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**Voluntariness and Controllability - The Effects of Perceived Risk Characteristics  
on Willingness to Pay**

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**Abstract:** This study aims to gain insight into the psychological factors which influence willingness-to-pay for public health policies. By replicating Savage (1993) with a few key changes, this paper studies the impact of perceived risk characteristics on valuations of health policies mitigating risks with varying qualities, focusing on perceptions of controllability and voluntariness of risks. The study follows a detailed pre-registered plan for data collection and analysis, conducting a survey of 746 individuals on perceived risk characteristics of 4 different hazards and willingness-to-pay for health policies to mitigate them. The results of the pre-registered analysis confirm the hypothesis that individuals have a lower willingness-to-pay to mitigate risks considered to be more controllable. The results of an exploratory analysis show that self-interest is the largest single factor in determining willingness-to-pay and find that, of the risk characteristics included in the survey, perceptions of voluntariness and controllability exhibit the lowest level of consensus among the surveyed population. These results have implications for how to craft politically viable environmental policy and public health programs addressing substance dependency, namely the opioid epidemic in the United States. Results highlight the importance of informational campaigns informing individuals within a population about the characteristics of health risks the population faces as well as individuals' personal exposure to these risks, in order to enable efficient policy.

**Keywords:** Risk characteristics, Public health policy, Psychological risk dimensions, Controllability, Opioid epidemic, Environmental policy

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# 1 Introduction

Increasingly in the field of economics, researchers are finding that the concept of rationality as exhibited by human behavior is complex and multi-faceted. As rationality is a central assumption of economics, this blurring of the rules of rationality permeates human behavior in a vast range of circumstances, having implications for each discipline within the field. This thesis focuses on how these effects manifest themselves, specifically within the field of public health and policy valuation.

Before even accounting for factors that may cause human behavior to deviate from traditional interpretations of rationality, attempting to simply value health already raises a number of issues. The concept of the value of a statistical life (VSL) may be the most widely used measure for valuing health, but has been plagued by these complications since its origins in the mid-20th century (Banzhaf, 2014). The issue of valuing loss of life, even in a statistical context separate from the individual, is rife with inconsistencies (Ashenfelter, 2006); in other words, human behavior reflects a perceived importance of a range of factors surrounding the context of loss of life, a finding that may not come as a surprise to many, considering the moral implications involved.

## 1.1 Risk Characteristics

These inconsistencies in valuing health and life are in turn reflected in public health policy. A wealth of research has shown that when individuals consider the value of health policies, they do not turn solely to statistical measures, such as number of lives saved or savings in healthcare costs, but consider a much wider range of factors, which are understood to different extents (Carlsson *et al.*, 2010, Fox-Glassman & Weber, 2016, Jones-Lee & Loomes, 1995, Slovic *et al.*, 1980, Subramanian & Cropper, 2000). One set of factors individuals consider when they value health policies are perceived risk characteristics, or perceptions of the circumstances surrounding a risk. For example, one characteristic might be the involvement of physical pain; an individual may feel a different sense of nervousness when considering a death they believe to be painful, than when considering a "peaceful" death.

With the concept of perceived risk characteristics, and their effects on valuations of health and loss of life established, research has identified and began to investigate a number of such characteristics. The most notable of these characteristics include how well-informed an individual feels about a risk, how personally exposed to a risk an individual feels, how much dread an individual feels when considering a risk, and the two characteristics which will be the focus of this study; "voluntariness"; the extent to which an individual exposes themselves to a risk voluntarily and "controllability"; the extent to which an individual can, *once exposed to a risk*, avoid the consequences of the risk being realized through skill or diligence (from here forward these will be referred to as "voluntary factor" and "control factor" respectively).

## 1.2 "Voluntariness" and "Controllability"

A number of reasons drove the decision to focus on voluntary and control factors in this study. First is their relevance to a major health crisis that has affected the United States as well as a number of other countries in recent years and is projected to grow (Skolnick, 2018); the opioid epidemic. Substance abuse is a complex issue, increasingly understood to be a medical illness like many others that do not carry a similar taboo, however public opinion on the issue is still largely influenced by ideas which have long been abandoned by medical research (Fraser *et al.*, 2017). When considering a comparison between the risk of death by an illness such as leukemia and risk of death from opioid overdose, the idea of how perceptions of voluntary and control factors influence individuals' attitudes towards such risks becomes clear. As the opioid epidemic grows and public health interventions become increasingly necessary, understanding of the factors that influence a public's willingness-to-pay (WTP) to mitigate such risks on a societal level will become central to the issue of crafting and politically justifying policies that address this need. Additionally, this understanding will be helpful in policy-making to address other health risks which more consistently affect populations over time, such as those associated with smoking and drinking, or even with risks that carry little-to-no taboo such as traffic accidents.

The second factor driving this thesis to focus on voluntary and control factors specifically is the potentially subjective way in which individuals set their beliefs about such characteristics. One example of this, as mentioned previously, is differences in understandings of illnesses such as substance abuse between medical experts and the wider public. If individuals' perceptions of risk characteristics are formed with imperfect information or based on personal experiences, then might these also be subject to change? Although a lack of consensus on how individuals within a population perceive risk characteristics would not explicitly indicate subjectivity, it could imply it, motivating research into how these perceptions change with differing levels of information or based on experiences. Again, an understanding of this is important for policy-making as a subjective nature of the formation of such perceptions would imply that perceptions could change over time or with education, such as that provided by public information campaigns.

Finally, in addition to the two previously mentioned aspects in which voluntary and control factors are important, the decision to focus on these factors was also motivated by a research gap. Although many previous studies have investigated a range of risk characteristics and their effects on WTP to mitigate risks, there has been little focus on these two characteristics specifically. Considering this, as well as the factors that may make understanding of these characteristics important, this seemed like fertile ground for further study.

## 1.3 Overview

This study aims to investigate the effects of perceived risk characteristics on WTP to reduce a fatality risk posed by a given hazard, with a specific focus on voluntary and control factors as defined above by replicating the experiment of Savage (1993) with a few key differences. An

important aspect of this study that must be emphasized is that it does not aim to investigate how risk characteristics affect an individual’s WTP to reduce a risk for themselves personally, but for an *entire population* to which they belong, thus invoking public health policies, rather than personal decisions by individuals. With regard to these risk characteristics, the following hypotheses were set:

- **H1:** Individuals will have a higher WTP to mitigate risks perceived to be less voluntary
- **H2:** Individuals will have a higher WTP to mitigate risks perceived to be less controllable

Additionally, this study contains an exploratory analysis investigating the level of consensus within the surveyed population on perceptions of the risk characteristics of different hazards, in order to begin gaining an understanding of the level of subjectivity involved with forming such perceptions.

This study recruited a sample of 746 individuals within The United States to complete a survey on perceived risk characteristics of four hazards, and WTP for public policies to mitigate said hazards, as determined by the perceived risk characteristics. The study was carried out following a pre-registered framework designating methods for data collection and analysis.

## 2 Previous Literature

The previous work most central to this study is Savage (1993), as this study intends to replicate the experiment used within it with a few deliberate changes. Broadly, Savage (1993) seeks to gain understanding into how the perceptions surrounding different risks factor into individuals’ valuations of health policies aiming to mitigate those risks, through use of a survey. This section highlights the literature which informs both the design and motivation of Savage (1993) and how this study intends to build on the relevant concepts. A more detailed summary of Savage (1993) and how this study builds upon it is laid out in [section 2.3.4](#).

### 2.1 VSL & Valuing Health

Fundamentally, this study is concerned with the way individuals value health and decreases in mortality risks for a population as well as the factors that shape these valuations. Although this study does not seek to attach any monetary values to these valuations, concepts that do, such as the value of a statistical life (VSL), are useful in understanding the approach of economics as a field to valuing health benefits.

VSL is a good starting place for discussing economists’ approach to valuing public health and decreased mortality, as it represents one of the earliest methods used. The work which eventually lead to the coining of the term VSL began in the early days of the Cold War, when the RAND corporation was commissioned by the US military to craft a method of incorporating loss of

life into their statistics-driven military response plans (Banzhaf, 2014). Although VSL aims to represent valuations of incremental decreases in mortality risk within a larger population, rather than pertaining to any single individual, as might be expected considering the sensitive subject, it has attracted controversy and questions of moral dilemma since its inception. Despite this, VSL has proved to be useful in various forms of policy-making, most often concerning decisions regarding traffic safety, environmental regulations, medical procedures, and medical investments, demonstrating its usefulness (Ashenfelter, 2006).

### **2.1.1 Estimating VSL**

There exist various approaches to estimating VSL, each with their own set of benefits and drawbacks, which can generally be split into stated preference and revealed preference approaches. Stated preference approaches involve directly asking individuals to either state their WTP for a given level of health benefits or decrease in mortality risk (known as contingent valuation), or to choose between funding different health programs based on information provided about the costs and benefits of programs (known as choice modeling) (OECD, 2012). Stated preference approaches have the benefit of being easy to interpret and allow a researcher to craft questions towards specific relationships or variables, for example gauging how VSL estimates are affected by demographics, cause of death, baseline risk level, and other factors. However, stated preferences approaches also have the inherent drawback that the preferences that individuals state in a survey, may not always accurately reflect their decisions and behavior in real life scenarios, limiting the validity of these estimates.

In contrast to stated preference approaches, revealed preference approaches aim to skirt the issue of individuals stating different preferences than are represented in their behavior by deriving preferences from actual observed behavior. The two main types of revealed preference approaches to estimating VSL are the hedonic wage approach and the purchase choices approach. The hedonic wage approach estimates the value individuals place on incremental reductions in their own mortality risk by observing decisions individuals make regarding the tradeoff between occupational safety and wages, demonstrating the amount of compensation an individual is willing to give up for decreased mortality risk (Freeman, 2014). The purchase choices approach aims to derive valuations from individuals' decisions regarding purchases of products carrying different levels of mortality risk, such as cars with different safety ratings or safety measures such as smoke or carbon monoxide alarms (Freeman, 2014). Although these revealed preference approaches have the advantage of deriving estimates directly from observed behavior, they also contain the drawbacks of imperfect information, for example where individuals have misconceptions about mortality risk associated with different jobs or products, and the difficulty in identifying natural experiments suitable for study.

### 2.1.2 Criticisms of VSL

Although much of the controversy surrounding VSL stems from misunderstandings of its aims and misguided applications of its estimates, there also exist many valid criticisms of the approach. Ashenfelter (2006) compiles and discusses a number of these criticisms. First, endogeneity of risks poses a major obstacle for conducting valid experiments in order to estimate VSL, resulting from the difficulty in identifying exogenous events that affect both wealth and fatality risk separately. For example, although the natural experiment behind the hedonic wage approach has the advantage of its simplicity, in practice, finding jobs with different wages and mortality risks that are otherwise identical poses a great challenge. Additionally, the relationship between wages and mortality risk is less clean than it may initially appear, as higher wages may also reflect higher skill levels which might in turn lower fatality risk.

A second issue highlighted by Ashenfelter (2006) is that of identifying whose preferences should be estimated by VSL. The approaches to VSL mentioned above each result in a single value that can be referred to as VSL, however they may reflect very different perspectives; the hedonic wage approach estimates individuals' value of incremental reductions in *their own* mortality risk, while choice modeling approaches invoking the context of public policy reflect individuals' value of incremental reductions in the mortality risk faced by an entire public, which may or may not include themselves. This issue of identification can further be extended to an agency problem, wherein a VSL estimate may reflect the preferences of a person making a decision, such as a public official, but not the preferences of those who will be affected by the decision. Although these nuances in VSL estimates can be accounted for, for example by policy-makers deliberately using VSL estimates that aim to reflect the preferences of the individual within the affected population at the middle of a distribution of risk preferences, it is easy to gloss over them when interpreting and applying VSL as a tool.

Lastly, Ashenfelter (2006) points out a simple problem involved with estimating VSL with potentially large consequences. This problem, as referred to previously, is that of imperfect information. Although government agencies such as OSHA aim to inform individuals about occupational safety involved with their employment decisions and agencies such as the FDA aim to inform individuals on safety implications involved with purchasing decisions, it isn't always clear to what extent individuals absorb this information and factor it into decision-making. Because dissemination and takeup of safety information are complex issues in and of themselves, imperfect information is difficult to combat and may be a large bias in revealed preference estimates of VSL.

### 2.1.3 Factors Influencing VSL

As all of this demonstrates, estimates of VSL are by no means cut and dry, and thus when comparing them, significant inconsistencies are found. A number of studies have investigated which factors, other than measurement errors mentioned above, influence estimates of VSL. Zan & Scharff (2017) compare VSL estimates obtained from a hedonic wage approach within different

geographic regions in the United States, and find significant differences in VSL based on differing local income levels, noting a high level of income elasticity of VSL estimates. Additionally, Majumder & Madheswaran (2017) directly investigate these inconsistencies by conducting a meta-analysis of 30 hedonic wage-based VSL studies, finding a negative relationship between VSL estimates and average mortality risk, a U-shaped relationship between age and VSL estimates, and finally conclude that a large portion of the variance between VSL estimates in the studies included in the analysis can be attributed to unobserved heterogeneity.

This study is not directly concerned with evaluating the validity of VSL as a tool for valuing public health programs, however it is still useful to understand what leads to inconsistencies in estimates of VSL, because these begin to outline the issue with which this study *is* concerned; which factors influence individuals' valuations of decreases in health risks.

## 2.2 Willingness-to-Pay for Public Health

### 2.2.1 Quantitative vs. Qualitative Factors

When viewing policy-making decisions on public health programs through a lens of the traditional understanding of rationality, these decisions might appear to be simple. If we narrow our scope to evaluating policies that reduce specifically the *mortality risk* of various hazards, a rational decision-maker would seek to maximize number of lives saved within a given budget constraint. If policy decisions were made using this interpretation of rationality, cost-per-life-saved would be equalized across all public health policies, however in practice this is not the case (Subramanian & Cropper, 2000).

Observing that the quantitative factor of cost-per-life-saved is not equalized across public health and environmental policies, Subramanian & Cropper (2000) seek to investigate the trade-off between quantitative and *qualitative* factors involved with public health policies. Subramanian & Cropper (2000) conduct a survey asking respondents to choose between different pairs of environmental and public health policies, given information on cost and number of lives saved, and then to indicate beliefs about a number of qualitative factors of these policies. These qualitative factors include characteristics of the risks being mitigated by the policy and characteristics of the programs themselves (such as perceptions about effectiveness and latency of benefits). The authors interpret this data through a model of utility from a life saving program as a function of number of lives saved and a vector of qualitative risk and program characteristics. Using this model, the authors find that, given an equal number of lives saved, individuals tend to have a strong preference for environmental policies over other public health policies and that, contrary to expectations, this preference was not significantly driven by qualitative risk characteristics.

### 2.2.2 Demographics

As Subramanian & Cropper (2000) show that quantitative factors are only one of a wider array of considerations individuals make when determining preferences for public health programs,

the next set of relevant studies aim to further investigate these other considerations. Bosworth *et al.* (2010) conduct another study investigating which factors influence individuals' WTP for public health policies. The researchers conduct a survey similar to that used by Subramanian & Cropper (2000) wherein respondents in the United States choose between pairs of randomly generated public health policies based on information provided about cost, deaths prevented, and who would receive the benefits. The authors note two main distinctions between their study and others; that the respondents are informed that they should regard all policies as benefiting *others* and that policies are targeted at benefiting individuals who already have an illness or injury. The results of the study show that in addition to quantitative factors such as number of increased recoveries, avoided premature deaths, and number of individuals initially affected by the illness or injury, WTP for public health policies is significantly affected by a number of factors including respondent's demographics (mainly age), demographics of benefiting population (specifically English proficiency, US citizenship, and immigration status), proportion of beneficiaries who are children, and the time horizon over which benefits of the program are realized. However, by a wide margin, the largest factor influencing WTP is self-interest, or how personally individuals feel affected by the given illness or injury.

### 2.2.3 Context

Subramanian & Cropper (2000) demonstrate that quantitative considerations are one factor of many influencing individuals' WTP for public health, and Bosworth *et al.* (2010) begin to flesh this out by investigating to what extent demographics and other variations in how the benefits of a public health policy are realized affect WTP. Working towards the subject of this study, we next look at studies investigating the effects of the context surrounding the risks which are being mitigated by a given public health policy on WTP, shifting towards the concept of risk characteristics.

Carlsson *et al.* (2010) aim to measure how differences in risk characteristics of hazards being mitigated influence VSL estimates. In order to assess this, the authors survey individuals on a number of risks possessing different characteristics, and their WTP for incremental decreases in those risks for themselves. Before discussing their results, the authors highlight a number of ways in which risk characteristics can differ between hazards, such as differences in baseline risk level prior to implementation of a policy and psychological perceptions of risks including some of the subjects of this study; voluntary factor, control factor, and dread. The authors' results indicate that, of the risks on which participants were surveyed, traffic accidents stand apart from the others in terms of VSL, attributed to a higher level of nervousness individuals feel when considering the risk. The authors also find a negative relationship between VSL and baseline risk level, which they hypothesize may be attributed to either individuals having a "risk threshold" below which they do not concern themselves with a given risk, or individuals having a preference for relative risk reduction over absolute risk reduction. Carlsson *et al.* (2010) touch on the subjects of control and voluntary factor and although they do not find significant results

regarding those subjects, the results showing traffic accidents to be given special consideration begin to outline how individuals perceive different hazards and take into consideration differences in risk characteristics.

Jones-Lee & Loomes (1995) investigate these contexts and risk characteristics posed by different forms of transportation, with a focus on scale effects. The main subject which the authors aim to investigate is how policy-makers, when allocating funds from a set budget, should approach the issue of dividing funds between improving traffic safety and public transportation safety, with a focus on assessing the importance of the scale hypothesis, which states that individuals perceive larger-scale incidents that result in loss of life to be disproportionately less-desirable than smaller-scale incidents (i.e. the loss of 30 lives in a single incident is inherently worse than the loss of 30 lives in a number of smaller incidents). After conducting an indirect choice-modeling approach in individual focus groups, the authors find that individuals are willing to pay 50% more for increased safety in public transportation than for an equivalent increase in road traffic safety, however they do not find evidence that this is driven by the scale hypothesis. Instead, the results point towards the premium on safety in public transportation being entirely attributed to context effects, specifically control and voluntary factors in addition to the extent which they feel personally responsible for a hazard.

## 2.3 Psychological Risk Characteristics

When further investigating the qualitative factors that influence WTP for public health programs, the results of both Carlsson *et al.* (2010) and Jones-Lee & Loomes (1995) point towards the importance of perceived risk characteristics. Specifically, these studies highlight the importance of psychological risk characteristics such as voluntary and control factors, as well as dread felt about a given hazard and personal responsibility. Building upon this, a number of studies have focused on expanding understanding of these psychological risk characteristics, how they relate to each other, and which appear to carry the greatest influence over individuals' valuations of health benefits or risk reductions.

### 2.3.1 Slovic *et al.* (1980)

Slovic *et al.* (1980) conducted some of the first research with the specific goal of furthering understanding psychological risk characteristics. The study begins highlighting current understandings of how individuals perceive risk levels of different hazards with a focus on heuristics; mental rules individuals subconsciously employ to simplify the process of decision-making under imperfect information. Specifically, the authors detail the heuristic theories of availability, where individuals estimate frequency of events based on ease of recalling instances of such events, and overconfidence, where individuals overestimate the precision and accuracy of their own judgments and think of themselves as being immune to risks which they acknowledge to be a greater danger to a population of which they are a part.

The authors then move on to their experiment, which has proven to be a cornerstone for future research into psychological risk characteristics, conducting a survey where respondents rate 30 different activities and technologies on how much of a health risk and how much of a benefit they each pose to society, as well as to what extent they possess 9 different risk characteristics (including dread, voluntary and control factors, and more). The authors' results support the heuristics theories detailed above and, more importantly for the subject of this paper, demonstrate a number of significant relationships between the different risk characteristics. Based on pairwise correlations, the authors contend that the 9 risk characteristics can be grouped into three factors, which they label dread, familiarity, and exposure. Of importance to this study, the authors note that control factor and voluntary factor especially appear to be correlated with dread, to such a degree that perceptions of dread itself can account for voluntary and control factors among others. Although Slovic *et al.* (1980) have been critiqued for the small and homogeneous sample used in their experiment, these results concerning grouping risk characteristics have become widely influential, and significantly shaped future research, and for that reason they will be especially relevant to the analysis involved in this paper.

### **2.3.2 Fox-Glassman & Weber (2016)**

Seeking to address the issues with the sample used in Slovic *et al.* (1980) and see how the attitudes represented in the paper's results have evolved over time, Fox-Glassman & Weber (2016) replicate the experiment, surveying individuals on the same 30 activities and technologies regarding the same 9 risk characteristics, with a larger and more diverse sample. When compared to the original findings of Slovic *et al.* (1980), the results indicate that all 30 risks are now perceived to be less risky, and that there is less consensus on which risk characteristics each of the 30 risks possesses. Additionally, Fox-Glassman & Weber (2016) find that based on pairwise correlations, the 9 risk characteristics do not map into the three factors posed by Slovic *et al.* (1980) as cleanly as in the original experiment, and one of these 9 characteristics, voluntary factor, appears to be the best predictor of perceptions of both benefits and risks associated with each activity and technology. These results were pivotal to shaping the research question of this paper for two main reasons. First, the changes in perceptions of risk characteristics show that psychological risk characteristics are subject to change over time which, although this change could be potentially caused by a number of different factors, provides basic support for the idea that perceptions of these risk characteristics might be highly subjective, motivating further research into this topic. Second, the finding that the risk characteristics do not so clearly map into the original groupings posed by Slovic *et al.* (1980) becomes key to the experimental design of this paper, studying the risk characteristics voluntary and control factors individually rather than grouped together.

### **2.3.3 Henrich *et al.* (2018)**

In order to gain further understanding of how these risk characteristics correlate with each other and whether they are suitable for individual study the results of Henrich *et al.* (2018) are useful.

Henrich *et al.* (2018) conduct a survey on risk characteristics and preferences for risk mitigation of earthquakes, alongside 5 other hazards. The results of this survey yield a number of interesting insights in terms of how governments should approach mitigating these risks, however what is most useful for the scope of this study are the results concerning pairwise correlations between the risk characteristics. The results indicate much lower correlation levels between dread and voluntary and control factors, which will again become important in shaping the experimental design of this paper.

#### **2.3.4 Savage (1993)**

Savage (1993) is of special importance because this study aims to directly replicate the experiment used by Savage with some key differences in order to study control and voluntary factors individually. Savage (1993) brings the subjects of risk characteristics and WTP together, conducting a survey to evaluate how a number of psychological risk characteristics influence individuals' WTP to mitigate a given fatality risk for the general population. Savage (1993) collects data as part of a larger survey of about 1,000 residents in the Chicago metropolitan area. The questions included by the author in the survey ask respondents to rate 4 different hazards (stomach cancer, home fires, car accidents, and aviation accidents) on two different risk characteristic dimensions, "dread" and "unknown", as well as how personally exposed to the hazard respondents believe themselves to be, which, based on the results of Slovic *et al.* (1980) are meant to capture the 9 previously mentioned risk characteristics through factor analysis. Next, respondents are asked to split a \$100 allocation between donating towards research with the goal of mitigating each of the 4 previously mentioned hazards, indicating their WTP.

In order to clarify what is meant to be captured by each of these risk characteristics, the author notes factors which would result in higher levels of each characteristic. "Dread" is rated higher when the risk associated with a hazard is catastrophic, causes drawn-out death, is involuntary, or has low controllability. "Unknown" is rated higher for hazards that are not necessarily observable during occurrence, are less personally known to an individual, or have a probability of occurrence or consequences which are unknown to scientists or experts.

Savage (1993) conducts three basic OLS regressions using the collected data and finds a few main significant results. First, results indicate that certain hazards which engender high levels of dread seem to stand in a class of their own when individuals make decisions regarding WTP, namely stomach cancer and risks associated with nuclear power. In terms of the direct relationship between WTP and the surveyed risk characteristics, Savage (1993) finds that individuals have a higher WTP to mitigate hazards rated to be associated with a higher level of dread, and individuals have a lower WTP to mitigate hazards to be considered more "unknown"

## 2.4 Context Within Literature

In particular, this study aims to build upon and contribute to the discussion started by the work of Savage (1993), Subramanian & Cropper (2000), and Carlsson *et al.* (2010). Each of these studies takes a different approach to investigating the impacts of perceived psychological risk characteristics on WTP for increased safety or reduced mortality risk. This study adds to this field by directly assessing the impacts of perceived voluntary and control factors of risks on WTP to mitigate them, by investigating the level of consensus within a population on which and to what extent risks possess different psychological risk characteristics, and by conducting this research in a detailed pre-registered setting.

Taken together, these contributions are valuable in that they further understanding of how perceptions of these risk characteristics are determined, and to what extent they are subjective. Although studies such as Fox-Glassman & Weber (2016) have found evidence that perceptions of risk characteristics are subject to change over time and a number of the previously mentioned studies have included information on mean perceptions of risk characteristics, none have conducted an in-depth analysis of variance or consensus on these perceptions within a population. The extent to which these perceptions are subjective and subject to change matters because subjectivity could mean that the implications for how efficient public health policy should be built are also subject to change. For example, on average, a population may find a given risk such as alcoholism to be voluntary, and thus have a lower WTP to mitigate it, however if the variance of this perception within the population is wide, this may be indicative of differences in information or experience. In this case, an informational campaign informing on medical experts' current belief of alcoholism to be an illness similar to others with less taboo might change perceptions within a population, and thus change how an efficient public health policy to mitigate the risk of alcoholism should be formulated.

## 3 Theory

### 3.1 Willingness-to-Pay

This study expands upon the experimental framework set up in Savage (1993) and is thus derived from the same theory of WTP and the mechanisms by which different factors influence it as used in Savage (1993).

In following with Savage (1993), this study interprets willingness-to-pay to avoid a given hazard as defined by the following equation:

$$WTP_i = P_i * [E_i + U_i] \tag{1}$$

Where:

- $P_i$  is a matrix of the assumed probabilities of various levels of harm (death, disability, etc.)
- $E_i$  is a matrix of the assumed consequences of a death or injury in traditional economic terms (loss of potential earnings, bereavement, etc)
- $U_i$  is a matrix of the value of the disutility associated with the occurrence of specific harm (i.e., certain forms of death or injury have greater disutility attached to them)

This study seeks to gain insight into the valuation of life (VOL), which in this equation is represented by the  $[E_i + U_i]$  portion of the equation. Although, in keeping with Savage (1993) this is referred to as "valuation of life", this also contains within it valuation of all possible harms that might result from a given risk, rather than only loss of life. This can be observed in how the questions in the survey used are formulated.

Within the framework of this theory, this study operates on the hypothesis that the valuation of life varies due to the existence of the  $U$  matrix. The subscript  $i$  used in these equations can refer to either individuals or different types of hazards. In other words, this study seeks to investigate and assess impact on WTP of the differences in perceived risk characteristics contained within the  $U$  matrix for different individuals *and* different hazards.

### 3.2 Risk Characteristics

In Savage (1993) the risk characteristics which survey respondents are asked to rate are:

- **Dread:** how nervous a respondent feels when thinking about a given hazard
- **Unknown:** how informed the respondent feels about the *risk and seriousness* of a given hazard
- **Personal:** how much of a threat the respondent feels a given hazard poses to them personally

The author's reasoning for collecting data on only these three characteristics rather than the standard 9 characteristics used in Slovic *et al.* (1980) and other studies is based on the finding of Slovic *et al.* (1980) that, due to correlations between the 9 risk characteristics, they can be pooled into these three broader categories to avoid problems of excessive multicollinearity. Specifically, Slovic *et al.* (1980) exclude voluntary and control factors based on their correlation with dread, which they find to be 0.58 and 0.72 respectively. However, it should be noted that the robustness of the results of Slovic *et al.* (1980) suffers from a low sample size and homogeneous population. Additionally, later research into these risk characteristics has found weaker correlations between control and voluntary factors and dread. When following the experimental design of Slovic *et al.* (1980) years later with a larger, more diverse sample, Fox-Glassman & Weber (2016) find weaker support for the grouping of the risk characteristics, while Henrich *et al.* (2018), when

conducting a survey on the same standard 9 risk characteristics, find dread to correlate only 0.29 and -0.28 with voluntary and control factors respectively. Based on these considerations, this study considers it viable to separate out voluntary and control factors from dread to be assessed individually.

This brings the risk characteristics being considered to a total of 5:

- **Dread:** how nervous a respondent feels when thinking about a given hazard
- **Unknown:** how informed the respondent feels about the *risk and seriousness* of a given hazard
- **Personal:** how much of a threat the respondent feels a given hazard poses to them personally
- **Voluntary:** how voluntary an individual believes *exposure* to a given hazard to be
- **Control:** the extent to which the respondent believes, *once exposed to* a given hazard, one can avoid the negative consequences of the hazard through skill or diligence

### 3.3 Hazards

The hazards on which respondents are surveyed in order to gauge perceptions of the risk characteristics in Savage (1993) are the following:

- Commercial airplane accidents
- Household fires
- Automobile accidents
- Stomach cancer

These hazards were chosen based on evidence found in Slovic *et al.* (1980) showing that they are cognitively viewed as having very different characteristics. For this study, a wide range of hazards were considered including drowning, opioid overdose, public transportation accidents, and more. Based on evidence in previous literature about what risk characteristics the various hazards were expected to invoke, the following four hazards were selected with the same aim of capturing a wide range of perspectives, however with an added focus on capturing widely varying perceptions of voluntary and control factors:

- **Pancreatic cancer:** Similar to stomach cancer in that it is expected to invoke high levels of unknown and low levels of control and voluntary factors (Savage, 1993)

- **Lung cancer:** Expected to invoke high levels of voluntary factor and low levels of unknown (Fox-Glassman & Weber, 2016)
- **Automobile accidents:** Expected to invoke low levels of unknown and high levels of control factor (Fox-Glassman & Weber, 2016, Henrich *et al.*, 2018, Savage, 1993)
- **Household fires:** Expected to invoke close to average levels of all characteristics (Fox-Glassman & Weber, 2016, Savage, 1993)

Household fires and automobile accidents were carried over from Savage (1993), however the other two hazards were chosen with the intent of being more relevant to the focus of this study. Lung cancer was selected in order to invoke a high level of voluntary factor, as it is widely known that certain behaviors and exposures such as smoking put individuals at higher risk for lung cancer. For similar reasons, stomach cancer was replaced with pancreatic cancer, in order to avoid any perceptions (whether true or false) that certain behaviors, such as diet, can increase individuals' risk for stomach cancer.

As the motivation for this study and the policy implications it yields largely revolve around health risks posed by environmental degradation and the United States opioid epidemic, it might seem natural to include hazards more directly associated with these topics in the survey. This was considered, but was eventually deemed non-viable for a number of reasons. In terms of environmental health risks, the main difficulty posed was pinpointing a health risk that could be attributed solely to environmental factors. For example, lung cancer is a health risk exacerbated by poor air quality, but is also exacerbated by habits such as smoking, and therefore perceived risk characteristics of lung cancer cannot necessarily be interpreted as reflecting environmental risks. In terms of the opioid epidemic, opioid overdose was considered for inclusion as a hazard, but was excluded based on expectations that it would elicit emotional responses not elicited by the other hazards included on the survey (Fraser *et al.*, 2017).

## 4 Method

The experimental design for this study is intended to replicate the framework used in Savage (1993). This consists of a survey wherein respondents rate their perceptions of a number of risk characteristics for four different hazards as well as indicate their WTP to reduce the risk of these hazards on a societal level. After collecting data through this survey, a pre-registered statistical analysis was carried out to obtain results and assess hypotheses.

### 4.1 Survey Design

The survey, which can be found in full [in the appendix](#), was created and administered through the Qualtrics platform and was split into three main sections:

#### 4.1.1 Demographics

This section is included to collect data to be used as a control in OLS regressions and consists of one question; respondent’s age. Initially more controls were included, however based on a few considerations, these were excluded. The first consideration was evidence found in Savage (1993). After conducting the OLS regressions replicated in this study, Savage (1993) uses the demographic data collected in the larger survey within which the author’s questions were included, to conduct a basic analysis of how these dimensions are related to WTP. The data included in this analysis are age, education, income, gender, and race. Savage (1993) finds that age has a relationship with WTP which is statistically significant to the  $p < 0.01$  level across all hazards. However, of the other data included, the results indicate that no other demographics have statistically significant relationships with WTP across all hazards, even when using a threshold of  $p < 0.10$ .

The second consideration was survey length. As will be detailed later, respondents were compensated an amount calculated to be a fair hourly wage for completing the survey. Thus, an increase in survey length would force compensation per response to be increased which, due to the limited budget of this study, would reduce sample size. Given the weak evidence for relationships between the other demographics and WTP, it was decided to prioritize increased sample size over the collection of this data. Additionally, as detailed in [Section 7.1.4](#), one of the ways this study aims to build on the work of Savage (1993) is through reduced fatigue of respondents included in the sample, which also contributed to the motivation for limiting the length of the survey.

A final consideration in choosing not to collect more demographic dimensions was the potential for character misrepresentation by respondents recruited for the study. As will be detailed later, certain measures were taken to ensure that respondents were being truthful about their location and preventing duplicate responses, however implementing similar controls to ensure data quality in demographics is more difficult. Wessling *et al.* (2017) for example, find that the potential for character misrepresentation often significantly distorts research findings.

#### 4.1.2 Allocation

After collecting control data, the survey proceeds to collect data concerning WTP to mitigate the four hazards. This was formatted as one question with the order in which the hazards were listed randomized for each respondent (shown in Figure 1).

This question contains a slight departure from the design used in Savage (1993) in that instead of invoking the context of splitting a charitable donation between the hazards, a referendum context was used instead. The decision to depart from the charitable context was based on evidence within the field of behavioral economics indicating that when presented with charitable contexts, individuals take into consideration factors such as social esteem, which might bias behavior (Ariely *et al.*, 2009). The referendum on the other hand represents the private context of a democratic vote which shouldn’t invoke these biases, while directly invoking the societal impacts of the allocation. It is possible that the referendum context does introduce the downside

Part 1: Allocation

Imagine you are voting in a referendum on how to allocate a budget between research into technologies to reduce the risk of the four following hazards. Given that research into each technology would be equally effective in saving lives, what percentage of the total budget would you vote to allocate towards reducing the risk of each hazard?

|                   |                                  |
|-------------------|----------------------------------|
| Car accidents     | <input type="text" value="0"/> % |
| Lung Cancer       | <input type="text" value="0"/> % |
| Home Fires        | <input type="text" value="0"/> % |
| Pancreatic cancer | <input type="text" value="0"/> % |
| Total             | <input type="text" value="0"/> % |

Figure 1: Survey: Allocation Question

of invoking apathy about political processes. For example, individuals voting in a referendum may not believe their individual vote to significantly impact tangible outcomes. However, this effect is not expected to be large, may also be present to an extent in the original charitable donation context, and would likely result only in rushed answers, which evidence from robustness checks [in the appendix](#)) does not support.

Initially, the question included a note highlighted in red reminding respondents that they should regard research into each hazard as equally efficient in using budget towards saving lives (i.e. an allocation of 1% of the budget will have the same quantitative effect on improving health regardless of which hazard it is used towards). However, after conducting pilot tests including this note, it was found that respondents interpreted the note as implying that there is a "correct answer" to the question; that budget should be split equally between the hazards. Thus, the question was rephrased to include this message in a more subtle way, within the actual text of the question rather than as a separate note.

In the survey used by Savage (1993), the Allocation section is preceded by the Risk Characteristics section, but for this study the order has been deliberately switched. This decision was based on the potential for unintentional priming caused by asking individuals to consider risk characteristics *before* choosing how to allocate funds between the different hazards. Some of the risk characteristics, such as control and voluntary factors especially, may have moral implications attached to them. If individuals make these moral considerations about the hazards before choosing how to allocate the budget, their allocation choices may be biased by concerns about social image and esteem (Ariely *et al.*, 2009), which this study does not aim to capture. By reordering this questionnaire, this bias is hopefully minimized.

### 4.1.3 Risk Characteristics

The next section consists of 5 questions, one for each risk characteristic being investigated. Figure 2 shows the questions asking individuals to rate each hazard in terms of voluntary and control factors respectively.

How voluntary to you believe **exposure** to each hazard to be? Rate this on a 7-point scale where a value of 1 implies "completely involuntary" and a value of 7 implies "completely voluntary".

|                   | Completely involuntary |   |   |   | Completely voluntary |   |   |
|-------------------|------------------------|---|---|---|----------------------|---|---|
|                   | 1                      | 2 | 3 | 4 | 5                    | 6 | 7 |
| Lung cancer       |                        |   |   |   |                      |   |   |
| Car accidents     |                        |   |   |   |                      |   |   |
| Pancreatic cancer |                        |   |   |   |                      |   |   |
| Home fires        |                        |   |   |   |                      |   |   |

**Once exposed to each hazard**, to what extent do you believe one can avoid the negative consequences of the risk through skill or diligence? Rate this on a 7-point scale where a value of 1 implies "not controllable" and a value of 7 implies "controllable".

|                   | Not controllable |   |   |   | Controllable |   |   |
|-------------------|------------------|---|---|---|--------------|---|---|
|                   | 1                | 2 | 3 | 4 | 5            | 6 | 7 |
| Lung cancer       |                  |   |   |   |              |   |   |
| Home fires        |                  |   |   |   |              |   |   |
| Pancreatic cancer |                  |   |   |   |              |   |   |
| Car accidents     |                  |   |   |   |              |   |   |

Figure 2: Survey: Risk Characteristic Questions

In keeping with the survey design used in Savage (1993), respondents are asked to rate each of the hazards in terms of each characteristic on a 7-point scale (using a "slider" on the Qualtrics platform).

Although, as in the allocation section, the order in which the hazards were listed was randomized, the order in which respondents were asked to consider the risk characteristics was not randomized. In initial pilot tests, the order of the risk characteristics *was* randomized, however respondents found this to be confusing in a way that might bias their answers by affecting what they factored into their rating of each characteristic, so instead characteristics were set to a specific order; personal, voluntary, control, unknown, dread. This ordering was settled on with the specific intention of clarifying the differences between the risk characteristics. For example, individuals' answers for how personally at risk they believe themselves to be to a hazard should not factor into their rating of the dread factor, so the survey is ordered such that individuals

must first separately consider how personally at risk they are to a hazard before rating the dread factor.

Finally, at the end of the survey, individuals are shown a randomly generated ID code with the instructions to copy and paste this into the AMT platform, through which they were recruited. This allowed for responses to be linked between the AMT and Qualtrics platforms so that only individuals who completed the survey in its entirety would be compensated.

## 4.2 Survey Implementation

### 4.2.1 Data Collection

Data was collected through the Qualtrics survey detailed above (which can be viewed in full [in the appendix](#)) from respondents recruited through the Amazon Mechanical Turk (AMT) platform. In-person pilot tests of the survey showed that individuals were able to complete the survey comfortably within slightly under 3 minutes. Using this information, compensation for respondents recruited through AMT was set at \$0.20, corresponding to an hourly wage of approximately \$5 per hour, which was judged to be a fair wage based off of estimates of wages earned on AMT (Hara *et al.*, 2018). The pool of respondents was narrowed to only individuals living in the United States, mainly attributed to the wish to avoid collecting rushed responses from click farms, which have been found to be more common in other countries (Kennedy *et al.*, 2020).

On the AMT platform, potential respondents can browse different tasks (referred to as "HIT's") and choose which to complete based on compensation, title, and a short description of the task. For this survey, the title displayed was "(3 Minute Survey) Research Funding Referendum" with the description "3 minute survey: Referendum on how to split a research budget between different applications." Once individuals accepted the task, they were shown the bellow instructions, including a link to the Qualtrics survey, shown in Figure 3.

In order to improve data quality, by preventing duplicate responses and falsified locations, the survey was conducted using the MTurk Pro toolbox from CloudResearch. This toolbox prevents duplicate responses and falsified locations by excluding respondents based on information that can be gathered from their IP Address.

The survey was initially published at 12AM EST on March 19th 2020, and was closed after reaching target sample size on March 20th.

### 4.2.2 Sample Size and Rationale

The target sample size for this study was set at  $N=750$ , or 750 different individuals. Due to unexpected fees from AMT, the final sample size reached was  $N=746$ .

A number of factors influenced the decision to set this target sample size. The first was comparability to Savage (1993), which had a sample size of approximately  $N=914$ . In order to replicate this as closely as possible, a goal was set to reach a sample size as close to, if not

**Research Funding Referendum (3 Minutes Survey)(~ 3 minutes)**

**Description:** 3 minute survey: Referendum on how to split a research budget between different applications

**Instructions**

Go to [Link](#) and follow the study instructions. Note the secret key found at the end of the study which you will need to complete the HIT.

\* 1. Enter the SECRET KEY (not your Worker ID) found at the end of the linked survey. Do not add any comment or text here

Figure 3: AMT Instructions

exceeding that of Savage (1993). The second main consideration was budgetary constraints. After setting compensation level at \$0.20 based on the guidance detailed above, factoring in AMT’s commission fees, the cost of 750 responses comes out to \$232.50, after including fees associated with CloudResearch’s MTurk Pro toolbox, exhausting the budget for this study.

The exclusion of the CloudResearch pro features used to prevent duplicate responses and falsified locations would have freed up an additional \$52.50 of budget, allowing for an increased sample size. However, due to concerns about data quality, as noted by researchers previously using AMT (Chmielewski & Kucker, 2020), the improvements in data quality were judged to outweigh the drawbacks of reduced sample size. Although  $N=750$  is below the sample size of Savage (1993), it is in a range close enough to the original study to make comparisons viable.

## 5 Results

The results of this analysis are split into 2 sections; confirmatory results which follow a detailed analysis plan set out in the pre-registration plan prior to collection of data, and exploratory results which consist of analysis beyond the pre-registered plan. Based on the work of Benjamin *et al.* (2017), significance thresholds have been set in the pre-registered plan such that results meeting  $p < 0.005$  will be considered robust, while results meeting only  $p < 0.05$  will be considered suggestive.

Additional summary statistics concerning age of respondents and duration of responses are included in [Appendix Section C](#) for further assessment of robustness.

## 5.1 Risk Characteristics and Willingness-to-Pay

### 5.1.1 Adjusted Variables

Before data analysis one variable, Unknown, is adjusted. Following the procedure used in Savage (1993), responses to how well-informed individuals feel they are about a given hazard on a 7-point scale are transformed by subtracting 8 from each response. The rationale for this is that in the phrasing of the question, a response of 7 indicates that an individual feels well-informed about the hazard, which is, as put by Savage (1993), "the reverse of the other questions where the 'worst' outcome corresponded to 7."

### 5.1.2 Multicollinearity

The pre-registered analysis plan consists of 3 main stages. The first stage addresses the issue of potentially problematic correlation between the dread and control variables, as highlighted by Savage (1993), Slovic *et al.* (1980). This is an important issue to address, as a key difference between this study and Savage (1993) is that Savage chooses to exclude voluntary and control factors from analysis based on their expected correlation with dread.

Following the pre-registered analysis plan, the first step in assessing the issue of multicollinearity is producing the below table showing pair-wise correlations between all risk characteristics:

|           | Personal  | Voluntary | Control   | Unknown   | Dread |
|-----------|-----------|-----------|-----------|-----------|-------|
| Personal  | 1         |           |           |           |       |
| Voluntary | 0.341***  | 1         |           |           |       |
| Control   | 0.175***  | 0.524***  | 1         |           |       |
| Unknown   | -0.344*** | -0.321*** | -0.328*** | 1         |       |
| Dread     | 0.409***  | 0.166***  | 0.110***  | -0.242*** | 1     |

\*  $p < .05$ , \*\*  $p < .005$ , \*\*\*  $p < .001$

Table 1: Pairwise Correlations

In the pre-registered analysis plan, it was stated that if control factor and dread had a correlation greater than 0.5, a "horse race" would be conducted, consisting of multiple regressions in succession (detailed in the full pre-registration plan included [in the appendix](#)) with the goal of determining which variable, if either, should be excluded from the later analysis. However, as this table shows, control factor and dread share a correlation of only 0.110 ( $p < 0.001$ ), so the "horse race" is deemed unnecessary, and the analysis proceeds to the next steps.

The pre-registration plan did not specify a similar "horse race" between dread and voluntary factor due to less support in the previous literature for these two factors having a problematic level of correlation. However, it is also notable that this correlation table shows that voluntary factor and dread were correlated only 0.341 ( $p < 0.001$ ), also not reaching the threshold set out for the "horse race" between control factor and dread.

Although the pre-registered analysis plan did not specify a "horse race" between voluntary and control factors, it is additionally notable that this table shows these two variables to share a fairly high level of correlation (0.524,  $p < 0.001$ ). The reason that this wasn't included centered around previous studies excluding these variables mainly based on their correlation with dread, rather than with each other. Although it is important to acknowledge this correlation, it doesn't significantly hinder the interpretation of the following results as the magnitude of this correlation is still not exceptionally great, and because, as will be outlined in the following sections, this study only draws conclusions about one of these variables and does not concern itself with the relative magnitude of effect between these two variables.

### 5.1.3 Model 1

After addressing the issue of multicollinearity, analysis, replicating Savage (1993), proceeds to the first of three OLS regressions assessing the relationship between the risk characteristics and WTP. Each of these regressions uses the same empirical approach as Savage (1993) with the addition of the variables for voluntary and control factors. Estimations were set as semi-log-linear OLS due to the theory outlined above behind the relationship between WTP and disutility from hazard characteristics, and because the dependent variable may take the value of 0.

The first model is given by equation 2:

$$WTP_i = \alpha_0 + \beta_{1j} \ln(P_{ij}) + \beta_{2j} \ln(D_{ij}) + \beta_{3j} \ln(K_{ij}) + \beta_{4j} \ln(V_{ij}) + \beta_{5j} \ln(C_{ij}) + \beta_{6j} \ln(AGE_i) + \epsilon_j \quad (2)$$

Where subscript  $i$  represents individuals, subscript  $j$  represents hazards,  $P$  is perceived personal threat,  $D$  is dread factor,  $K$  is unknown factor,  $V$  is voluntary factor and  $C$  is control factor

This model offers analysis of the effects of risk characteristics on WTP across individuals for each hazard. In other words, this consists of one regression for each of the 4 hazards, with 21 explanatory variables each. The results of this regression are shown in Table 2.

|                               | (1)                  | (2)                  | (3)                  | (4)                 |
|-------------------------------|----------------------|----------------------|----------------------|---------------------|
|                               | Pancreatic Cancer    | Lung Cancer          | Car Accident         | Home Fire           |
| Pancreatic Cancer - Personal  | 8.124***<br>(1.222)  | 0.00123<br>(1.229)   | -6.614***<br>(1.466) | -1.512<br>(1.103)   |
| Pancreatic Cancer - Voluntary | -1.186<br>(1.027)    | 0.296<br>(1.032)     | 0.748<br>(1.232)     | 0.143<br>(0.927)    |
| Pancreatic Cancer - Control   | -5.060***<br>(1.061) | 1.318<br>(1.067)     | 0.455<br>(1.273)     | 3.287***<br>(0.958) |
| Pancreatic Cancer - Unknown   | -1.747<br>(1.100)    | 2.342*<br>(1.106)    | -1.536<br>(1.320)    | 0.942<br>(0.993)    |
| Pancreatic Cancer - Dread     | 1.954<br>(1.397)     | -0.0674<br>(1.404)   | -1.093<br>(1.675)    | -0.793<br>(1.261)   |
| Lung Cancer - Personal        | -3.465**<br>(1.208)  | 5.116***<br>(1.214)  | 1.224<br>(1.449)     | -2.875*<br>(1.091)  |
| Lung Cancer - Voluntary       | 0.473<br>(1.009)     | -2.253*<br>(1.014)   | 0.211<br>(1.210)     | 1.570<br>(0.911)    |
| Lung Cancer - Control         | 1.534<br>(1.132)     | -3.050*<br>(1.137)   | 2.342<br>(1.357)     | -0.826<br>(1.021)   |
| Lung Cancer - Unknown         | 2.173<br>(1.210)     | -2.499*<br>(1.216)   | 1.582<br>(1.452)     | -1.257<br>(1.093)   |
| Lung Cancer - Dread           | 0.809<br>(1.476)     | 1.590<br>(1.484)     | -2.066<br>(1.771)    | -0.333<br>(1.333)   |
| Car Accident - Personal       | -6.596***<br>(1.409) | -5.904***<br>(1.416) | 14.89***<br>(1.690)  | -2.389<br>(1.272)   |
| Car Accident - Voluntary      | -1.217<br>(1.128)    | -1.926<br>(1.134)    | 3.476*<br>(1.353)    | -0.332<br>(1.018)   |
| Car Accident - Control        | 1.385<br>(1.093)     | 1.738<br>(1.099)     | -2.061<br>(1.311)    | -1.062<br>(0.987)   |
| Car Accident - Unknown        | -1.802<br>(1.086)    | -1.535<br>(1.092)    | 0.516<br>(1.303)     | 2.822**<br>(0.980)  |
| Car Accident - Dread          | -3.311*<br>(1.484)   | 1.501<br>(1.491)     | 2.485<br>(1.780)     | -0.676<br>(1.339)   |
| Home Fire - Personal          | -0.666<br>(1.213)    | -4.436***<br>(1.219) | -3.218*<br>(1.455)   | 8.320***<br>(1.095) |
| Home Fire - Voluntary         | 2.098<br>(1.124)     | 2.692*<br>(1.130)    | -4.241**<br>(1.348)  | -0.549<br>(1.015)   |
| Home Fire - Control           | 1.190<br>(1.153)     | -0.598<br>(1.159)    | -0.439<br>(1.383)    | -0.153<br>(1.041)   |
| Home Fire - Unknown           | -0.569<br>(1.113)    | 0.398<br>(1.119)     | 2.353<br>(1.335)     | -2.182*<br>(1.005)  |
| Home Fire - Dread             | -3.347*<br>(1.334)   | -3.540*<br>(1.341)   | 2.788<br>(1.600)     | 4.099***<br>(1.204) |
| Age                           | -0.662<br>(1.396)    | 1.027<br>(1.403)     | -1.111<br>(1.674)    | 0.746<br>(1.260)    |
| Constant                      | 41.52***<br>(6.255)  | 36.45***<br>(6.286)  | 11.39<br>(7.502)     | 10.64<br>(5.646)    |
| $N$                           | 746                  | 746                  | 746                  | 746                 |
| $R^2$                         | 0.232                | 0.187                | 0.220                | 0.233               |
| adj. $R^2$                    | 0.210                | 0.163                | 0.197                | 0.211               |

Standard errors in parentheses

\*  $p < .05$ , \*\*  $p < .005$ , \*\*\*  $p < .001$

Table 2: Model 1 Results

As shown by the adjusted R-squared values, goodness of fit is significantly higher than the adjusted R-squared values of the corresponding regressions in Savage (1993) which range between approximately 0.05 and 0.1. The size of this table may make the results of this model difficult to interpret, so it is worth noting that the most relevant results are the effects of risk characteristics on WTP for the corresponding hazard. In other words, in regression (1) for pancreatic cancer, emphasis should be placed on estimates in the first 5 rows, in the regression (2) for lung cancer, emphasis should be placed on the following 5 rows, and so on for the final 2 regressions (these cells have been shaded for ease of reading).

In terms of H1, stating that individuals will have a higher WTP to mitigate risks considered less-voluntary, these estimates provide suggestive evidence supporting the hypothesis only for lung cancer ( $p < 0.05$ ). In terms of H2, stating that individuals will have a higher WTP to mitigate risks considered less-controllable, these estimates provide robust evidence supporting the hypothesis for pancreatic cancer ( $p < 0.001$ ) and suggestive evidence supporting the hypothesis holding for lung cancer ( $p < 0.05$ ).

Moving on to exploratory analysis of these results, we notice a few interesting findings. One result that might easily draw attention is that Personal has a positive coefficient significant to the  $p < 0.001$  level for each hazard. This falls in line with previous research, such as that of Bosworth *et al.* (2010) which finds that the greatest determinant of an individual's WTP to mitigate public health risks is self-interest.

In terms of the other risk characteristics, there is some suggestive evidence for Unknown having a negative relationship with WTP for lung cancer and home fires ( $p < 0.05$ ). In other words, the less informed individuals feel about these risks, the lower their WTP to mitigate them. For the dread risk characteristic, there is robust evidence for a positive relationship with WTP for home fires ( $p < 0.001$ ), but not for the other risks.

#### 5.1.4 Model 2

The second of the three OLS models, given by equation 3, analyzes the effects of risk characteristics across individuals and hazards.

$$WTP_{ij} = \alpha_0 + \beta_1 \ln(P_{ij}) + \beta_2 \ln(D_{ij}) + \beta_3 \ln(K_{ij}) + \beta_4 \ln(V_{ij}) + \beta_5 \ln(C_{ij}) + \beta_6 \ln(AGE_i) + \epsilon \quad (3)$$

The results of this regression, shown in Table 3, are somewhat easier to interpret as they consist of only one set of estimates.

Goodness-of-fit for this regression is fairly low, with an adjusted R-squared of 0.095, however still remains well above that of the corresponding regression in Savage (1993). With respect to the pre-registered hypotheses, these results offer no support for H1, as the coefficient on Voluntary is not significant, but offer robust evidence supporting H2, as the coefficient on Control is negative and significant to the  $p < 0.001$  level.

|                                              | (1)                  |
|----------------------------------------------|----------------------|
|                                              | Willingness-to-Pay   |
| Personal                                     | 6.799***<br>(0.545)  |
| Voluntary                                    | -0.627<br>(0.440)    |
| Control                                      | -4.465***<br>(0.461) |
| Unknown                                      | 0.179<br>(0.455)     |
| Dread                                        | 1.088*<br>(0.466)    |
| Age                                          | 0.408<br>(0.760)     |
| Constant                                     | 18.54***<br>(3.113)  |
| $N$                                          | 2984                 |
| $R^2$                                        | 0.097                |
| adj. $R^2$                                   | 0.095                |
| Standard errors in parentheses               |                      |
| * $p < .05$ , ** $p < .005$ , *** $p < .001$ |                      |

Table 3: Model 2 Results

Beyond our pre-registered analysis, these results offer a number of exploratory insights. As in the results from model 1, there is again strong evidence for self-interest being the largest factor in determining WTP, as the coefficient on Personal is the largest of all of the risk characteristics and is significant at the  $p < 0.001$  level. The results also show suggestive evidence for the effect of Dread on WTP, however no support for the effect of Unknown on WTP.

### 5.1.5 Model 3

The third OLS model, given by equation 4, is a repetition of model 2 after adjusting for individual response scaling, following the procedure of Savage (1993).

$$WTP_{ij} = \alpha_0 + \beta_1 \ln(P_{ij}^*) + \beta_2 \ln(D_{ij}^*) + \beta_3 \ln(K_{ij}^*) + \beta_4 \ln(V_{ij}^*) + \beta_5 \ln(C_{ij}^*) + \beta_6 \ln(AGE_i) + \epsilon \quad (4)$$

Where \* superscript denotes adjustment for individual response scaling (ie. panel data techniques will be employed by subtracting each individual's mean response value for that variable from each observation).

The individual response scaling aims to account for individuals anchoring their response around different numbers on the 7-point scale. For example, two individuals may rank the four hazards identically for one of the risk characteristics, but one might think of a rating of 3 as a "standard" level, while the other might think of a rating of 5 in the same way. By subtracting each individual's mean response value for each risk characteristic from observations of that individual, this anchoring is accounted for.

As noted by Savage (1993), although this technique works to account for the issue of differences in anchoring, it does not necessarily make model 3 superior to model 2 because in the process of adjusting the variables for individual response scaling, some potentially useful information is lost. For example, an individual who rates the dread factors of all hazards between 6 and 7 might truly feel higher levels of dread for these hazards than an individual rating the dread factors of all hazards between 1 and 2, and this adjustment would remove this nuance from analysis. Considering this, model 3 should be regarded as a supplement to model 2, and not an improvement upon it, such that both should be considered in tandem when drawing conclusions from the results.

The results, shown in Table 4, have an adjusted R-squared above that of the estimates for model 2 and significantly above that of the corresponding regression in Savage (1993). The estimated coefficients of the regression paint a similar picture of the relationship between the risk characteristics and WTP as those of model 2. Again, the results provide no support for H1, but provide robust evidence for H2 ( $p < 0.001$ ).

Exploratory analysis of these results yields a few notable insights. As is the case in Savage (1993), most of the coefficients on the risk characteristic variables are of a higher magnitude in model 3 than in model 2. As in the previous regression results, Personal still appears to have

|            | (1)                  |
|------------|----------------------|
|            | Willingness-to-Pay   |
| Personal   | 16.42***<br>(0.931)  |
| Voluntary  | -0.733<br>(0.935)    |
| Control    | -9.675***<br>(0.819) |
| Unknown    | 1.040<br>(0.903)     |
| Dread      | 5.901***<br>(1.102)  |
| Age        | -0.233<br>(0.709)    |
| Constant   | 4.295<br>(4.210)     |
| $N$        | 2984                 |
| $R^2$      | 0.185                |
| adj. $R^2$ | 0.183                |

Standard errors in parentheses

\*  $p < .05$ , \*\*  $p < .005$ , \*\*\*  $p < .001$

Table 4: Model 3 Results

the largest effect on WTP, significant to the  $p < 0.001$  level, again demonstrating the importance of self-interest in individuals' decisions regarding WTP. Additionally, the coefficient on Dread is now significant to the  $p < 0.001$  level, showing a modest positive relationship between perceived dread and WTP.

## 5.2 Consensus on Risk Characteristics

After conducting analysis on the relationships between risk characteristics and WTP replicating Savage (1993), the study now shifts focus to an exploratory analysis of consensus on perceptions of risk characteristics across the surveyed population. As noted previously, an understanding of the level of consensus among the population is important, as it may have implications for subjectivity and potential for change of perceived risk characteristics. No hypotheses for this analysis were established in the pre-registration plan due to lack of previous literature on this topic to guide hypotheses and as such; this analysis should be regarded as exploratory.

Analysis of the consensus is limited to the variation of perceived risk characteristics within each hazard rather than across hazards. This is because differences in perceived risk characteristics across hazards may be attributed to differences in the hazards, and thus not reflective of subjectivity in formation of perceptions.

### 5.2.1 Non-adjusted Risk Characteristics

We first view consensus on perceived risk characteristics before adjustment for individual response scaling. Table 5 presents a number of summary statistics for each risk characteristic in order to gain insight into the issue of consensus:

|           | Pancreatic Cancer |       |       | Lung Cancer |       |       | Car Accident |       |       | Home Fire |       |       |
|-----------|-------------------|-------|-------|-------------|-------|-------|--------------|-------|-------|-----------|-------|-------|
|           | Mean              | SD    | Var.  | Mean        | SD    | Var.  | Mean         | SD    | Var.  | Mean      | SD    | Var.  |
| Personal  | 4.312             | 1.751 | 3.066 | 4.413       | 1.730 | 2.994 | 5.106        | 1.418 | 2.012 | 4.218     | 1.621 | 2.627 |
| Voluntary | 3.082             | 1.915 | 3.667 | 3.956       | 1.797 | 3.229 | 4.240        | 1.689 | 2.854 | 3.845     | 1.731 | 2.996 |
| Control   | 3.190             | 1.803 | 3.252 | 3.824       | 1.775 | 3.152 | 4.469        | 1.597 | 2.550 | 4.586     | 1.569 | 2.460 |
| Unknown   | 3.851             | 1.747 | 3.050 | 3.233       | 1.483 | 2.198 | 2.621        | 1.269 | 1.610 | 2.997     | 1.385 | 1.919 |
| Dread     | 4.558             | 1.851 | 3.426 | 4.630       | 1.829 | 3.345 | 4.869        | 1.653 | 2.732 | 4.603     | 1.771 | 3.136 |

Table 5: Non-Adjusted Risk Characteristic Summary Statistics

Viewing this table yields a number of notable insights. Observing the variance levels for the different risk characteristics across the hazards, we find that generally, the top 3 characteristics in terms of variance are voluntary factor, dread, and control factor. The evidence for voluntary factor being the risk characteristic with the lowest level of consensus is also bolstered by the observation that voluntary factor is the risk characteristic with the greatest standard deviation across all hazards.

Across all risk characteristics and hazards, the single highest variance value is that for voluntary - pancreatic cancer, and indeed variance in all of the perceived risk characteristics for pancreatic cancer tend to be significantly higher than the other hazards. This may simply reflect low levels of familiarity with pancreatic cancer among the population, which is supported by the high mean rating for unknown - pancreatic cancer. Conversely, variance in the perceived risk characteristics tends to be lowest for car accident, which is most likely attributed to high familiarity with this hazard, again supported by a low mean rating for unknown - car accident.

Unrelated to consensus, but also notable is the high mean value for dread - car accident. This is further support for the findings in Jones-Lee & Loomes (1995) that car accidents are generally regarded as an especially dreadful hazard.

The insights about consensus found in Table 5 can also be visualized through the box plots in Figure 4.

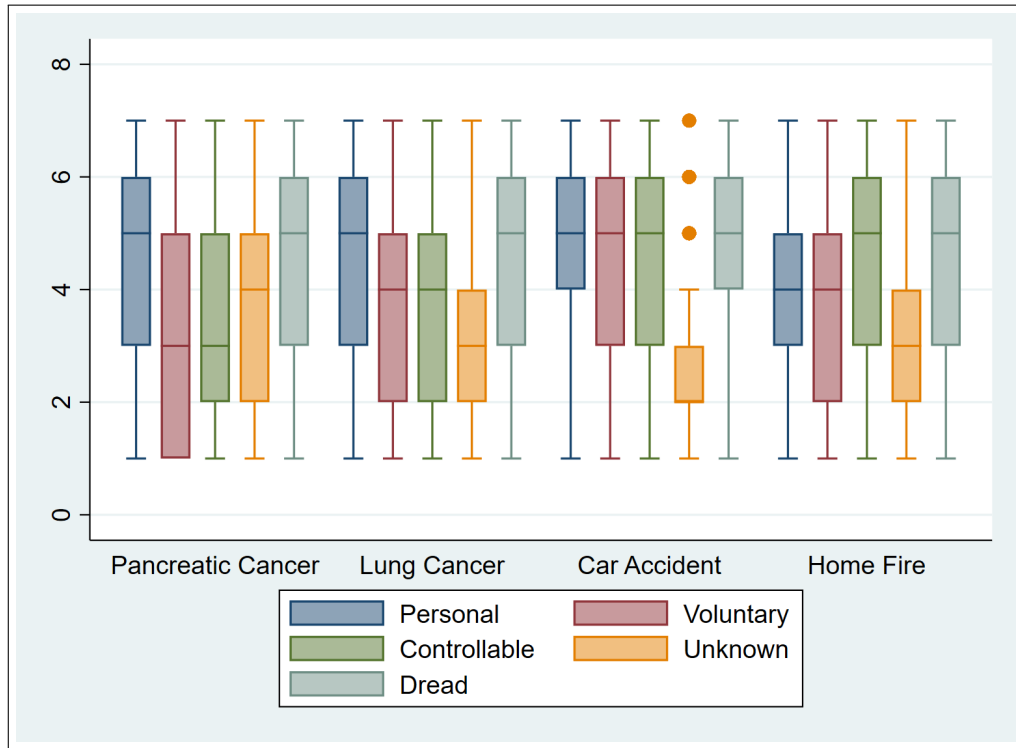


Figure 4: Box Plots Before Individual Response Scaling Adjustment

Although the use of the 7-point scale for ratings of risk perceptions limits the amount the box plots can vary from each other visually (before adjustment for individual response scaling), a few insights can be viewed. The box plots are useful in visualizing the low level of consensus on voluntary factor across the hazards, as well as the low level of consensus on all risk characteristics

for pancreatic cancer. Additionally, the only box plot to show outliers is that of unknown factor for car accidents, which emphasizes a high level of familiarity with the risk posed by car accidents across the population.

### 5.2.2 Adjusted Risk Characteristics

Analysis next shifts to evaluating consensus on perceived risk characteristics after adjustment for individual response scaling. This adjustment is the same as performed for Model 3; subtracting each individual's mean response value for each given variable from each observation. As is the case for Model 3, this adjustment should not be thought of as an improvement over analysis of the risk characteristics before adjustment because, although the issue of differences in anchoring of risk characteristic perceptions is now accounted for, some potentially useful information has been lost in the process. Table 6 shows the same summary statistics as Table 5 after adjustment for individual response scaling:

|           | Pancreatic Cancer |       |       | Lung Cancer |       |       | Car Accident |       |       | Home Fire |       |       |
|-----------|-------------------|-------|-------|-------------|-------|-------|--------------|-------|-------|-----------|-------|-------|
|           | Mean              | SD    | Var.  | Mean        | SD    | Var.  | Mean         | SD    | Var.  | Mean      | SD    | Var.  |
| Personal  | -0.200            | 1.090 | 1.188 | -0.100      | 1.062 | 1.127 | 0.593        | 1.212 | 1.469 | -0.294    | 1.093 | 1.194 |
| Voluntary | -0.699            | 1.015 | 1.030 | 0.175       | 1.098 | 1.206 | 0.459        | 1.027 | 1.055 | 0.064     | 0.950 | 0.902 |
| Control   | -0.827            | 1.094 | 1.197 | -0.193      | 1.061 | 1.126 | 0.452        | 1.106 | 1.223 | 0.568     | 1.116 | 1.245 |
| Unknown   | 0.676             | 1.140 | 1.299 | 0.058       | 0.835 | 0.698 | -0.555       | 0.924 | 0.853 | -0.178    | 0.911 | 0.830 |
| Dread     | -0.107            | 1.047 | 1.097 | -0.035      | 0.980 | 0.960 | 0.204        | 1.032 | 1.065 | -0.062    | 1.067 | 1.139 |

Table 6: Risk Characteristics After Adjustment Summary Statistics

Interestingly, after adjustment there appears to be a large shift in which characteristics vary the most. The characteristics which tend to have the highest levels of variance across the hazards are now personal, control factor, and dread. As voluntary factor had the highest variance before adjustment, this change shows that a great deal of the variance in voluntary factor may be attributed to either differences in anchoring of ratings or differences in sensitivity to voluntary factor. Depending on how one views the validity of adjusting for individual response scaling (i.e. whether its dominant effect is accounting for differences in anchoring or is resulting in the loss of information previously noted when detailing Model 3), either of these hypotheses could be true, however the data collected in this study is not sufficient to answer this question definitively.

Additionally, the highest single variance value is now that of personal - car accident, which may simply reflect differences in driving habits or surrounding environment (i.e. urban vs. rural) of respondents. However, consistent with the values shown before adjustment, pancreatic cancer still tends to have higher values of variance than other hazards, which again can likely be attributed to low familiarity with the hazard, as exhibited by the high mean rating for unknown - pancreatic cancer.

Again, box plots have been produced to visualize these insights in Figure 5.

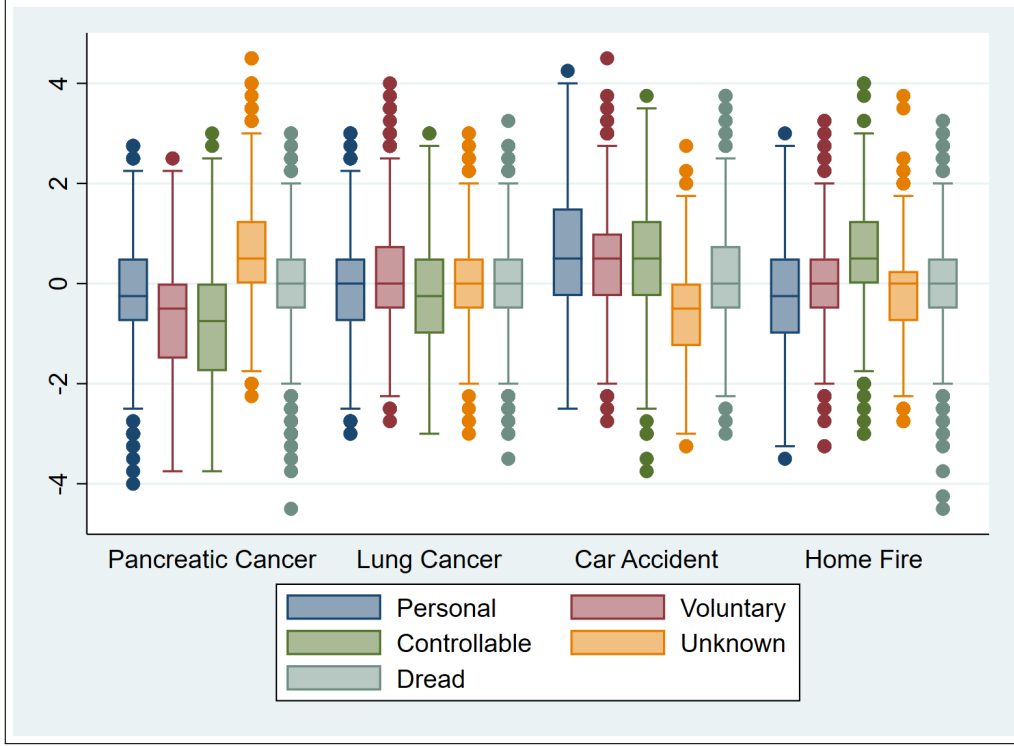


Figure 5: Box Plots After Individual Response Scaling Adjustment

As, after adjustment, risk characteristic ratings are no longer bound to the 7-point scale, there is now more room for these box plots to vary in shape. These box plots mostly serve to visualize the insights which have been previously noted, not yielding any new insights on their own.

## 6 Discussion and Policy Implications

### 6.1 Building on Savage (1993)

As the design of this study replicates the work of Savage (1993) it is important to clarify a number of ways in which these results build on the work of the original study.

#### 6.1.1 Voluntariness and Controllability

The clearest contribution to the work started by Savage (1993) is found in where it deliberately diverges from the original design, by including voluntary and control factors as individual variables. As detailed earlier, Savage (1993) excludes these two variables from analysis based on previous research (see Slovic *et al.* (1980)) finding voluntary and control factors to be highly

correlated with dread. However, as more recent research with larger and more diverse samples has been conducted (see Fox-Glassman & Weber (2016), Henrich *et al.* (2018)), evidence for the magnitude of these correlations has been diminished.

This study views these developments as an opportunity to gain further understanding into the impacts of perceived voluntary and control factor on WTP. In the seminal study on this subject, Slovic *et al.* (1980), at the same time as making note of the problems posed by multicollinearity in the risk characteristics, the authors find significant evidence that individuals are willing to pay much greater amounts (up to a factor of 1,000) to reduce risks considered involuntary than those considered voluntary. By conducting analysis into voluntary factor, and the closely related control factor, this study alters the design of Savage (1993) to build on the work of Slovic *et al.* (1980).

### **6.1.2 Evaluation of Consensus**

The other main diversion in this study from Savage (1993) is the exploratory analysis of consensus within the population. Although the results of this analysis are rudimentary, they are useful for informing future research. Future research could build further upon Savage (1993) by introducing more dimensions to the experimental design, such as assessing changes in responses over time or adding treatments exposing respondents to different levels of education about the hazards.

### **6.1.3 Removed Sources of Potential Bias**

In addition to these more overt differences between this study and Savage (1993), a few smaller changes were made to the original experimental design with the goal of reducing various biases.

The first change made towards this goal can be seen in the phrasing of the allocation question in the survey. Although in Savage (1993) survey administrators were instructed to inform respondents that allocations would be just as efficient in terms of producing health benefits regardless of which hazard they were dedicated towards if asked, it can be presumed that many respondents did not ask. Although in pilot tests of the survey for this study, when a note highlighted in red was included with the allocation question informing respondents of this same equality of efficiency, this was found to bias responses, the final survey incorporated this information into the question in a more subtle way. This is important because if respondents believe that their allocations will have different magnitudes of effects depending on which hazard they are put towards, this introduces a whole new dimension of considerations of efficiency into their answer, which this research does not aim to capture.

A second deliberate change which has been mentioned earlier is the change in context of the allocation question. The context of charitable donations used by Savage (1993) has been changed to a referendum context. This change was made with the goal of reducing bias from factors such as social esteem or social image that may be invoked by the charitable context (Ariely *et al.*, 2009).

Lastly, the order of the questions in the survey has been deliberately changed in order to reduce bias. First, in this study the allocation question has been placed *before* the questions asking respondents to rate the risk characteristics, a reversal from the questionnaire used by Savage (1993). This change was made again with the goal of reducing bias from social esteem or social image, as asking respondents to consider the risk characteristics before their allocation decision may prime them to consider moral associations they might have with the risk characteristics when choosing their allocation. In addition, as noted earlier, during pilot tests it was found that the ordering of the risk characteristic questions had the potential to confuse respondents as to the differences between the risk characteristics. As detailed in [Section 4.1.3](#), the order in which respondents were asked to rate the 5 risk characteristics was deliberately chosen with the goal of minimizing this confusion and the bias it might cause.

#### **6.1.4 Respondent Fatigue**

Although the data collected for Savage (1993) is mainly accomplished through 3 questions, these 3 questions were included as part of a much longer survey, including around 108 questions, of which the relevant questions were placed close to the middle. Taking into account the full length of the survey, respondent fatigue becomes a concern, potentially reducing data quality by causing respondents to rush their responses (Hess *et al.*, 2012). As for this study, the survey used to collect data was standalone, this source of bias is all but eliminated.

#### **6.1.5 Pre-Registration**

Pre-registration is a somewhat recent development in the field of social sciences, and for that reason Savage (1993) and other studies discussed in this paper have not been conducted based on pre-registered methodology and analysis plans. Although, at the time of writing, research yielding empirical evidence of the benefits to replicability of pre-registration in social sciences is still in progress, a number of researchers have called for its use based on benefits observed in other fields (Chambers & Munafò, 2013, Van't Veer & Giner-Sorolla, 2016). By following a plan designating detailed methods for collection and analysis of data, which was registered [on the OSF network](#) prior to collection of data, this study aims to bolster the credibility of its results, taking advantage of these newer tools now at the disposal of researchers in social sciences.

## **6.2 Contribution to Literature**

### **6.2.1 Control Factor**

The central finding of this study is robust support for perceived controllability of a given hazard to have a negative relationship with WTP to mitigate that hazard. Additionally, of the variables included in analysis, control factor has the 2nd largest magnitude of effect on WTP across both models 2 and 3, behind how personally at risk to a hazard an individual believes themselves to be. The finding that perceived personal exposure is the largest single determinant of WTP supports

the findings of a number of previous studies (see Bosworth *et al.* (2010), Savage (1993)), however the results concerning the relationship between control factor and WTP are novel and have notable implications.

Although, since the work of Slovic *et al.* (1980), much research has operated on the belief that risk characteristics such as voluntary and control factors are too strongly correlated with dread to make individual study viable, these results call this conclusion into question. This study's results about the relationship between control factor and WTP are bolstered by pairwise correlations showing that control factor and dread are not necessarily correlated to such a high degree (0.110,  $p < 0.001$ ). These pieces of evidence can be regarded as providing a robust argument that future research into the relationship between risk characteristics and efficient public health policy should pay close attention to control factor, rather than turning a blind eye to it.

### 6.2.2 Consensus on Perceived Risk Characteristics

Although a number of previous studies on perceived risk characteristics have provided statistics on mean values of characteristics for different hazards (see Carlsson *et al.* (2010), Fox-Glassman & Weber (2016), Henrich *et al.* (2018), Savage (1993), Slovic *et al.* (1980)), none have looked into the level of consensus on these perceptions across the surveyed population. By conducting a basic analysis of this, before and after adjustment for individual response scaling, this study provides a jumping-off point for further research into this subject, focusing on those risk characteristics which were found to vary the most across the population (namely, control factor and dread). In particular, future research could investigate the mechanisms behind how perceptions of these risk characteristics change over time, as Fox-Glassman & Weber (2016) has shown additionally that over the years perceptions of risks have indeed changed.

It is notable that control factor is one of the top three risk characteristics in terms of variance both before and after adjustment for individual response scaling. When considering the results concerning the relationship between perceived risk characteristics and WTP and those about consensus in conjunction, further study of control factor specifically is warranted. Although the magnitude of effect on WTP is greater for perceived personal exposure than for control factor, much of the variation in responses about personal exposure can be attributed to genuine differences in personal exposure (such as frequency of driving), whereas variation in perceived control factor cannot be so easily explained. It is additionally possible that perceptions of control factor may be especially subject to change with differing levels of education (for example on current beliefs about addiction as an illness within the field of medicine) or due to the impacts the heuristic factors discussed by Slovic *et al.* (1980).

## 6.3 Limitations

### 6.3.1 Sample Demographics

A common concern raised about data collected using AMT is whether samples of respondents recruited through the platform can be considered representative of a wider population. Indeed, studies have found that AMT respondents tend to have a higher level of education than the average population, and have previously skewed towards female respondents (although this gap appears to be closing) (Huff & Tingley, 2015, Ross *et al.*, 2010). It is important to acknowledge that this may pose a limitation on the interpretation of the results of this study, however, the choice to recruit through AMT can be viewed as a trade-off. Although population samples from AMT may not be perfectly representative, researchers have found AMT samples to not be much less representative than those from other recruitment options (Huff & Tingley, 2015). Especially considering the budget constraints of this study, it is likely that other recruitment options (such as email blasts) would have produced even less-representative samples. For these reasons, these concerns about sample population should be considered when interpreting results, but do not pose a great threat to their validity.

## 6.4 Policy Implications

### 6.4.1 Environmental Policy

Although investigating the effect of perceived personal exposure on WTP to mitigate a risk was not the central objective of this study, the results obtained concerning this relationship were especially notable in magnitude of effect. It may not come as a surprise to many that individuals' WTP to mitigate a hazard is influenced by how personally exposed they feel to it, however it is still important to acknowledge that evidence provided by this study and others such as Bosworth *et al.* (2010), Savage (1993) shows that the magnitude of this effect dwarfs that of any other perceived risk characteristics. Although perceptions of control factor and dread have significant effects on WTP, self-interest is clearly the dominant influence, and understanding this might be useful for policy-makers.

The influence of perceptions about personal exposure to a risk may be especially important when considering environmental policies. By nature, most health impacts caused by environmental risks are delayed and not easily observable to the average individual, and as a result perceptions of personal exposure may be skewed. This highlights a central obstacle in the field of environmental policy-making, wherein differing levels of information and education lead individuals to discount the value of environmental quality. For example, Campa (2018) finds that density of local newspapers and probability of reporting on emissions are associated with lower toxic emissions from energy plants, falling in line with the heuristics theories (namely availability) discussed in Slovic *et al.* (1980). Essentially, the results of this study concerning the influence of self interest on WTP to mitigate hazards contributes to the wealth of evidence pointing towards the importance of disseminating information concerning environmental risks to the wider

public. In order to properly value environmental quality, individuals must first be informed of their exposure to the environmental risks, so an essential aspect of implementing efficient and effective environmental policy in a democratic setting is making sure that voters are informed of risks, in order to make such policy politically viable. Additionally, this logic that is useful for crafting politically-viable environmental policy could be used to explain differences in the environmental quality experienced by different populations, such as in the field of environmental justice. Because this study does not analyze the relationships between demographics and WTP for health policies, this question is beyond the scope however, this could be a direction for future research.

At the time of writing, valuations of health benefits of environmental policies may be an especially relevant topic due to the interaction between air pollution and mortality from the COVID-19 virus. Although understanding of COVID-19 is still evolving, early research shows that minuscule increases ( $+1 \mu g/m^3$ ) in  $PM_{2.5}$  are associated with increased mortality from COVID-19 of up to 15% (Wu *et al.*, 2020). As many countries are taking unprecedented measures enforcing social distancing in order to limit spread of the virus and the resulting deaths, most policies directly addressing pollution and air quality remain unchanged, despite this evidence showing improved air quality to be of great importance in reducing mortality from COVID-19. In terms of the results found in this study, this could be further evidence for inefficient policy resulting from misguided perceptions of how personally exposed to the risks associated with air pollution individuals believe themselves to be. Although the concept of mortality of COVID-19 being increased through the route of faster spread as a result of individuals being in closer proximity to each other is familiar to many in it's similarities to hygienic measures taken every flu season, the concept of increased mortality from air pollution remains more abstract, and as a result individuals likely have skewed perceptions of their personal exposure to these risks. This in turn potentially results in less political pressure towards implementing policies that might be vitally important in minimizing the impact of the virus through improved air quality, explaining the misguided low priority given to environmental regulation in managing the COVID-19 crisis.

#### **6.4.2 Public Health & Addiction**

One of the central motivations for this study and the objective to gain insight into the effects of voluntary and control factor on WTP were the policy-making implications for these two factors specifically. For the previously mentioned reasons, past research has tended to group these factors together with dread, however the importance of level of dread an individual feels about a risk in determining WTP has vastly different policy implications than the implications of voluntary and control factors. Dread, as defined in this field of literature, broadly refers to how nervous an individual feels when considering a risk; a highly personal factor based on opinion, which is generally outside of the hands of any policymaker. On the other hand, perceptions of voluntary and control factors may still be based on "feeling", but are related to more tangible aspects of hazards and the context surrounding them, and thus are more concrete concepts for

policy-makers to work with.

Although this study did not find significant evidence for the relationship between perceived voluntary factor and WTP it found robust evidence for a negative relationship between perceived control factor and WTP, which still has important policy implications on its own. Similar to the relationship between environmental policy-making and perceptions of personal exposure to hazards, there are public health programs that may be undervalued due to under-informed perceptions of controllability of different hazards. Of the hazards assessed in this study, car accidents and home fires each had high mean values for control factor, however attitudes towards these hazards are not as likely to be biased by factors such as taboo and social stigma as other risks which are likely to be considered highly controllable, such as substance dependency, as was noted in the introduction of this paper. In this way, further understanding of the impacts of perceived control factor on WTP is especially useful, as the hazards posed by substance dependency are the target of a number of large public health policies; those combating the opioid epidemic in the US and widespread alcoholism in other countries.

At this point in the discussion it is important to once again highlight the difference between voluntary and control factor. Voluntary factor refers to how voluntary an individual believes *exposure* to a risk is, whereas control factor refers to beliefs about an individual's ability to avoid the consequences of a risk through skill or diligence once *already exposed* to a hazard. In terms of substance dependency, this means that voluntary factor can be interpreted as beliefs about how voluntarily one begins repeated use of a substance, whereas control factor can be interpreted as beliefs about one's ability to avoid the significant negative consequences of substance abuse once repeated use has already been established. As policy discussion will be focused on control factor, the most relevant public health programs are those concerned with rehabilitation of those affected by substance dependency and prevention of relapse. In terms of alcoholism, such policies include distribution of alcohol antagonist medications and public rehabilitation programs, and in terms of opioid dependency such policies include methadone programs and distribution of naloxone, in addition to public rehabilitation programs.

Focusing on the opioid epidemic in the United States as an example, as the crisis has escalated, public rehabilitation programs have continued to be chronically underfunded (Buck, 2011, Skolnick, 2018). Although there is likely a wide array of reasons for this under-funding, the evidence of this study outlines one potential factor, which is a perception of high controllability of the health risks associated with substance abuse reducing public WTP for such programs. There exists a wealth of literature supporting the idea that stigmatization of substance abuse is persistent within the United States despite experts increasingly advocating for substance abuse to be regarded as an illness (see Birtel *et al.* (2017), Fraser *et al.* (2017), Luoma *et al.* (2007), McFarling *et al.* (2011)), bolstering the argument that under-funding of public health programs targeting substance abuse can be at least partially attributed to uninformed perceptions of controllability of the risks associated with substance abuse.

Additionally, implications of the strong relationship between WTP for health policies and

perceived personal exposure go hand-in-hand with those of the relationship with control factor. It is likely that, just as individuals might be misinformed as to how controllable the risks associated with opioid dependence are, they may also be misinformed of their exposure to it as a risk. It is easy to imagine those who develop opioid dependence as being in social circumstances different from one's own, however in reality, most individuals who develop opioid dependence begin use through legal prescriptions meant to treat a wide range of very common ailments (Skolnick, 2018). In this way, exposure to the risks associated with opioid dependence is likely much more common than individuals perceive, compounding the under-funding of public health policy to address this issue caused by misconceptions of the controllability of these risks.

As far as actual policy to enact addressing this issue, the results of this study's exploratory analysis of consensus on perceived risk characteristics come into use. As noted earlier, control factor was one of the variables with the highest levels of variation across the population both before and after adjustment for individual response scaling. Although the evidence of this study alone cannot show that perceptions of control factor might change with differing levels of information, the evidence provided along with the work of Fox-Glassman & Weber (2016) showing that perceptions change over time, highlight this as a possibility. All in all, this does not lead to one definitive policy recommendation, but the evidence demonstrating the importance of perceived control factor in determining WTP to mitigate risks as well as the rudimentary understanding obtained of how these perceptions might be subject to change begin to support efforts to further inform the general public about the mechanisms behind the risks of substance abuse, as a method of combating chronic under-funding of public health programs for substance abuse in a democratic setting. With further research into how risk characteristic perceptions change with education, this policy recommendation may become more solidly supported and understood in more detail.

## 7 Conclusions

### 7.1 Hypothesis 1: Voluntary Factor

Hypothesis 1 stated that individuals will have a higher WTP to mitigate risks perceived to be less-voluntary. Based on the criteria set out in the pre-registered analysis plan, hypothesis 1 is *not* supported. Although suggestive evidence was found that voluntary factor has a negative relationship with WTP to mitigate lung cancer, this was the only support found for the hypothesis and is not sufficient to confirm it.

### 7.2 Hypothesis 2: Control Factor

Hypothesis 2 stated that individuals will have a higher WTP to mitigate risks perceived to be less-controllable. Based on the criteria set out in the pre-registered analysis plan, hypothesis 2 is supported with robust evidence. The coefficient on control factor is negative and significant to

the  $p < 0.001$  level in models 2 and 3, fulfilling the criteria set out in the pre-registered analysis plan.

### 7.3 Consensus

As noted above, due to lack of previous literature, no hypothesis for analysis of the consensus on perceived risk characteristics among the population was established in the pre-registered analysis plan, and thus this study only conducts an exploratory analysis into this subject. Based on the summary statistics and charts provided in [section 5.2](#), it appears that the perceived risk characteristics with the lowest levels of consensus among the population are control factor, voluntary factor, and dread.

This may be intuitive as these three risk characteristics are those which are most based off of "feeling" rather than quantitative factors. For example, one could attempt to easily quantify how personally exposed they are to car accidents as a hazard by measuring how often they drive or ride in a car, whereas there is no such simple, quantifiable measure of how voluntary exposure to car accidents as a hazard is. From the evidence in this study, it can be said that perceptions of these risk characteristics based on "feeling" vary more widely in relation to those of theoretically quantifiable risk characteristics, and thus could be considered to be more subjective. This evidence may be suggestive that perceptions of these risk characteristics could change over time or with different levels of information or education, however these concepts fall outside of the scope of this study, and thus definitive conclusions regarding them cannot be drawn. This study offers only a surface-level understanding of the subjectivity of perceived risk characteristics, but should be regarded as motivating further study into this subject, as the evidence provided points towards fundamental differences between these three characteristics based on "feeling" and the others included in analysis.

### 7.4 Overview

The main conclusions of this study, concerning the negative relationships between perceived personal exposure or perceived controllability of a hazard and willingness-to-pay to mitigate the risk associated with that hazard, help to explain the mechanisms behind under-funding of public health programs and efforts towards improving environmental quality. Additionally, they support conclusions drawn by previous literature about self-interest being the strongest determinant of individuals' willingness-to-pay to mitigate health risks on a societal level, and provide new support for the importance and viability of individual study of perceptions of voluntary and control factors. Future research should aim to further explore these topics, investigating how perceptions of these risk characteristics might change with differing levels of education or information.

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## A Pre-Registration

The Pre-registration plan was submitted to OSF on March 17th, 2020. The plan can be found on the OSF website at the following URL: <https://osf.io/34c9m>

### A.1 Study Information

#### A.1.1 Title

Voluntariness and Controllability - The Effects of Perceived Risk Characteristics on Willingness to Pay

#### A.1.2 Authors

Terence Carr

#### A.1.3 Description

This study investigates the effects of perceived psychotropic risk characteristics on willingness-to-pay (WTP) to reduce the fatality risk posed by a given hazard, as well as the level of consensus on perceived risk characteristics across a population. Specifically, this study will focus on the effects of perceptions of "voluntariness"; the extent to which an individual is exposed to a risk voluntarily, and "controllability"; the extent to which an individual can, once exposed to a risk, avoid the consequences of the risk being realized through skill or diligence (from here forward these will be referred to as "voluntary factor" and "control factor", respectively). Although previous literature has assessed the effects of psychotropic risk characteristics on WTP to reduce a hazard, none have focused specifically on voluntary and control factors. It is useful to ascertain the effects of these factors individually, due to the implications they have for the funding of public health policies seeking to reduce the risk of hazards with widely varied perceptions among populations (consider the differences between an individual's attitudes towards pancreatic cancer and opioid overdose). Additionally, previous literature has not assessed the level to which individuals within a population agree about the characteristics of different hazards, a gap which this study aims to fill. Assessing this will be useful as, if consensus among a population is low, this would highlight the subjective nature of such risk characteristics, potentially indicating that perceptions could change over time, as noted in Fox-Glassman Weber (2016), or with different levels of information, which would have implications for funding and policy decisions.

The experimental design for this paper is based off of Savage (1993) with a few key differences. First, this study will modify Savage's questionnaire to include questions directly assessing perceptions of voluntary and control factors, allowing for the addition of 2 variables to the models employed by Savage. Second, to avoid invoking the charitable context of Savage's questionnaire, and the potential bias that may come with it, the questionnaire for this study asks individuals

to allocate a budget in a referendum context between mitigating the hazards, rather than asking them to split a donation between the hazards.

#### **A.1.4 Hypotheses**

The main hypotheses for this study are as follows:

H1: Individuals will have a higher WTP to mitigate risks perceived to be less-voluntary H2: Individuals will have a higher WTP to mitigate risks perceived to be less-controllable

### **A.2 Design Plan**

#### **A.2.1 Study type**

Observational Study - Data is collected from study subjects that are not randomly assigned to a treatment. This includes surveys, “natural experiments,” and regression discontinuity designs.

#### **A.2.2 Blinding**

No blinding is involved in this study.

#### **A.2.3 Is there any additional blinding in this study?**

*No response*

#### **A.2.4 Study design**

The experimental design for this study is based off of the framework set up in Savage (1993), resulting in the attached survey. Participants for the survey will be recruited through Amazon Mechanical Turk (AMT). The survey is laid out as follows; first, individuals will be asked their age, to be later used as a control during analysis. Age was selected as the only relevant control for this study based on the results in Savage (1993) concerning the effects of demographics on WTP, where it is found that only age significantly influences WTP across all hazards.

Following this control, respondents will proceed to the allocation section of the survey. In this section, respondents are asked to imagine they are participating in a referendum to decide how to split a government research budget between research to mitigate 4 different hazards, selected to invoke a wide range of perceptions of voluntary and control factors; pancreatic cancer, lung cancer, car accidents, and home fires. Individuals’ responses to this will take the form of allocating different percentages of the budget to each risk, with the requirement that the total adds up to 100%. Initially, a separate note highlighted in red was included with this question to ask respondents to assume that research towards mitigating each hazard is identically efficient at spending money towards saving lives, in other words, 1% of the budget would save the same number of lives regardless of which hazard it is put towards. However, this note was removed after pilot tests of the survey showed that participants interpreted this note as meaning there

was a “correct” answer; to allocate budget evenly between the hazards. Instead, the question was rephrased to contain this information about equal cost-efficiency in a less attention-grabbing manner.

After submitting their allocation, respondents then move on to the risk characteristics section of the survey. In this section, individuals rate each hazard on a 7-point scale for each risk characteristic. These characteristics include (and are asked in the following order) how at risk they believe themselves to personally be to a hazard, how voluntary they believe exposure to the hazard is, how controllable the consequences of the hazard are once an individual is exposed to it, how informed they feel about each hazard, and how much dread they feel about the hazard. During the initial pilot tests of the survey, the order in which individuals were asked to consider these characteristics was randomized, however it was decided to designate a specific order to clarify what should be factored into each characteristic. For example, individuals’ answers for how personally at risk they believe themselves to be to a hazard should not factor into their rating for the dread factor, so the survey is ordered so that individuals must first separately consider how personally at risk they are to a hazard, before rating the dread factor.

At the end of the survey, a unique ID is displayed to the respondent, with instructions for them to copy and paste it into AMT. This allows for survey responses in Qualtrics to be connected back to the AMT platform to prevent duplicate responses and allow for compensation to be paid out.

In addition to 3 in-person pilot tests, this survey was piloted on the AMT platform with 9 respondents prior to the posting of the full study. The responses from the pilot run will not be included in analysis.

- [WTP\\_Survey\\_Final.pdf](#)

#### **A.2.5 Randomization**

*No response*

### **A.3 Sampling Plan**

#### **A.3.1 Existing Data**

Registration prior to creation of data

#### **A.3.2 Explanation of existing data**

*No response*

#### **A.3.3 Data collection procedures**

Data will be collected via an online survey created and hosted on the Qualtrics platform (attached). Respondents to the survey will be recruited via Amazon Mechanical Turk (AMT), with

each respondent receiving compensation of 0.20 *for their response* (amounting to 5/hour). The recruitment pool for respondents will be narrowed to only respondents living within the United States. On the AMT platform, the survey will be displayed with the title “(3 Minute Survey) Research Funding Referendum” with the description “3 minute survey: Referendum on how to split a research budget between different applications”. Potential respondents browsing the platform will be able to see the title and description before choosing to participate in the survey, but no other information.

In order to improve data quality, mainly by preventing duplicate responses, the AMT request will be created using the MTurk Pro toolbox from CloudResearch. This toolbox allows for blocking of multiple responses from the same IP address.

The survey will be posted to the AMT platform on 3/18/20 and will be open for responses for 25 days (i.e. closing on 4/12/20). During this period of data collection, none of the data will be observed or analyzed. Analysis of the data will only begin at the end of this time frame or once the stopping rule is met.

#### **A.3.4 Sample size**

The target sample size for this study is set at  $N=750$ . This simply consists of 750 individuals in total responding to the survey.

#### **A.3.5 Sample size rationale**

A number of factors influenced the decision of how to set the target sample size. The first was comparability to the main literature after which this study is modeled, Savage (1993). Savage (1993) had a sample size of approximately  $N=914$ . Considering this, a goal was established to achieve a sample size as close to, if not exceeding, that of Savage (1993). The second main consideration was budgetary constraints. After establishing an estimate of the time required to complete the survey (3 minutes), \$0.20 per response was identified as an acceptable reward for respondents recruited through AMT. With a reward set at this level, factoring in AMT’s commission, the cost of 750 responses comes out to \$232.50 including CloudResearch Pro features to prevent duplicate IP addresses, exhausting the budget for this study.

The exclusion of the CloudResearch pro features preventing duplicate ID addresses would free up \$52.50 of budget, allowing for an increase in sample size, however due to concerns about data quality without these features, the improved data quality is considered to outweigh the cost of reduced sample size. Although  $N=750$  is below the sample size of Savage (1993), it is a high enough number to make comparison between the two studies viable.

#### **A.3.6 Stopping rule**

The survey will close, and respondents will cease to be recruited from AMT once one of two conditions is met. These conditions are that 750 responses have been accumulated, or 25 days

have elapsed since the survey was opened and posted to AMT.

## **A.4 Variables**

### **A.4.1 Manipulated variables**

Following the procedure used in Savage (1993), responses to the question asking individuals to rate each hazard in terms of how well-informed they believe themselves to be about it on a 7-point scale will be transformed by subtracting 8 from each response. The rationale for this is that in the phrasing of the question, a response of 7 indicates that an individual feels well-informed about the hazard, which is, as put by Savage, “the reverse of the other questions where the ‘worst’ outcome corresponded to 7.”

Additionally, when conducting the third regression model and analysis of the consensus on risk characteristics amongst the population, responses to each of the questions asking individuals to rate risk characteristics will be adjusted for individual response scaling. Each individual’s mean response value for each variable will be subtracted from each observation. The rationale behind this and the specifics of where it will be employed are detailed in the Analysis Plan.

### **A.4.2 Measured variables**

The main outcome variable will be WTP. This variable measures the percentage of the total budget allocated to each hazard in the allocation portion of the questionnaire.

Additionally, a variable will be measured for the rating of each risk characteristic on a 7-point scale for each hazard. These characteristics are personal risk level, voluntariness, controllability, dread, and “unknown”.

Lastly, respondent’s age will be included as a control variable.

### **A.4.3 Indices**

*No response*

## **A.5 Analysis Plan**

### **A.5.1 Statistical models**

Analysis will consist of 3 main stages. The first stage addresses the issue of potential correlation between the dread and control factor variables, as highlighted by previous literature Slovic, Fischhoff, and Lichtenstein (1980) and Savage (1993). This is important to address, as a key difference between this study and Savage (1993) is that Savage chooses to exclude voluntary and control factors from his analysis based on their correlation with dread. In order to assess the level of correlation, a correlation table showing correlations between all risk characteristic responses will be produced, modeled off of Table 3 in Fox-Glassman Weber (2016). If in this correlation table the correlation between dread and control factor is greater than 0.5, a “horse race” between

dread and control factor will be conducted to determine which will be included in the following regression analyses. Within the “horse race”, the p-value threshold for statistical significance is set at  $p < 0.05$ .

The first step of the “horse race” will be a regression with WTP as the outcome variable, using dread and control factor as explanatory variables alongside the age control variable (this is shown as equation [(5)] in the attached supplement PDF). If the regression results show both dread and control factor to have significant effects, both will be included in the later regressions. If the regression results show only one of the variables to have a significant effect, the other will be excluded from the later regressions. If neither variable has a significant effect, the next step will be to test these variables one-by-one. This one-by-one testing will consist of 2 regressions, each with WTP as the outcome variable and one of either dread or control factor as explanatory variable alongside the age control (shown as equation [(6)] in the supplement PDF). If these regressions show both variables to have significant effects, the variable with the smaller magnitude of effect will be excluded from the later regressions. If only one variable is shown to have significant effects, the other will be excluded from the later regressions. If neither variable is shown to have significant effects, both will be excluded from future regressions.

Following the “horse race”, the second stage of analysis will be comprised of 3 OLS models assessing the relationship between the risk characteristics and WTP. These models are based off of equations 2, 3, and 5 from Savage (1993), modified to include the additional risk characteristic variables assessed in this study. The equations for these 3 models can be found in the attached supplement PDF. Estimations were set as semi-log-linear OLS due to theory behind the relationship between WTP and disutility from hazard characteristics, and because the dependent variable may take the value of 0 (Savage (1993)).

The first model, shown as equation [(7)] in the attached PDF offers analysis of the effects of risk characteristics on WTP across individuals for each hazard. In other words, this will consist of one regression for each of the 4 hazards, with 21 explanatory variables each.

The second model, shown as equation [(8)] in the attached PDF analyzes the effects of risk characteristics across individuals and hazards. This will consist of one regression with one explanatory variable for each of the 5 risk characteristics.

The final model, shown as equation [(9)] in the attached PDF consists of the same analysis as the second model, while adjusting for individual response scaling in the rating of risk characteristics. In practice, this means that panel data techniques will be used, subtracting each individual’s mean response value for that variable from each observation.

The final stage of analysis will be geared towards assessing the level of consensus among the population on perceptions of risk characteristics. This will consist of a table showing means and measures of variability (standard deviation, variance) of responses to risk characteristic questions, first in absolute terms, and then after adjustment for individual response scaling, as specified above. Additionally, dispersion of responses on perceived risk characteristics will be graphically represented in box plots, both before and after adjustment for individual response scaling.

In order to assess whether the 2 hypotheses designated earlier are supported, the following criteria will be used:

H1: In the first model, for each hazard, if the corresponding coefficient for that hazard and the voluntary factor is negative and meets significance thresholds set out in Inference Criteria section, the hypothesis will be considered to be supported, but only necessarily for that specific hazard. In the 2nd and 3rd models, if the coefficient for the voluntary factor is negative and meets significance thresholds set out in the Inference Criteria section, the hypothesis will be considered to be supported, and will be considered to be robust if this condition is met in both models.

H2: If the control factor is left in the model after the “horse race”, the same criteria for assessing H1 will be used, replacing voluntary factor with control factor. If control factor is excluded and dread factor is included after the “horse race”, the same criteria for assessing H1 will be used, replacing voluntary factor with dread, however if conditions are met, this result will only be considered suggestive of H2. If both dread and control factor are excluded from analysis after the “horse race”, results for H2 will be considered inconclusive.

- [Equations\\_Supplement.pdf](#)

#### **A.5.2 Transformations**

Where applicable, responses to risk characteristic questions will be adjusted to account for individual response scaling, as detailed above.

#### **A.5.3 Inference criteria**

Regression results will be interpreted as conclusions based on significance thresholds. Any results meeting the threshold of  $p < 0.005$  will be considered robust, and any results meeting the threshold of  $p < 0.05$  will be considered suggestive. These thresholds are set based on Benjamin et al (2017).

#### **A.5.4 Data exclusion**

Any survey responses which have not completed all 8 questions will be excluded from analysis.

#### **A.5.5 Missing data**

In order to prevent the collection of incomplete data, the Qualtrics questionnaire has been set up so that an individual cannot submit a response without completing the survey in its entirety. If an individual does not complete and submit a response, they will not receive compensation from AMT.

### A.5.6 Exploratory analysis

Exploratory analysis will consist of interpreting the results of the final stage of analysis, assessing consensus on perceived risk characteristics across the population. This analysis will be considered exploratory as there will not be hypotheses for these results set out in advance, due to lack of previous literature in this area.

The exploratory analysis will specifically look at measures of variance of responses to the risk characteristic questions on the survey for each risk characteristic, and explore which ones of these are notably high or low, as well as how they compare to each other. The importance of these comparisons is the implications they may have for the level of subjectivity of these risk characteristics.

## A.6 Other

### A.6.1 Other

*No response*

## A.7 Pre-Registration Equation Supplement

**"Horse Race" Equations:**

$$WTP_{ij} = \alpha_0 + \beta_1 \ln(D_{ij}) + \beta_2 \ln(C_{ij}) + \beta_3 \ln(AGE_i) \quad (5)$$

Where subscript  $i$  represents individuals, subscript  $j$  represents hazards,  $D$  is dread factor and  $C$  is control factor.

$$WTP_{ij} = \alpha_0 + \beta_1 \ln(X_{ij}) + \beta_2 \ln(AGE_i) \quad (6)$$

Where subscript  $i$  represents individuals, subscript  $j$  represents hazards and  $X$  represents each variable being tested in the "horse race" (i.e. either dread factor or controllability factor)

### 3 Main Models:

$$WTP_i = \alpha_0 + \beta_1 \ln(P_{ij}) + \beta_2 \ln(D_{ij}) + \beta_3 \ln(K_{ij}) + \beta_4 \ln(V_{ij}) + \beta_5 \ln(C_{ij}) + \beta_6 \ln(AGE_i) \quad (7)$$

Where subscript  $i$  represents individuals, subscript  $j$  represents hazards,  $P$  is perceived personal threat,  $D$  is dread factor,  $K$  is unknown factor,  $V$  is voluntariness factor and  $C$  is controllability factor

$$WTP_{ij} = \alpha_0 + \beta_1 \ln(P_{ij}) + \beta_2 \ln(D_{ij}) + \beta_3 \ln(K_{ij}) + \beta_4 \ln(V_{ij}) + \beta_5 \ln(C_{ij}) + \beta_6 \ln(AGE_i) \quad (8)$$

$$WTP_{ij} = \alpha_0 + \beta_1 \ln(P_{ij}^*) + \beta_2 \ln(D_{ij}^*) + \beta_3 \ln(K_{ij}^*) + \beta_4 \ln(V_{ij}^*) + \beta_5 \ln(C_{ij}^*) + \beta_6 \ln(AGE_i) \quad (9)$$

Where \* superscript denotes adjustment for individual response scaling (ie. panel data techniques will be employed by subtracting each individual's mean response value for that variable from each observation).

## B Survey Design

### Demographics

What is your age?

### Part 1: Allocation

Imagine you are voting in a referendum on how to allocate a budget between research into technologies to reduce the risk of the four following hazards. Given that research into each technology would be equally effective in saving lives, what percentage of the total budget would you vote to allocate towards reducing the risk of each hazard?

|                   |                                  |
|-------------------|----------------------------------|
| Home Fires        | <input type="text" value="0"/> % |
| Lung Cancer       | <input type="text" value="0"/> % |
| Pancreatic cancer | <input type="text" value="0"/> % |
| Car accidents     | <input type="text" value="0"/> % |
| Total             | <input type="text" value="0"/> % |

### Part 2: Risk Characteristics

For each of these hazards, how much of an actual threat do you believe it poses to you personally? Rate this on a 7-point scale where a value of 1 implies "no threat" and a value of 7 implies "high threat".

|                   | No Threat |   |   |   |   |   | High threat |
|-------------------|-----------|---|---|---|---|---|-------------|
|                   | 1         | 2 | 3 | 4 | 5 | 6 | 7           |
| Lung cancer       |           |   |   |   |   |   |             |
| Pancreatic cancer |           |   |   |   |   |   |             |
| Home fires        |           |   |   |   |   |   |             |
| Car accidents     |           |   |   |   |   |   |             |

How voluntary to you believe **exposure** to each hazard to be? Rate this on a 7-point scale where a value of 1 implies "completely involuntary" and a value of 7 implies "completely voluntary".

|                   | Completely involuntary |   |   |   |   | Completely voluntary |   |
|-------------------|------------------------|---|---|---|---|----------------------|---|
|                   | 1                      | 2 | 3 | 4 | 5 | 6                    | 7 |
| Lung cancer       |                        |   |   |   |   |                      |   |
| Car accidents     |                        |   |   |   |   |                      |   |
| Home fires        |                        |   |   |   |   |                      |   |
| Pancreatic cancer |                        |   |   |   |   |                      |   |

**Once exposed to each hazard**, to what extent do you believe one can avoid the negative consequences of the risk through skill or diligence? Rate this on a 7-point scale where a value of 1 implies "not controllable" and a value of 7 implies "controllable".

|                   | Not controllable |   |   |   |   | Controllable |   |
|-------------------|------------------|---|---|---|---|--------------|---|
|                   | 1                | 2 | 3 | 4 | 5 | 6            | 7 |
| Home fires        |                  |   |   |   |   |              |   |
| Pancreatic cancer |                  |   |   |   |   |              |   |
| Car accidents     |                  |   |   |   |   |              |   |
| Lung cancer       |                  |   |   |   |   |              |   |

For each hazard, rate how informed you are about the risk it poses and its seriousness. Use a 7-point scale where a value of 1 indicates that you know basically nothing about the risk and seriousness, and a value of 7 indicates that you are well-informed.

|                   | Don't know anything |   |   |   |   | Well-informed |   |
|-------------------|---------------------|---|---|---|---|---------------|---|
|                   | 1                   | 2 | 3 | 4 | 5 | 6             | 7 |
| Lung cancer       |                     |   |   |   |   |               |   |
| Pancreatic cancer |                     |   |   |   |   |               |   |
| Home fires        |                     |   |   |   |   |               |   |
| Car accidents     |                     |   |   |   |   |               |   |

Rate each hazard on a 7-point scale where a value of 1 implies that you remain calm when thinking about it and a value of 7 implies that you become nervous when thinking about it.

|                   | Remain calm |   |   |   |   | Become nervous |   |
|-------------------|-------------|---|---|---|---|----------------|---|
|                   | 1           | 2 | 3 | 4 | 5 | 6              | 7 |
| Pancreatic cancer |             |   |   |   |   |                |   |
| Lung cancer       |             |   |   |   |   |                |   |
| Car accidents     |             |   |   |   |   |                |   |
| Home fires        |             |   |   |   |   |                |   |

### Random ID

Here is your ID: `#{e://Field/Random%20ID}`

Copy this value to paste into mTurk.

When you have copied this ID, please click the next button to submit your survey. If the survey is not submitted, you will not receive compensation for your response.

## C Robustness Checks

### C.1 Age Summary Statistics

|     | N   | Mean  | Var.   | SD    | Min | Max |
|-----|-----|-------|--------|-------|-----|-----|
| Age | 746 | 35.70 | 125.51 | 11.20 | 18  | 72  |

Table 7: Age Summary Statistics

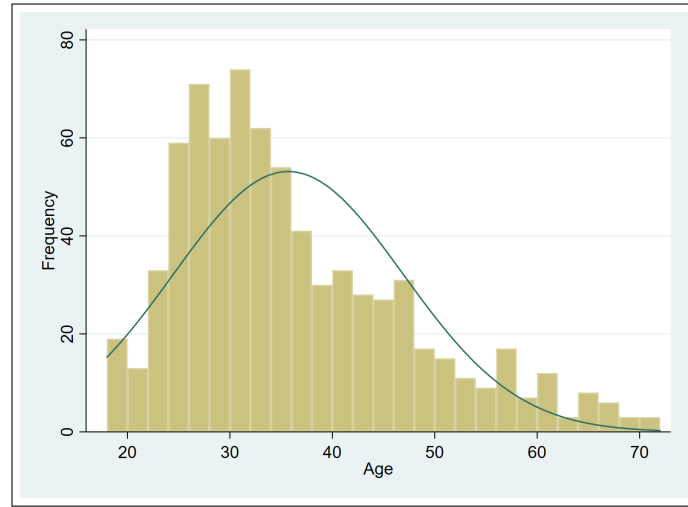


Figure 6: Age of Respondent Distribution

## C.2 Survey Response Duration Summary Statistics

|          | N   | Mean   | Var.       | SD      | Min | Max   |
|----------|-----|--------|------------|---------|-----|-------|
| Duration | 746 | 241.01 | 2146834.34 | 1465.21 | 36  | 40040 |

Table 8: Response Duration Summary Statistics

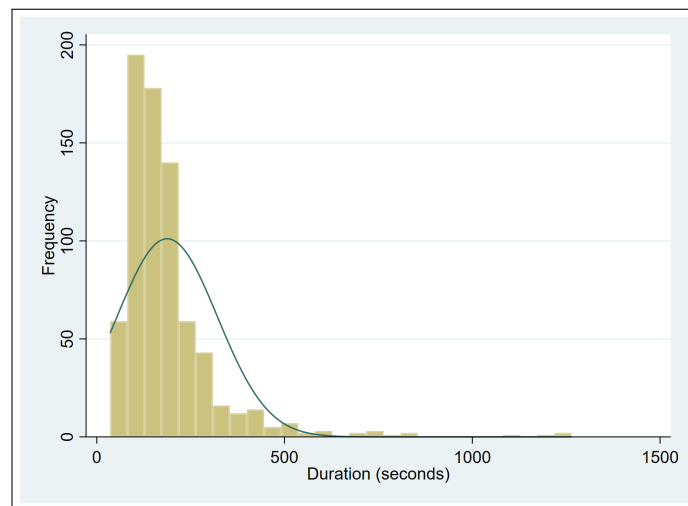


Figure 7: Response Duration Distribution (after dropping max outlier)