refer to Study 2a, which will consider the implications for risk preference. Chapter 7, which reports Study 2b, will use the insights from Study 2a and generate time preference estimates and functional form inferences.

CHAPTER 6. Towards a Measure of Risk Preference in Health

6.1 Introduction and Motivation

Estimating the absolute or relative value of statistical life is inextricably linked to the concepts of risk and risk attitude because, as defined in Chapter 2 on pg.20, the VSL is estimated by aggregating willingness to pay for marginal changes in fatality risk. There are two channels through which risk preference can be expected to influence the VSL_{CAN}:VSL relativity. These effects work in opposing directions, and so their combined influence is essentially an empirical question.

Firstly, considering the Risk-Risk methodology set out in Chapter 3 (pg.56), high levels of risk aversion will tend to reduce the overall level of risk that is acceptable to a respondent, which is likely to *reduce* the observed relativity from risk-risk trade-offs through this 'size of overall risk' channel.

Additionally, any latent outcome is inherently risky (see Gafni and Torrance (1984)) and as such, higher levels of risk aversion will, increase aversion to a more delayed outcome through this second 'latency of risk' channel. In the empirical work in Study 2, reported in this Part of the thesis, the delayed outcome is always cancer[32]. This means that higher levels of risk aversion would tend to *increase* the overall VSL_{CAN}:VSL relativity. Given that this Part of the thesis is intended to explore the effects of latency on the VSL for cancer, understanding and controlling for this risk preference effect assumes additional importance.

So, this Chapter takes as its starting point this observation that risk preferences are likely to influence the relativities elicited and reported in Studies 1 and 2, but the direction of this effect is ambiguous because of the offsetting 'size of overall risk' and 'latency of risk' channels through which risk aversion can be expected to influence the VSL_{CAN}:VSL relativities reported in the R-R framework. Typically, researchers control for risk preference effects using measures of risk aversion defined over financial outcomes. However, it was discussed in the literature review that this might not be the most appropriate approach to take, because risk preferences in different domains have been shown to vary. As such, a measure of risk aversion defined over health outcomes

[32] The exception is Q10 where the fatality would occur at the same time.

might be better suited to explain the role of risk preferences in generating the VSL_{CAN}:VSL relativity.

The elicitation of risk preferences over finance is well established. The seminal work of Pratt (1964) and of Arrow (1971) formalised the framework for thinking about risk aversion in terms of a single parameter (the coefficient of relative risk aversion, CRRA) and the work of Holt and Laury (2002) is still dominant amongst methods of eliciting this parameter in experimental settings. However, the elicitation of risk preferences in health is less well established. Harrison *et al.* (2005) provide a systematic review of existing options for controlling for risk preferences using the literature from psychology and medical decision making. These options mostly consist of self-rating on Likert scales and as such are not grounded in economic choice theory. To fill this gap, the requirements for reliably estimating health risk aversion are twofold: initially, to lay out the theoretical underpinnings; then to establish a framework for the empirical estimation. This Chapter addresses both the theoretical and empirical concerns.

The structure of this Chapter is first to set out the existing theoretical framework which underpins the standard Holt-Laury (HL) elicitation procedure for risk aversion in the financial domain. The aim of the present chapter is then to adapt this framework to consider the utility over health instead of the utility over financial outcomes. This new framework formalises the basis of a novel elicitation procedure in which the Holt-Laury empirical procedure is also adapted for the health domain. From this basis, preliminary empirical estimates for health risk aversion are generated using the question as described on pg.167. These values will be taken forward to Chapter 7 and used as explanatory variables in explaining both discounting behaviour and the overall Risk-Risk relativities in Study 2b.

In this Chapter, the new contributions to knowledge are:

1) The adaptation of the utility theory underpinning Holt-Laury risk aversion elicitation to the domain of health.
2) The adaptation of the Holt-Laury empirical estimation procedure to allow the elicitation of health risk aversion.
3) Preliminary evidence about the values of the health risk aversion coefficients.

The insights generated are therefore relevant to this thesis, but also to VSL research more generally. The theoretical and methodological developments presented have the

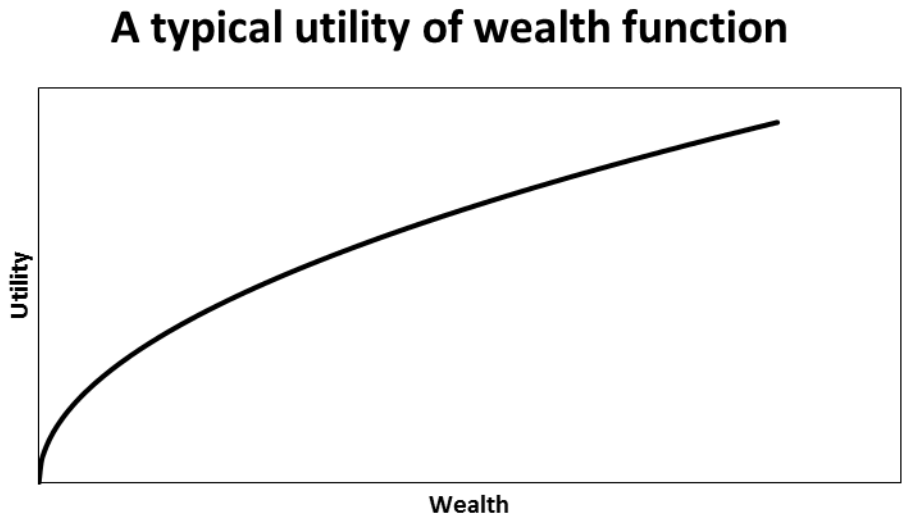
potential to benefit a wide range of future work including, but not limited to, VSL elicitation and health valuation exercises.

6.2 Theory Underlying the Elicitation of Risk Preferences for Financial Outcomes

6.2.1 *Utility of wealth*

As a baseline case, consider the risk aversion over financial outcomes. Individual utility functions (under the assumptions of Expected Utility Theory[33]) incorporate risk preference. Typically this is assumed to be risk aversion, and so the utility function is assumed to be increasing and concave as shown in Figure 6.1.

Figure 6.1: Utility of wealth incorporating risk aversion



6.2.2 *Certainty equivalence levels of wealth*

Under Expected Utility Theory, concavity of the utility function implies risk aversion because it implies that an amount, x, to be received for certain gives higher utility than the expected utility of a gamble with expected value equal to x. Similarly, a risk averse individual will be indifferent between a gamble with expected value y and some amount, to be received for certain, and which is less than y. This amount is referred to as the 'certainty equivalent' level of wealth (w_{CE}). Consider a highly risk-averse individual: the level of w_{CE} will be lower than for the average person, because they receive less expected utility from a gamble, due to their aversion to risk. Conversely, an individual who is only slightly risk averse will have a value for w_{CE} that is only slightly

[33] Justification for using the EUT assumption in this thesis despite its limitations was provided in Section 2.2

below the expected value of the gamble. The certainty equivalent level of wealth can therefore be interpreted as an inverse measure of risk aversion.

Figure 6.2: Demonstrating risk aversion over finance: 50:50 chance of receiving w_L and w_H

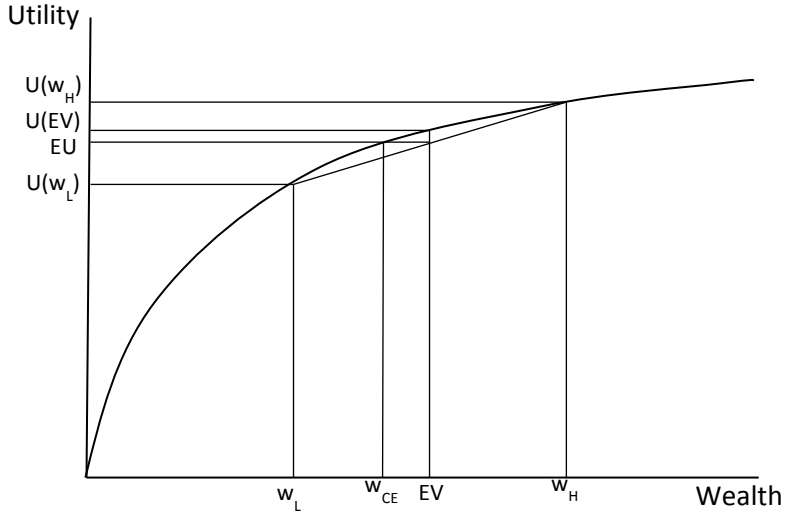


Figure 6.2 demonstrates the concept of the certainty equivalent level of wealth for a risk averse individual considering 50:50 gamble between receiving amount w_L and amount w_H. The gamble has an expected value (EV) which is the midpoint between w_L and w_H, but the gamble generates a lower expected utility (EU) than the utility of the expected value (U(EV)), because of the individual's aversion to risk. Reading across from the EU allows the specific level of wealth w_{CE} to be established, i.e. the level of wealth which when received with certainty leaves the individual just indifferent between taking it and taking the gamble.

6.2.3 *The Pratt-Arrow coefficient of relative risk aversion*

Risk aversion is captured by the Coefficient of Relative Risk Aversion (Pratt (1964) andArrow (1971)). The formula is:

$$RRA = -\frac{wU''(w)}{U'(w)} \qquad (59)$$

Given a utility of wealth function such as

$$U(w) = \frac{w^{1-\alpha}}{1-\alpha} \qquad (60)$$

the Pratt-Arrow CRRA defined in equation (59) simplifies to α. This specific form of the utility of wealth function rests on a simplifying assumption, used here for analytical

tractability. The analysis could be repeated for different utility of wealth functions but the interpretation of the risk aversion coefficient is less straightforward.

6.2.4 *Holt-Laury risk preference elicitation*

The Holt-Laury procedure (Holt and Laury, 2002) has become the established method for eliciting individuals' degrees of risk aversion. It was used in Study 1 (reported in Part II) to elicit financial risk aversion measures for inclusion in the regression analyses in Sections 4.3 to 4.9. The procedure for capturing the parameter α is to elicit the indifference point in a list of binary lottery choices where the outcomes are constant but the probability of receiving the outcomes changes. In this Study, the outcomes were £5 and £6 for the safe option, option A; and £1 and £12 for the risky option, option B. Respondents filled in the table as shown in Table 6.1, which was introduced as Table 5.2 on pg.153.

Table 6.1: Holt-Laury style financial lottery comparisons

Decision number	A		B	Your choice	Minimum α if switch in this row
1	10% chance of £6 90% chance of £5	OR	10% chance of £12 90% chance of £1		No minimum
2	20% chance of £6 80% chance of £5	OR	20% chance of £12 80% chance of £1		-1.69
3	30% chance of £6 70% chance of £5	OR	30% chance of £12 70% chance of £1		-0.88
4	40% chance of £6 60% chance of £5	OR	40% chance of £12 60% chance of £1		-0.38
5	50% chance of £6 50% chance of £5	OR	50% chance of £12 50% chance of £1		0
6	60% chance of £6 40% chance of £5	OR	60% chance of £12 40% chance of £1		0.34
7	70% chance of £6 30% chance of £5	OR	70% chance of £12 30% chance of £1		0.67
8	80% chance of £6 20% chance of £5	OR	80% chance of £12 20% chance of £1		1.01
9	90% chance of £6 10% chance of £5	OR	90% chance of £12 10% chance of £1		1.40
10	100% chance of £6	OR	100% chance of £12		1.96

The switch-point, which is the first row in which the probability of winning is enough that the respondent is willing to take the risky option, gives a lower bound on the risk aversion coefficient. This is because, assuming that an individual is acting to maximise her expected utility, she can have a risk aversion coefficient no greater than α^* to have taken the risky gamble in that row. The lower bound coefficient for each row is given in the righthand column in Table 6.1 for reference, but of course this column was omitted from the response sheets that the respondents received. A diagrammatic representation of indifference for a respondent with $\alpha = 0.5$ is given in Figure 6.3.

6.2.5 *The utility maximisation problem in the Holt-Laury procedure*

Figure 6.3: Indifference between options A and B in the Holt-Laury style financial lottery table for an individual with $\alpha = 0.5$.

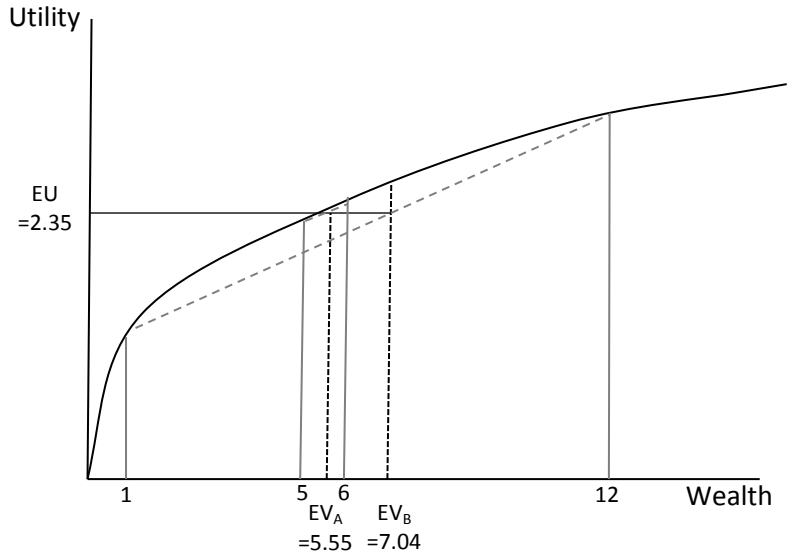


Figure 6.3 is equivalent to Figure 6.2, except that the respondent in question is simultaneously considering two gambles, a "risky" gamble between 1 and 12, and a "safe" gamble between 5 and 6. At the point marked, the respondent is indifferent between the two because the expected utility is the same for both gambles, at 2.35.

The utility maximisation problem is given in equation (61). The respondent is indifferent between options A and B where

$$pU(6) + (1-p)U(5) = pU(12) + (1-p)U(1) \qquad (61)$$

That is, where

$$p6^{(1-\alpha)} + (1-p)5^{(1-\alpha)} = p12^{(1-\alpha)} + (1-p)1^{(1-\alpha)} \qquad (62)$$

As such, there is a unique value of α for every row of the table, with its corresponding value for p such that the individual is indifferent in that row.

She will choose the safe option A as long as

$$p6^{(1-\alpha)} + (1-p)5^{(1-\alpha)} > p12^{(1-\alpha)} + (1-p)1^{(1-\alpha)} \quad (63)$$

6.3 A Note on Types of Risk Aversion

Two types of risk aversion are identified in Robinson et al (2001). As originally suggested by Dyer and Sarin (1982), lottery choices indicating aversion to risk are likely to be reflecting two separate effects, firstly diminishing marginal utility of wealth (which is reflected in the concavity of the utility function) and secondly aversion to gambles *per se* (which would give added reason to choose the safe option instead of the risky one). As argued by Dyer and Sarin (1982) and neatly summarised in Bleichrodt (2002) and in Robinson *et al.* (2001), where values are elicited under conditions of certainty, the implied value function $v(.)$ reflects the diminishing marginal return on the good being valued (for example, an individual's valuation of six apples is likely to be less than 120% of their valuation of 5 apples, purely as a result of diminishing marginal utility in apples). The utility function $u(.)$ on the other hand, by definition reflects the utility gained from outcomes under conditions of uncertainty. It will, therefore, incorporate not only diminishing marginal utility but also aversion to gambles. This is an important distinction that will be of relevance later in this analysis. HL risk aversion elicitation (Holt and Laury, 2002) generates coefficients under uncertainty, so encapsulates the full definition of risk aversion.

6.4 Health State Risk Aversion

So far, this analysis has set out the existing framework, which is designed to elicit financial risk aversion. However, as discussed in the literature review (Section 5.6), there is evidence to suggest that risk aversion differs across domains. That is, the inclusion of measures of financial risk aversion may be inappropriate when the effect under consideration is the risk aversion over health states.

The aim of this Chapter is to provide an alternative measure of risk aversion defined over health states. This requires two things: firstly to formalise the translation of the financial utility framework into a framework for utility over health (which is carried out in this Chapter and presented in Section 6.4.1) and then to develop the elicitation

procedure to capture health risk aversion. The approach taken is to adapt the HL elicitation procedure described above on pg.153, substituting health states instead of monetary amounts. The theory and practice is outlined in the coming Sections.

6.4.1 *Utility over health states*

As described on pg.162, the elicitation procedure developed by Holt and Laury for eliciting financial risk aversion is underpinned by a utility over wealth function as displayed in Figure 6.3. To convert this to the health domain, it necessary to assume that utility can be defined directly over health. This is not the first analysis that allows health to enter directly as an argument in the utility function, for example see Torrance *et al.* (1996), although it contrasts with the common convention of applying health to the utility framework either as a 'lump sum' change in utility (i.e. a parallel shift of the utility over wealth function) or as a parameter altering the marginal utility of wealth (i.e. altering the slope of the utility of wealth function).

The underlying assumption is that it is conceivable to have a ratio scale upon which to measure health (i.e. a cardinal scale with a set zero), and that utility over health is monotonically increasing in the health level. As with the utility of wealth function, the utility of health function is assumed to be smooth and continuously differentiable.

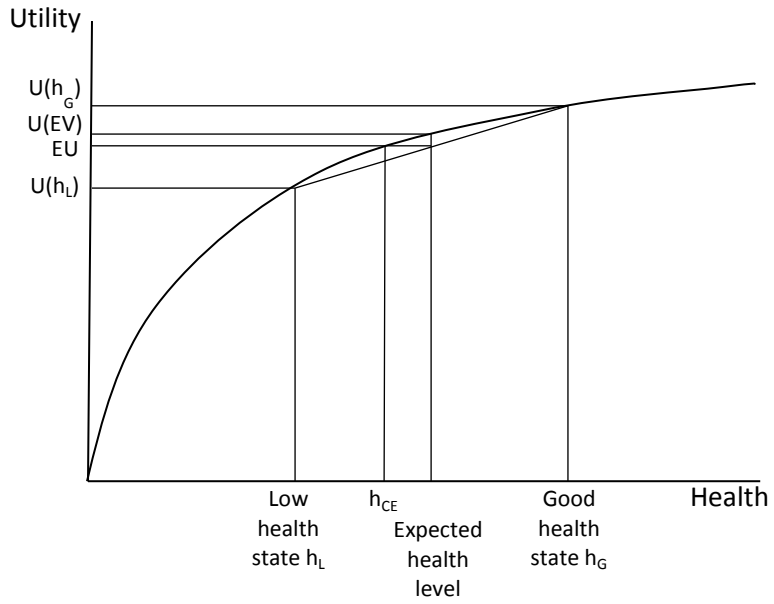
6.4.2 *Health risk aversion coefficient*

Figure 6.4 replicates Figure 6.2, except that the x axis measures the level of health as opposed to wealth. From this point, just as for the financial gambles, assuming some underlying risk aversion coefficient in the utility of health function, and given the degree of risk aversion, an individual will be indifferent between some health state h_{CE} a lottery between two health states h_G and h_L with expected value- insofar as this is meaningful in the domain of health- greater than the level of health h_{CE}.

For simplicity, and in the absence of any better indication, the same functional form is assumed to hold for utility of health as for the utility of wealth function, but for clarity the coefficient of health risk aversion is labelled β.

$$U(h) = \frac{h^{(1-\beta)}}{(1-\beta)} \qquad (64)$$

Figure 6.4: Demonstrating risk aversion over health



Given these assumptions, two pairs of health states can be used instead of two pairs of money amounts and in all other respects the setup is identical to that underpinning the financial Holt-Laury trades.

6.4.3 *Holt-Laury risk preference elicitation in health*

Examples of health lotteries are presented in Table 6.2. For now, it is sufficient to assume that h_1 is unambiguously worse than h_2, which in turn is worse than h_3 and then h_4. As in the financial case, even the most risk averse of individuals would be expected to choose the 'risky' option in row 10, because it is guaranteed to give them the minor illness h_4. The further down the table a respondent goes without switching, the lower the risk of the severe illness h_1 has to be before the respondent will take the chance of getting only h_4. As such, the interpretation that the individual will switch later down the table the more risk averse she is holds just as well intuitively for the health scenarios as for the financial scenarios.

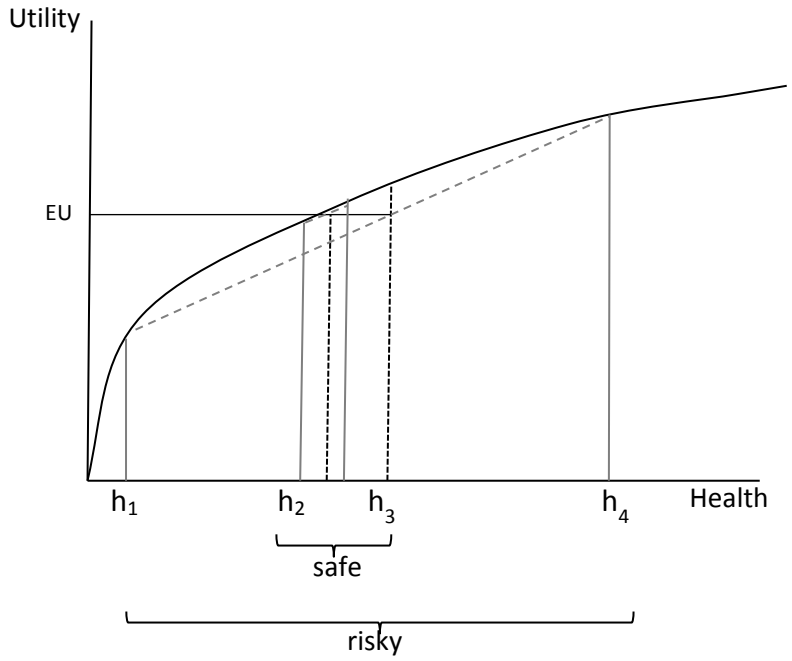
Table 6.2: Holt-Laury style health lottery comparisons

Decision number	A		B	Your choice
1	10% chance of h_3 90% chance of h_2	OR	10% chance of h_4 90% chance of h_1	
2	20% chance of h_3 80% chance of h_2	OR	20% chance of h_4 80% chance of h_1	
3	30% chance of h_3 70% chance of h_2	OR	30% chance of h_4 70% chance of h_1	
4	40% chance of h_3 60% chance of h_2	OR	40% chance of h_4 60% chance of h_1	
5	50% chance of h_3 50% chance of h_2	OR	50% chance of h_4 50% chance of h_1	
6	60% chance of h_3 40% chance of h_2	OR	60% chance of h_4 40% chance of h_1	
7	70% chance of h_3 30% chance of h_2	OR	70% chance of h_4 30% chance of h_1	
8	80% chance of h_3 20% chance of h_2	OR	80% chance of h_4 20% chance of h_1	
9	90% chance of h_3 10% chance of h_2	OR	90% chance of h_4 10% chance of h_1	
10	100% chance of h_3	OR	100% chance of h_4	

6.4.4 *The utility maximisation problem in the Holt-Laury procedure for health states*

The interpretation of Figure 6.5 is identical to that for Figure 6.3. The individual is considering a risky gamble (between h1 and h4) and a safe gamble (between h2 and h3). The situation depicted in Figure 6.5 implies that the probabilities of success are such that the individual is indifferent between the safe and risky options, because the expected utility is the same in both cases.

Figure 6.5: Indifference between risky and safe options in the Holt-Laury style health lottery table



The utility maximisation problem is given in equation (65). This mirrors equation (61) on pg.163, except that the outcomes are health which enters directly into the utility function. The respondent is indifferent between options A and B where

$$pU(h_3) + (1-p)U(h_2) = pU(h_4) + (1-p)U(h_1) \qquad (65)$$

That is, where

$$ph_3^{(1-\beta)} + (1-p)h_2^{(1-\beta)} = ph_4^{(1-\beta)} + (1-p)h_1^{(1-\beta)} \qquad (66)$$

As such, there is a unique value of β for every row of the table, with its corresponding value for p such that the individual is indifferent in that row.

She will choose the safe option A as long as

$$ph_3^{(1-\beta)} + (1-p)h_2^{(1-\beta)} > ph_4^{(1-\beta)} + (1-p)h_1^{(1-\beta)} \qquad (67)$$

To summarise, the utility theoretic underpinnings of the financial Holt-Laury procedure have been shown to translate well into the health domain, if the researcher is willing to accept that utility can be defined directly over health states, and that a similar utility function is appropriate in health as in finance. In the absence of evidence to the contrary, this analysis will proceed under the assumptions and use this as a basis for setting up a framework for eliciting risk aversion over health states.

6.5 Implementation: Communicating Health States (h)

Moving from the abstract framework set out in the Sections above to implementation in practice is not straightforward. This is because interpretation of the switch points will differ depending on which measure of health is used as an input. To clarify, recall that the measure of health ideally has to be comparable with the money amounts to be entered into the financial calculations. That is, they have to be objective amounts that reflect the intrinsic amount of health in each scenario measurable on a ratio scale (i.e. a cardinal scale with a clear origin). This metric does not appear to exist in any well-defined way at present. Put simply, there is no obvious health-state equivalent of £5.50. There is significant debate in the health economics literature about what is meant by 'health', and the concept of a health measure that does not incorporate subjective valuation could be difficult to crystallise, and as such it will be necessary at least at present to work with some existing proxy for increasing health severity.

The author can conceive of three potential alternative ways to communicate increasing health increments, although each comes with its own caveats and problems. These are to use the Person Trade-Off (PTO) approach, the Time Spent Ill (TSI) approach, or the EQ-5D descriptors. See Appendix C for examples of how each could be implemented in practice in the Holt and Laury framework. The choice of input health measure is subjective, and the method outlined in the preceding Section would be tractable for any of the three. However, the researcher opting to use one of these alternative approaches must recognise the costs that they are incurring in the interpretation of the outcomes.

6.5.1 *Health state descriptions*

Person Trade Off (PTO) uses the number of people to be affected by the illness as the measure of the severity of the health problem, so that more people would be affected in h_1 than in h_2, h_3 and h_4. This is a measure of objectively increasing severity, but because the respondents are required to consider people other than themselves, there is a chance that elements of altruism or warm glow might be influencing responses. Time Spent Ill (TSI) sidesteps this problem because $h_1 – h_4$ would now describe how long they would be ill, and as such the scenario relates only to the individual. However, the decision would be subject to the influence of time preference. For example, an individual who discounts at a high rate might not perceive the prospect of 20 days of illness as twice as bad as ten days of illness, because the additional ten days would be subject to discounting. For this individual, the spread in the risky scenario would

effectively be less wide than the researcher assumes, and as such the person's risk aversion would likely be underestimated[34]. Finally, even without these problems, in both cases the health measure, and the resulting coefficient of risk aversion, would be specific to the illness described with no way of knowing whether the insights would generalize. For these reasons, both PTO and TSI are disregarded as tools for communicating the concept of a scale of health outcomes.

Instead, the EQ-5D-5L system is used, because it is well established in the literature, will generalise across health states, and allows a direct and unambiguously increasing level of health state severity. Of course, this measure is not without flaws, and these are discussed in Section 6.7.1 (pg.173). However, it is chosen as the most appropriate option currently available in the absence of a direct measure of health, h.

6.5.2 *EQ-5D*

The EQ-5D framework was developed in order to generate a measure of health outcomes that will generalise over different illnesses and life expectancies, to facilitate comparison of health interventions. The basic premise is to combine a health-state utility score with the length of time to be spent ill, which provides a 'healthy years equivalent' value for the health outcome. This unit of measurement is called a Quality Adjusted Life Year, or QALY. For example, if treatment for a lung complaint was estimated to give a quality of life that was 50% of full health, and would last for two years, it would have a QALY score of 1. This would be judged equivalent to an intervention giving five years of life expectancy but with a quality of life that was 20% of full health.

For the purposes of this methodology, it is the measure of quality of life or severity that is of interest. The EQ-5D-5L[35] system allows a generic description of any illness in terms of a profile in which the illness receives a score from 1 (no problems) to 5 (extreme problems) on each of five general attributes of illness (mobility, ability to perform self-care, ability to carry out usual activities, pain and suffering, and anxiety and depression). As such, it is possible to describe illnesses in a generic,

[34] Consider an individual who, if discount rates were zero, would switch when the probabilities were 50:50. This implies 0.5U(6days)+0.5U(8 days) ≈ 0.5U(2 days)+0.5U(20 days). If, with time preference, 20 days were reduced to the equivalent of just 17 days in utility terms, then 0.5U(6days)+0.5U(8 days) < 0.5U(2 days)+0.5U(20 days discounted), and so the respondent would switch further up the table.

[35] The 5L refers to the 5 levels of severity on which each attribute can place. This method is more detailed than its alternative (EQ-5D-3L).

unambiguously increasing or decreasing sequence of severity. The respondent is therefore directly comparing severity of health states and, given their assessment of the severity of the health states, engaging in a Holt-Laury procedure that most directly matches the theoretical framework described in Figure 6.5.

As such, the procedure directly and unambiguously matches the Holt-Laury procedure in so far as the respondent's answers to the questions, and in terms of the way that the respondent compares the alternatives. It is, in this respect, a very clean basis for comparison of risk preferences across domains.

6.6 Estimates of the EQ-5D-described Health States

In the preceding Section, the generic EQ-5D illness descriptions were chosen as the method for communicating the health states h_1 to h_4, although as discussed the framework would support other measures of health state if necessary. The next task is to decide what values are appropriate to substitute in for these health states in the analysis. Recalling the financial Holt-Laury, it was simply a case of inputting the money amounts (£1, £5, £6, £12, see pg.162) directly to the utility maximisation equation and to solve on an individual or sample level. However, it is not possible to simply substitute the EQ-5D descriptions into the maximisation problem, because they are qualitative and descriptive.

Efforts to establish values for the EQ-5D descriptions have generated a number of methodological options, two of which are considered here. These are the Visual Analogue Scale (VAS) approach, where respondents rate their perceptions of the severity of the health state described to them on a simple sliding scale; and Time-Trade-Off (TTO) or Standard Gamble (SG) approaches which use more complex choice tasks to evaluate the severity of the health problem. Typically, the (VAS) approach has been used in conjunction with TTO or SG elicitation procedures. See Carthy *et al.* (1999) for a full description and see Bleichrodt and Johannesson (1997), Robinson *et al.* (2001), Bleichrodt (2002) and others for a comparison of the VAS, SG and TTO methods in evaluating the EQ-5D scores.

The options considered here are personalised VAS scores elicited for individuals participating in this Study; and the most comprehensive 'off the shelf' set of population utility scores derived using TTO methods by the EuroQol group (Dolan *et al.*, 1996). These options are explained and evaluated in the next Sections.

6.6.1 *Visual Analogue Scales (VAS)*

The VAS method involves respondents being presented with a line either on a computer screen or on paper. This line has two anchor points: full (or sometimes normal) health and "as bad as death". The respondent then marks on the scale where they think the health state described by the EQ-5D description would place them. The proportional distance from full health indicates the proportional loss from full or normal health as perceived by the individual. The health state is described with certainty, and as such the response can be considered to show the value ($v(h)$) of the health state. See Section 6.3 on pg.164 for a discussion about the difference between utility values $u(h)$ and values $v(h)$.

6.6.2 *EuroQol Utility Scores*

In 2013, EuroQol published a country-specific set of utility scores for EQ-5D profiles. The utility scores are derived using a time trade-off (TTO) approach (Dolan *et al.*, 1996). The TTO approach relates the quality of life to the specified remaining life expectancy in a linear fashion. Respondents are asked to consider problems of the form:

> "Imagine you have ten years left to live in health state A (described using the EQ-5D scale). How much time alive in full health, followed by death, would you consider to be about as bad as living for ten years in health state A?"

This simplifies to a comparison between 10 years in health state A and x years in full health. The respondent specifies a level of x (number of years) and this is interpreted very simply as follows: x/10 is the proportional quality of life, compared to full health, in which health state A would place the respondent. A person in health state A is typically described as having a utility level x/10 of that of a person in full health.

Using either the VAS scores or the TTO-derived scores allows an assessment of the quality loss compared to full health that results from an illness with the generic profile in question. As such, using either value to identify the health state on the x axis of the utility over health function (see figure 6.4 pg.166) fulfils the requirement that the x axis is an increasing measure of severity. In both cases, the scale can be normalised from zero (as bad as death) to one (full health). Arguably, the measure therefore provides an increasing ratio scale for health that is comparable to money.

6.7 *Interpretation of VAS and TTO based EQ-5D Values*

There are two issues with the use of TTO and VAS scores as the measure of h_1-h_4. The first relates to time preference and its role in determining the EuroQol scores. This, as will be shown in Section 6.7.1, is relatively straightforward to correct for using a fix that will be developed and explained in what follows. The second relates to the nature of the measure as a value v(h) of the health state, as opposed to the health state itself (h). This is less easy to correct for, and alters the interpretation of the coefficient of risk aversion elicited through the technique described. It should be noted at this stage that if a direct measure of h was developed, both the theory and empirics presented here would generate relative risk aversion coefficients in health that are the exact counterpart of the financial CRRA. As such, the drawbacks presented next are more of a data issue than a conceptual one. Nonetheless, they are discussed in Sections 6.7.1 and 6.7.2.

6.7.1 *Issue 1: time preference and the TTO*

The QALY index derived from TTO questions in the EuroQol project is typically interpreted as a "utility score". This makes the implicit assumption that the respondent has a utility function that is linear in remaining life expectancy. That is, their utility over remaining life can be described as

$$u^h(T) = kT \qquad (68)$$

Where k is a quality of life parameter (1 in full health, 0 in a health state as bad as death and linearly increasing with severity) and T is the number of years remaining life expectancy.

In TTO studies, the level of k is elicited by comparing the number of years (T^*)in full health that are considered equivalent to ten years in health state h as follows, with the k value for full health set equal to 1 with no loss of generality.

$$10 = T^*k \qquad (69)$$

$$k = \frac{T^*}{10} \qquad (69a)$$

However, it is quite conceivable that in fact the utility of remaining life expectancy is not linear in time, and this would be likely due to two factors: the first is diminishing marginal utility of remaining life years, and the second is time preference (a year of life

10 years from now might have lower present value than a year of life two years from now, *ceteris paribus*).

$$u^h(T) = ku(T) = kT^{\delta} \qquad (70)$$

where T^{δ} is the number of remaining life years adjusted for the diminishing marginal utility of survival time and for time discounting.

If it is possible to consider that the true preference for the severity of the illness is translated via a concave utility of remaining life expectancy function into the observed time trade off, then it ought to be possible to translate them back again, as long as the average curvature is known. The effects of diminishing marginal utility and of discounting are confounded in this case but for the present purposes it is not necessary to separate them. Through analysis of the way that the value of preventing a statistical fatality (VSL) typically reacts to age, Jones-Lee *et al.* (2007) derived a functional form for the typical individual's utility over remaining life expectancy function that is

$$u^h(T) = kT^{0.8} \qquad (70a)$$

where the 0.8 captures both the diminishing marginal utility and the time preference effect, where the timescale considered is at least ten years. This is dependent on a number of assumptions about the relationship between the VSL and the value of an additional year of life expectancy, and the value of a life year (assumed to be roughly £30,000 based on work by Chilton *et al.* (2004) for Defra in the UK and Desaigues *et al.* (2007) for the EU-15 area). There is a rich literature that investigates these assumptions and relationships, but its exploration is beyond the scope of this research. Further investigation has been conducted into the need to correct for time preference by Attema and Brouwer (2013) who estimate correction factors for a range of EQ-5D profiles for the Dutch population. These authors find that the correction factor ought to alter with the severity of the illness, but this advice would be relatively complicated to transfer to the present Study without further empirical work. Therefore, at this stage the 0.8 estimate will be used. This is an area for development in future research.

The approach taken in the present adaptation of the HL procedure will be to re-inflate the TTO-based utility scores published by EuroQol using the 0.8 assumption. 'Adjusted' coefficients of relative health risk aversion will be calculated on this basis.

$$k = \left(\frac{T}{10}\right)^{0.8} \qquad (71)$$

As such, the k values in this case would be raised to the power of 0.8 in order to control for the effects of time preference and diminishing marginal utility in remaining survival time. This is a potentially important methodological contribution, whose applications can feasibly stretch beyond this risk preference elicitation and into any application where the EQ-5D values need to be adjusted for the influence of time preference and diminishing marginal utility of survival time.

6.7.2 *Issue 2: the interpretation of $v(h)$ as h*

Through the previous discussion, in the methodology (see Figure 6.5) and in the elicitation Table 6.2, it was assumed that the health states h could be quantified and entered into the calculation of the coefficient of relative health risk aversion (β) as in equation (67) on pg. 168, providing a direct counterpart to the financial coefficient of relative risk aversion, α. However, using either the VAS or the TTO-based EuroQol scores, the available measure is $v(h)$ as opposed to h itself. This has implications for the way that the switch-point in the adapted HL elicitation table and the calculated coefficient of health risk aversion (HRA) can be interpreted.

Given that the elicited TTO estimates and VAS scores measure individuals' perceptions of the quality of life (and duration of illness in the TTO method) the elicited value for k is in fact representative of the individual's riskless *valuation* for the health state. As such, k will still incorporate the diminishing marginal utility of health state improvement and should be interpreted as drawing from an individual's Dyer and Sarin riskless 'value function', $v(.)$, defined over health states, as opposed to an objective ratio-scale measure of the individual's 'level of health'. In the argument that follows, k will therefore be treated as being conceptually equivalent to $v(h)$.

So, for the TTO approach, $u^h(T) = ku(T)$, with $k = v(h)$, so that:

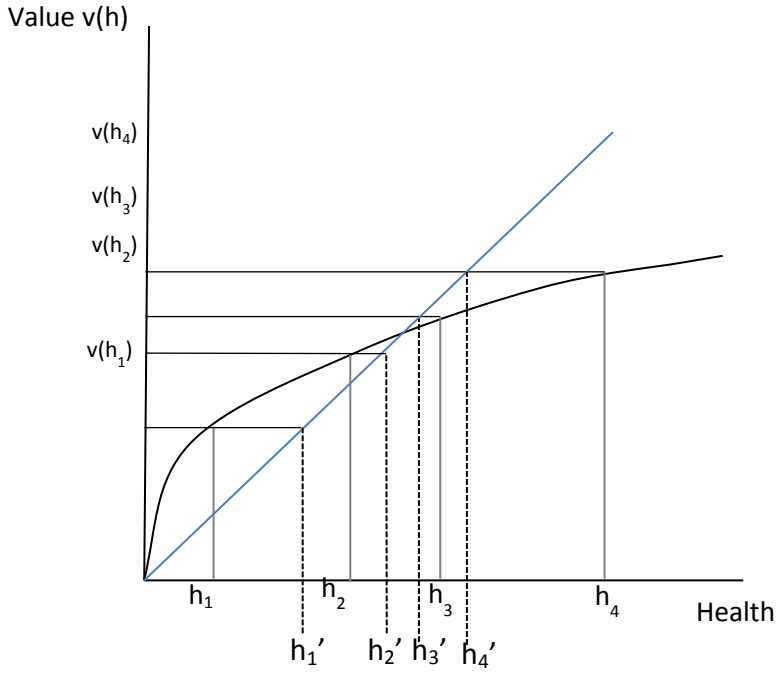
$$u^h(T) = v(h)T^{0.8} \qquad (72)$$

Substituting the values $k = v(h)$ as a measure of h is likely to distort the true health levels by overestimating the figures for the lower health states relative to those for the higher states as a result of the diminishing marginal utility of health state improvement[36]. Figure 6.6 displays the value function in relation to the 45 degree line,

[36] Nonetheless, if using the TTO EuroQol estimates, the extent of the distortion will be less when adjusting for time preference than would be the case if simply using the unadjusted TTO scores.

and demonstrates how the inferred values h_j' relate to the true underlying health amounts h_j. Specifically, at the lower end of the health scale the values are overstated relative to the values at the higher end of the scale, because of the relationship $k = v(h)$ which is captured in the concave value function.

Figure 6.6: Distortion of the value function demonstrating under- and over-estimation of h_1-h_4



The concave function reflects diminishing marginal utility of health[37]. Taking h_1 as an example, when health state h_1 is described, the value placed on that health state by a respondent is $v(h_1)$ as shown on the diagram. $v(h_1)$ is the observed value elicited through TTO or VAS in response to the description of symptoms relating to health state (h_1), because h_1 itself cannot be directly observed. However, if the researcher does not recognise this curvature, in effect assuming that the observed $v(h_1)$ (i.e. h_1') is equivalent to the underlying unobservable h_1, then the researcher will overestimate the underlying health state by $h_1' - h_1$. Similarly, if the researcher assumes $v(h_4)$ is equivalent to the underlying (unobservable) h_4, then h_4 would be underestimated by $h_4' - h_4$.

[37] The curvature in Figure 6.6 is deliberately exaggerated for illustrative purposes.

Of course, in the field or laboratory, the observed switch-point is still characterised by the probabilities that make the respondent indifferent between the true, unobserved values of h such that

$$ph_3^{(1-\beta)} + (1-p)h_2^{(1-\beta)} = ph_4^{(1-\beta)} + (1-p)h_1^{(1-\beta)} \quad (73)$$

In equation (73), all the values are the true underlying values relating to the utility of health function depicted in Figure 6.6. However, the imposition of value function estimates as opposed to the true health level values means that the values that the researcher inputs to the calculation are distorted estimates of the true levels of health as shown in Figure 6.6.

As such, the elicited γ parameters in equation (74) may not be equivalent to β parameters in equation (66), with the discrepancy dependent upon the degree of distortion of the input values, i.e. the degree of curvature of the value function.

$$ph_3'^{(1-\gamma)} + (1-p)h_2'^{(1-\gamma)} = ph_4'^{(1-\gamma)} + (1-p)h_1'^{(1-\gamma)} \quad (74)$$

Given that the probability figures are correct for equation (74), that they hold by definition for equation (66), and that $h_i' = h_i^{(1-\theta)}$ with θ reflecting the extent of diminishing marginal utility of health in the value function, the relationship becomes

$$h_i'^{(1-\gamma)} = \left(h_i^{(1-\theta)}\right)^{(1-\gamma)} = h_i^{(1-\beta)} \quad (75)$$

and as such

$$h_i^{(1-\theta)(1-\gamma)} = h_i^{(1-\beta)} \quad (75a)$$

which implies

$$\beta = \gamma + \theta - \gamma\theta \quad (75b)$$

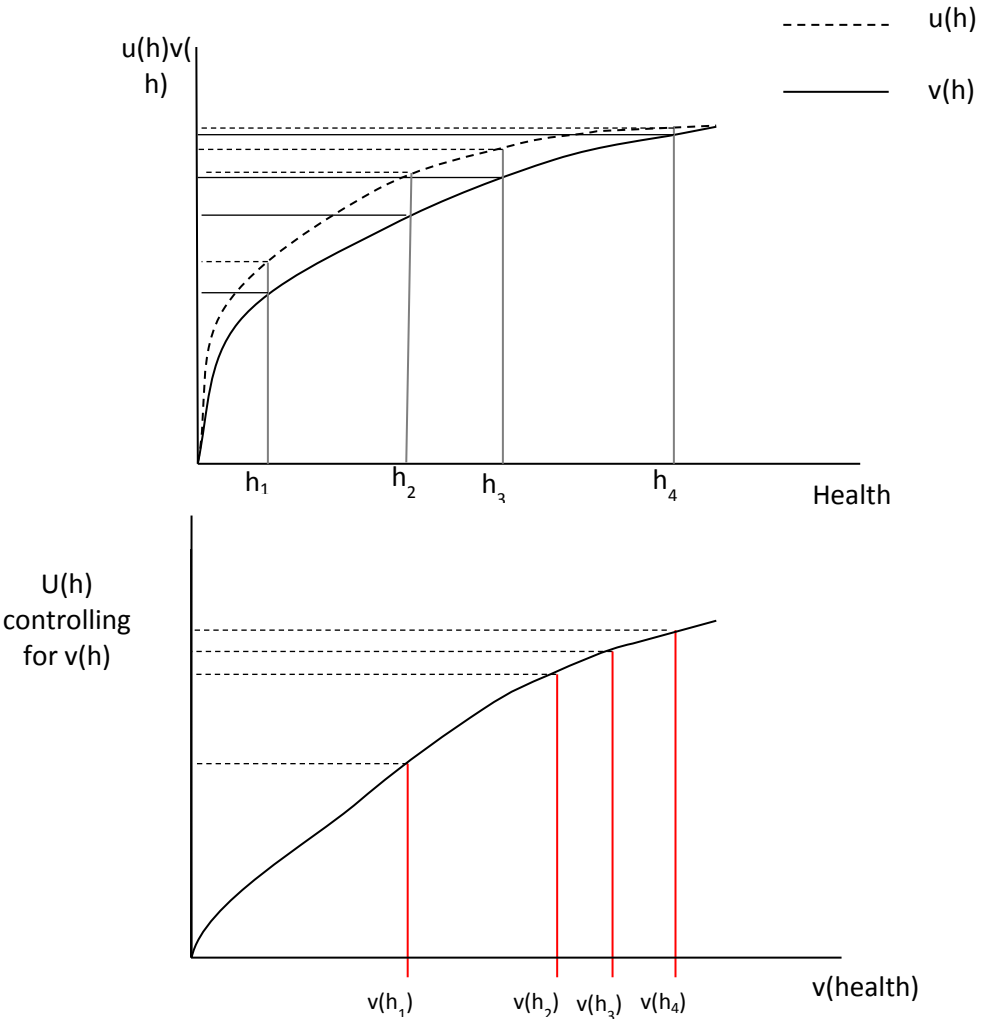
hence

$$\gamma = \frac{\beta-\theta}{1-\theta} = \frac{(1-\theta)-(1-\beta)}{(1-\theta)} \quad (75c)$$

That is to say, γ reflects the additional curvature of the utility function (captured by the parameter β) above the curvature of the value function (captured by θ). That is, γ captures gambling risk aversion as suggested by Dyer and Sarin (1982). This is

demonstrated in Figure 6.7 where γ determines the curvature of the schedule in the lower panel.

Figure 6.7: Comparison of utility and value functions



In summary, the theory and elicitation procedure are designed to allow the elicitation of the coefficient of relative health risk aversion (β), and if an appropriate quantitative measure of health states was available, then this is exactly what would be obtained. However, at the time of writing no such measure is available. This means that the choice of input values for health states has significant consequences for the interpretation of the health risk aversion estimates. Existing measures of health levels such as TTO-based EuroQol scores and VAS scores are typically values from the value function $v(h)$. This means that the output measure, γ, captures the aversion to health gambles as opposed to full risk aversion.

While this renders it not directly comparable to the financial measure, α, or the underlying health coefficient of relative risk aversion, β, the method is robust in generating parameters that can be interpreted without ambiguity. This procedure arguably provides the most sophisticated health risk preference measure available at present, not least because its limitation- which is its ability to capture only gambling aversion- is fully accounted for. In addition, if a direct quantification of health state were to be developed the methodology outlined here would allow the elicitation of full relative risk preference (β).

As an extension to this analysis, Appendix D provides a theoretical analysis of the case where the input scores are full utility measures. Essentially, the elicited parameter becomes risk aversion relative to the average member of the population, a potentially useful outcome for future survey work.

6.8 Implementation of the Adapted Holt and Laury Procedure

Having established a theoretical and empirical framework for converting the financial Holt-Laury procedure to allow the elicitation of health state values for risk aversion, the next stage is to demonstrate the procedure. To do so, the HL elicitation procedures described above, both for health and financial domains, were embedded within a wider survey protocol, referred to as Study 2. The analysis of the R-R relativities will be presented in Chapter 7 and will not be the focus here. Instead, the next Section sets out the implementation of the Holt and Laury Risk Preference Elicitation protocol adapted for health states which is the focus of this Chapter. There follows a presentation and brief discussion of the resulting estimates of the risk aversion coefficients for health.

Initially, the four health states to be compared were described to respondents using EQ-5D descriptions, for the reasons discussed in Section 6.5.2 (pg.170). The illnesses described ranged from minor to severe (to reflect h_4 to h_1 from the generic survey design), as shown in Figure 6.8. Their features as they relate to the EQ-5D scoring system are given in Table 6.3.

Figure 6.8: EQ-5D descriptions

Minor illness
- You would have no problems moving about
- You would have no problems with self-care
- You would have no problems carrying out your usual activities
- You would experience slight pain and discomfort
- You would experience no anxiety and depression

Moderate illness
- You would have no problems moving about
- You would have slight problems with self-care
- You would have slight problems carrying out your usual activities
- You would experience moderate pain and discomfort
- You would experience no anxiety and depression

Moderately severe illness
- You would have no problems moving about
- You would have slight problems with self-care
- You would have moderate problems carrying out your usual activities
- You would experience severe pain and discomfort
- You would experience moderate anxiety and depression

Severe illness
- You would have slight problems moving about
- You would have slight problems with self-care
- You would have severe problems carrying out your usual activities
- You would experience severe pain and discomfort
- You would experience moderate anxiety and depression

The particular illnesses were chosen to cover a range of utility scores based on the EQ-5D value sets as reported in the right-hand column of Table 6.3. The illnesses are unambiguously increasing in severity as they descend the table: every attribute is set at a level at least as severe as it was in the illness above. As such, there is a built-in rationality check that can be applied when considering respondents' VAS scores. Also at least at a within- individual level, switching further down the Holt-Laury table is evidence of higher risk aversion. The four illnesses were all described as persisting for ten days and then going away without the need for treatment. This avoids any issues of time preference, because the timescale does not vary between options. The short timescale is intended to approximate a single period change in health.

Table 6.3: Illness descriptions and EQ-5D scores

	Mobility	Self-care	Usual Activity	Pain and suffering	Anxiety and deprssion	EQ-5D score	Adj EQ-5D score ($k^{0.8}$)	EQ-5D score based on VAS mean	EQ-5D score based on VAS median
Minor	1	1	1	2	1	0.837	0.867	0.900	0.91
Moderate	1	2	2	3	1	0.795	0.832	0.723	0.73
Moderate-ly severe	1	2	3	4	3	0.617	0.680	0.537	0.50
Severe	2	2	4	4	3	0.263	0.344	0.371	0.32

1= "no" 2= "slight" 3= "moderate" 4= "severe" 5= "unable"

Each respondent marked where they perceived each illness to place them on a Visual Analogue Scale, which as described in Section 6.5.1 (pg.169) involved expressing where they felt the illness would fall on a scale from 'full health' to 'as bad as death' or even lower. This process provides a per-individual input into the severity of each illness and in addition allows the individual to focus on each illness in detail prior to completing the lottery questions. After this, each respondent filled in their answers to the lottery questions as shown in table 6.2 (pg.167). Respondents had previously completed ten R-R questions and a financial Holt-Laury exercise. They would go on to answer a selection of demographic questions as shown in the protocol in Appendix A.

6.9 Summary

This Section discussed the theory underlying the financial HL risk aversion elicitation procedure, and proposed a novel way to apply the same concept in the domain of health risks. The discussion considered the different potential inputs to the health risk calculations, and concluded that despite its drawbacks, the EQ-5D inputs most closely match the desired properties of the underlying health level variable. It discussed how the EQ-5D descriptors can be quantified using either the EuroQol TTO (time trade-off) scores that are available on the population level, or the VAS (visual analogue scale) scores that are available on the level of the individual. Both have their benefits and drawbacks and as such both will be used and compared.

6.10 Analysis

6.10.1 *Introduction to analysis*

The structure of the subsequent Sections is as follows. First, the input values are discussed. The central tendencies (mean and median) of these measures for describing h_1-h_4 are presented and discussed. Then the financial and health related risk aversion coefficients elicited from the financial and adapted HL elicitation procedures are discussed. Comparisons are drawn between the results using the financial and health domains, and between the alternative health inputs.

6.10.2 *Analysis: assigning values to h_1-h_4*

The information available to the researcher on the basis of the Study includes a population-average utility score for each of the four illness profiles based on TTO analysis conducted previously (Dolan, 1997); an individual VAS score for each of the four illness profiles for each respondent; and the row of the table (with associated probabilities for each of the four illness profiles) in which each respondent switched from the 'safe' to the 'risky' health gamble. On this basis, there are multiple ways to calculate and assign coefficients of health-related risk aversion (hereafter HRA) for each respondent.

This analysis will therefore use five different procedures, which will be compared in the results Section. These are summarised in Table 6.4 and discussed in the following Sections.

6.10.2.i *Financial amounts*

The standard approach in economics for controlling for risk preference in surveys is to elicit CRRA estimates over financial gambles. This generates financial risk aversion measures. This approach is simple, well established and easy to interpret, and it captures full risk aversion. However, as discussed in the literature review it is not clear that financial risk preference is an adequate proxy for risk preferences over health. As such, this method will be used as a benchmark for comparison only.

Table 6.4: Risk aversion inputs

Input	Symbol	Benefits	Drawbacks
Money amounts	£	Objective cardinal ratio scale. Shows the full risk aversion (gambling aversion and diminishing marginal utility of wealth). Comparable to other estimates in the literature.	Not a physical risk.
EQ-5D unadjusted	k	Large representative sample, well understood in the literature, easy to use (single input value), physical risk measure.	Possible confound of time preference and diminishing marginal utility of remaining life expectancy. Assumes can generalise from population to this sample.
EQ-5D adjusted	$\hat{k}$	All the benefits of k, resolving the TTO problem of diminishing marginal utility and time preference.	The 0.8 value requires empirical verification. Assumes can generalise from population to this sample.
VAS average over sample	$\bar{h}$	Based on individual values in this sample, easy to implement, no need for the readjustment in the EQ-5D.	VAS measure has been shown to be susceptible to biases in estimation. Sample average of VAS scores removes some information on the individual level.
VAS individual-specific	h_i	Individual-specific values, personalised risk coefficients, sensitive to value of health as well as row of table.	More room for individual error in completing VAS form to influence the inferred coefficient. Time-intensive and cumbersome.

6.10.2.ii *EQ-5D population average scores(unadjusted)*

As discussed in Section 6.5.2, the EQ-5D scores are available for the full population based on previous work using TTO methods to generate utility scores for the EQ-5D

profiles. In the EuroQol project, values were generated for a subset of possible EQ-5D profiles and then extrapolated to provide scores for all potential combinations. The values were generated on a country-specific level using representative samples of the population. As such, they are representative of the full UK population but not necessarily representative of the sample of 18-25 year olds used in Study 2. In addition, the values can be criticised in that they assume constant marginal utility of life expectancy. See Section 6.7.2 for a discussion.

6.10.2.iii *EQ-5D population average scores (adjusted)*

As stated, the TTO method which generates the EQ-5D scores can be criticised if discounting and diminishing marginal utility apply to future life expectancy. Using the admittedly strong assumption that the specification in Jones-Lee *et al.* (2007) is appropriate on average in the population, the EQ-5D scores can be deflated for this effect as discussed in Section 6.7.1 by raising to the power of 0.8, acknowledging that this figure requires refinement using further experimentation. The same problems with generalising to the present sample apply as for the unadjusted EQ-5D scores.

6.10.2.iv *Individual-specific VAS scores*

The VAS scores are based on individual value functions of members of the sample and as such there is no issue with applying a population value to individual decisions. In addition, they are not subject to the issues of time discounting and diminishing marginal utility over life expectancy which complicate the EQ-5D approach. However, they are subject to potential biases in framing as documented above and they are not based on choices so the link to underlying utility theory is not straightforward. As such, they are not to be solely relied upon instead being reported alongside the TTO-based measures.

6..10.2.v *Sample average VAS scores*

Using individual-specific values for the VAS for every individual is cumbersome, and any individual error or exaggeration in responding to the VAS will generate HRA coefficients that are strongly influenced by this error. As such, it was decided to aggregate the VAS scores for this sample and use the sample average VAS scores for each of the four input health states. These are combined with individual switch-points to generate the coefficient of HRA for each individual.

As such, there are five categories of inputs for the "x variable" of the calculation of risk aversion in this Study. These are the money amounts (£1, £5, £6 and £8) and the scores for h_1-h_4. These health scores are summarised in Table 6.5. Input values for the individual-specific VAS scores are not aggregated and so they are omitted from this Table.

Table 6.5: Health state input scores

	h_1	h_2	h_3	h_4
EQ-5D TTO unadjusted	0.261	0.390	0.681	0.837
EQ-5D TTO adjusted	0.341	0.471	0.735	0.867
Sample VAS scores (median)	0.32 [25%=0.19, 75%=0.52]	0.50 [25%=0.38, 75%=0.67]	0.73 [25%=0.63, 75%=0.83]	0.91 [25%=0.87, 75%=0.95]

Reassuringly, the increasing pattern expected from h_1-h_4 can be observed in the VAS average scores. Further, the sample VAS scores appear to match the adjusted TTO-based EQ-5D values more closely than the unadjusted values, providing tentative support to the practice of adjusting the EQ-5D scores for time effects. In addition, the adjusted value for h_4 is just included in the confidence interval around the sample VAS score. However, both the adjusted and unadjusted values for h_1-h_3 lie within the VAS confidence intervals so the process of adjusting appears not to make a very dramatic difference to the input values.

6.10.3 *Calculating the coefficient of health risk aversion*

Individual-specific risk aversion coefficients are generated for each individual for each of the input measures. The process for the financial inputs is simple, and was described in Section 6.2.3 above. For the health state input measures the basic procedure is the same, with the switching row probabilities and inputs assumed to solve equation (74) originally introduced on pg.177.

$$ph_3'^{(1-\gamma)} + (1-p)h_2'^{(1-\gamma)} = ph_4'^{(1-\gamma)} + (1-p)h_1'^{(1-\gamma)} \qquad (74')$$

However, there is no analytical solution to the equation and as such the coefficients of risk aversion are found by simulation. This involves a procedure of iteration from a possible value for γ to the γ value that solves the equation, supplemented by graphical analysis where multiple solutions are possible.

6.10.4 *Data cleaning*

The calculation process usually generates a clear unique solution for γ, but in two cases the solutions for the individual VAS scores based on h_i were implausible in that the only valid solutions were exactly 1, which is an algebraically valid solution for all cases, but which is uninformative in economic terms. In sixteen further cases it was found that all γ coefficients greater than or equal to some level γ^* would class as solutions. This is difficult to interpret, because if indifference holds for a row of the table given a certain level of risk aversion, by design a more risk averse respondent ought not to be indifferent in that row. A trade-off therefore needs to be made between using these 'threshold' solutions in the interests of maintaining the already small sample size, or discarding these in the interests of maintaining the integrity of the interpretation of the data. There is no clearly superior option here, and as such both 'cleaned' and 'uncleaned' versions will be reported.

Responses based on the individual VAS scores for two further respondents are dropped because they suggest extremely low health risk aversion coefficients[38]. Both of these individuals indicated health state values on the VAS questions at 90% or more for the three least severe health complaints. This suggests that the variation in h_i was too limited to reliably generate the coefficient of HRA for these individuals. Taking the HRA coefficients at face value would suggest extreme preference in favour of taking gambles in health, which does not appear to be consistent with the majority of the sample or with these respondents' risk preferences characterised over finance (slight risk lovingness and risk neutrality, respectively).

In total, six variables are defined, each providing a measure of risk aversion for each individual (Table 6.6).

[38] The threshold was to delete responses implying coefficients of HRA of less than -10 (-12.066 and -18.310)

Table 6.6: Risk aversion variables

Variable	Captures	Inputs to calculation
Financial relative risk aversion	Financial risk aversion	Money inputs, £
Population unadjusted health risk aversion	Health gambling aversion and preferences over remaining life expectancy	EQ-5D unadjusted, k
Population adjusted health risk aversion	Health gambling aversion	EQ-5D raised to the power of 0.8, $\hat{k}$
Sample average VAS health risk aversion	Health gambling aversion	Average VAS scores for this sample $\bar{h}$
Individual health risk aversion uncleaned	Health gambling aversion	Personal VAS scores h_i untrimmed
Individual health risk aversion cleaned	Health gambling aversion	Personal VAS scores h_i deleting 'threshold' cases

6.10.5 *Central tendencies*

To provide an overview of all of the risk aversion measures, Table 6.7 presents the central tendencies for the sample. The mean coefficients are all positive (although the medians cannot be distinguished from zero, implying risk-neutrality to gambling in health and in finance). They are all within a similar range although the uncleaned individual coefficients appear to be quite high. This supports the use of the cleaned sample which excludes the 'threshold' cases, despite the detriment to the sample size.

Table 6.7: Central tendencies for risk aversion estimates by input option

	MEAN (S.D.) [CI]	MEDIAN [25%, 75%]
Financial relative risk aversion n=107	0.168 (0.588) [0.055, 0.280]	0.340 [-0.387, 0.665]
Population unadjusted health risk aversion n=111	0.402 (0.814) [0.249,0.555]	0.223 [-0.253, 0.697]
Population adjusted health risk aversion n=111	0.252 (1.018) [0.061, 0.444]	0.029 [-0.566, 0.621]
Sample average VAS health risk aversion n=111	0.214 (0.991) [0.028, 0.401]	0.001 [-0.582, 0.577]
Individual health risk aversion uncleaned n=98	0.943 (2.695) [0.403, 1.483]	0.698 [-0.119, 2.768]
Individual health risk aversion cleaned n=82	0.225 (2.249) [-0.269, 0.719]	0.429 [-0.535, 1.453]

6.10.6 *Risk aversion over financial gambles*

Recall that the HL lottery comparisons were between £5 and £6 in the 'safe' option and between £1 and £12 in the 'risky' option. The probability of the high outcome in each option increased down the table, so a higher switching row indicates higher levels of risk aversion (and a higher financial CRRA).

The modal choice of switching row, row 5, implies risk neutrality over these financial stakes, with the coefficient (α) equal to zero. The mean coefficient is 0.168, and the median is 0.340, which suggests that the mean is influenced by a substantial number of low end values which imply risk seeking behaviour over these small stakes. The mean is significantly higher than zero implying that the sample as a whole is characterised by

risk aversion but based on the medians it is not possible to reject the hypothesis of risk neutrality over financial gambles.

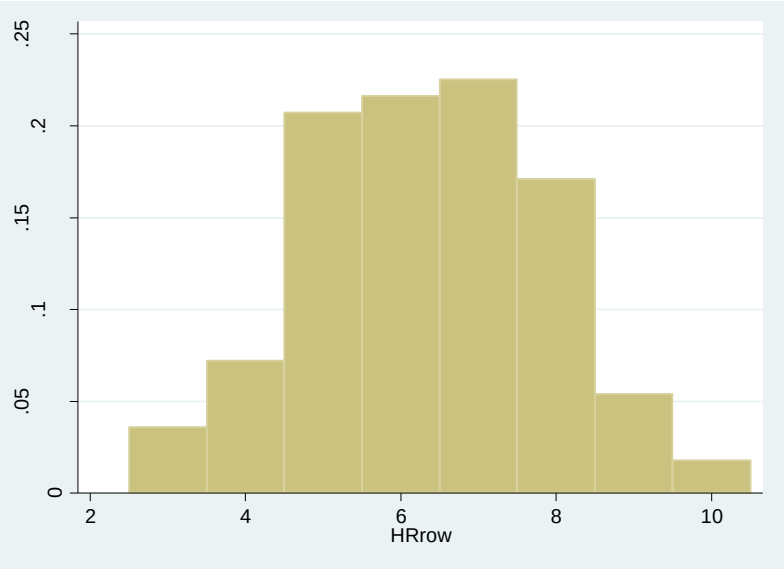
The magnitude of these estimates is comparable with existing estimates in the literature. The original Holt-Laury experiments found CRRA coefficients in the region of 0.3-0.5 (Holt and Laury, 2002), which includes the median from this sample. However, the estimates fromAndersen *et al.* (2008) are higher, at 0.74.

Next the HRA coefficients are presented. The distribution is considered first, and then the central tendencies are presented and analysed. This is done first for the coefficients based on aggregated h_1-h_4 scores. That is, for the EQ-5D adjusted and unadjusted measures on the population level, and for the sample average VAS scores. After this, the individual-specific VAS scores are considered, both with and without trimming of the 'threshold responses' introduced on pg.186 above.

6.10.7 *Risk aversion over health gambles based on sample and population averages*

6.10.7.i *Distribution of switching rows*

Figure 6.9: Health risk aversion based on the population/sample averages. Histogram applies for all three values.



The modal switching row (7) implies HRA coefficients of 0.697 in the unadjusted TTO EQ-5D case, 0.621 in the adjusted TTO EQ-5D case, and 0.577 in the VAS average case. This suggests that the average respondent is risk averse over health risks. These figures are higher than for the financial case, which is something of a surprise given that

they do not include the curvature from the value function, instead only the additional curvature from gambling aversion. This suggests that even if respondents had linear value functions for health (i.e. h_i' is equivalent to the true h_i), there is more risk aversion over health than finance. However, so far this analysis rests only on the modal row, and the diagram shows that an almost equal number of respondents switch in rows 6 and 5 as in row 7, and rows 6 and 5 suggest less risk aversion. Section 6.10.7.ii considers the central tendencies, which will provide more insight.

6.10.7.ii *Central tendencies and spread*

Having considered the distribution, this analysis turns to consider the central tendency and spread measures for the coefficients of health risk aversion in this sample.

Table 6.8: population average HRA coefficients central tendencies

	MEAN S.D [CI]	MEDIAN [25%, 75%]
Population unadjusted health risk aversion n=111	0.402 (0.814) [0.249,0.555]	0.223 [-0.253, 0.697]
Population adjusted health risk aversion n=111	0.252 (1.018) [0.061, 0.444]	0.029 [-0.566, 0.621]
Sample average VAS health risk aversion n=111	0.214 (0.991) [0.028, 0.401]	0.001 [-0.582, 0.577]

The coefficients of HRA are smaller using the population adjusted EQ-5D TTO scores than the unadjusted scores, which is because, as argued above, the unadjusted scores underestimate the lower health state levels relative to the higher levels and thereby result in an 'overstatement' of the curvature of the utility function. The adjustment process effectively rectifies this overstatement. As such, the curvature picked up by the adjusted measure is less pronounced. However, the difference in the mean inferred HRA coefficients is not significant. Nonetheless, the coefficients as derived from the adjusted values may be more reliable in absolute terms. This latter statement is supported to an extent by the comparison with the coefficients implied when using the

VAS sample averages. The adjusted EQ-5D TTO scores give a closer match with the VAS averages than the unadjusted ones.

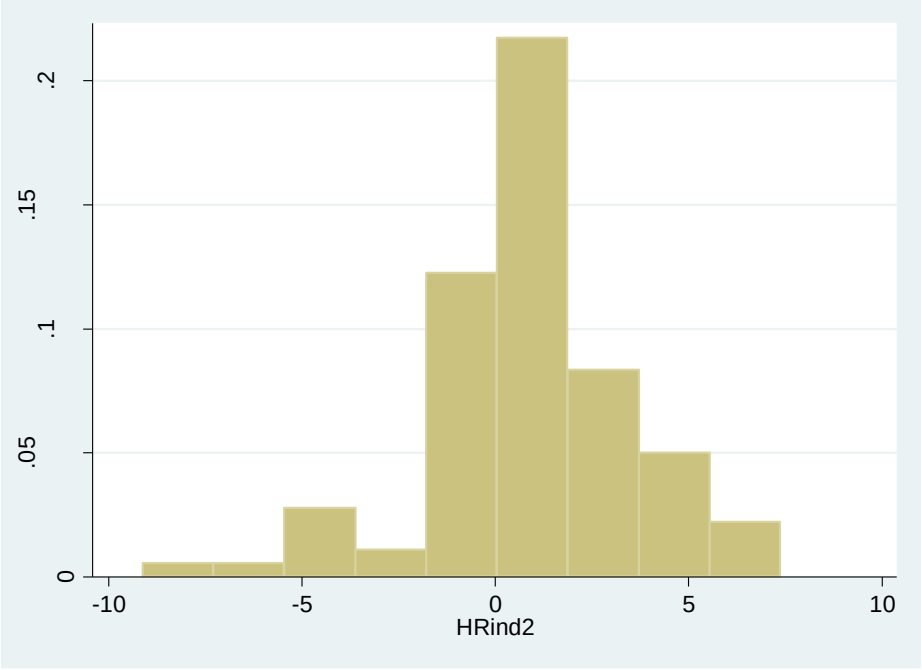
The coefficients of health risk aversion defined over sample or population average health scores are low. The difference from zero using the mean scores is just significant, implying risk aversion. However, the median values are much lower at 0.029 and 0.001 (using the EQ-5D adjusted and average VAS respectively). This contradicts the evidence from the modal score, which suggested that the health risk aversion was higher in health than in finance, but this might be because the difference between the modal row and the frequency in other rows is small.

Based on the central tendencies it appears that the sample is slightly averse to gambles in health. Of course, this does not preclude stronger risk aversion as defined by the curvature of the value function ($v(h)$).

6.10.8 *Risk aversion over health gambles based on individual VAS scores*

6.10.8.i *Distribution of health risk aversion coefficients based on individual VAS*

Figure 6.10: Health risk aversion based on individual VAS scores



Unlike the sample or population average coefficients, the individual-specific based coefficients of HRA the coefficient might be different for individuals switching in the same row, because they report different VAS scores for h_1-h_4. The underlying input values and the switch-point combine to provide a unique coefficient for each respondent

and Figure 6.10 gives the histograms for the uncleaned individual-specific HRA coefficients. The modal HRA coefficient is between 0 and 1 again implying slight risk aversion. This is within the range from the financial literature as discussed in Part I.

6.10.8.ii *Central tendencies and spread*

Turning to the central tendency measures, the coefficients implied are much larger than for the population average based coefficients reported in Table 6.8 and the confidence intervals are wide. The untrimmed values imply fairly extreme HRA, at least using the mean, and the 95% confidence interval around the mean excludes all estimates based on the sample or population average values from Table 6.8. The median is more inclusive, allowing neutrality or even a preference for health risks inside the 25-75 percentile range, but this range is very wide and the median itself is high. Removing the 'threshold' case coefficients gives the cleaned values and these align much better with the sample average, and give more intuitively sensible results than the uncleaned version. This supports the earlier conclusion from pg.186 that trimming the VAS-based scores is appropriate due to the possible compounding of error with an individual's responses. These results, similarly to the population average results, suggest some health risk aversion on average, but do not exclude the possibility of risk neutrality or even risk lovingness in the sample, bearing in mind that this risk aversion refers exclusively to gambles over health states.

Table 6.9: Individual specific coefficients central tendencies

	MEAN S.D [CI]	MEDIAN [25%, 75%]
Individual RA uncleaned n=98	0.943 (2.695) [0.403, 1.483]	0.698 [-0.119, 2.768]
Individual RA cleaned n=82	0.225 (2.249) [-0.269, 0.719]	0.429 [-0.535, 1.453]

6.10.9 *The influence of demographic characteristics on risk attitude*

Regressions were run of each of the risk aversion coefficients upon demographic characteristics. The regression output for the full models is reported in Table 6.10. As

in Part I of this thesis, the *vselect* tool in Stata is used to determine the explanatory variables for the best-fit regressions, which are reported in Appendix E.

Table 6.10: Regression of health risk preferences on demographics

	Population average EQ-5D (adjusted) RA coeff n=87 r2=0.097	Sample average VAS score RA coeff n=87 r2=0.097	Individual VAS score (untrim) RA coeff n=76 r2=0.038	Individual VAS score (trim) RA coeff n=64 r2=0.094	Financial (money amounts) RA coeff n=83 r2=0.178
	Coef. (r.s.e.)	Coef. (r.s.e.)	Coef. (r.s.e.)	Coef. (r.s.e)	Coef. (r.s.e.)
Log of household income	0.005 (0.13)	0.004 (0.13)	0.121 (0.36)	0.314 (0.33)	**-0.144**** (0.07)
Female	0.033 (0.24)	0.035 (0.24)	0.782 (0.66)	0.243 (0.59)	0.194 (0.15)
Age	0.098 (0.06)	0.096 (0.06)	0.182 (0.34)	-0.175 (0.308)	-0.037 (0.038)
Size of household	0.002 (0.06)	0.002 (0.06)	0.080 (0.23)	0.178 (0.20)	0.053 (0.03)
Renting one's home	0.362 (0.34)	0.352 (0.34)	-0.081 (0.87)	0.400 (0.66)	-0.016 (0.18)
Experience of cancer (self or close friend or family member)	0.298 (0.27)	0.292 (0.26)	0.304 (0.88)	-0.423 (0.90)	0.260 (0.18)
Experience of road accidents (self or close friend or family member)	-0.195 (0.25)	-0.191 (0.25)	-0.022 (0.77)	-0.032 (0.73)	-0.006 (0.14)
Self-reported health state	-0.019 (0.22)	-0.019 (0.21)	-0.447 (0.78)	-0.730 (0.72)	0.121 (0.11)
Self-reported roads risk	0.197 (0.14)	0.191 (0.14)	0.046 (0.44)	0.491 (0.42)	0.098 (0.07)
Constant	-2.147 (1.78)	-2.123 (1.73)	-4.392 (7.99)	0.916 (7.49)	1.507 (1.04)

The literature (see Hartog *et al.* (2002), Binswanger (1980) and Donkers *et al.* (2001) for example) suggests that gender is positively correlated with risk aversion and that income and education are negatively correlated with risk aversion. The income effect is replicated for the financial CRRA, which lends support to the validity of the findings.

The education effect is not testable in this analysis because the respondents all had the same educational attainment, but the lack of gender effect is interesting because of its persistence in the literature (see Croson and Gneezy (2009) for a survey of evidence specific to gender and risk). One explanation could lie in the youth and homogeneity of this sample in other respects, if gender differences come in to effect when occupational or lifestyle gender roles have been established.

Clearly, for this sample, demographics are largely unable to explain HRA coefficients, with the exception of a marginally significant positive coefficient on perceived road accident risks when using a best fit regression and when using population or sample average inputs to the coefficients of HRA. The general lack of significance may be because of the lack of variation in the characteristics of the sample used in Study 2. Alternatively, it suggests that risk preferences over health states are exogenous as is typically assumed in the theoretical literature.

6.10.10 *Comparing risk preferences in health and finance*

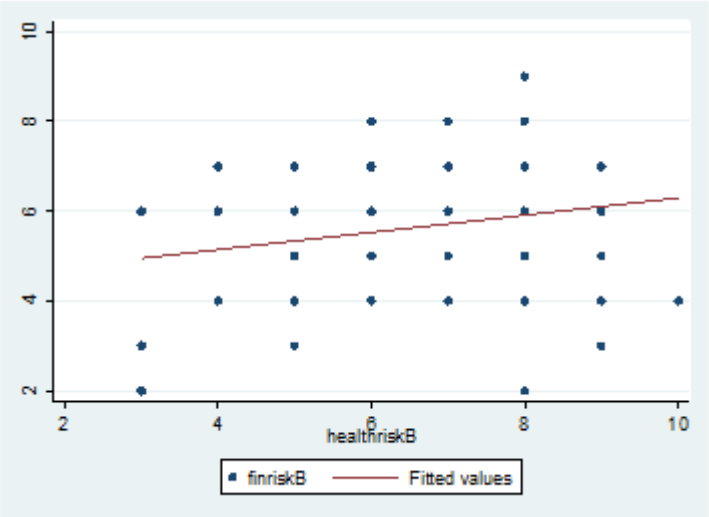
The analysis in Section 6.10.7 observed that risk preferences defined over health appeared to be lower (based on population or sample average health state scores) than financial risk aversion coefficients. However, it is impossible to know whether the full risk aversion would have been higher in the domain of health or finance based on this comparison. This is because the health coefficients measure gambling aversion as opposed to full risk aversion, and so simple direct comparison of the financial and health risk aversion coefficients is not meaningful in absolute terms.

However, correlation of switching rows (which arguably reflect the true risk aversion because no values have been imposed) will provide an idea of the correlation between financial and health risk aversion.

The correlation coefficient for switching rows in the domains of health and finance is 0.191, and a simple regression of health risk preferences on financial risk preferences generates significance (P statistic 0.045). However, Figure 6.11 shows that while financial risk preferences are positively correlated with health risk preferences based on switching row, the correlation is low by any practical standards. Ranking individuals by their switch row in each domain generates even lower correlation, at 0.15. This generates support for the argument that the HRA measure generated in this Chapter is likely to be a better proxy for the true health risk aversion despite its limitations because

the support for using financial as a proxy for health choices appears to be low. This also provides evidence in support of the wider argument that domain independence of risk preferences is not a realistic assumption.

Figure 6.11: Correlation between financial and health risk aversion switching



6.10.11 *Summary of results analysis*

The analysis Section began by presenting and discussing the central tendencies of the risk aversion proxies. The magnitude of the risk aversion coefficients for both finance and health appeared to be reasonable. It was demonstrated that demographic characteristics are poorly able to explain the risk preference proxies, especially those defined over health states. This suggests that the methodology provides a useful measure of person-specific risk preference, which appears to be exogenous in terms of demographics. The usefulness of the HRA measure was given further support by the result that correlation between the financial and health risk aversion domains is low.

6.11 Conclusions

Study 2a had two principle aims: to reconcile the theory underpinning financial and health domain risk aversion elicitation; and to develop a methodology to elicit risk aversion in health.

The theoretical development has been successful. With some assumptions, the financial framework for thinking about risk aversion is shown to be readily transferable into the health domain. The empirical methodology takes as its basis the classic elicitation procedure from Holt and Laury (2002), and converts it to the health domain. This

framework allows the elicitation of the coefficient of relative risk aversion (CRRA) in the domain of health.

A key contribution in this Chapter is the formalisation of the theory underpinning exactly what is elicited using this methodology. The health states in this Study are described using the EQ-5D description system[39]. Because there currently exists no direct way to quantify these health states to input to the risk aversion calculations, value inputs are used instead (either the TTO-based values from the EuroQol study or the VAS scores collected during this survey). It was shown that the interpretation of the coefficient should be as a measure of preferences over gambling in health, instead of the full curvature of the von-Neumann Morgenstern utility function over health. While this is a restriction, the clarification of this issue provides a good basis for analysis and future investigation.

As a proxy for risk aversion in the domain of health, this measure may be more appropriate than the financial coefficient of relative risk aversion, despite its limitations, because risk preferences have been shown to be domain-dependent. Arguably, a measure of gambling aversion in health is more useful to health-related valuation than a measure of full risk aversion in finance. In addition, if a ratio scale measure of increasing health severity can be developed in the future, this methodological framework is ready and able to generate a full measure of risk preference over health.

As such, the aims of the Chapter have been met, and the proxies for health risk aversion have been developed for inclusion in the analysis of the Risk-Risk questions in Study 2b, which will be conducted in Chapter 7.

[39] Respondents proved capable of sensibly answering the risk trade questions in the health domain and the methodology appears to be tractable in a survey setting.

Chapter 7. Latency, Discounting and the Value of Preventing a Statistical Cancer Fatality: Eliciting Effective Discount Rates from Survey Data

7.1 Introduction

As hypothesised in Part I of this thesis and verified in Part II, a key driver of the VSL_{CAN} is the period of latency that typically precedes the fatality. As such, an individual's rate of time preference is likely to influence their relative value of changes in their risk of fatality which occur at different future time periods, and so developing insights about time preferences will be important in understanding the VSL_{CAN}.

As discussed in the second literature review (Chapter 5), studies have typically controlled for time preferences using financially derived estimates of the discount rate, for example employing the procedure from Coller and Williams (1999) in which the respondent compares (hypothetical or real) financial payoffs at different times. However, the evidence discussed in the review (pg.144) suggests that the discount rate defined over finance is not ideally suited as a proxy for time preference over health and physical risk outcomes. In addition, there is no firm consensus about the best method of eliciting time preferences in the domains of health and physical risk, and (perhaps as a result of this) there is limited evidence about the likely functional form that characterises discounting in this domain.

If typical discounting behaviour can be reliably established, this will not only answer these academic questions, but will also allow more robust policy analysis of a wide range of fatality risks. This is because in the absence of alternative evidence, the government discounts health benefits using a constant rate. The implications of this are explored in the policy implications Section on pg.248.

Study 2b, reported in this Chapter, adapts the methodology of the Risk-Risk survey from Study 1 (see Part II of this thesis) in order to allow inference of discounting functions as applied to decisions surrounding latent fatality risks. The survey was designed to incorporate a range of time profiles for the latent fatality risk, so the discount functions can be explored in more detail than was possible in Study 1. This allows estimation of the proportion of the sample whose decisions are compatible with standard exponential discounting function. The following analysis will allow inference of the appropriate discounting function for those respondents whose preferences were

not well characterised by the exponential discounting assumption, providing a basis for future research on more representative samples.

The literature review and the results from Study 1 in Part II have led to two research questions:

1. What is the functional form of discounting in the domain of fatality risk?
2. What discount rate best reflects risk-trading behaviour under each discounting assumption in the domain of fatality risk?

Normative arguments about what rates and functional forms ought to be used are on-going. However, their treatment is postponed to Part IV which considers the implications for policy. The analysis and results are simply descriptive, exploring the way that respondents appeared to be discounting in reality.

The rest of the Chapter is organised as follows. First, the alternative discounting hypotheses are outlined, building upon the discussion in the literature review on pg.138. Next, the methodology is briefly recapped, and an overview of the results is provided. The analysis has three main Sections: initially the overall relativities between latent cancers and road accidents are examined in terms of their behaviour with respect to elements of the timing of the risk scenarios. Then exponential rates are derived and analysed on the sample and the individual level. This allows respondents to be categorised into discounting types, with the conclusion that nonstandard discounting appears to categorise the sample in aggregate as well as the majority of individuals. Probit analysis is used to examine whether personal characteristics are related to the form of the discounting function. Finally, the discount rates are re-estimated to account for differences in discounting type, and conclusions are drawn as to the most descriptively accurate rate and functional form for VSL calculations in this sample.

7.2 Discounting Hypotheses

The literature review identified three main testable classes of discount function with different properties which distinguish them. The literature review provided the basis upon which each model was developed and outlined the empirical evidence for each. This Section re-states the basic principles but focuses on the application to the VSL literature and the VSL_{CAN}:VSL relativities (see pg.53 in Part I for an explanation of the $C_T R_t$ relationship). The three models are presented below, and summarised in Table 7.1.

7.2.1 *Standard exponential discounting*

Exponential discount functions characterise early thought on time discounting, for example see Samuelson (1937). The first formal models of time preference used the exponential discounting function, although it should be noted that their proponents, for example Koopmans (1960) who provided axiomatisation, did not intend the models to be taken as descriptive of real behaviour. For a fuller account of the history of the exponential discounting assumption, and indeed of all the major discounting discoveries up to 2002, see Frederick *et al.* (2002).

Standard exponential discounting involves a discount function of the form:

$$X_\tau = \frac{X_0}{e^{\delta\tau}} \qquad (75)$$

The proportional decline from, say, 2-5 years is the same as the decline from 12-15 years, which generates the time consistency property that makes the exponential discounting function normatively appealing.

In terms of the future cancer to current roads relativities, assuming a constant context premium of $(1 + x)$ (see pg.53 for a discussion), we can show that the $C_T R_t$ relativity is defined as

$$C_T R_t = \frac{(1+x)}{e^{\delta(T-t)}} \qquad (76)$$

7.2.2 *Hyperbolic discounting and quasi-hyperbolic discounting*

As discussed in the literature review and in the comprehensive review by Frederick *et al.* (2002), exponential discounting is often shown to fare badly in predicting intertemporal choice behaviour. Short delays tend to imply higher discount rates than longer delays. This observation prompted the formulation of hyperbolic discounting models. There are various formulations in the literature, three of which are presented below.

7.2.2.i *Generalised hyperbolic discounting Loewenstein and Prelec (1992)*

The generalised model has the functional form:

$$X_\tau = \frac{X_0}{(1+\delta\tau)^{\gamma/\delta}} \qquad (77)$$

δ refers to the difference between this and the simple exponential model. γ reflects the individual's time perception, which refers to how quickly they perceive a unit of time to pass. The present value clearly depends on the temporal distance between now and the fatality. Again the present value declines with delay. This time, however, the decline is steeper over the near term and shallower over the longer term. This is formalised in the declining relativity with T. This can generate inconsistent preferences over time, which is descriptively accurate but normatively unappealing. See the policy implications Section (particularly Section 8.4.2) for a discussion.

In terms of the VSL_{CAN}:VSL relativities, assuming a constant context premium of $(1 + x)$, this discounting function implies

$$C_T R_t = (1 + x) * \left(\frac{(1+\delta T)}{(1+\delta t)}\right)^{\gamma/\delta} \quad (78)$$

7.2.2.ii *Simple hyperbolic discounting*

The generalised model can be simplified by assuming that $\gamma = \delta$. This makes the model more analytically tractable and is a common specification in the applied discounting literature.

With this assumption, the discount function becomes

$$X_\tau = \frac{X_0}{(1+\delta\tau)} \quad (79)$$

The VSL_{CAN}:VSL relativity is

$$C_T R_t = \frac{(1+x)(1+\delta t)}{(1+\delta T)} \quad (80)$$

7.2.2.iii *Quasi-hyperbolic discounting*

Quasi-hyperbolic discounting, as first proposed and formalised for intrapersonal discounting by Laibson (1997) combines some of the qualitative features of hyperbolic discounting (i.e. strong preference for the immediate future, lower rates with long delays) with the analytical tractability of the exponential discounting model. In settings where there is no immediate option, quasi-hyperbolic discounting does not generate inconsistency. While it is gaining popularity in the literature, it is impossible to distinguish using the data available in this Study. However, for completeness the functional form of the discount factor is presented here:

For a person that lives T periods, the present value at time T of utility of future consumption is defined as

$$U_t(c_0, c_1, \dots, c_T) = u(c_t) + \beta \sum_{i=1}^{T-t} \delta^i u(c_{t+i}), \quad 0 < \beta < 1 \qquad (81)$$

So the β mimics the qualitative properties of the hyperbolic discount function, while the remaining years are hyperbolic.

To place it in a utility-free present-value sense, this becomes

$$X_\tau = \beta \left(\frac{X_0}{e^{\delta\tau}}\right) \; where \;\; 0 < \beta < 1 \; for \; \tau > 0, \beta = 1 \; for \; \tau = 0 \qquad (82)$$

7.2.3 *Sub-additive discounting*

Sub-additive discounting does not have its basis in a discounting function, instead being a qualitative fit to the anomaly that longer intervals between outcomes tend to be discounted at a lower rate than shorter intervals. The qualitative predictions are largely similar to those of hyperbolic discounting and as such the difference is somewhat harder to define. However, the model can be summarised using the relativity between latent and sooner outcomes. By definition, there is no discount function or discount factor to be applied to a single future outcome, because the phenomenon of sub-additive discounting requires comparison. Sub-additive discounting can take as its base either hyperbolic or exponential functions.

7.2.3.i *Hyperbolic based sub-additive discounting*

The VSL_{CAN}:VSL relativity is

$$C_T R_t = \frac{(1+x)}{(1+\delta(T-t)^s)} \qquad (83)$$

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

7.2.3.ii *Exponential based sub-additive discounting*

The VSL_{CAN}:VSL relativity is

$$C_T R_t = (1+x)\delta^{(T-t)^s} \qquad (84).$$

The different discounting assumptions are summarised in Table 7.1.

Table 7.1: Discount functions

	Standard exponential	Hyperbolic	Sub-additive
Discount function	$X_\tau = \frac{X_0}{e^{\delta\tau}}$	GENERALISED: $X_\tau = \frac{X_0}{(1+\delta\tau)^{\gamma/\delta}}$ SIMPLE ($\gamma = \delta$): $X_\tau = \frac{X_0}{(1+\delta\tau)}$	N/A qualitative descriptive model
Instantaneous discount rate at time τ, defined as $\frac{f'(\tau)}{f(\tau)}$, $f(\tau)$ being the discount function	δ	GENERALISED: $\frac{\gamma}{(1+\delta\tau)}$ SIMPLE ($\gamma = \delta$): $\frac{1}{(1+\delta\tau)}$	N/A qualitative descriptive model
Relativity between outcome at time T and identical outcome at time t (with T>t)	$e^{-\delta(T-t)}$	GENERALISED: $\left(\frac{(1+\delta t)}{(1+\delta T)}\right)^{\gamma/\delta}$ SIMPLE ($\gamma = \delta$): $\frac{1+\delta t}{1+\delta T}$	HYPERBOLIC BASE: $\frac{1}{1+\delta(T-t)^s}$ EXPONENTIAL BASE: $\delta^{(T-t)^s}$
Distinguishing features	Discount rate is constant over time and unaffected by intervals. That is, present value declines at a constant rate w.r.t. time delay.	Discount rate is negatively related to the delay between the present and the future outcome. That is, present value declines at a decreasing rate w.r.t. time delay.	Discount rate is negatively related to the interval between the two outcomes, and in the hyperbolic case also to the delay between the present and the future outcome.
Relativity	Decreases with T and with (T-t) at the same rate	Decreases with T and with (T-t)	

7.3 Summary: What is the Scope of this Research?

It is clear from Table 7.1 that the discounting assumptions have different distinguishing features. It is possible to infer the discount rate using the exponential assumption in the domain of physical risk using the methodology introduced in Part II and demonstrated on pg.129. The resultant discount rates can then be analysed using regression on timing

elements to identify these distinguishing features. This means that survey data like the R-R data from Study 2 is sufficient to infer discount rates and discount functions, motivating the analysis in this Chapter. The analysis will consider whether simple hyperbolic, exponential or sub-additive discounting is the most appropriate assumption for the majority of the sample, as well as eliciting rates of time preference under each assumption. This will then provide empirical evidence about the appropriateness of the process used in typical studies and in government policy, which is to enter latency linearly into calculations considering outcomes at different times.

7.4 Study 2b Methodology and Plan for Analysis

The methodology for Study 2 was outlined in Chapter 5, Section 5.8. It formed the basis for the risk preference analysis in Chapter 6 and will again be analysed here, but with a focus on time preferences and latency. The main features of the methodology are re-capped in this section.

Table 7.2: Latency differentials and average delays

Question	Code	Cancer	Roads	Latency differential (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_5R_2	5	2	3	3.5
5	C_7R_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

In order to analyse time preference in the context of health and physical risk, a series of R-R trades with different underlying time scales were presented to respondents. Respondents answered ten risk-risk trade questions with cancer and road accident timings as shown in Table 7.2. In every question, respondents compared cancer fatality risks in the future (between 5 and 25 years from now) to road accident risks sooner (between 1 and 10 years from now).

Respondents also provided information about their risk preferences in the domains of finance and health (see Chapter 6 for a full discussion) and then completed a financial time preference elicitation exercise, which involved "larger later or smaller sooner" choices between money amounts (Coller and Williams, 1999). See the methodology Section for more details.

So far this Chapter has discussed the three main alternative discounting hypotheses- exponential, hyperbolic and sub-additive- and has recapped the methodology employed to elicit the Risk-Risk trade-off data that will form the basis for the coming analysis. The following Sections will discuss the sample and the results in overview, then analyse the data to ascertain likely discounting functions and rates for this sample.

The results analysis will take the following structure: Initially the information about financial time preferences will be discussed, in order to allow comparison of this sample with estimates from the literature. Next, a preliminary discussion of the relativities and latency will be provided. This takes the same structure as the analysis of latency in Study 1, reported in Chapter 2, and confirms that latency matters in determining the VSL for this sample, mirroring the result from Study 1.

Building upon this basis, the analysis takes account of the different latency periods in more detail. The behaviour of the overall relativities (C_TR_t) in response to the underlying timing of the scenarios will be presented. Following this, discount rates will be derived under the assumption of exponential discounting, and will be analysed both at the aggregate level and at the level of the individual. This latter analysis will result in the classification of individuals as either standard or non-standard discounters, and within this will provide the basis for a Probit analysis to examine whether the discounting classification can be predicted by personal characteristics. Finally, for each discounting assumption, rates will be estimated and discussed. The sample statistics were provided in Chapter 5 and so will not be discussed here.

7.5 Results

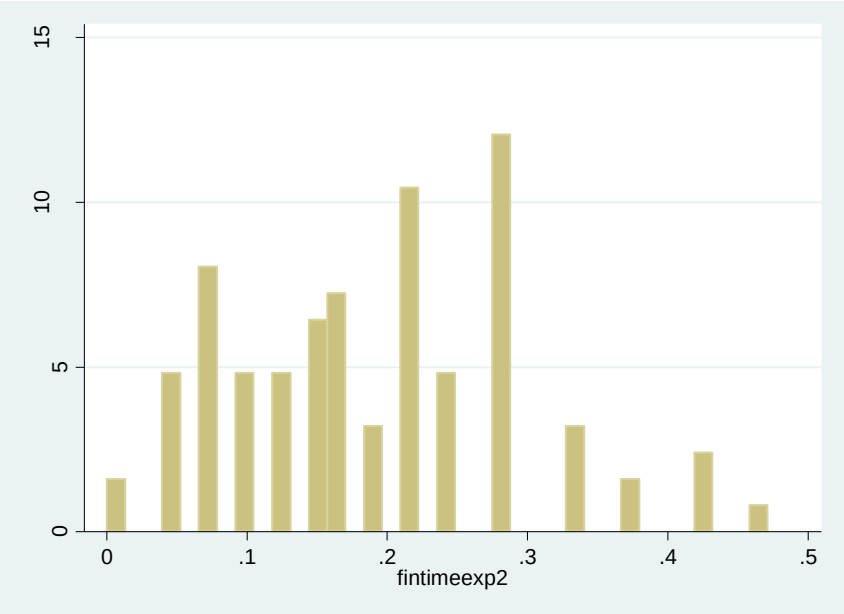
7.5.1 *Financial time preference*

As explained in the Methodology Section, financial time preferences are elicited for each individual using a "smaller sooner or larger later" framework, similar to that proposed by Coller and Williams (1999) and used in Andersen *et al.* (2008). Of course, budget constraints and hypothetical biases may have had a role to play in determining

the choice of switching row, but the switching rows are assumed to provide a reasonable proxy for the respondents' preferences over timings of outcomes. This information is converted into an exponential discount rate, under the assumption that the individual would always choose the option with the largest present value. The resulting distribution is presented in Figure 7.1.

The distribution of the elicited financial discount rates is fairly even across options, although it appears to decline after the 30%p.a. mark. There is no clearly discernible peak. It ought to be noted that the design allows only positive discount rates and the highest possible discount rate to be inferred is below 0.5. However, if this was a constraint for respondents, it would be expected that there would be peaks at the upper and lower ends of the distribution, and this is not the case.

Figure 7.1: Exponential discount rate from financial comparisons



The mean financial exponential discount rate is 18.5% p.a. (s.d. 10.7%) and the median is 17%. This is comparable to estimates in much of the literature. Coller and Williams (1999) cite a range in the literature from 1% to over 1000%, while their own procedure (which is replicated in this Study) generates estimates between 17.5% and 20%. Andersen *et al.* (2008), who elicit discount rates with and without controlling for risk preferences, find a discount rate of 25.2% in the case without controlling for risk preference, which drops to 10.1% when they do control for risk aversion. This suggests that the estimate from Study 2b is not dissimilar to estimates from the literature.

7.5.2 *Risk-Risk relativities data*

Having discussed the financial time preferences of this sample, the analysis will turn to focus on the responses to the ten Risk-Risk trade-off questions that formed the main body of the experiment. This will provide the basis for subsequent elicitation of the discount rate. As described, the ten R-R questions elicited the relative strength of preference for avoiding risks of cancer T years in the future compared to risks of road accidents t $(\leq T)$ years into the future.

7.5.2.i *Trimming*

Table7.3: Deletions

	Question	**Cleaning (untrimmed) n**	**Trimming (30million +) n**
1	C_{10} :R_1	106	104
2	C_{10}:R_2	105	104
3	C_{25}:R_2	106	105
4	C_5:R_2	106	105
5	C_7:R_2	105	105
6	C_{15}:R_2	107	106
7	C_{10}:R_5	106	106
8	C_{10}:R_7	104	104
9	C_{25}:R_{10}	108	107
10	C_{10}:R_{10}	98	96

Similarly to the main sample, some respondents gave answers to the R-R questions that were above the *a priori* defined cut off level of 30million in 60 million. That is, they gave relativities above 600,000:1. Trimming the sample to remove these responses resulted in less proportional loss than in Study 1. Details are provided in Table 7.3.

The high deletion rate for Q10 is likely to be due to a combination of two things. It was always the last question to be answered so there may have been effects of fatigue. In addition, it was the only question in which the scenarios differed along just one

attribute, in this case context. The discussion of Study 1 showed that single attribute questions tended to produce more extreme and potentially exaggerated results. For these reasons, it is perhaps unsurprising to observe a higher mean response for Q10 compared to the earlier 9 questions.

7.5.2.ii *Central tendencies*

Table 7.4: 30 million trim central tendencies

Question		Arithmetic Mean [confidence interval] (*standard deviation)*	Median (percentiles)	Geometric mean [confidence interval]	Index [confidence interval]
1 ($C_{10}R_1$)	(N=104)	**1162** [-1126, 3451] *(11766)*	**0.67** *(25% = 0.25)* *(75% = 4.40)*	**0.97** [0.59, 1.60]	**0.93** [0.73, 1.19]
2 ($C_{10}R_2$)	(N=105)	**8.65** [2.58, 14.72] *(31.20)*	**0.67** *(25% = 0.19)* *(75% = 4.00)*	**0.72** [0.42, 1.23]	**0.89** [0.70, 1.14]
3 ($C_{25}R_2$)	(N=105)	**61.14** [-52.14, 174.41] *(585.33)*	**0.25** *(25% = 0.14)* *(75% = 2.40)*	**0.35** [0.21, 0.59]	**0.57** [0.43, 0.73]
4 (C_5R_2)	(N= 105)	**12.68** [4.81, 20.55] *4.047)*	**2.2** *(25% =0.35)* *(75% = 6.80)*	**1.67** [1.08, 2.58]	**1.29** [1.02, 1.65]
5 (C_7R_2)	(N= 105)	**10.34** [3.68, 17.01] *(34.46)*	**1.5** *(25% = 0.26)* *(75% = 5.40)*	**1.16** [0.71, 1.89]	**1.13** [0.89, 1.45]
6 ($C_{15}R_2$)	(N= 106)	**11.91** [-0.07, 23.88] *(61.88)*	**0.36** *(25% = 0.19)* *(75% = 3.8)*	**0.61** [0.37, 1.01]	**0.74** [0.58, 0.95]
7 ($C_{10}R_5$)	(N= 105)	**959.73** [-928.74, 2848.20] *(9758.31)*	**1.3** *(25% = 0.28)* *(75% = 4.40)*	**1.02** [0.59, 1.77]	**1.05** [0.83, 1.34]
8 ($C_{10}R_7$)	(N= 104)	**1356.56** [-1313.03, 4026.15] *(13727.14)*	**2.5** *(25% = 0.48)* *(75% = 6.10)*	**1.67** [1.00, 2.80]	**1.35** [1.07, 0.71]
9 ($C_{25}R_{10}$)	(N= 107)	**7.964** [1.07, 14.86] *(35.81)*	**0.38** *(25% = 0.19)* *(75% = 2.80)*	**0.49** [0.29, 0.83]	**0.71** [0.55, 0.89]
10 ($C_{10}R_{10}$)	(N=98)	**17.24** [8.29, 26.19] *(44.17)*	**4.60** *(25% = 1.40)* *(75% = 8.10)*	**3.58** [2.37, 5.41]	**2.18** [1.73, 2.83]

The analysis will be performed on the responses trimmed to the 30million level. None of the central tendency measures are significantly different between the 30 million and the untrimmed levels with the exception of the arithmetic mean which, as discussed, extensively in Section 3.3.1, is sensitive to high outliers. As previously, this analysis will use the geometric mean as the predominant central tendency measure.

7.5.3 *Basic insights about latency and the R-R relativities*

Initially, a general overview of the responses to the Risk-Risk questions is presented, highlighting patterns that will be explored throughout the rest of this Chapter. The analysis mirrors Sections 4.7 and 4.9 in treating latency as an explanatory variable with a constant effect. The explanatory variables chosen are those providing best fit from the full model used throughout the analysis of study 1.

Table7.5: Study 2b basic regression

Log of relativities	Model (1) student N=1022 R^2= 0.064	Model (2) student N=993 R^2= 0.110	Model (3) student N=814 R^2=0.155
Latency (differential in years)	**-0.084***** (0.009)	**-0.085***** (0.009)	**-0.088***** (0.016)
Self-Reported road accident risk	- 	**-0.420**** (0.174)	**-0.464**** (0.188)
Experience of cancer	-	0.609 (0.379)	**0.706*** (0.421)
Health state	-	-	0.420 (0.286)
Health risk aversion	-	-	-0.132 (0.128)
Financial time preference	-	-	-1.067 (1.423)
Female	-	-	-0.130 (0.390)
Financial risk preference	-	-	-0.287 (0.396)
Constant	**0.837***** (0.178)	**1.145***** (0.411)	**1.766*** (0.950)

The respondents in the student sample answered ten cancer-later or roads-sooner risk-risk questions as discussed above. The central tendencies, at the 30million trim level,

are provided in Table 7.4. As would be expected, the larger the interval between cancer and road accidents, the smaller the VSL_{CAN}:VSL relativity. While the 'context' question, Q10, provided a relativity significantly greater than 1 indicating a preference for avoiding cancer risk increases *ceteris paribus*, the central tendencies for most of the questions are less than one. This suggests that for this sample, latency offsets dread over the time intervals considered. This mirrors the main insights from Study 1.

A basic multiple regression of the relativities on attributes is presented in Table7.5. In this regression, latency is entered linearly. Clearly, timing as defined by the difference in latency periods between the two fatality risk scenarios was very important (significant at the 1% level in all specifications) in determining the overall VSL_{CAN}:VSL relativity. This regression is the counterpart of the summary regression in Chapter 2, although contains fewer attribute variables because there is no variation in context and morbidity between the questions in Study 2.

Following the procedure in the analysis of Study 1 in Chapter 2, the regression analysis reported in Table7.5 enters latency linearly into the regression, with an additional year of latency prior to the cancer fatality assumed to have a constant effect on the logged relativity, holding the timing of the road accident constant. This serves as a benchmark against which the more sophisticated analysis provided in the rest of this Chapter can be compared.

This survey was designed to allow much richer analysis of time preferences by incorporating a range of latency differentials, which can be plotted and compared in a variety of ways to attempt to *infer* the nature of discounting in this sample, and hence eliminating the need to assume the relationship. The plan for the analysis is presented next.

7.5.4 *Discounting analysis roadmap*

In the coming sections, the data will be analysed to fully explore the impact of timing and discounting in this Study. Initially, the effect of the latency periods on the relativities for Study 2 is analysed is detail. The relativities display a decreasing pattern with the increase in interval, as expected. The relativities are regressed against various timing elements of the scenarios, including the timing of the latest risk increase, the average delay and the latency differential. This analysis is conducted using the

relativities on an individual level, to maximise the sample size and allow the inclusion of demographics in explaining the relativities.

Subsequently, underlying discount rates are elicited under the assumption of exponential discounting. The ten questions are paired into 45 combinations and simultaneous equation techniques as set out in Section 4.11 in Chapter 2 are used to generate up to 45 discount rates per individual. The rates are analysed to explore their sensitivity to the latency differential and the delay incorporated in the scenarios that underpin them. Both the latency differential and the average delay are statistically significant in explaining the discount rates, which suggests that exponential discounting may not be an appropriate assumption for the sample.

Finally, the individuals themselves are categorised as being exponential or non-standard discounters. Probit analysis is unable to explain the difference, with the exception that a higher coefficient of health risk aversion (HRA) reduces the likelihood that the individual is classified as an exponential discounter. The discount rates are re-estimated under the assumption of non-exponential discounting using first hyperbolic and then sub-additive discounting assumptions. These rates are analysed with the conclusion that a sub-additive assumption best reflects the preferences of the majority of non-standard discounters.

7.5.5 *How does the relativity behave as a function of timing?*

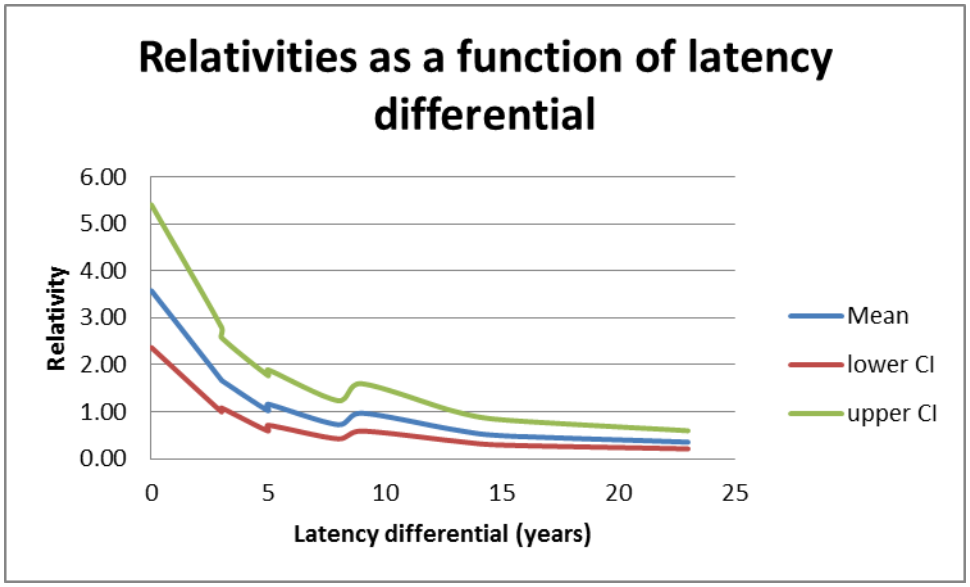
As described, the data is first analysed in aggregate, using sample geometric mean relativities for each question. The first stage in estimating the functional form of the relationship between the VSL_{CAN}:VSL relativity and latency is to plot the sample average relativities against the latency differential underpinning them. Here, the latency differential is defined as the number of additional years of latency in the cancer case compared to the road accident case.

Table 7.6 with question numbers, codes, latency differentials and central tendencies is provided for reference. The geometric mean, along with the upper and lower confidence intervals, can be plotted in a simple line graph, as shown in Figure 7.2.

Table 7.6: Latency differentials, average delays and corresponding relativities

Question	Code	Latency differential (years)	Average Delay (years)	Geometric mean (30mill trim)	95% confidence interval
1	$C_{10}R_1$	9	5.5	0.97	[0.59, 1.60]
2	$C_{10}R_2$	8	6	0.72	[0.42, 1.23]
3	$C_{25}R_2$	23	13.5	0.35	[0.21, 0.59]
4	C_5R_2	3	3.5	1.67	[1.08, 2.58]
5	C_7R_2	5	4.5	1.16	[0.71, 1.89]
6	$C_{15}R_2$	13	8.5	0.61	[0.37, 1.01]
7	$C_{10}R_5$	5	7.5	1.02	[0.59, 1.77]
8	$C_{10}R_7$	3	8.5	1.67	[1.00, 2.80]
9	$C_{25}R_{10}$	15	17.5	0.49	[0.29, 0.83]
10	$C_{10}R_{10}$	0	10	3.58	[2.37, 5.41]

Figure 7.2: Relativities as a function of latency differential



This places no parametric restrictions on the data and allows an initial investigation of the responses to be conducted by eye.

The plot shows a declining pattern as would be expected, because the further into the future the cancer risk is compared to the road accident risk, the weight it will have in the comparison with a road accident sooner. The latency differential appears to reduce the relativity, *ceteris paribus*. It is not immediately clear what functional form can best fit this data, although the decline appears to be more pronounced over shorter latency differentials.

7.5.5.i *Nonparametric and semi-parametric estimation*

Nonparametric estimation allows the models to be estimated without pre-specifying a linear relationship between the dependent and independent variables. The *Lowess* (locally weighted scatterplot smoother) command in Stata conducts a local polynomial regression technique in order to plot a smooth curve through the data-points. At regular points along the x axis, so in this case for every latency period, the data-points within a pre-defined bandwidth around the x value are weighted according to their distance from the focal point, and a best fit line is generated for them. This is repeated for each x, generating a smoothed function for the data. The resulting graphs are given in Figures 7.3 and 7.4, with the former representing the relativities themselves and the latter illustrating the 95% confidence intervals around the Lowess line, and using logged relativities.

Figure 7.3: Relativities as a function of latency differential, Lowess smoothing

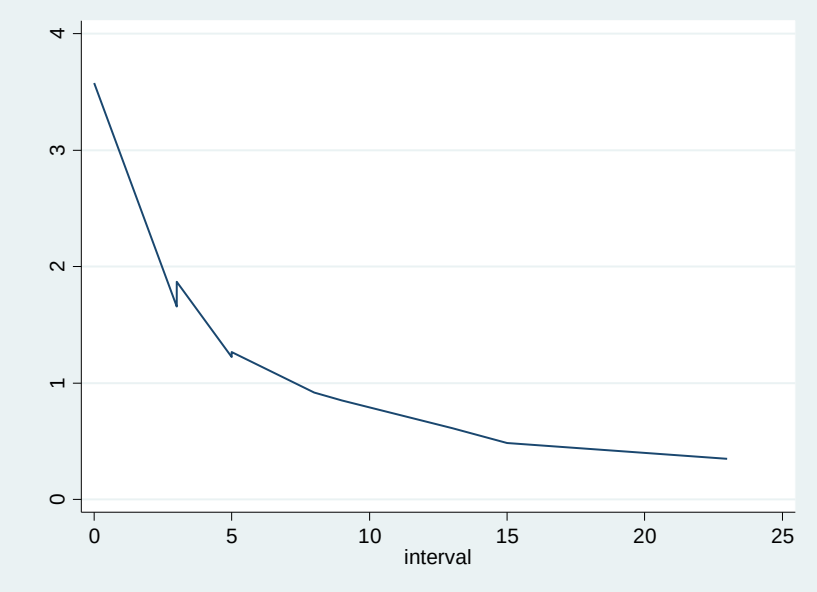
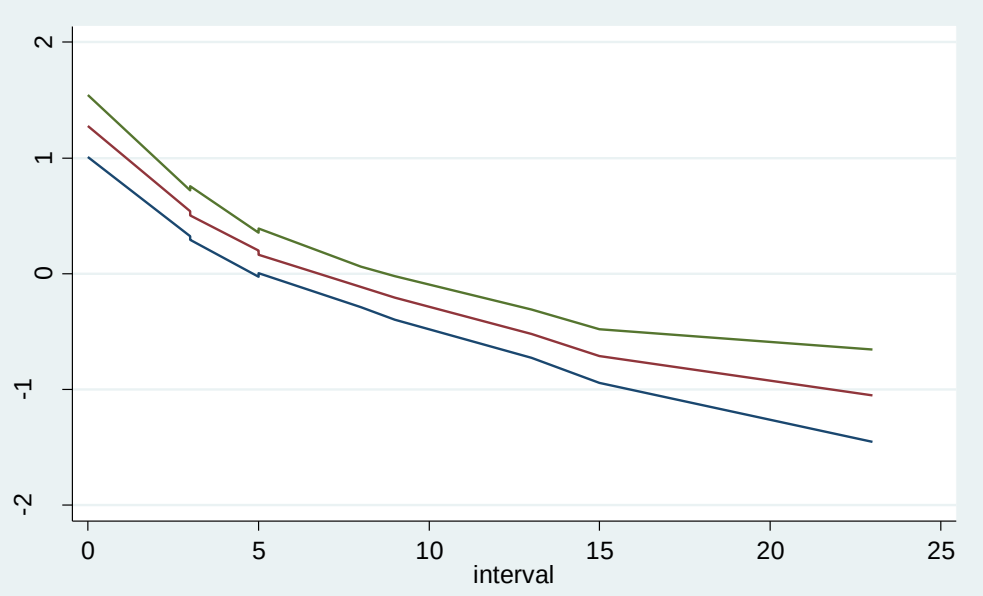


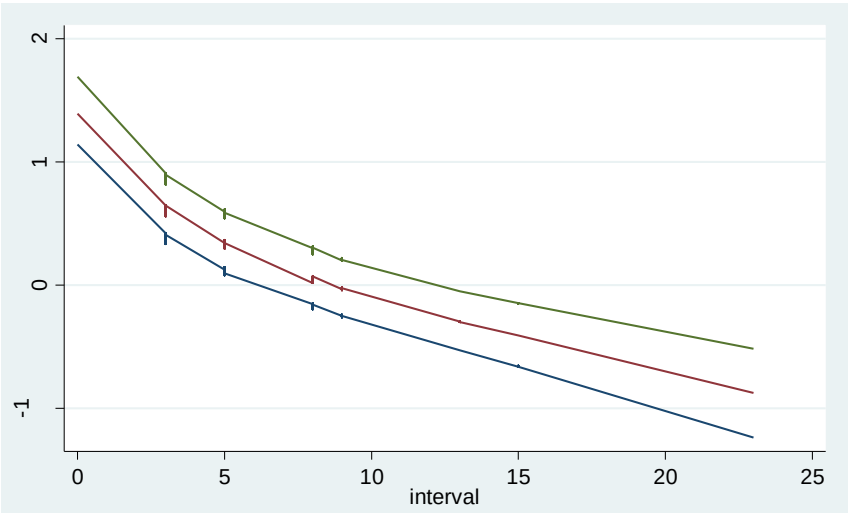
Figure 7.4: Log of relativities as a function of latency differential, Lowess smoothing with 95% confidence intervals



7.5.5.ii *Individual-level analysis*

The preceding analysis simply used the sample average relativities and as such relied on ten data-points, but data are generated on the level of the individual. Plotting this pooled data allows a larger sample size and in addition allows the analysis of demographics. As a first step, each of the 1042 individual relativities are pooled and plotted as a function of the latency differential. Again, Stata's Lowess command is used to allow the data to speak without imposing any functional form onto the relationship.

Figure 7.5: Log of relativities as a function of latency differential, individual level relativities



Again a downward trend emerges in the logged relativity as a function of latency, which suggests that the effective discount rate is positive.

The previous basic regressions for this sample, reported in Table 7.5, suggested that cancer experience and self-reported road accident risks are also important in determining the relativity. As such, and given the dummy nature of these explanatory variables, a semi-parametric model is likely to be useful in determining the influence of latency on the relativity. As such, the following two models will be estimated:

$$logratio_i = \beta_1 carrisk_i + \beta_2 canexp_i + f(time_i) + \varepsilon_i \quad \textit{(Model2a/3a)}$$

$$logratio_i = \beta_1 carrisk_i + \beta_2 canexp_i + \beta_3 healthstate_i + \beta_4 healthrisk_i + \beta_5 fintimeexp2_i + \beta_2 female_i + \beta_2 finrisk_i + f(time_i) + \varepsilon_i$$

(Model 2b/3b)

Table 7.7: Semi-parametric regressions

Logged relativity	Model (2a) N=992 Adj-R^2= 0.0004	Model (3a) N=843 Adj-R^2= 0.0514	Model (2b) N=992 Adj-R^2= 0.0006	Model (3b) N=857 Adj-R^2= 0.0351
Latency (differential in years)	**V=8.786** (P>|V|= 0.000)	**V=8.097** (P>|V|= 0.000)	-	-
Delay (average in years)	-	-	**V=4.812** (P>|V|= 0.000)	**V=3.233** (P>|V|= 0.001)
Self-Reported road accident risk	0.541 (0.338)	**-0.547*** (0.330)	0.469 (0.333)	**-0.577*** (0.332)
Experience of cancer	-0.688 (0.510)	**1.230***** (0.478)	-0.748 (0.506)	**0.922*** (0.483)
Health state	-	0.331 (0.293)	-	0.366 (0.296)
Health risk aversion	-	**-0.351***** (0.126)	-	**-0.313**** (0.127)
Financial time preference	-	**-2.969***** (1.019)	-	**-2.862***** (1.030)
Female	-	**-0.401*** (0.237)	-	**-0.423*** (0.239)
Financial risk preference	-	**-0.292*** (0.175)	-	-0.274 (0.178)

The logged relativity is assumed to be linearly related to road accident risks, cancer experience, and in model b also to current health state, health risk aversion, financial time preference, gender and financial risk aversion, which is the 'full' regression model reported in Table7.5 (pg.208). The relationship with the timing differences is left unparameterized.

Time is included in two ways, first as the latency differential between the scenarios under comparison, and second as the average delay until the outcomes. As discussed in the theory section, the relativities and discount rates are likely to behave differently as a function of the latency differential compared to the average delay.

Assuming additive separability of the partial and non-partial effects, that the timing function is a smooth and single-valued function with bounded first derivative, and that the error term is independently and identically distributed, the differencing procedure described in Lokshin (2006) can be performed using the Stata command *plreg*[40].

The adjusted R^2 of model (2a) is low, at 0.0004, but the influence of latency is estimated to be significant at the 1% level, with a p-value of <0.0001. Neither road accident risk or cancer experience is significant in this specification. However, the inclusion of other demographics in model (3a) generates significant coefficients for self-reported road accident risk and experience of cancer in the expected direction. In addition, risk aversion over health states and finance, and having higher financial discount rates and being female all appear to significantly reduce the logged relativity. The difference between the two models suggests some instability of the coefficients, although the main effects of interest, latency differential and delay, are significant in both models.

To complement the analysis in table 7.7A, four further regressions are run. This time, a different approach to the non-parametric inclusion of delay and of interval is taken, with the different delays and intervals are included as dummy variables. This allows better interpretation of significance than the previous non-parametric results. The choice of bandwidth is determined by the survey design- breaking the intervals and delays down would result in empty intervals, while including fewer dummy variables would mean losing detail. As such, the existing delays and intervals are used. The reference categories omitted from the regressions are zero differential and 3.5 year delay. The sign and significance of the coefficients on these dummy variables allows the importance of the delay and differential to be established. The results are in table 7.7A.

The dummies for the delay and for the differentials are significant which supports the previous results in suggesting that timing significantly influences the ratio between the latent cancer and the sooner road accident. R^2 is slightly higher for the differential cases than the delay cases. The demographic variables are stable across each model.

[40] The regression model uses Yatchew's weighting matrix to estimate the impacts of latency on the logged relativity.

Table 7.7A: Regressions using dummy variables for timing aspects

Logged relativity	Model (2a) N=1013 R^2= 0.0840	Model (3a) N=858 R^2= 0.1408	Model (2b) N=1013 R^2= 0.0770	Model (3b) N=858 R^2= 0.1292
Differential = 3	**-0.766***	**-0.690***	-	-
	(0.164)	(0.176)		
Differential = 5	**-1.160***	**-1.045***	-	-
	(0.181)	(0.180)		
Differential = 8	**-1.603***	**-1.448***	-	-
	(0.220)	(0.203)		
Differential = 9	**-1.297***	**-1.375***	-	-
	(0.216)	(0.203)		
Differential = 13	**-1.760***	**-1.820***	-	-
	(0.206)	(0.239)		
Differential = 15	**-2.012***	**-1.980***	-	-
	(0.234)	(0.223)		
Differential = 23	**-2.340***	**-2.396***	-	-
	(0.233)	(0.261)		
Delay = 3.5	-	-		
Delay = 4.5	-	-	**-0.354***	**-0.249***
			(0.112)	(0.071)
Delay = 5.5	-	-	**-0.524***	**-0.578***
			(0.183)	(0.156)
Delay = 6	-	-	**-0.830***	**-0.651***
			(0.176)	(0.130)
Delay = 7.5	-	-	**-0.419***	-0.247
			(0.236)	(0.232)
Delay = 8.5	-	-	**-0.491***	**-0.414***
			(0.116)	(0.111)
Delay = 10	-	-	**0.773***	**0.797***
			(0.154)	(0.172)
Delay = 13.5	-	-	**-1.567***	**-1.599***
			(0.178)	(0.199)
Delay = 17.5	-	-	**-1.239***	**-1.183***
			(0.233)	(0.231)
Self-Reported road accident risk	**-0.360***	**-0.402***	**-0.360***	**-0.402***
	(0197)	(0.207)	(0.197)	(0.208)
Experience of cancer	0.650	0.672	0.651	0.672
	(0.440)	(0.428)	(0.440)	(0.428)
Health state	-	**0.562***	-	**0.561***
		(0.309)		(0.309)
Health risk aversion	-	-0.104	-	-0.104
		(0.210)		(0.211)
Financial time preference	-	-2.530	-	-2.541
		(2.054)		(2.057)
Female	-	-0.383	-	-0.383
		(0.465)		(0.466)
Financial risk preference	-	-0.387	-	-0.384
		(0.366)		(0.367)
Constant	**0.722****	**1.070***	-0.052	0.274
	(0.343)	(0.593)	(0.368)	(0.625)

The significance of the demographic variables is not the same as for the semi parametric cases. Subjective risk of road accident fatality becomes negative and significant in the dummy models while current health state is positive and significant. The semi-parametric model looks very different. Having said this, estimates of significance are more reliable using a parametric model (the dummy variable models in this case) than when using semi-parametric analysis.

7.5.5.iii *Testing delay versus differentials in explaining the discount function*

As described, there are two distinct concepts to do with timing: delay and differential. The former refers to the delay from the present until the time of the future outcome. Given that the relativities incorporate two time periods (one for roads and one for cancer) either the average delay or the cancer delay could be used to capture this effect. The second concept, the latency differential, captures the length of time between the two outcomes under comparison, i.e. the time between the road accident fatality date and the cancer fatality date. These definitions are summarised and exemplified in Figure 7.6.

Figure 7.6: Definition of latency differential and average delay

DEFINITIONS:

Differential: the *difference* between the time of the fatality from cancer and the time of the fatality in a road accident

Average delay: the *mean* of the time until the fatality from cancer and the time until the fatality in a road accident

EXAMPLE: Cancer in 10 years and road accident in 2 years ($C_{10}R_2$)

Differential: 10 – 2 = 8 years

Average delay: (10+2)/2 = 6 years

Delay is the more relevant concept for testing for hyperbolic discounting, as argued in Read (2001) and discussed in Section 7.2.3. Any evidence of the impact of the latency differential on the relativity is indicative of sub-additive discounting as opposed to hyperbolic discounting, unless declining discount rates with delay can also be found.

In this regression, latency differential and delay are both significant and both reduce the relativity. However, as discussed, the differential and delay are confounded because a

long differential between cancer and car implies a long delay for the cancer risk. When both differential and average delay change, the effects are difficult to disentangle. As such, first the central tendencies will be revisited, and then further regressions run.

Table 7.8: Same latency differential different delay central tendency comparison

Latency differential	Roads the year after next	Roads later (5 or 7 years from now)
3 years	C_5R_2	$C_{10}R_7$
	1.67	**1.67**
	[1.08, 2.58]	[1.00, 2.80]
5 years	C_7R_2	$C_{10}R_5$
	1.16	**1.02**
	[0.71, 1.89]	[1.00, 2.80]

There is no significant difference between the central tendencies of the relativities for the questions where the intervals are the same, but delay until the road accident risk is different. This might suggest that the interval, not the delay, is the most important feature of the timing of the response. These results are drawn from Table 7.8.

To further explore this, four further regressions are run to investigate delay at face value. Regression on delay is run for questions where road accident risks occur in 2 years (Q2-6). Next the regression is repeated for those questions where cancer risks occur in 10 years (Q1-2,Q7-8,and Q10). Both regressions capture the differential effect. Finally, regression is run for those questions where the differential is 3 years (Q4 and Q8) and where it is 5 years (Q5 and Q7) in order to explore the 'pure' delay effect because the latency differential is held constant. The results are presented in Table 7.9.

Table 7.9: Semi-parametric regressions on specific question sets

log ratio	Model (4) Road accidents in 2 years N=425 Adj-R^2= 0.0658	Model (5) Cancer in 10 years N=416 Adj-R^2= 0.0143	Model (6) Differential of 3 years N=168 Adj-R^2= -0.0177	Model (7) Differential of 5 years N=169 Adj-R^2= -0.0178
Delay (average in years)	**V=2.031**** (P>|V|= 0.021)	**V=2.797***** (P>|V|= 0.003)	V=0.527 (P>|V|= 0.299)	V=-0.103 (P>|V|= 0.514)
Self-Reported road accident risk	-0.634 (0.403)	**-0.698*** (0.378)	-0.906 (0.710)	-0.785 (0.755)
Experience of cancer	**1.684***** (0.567)	0.289 (0.531)	0.328 (0.862)	0.293 (0.915)
Health state	0.153 (0.342)	0.529 (0.326)	0.311 (0.512)	0.422 (0.227)
Health risk aversion	**-0.545***** (0.144)	-0.192 (0.135)	-0.087 (0.214)	-1.672 (0.227)
Financial time preference	-0.531 (0.932)	-0.930 (0.890)	-1.054 (1.382)	-1.245 (1.463)
Female	-0.078 (0.278)	-0.141 (0.261)	-0.012 (0.407)	-0.112 (0.433)
Financial risk preference	-0.083 (0.208)	-0.020 (0.198)	0.219 (0.316)	0.028 (0.0329)

7.5.5.iv *Summary of the analysis of relativities*

The analysis of latency's impact on the relativity suggests a declining pattern of relativities with the interval between cancer and road accidents. This is apparent in regression, both parametric and non-parametric, and additionally in the patterns when the relativities are plotted against latency intervals. Demographic characteristics generally have limited influence on the relativity, but experience of cancer and self-reported road accident risks appear to have a significant effect. In addition, risk preferences over health are significant. The declining relativity with latency is unsurprising from a theoretical perspective: the more distant the bad outcome[41] the less bad it appears to be.

[41] Cancer can be shown to be considered the "bad outcome" through observing the high relativity in question 10, $C_{10}R_{10}$.

In terms of the discounting function likely to characterise this sample, two main observations can be made so far. First, the declining pattern of the relativity with latency would suggest that discount rates above zero characterise the majority of the sample. Second, the central tendency measures are indistinguishable for the questions with the same latency differential (3 years and 5 years in Q4 and 7 and in Q5 and 6 respectively) but which differ in terms of whether the soonest risk is now or in the future. This could be seen as evidence for exponential discounting or for sub-additive discounting, and against hyperbolic discounting. Although the wide confidence intervals would preclude using this alone as grounds to dismiss hyperbolic discounting, regression analysis of the relevant questions on delay suggested that delay is insignificant except as a proxy for the differential.

As such, there is some evidence for non-standard discounting but also some evidence against it, and further investigation of the effective discount rates implied by the data will be necessary to give a clear understanding of whether exponential or non-standard discounting assumptions are better suited for these data. To this end, the underlying exponential discount rates themselves will be elicited and analysed in Sections 7.5.6 to 7.5.8.

7.5.6 *Eliciting exponential discount rates*

Typically, the literature assumes that either exponential or hyperbolic discounting applies in the judgements of members of the public. However, there is rarely any attempt made to distinguish which of these models best reflects the actual preferences of the sample. Traditionally, a constant exponential discount rate is assumed. Following this precedent, Chapter 2 specified the relationship in two equations:

$$C_t = R_t(1 + x) \qquad (A1)$$

$$X_{t+\varphi} = \frac{X_t}{(1+r)^{\varphi}},\ X = \{C, R\} \qquad (A2)$$

the second of which demonstrates the exponential discounting assumption.

For this Section, assumption (A1) is retained. Assumption (A2) will be replaced with an alternative specification (assumption (A3)) which allows for more straight forward elicitation, and applies a continuous discounting assumption.

$$X_{t+\varphi} = X_t e^{-\varphi r},\ X = \{C, R\} \qquad (A3)$$

The exponential discount rates can be elicited on a sample and a per-person level, and the patterns studied to determine whether exponential discounting appears to be a reasonable approximation for this Study.

7.5.6.i *Exponential discount rates- sample averages*

Equations (A2) and (A3) are applied to the C_TR_t VSL framework, and give equation (85).

$$C_T = R_t(1+x)e^{-(T-t)r} \qquad (85)$$

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

$$\varphi = e^{-\delta\left((T-t)-(T'-t')\right)} \qquad (86)$$

where the only unknown is δ.

Solving for δ generates a mean discount rate of 11.0% (s.d. 9.15%) and a median of 10.1%. These rates are lower than the discount rates elicited over finance (18% p.a., pg.204), but the difference is not significant. The elicited rates are all positive except where Q1 and Q2 are combined. This anomaly reflects the increase in relativity from Q1 to Q2 which is likely due to a perceived increase in baseline road accident risks upon graduation, as discussed in more detail in the upcoming Section 7.5.7. The discount rates are within sensible bounds in comparison to the literature (see the discount rate table in the earlier literature review, Chapter 2, pg.44), although there is substantial variation between question combinations. The general picture supports the theoretical prediction, largely supported in the literature, that health (and perhaps fatality risk) is discounted at a lower rate than money. See the literature review for more detail on this argument.

Each relativity combination, φ, and hence each elicited discount rate, comes with an associated average latency differential (for example the rate calculated from $C_{25}R_{10}$ and C_5R_2 has an average interval of (15+3)/2 = 9 years) and with an average associated delay (for the same example, ((25+10)+(5+2))/4 = 21 years). Information is available on the timing of each of the risks faced in each of the four scenarios that combined to generate the discount rate, so it is also possible to control for the pairs where at least one of the risks occurred during the coming year or the year after next, and where neither risk occurs until much later.

Table 7.10: Matrix of elicited effective discount rates- exponential assumption

Cause A / Cause B	C10R1	C10R2	C25R2	C5R2	C7R2	C15R2	C10R5	C10R7	C25R10	C10R10
	0.97	0.72	0.35	1.67	1.16	0.61	1.02	1.67	0.49	3.58
C10R1	.	.	.	.	.	.	.	.	.	.
C10R2	-0.29	.	.	.	.	.	.	.	.	.
C25R2	0.07	0.05	.	.	.	.	.	.	.	.
C5R2	0.09	0.17	0.08	.	.	.	.	.	.	.
C7R2	0.04	0.16	0.07	0.18	.	.	.	.	.	.
C15R2	0.11	0.03	0.06	0.10	0.08	.	.	.	.	.
C10R5	0.01	0.11	0.06	0.25	.	0.06	.	.	.	.
C10R7	0.09	0.17	0.08	.	0.18	0.10	0.25	.	.	.
C25R10	0.11	0.06	0.04	0.10	0.09	0.11	0.07	0.10	.	.
C10R10	0.15	0.20	0.10	0.25	0.23	0.14	0.25	0.25	0.13	.

The discount rates in Table 7.10 are calculated using the sample average relativities, and as such there are just 43 rates for the analysis. Therefore regression analysis on this level would not be particularly robust. However, it is insightful to consider the population average exponential discount rates diagrammatically. The discount rate is plotted against the latency differential and against the average delay for the two questions used to elicit them. Initially, this is done for every point estimate (Figures 7.7 and 7.8), then repeated averaging the rates for each question (1-10) in order to decrease the influence of any outlier question pairs and to provide a smoother curve for interpretation in Figures 7.9 and 7.10. Finally, the Lowess smoothed plot is used to give a simplified idea of the pattern while not imposing any parametric assumptions (Figures 7.11 and 7.12).

Figure 7.7: All point estimates against latency differential

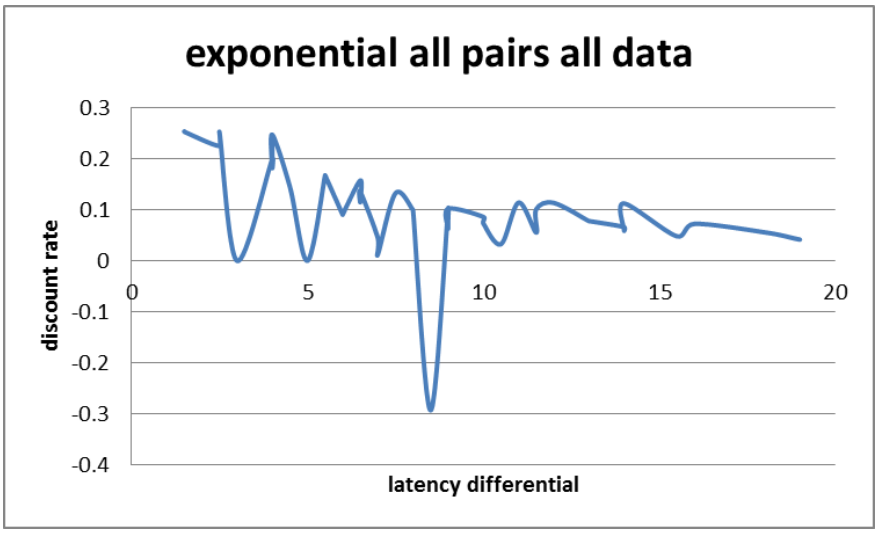


Figure 7.8: All point estimates against average delay

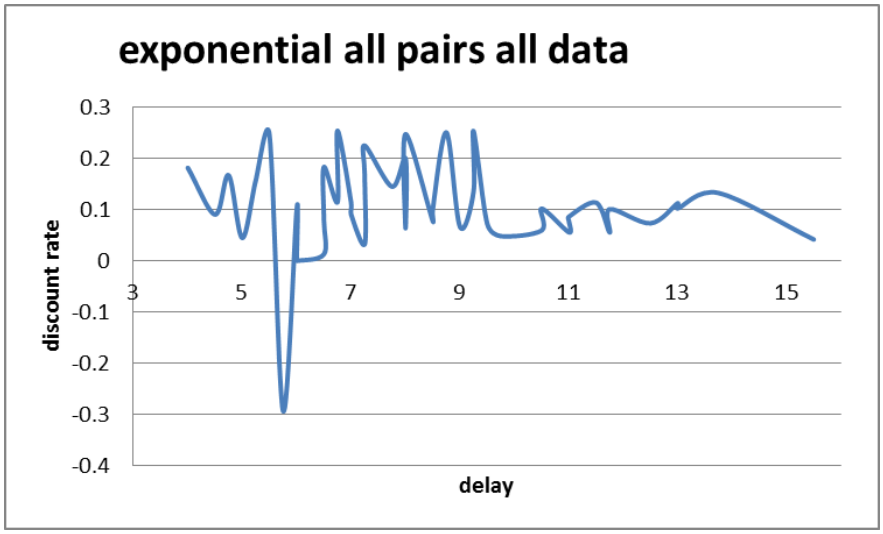


Figure 7.7 appears to display a downward trend, so it appears that the latency differential has a negative effect on the exponential discount rate. This could be symptomatic of sub-additive discounting. Figure 7.8 is harder to interpret because of the clear outlier apparent in the delay specification at 5.5 years, which relates to the combination of Q1-Q2. This can be smoothed out somewhat by using the question average data as follows:

Figure 7.9: Question average exponential discount rates against latency differential

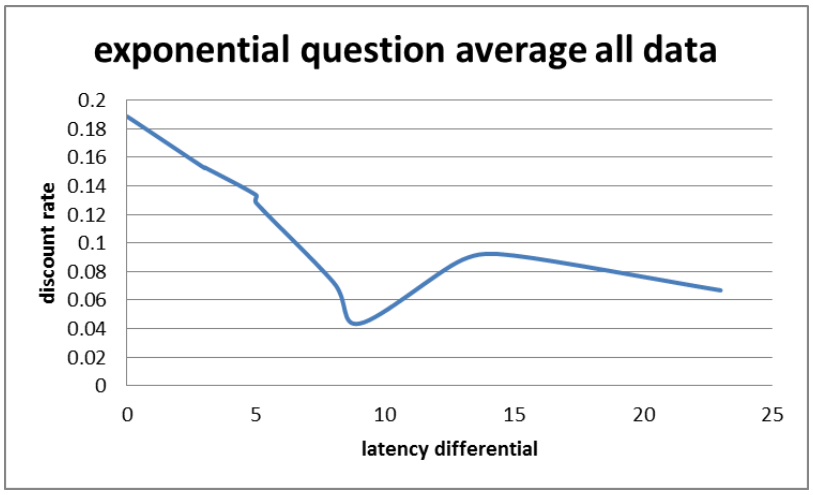
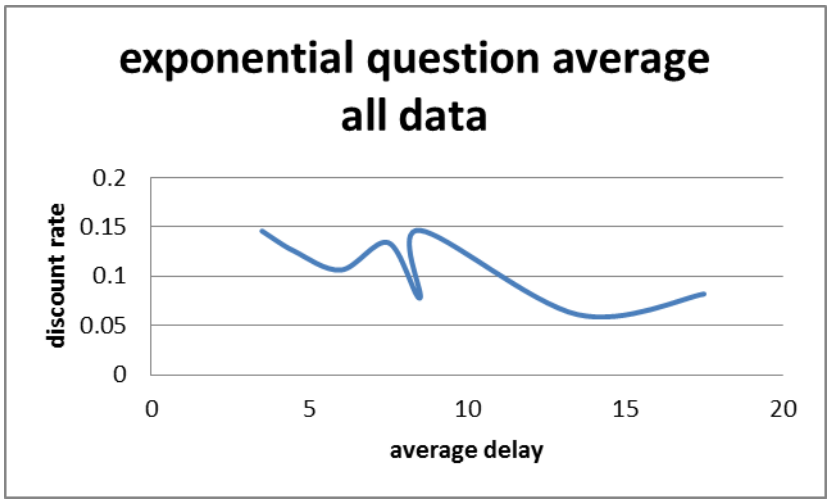


Figure 7.10: Question average exponential discount rates against average delay



Again, peculiar behaviour can be seen around the 9 year differential mark which indicates behaviour in Q1 that is anomalous compared to the rest of the sample. The plots are re-run without Q1 and also without Q1 or Q10 in order to remove the influence of both questions over which concerns had been raised (see Section 7.5.2.i). The plots are provided in Appendix G. This smooths the graph over the latency differential, but not over average delay. This might suggest that there is something fundamentally non-linear about the way that the discount rate behaves with respect to delay, which is not related to anomalous answers. To explore how the data appears when smoothed, Lowess regressions are run, and reported in Figures 7.11 and 7.12.

Figure 7.11: Lowess smoothing sample average exponential discount rates against latency differential

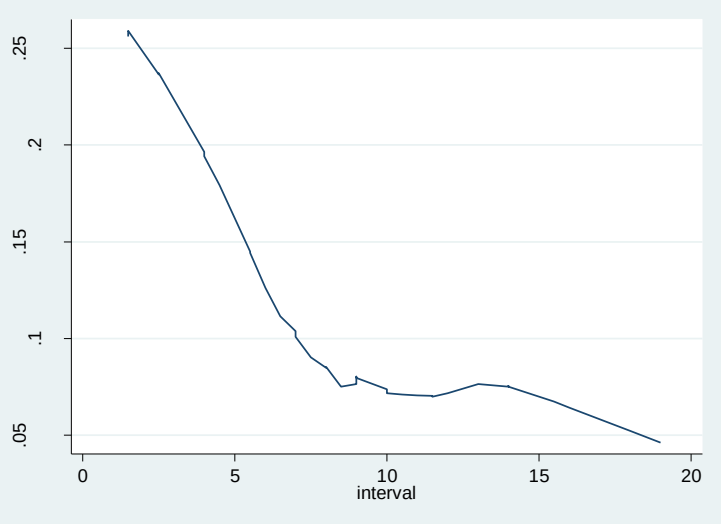
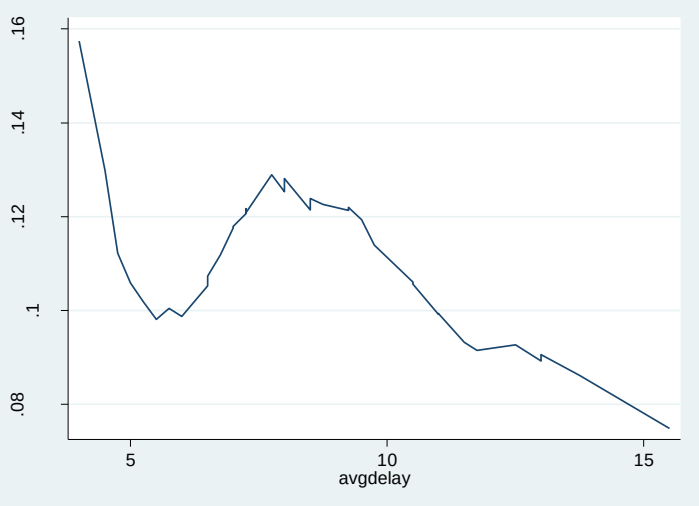


Figure 7.12: Lowess smoothing sample average exponential discount rates against average delay



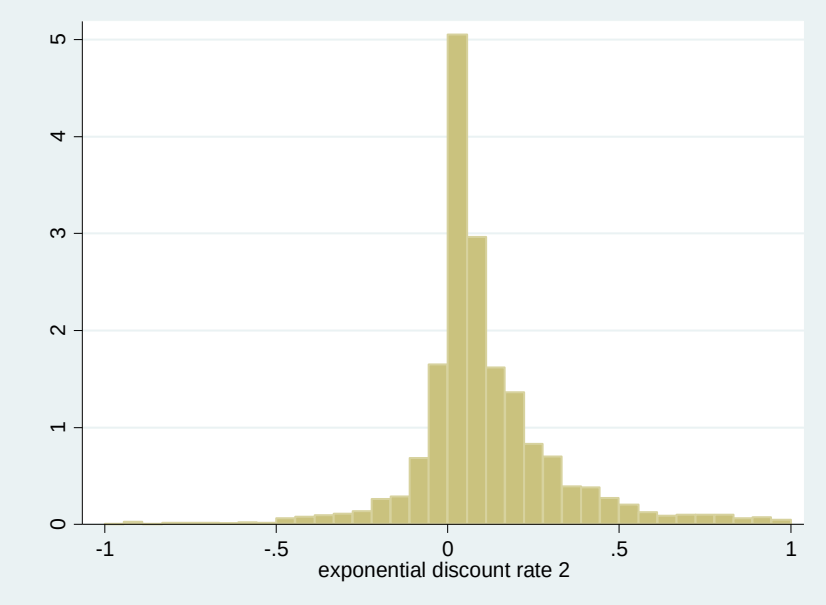
As expected, the function for the latency differential is smooth and decreasing while the function for the average delay is not monotonically decreasing. However, in all it does appear that the exponential discount rate declines both with the average delay and with the latency differential.

7.5.6.ii *Exponential discount rates- individual level*

In exactly the same way as for the sample average relativities, exponential discount rates are elicited on an individual level. The mean discount rate is 12.0% (s.d. 42.0%) and the median is 6.0%. Again, this falls within the range in Table 2.1 (Chapter 2) which outlined existing estimates in the literature.

The discount rates can be represented as a histogram, as shown in Figure 7.13. Observations that fall outside the bounds + or -1 are excluded, in order to 'zoom in' and display the shape of the distribution of discount rates. There is a peak at zero or low discounting and the majority of observations are positive, but with some exceptions. The data have long tails in both directions.

Figure 7.13: Exponential discount rate from fatality risk relativities (Zoomed in to between -



Eliciting the exponential discount rates on the per-person level generates a sample incorporating up to 43 rates per person, so regressions can be run on this (pooled) sample with some degree of confidence.

7.5.7 *Regression on attributes*

Initially, regressions are run on variables that capture aspects of the timing of the scenarios. If the exponential discounting function is appropriate, regression of the discount rate on the latency differential or on the average delay should generate an insignificant coefficient on the timing variable. The same can be said for the timing of the soonest risk and of the latest. Significance of any of these coefficients indicates non-standard discounting. However, the simple plots on the sample level did suggest a negative relationship in both the average delay and the latency differential specifications, and as such it would be unsurprising to find significance.

The results are clustered on the individual as opposed to on the question[42]. Robust standard errors are estimated. The results are presented in Table7.11.

Table 7.11: Exponential, per-individual discount rate: regressions on scenario attributes

Discount rate	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
	N=4345	N=4345	N=4345	N=4345	N=4345
	R^2=0.014	R^2= 0.017	R^2= 0.004	R^2=0.017	R^2= 0.001
latency differential	-	**-0.013***** (0.002)	-	**-0.014***** (0.002)	**-0.011***** (0.003)
Average delay	-	-	**-0.010***** (0.004)	0.003 (0.004)	-0.000 (0.003)
Delay until soonest road accident risk	**0.005***** (0.002)	-	-	-	-
Delay until latest cancer risk	**-0.006***** (0.002)	-	-	-	-
C10R1dum	**-0.035**** (0.014)	-	-	-	**-0.023**** (0.011)
C10R10dum	**0.050*** (0.027)	-	-	-	0.028 (0.030)
Constant	**0.208***** (0.044)	**0.229***** (0.028)	**0.207***** (0.039)	**0.213***** (0.039)	**0.223***** (0.042)

Model (1) picks up the influence of the timing of the earliest and latest risks and as predicted by non-standard discounting the sooner the soonest risk, the higher the discount rate. The rates decline over time as the latest risks are postponed. A dummy variable for $C_{10}R_{10}$ is included because of the potentially anomalous behaviour seen in response to this question as discussed above. Comparisons including the $C_{10}R_{10}$ question tend to elicit significantly higher discount rates, the reason for which is unclear. Although the dummy for $C_{10}R_1$ is significant, its sign is negative suggesting that the average discount rate is lower when one of the four scenarios is road accidents in the very near future. This is opposite to the quasi-hyperbolic prediction but can be explained by the fact, recorded qualitatively by some respondents, that while they are

[42] It was considered that individual-specific homogeneity in answering the questions would be more important than question-specific homogeneity because of the wide range of between-individual heterogeneity in answering and the relative stability of responses within individuals across questions. Also attributes of the questions are investigated using the dummy variables for timing.

students they rarely drive but during the year after next they will have graduated and hence be in cars more often. However, further tests (not reported here) suggest that including these variables does not appear to destabilise the coefficients on the other significant parameters.

Models (2)-(5) explore latency differentials and delay as explanations for the discount rate. Model (2) includes the latency differential, whose coefficient is negative and significant at the 1% level. That is, the outcomes where the latency differential is larger are discounted less than those where the outcomes are closer together. This provides support for the theory of sub-additive discounting. Model (3) repeats this analysis using delay as the timing variable and finds a similar result: the longer the average delay involved in the generation of the discount rate, the lower the rate is likely to be. This is in line with the theory of hyperbolic discounting but not incompatible with sub-additive discounting.

Model (4) addresses the problem that the delay parameter might simply be acting as a proxy for the interval between the two outcomes. As such, both are included and the coefficients can be interpreted as the effect of one timing variable when controlling for the other. This time, delay is insignificant even at the 10% level, while the significance of the latency differential is maintained and the coefficient appears to be stable. Model (5) extends model (3) to control for the influence of the 'outlier' questions $C_{10}R_1$ and $C_{10}R_{10}$. The pattern of sign and significance is robust to their inclusion.

Taken together, these results suggest a declining pattern of discount rates with latency differential, indicating elements of non-standard discounting. While the delay parameter is negative and significant, it is not robust because the inclusion of the latency differential removes the significance of delay. It is likely that the negative coefficient on delay simply reflects its role as a proxy for the latency differential.

It is not possible to reliably test for quasi-hyperbolic discounting with these data. The discussion above of the significant negative coefficient on the dummy for $C_{10}R_1$ suggests that the dummy for road accident risks now might be picking up more of a baseline risk effect than a discounting effect, and therefore it cannot be claimed that the result provides any reliable insight into the presence or absence of quasi-hyperbolic

discounting in the traditional sense. The analysis will therefore consider only exponential, simple hyperbolic[43] and sub-additive discounting.

7.5.8 Regression on attributes and demographics

A great advantage of using information at the level of the individual is that demographic and preference-related characteristics can be controlled for. As discussed, information is available on basic demographics, on exposure and experience with the risks in question, and also on preferences over time in the financial domain. The models are threefold: model (1) incorporates preference related characteristics, model (2) observable demographics, and model (3) incorporates all of these explanatory variables.

Table 7.12: Exponential, per-individual discount rate: regressions on scenario attributes and demographics

Discount rate	Model (1) N=3606 R^2= 0.010	Model (2) N=3770 R^2= 0.001	Model (3) N=3065 R^2= 0.019
Self-Reported road accident risk	-0.019	-	-0.022
	(0.017)		(0.017)
Experience of cancer	-0.009	-	**-0.042****
	(0.020)		(0.018)
Health state	-0.008	-	-0.008
	(0.022)		(0.018)
Health risk aversion	0.029	-	**0.033***
	(0.018)		(0.018)
Financial time preference	0.097	-	-0.036
	(0.173)		(0.131)
Financial risk preference	-0.015	-	0.006
	(0.027)		(0.016)
Road accident experience	0.044	-	**0.076*****
	(0.027)		(0.024)
Female	-	0.021	0.014
		(0.021)	(0.021)
Age (years)	-	0.000	0.000
		(0.006)	(0.006)
Household income	-	-0.000	0.000
		(0.000)	(0.000)
Constant	0.084	0.100	0.091
	(0.024)	(0.117)	(0.119)

[43] In principle the methodology could be extended to capture quasi-hyperbolic effects if personalised baseline risks could be presented and controlled for.

Exponential financial discount rates as inferred from the financial intertemporal trade-off questions (see pg.204 for a discussion) are insignificant in explaining the size of the discount rate. In fact, no demographics or preference related characteristics are able to explain the discount rate when either observable (in model (1)) or preference-related (in model (2)) characteristics are considered separately. This includes the risk preferences defined over health as elicited in Chapter 6, but also the financial risk preference proxies. In Study 1, it was shown that preferences over latency were intrinsic and unrelated to demographics. This result appears to have been replicated here, because preferences over time are not dependent upon characteristics or experience. However (in model (3)), which pools models (1) and (2), the parameters on cancer experience, road accident experience and risk aversion in health all become significant. The reason for this is unclear.

In summary, the discount rate seems mostly intrinsic to the individual and is largely unrelated to personal characteristics. The wide spread of discount rate values suggests a substantial heterogeneity in discounting preferences in this sample. This might imply heterogeneity in terms of whether exponential discounting or non-standard discounting best reflects their preferences for intertemporal outcomes. The following Section looks in more detail at this issue, categorising individuals into their most appropriate discounting 'types'.

7.5.9 *Classification of individuals*

First, the method for classifying individuals into discounting types is explained. Then individuals are classified as exponential or non-standard, and Probit analysis is presented which aims to explain the difference in terms of demographics. The next stage is to identify likely hyperbolic and sub-additive discounters amongst those who are non-standard in their discounting behaviour. Further Probit analysis is used to explain this categorisation. The following Section considers how to elicit discount rates for these individuals.

7.5.9.i *Method*

The two indicators of non-exponential discounting used in this analysis are that the discount rate declines with increasing length of the latency differential (sub-additive discounting) and that the discount rate declines with the delay when controlling for the differential (hyperbolic discounting). As such, for every individual (n-112), OLS

regression of their own inferred exponential discount rates on the latency differential and delay is conducted, and the label 'non-exponential' is assigned to any individual whose coefficient on one or both of the latency variables significantly differs from zero. Subsequently, for the non-exponential discounters, the significance and sign of the coefficient(s) is examined to categorise them as 'hyperbolic', 'sub-additive', 'both' or 'other'. The n for each of the 104 regressions is usually 43, reflecting the maximum combinations of questions into pairs for the elicitation procedure (see pg.220) although for 8 individuals n is 34 (because the respondent did not answer one of the 10 questions). Four further respondents had between 14 and 27 elicited exponential discount rates. 8 individuals were dropped because they did not answer enough questions to elicit the coefficient (the n for the regressions would be ten or below).

7.5.9.ii *Exponential versus non-standard discounting*

Any respondent with significant coefficients on one or both of the latency differential and delay parameters is classed as a non-standard discounter. Out of the usable sample of 104, 36 respondents can be classed as likely exponential discounters, and 68 as non-standard discounters. That is, one third of respondents appear to apply constant discount rates across all time periods, regardless of the delay or the latency interval under consideration. It should be noted that any respondent that consistently displayed zero discount rates would classify as an exponential discounter by these criteria.

Table 7.13: Probit analysis on risk and time

PROBIT: Exponential	n=87 LL= -52.25, Pseudo R2 = 0.0546 Coef. (Standard Error)
Financial time preference	1.551
	(1.315)
Time preference estimate (physical risk)	0.703
(Q2-3 exponential)	(1.426)
Financial risk preference	0.378
	(0.252)
Health risk preference	**-0.286***
	(0.156)
Constant	**-0.805*****
	(0.290)

Probit analysis of the likelihood of being an exponential discounter does not generate any significant coefficients, either for the preference-related parameters, risk preferences or financial time preferences. This suggests again that discounting is an intrinsic personal characteristic and cannot be explained by demographics or other preferences. The variable selection tool *vselect* in Stata suggests that the most influential factors are financial time preference, financial risk preference and health state risk aversion. A regression on only (health and finance versions of) risk and time preference generates significance on the coefficient on the health-state risk aversion. The more risk averse a person is over health states, the more likely they are to display non-standard discounting, with a preference for avoiding risk increases sooner. The full Probit results are provided in Appendix J, but the model on risk and time preferences is provided in Table7.13.

7.5.9.iii *Non-standard discounting: hyperbolic, sub-additive, both or other?*

Having established that exponential discounting can only account for around 35% of the sample, it is interesting to examine how the remaining 65% behave. Recall, those categorised as 'sub-additive' have discount rates that decline with the interval between the outcomes, and those categorised as 'hyperbolic' have discount rates that decline with the delay from the present until the outcome. The two classifications are not mutually exclusive, unlike exponential versus non-standard. Alternatively, individuals may have discount rates that increase with one or both of the time variables, although there is no discounting theory to explain this in the health and physical risk domains[44].

'Tight' and 'weak' levels of each of sub-additive and hyperbolic discounting can be defined. Tight classifications are where the coefficient on the relevant parameter is negative and significant, and the coefficient on the other parameter is insignificant. Weak classifications allow the coefficient on the other time variable to be positive and significant. The classifications are summarised in Table 7.14.

[44] In financial theory, "liquidity preference theory" explains the observation that interest rates are sometimes higher for securities held over longer periods of time, which is analogous to the observed positive relationship between interval or delay and the discount rate. However, the financial theory is based on price risk and the costliness of extending shorter investments, and as such appears not to translate well intuitively into the health domain.

Table 7.14: Classifications

Classification	Coefficient on Delay	Coefficient on Interval	N (% of usable sample of 104)
Tight exponential	insignificant	insignificant	36 (34.6%)
Tight hyperbolic	negative significant	insignificant	12 (11.5%)
Tight subadditive	insignificant	negative significant	25 (24.0%)
Tight both	negative significant	negative significant	2 (1.9%)
Tight other	positive significant	positive significant	1 (1.0%)
Weak hyperbolic	negative significant	unspecified	16 (15.4%)
Weak subadditive	unspecified	negative significant	43 (41.4%)
Weak both	Unspecified but significant	Unspecified but significant	21 (20.2%)
Weak nonstandard	Significant (at least one coefficient)	Significant (at least one coefficient)	68 (65.4%)

As discussed, 35% of the sample classify as exponential discounters because the discount rate does not depend on the delay or on the interval between the outcomes under consideration. Of the remaining 65%, 40 respondents belong to the 'tight' specifications of the 'hyperbolic', 'sub-additive', 'both' or 'other' categories. Table 7.14 clarifies the distinction. That is, 38% of the sample can be unambiguously classified within the different definitions of non-standard discounting.

The majority of non-standard discounters can be characterised by a sub-additive discounting function, and these individuals comprise 24% of the sample. Those best categorised by a hyperbolic discount function comprise just 11.5% of the sample. One individual had positive and significant coefficients on both time variables, suggesting a discount rate that increases with both delay and interval. Two had negative and significant coefficients on both, suggesting that a hyperbolic-based sub-additive discount function best applies.

27% of the sample does not class as exponential or unambiguously as hyperbolic, sub-additive, both or other. This is because of the restriction in the 'tight' specification that the alternative coefficient must be insignificant. In fact, four respondents had negative and significant parameters on delay (so were weakly hyperbolic) but positive and significant coefficients on the interval. A more substantial subset, comprising 18 respondents, had a negative significant coefficient on the interval (so were weakly sub-additive) but a positive coefficient on delay. Extending to this broader definition,

hyperbolic discounting categorises 15% of the sample while sub-additive discounting categorises 41%. This is further evidence that sub-additive discounting better mirrors the majority of the sample.

Even using the 'weak' definition, the sample sizes are very small for Probit analysis. However, it is conducted for completeness and the results are reported in Table 7.15. No demographics or preference related characteristics are significant in explaining the likelihood of being a sub-additive discounter according to the full model. However, having experience of road accidents appears to reduce the likelihood that the individual classifies as a hyperbolic discounter, the reason for which is unclear. The *vselect* tool suggests that the optimal fit model for the hyperbolic case is simply to use the road accident risk as the single explanatory variable. The sub-additive case, however, suggests that risk preference variables are important. As such, and for comparison with the exponential case in Table 7.13 above, Probit analysis is repeated based on risk and time preference information.

This Probit on risk and time preference fails to find any significant parameters for the hyperbolic case. Previously, the significant variable was road accident experience, which was shown to reduce the likelihood that the discount rate declines with delay. Arguably, having had road accident experience could be related to an increased dread of risks that are sooner, which would go some way to explain the negative coefficient. However, the health related risk and time preferences are much more effective in explaining the discounting classification for the sub-additive case. High health-related risk aversion and low (physical) discount rates appear to increase the likelihood that the elicited exponential discount rate declines with the interval between the two fatality risks. This suggests that the factors taken into consideration by the hyperbolic and sub-additive discounters might be quite different. The Probit results are reported in Table 7.15.

The health risk aversion coefficient reduces the likelihood of being either exponential or sub-additive, which might suggest that it increases the likelihood of hyperbolic discounting. While this is insignificant in Table 7.15, this may of course be an artefact of the small sample of hyperbolic discounters. Interestingly, it appears that time preference elicited from the risk-risk survey (defined exponentially and treated as a proxy) helps to explain the likelihood of sub-additive discounting, but not the likelihood of exponential discounting. It is unclear why this is the case.

Table 7.15: Probit analysis: classification of non-standard discounting

PROBIT	Weak hyperbolic n=87 LL= -36.47, Pseudo R2 = 0.0060 Coef. (Standard Error)	Weak sub-additive n=87 LL= -55.35, Pseudo R2 = 0.0671 Coef. (Standard Error)
Financial time preference	-0.127	-0.289
	(1.605)	(1.291)
Time preference estimate (physical risk) (Q2-3 exponential)	0.380	**-3.431***
	(1.820)	(1.760)
Financial risk preference	-0.171	-0.249
	(0.283)	(0.250)
Health risk preference	0.056	**0.298****
	(0.167)	(0.151)
Constant	**-1.017*****	0.042
	(0.337)	(0.281)

In all, it appears that risk and time preferences have some role to play in determining whether an individual's discount rate is sensitive to timing or not. The insignificance of other demographics further reinforces the continuing theme that demographics are poorly equipped to explain aspects of preferences that have, in the literature, typically been assumed exogenous. This is reassuring for the continuation of this assumption, although it appears that controlling for risk and time preferences may be important.

7.5.10 *Summary of basic relativities and exponential discounting analysis*

So far, this analysis has considered how the responses depend upon the time frames of the scenarios in the main risk-risk questions from which they are elicited. The result from Study 1 is replicated here: that the relativity declines significantly with the differential between the latency periods under consideration.

However, the design of the survey allows a much more in depth investigation of time preferences than was possible in Study 1. As such, the assumption made in Study 1 and in much of the existing literature- that latency can be entered linearly into the regressions explaining the relativities- could be examined. To do this, (up to) 43 individual discount rates were elicited per respondent, and 43 rates were elicited on the sample level, assuming an exponential functional form. These elicited exponential discount rates were analysed to test for any influence of the timing of the risk increase

scenarios, because if so, this is evidence against the exponential discounting hypothesis. Timing was considered in two ways: the average delay from the present until the risk increases and the interval between the two risk increases. Sensitivity to these timing elements indicates hyperbolic and sub-additive discounting, respectively. Regression analysis showed that the discount rates are sensitive to the latency interval, and that they show some sensitivity to delay. As such, the assumption of exponential discounting does not appear to hold for the sample as a whole.

To evaluate what proportion of the sample appears to be characterised by which discounting assumption, regressions were run of the individual elicited discount rates on latency interval and delay, and on this basis respondents were categorised by their most suitable discounting type. It appears that sub-additive discounting characterises the majority of respondents, with exponential discounting the second most common and hyperbolic third. A minority of respondents gave answers that could not be easily characterised by hyperbolic, sub-additive or exponential discounting functions. Probit models had low goodness of fit in explaining the categorisation, suggesting that discounting functions, similarly to the discount rates themselves, are largely unrelated to respondents' characteristics. The exceptions to this include health risk preferences which appear to be significant in explaining some of the categorisation.

Because the analysis so far has found that for the majority of respondents the standard exponential assumption appears to be unsuitable, discount rates will be elicited on an individual and sample level using the hyperbolic and sub-additive assumptions. This allows a menu of discounting options that could categorise the sample.

7.5.11 *Eliciting hyperbolic and sub-additive discount rates*

Given that a large proportion of the sample cannot be classified as exponential discounters, discounting parameters need to be elicited under the alternative assumptions of hyperbolic and sub-additive discounting. The elicitation procedure is similar to that for the exponential rates, described in Section 4.11 in Part II. Again, simultaneous equations can be used to elicit the parameters in question. However, the equations to be solved are different.

This Section sets out the discounting assumptions and then provides the results of this estimation procedure. The full derivation for each assumption is provided in Appendix F.

7.5.11.i *Generalised hyperbolic*

Recall that the C_TR_t relationship is

$$C_TR_t = (1+x) * \left(\frac{(1+\delta T)}{(1+\delta t)}\right)^{\gamma/\delta} \quad (87)$$

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

$$\varphi = \left(\left(\frac{(1+\delta T)}{(1+\delta t)}\right) * \left(\frac{(1+\delta t')}{(1+\delta T')}\right)\right)^{\gamma/\delta} \quad (88)$$

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

$$\varphi = \left(\frac{(1+\delta t)}{(1+\delta T)}\right) * \left(\frac{(1+\delta T')}{(1+\delta t')}\right) \quad (89)$$

While this is one equation in one unknown, it is not always possible to find a solution without resorting to complex numbers. This is likely due to the functional form assumed.

7.5.11.ii *Sub-additive (exponential base)*

For the sub-additive exponential (SAE) case, the C_TR_t relationship is

$$C_TR_t = (1+x)\delta^{(T-t)^s} \quad (90)$$

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

$$\varphi = \left(\frac{\delta^{(T-t)^s}}{\delta^{(T'-t')^s}}\right) = \delta^{[(T-t)^s-(T'-t')^s]} \quad (91)$$

$$\delta = e^{\left(\frac{ln\varphi}{[(T-t)^s-(T'-t')^s]}\right)} \quad \delta = e^{\left(\frac{ln\varphi}{\left[\sqrt{(T-t)}-\sqrt{(T'-t')}\right]}\right)} \quad (92)$$

The estimation of the parameters δ, s is not straightforward, especially given the way that they enter into the equation. Assuming s=0.5 allows some simplification of the estimation procedure, with the equation for solution being

$$\delta = e^{\left(\frac{ln\varphi}{\left[\sqrt{(T-t)}-\sqrt{(T'-t')}\right]}\right)} \quad (93)$$

7.5.11.iii *sub-additive (hyperbolic base)*

Finally, for the sub-additive hyperbolic (SAH) case, the C_TR_t relationship is

$$C_T R_t = \frac{(1+x)}{(1+\delta(T-t)^s)} \quad (94)$$

As such, in this case

$$\varphi = \left(\frac{(1+\delta(T'-t')^s}{(1+\delta(T-t)^s}\right) \quad (95)$$

As with the generalised hyperbolic discounting model, the estimation of the parameters δ, s is not straightforward. Again assuming s=0.5 allows some simplification of the estimation procedure, with the equation for solution being

$$\delta = \left(\frac{1-\varphi}{(\varphi\sqrt{(T-t)}-\sqrt{(T'-t')}}\right) \quad (96)$$

From these equations, the parameters can be elicited on an individual level or for the sample in aggregate. The geometric mean and median values for the individual discount rates are provided in Table 7.16 with the exponential case for comparison, alongside the maximum likelihood estimates for each discounting functional form assumption.

The maximum likelihood estimates of the discount rates under each assumption are calculated using all of the data with the exception of cases where the individual had not switched by 1000 in 60 million. This is to allow the estimation tool to find a starting range of values, without which the estimation procedure fails.

Table 7.16: Discounting parameter summary

	Arithmetic mean and 95% CI	Median and 25:75 percentiles	Maximum likelihood estimate and standard error
Exponential	0.119	0.064	0.0169
	[0.106,0.133]	[0.00,0.190]	(0.005)
Hyperbolic	2.31*e^11	-0.011	0.0205
	[-1.1*e^11,	[-0.197, 0.073]	(0.007)
	1.51*e^12]		
Sub-additive	1.14*e^13	0.719	0.8708
exponential	[-9.3*e^12,	[0.41, 1.00]	(0.032)
	3.22*e^13]		
Sub-additive	14.703	-0.191	0.0672
hyperbolic	[-12.20, 41.61]	[-0.58, 0.20]	(0.019)

The arithmetic mean can be discarded because it is affected by extreme outliers to such an extent that the resulting values are implausible for both hyperbolic and sub-additive exponential rates. Using the median, negative rates are found on average for both the hyperbolic and the sub-additive hyperbolic cases. This does not agree with the finding throughout this Chapter that positive discount rates are applied (for example, see the diagram on pg.211 which depicts the relativities declining with latency). As such, the maximum likelihood estimates can be considered to be the most informative. The values and their implications are discussed in Section 7.6.

7.5.12 *Summary*

The analysis first confirmed that the cancer to roads relativities decline with the latency period under consideration. As such, the analysis was quickly able to verify that the appropriate effective discount rates for the sample in aggregate are positive. This corresponds to the majority of the existing literature on discounting in the domains of health and physical risk (see Table 2.4).

However, this Study was designed to allow a much more detailed investigation of the effects of latency and the effective discount rates underpinning the choices made in the survey. The Chapter sets out three main hypotheses about the discount function. These are:

1) Exponential discounting: implying discount rates that are constant over time
2) Hyperbolic discounting: implying discount rates that decline with the delay until the outcome
3) Sub-additive discounting: implying discount rates that decline with the interval between the outcomes

These discounting hypotheses were tested using a two-stage procedure. First, discount rates were elicited for each of the 43 combinations of questions. This resulted in a sample of 43 exponential discount rates, each with associated underlying timing indicators. Second, simple OLS regressions were run on these 43 discount rates, with the explanatory variables being the average delay until fatality and the interval between the times of the two fatalities. The significance and sign of the coefficients on these variables were used to infer which discounting assumption best suited the respondents' choices. This two-step procedure was carried out on the sample level (using discount rates inferred from the sample average relativities) but also for each individual separately (using the discount rates based on their own relativities). This allows analysis on both the individual-specific and sample levels.

The conclusion on a sample level was that sub-additive discounting behaviour best reflects the sample in aggregate, because the latency differential was more robustly significant than the delay in explaining the elicited discount rates. For the elicitation on the individual level, sub-additive discounting is the most common category, followed by exponential discounting and then hyperbolic discounting. This lends support to the work of Read (2005), although the evidence comes from a different domain.

Given that the majority of the sample displayed non-standard discounting, effective discount rates were then elicited under both of the alternative discounting assumptions. In total, four different discount rates were elicited for each individual and at the sample level, one for each discounting functional form assumption. These were given in Table 7.16.

7.6 Discussion

Exponential discounting is often argued to be the most suitable or normatively appealing discounting function, because it does not result in inconsistent preferences and decisions over time. However, the empirical evidence provided in Study 2 suggests that the exponential discounting assumption does not fully reflect the preferences of individuals in this sample. As such, imposing constant discounting might result in intertemporal allocations of resources that are sub-optimal from the perspective of the present.

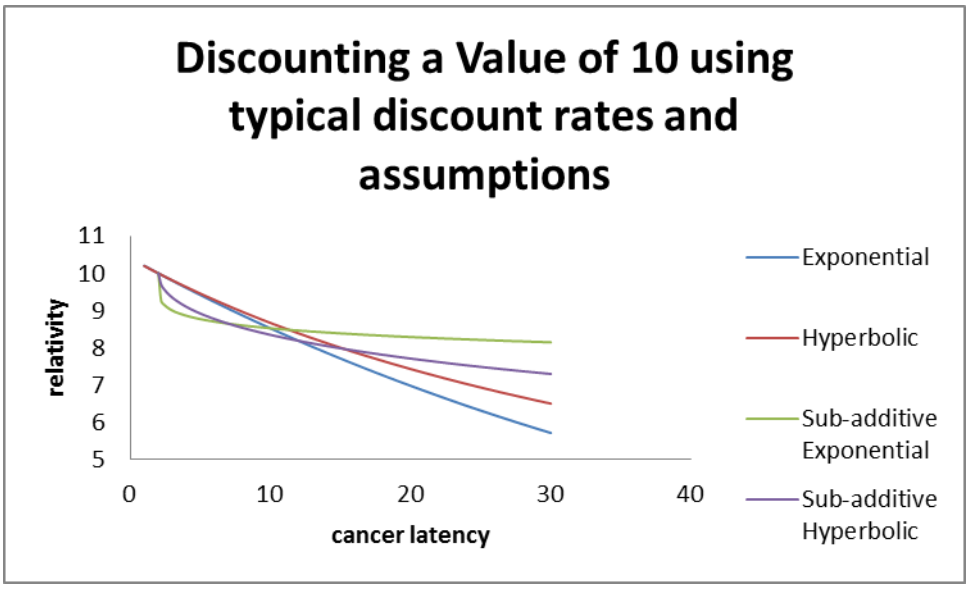
The implications of the four different discounting assumptions can be demonstrated using Table 7.17 which shows the decline in value of a hypothetical outcome over a period of time. Each of the discount rates (maximum likelihood estimates) and discount functions combine to generate the present value of an outcome with immediate value 10, but which would occur at 5, 10, 20 or 40 years from now.

Table 7.17: Decline in value in alternative discounting frameworks

Delay from the present	Exponential	Hyperbolic	Sub-additive exponential	Sub-additive hyperbolic
0	10	10	10	10
5	9.19	9.07	8.50	8.69
10	8.45	8.30	8.40	8.25
20	7.13	7.09	8.30	7.69
40	5.09	5.49	8.19	7.02

The outcome loses its value more quickly over the shorter time periods under the sub-additive assumptions than under the exponential and the hyperbolic, but its value then declines only very slowly. The exponential and hyperbolic assumptions both result in a loss of value which is much more pronounced. The classic pattern of a higher initial drop with but lower loss over longer time frames can be observed for the hyperbolic function, as compared with the exponential.

Figure 7.14: Discounting a value of 10 under each discounting assumption



Clearly, the very slight loss in value over the 20 year time frame for the sub-additive cases contradicts the direct finding in the result for Q3 ($C_{25}R_2$) where the relativity was significantly lower than in Q2 ($C_{10}R_2$), as a result of the cancer being postponed for 15 years. This result warrants further empirical investigation.

This Chapter has provided a framework for eliciting time preferences from survey data over physical risks, and has established that that a large proportion of the sample appears to use non-standard discounting functions. This suggests that the standard procedure of assuming constant discounting over time is likely to be an over-simplification. Whether this simplification is justified by the normative aspects of the exponential discounting framework is a question for policy. This question is considered in Part IV, which provides policy insights and conclusions.

PART IV: DISCUSSION, POLICY RECOMMENDATIONS AND CONCLUSIONS

Chapter 8. Discussion, Policy Recommendations and Conclusions

8.1 Summary

This thesis aimed to disentangle the effects of context and latency on the relativity between the Value of Preventing a Statistical Cancer Fatality (VSL_{CAN}) and the VSL for road accident fatalities. Achieving this aim would facilitate policy analysis where the risk of latent cancer fatalities is likely to change. In addition, it would add to the growing international literature on the VSL_{CAN}. To fully understand the VSL_{CAN} requires exploring and quantifying two main effects. These are the context effect, which includes the effect of additional morbidity prior to fatality as well as any dread of the cause 'cancer'; and the latency effect which incorporates time preferences and risk preferences.

To this end, two stated preference studies were conducted. Study 1 addressed the full VSL_{CAN} :VSL comparison. Its main aim was to verify the hypotheses that the context of cancer increases the VSL and that latency decreases it. In doing so, it addressed questions about morbidity and label dread. Verification of these hypotheses allowed the VSL_{CAN}:VSL relationship to be distilled into a simple relationship, referred to as C_TR_t. This reduces the comparison between the standard roads VSL and the cancer VSL to a simple relationship whereby VSL_{CAN} is assumed equivalent to the roads VSL inflated for context effects by the context premium (1+x) and then discounted at an effective discount rate r back to its present value. This relationship allows the elicitation of the underlying r and x parameters using simple algebra and relativities data.

However, the treatment of latency in study 1 was necessarily limited to a subset of questions to allow dread, morbidity and context to be considered as well. This limitation motivated study 2 which specifically focussed on the implications of latency on the VSL. Because delayed outcomes are inherently risky, the exploration of latent outcomes would not be complete without controlling for risk preferences. A gap was seen in the current literature in that the theoretical and empirical frameworks for eliciting risk aversion coefficients in the domain of health have not been fully developed. This was addressed in study 2a in chapter 6. With the proxy for health risk aversion developed, the analysis turned to considering the appropriate rate and functional form at which latent cancers are discounted. The C_TR_t relationship developed and verified in study 1 was adapted to allow for different discounting hypotheses, and analysis was performed a the sample level and at the level of the

individual which aimed to discover what functional forms and rates are the most appropriate in characterising choice behaviour in the RR questions in study 2b.

Through these studies, some important empirical findings emerged. In addition, methodological and theoretical contributions were made which have the potential to enhance future research into VSL questions as well as wider studies involving latent or risky health and safety outcomes. These contributions are outlined in the next section. Finally, the implications for policy[45] are outlined in section 8.4 and future research questions are presented in section 8.5.

8.2 Findings and Contributions

8.2.1 *Study 1 findings*

Study 1 provided insight into the preferences of members of the public over the VSL_{CAN}:VSL relativity, and in the process it provided evidence about the significance and magnitude of context, morbidity, label dread and latency effects in explaining this relativity.

The main empirical contribution was that the VSL_{CAN}:VSL relativity, including 10 years of latency, is indistinguishable from 1:1. For longer latency periods this was shown to fall to a value significantly below 1:1. This result is also the main policy implication for the chapter and will be re-iterated in the policy implications section. However, in establishing the 1:1 relativity, three additional insights about the underlying effects were generated.

First, it was confirmed that when controlling for time, a cancer fatality (incorporating illness) was held at a 40% premium compared to road accident fatality. Second, the somewhat surprising result was made that this context premium was not generated by a particular dread of the label 'cancer' *per se*, instead being driven by the aversion to the period of morbidity prior to fatality. Finally, the effective discount rate at which the VSL_{CAN} is discounted was found to be 7.37% p.a under the exponential assumption. This is sufficient to offset the context premium for latency periods of 10 years or more. These three results confirm the prior hypotheses about the direction of the effects of

[45] It is acknowledged that in practice, any changes on the basis of the policy implications provided here would rely on the replication of these results on a large scale representative sample of the population.

morbidity and latency, but provide a new and thought-provoking conclusion that the 'label dread' of cancer seems not to apply.

The main contributions in this chapter outlined above were empirical, because the survey instrument was carefully designed to elicit strength of preference estimates. However, the chapter also made a methodological contribution through the establishment of the C_TR_t relationship (pg.53) and the procedure by which the underlying parameters r (effective discount rate) and (1+x) (context premium) were elicited. This relationship was shown to elicit reasonable parameters in study 1, and additionally proved useful in study 2 where it was demonstrated to be effective in the context of hyperbolic and sub-additive discounting.

8.2.2 *Study 2a: risk aversion findings*

While the main contributions from study 1 were empirical, in the risk aversion chapter in study 2 the main contributions were theoretical and methodological. The major methodological contribution of this chapter was to provide the framework for eliciting the risk aversion coefficient for health states. This not only involved adapting the elicitation procedure from the financial domain to the health domain and selecting a communication tool for health states, but also selecting the health state input values.

The theoretical contributions are twofold. Initially, the theoretical framework was established for eliciting parameters for health risk aversion. This involved adapting the work of Holt and Laury (2002) to the domain of health. The second theoretical conclusion was rooted in the observation that the health measures available reflect the value of health states as opposed to directly quantifying the health state. The underlying utility functions were reconsidered in light of this, clarifying the interpretation of the elicited risk aversion parameter.

The empirical results were almost of secondary concern in this chapter, whose aim was to develop the theoretical and methodological frameworks for eliciting risk aversion proxies in health. Nonetheless, the chapter provided further evidence that risk preference in health is not well approximated by risk preference defined over financial outcomes, and tentatively supports the conclusion that risk aversion in health is lower than in finance. This adds to the domain-dependence debate, and provides support for the use of alternative methods like the one developed here.

8.2.3 *Study 2b: time preference findings*

The contributions from study 2b are mostly empirical although some theoretical and methodological output was also generated. The theoretical clarification of the way that the VSL_{CAN}:VSL relativity would behave under each discounting assumption, and particularly of the way that the discount rate can be elicited under each assumption, will be valuable in future R-R studies involving latent outcomes. In addition, the method for categorising individuals by discounting type has not, to the author's knowledge, been used before. However, the empirical results are arguably more generally interesting.

The main result confirms the general finding in the literature that time discounting is not typically exponential. The novel procedure of eliciting discounting types on an individual level allows the confirmation that while exponential discounting holds for a large minority (35%) of the population, there is more support for the non-standard discounting assumptions. The findings in support of sub-additive discounting as opposed to hyperbolic are important, because the design of study 2 is unusual in allowing both delay and interval to be considered in the domain of fatality risks. The range of values for the exponential discount rate is (1-20%). A lot of variation in both the rates and the discounting functions is apparent from these results.

8.3 Comparison of Studies 1 and 2

However, before the implications for policy can be drawn it is necessary to consider to what extent the responses from study 2 can be assumed to apply to the population more generally. study 2 was conducted with a student sample while study 1 surveyed 30-50 year olds. To consider how generalizable the results are, the comparable responses from the two samples are set out and analysed in appendix L. This is kept brief, because the results are intended to be illustrative.

The samples are different in terms of demographics and sample size, and their preferences are more homogeneous. However, the two samples are very close on the central tendencies of comparable questions and the size of the elicited effective discount rate and context premium are comparable as well. In all, the student preferences do not appear to be dramatically different than the 30 to 50 year olds, so policy implications can be based on a combination of insights from both studies 1 and 2, albeit tentatively.

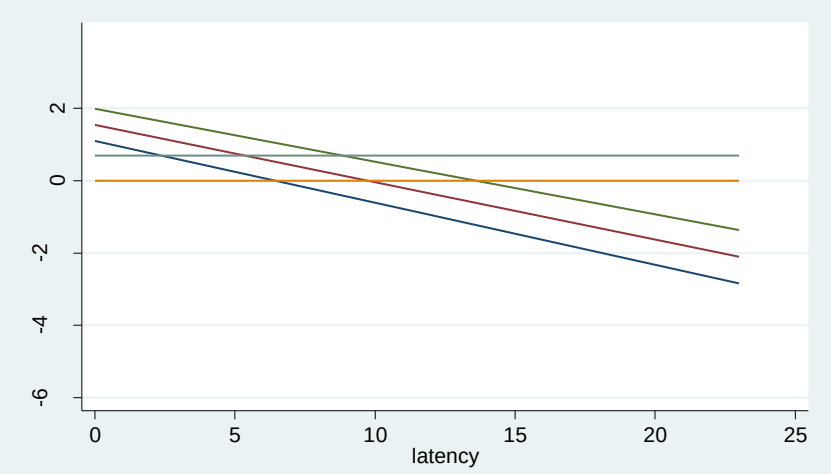
8.4 Policy Implications

The policy implications arising from this thesis can be summarised in two main categories. The first covers the 'policy numbers', which include the elicited overall cancer premium (or more accurately the lack of overall premium) and the values of 1.4 for the context multiplier and 7.37% for the effective discount rate. The second is less concrete, and relates to the appropriateness of reflecting public opinion over intertemporal choices in policy decisions. These two angles are discussed in sections 8.4.1 to 8.4.3.

8.4.1 *Policy implications: 'policy numbers'*

The main implication from study 1 is that the current practice in the UK guidance of applying a multiplier of 2 to cancer fatality risk reductions is unjustifiable based on these results. Instead, a value of 1:1 is recommended, declining below this level for long latency cancers. This is best shown using the fitted values for the C_TR_t relativity from study 1 with associated confidence intervals.

Figure 8.1: Reconstructed C_TR_t relativity for t=2 as a function of T



As explained on pg.113, the relativity is predicted as a function of latency, and plotted with 95% confidence intervals. The context dummy is set to 1 (implying a cancer to roads comparison), and the morbidity period is assumed to be 12 months. The relativity for this typical cancer as a function of latency is shown in figure 8.1. The lower horizontal line indicates the recommended 1:1 relativity (it is at zero because the diagram plots the predicted log of the ratio, and ln(1)=0). This is shown to be valid in a range from about 7 to 14 years of latency. For longer latency periods, a lower relativity

would be more appropriate. The upper horizontal line indicates the 2:1 relativity currently used in policy. This is too high for latency periods of around 8 years or more. This provides the basis for the 1:1 recommendation in this study. See Appendix K for some additional sensitivity analysis which supports the 1:1 recommendation.

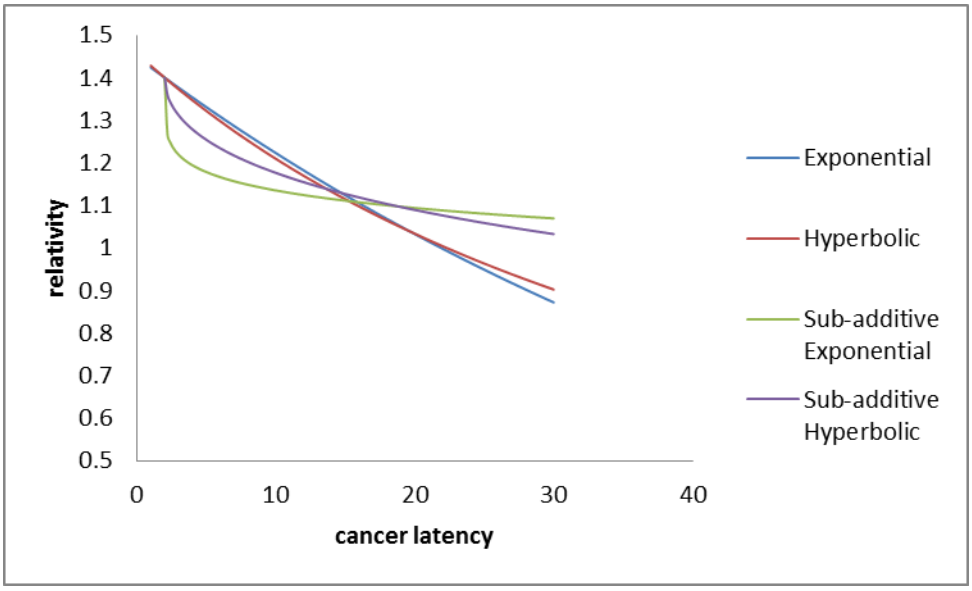
As an alternative to applying a single value for the VSL_{CAN}, policymakers could decide to use a value based on the length of latency involved in the cancer. This would require the use of a context premium to adjust for the context of cancer (and the associated morbidity). Then this value would be discounted to the present at the appropriate rate. Study 1 provided estimates for both of these values, elicited in conjunction with one another. These are a context premium (based on 12 months of morbidity prior to fatality) of 1.4 and a discount rate of 7.37%p.a.

Of course, in policy the treatment of discounting is an important issue. The magnitude of the discount rate greatly exceeds the social rate of time preference (STPR) recommended in policy, which is 1.5%. However, caution must be taken when using the context premium and applying a different discounting rate. Because x and r were elicited in conjunction, to use the x value but in combination with a different r value would necessarily imply overriding the overall relativity that best reflects the preferences of members of the public. As such, the rates should be used in conjunction with one another.

8.4.2 *Normative policy concerns: focus on discounting*

The x and r values were elicited assuming an exponential discount rate, and the results of study 2b suggest that this is not the most accurate assumption for describing the time preferences of members of the public. As discussed, the sub-additive approach appears to be more descriptively accurate for the respondents studied. Figure 8.2 shows the implications over a 30 year horizon of employing the four different discounting assumptions to a context premium of 1.4, assuming that the road accident occurs 2 years from now. The hyperbolic and exponential versions are similar, while the sub-additive versions have a more dramatic decline in relativity over the short run but then level off after around 15 years. The fairly extreme patterns with sub-additive discounting mean that perhaps more evidence is required before this discounting assumption can be adopted. On the other hand, exponential discounting gives a very different pattern of relativities and as such if sub-additive discounting does hold in aggregate, the implications for the distortion of allocative decision making are relatively serious.

Figure 8.2: Discounting a 1.4 context premium under different assumptions



However, the result is of course descriptive and not normative. It is appropriate for the policymaker to make a decision between respecting the preferences of the public despite the lack of normative appeal that non-standard discounting implies, or to override the preferences of the public essentially in the best interests of society, in order to generate time consistent decisions. It is beyond the scope of this thesis to fully explore this issue, although it ought to be noted that for intertemporal allocative decisions that will not affect future generations, the arguments for overriding the preferences of the public are not convincing. As such, the decision about which discounting function to employ may be dependent on the specific context.

8.4.3 *Overall messages for policy*

The guiding principle behind the WTP literature is that good allocative policymaking ought to reflect the preferences of members of the public. As such, the plethora of evidence regarding public valuation of non-market goods like fatality risks reflects this intention. However, respecting preferences is not as simple as just eliciting a value (VSL_{CAN}), particularly when the good in question is as heterogeneous and complex as cancer. Rushton et al.(2010) discuss the extreme variation in cancer latency and morbidity periods, and the work presented in this thesis has verified that these characteristics influence the relative value of cancer risk changes. Put simply, different morbidity and latency characteristics result in different WTP-based VSLs.

However, given the resource intensity of eliciting VSL estimates, and the vast range of latency-morbidity combinations that could characterise cancer scenarios, it is not feasible to re-estimate the VSL for every case that comes under policy scrutiny. As such, there are two options for policy. One is to use a value based on the "typical" cancer case, and in that case these results would suggest that no premium ought to be in place, if 10 years' latency and 1 year of morbidity could be considered average for a cancer. Alternatively, some benefits transfer activity could be employed, to adapt the VSL to the specific circumstances to account for the latency and morbidity periods involved. This could be extended to consider cancers with different levels of risk change and different baseline risks. If this is adopted, the results of study 2 need to be respected.

Study 2a demonstrated domain dependence in risk aversion. That is, risk preference was not directly transferable between the financial and health domains. Study 2b found similar results for time preference. As such, different levels of risk aversion and varied time preferences can be found across individuals and even within individuals across contexts. It is ultimately a question for policy whether to respect non-standard discounting, to control for attributes of the cancer scenario and to respect differences in risk attitude, and the arguments surrounding this debate are far from clear-cut. Nonetheless, the author hopes that the quality of this debate will be enhanced by the findings of this thesis and by future studies that use the tools developed here.

8.5 Questions for Further Research

A number of avenues for future research have been uncovered in this thesis. Of course, the policy implications would be strengthened by conducting this survey on a large, representative sample of the population. However, four additional areas that the author considers ripe for investigation are outlined in this section. Some of these address shortcomings in the present state of understanding, while others would simply provide additional validity to the conclusions drawn in this thesis.

- The somewhat surprising finding was made in study 1 that the context premium for cancer is driven almost exclusively by aversion to the morbidity period preceding it, as opposed to the 'label dread' that cancer is typically assumed to engender. However, the analysis was exploratory and morbidity was tested exclusively by the length of time spent ill. As such, further investigation into the way that morbidity drives the context premium would allow more flexibility

to the application of the study's findings across different types of cancer with different lengths and severities of illness prior to fatality.

- Study 2 highlighted an important gap in the present data. The health risk aversion elicitation procedure assumed that health could be measured on a cardinal scale comparable to money. However, no direct measure currently exists to quantify health states as described by the EQ-5D system. The development of such a measure would require a multi-disciplinary approach and its conceptual basis needs to be established as well as its empirical foundation. However, the existence of such a scale would have benefits beyond this study, for example allowing any economics experiments or surveys that have traditionally been defined over cash outcomes to be translated into the domain of health. The possible implications for experimental and behavioural health economics are vast.

- A more niche problem with the risk aversion elicitation, and perhaps one more easily addressed, was noted on pg.173 and relates to the time preference effect that distorts the TTO-based values for the EQ-5D health states. The approach taken in this study was to raise the TTO scores to the power of 0.8, reflecting discounting effects as estimated by Jones-Lee (2007). However, this value requires validation and possible refinement. Attema and Brouwer (2013) demonstrate a method for eliciting correction factors, and this procedure could be replicated with UK data to improve upon the 0.8 assumption used in this thesis.

- Finally, and again in the risk preference analysis (chapter 6, reporting study 2a) it was assumed that the utility over health function could be modelled like the utility of wealth function. However, the basis for this assumption is not well established. Theoretical and/or empirical work to validate the appropriateness of assuming a concave utility of health function would allow more confidence to be placed in the risk preference elicitation procedure developed in study 2a.

These areas for future research demonstrate that this thesis has the potential to be validated and extended in the future.

Appendix A. Survey Protocol for Study 1

FINAL VERSION 18/12/2011 [SLIDES = OVERHEADS (C)]
INTRODUCTION/WELCOME

[click: **SLIDE 1**: WELCOME THE RESPONDENTS. - THANK THEM FOR COMING - INTRODUCE YOURSELVES]

I will give you a brief background to the study but will be happy to answer any further questions you might have after the session has finished.

The study is funded by the Health and Safety Executive (HSE), as part of on-going research into safety and decision making. The HSE wish to take account of what the public think, to help them to advise policy makers. Essentially, safety costs money and policy makers have to choose which areas to prioritise. They want to know whether their choices reflect our choices and, if not, how they differ.

While the way we ask the questions might seem slightly strange, we will combine your answers to some tables we will ask you to fill in with the things you write down, so we can answer the specific questions that the policymakers ask us.

When answering, you should concentrate solely on your own opinions and the choices you would make for yourself. Please try not to think about other people or what they would choose. This study will eventually take place in various locations across the country and by asking a broad range of people we will get a very good idea of what other people would choose. So please just think about yourself.

There will be an introductory section first, with a chance for questions and discussions. Then there will be ten main questions, and three follow up questions. The whole process should take about ninety minutes.

We will go into quite a lot of detail before we ask some of the questions. This is meant to help you to think carefully about your answers, since your answers will be reported through to decision makers and may influence government policy.

I would also like to make it clear from the beginning that what is the right answer for you [PICK SOMEONE] might be the wrong answer for you [PICK SOMEONE ELSE] and so on. All of your answers will remain anonymous.

[PART 1: LEARNING]

[INTRODUCTORY IDEA 1: INDIFFERENCE]

Every day, we make lots of choices between options. Sometimes the choices are easy, because one option is clearly better suited to us. But sometimes they're harder, because we aren't sure which one suits us best. Sometimes, we really don't mind between the two options, because we see them as equally good. This is what we are interested in for today's session. In a few minutes, we will be choosing between risk increases.

[INTRODUCTORY IDEA 2: RISKS]

So first, let's think about what we mean by risk. A risk is the chance of something bad happening. Every day you make decisions where you are, in some way, choosing between risks: for example, if you have ever taken a medicine with possible side effects, you have chosen to take the risk of getting the side effects to avoid a higher risk of the illness itself, and if you have ever crossed a road without using a pedestrian crossing to save time, you have made a decision to take a higher risk of being hurt crossing the road to reduce the risk of being late.

So choosing between risks is not so unusual, even though we don't usually think about it in so much detail! In this study, we are interested in risks to your life.

You will be asked to think about risks like this one **[**click: **SLIDE 2]:**

RISK OF DYING
200 in 60 million

So for this example, your current risk of dying by some cause is 200 in 60 million. 60 million is approximately the population of the UK. This means that we would expect around two hundred people in the UK to die from this unnamed cause, during the coming year. Because you live here, you could be one of those 200 people (although of course you might not be!). So these are risks to yourself, and we need you to think about the increase in your own risk of dying, not anybody else's risk of dying. Does anyone have any questions?

[INTRODUCTORY IDEA 3: CHOOSING BETWEEN RISK INCREASES]

Policy makers implement policies that affect risks. However, their budget is limited. Sometimes, money has to be saved: policymakers need to make decisions about which spending reductions to implement, and therefore certain risks will increase. Because they want their decisions to reflect what you would choose (as much as possible), we will ask you to select which of your personal risks of dying you would choose to have increased, if you had to.

Just as an aside, we tend to ask about risk increases simply because we've found that people find it easier to think about them than about risk decreases. But we can use the information in your answers to help with decisions where the policymakers are implementing risk reductions too, for example when budgets are increased.

[PRACTICE QUESTION 1: INFLUENZA AND FIRE EPIDEMIC TRADEOFF]

We'll do a practice, to let you think about risks and also get used to the methods we'll be using later.

We will still be thinking about risks, but now we will name the context of the risks. Some people find that context changes the way they feel about risk increases. Others find that it doesn't matter much to them. Your answers might all be different, and that's fine; just consider how you feel.

So, let's say the causes of death were dying in an influenza epidemic, and dying in a fire in your home. **[**click: **SLIDE 3]**

Which cause seems worst to you? Who thinks fire's worst? [SHOW OF HANDS] Why? And what is it about the influenza epidemic that didn't seem so bad? And who thinks flu's worst? [SHOW OF HANDS]. Why? And what was it about fire that didn't scare you so much? Did anyone think they'd be equally bad?

[click: **SLIDE 4]** If money had to be saved in one area of the safety budget or the other, this would mean an increase in your risk of dying by one of the causes.

[ASSISTANT HAND OUT ANSWER SHEET 1]

Your answer sheet shows that the current risk of dying is about 200 in 60 million for each of the causes. Would you choose to increase your risk of dying in an influenza epidemic by 10 in 60 million, or to increase your risk of dying in a fire in your home by 10 in 60 million, if you had to?

Please write your initials and the date on the top left hand corner.

[MODERATOR GO THROUGH TABLE]

Your current risk of dying by each cause is **200 in 60 million**.
Which would you choose, if you had to:

Y	Z
An increase in your risk of dying in an **influenza epidemic** of 10 in 60 million	An increase in your risk of dying in a **fire in your home** of 10 in 60 million

Those of you who would choose Y, please circle 'dying in an influenza epidemic' like this [CLICK]. If you would choose Z, circle 'dying in fire in your home' instead [CLICK]. If you really can't choose, put an 'equals' sign between them [CLICK], which means you would be happy to let a policy maker decide for you which risk increase would happen.

Remember that one of the risk increases would eventually be chosen, and your opinion is important in helping to decide which one.

As this is a practice, I just need to check we haven't confused you: If you were more scared of fire, did you choose to increase the flu risk? And if you were more scared of flu you chose the fire risk? Remember, we're asking you to choose a risk increase, so

we'd expect you to increase the risk of the one you're least scared of. This will be important in future questions.

[THEY MIGHT SAY THAT THEY CHOSE THE ONE THEY FEAR MORE. THIS IS OK IF THEIR REASONING HOLDS (e.g. PERCEIVE THEIR RISK TO BE DIFFERENT FROM THAT PRESENTED), BUT NOT IF THEY MISUNDERSTAND (e.g. THOUGHT WE MEANT RISK DECREASE)]

Now let's practice filling in a table to record the choices you would make if the risk increases were different sizes. We'll be using this method a lot today, so we need to make sure everyone can do it, but don't worry, I'll talk you through it step by step. Please ask questions as we go along- this is only a practice.

Here is a new answer sheet [ASSISTANT HAND OUT IAS1A and IAS1B].

You should see a second table, a bit like this one…

[click: **SLIDE 5**: INFLUENZA]

For those that chose Y; the left hand column on your sheet has Y for flu and the middle column has Z for fire. Your risk increase for flu (in the first column) gets larger as you go down the table. The risk increase for fire stays the same.

Y INFLUENZA RISK INCREASE		Z FIRE RISK INCREASE	CHOICE
10 in 60 million	OR	10 in 60 million	Y
20 in 60 million	OR	10 in 60 million	
...		...	
100 in 60 million	OR	10 in 60 million	
	OR	10 in 60 million	

[click: **SLIDE 6**: FIRE] – skip if all chose flu increase

If you chose Z, your table's exactly the same, except it has fire in the first column (with risk increases that get bigger) and flu in the second column (with risk increases that stay the same)

Does everyone have the correct sheet?

Z FIRE RISK INCREASE		Y INFLUENZA RISK INCREASE	CHOICE
10 in 60 million	OR	10 in 60 million	Z
20 in 60 million	OR	10 in 60 million	
...		...	
100 in 60 million	OR	10 in 60 million	
	OR	10 in 60 million	

skip if all chose flu

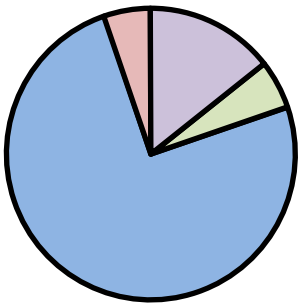
The first row's choice column is filled in for you, depending on the choice you made just before [FLICK BACK AND FORWARD BETWEEN PREVIOUS SLIDE TO SHOW "Y" AND "Z"]. I'll tell you what to do with the rest of the table in a minute. But first, let's think about what taking a bigger increase in your risk of dying really means.

[click **SLIDE 7**: PIE CHART]

This picture shows the risks you are facing now. This is not to scale. If we did draw in the 10 in 60 million increases the right size, they would be so tiny you wouldn't see them! So we've had to make the picture bigger. All it's meant to do is to help you understand the effect of a risk increase on your chance of dying. There is a small risk of dying in an influenza epidemic (pink), and an equal sized risk of dying in a fire in your home (green), this year.

There is a bigger section: this is the risk of dying from some other cause this year (purple).

The rest of the chart, which is much bigger, is your chance of not dying this year (blue).



If you choose to increase your risk of dying from flu, **[**click: **SLIDE 8]** that means you are making your overall risk of dying bigger (in other words, reducing the blue area, which represents your chance of not dying during the year)! Notice that the other 2 areas, fire and all other causes, stay the same.

In the first column of the table: the risk increase you decided to circle gets bigger and bigger. If we let your flu risk increase get bigger [CLICK, CLICK], your chance of not dying gets smaller and smaller. In the extreme, if you continued to increase your risk so much that there is no more blue [CLICK]- you would die for definite!

The same goes for fire [click: **SLIDE 9**: CLICK CLICK CLICK] So if you accept a bigger increase in your risk of dying in a fire, you are increasing your overall risk of dying during this period!

Let's look at the pie charts again in terms of the decision table. In the table, you are choosing between risk increases in the cause you chose originally, or a fixed increase in your risk of dying by the other cause. Let's see what that means...

skip if all chose

flu increase

[click: **SLIDE 10**: Flu vs Fire]

If you originally chose to increase your flu risk: You are comparing the risk increase in flu, which gets bigger and bigger [CLICK CLICK], with the fixed, small increase in your risk of dying in a fire in your home [INDICATE OTHER PIE CHART].

So the alternative to the bigger risk increase is to switch to the small increase in your risk of dying in a fire, at any row of the table.

[click: **SLIDE 11**: Fire vs Flu]

If you originally chose to increase your fire risk, this is the case for you: [CLICK CLICK]. So the alternative to the bigger fire risk increase is to switch to the small increase in your risk of dying from flu, in the right hand pie chart.

Does anyone have any questions?

skip if all chose

flu increase

[ASSISTANT HAND OUT INTRO_PIE]

So, let's go back to the table and fill in our choices together.

[click: **SLIDE 12]**

Like we said, your answer sheet already has the letter for the choice you made when the risk increases were equal filled in in the first row.

Now look at the second row. This time your chosen risk increase is larger, at 20 in 60 million. The one for the other cause is still 10 in 60 million.

Remember about the pie chart- taking 20 in 60 million means moving around your pie chart like in the little picture in column 1. You need to decide if 20 in 60 million is too

big an increase in your risk of dying, or not. Please fill in your choice, Y or Z. **[MODERATOR PAUSE WHILE THEY CHOOSE]**

Work your way down the table, writing in your choice in each row, given the risk levels. Going down the table is like going round the pie chart, increasing your overall risk of dying (you can see a reminder in the top of the first column), The other risk, which is fixed, is shown in the pie chart in the top of the right hand column.

[WAIT UNTIL THEY HAVE DONE].

If you reach the bottom row and you still haven't switched to the other cause, then write the increase in your risk of dying that WOULD be bad enough to make you switch: in other words, where the overall risk of dying would be too high.

[Ask a couple of people- where did they switch? Point out to them:

Anyone who switched at 30, 40, 50 or above, your answer tells us that you would accept a higher overall risk of dying, compared to the 10 in 60 million increase you could have had by switching. [SHOW PIE CHARTS AGAIN?] That's fine, as long as you feel strongly enough about the cause of death to justify accepting this higher overall risk of dying.

At the same time, do notice: while these numbers might seem small to some of you, for some people at least a change of 10 in 60 million seems very different to 100 in 60 million. How you view this information is really up to you- remember there are no right or wrong answers.

Does anyone have any questions about that?

[DISCUSSION QUESTION 2: TIMING TRADEOFF]

[click: **SLIDE 13]**

Now, think back to your answer to the previous decision.

But now let's think: what if both of the risk increases were postponed for 15 years? Would you change your mind?

Now let's think, what if only ONE of the risk increases was in the future?

What if it was fire in 15 years' time, and flu now?

[click: **SLIDE 14**: FIRE IN 15 YEARS or FLU NOW?]

Or what if it was the other way round: flu in 15 years' time, and fire now?

[click: **SLIDE 15**: FLU IN 15 YEARS or FIRE NOW?]

[DISCUSS THE FOLLOWING USING DIRECTED QUESTIONS DEPENDING WHAT THEY ANSWER]

Did you think about:

- Not getting there?
- Whether the future matters to you as much as the present?
- How your life in general would be different?

It will be important to keep in mind how you feel about the timing of death as well as the cause of death, because both will feature in the questions you answer later today.

P*ractice Question 2: Car and cancer- discussion*

Now let's introduce a new pair of causes.

We still want to think about risks of dying. This time, though, we are interested in the risk of dying in a car accident, and the risk of dying from cancer. These will be the risks we think about for the rest of this session, so we're going to take a bit of time to think about them now before we get on to the main questions.

These topics are, by their nature, quite difficult and emotional. And, as I mentioned right at the start, the way we ask the questions might seem a bit detached and abstract, but we combine your number answers with the thoughts that you write down, so we are able to provide answers to the specific questions that the HSE asks us. I can give you some examples after the session is finished, if you like.

[click: **SLIDE 16]**

Some people might find some of the questions a bit upsetting. If at any point you feel too distressed, do let one of the assistants know, who will take you outside of the room for privacy and see what we can do to help. We would much prefer for you to tell us, than to keep quiet. Having said that, lots of people have done these questions before you and most people have found them OK even though they are difficult. Your answers to the questions are very important and we do feed them through to decision makers.

Suppose the government had to choose between saving money in two areas of the safety budget. This would result in either an increase in your risk of dying from cancer; or an increase in your risk of dying in a car accident. The same amount of money would be saved from either budget, and the resulting risk increases would be the same size for either cause. Think about which you would choose, if you had to. Don't say anything, though. We'll give you an answer sheet for you to write it down.

[ASSISTANT HAND OUT ANSWER SHEET 2]

Write your initials and date on this answer sheet, and then tick whether you would increase your risk of dying from cancer or your risk of dying in a car accident, if you had to choose.

Once you've decided, please take a minute to write down some of the issues that came to mind when you thought about these two causes of death.

So, these issues make people think about lots of different things (we'd expect the things you've written down to be quite different from one another's). We are going to narrow down what we mean by cancer and by car accidents so we can be more precise.

[ASSISTANT PASS OUT CANCER INFO SHEET]

First let's think about cancer. [click: **SLIDE 17**: APPEARING AS WE TALK] We are interested in those cancers that are caused by exposure to harmful substances that you come across on a day-to-day basis, for example at work or from near to where you live [CLICK]. They are NOT caused by lifestyle choices like smoking or drinking to excess, or solely by genetics. Please notice that this distinction means that your personal risk level is unlikely to differ much from the average risk [CLICK].

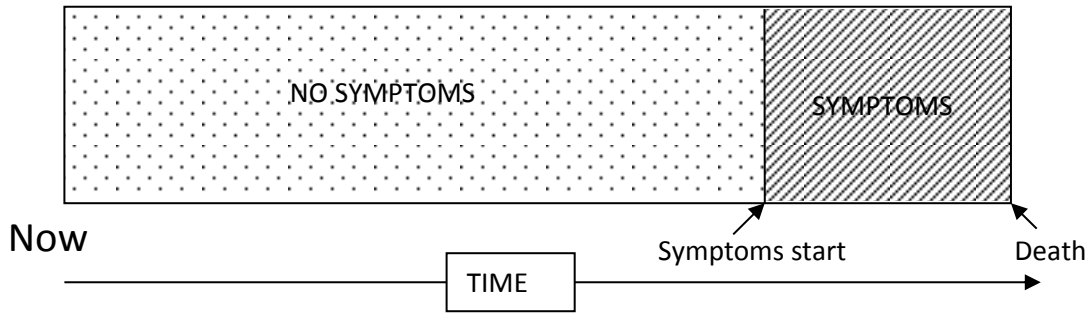
Another important point is that we are talking about cancers where the chance of survival is extremely small and we shall treat them as terminal. [CLICK] Please be aware that although cures for some types of cancer might be developed over time, it is extremely unlikely that a cure would be found for all of the cancers we are thinking about.

Also, there are a wide variety of cancers and they all have different characteristics. We can't ask about every cancer separately, so instead we'll try to cover as many as we can using groups of cancers with similar characteristics.

[CLICK: **SLIDE 18**]

Doctors can group cancers together into 'types' according to the length of time that it takes between when you get exposed to the cancer and the onset of symptoms. They can also use the average length of time that the person is ill before they die.

The cancer groups can be described in the form of pictures, like the one on the overhead. [click: **SLIDE 19**]



This is now [point]. You are currently at risk of being exposed to substances that give you a higher chance of developing cancer. If this happens, there will be a period when you will be without any noticeable symptoms. Then there will be a period when the symptoms become increasingly severe and then you will die. We will vary the times when these things happen in the questions that follow:

[CLICK- SYMPTOMS]

For the cancers we are concerned with, the symptoms might include unexplained weight loss, having fevers and feeling generally unwell, and also having less energy than before. You will have some pain and might need to be treated using drugs that make you sick.

You would go through stages of illness, each one a bit more severe than the one before it. It is hard to be precise about how bad the symptoms would be, but usually they get worse as time passes. A longer time with symptoms means you would be in each stage of the illness for a bit longer.

These are the symptoms of a typical cancer case, and you should imagine that this is what it would be like for you.

So the key things that characterise cancer are the time that symptoms start, the symptoms themselves, and the time of death.

Does that all seem clear?

We will be thinking about risks out of 60 million. If the risk is 1000 in 60 million, we mean that on average, each year, 1000 people in the UK will die from that **group** of cancers. You might be one of those people, and we need you to think of changes to the cancer risks in terms of how they affect your risk of dying, not other people's risk of dying.

The information sheet that you received before summarises what we mean when we ask you about cancers.

[ASSISTANT PASS OUT CAR INFO SHEET]

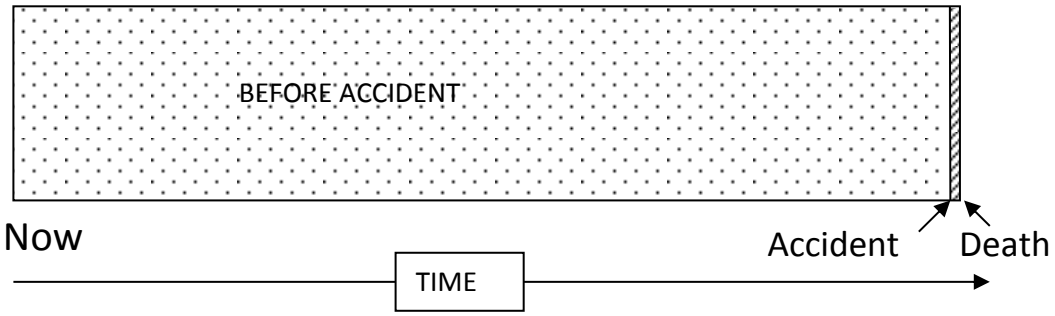
For car accidents, [click: **SLIDE 20**: APPEARING AS WE TALK] we mean accidents where you die within minutes or hours of the accident, so there is no lengthy period of illness [CLICK]. We also only consider cases where you are the driver or passenger [CLICK].

We're going to give you less general information about car accidents than we did for cancer. This is just because most people are a bit more familiar with what car accidents would be like.

Like for cancer, you can think of it using the profile, although it looks a bit simpler.

[click: **SLIDE 21**]

Just like for the cancer case, this [POINT] is now. However, nothing happens until the time when the accident might occur. If the accident does happen, you would die within minutes or hours.



Again we will be thinking about risks out of 60 million. So a risk of 1000 in 60 million means that on average, each year, 1000 people in the UK die in car accidents either as the driver or passenger.

The car accident information is on your information sheet.

Does anyone have any questions?

For the cancers, we explained that your risk probably does not vary much compared to the average, because these cancers are caused by day-to-day things, and are largely out of your control (remember we aren't talking about cancers caused by smoking or drinking, or by genetics alone). However, your risk of dying in a car accident as a driver or passenger might differ a lot from the average. We would like you to indicate where you think you are on this scale:

[ASSISTANT HAND OUT AS3. Click: **SLIDE 22**].

Please put your initials and the date on your answer sheet.

How likely do you think you are to die in a car accident, as the driver or passenger, compared to the average person:

Much more likely than the average person ☐

A bit more likely than the average person ☐

The same as the average person ☐

A bit less likely than the average person ☐

Much less likely than the average person ☐

Please put all of your sheets so far into your folder, except for your information sheets.

INTRO TO MAIN RISK-RISK SECTION

We have finished with the learning part of the session. From now on your answers will be passed on to decision makers and might be used in policy decisions. I would like to reiterate that what's the right choice for you might be the wrong choice for someone else, and it is most important that you think carefully about your answers. All of your answers will remain anonymous.

There are ten questions in this section. In each question, you will need to choose between increases in your risk of dying by one of two causes. The necessary decrease in expenditure would be implemented during the coming year.

As we said before, these are annual risks and they're all out of 60 million.

SECTION 1

PREMIUM QUESTIONS

In the next three questions there will be car accident risks during the coming year or in the year after next, and cancer risks in the future, either 10 or 25 years from now.

[click: **SLIDE 23]**

In each question you will...

1. Choose between risk increases of the same size. Then
2. Choose again, when the risk increases are different sizes.

Question 1
HSE: cars 1 and cancer 10 years
[click: **SLIDE 24**]

[READ FROM THE SLIDE: DESCRIBE OPTIONS then…]

Let's think of it in terms of the profile pictures...

If you were one of the unlucky 1050 people who die in car accidents, the accident would happen during the coming year, and death would happen within minutes or hours of the accident. If you were one of the unlucky 1050 who die from this group of cancers, you would be exposed to the cancer-causing substance now, and then after there would be some time with no symptoms. You would be ill for about a year before you die, which would be during the tenth year from now.

Remember, you could die from something else during this period [INDICATE ON A] or this period [INDICATE ON B].

[ASSISTANT HAND OUT ANSWER SHEET 1]

Please write your initials and the date on the answer sheet.

Circle the one you would choose, **or put an equals sign if you find it hard to choose** (remember, the increase would still happen, but a policy maker would decide for you which one).

A	B
An increase in your risk of dying in a **car accident** during the **coming year (2012)** of 50 in 60 million	An increase in your risk of dying from **cancer ten years** from now of 50 in 60 million

Here is another answer sheet. Please write your initials and the date on the answer sheet.

[ASSISTANT HAND OUT ANSWER SHEET 1A AND 1B]

The left hand column on your sheet has the cause you circled. Does everyone have the correct sheet?

Notice the first column has risk increases which get larger as you go down the table. Fill in the table as before- remembering that the pie chart handout explains the implications of taking the bigger risk (in the 1st column) compared to the fixed risk (2nd column).

[ASSISTANT CHECK THAT ANYONE WHO REACHES THE BOTTOM ROW WRITES IN A NUMBER]

[AS1A]

A **Dying in a car accident during the coming year** 1000 in 60 million RISK INCREASE: 		**B** **Dying from cancer ten years from now** 1000 in 60 million RISK INCREASE: 	**Choice**
50 in 60 million	OR	50 in 60 million	A
...		...	...

etc.

[AS1B]

B **Dying from cancer ten years from now** 1000 in 60 million RISK INCREASE: 		**A** **Dying in a car accident during the coming year** 1000 in 60 million RISK INCREASE: 	**Choice**
50 in 60 million	OR	50 in 60 million	B
...		...	...

etc.

Question 2

HSE: cars 2 and cancer 10 years

[click: **SLIDE 25**]

[READ FROM THE SLIDE: DESCRIBE OPTIONS]

Let's think of it in terms of the profile pictures...

If you were one of the unlucky 1050 people who die in car accidents, the accident would happen during the year after next, and death would happen within minutes or hours of the accident. If you were one of the unlucky 1050 who die from this group of cancers, you would be exposed to the cancer-causing substance now, and then there would be some time with no symptoms. You would be ill for about a year before you die, which would be during the tenth year from now.

Remember, you could die from something else during this period [INDICATE ON C] or this period [INDICATE ON D].

[ASSISTANT HAND OUT ANSWER SHEET 2]
Please write your initials and the date on the answer sheet.

Circle the one you would choose, **or put an equals sign if you find it hard to choose** (remember, the increase would still happen, but a policy maker would decide for you which one).

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

Here is a new answer sheet. Please write your initials and the date on the answer sheet.

[ASSISTANT HAND OUT ANSWER SHEET 2A AND 2B]

The left hand column on your sheet has the cause you circled. Does everyone have the correct sheet?

Fill in the table as before- remembering that the pie chart handout explains the implications of taking the bigger risk (in the 1st column) compared to the fixed risk (2nd column).

[AS2A]

C **Dying in a car accident during the year after next** 1000 in 60 million RISK INCREASE: 		**D** **Dying from cancer ten years from now** 1000 in 60 million RISK INCREASE: 	**Choice**
50 in 60 million	OR	50 in 60 million	C
...		...	...

etc.

[AS2B]

D **Dying in a car accident during the year after next** 1000 in 60 million RISK INCREASE: 		**C** **Dying from cancer ten years from now** 1000 in 60 million RISK INCREASE: 	**Choice**
50 in 60 million	OR	50 in 60 million	D
...		...	...

etc.

[ASSISTANT CHECK THAT ANYONE WHO REACHES THE BOTTOM ROW WRITES IN A NUMBER]

Questions 3-9 follow this format but with the scenarios as follows:

Table A1. Questions 3-9 in study 1

Set	Question	Code	Description
Context	Q4	C_2R_2	Cancer the year after next compared to road accidents the year after next
	Q5	$C_{10}R_{10}$	Cancer in 10 years compared to road accidents in 10 years
Latency	Q6	C_2C_{10}	Cancer the year after next compared to cancer in 10 years
	Q7	C_2C_{25}	Cancer the year after next compared to cancer in 25 years
Morbidity	Q8	$C_{10}[12]C_{10}[6]$	Cancer in 10 years (12 months illness) compared to cancer in 10 years (6 months illness)
	Q9	$C_{10}[36]C_{10}[6]$	Cancer in 10 years (36 months illness) compared to cancer in 10 years (6 months illness)

Question 10
Morbidity: cancer and car 10 years, 2 weeks morbidity

This is the last question in the main bit of today's session. We're back to comparing cancer and car accidents. [click: **SLIDE 39**]

This time both risk increases would be ten years from now. In either case you would endure pain and suffering for 1 or 2 weeks prior to your death.

READ FROM THE SLIDE: DESCRIBE OPTIONS
Let's think of it in terms of the profile pictures...
For S, if you were in the unlucky 1050, the car accident would happen during the tenth year from now, and death would happen after 1 or 2 weeks of deteriorating symptoms. For T, if you were in the unlucky 1050, you would be exposed to the cancer-causing substance now, and there would be some time with no symptoms. You would be ill for 1 or 2 weeks before you die, which would be sometime during the 10th year from now.

Remember, you could die from something else during this period [INDICATE ON S] or this period [INDICATE ON T].
[ASSISTANT HAND OUT ANSWER SHEET 10] Please write your initials and the date on the answer sheet.
Circle the one you would choose, **or put an equals sign if you find it hard to choose** (remember, the increase would still happen, but a policy maker would decide for you which one).

S	T
An increase in your risk of dying in a car accident **ten years** from now including **1 or 2 weeks' pain and suffering.** of 50 in 60 million	An increase in your risk of dying from **cancer** **ten years** from now including **1 or 2 weeks' pain and suffering.** of 50 in 60 million

[ASSISTANT HAND OUT ANSWER SHEET 10A AND 10B]

Please write your initials and the date on this answer sheet.
The left hand column on your sheet has the cause you circled. Does everyone have the correct sheet?

Fill in the table as before- remembering that the pie chart handout explains the implications of taking the bigger risk (in the 1st column) compared to the fixed risk (2nd column).

[AS10A]

S **Dying in a car accident including 1 or 2 weeks' pain and suffering** 1000 in 60 million RISK INCREASE:		**T** **Dying from cancer including 1 or 2 weeks' pain and suffering** 1000 in 60 million RISK INCREASE:	**Choice**
50 in 60 million	OR	50 in 60 million	S
...		...	...

etc.

[AS10B]

T **Dying from cancer including 1 or 2 weeks' pain and suffering** 1000 in 60 million RISK INCREASE:		**S** **Dying in a car accident including 1 or 2 weeks' pain and suffering** 1000 in 60 million RISK INCREASE:	**Choice**
50 in 60 million	OR	50 in 60 million	T
...		...	...

etc.

[ASSISTANT CHECK THAT ANYONE WHO REACHES THE BOTTOM ROW WRITES IN A NUMBER]
When you have finished, please put all of your sheets into your folder.

Thank you very much for your concentration so far.
[click: SLIDE 40]
We have now finished asking you the questions that compare risks of dying.

We would like to ask you to do three more questions for us before we finish. These questions can help us to understand your answers to the questions you have already completed.

Risk and Time Preferences.

FINANCIAL RISK AVERSION

You will now be asked to make some choices, each one between two lotteries. By lotteries, we mean a pair of outcomes, only one of which actually happens in the end.
The chance of each of the outcomes happening will be given as a percentage. For example [**SLIDE 41**], if this lottery were played out, you would have a 10% chance of winning £4 or a 90% chance of winning £10. This would make winning £10 more likely (which is nice!).

We can picture it like this. [**SLIDE 42** (SQUARES)]. There are 90 green squares, and 10 white ones. If you picked a square at random, and it was green, you'd get £10. But if it was white, you'd get £4.
Does anyone have any questions?

[ASSISTANT HAND OUT INFORMATION SHEET 1]
This information sheet is to help you think about the probabilities as we go along.
It shows you the probability grids for:

- 10% and 90%
- 30% and 70%
- 50-50
  ...And so on down to…
- 100% (and 0%)

On your answer sheet, which you will receive in a minute, you'll find a table like this one [**SLIDE 43**].

You will need to choose between the two lotteries in each row, by writing either A (if you'd like to have A played out) or B (if you'd like to have B played out) in the right hand column. You can only choose one option in each row. If you say you find it hard to choose, I will toss a coin to decide whether you write A or B.

I'll explain the table before you fill it in.

Going down the table, we alter the chances of winning in each of the decisions, but not the amount that can be won. So option A is always between £6 and £5, and option B is always between £12 and £1. But going down the table, the chances of winning change.

Decision number	Option A		Option B	Your choice
1	10% chance of £6 90% chance of £5	OR	10% chance of £12 90% chance of £1	
2	20% chance of £6 80% chance of £5	OR	20% chance of £12 80% chance of £1	
3	30% chance of £6 70% chance of £5	OR	30% chance of £12 70% chance of £1	
4	40% chance of £6 60% chance of £5	OR	40% chance of £12 60% chance of £1	
5	50% chance of £6 50% chance of £5	OR	50% chance of £12 50% chance of £1	
6	60% chance of £6 40% chance of £5	OR	60% chance of £12 40% chance of £1	
7	70% chance of £6 30% chance of £5	OR	70% chance of £12 30% chance of £1	
8	80% chance of £6 20% chance of £5	OR	80% chance of £12 20% chance of £1	
9	90% chance of £6 10% chance of £5	OR	90% chance of £12 10% chance of £1	
10	100% chance of £6	OR	100% chance of £12	

Let's begin to fill in the table together.

[ASSISTANT HAND OUT ANSWER SHEET 1]
Please write your initials and the date on your answer sheet.

[CLICK: BLANK OUT 2-10 ON OH TO DEMONSTRATE THE FOLLOWING]

So for decision 1: That's like having 10 green squares and 90 white squares. In option A, a green would get you £6 and a white gets you £5. In option B, a green gets you £12 and a white gets you £1. Think about which option you would prefer, and write your answer in the top box in the last column. [WAIT]

[CLICK: REVEAL ROW 10]

Now let's think about the bottom row. Option A gives you £6 for definite and option B gives you £12 for definite. Which would you choose? Write your answer in the bottom row.

[ALL SHOULD CHOOSE B IF THEY UNDERSTAND. ASSISTANT GO ROUND AND CHECK]

Out of interest, did anyone choose B for decision 1? [CLARIFY: RISK LOVING OR A MISTAKE?]

And did anyone choose A for decision 10? [CLARIFY: MISTAKE?]

[CLICK: REVEAL ALL]

As we go down the table, the chance of the good outcome in each lottery (6 or 12) gets bigger and bigger. Fill in the rest of the table, until you have filled in all of the rows. Remember though, there aren't any right or wrong answers.

Has everyone finished?

FINANCIAL TIME PREFERENCE

We now a similar type of question, but this time, instead of there being different chances of the outcomes, there are different timings of the outcomes. [**SLIDE 44**]

So, you will be asked to choose between getting £350 for certain in one month's time, or some other amount for certain in seven months' time.

We've got a table with 15 decisions. Like before, we need you to write your choice (A or B) in the end column.

Decision number	Option A Sooner: Receive the money **1 month from today**	Option B Later: Receive the money **7 months from today**	Your choice
1	£350 sooner	£354 later	
2	£350 sooner	£359 later	
3	£350 sooner	£363 later	
4	£350 sooner	£368 later	
5	£350 sooner	£372 later	
6	£350 sooner	£377 later	
7	£350 sooner	£381 later	
8	£350 sooner	£386 later	
9	£350 sooner	£390 later	
10	£350 sooner	£395 later	
11	£350 sooner	£404 later	
12	£350 sooner	£414 later	
13	£350 sooner	£423 later	
14	£350 sooner	£433 later	
15	£350 sooner	£443 later	

[ASSISTANT HAND OUT ANSWER SHEET 2]

Please write your initials and the date on your answer sheet

[CLICK: REVEAL ROW 1]

So for decision 1, you need to choose whether you would prefer £350 in one month or £354 in seven months' time. Write A for £350 sooner, or B for £354 later in the choice box.

[WAIT UNTIL EVERYONE HAS DECIDED ON ROW 1 THEN CLICK: REVEAL ROW 15]

In the bottom row, decide between £350 in 1 month (just like before) or £443 in seven months' time. Again write A for £350 sooner, or B for £443 later.

[WAIT UNTIL EVERYONE HAS DECIDED ON ROW 10 THEN CLICK: REVEAL ALL]

Fill in the whole table, choosing between getting the smaller amount of £350 in one month's time, or waiting until seven months later to get the larger amount on offer in that row. Keep going until you have filled in all of the rows.

HEALTH RISK AVERSION

[**SLIDE 45** and INFO SHEET 2 (ASSISTANT HAND OUT)]

This is the last question we will be asking you to do today. We're back to thinking about illnesses, although this time the illnesses are less serious and you will recover.

We're going to think about four illnesses, which vary in how severe they are from minor to severe. In each case the illness would last for ten days and then go away by itself.

We won't name the illnesses, but we will describe their effects.

[READ SYMPTOMS FROM THE OVERHEAD]

Let's consider your chance of getting these illnesses like the money amounts before. But the outcomes are these health issues instead of money.

[**SLIDE 46**]

So option A will always be between the moderate and moderately severe illnesses.

Option B will always be between the severe and minor illnesses. The chances of the illnesses will change as you go down the table, with the chance of the least severe illness (minor or moderate illness) getting bigger and bigger [ILLUSTRATE WITH REFERENCE TO TABLE].

You need to think about which of the options you would prefer to face in each row of the following table. You will choose by writing A for option A or B for option B in each row of the table, just like before.

[ASSISTAND HAND OUT AS3]

Fill in each row of the table, deciding which option you would prefer in each row.

It may help you to fill in the top and bottom rows first like before.

Decision number	Option A		Option B	Your choice
1	10% chance of moderate illness 90% chance of moderately severe illness	OR	10% chance of minor illness 90% chance of severe illness	
2	20% chance of moderate illness 80% chance of moderately severe illness	OR	20% chance of minor illness 80% chance of severe illness	
3	30% chance of moderate illness 70% chance of moderately severe illness	OR	30% chance of minor illness 70% chance of severe illness	
4	40% chance of moderate illness 60% chance of moderately severe illness	OR	40% chance of minor illness 60% chance of severe illness	
5	50% chance of moderate illness 50% chance of moderately severe illness	OR	50% chance of minor illness 50% chance of severe illness	
6	60% chance of moderate illness 40% chance of moderately severe illness	OR	60% chance of minor illness 40% chance of severe illness	
7	70% chance of moderate illness 30% chance of moderately severe illness	OR	70% chance of minor illness 30% chance of severe illness	
8	80% chance of moderate illness 20% chance of moderately severe illness	OR	80% chance of minor illness 20% chance of severe illness	
9	90% chance of moderate illness 10% chance of moderately severe illness	OR	90% chance of minor illness 10% chance of severe illness	
10	100% chance of moderate illness	OR	100% chance of minor illness	

PART SIX: DEMOGRAPHICS

[ASSISTANT HAND OUT DEMOGRAPHICS QUESTIONNAIRE]

Please take some time to fill in this last set of questions. The questions ask about yourself. There are questions on both sides of the page. Once you have filled in this information, the session will be over. When you have finished, put your answer sheets in your folder. We'll collect them in once everyone has finished and then you will receive payment for having come to the session today. Thank you very much for coming. [**SLIDE 47**]

About yourself

Are you male or female? M/F

Is your age:
- O 18-21
- O 22-25
- O 26-30
- O 31-40
- O 41-50
- O 51-60
- O 61 or above?

How many people live in your household (including yourself)? _____

How many children live in your household? _____

Ages of those children: _____

Do you rent or own your house/flat?

Rent/Own

What is your highest Education level?

Secondary/Further

Are you currently unemployed? Yes/No

If not, what is your current job? _____

What does your spouse/partner do? _____

Is your personal monthly income – before tax:

O Up to £1000
O £1001 to £1500
O £1501 to £2000
O £2001 to £3000
O £3001 to £4000
O £4001 to £5000
O £5001 to £6000
O More than £6000?

Is your Household monthly income– before tax:

O Up to £1000
O £1001 to £1500
O £1501 to £2000
O £2001 to £3000
O £3001 to £4000
O £4001 to £5000
O £5001 to £6000
O More than £6000?

Do you work in any of the following industries?

O Chemicals
O Agricultural
O Nuclear
O Construction

What are the first three or four digits of your postcode? (eg NE2, NE26)

_____

Have you or a close relative ever suffered from cancer?

Y/N

Have you or a close relative ever been involved in a car accident?

Y/N

For your age, would you consider your current health as:

O Below average
O Average
O Above average

Newcastle Winter 2011/2012

Appendix B. Variable Correlation

Highly correlated variables ought to be omitted from the regression analysis. Table B1 gives the correlation coefficients above 0.3 for this dataset. Any correlation below 0.3 is not reported. Correlation coefficients are omitted for variables that are, by definition, highly correlated, for example the interaction terms and their constituent parts

Table B1: Correlation coefficients above 0.3

Variable A	Variable B	Correlation coefficient
Under6	age	-0.3617
Under6	under18	0.3856
furthered	Under18	-0.3351
Roadexp	Under6	-0.3259
Roadexp	Canexp	0.3661
logincome	furthered	0.3287
loghhinc	rent	-0.3701
loghhinc	furthered	0.3331
loghhinc	spouseclass	**-0.4037**
Loghhinc	logincome	**0.6401**
Loghhinc_age	rent	**-0.4010**
Loghhinc_age	furthered	0.3274
Loghhinc_age	spouseclass	-0.3778
Loghhinc_age	logincome	**0.6261**
Female6	ownclass	0.3300

Problematically high correlation is not found between any of the variables tested, with the exception personal and household income. Personal income is very strongly skewed towards the lower end of the distribution, perhaps because of the overrepresentation of respondents not in employment. As such, household income will be used for future variable selection and analysis. Having said this, considerable negative correlation can be observed between having experience of road accidents and having children under six living in the household, with no obvious intuitive explanation. However the correlation coefficients are less than 0.4 in both cases.

In addition, there is logical correlation, again below 0.4, between a number of other variables in the dataset as reported in table B1. Some correlation is apparent for a number of the variables that could proxy for income. The VIFs (variance inflation factors) are given in table B2 for completeness, and because none is over 10 there is no evidence of serious multicollinearity in the model, with the exception of age, which

shows as collinear because of the inclusion of the dummies for old age at latent risk outcomes.

Table B2: Variance inflation factors

Variable	VIF	1/VIF
age	12.00	0.08
Being over 65 in 25 years	7.02	0.14
Motherhood (to under 18)	6.34	0.16
Gender (female)	4.63	0.22
Under 6	3.38	0.30
Motherhood (to under 6)	3.22	0.31
Being over 55 in 10 years	3.12	0.32
Interaction between household income and age	2.96	0.34
Under 18	2.88	0.35
Log of income	2.62	0.38
Own class (job-defined)	1.93	0.52
Spouse's class(job-defined)	1.67	0.60
Road accident experience	1.59	0.63
Cancer experience	1.56	0.64
Renting one's home	1.53	0.65
Risk aversion (defined over health outcomes)	1.47	0.68
Self-reported health state	1.46	0.68
Further education	1.41	0.71
Risk aversion (defined over financial outcomes)	1.29	0.78
Self-reported road accident risk	1.27	0.79
Time preference (defined over financial outcomes)	1.17	0.85
Mean VIF	**3.07**	

As such, there is not a large amount of correlation and the *vselect* model can be used with some confidence in order to select of variables in regression analysis from the full set of potential predictor variables.

Appendix C. Alternative Health State Measures for Input to Health Risk Aversion Elicitation

Person trade-off (PTO)

The person trade-off method involves describing a number of people that would be affected by the illness, as opposed to describing a health state itself. The lotteries would be along the lines of the ones in table C1, and the illness will be the same in each case.

Table C1: PTO Holt-Laury style health lotteries

Decision number	Option A	OR	Option B	Your choice
1	10% chance of 12 people ill 90% chance of 18 people ill	OR	10% chance of 2 people ill 90% chance of 28 people ill	
2	20% chance of 12 people ill 80% chance of 18 people ill	OR	20% chance of 2 people ill 80% chance of 28 people ill	
…	…	…	…	
10	100% chance of 12 people ill	OR	100% chance of 2 people ill	

Time spent ill (TSI)

The TSI method involves describing a number of days or weeks for which the individual would be affected by the illness, again as opposed to describing varying health states. This time the lotteries would be as described in table C2 and the illness will be the same in each case.

Table C2: TSI Holt-Laury style health lotteries

Decision number	Option A	OR	Option B	Your choice
1	10% chance of 6 days ill 90% chance of 8 days ill	OR	10% chance of 2 days ill 90% chance of 12 days ill	
2	20% chance of 6 days ill 80% chance of 8 days ill	OR	20% chance of 2 days ill 80% chance of 12 days ill	
…	…	…	…	
10	100% chance of 6 days ill	OR	100% chance of 2 days ill	

Appendix D. What if the Values Input are Utility Scores?

Standard-gamble derived population utility scores could be used for the health states h1-h4. This adds a further layer of complexity, because the comparison becomes simply the respondent's risk preference in comparison to the population's.

If on average, the population was risk neutral, then the interpretation of the curvature of the second order utility function would be exactly that of the financial coefficient α. However, substituting in the population utility scores for the value of the health states means that the implied difference between the health states, and as such the implied riskiness of the gambles, does not reflect the lotteries the individuals were really considering. As such, without knowing the underlying population utility function and CRRA, it is impossible to fully interpret the elicited value.

Call the elicited value γ. While the researcher assumes they are eliciting β using the the equation specified, in fact they are eliciting the following:

$$p\left[\frac{\left((u^*(h_3)(1-\beta^*))^{\frac{1}{(1-\beta^*)}}\right)^{(1-\beta)}}{1-\beta}\right]+(1-p)\left[\frac{\left((u^*(h_2)(1-\beta^*))^{\frac{1}{(1-\beta^*)}}\right)^{(1-\beta)}}{1-\beta}\right]$$

$$=p\left[\frac{\left((u^*(h_4)(1-\beta^*))^{\frac{1}{(1-\beta^*)}}\right)^{(1-\beta)}}{1-\beta}\right]+(1-p)\left[\frac{\left((u^*(h_1)(1-\beta^*))^{\frac{1}{(1-\beta^*)}}\right)^{(1-\beta)}}{1-\beta}\right]$$

Where $(u^*(h_i)(1-\beta^*))^{\frac{1}{(1-\beta^*)}}$ is the inverse of the population utility function for health level i.

It is clear that if the population in general is risk neutral ($\beta^*=0$), the interpretation of the elicited γ value is exactly as if the true health state values were known. However, given risk aversion in the population it is unlikely that ($\beta^*=0$) and as such the interpretation of the elicited γ values requires further consideration.

The values essentially represent risk aversion relative to the average person in the population.

Appendix E: Regression of Risk Preferences on Best-fit Demographics

Table E1: Best fit regression of health risk preferences on demographics

	Population average EQ-5D (adjusted) RA coefficient n=110 r2=0.042 Coef. (r.s.e.)	Sample average VAS score RA coefficient n=110 r2=0.042 Coef. (r.s.e.)	Individual VAS score (untrimmed) RA coefficient n=97 r2=0.020 Coef. (r.s.e.)	Individual VAS score (trimmed) RA coefficient n=81 r2=0.031 Coef. (r.s.e)
Female	-0.015	-0.012	0.571	0.535
	(0.19)	(0.19)	(0.51)	(0.47)
Age	0.071	0.069	0.205	-0.017
	(0.05)	(0.05)	(0.18)	(0.182)
Self-reported	**0.189***	**0.184***	0.060	0.273
roads risk	(0.11)	(0.11)	(0.30)	(0.28)
constant	-1.150	-1.157	-3.527	0.354
	(1.08)	(1.05)	(3.66)	(3.69)

Appendix F: Derivation of the Relativities Under Alternative Discounting Assumptions

EXPONENTIAL

$$C_T = \frac{R_0(1+x)}{e^{\delta T}} \quad (F1)$$

$$R_t = \frac{R_0}{e^{\delta t}} \quad (F2)$$

HYPERBOLIC

$$C_T = \frac{R_0(1+x)}{(1+\delta T)^{\gamma/\delta}} \quad (F3)$$

$$R_t = \frac{R_0}{(1+\delta t)^{\gamma/\delta}} \quad (F4)$$

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:

$$\varphi = \left(\left(\frac{(1+\delta T)}{(1+\delta t)}\right) * \left(\frac{(1+\delta t')}{(1+\delta T')}\right)\right)^{\gamma/\delta} \quad (F5)$$

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

$$\varphi = \left(\frac{(1+\delta t)}{(1+\delta T)}\right) * \left(\frac{(1+\delta T')}{(1+\delta t')}\right) \quad (F6)$$

While this is one equation in one unknown, it is not always possible to find a solution without resorting to complex numbers. This is likely due to the functional form assumed.

SUB-ADDITIVE (HYPERBOLIC BASE)

$$\varphi = \left(\frac{(1+\delta(T'-t')^s}{(1+\delta(T-t)^s}\right) \quad (F7)$$

$$\delta = \left(\frac{1-\varphi}{(\varphi(T-t)^s-(T'-t')^s}\right) \quad (F8)$$

Similarly with the generalised exponential model, the estimation of the parameters x, δ, s is not straightforward, especially given the way that they enter into the equation. Assuming s=0.5 allows some simplification of the estimation procedure, with the equation for solution being

$$\delta = \left(\frac{1-\varphi}{(\varphi\sqrt{(T-t)}-\sqrt{(T'-t')}}\right) \quad (F9)$$

SUB-ADDITIVE (EXPONENTIAL BASE)

$$\varphi = \left(\frac{\delta^{(T-t)^s}}{\delta^{(T'-t')^s}}\right) = \delta^{[(T-t)^s-(T'-t')^s]} \quad (F10)$$

$$\delta = e^{\left(\frac{ln\varphi}{\left[(T-t)^s-(T'-t')^s\right]}\right)} \qquad \delta = e^{\left(\frac{ln\varphi}{\left[\sqrt{(T-t)}-\sqrt{(T'-t')}\right]}\right)} \qquad \textit{(F11)}$$

Again, the estimation of the parameters x, δ, s is not straightforward, especially given the way that they enter into the equation. Assuming s=0.5 allows some simplification of the estimation procedure, with the equation for solution being

$$\delta = e^{\left(\frac{ln\varphi}{\left[\sqrt{(T-t)}-\sqrt{(T'-t')}\right]}\right)} \qquad \textit{(F11)}$$

Appendix G. Exponential Discount Rates Removing Q1 & Q10

Figure G1: Exponential discounting using averages per-question and average latency differential, deleting Q1.

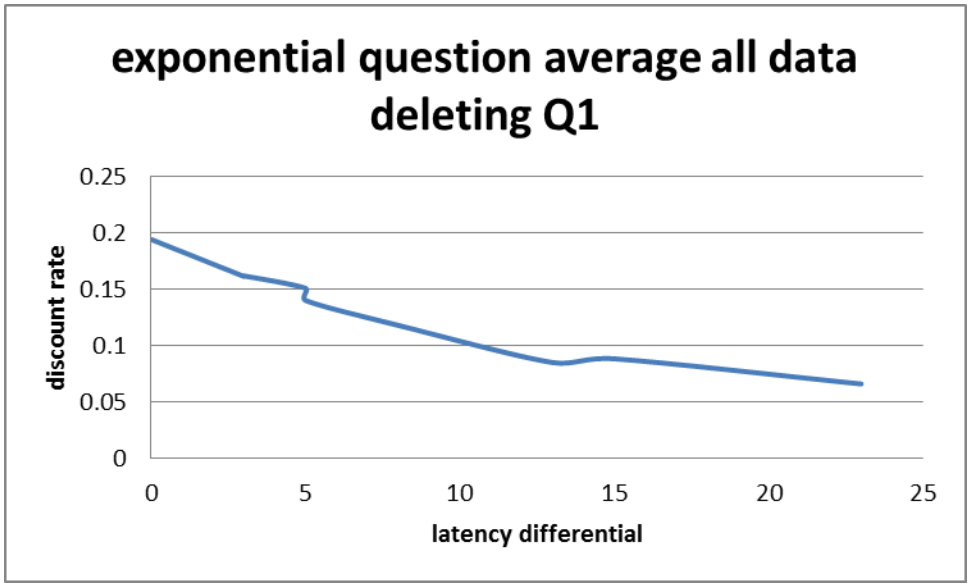


Figure G2: Exponential discounting using averages per-question and average latency differential, deleting Q1 and Q10.

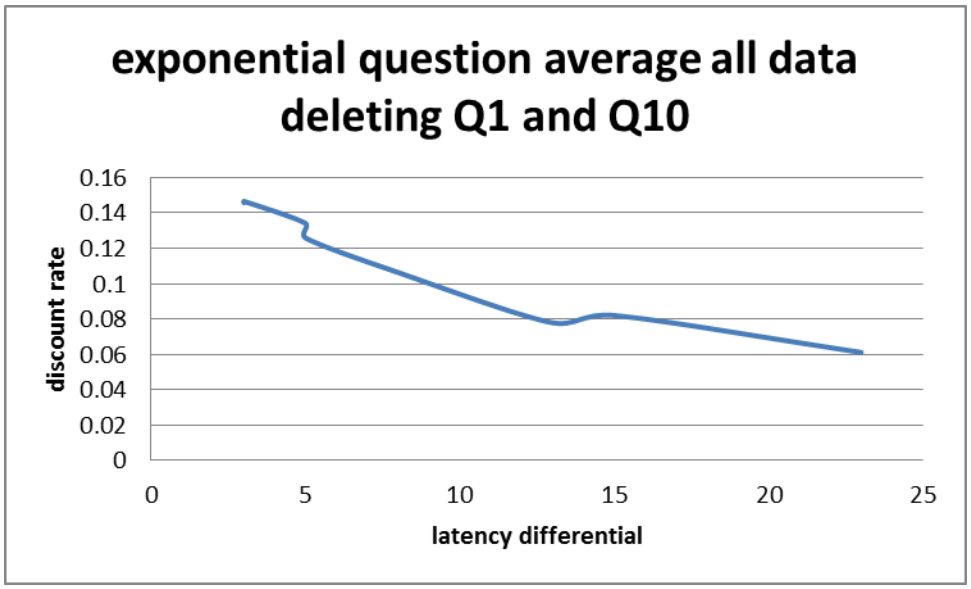


Figure G3: Exponential discounting using averages per-question and average delay, deleting Q1.

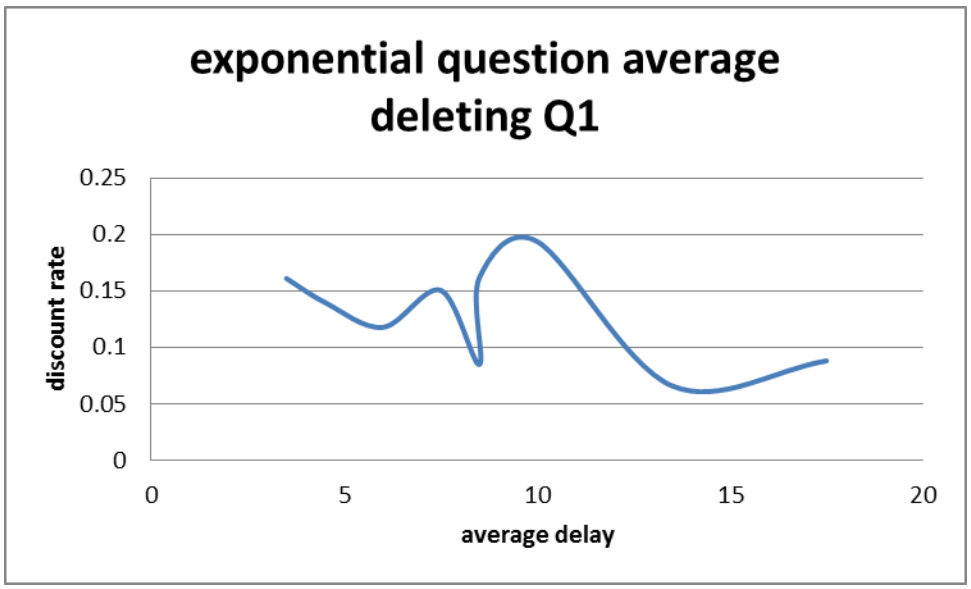
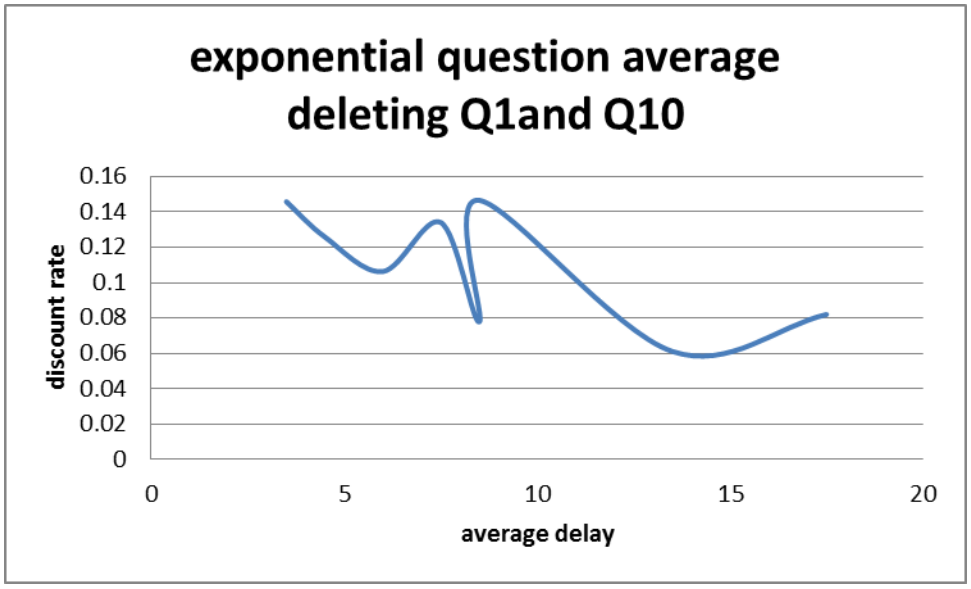


Figure G4: Exponential discounting using averages per-question and average delay, deleting Q1 and Q10.



Appendix H. Regression Analysis of Relativities on Demographics: Comparing Study 1 and Study 2

The explanatory variables are included stepwise. Model (1) presents only the latency differential, Model (2) incorporates the variables that are persistently significant, Model (3) is the best fit model as estimated using the *vselect* command in Stata and includes all relevant demographics for the student sample. The results are presented in table H1, with the student sample alongside the main. As previously, the standard errors are clustered on the individual.

Table H1: All models pooled analysis

log ratio	Model (1) Study 2 N=1022 R^2= 0.064	Model (1') Study 1 N=1410 R^2= 0.136	Model (2) Study 2 N=993 R^2= 0.110	Model (2') Study 1 N=1350 R^2=0.156	Model (3) Study 2 N=814 R^2=0.155	Model (3') Study 1 N=1224 R^2=0.194
Latency	**-0.084*** **	**-0.185*** **	**-0.085*** **	**-0.189*** **	**-0.088*** **	**-0.190*** **
(differential in years)	(0.009)	(0.015)	(0.009)	(0.016)	(0.016)	(0.016)
Self-Reported road	-	-	**-0.420** **	-0.118	**-0.464** **	-0.113
accident risk			(0.174)	(0.189)	(0.188)	(0.187)
Experience of cancer	-	-	0.609	**0.930*** **	**0.706***	**1.282*** **
			(0.379)	(0.344)	(0.421)	(0.407)
Health state	-	-	-	-	0.420	-0.299
					(0.286)	(0.227)
Health risk aversion	-	-	-	-	-0.132	-0.115
					(0.128)	(0.078)
Financial time	-	-	-	-	-1.067	0.179
preference					(1.423)	(0.628)
Female	-	-	-	-	-0.130	**-0.768** **
					(0.390)	(0.306)
Financial risk	-	-	-	-	-0.287	-0.045
preference					(0.396)	(0.202)
Constant	**0.837*** **	**1.371*** **	**1.145*** **	**0.913** **	**1.766***	**2.113*** **
	(0.178)	(0.167)	(0.411)	(0.431)	(0.950)	(0.707)

Appendix J: Probit Analysis for Exponential Discounting

Table J1: Probit analysis- exponential

PROBIT: Exponential	Exponential Model (1) n=71 LL= -40.91, Pseudo R2 = 0.0993 Coef. (Standard Error)	Exponential Model (2) n=87 LL= -52.25, Pseudo R2 = 0.0546 Coef. (Standard Error)
Self-Reported road accident risk	-0.203 (1.749)	-
Experience of cancer	0.272 (0.214)	-
Health state	-0.248 (0.309)	-
Health risk aversion	-0.292 (0.174)	**-0.286*** (0.156)
Financial time preference	1.281 (1.702)	1.551 (1.315)
Safety time preference estimate (Q2-3 exponential)	0.675 (1.749)	0.703 (1.426)
Financial risk preference	0.449 (0.303)	0.378 (0.252)
Road accident experience	0.157 (0.342)	-
Female	-0.283 (0.380)	-
Age (years)	0.002 (0.097)	-
Household income	0.000 (0.000)	-
Constant	-0.982 (2.154)	**-0.805***** (0.290)

Appendix K. Sensitivity Analysis for r and x

This sensitivity analysis focuses on the estimates of r and x as derived from Q2-3. The data is re-combined to estimate the overall premium (C_TR_2) using different assumptions about the discount rate and the context premium to explore how sensitive the results are to differences in these parameters. The overall conclusion- that dread and latency work to offset one another given long latency- appears robust to these tests.

These overall premia are reconstructed substituting various values for x and r, and using the relationship as defined above,

$$C_tR_2 = \frac{(1+x)}{(1+r)^{t-2}} \qquad (K1)$$

The values chosen for inclusion as possible discount rates r are the unaugmented social time preference rate (STPR) which is typically used in policy, which is 1.5%; the STPR augmented for survival probability and life expectancy effects,[46] which is 4.5%; the elicited 7.37% effective discount rate; and an arbitrarily chosen 'high' discount rate of 10%.

The values chosen for the time of the latent cancer risk increase, T, are 10 and 25 years for comparability with the study, and 40 years to explore the impacts of long latency (although of course this cannot fully include the implication of the oldest members of the cohort being less likely to survive to the 40 year mark, so any relativity is likely to be inflated compared to its 'true' level).

The values chosen as potential values for the time-invariant cancer premium $(1 + x)$ are 1.4 as elicited in the above, 2 to test the 'x2' cancer multiplier employed by the HSE in policy decisions with implications for cancer fatality risks, 4 as a midpoint between the upper and lower ends of the spectrum, and 10 to account for the results of the 'context' questions, Q4-5.

Different combinations of these values are used in conjunction with the relationship in equation (K1), and the resulting VSL_{CAN}:VSL relativities constructed from these combinations are reported in tables K1 to K3, and discussed below.

Initially, $(1 + x) = 1.4$ is maintained, but r and T vary.

[46] see Jones-Lee and Loomes (2010) for a discussion, which is outlined in more detail in the policy implications section of this thesis, chapter 8.

Table K1: Sensitivity analysis 1: reconstructed C_TR_t relativities

	r = 0.015	r = 0.045	r = 0.0737	r = 0.1
T = 10	1.242	0.984	0.793	0.653
T = 25	0.994	0.509	0.273	0.156
T = 40	0.795	0.263	0.094	0.037

Holding the context multiplier equal to 1.4 generates an overall relativity below 1 for almost all cases. The only exception is when using the non-augmented STPR of 1.5% and the shortest (10 year) latency period.

Next, $r = 0.737$ is maintained but x and t vary.

Table K2: Sensitivity analysis 2: reconstructed C_TR_t relativities

	(1+x) = 1.4	(1+x) = 2	(1+x) = 4	(1+x) = 10
T = 10	0.793	1.132	2.265	5.661
T = 25	0.273	0.390	0.779	1.948
T = 40	0.094	0.134	0.268	0.671

Holding the effective discount rate equal to 7.37% per annum generates an overall relativity below 1 in most cases, as above. Exceptions include cases with short latency (10 years) and high dread. Even with a seemingly high context multiplier of 4; the overall relativity is less than one for longer latency periods of 25 years or more.

Finally, T=25 is maintained and r and x vary.

Table K3: Sensitivity analysis 3: reconstructed C_TR_t relativities

	r = 0.015	r = 0.045	r = 0.0737	r = 0.1
(1+x) = 1.4	0.994	0.509	0.273	0.156
(1+x) = 2	1.420	0.727	0.390	0.223
(1+x) = 4	2.840	1.453	0.779	0.447
(1+x) = 10	7.100	3.634	1.948	1.117

Again, most of the calculated relativities are below 1. The exceptions are once again the more extreme values including the lowest discount rate, and highest levels of dread.

To summarise, the majority of the cases that use figures within the bounds of this data and of the estimates in the literature generate an overall relativity below 1, for these latent cancer to current roads relativities. This supports the conclusion that a 2:1 relativity is inappropriate under reasonable assumptions about public preferences.

Appendix L: Comparison of samples and results, studies 1 and 2

Central tendencies

Q1-3 were identical between the studies. In these questions the central tendency measures for the two samples are all but indistinguishable, although the student sample has much tighter confidence intervals. This implies a remarkable similarity between the two samples, which indicates a consistency of preferences for different fatality risks

Table L.1: 30 million trim central tendencies

Question		Arithmetic Mean [confidence interval] (*standard deviation)*	Median (percentiles)	Geometric mean [confidence interval]	Index [confidence interval]
($C_{10}R_1$)	Study 1 (N= 133)	**3629** [-2340, 9598] *(34799)*	**1** *(25% = 0.111)* *(75% = 7.20)*	**1.116** [0.576, 2.161]	**1.089** [0.847, 1.406]
	Study 2 (N=106)	**1162** [-1126, 3451] *(11766)*	**0.67** *(25% = 0.25)* *(75% = 4.40)*	**0.97** [0.59, 1.60]	**0.93** [0.73, 1.19]
($C_{10}R_2$)	Study 1 (N= 128)	**2042** [-1088, 5172] *(17894)*	**1** *(25% = 0.108)* *(75% = 7.20)*	**0.814** [0.429, 1.643]	**1.041** [0.805, 1.347]
	Study 2 (N=105)	**8.65** [2.58, 14.72] *(31.20)*	**0.67** *(25% = 0.19)* *(75% = 4.00)*	**0.72** [0.42, 1.23]	**0.89** [0.70, 1.14]
($C_{25}R_2$)	Study 1 (N= 127)	**1265** [-376, 2905] *(9342)*	**0.179** *(25% = 0.05)* *(75% = 4.80)*	**0.280** [0.139, 0.566]	**0.595** [0.446, 0.7766]
	Study 2 (N=106)	**61.14** [-52.14, 174.41] *(585.33)*	**0.25** *(25% = 0.14)* *(75% = 2.40)*	**0.35** [0.21, 0.59]	**0.57** [0.43, 0.73]
($C_{10}R_{10}$)	Study 1 (N= 129)	**9040.34** [1000, 17081] *(46154)*	**7.8** *(25% = 1)* *(75% = 40)*	**9.647** [4.841, 19.22]	**2.460** [1.904, 3.308]
	Study 2 (N=98)	**17.24** [8.29, 26.19] *(44.17)*	**4.60** *(25% = 1.40)* *(75% = 8.10)*	**3.58** [2.37, 5.41]	**2.18** [1.73, 2.83]

across age groups. The smaller variety in the students' responses could be as a result of the more homogenous demographics of this age group, both in terms of their age, their social status (all are in higher education) and their stage in life (predominantly on low

incomes and without family responsibilities). However, it may also be due to more familiarity with risk as communicated in these Studies, and the students are arguably more adept at processing difficult choice tasks like the ones presented to them in this study. If so, this could be expected to generate data with less noise. However, the students still displayed some of the idiosyncrasies as the 30-50 year olds, with a proportion indicating that they would "never switch" on certain questions, but this was less prevalent in the student sample.

Inferred r and x from studies 1 and 2

The context premium and discount rate inferred from Q2-3 for both studies are presented in table 8.1 for comparison.

Table L.2: Effective discount rate and context premium

	Study 1 (age range 30-50)	Study 2 (age range 18-25)
r (effective discount rate)	7.37%	4.93%
(1+x) (context premium)	1.434	1.058

The effective discount rates are not dissimilar for the two groups, with the students' result slightly lower but still within a comparable range. The students' context premium is much lower, however. This result suggests that less emphasis is placed on the cancer context by students than by their older counterparts, a result that is also reflected in the answers to the $C_{10}R_{10}$ comparison, where the 30-50 year old sample average relativity is significantly higher, at least when comparing the geometric means. The difference seems more pronounced when using the elicited (1+x) values.

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