

## DYNAMIC ENDOGENOUS RISKS & NON-EXPECTED UTILITY BEHAVIOR

RAM RANJAN\* · JASON F. SHOGREN\*\*

*The theory of endogenous risk captures the idea that people self-protect and self-insure to reduce risks to human and environmental health. Herein we extend the standard static model to include the realities of (1) dynamic and multiple risks, and (2) non-expected utility (non-EU) behavior. Our results suggest both self-protection and self-insurance decrease for any one risk when cumulative dynamic risks are large and when multiple risks exist. If people are non-EU maximizers, self-protection and self-insurance also decline when they follow the conservatism heuristic (insufficient weighting of new information). In addition, if non-EU people over- and under-weight probabilities of bad states, they can invest non-linearly in self-protection and self-insurance.*

JEL Classification: D8

Keywords: Self-insurance, Self-Protection, Perception, Probability Weighting, Risk Resilience

### I. INTRODUCTION

People protect themselves privately from risky events—either through self-protection or self-insurance or both (see e.g., Ehrlich and Becker, 1972; Shavell, 1979). In general, self-protection reduces the chance a bad

---

*Received for publication: July 22, 2009. Revision accepted: Oct. 2, 2009.*

\* Graduate School of the Environment, Macquarie University, NSW 2109 Australia, e-mail: rranjan@science.mq.edu.au.

\*\* Corresponding author: Department of Economics and Finance, University of Wyoming, Laramie WY 82071, USA, e-mail: jramses@uwyo.edu.

state of nature is realized; self-insurance reduces the severity of a realized bad state. Both actions make risk endogenous. For policy purposes, endogenous risk implies people have some control over the risks posed to both human and environmental health (e.g., Shogren and Crocker, 1999). People invest scarce resources to increase the chances good things happen and bad things do not. These private choices affect public policy and collective action just as policy and governments affect our private choices.

The standard endogenous risk model, however, has some limiting properties relative to real world challenges such as climate change and communicable disease prevention. The basic model has focused primarily on risk reduction choices within a static expected utility world of one risk. But people frequently make risk management decisions (i) over time (see Blomquist, 2004; Agee and Crocker, 2007),<sup>1</sup> and (ii) over multiple risks.<sup>2</sup> In addition, people do not always follow the precepts set for in expected utility theory (see Tversky and Kahneman, 1979). Many behavioural biases and heuristics have been documented. Two prominent heuristics are that people tend to over- and under-weight probabilities of states of nature, and they downplay new information in the updating process, i.e., the conservatism bias (see e.g., Edwards, 1968).<sup>3</sup> An environment of

---

<sup>1</sup> For instance, Blomquist (2004) designs a static model to derive the value of statistical life using a wtp analysis. Blomquist notes the limitations of a static model, however, and proposes a life-cycle model as a better approach. The individual entity may span the parent and the child. Using 1991 data from National Maternal and Infant Health survey for the US, Agee and Crocker (2007) find mothers valued their child's health more than their own, about 55 percent higher, for policies to reduce their children's exposure to risk.

<sup>2</sup> For instance, Muermann and Kunreuther (2008) consider positive externalities from interdependencies and deduce people under-invest in self-protection. Income has been found to reduce the perception of risks (Dosman et al., 2001)—the rich can afford safer products. Alternatively, poverty implies less ability to mitigate risks. The presence of multiple risks can also affect self-protection decisions. For example, Bhattacharya et al. (2007) find the willingness to pay for risk reduction for traffic mortality in Delhi, India is three times larger for people driving a two-wheeler relative to a pedestrian—even though the walker faces substantially higher risk.

<sup>3</sup> Over the years, experimental evidence has revealed a gap between subjective and objective risk (see e.g., Kahneman and Tversky, 1994, Sunstein, 2002, Anderson and Lundborg, 2007). In general, people tend to under-weigh large risks and over-weigh small risks. The classic paper is Lichtenstein et al. (1978), who observed people over-assessing small risks of dying, and understating larger risks. For instance, the statistical risks of dying from a plane crash are much lower as compared to dying from a motor accident, yet the perceived risk of a plane crash is much higher. Ganderton et al. (2000) find that subjects buy insurance for low probability but high loss events as the probability of loss is decreased—a behavior that is inconsistent to traditional expected utility maximization theory. Houtven et al. (2008) find people rank their willingness to pay (WTP) to pay for cancer risk reduction with 5 year latency three times more than their WTP to avoid dying in a

dynamic endogenous risks given non-expected utility behaviour could play a role in many public policy issues such as climate change, biodiversity, and human health decisions.<sup>4</sup> An open question is how the introduction of these realities affects the optimal mix of self-protection and self-insurance.

Herein we address this question by developing a dynamic endogenous risk model with many risks and behavioral heuristics. Two key results emerge. First, relative to a standard expected utility model, both self-protection and self-insurance decrease for any one risk when multiple risks exist, when cumulative risks are high, or when people are conservative in updating new information about risks, or in any combination. Second, if a person assigns non-expected utility weights to the probabilities of good and bad states, self-protection and self-insurance can switch abruptly from low to high levels as cumulative risk increases (e.g., climate risks or health risks from communicable diseases). Initially, when risks are low, a non-EU person over-weights them, leading to low self-protection effort for marginal increases in risk. But as cumulative risks increase, people now under-weigh the chances, leading to greater self-protection. While some non-expected utility approaches to evaluate self-protection and self-insurance show no change in behavior as compared to the expected utility models (e.g., Konrad and Skaperdas, 1993, Machina, 1995), our results show greater risk aversion can reduce self-protection. Multiple risks are enough to bring about this reaction.

Our results matter for public policy because they reflect cases in which the standard static single risk model could under- or over-represent investments in self-protection and self-insurance. These differences are magnified by population heterogeneity in time preferences, the set of

---

motor accident. Perception could be either influenced by individuals' attitude towards suffering, for instance preference for instant and intense pain versus slow and protracted suffering. A distorted perception could also be a result of time discounting. For instance if the risk of dying from a particular disease leads to a reduced life expectancy it might lead to a perverse behavior that increases risks of other diseases too. This effect may be characterized by emphasis on enjoying the current rather than enjoying the future, which can help explain why people seem to have a difficult time updating information about climate change risks (see Bleda and Schakley, 2005).

<sup>4</sup> See for example Shogren and Crocker (1991), Blomquist (2004), Muermann and Kunreuther (2008), Houtven et al. (2008), Leiserowitz 2006, Lorenzoni and Pidgeon (2006), Viscusi and Zeckhauser (2006), and Oppenheimer and Todorov (2006).

relevant risks, and conservatism in updating. For climate change, a static endogenous risk model would over-estimate likely investments in self-protection (or mitigation), whereas a non-expected utility endogenous risk model would predict lower self-protection because people under weigh or ignore new information. For communicable diseases, a non-expected utility endogenous risk model predicts less self-protection at high risks, thereby increasing the chances of further spread of the disease on the neighboring farms.

## II. BASELINE MODEL: MULTIPLE RISKS

Building on Shogren and Crocker's (1991) static endogenous risk model, consider a person exposed to multiple health risks from being in a particular environment. The hazard poses a risk to health  $h$  which could deteriorate stochastically and suddenly. The person is healthy up to time  $t$  and at time  $t$  he gets sick. This modeling of health hazard is based upon the dose-response approach that assumes as dose increases health depreciates and the critical thresholds for health breakdown are random (Rosen, 1981). Self-protection and self-insurance can reduce the probability and severity of poor health. When a person self-protects,  $s(t)$ , he mitigates the risk of a bad health; when he self-insures,  $z(t)$ , he reduces the severity of bad health if realized.

Suppose a person faces two kinds of risks,  $p_1(t)$  &  $p_2(t)$  both of which reduce health once crossing a random threshold. We represent the probabilities of reduced health from the two types of risks by random events with exponential distributions, the hazard rates of which are given as  $p_1(t)$  &  $p_2(t)$  and are defined as:

$$p_1(t) = \exp(-s_1(t)), \text{ and} \quad (1)$$

$$p_2(t) = \exp(-s_2(t)) \quad (2)$$

where  $s_1(t)$  &  $s_2(t)$  are the levels of self-protection adopted at time  $t$  to mitigate the risk to health. Define the cumulative sum of the hazard rate for health event 1 by the parameter  $\lambda_1(t)$  as:

$$\lambda_1(t) = \int_0^t p_1(s_1(t)) ds . \quad (3)$$

The cumulative sum of hazard rate for health event 2 can be determined as:

$$\lambda_2(t) = \int_0^t p_2(s_2(t)) ds . \quad (4)$$

The person self-insures through  $z(t)$  to reduce the damages from a health catastrophe. The level of health damages are a function of the accumulated stock of self-insurance defined as:

$$k_1(t) = \int_0^t (z_1(t) - \delta) ds , \quad (5)$$

and

$$k_2(t) = \int_0^t (z_2(t) - \delta) ds \quad (6)$$

where  $\delta$  is the decay rate of insurance capital. Assume the cost of self-protection is non-linear in efforts for the two risks as:

$$s^\beta(t) , \quad (7)$$

where  $\beta$  is the elasticity of self-protection cost. Cost of self-insurance is non-linear in effort as:

$$z^\varepsilon(t) , \quad (8)$$

where  $\varepsilon$  is the elasticity of self-insurance cost.

Health damages from event 1 are decreasing in self-insurance stock and increasing in damage parameter  $d_1$ . Assume health damages reduce the overall individual utility by a factor:

$$\frac{d_1}{\log(\varphi + k_1(t))}. \quad (9)$$

where  $\varphi$  is some constant that prevents the damages from going negative. Health damages from event 2 reduce utility likewise and are given as:

$$\frac{d_2}{\log(\varphi + k_2(t))}. \quad (10)$$

We decompose the inter-temporal sum of benefits from being healthy or sick into three parts: value ( $v_0$ ) before either of the health events take place; value ( $v_1$ ) after health event 1 is realized, and value ( $v_2$ ) after health event 2. For simplicity, we assume once either health events is realized, the person is then immune to the other event, no additional cost is imposed on him (i.e., when both risks are deadly).

We write the value function before either of the events is realized as:

$$v_0 = \left\{ \int_0^{\infty} U(w - c(s(t), z(t))) \cdot \exp(-\rho \cdot t) dt \right\}, \quad (11)$$

where  $U(w - c(s(t), z(t)))$  is the utility from wages  $w$  net of costs of self-protection and self-insurance and  $\rho$  is the discount rate. Assume a person receives fixed income from some activity which is a function of his health as:

$$w = h \cdot \tau, \quad (12)$$

where  $0 < h < 1$  and  $\tau$  is the income an individual derives when fully healthy, i.e., when  $h = 1$ . Assume utility is a Cobb-Douglas function of his health and income:

$$w^\alpha \cdot h^{1-\alpha} = h^\alpha \cdot \tau^\alpha \cdot h^{1-\alpha} = h \cdot \tau^\alpha. \quad (13)$$

Finally, bringing together the three value functions (see Appendix A

for their derivation), the objective function is to maximize:

$$\begin{aligned}
& E[v_0] + E[v_1] + E[v_2] \\
& = \left\{ \int_0^{\infty} \exp(-\lambda(t)_1 - \lambda_2(t)) \cdot (U(w - c(s(t), z(t)))) \cdot \exp(-\rho \cdot t) dt \right\} \\
& + \left\{ \int_0^{\infty} p_1(t) \cdot \exp(-\lambda_1(t)) \cdot \frac{U(w - d(k_1(t)))}{\rho} \cdot \exp(-\rho \cdot t) dt \right\} \\
& + \left\{ \int_0^{\infty} p_2(t) \cdot \exp(-\lambda_2(t)) \cdot \frac{U(w - d(k_2(t)))}{\rho} \cdot \exp(-\rho \cdot t) dt \right\}, \quad (21)
\end{aligned}$$

where  $d(k(t))$  is the damage factor impacting utility after the health events. These damages are given by equations (9) and (10). The current value Hamiltonian is:

$$\begin{aligned}
& \exp(-\lambda_1(t) - \lambda_2(t)) \cdot (h \cdot \tau^\alpha - z_1^\varepsilon(t) - s_1^\beta(t) - z_2^\varepsilon(t) - s_2^\beta(t)) \\
& - \exp(-s_1(t)) \cdot \exp(-\lambda_1(t)) \cdot \frac{h \cdot \tau^\alpha \cdot \frac{d_1}{\log(\varphi + k_1(t))}}{\rho} \\
& - \exp(-s_2(t)) \cdot \exp(-\lambda_2(t)) \cdot \frac{h \cdot \tau^\alpha \cdot \frac{d_2}{\log(\varphi + k_2(t))}}{\rho} \\
& + m_1(t) \cdot \exp(-s_1(t)) + n_1(t) \cdot (z_1(t) - \delta) \\
& + m_2(t) \cdot \exp(-s_2(t)) + n_2(t) \cdot (z_2(t) - \delta), \quad (22)
\end{aligned}$$

where  $m_1(t)$  and  $n_1(t)$  are the shadow prices of cumulative health risk 1 and the stock of accumulated self-insurance against health risk 1; likewise,  $m_2(t)$  and  $n_2(t)$  are the shadow prices of risk 2 and the self-insurance stock against risk 2.

An optimal time path of self-protection and self-insurance come out of the first order optimization conditions. First order conditions with respect to self-protection are:

$$-\exp(-\lambda_1(t) - \lambda_2(t)) \cdot (-\beta \cdot s_1^{\beta-1}(t)) + \exp(-s_1(t)) \cdot \exp(-\lambda_1(t)) \cdot$$

$$\frac{h \cdot \tau^\alpha \cdot \frac{d_1}{\log(\varphi + k_1(t))}}{\rho} - m_1(t) \cdot \exp(-s_1(t)) = 0 \quad (23)$$

and

$$-\exp(-\lambda_1(t) - \lambda_2(t)) \cdot (-\beta \cdot s_2^{\beta-1}(t)) + \exp(-s_2(t)) \cdot \exp(-\lambda_2(t)) \cdot \frac{h \cdot \tau^\alpha \cdot \frac{d_2}{\log(\varphi + k_2(t))}}{\rho} - m_2(t) \cdot \exp(-s_2(t)) = 0. \quad (24)$$

We can derive similar conditions for self-insurance. Further, the no-arbitrage conditions for self-protection require:

$$\begin{aligned} & \exp(-\lambda_1(t) - \lambda_2(t)) \cdot (h \cdot \tau^\alpha - z_1^\varepsilon(t) - s_1^\beta(t) - z_2^\varepsilon(t) - s_2^\beta(t)) \\ & - \exp(-s_1(t)) \cdot \exp(-\lambda_1(t)) \cdot \frac{h \cdot \tau^\alpha \cdot \frac{d_1}{\log(\varphi + k_1(t))}}{\rho} \\ & + \rho \cdot \lambda_1(t) = \dot{\lambda}_1(t) \end{aligned} \quad (25)$$

and

$$\begin{aligned} & \exp(-\lambda_1(t) - \lambda_2(t)) \cdot (h \cdot \tau^\alpha - z_1^\varepsilon(t) - s_1^\beta(t) - z_2^\varepsilon(t) - s_2^\beta(t)) \\ & - \exp(-s_2(t)) \cdot \exp(-\lambda_2(t)) \cdot \frac{h \cdot \tau^\alpha \cdot \frac{d_2}{\log(\varphi + k_2(t))}}{\rho} \\ & + \rho \cdot \lambda_2(t) = \dot{\lambda}_2(t). \end{aligned} \quad (26)$$

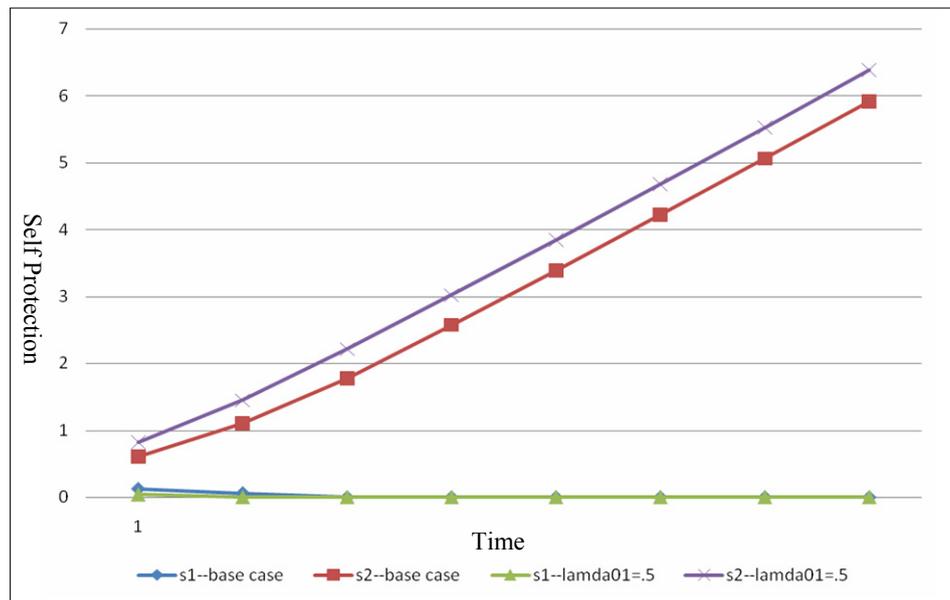
Equations (23) and (24) require the marginal cost of self-protection on the two health events equals the health benefits (or loss) plus the impact of self-protection on reducing the shadow price of the health risks. The first-order and no-arbitrage conditions in equations (25) and (26) contain the shadow prices of both health risks, implying self-protection and self-insurance for one risk is not independent of the other risks.

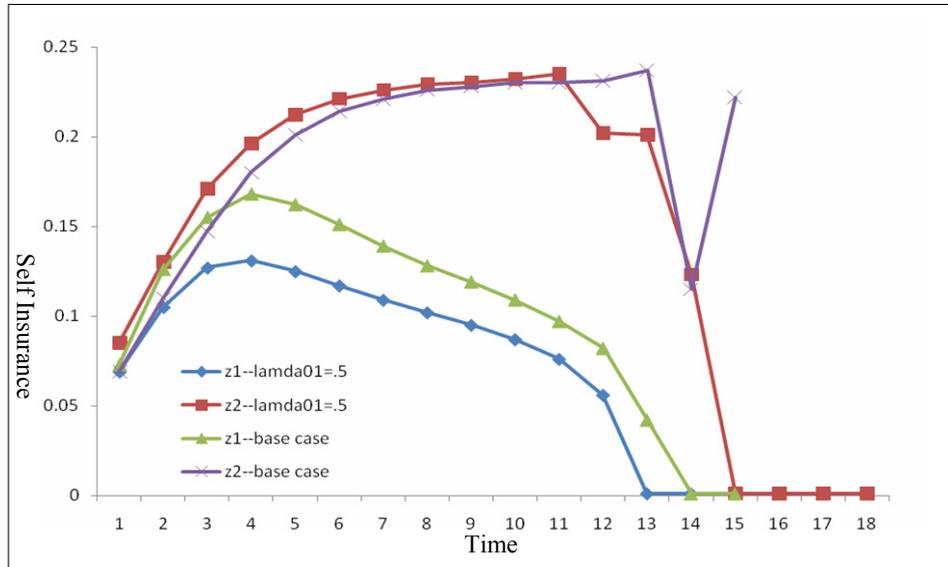
We gain insight into this interdependence by using numerical simulations to explore the role of key parameters and the initial values on optimization strategies. Table 1 in Appendix B shows the hypothetical base case values.

## 2.1. A Numerical Illustration

In the numerical example, assume the health risk 2 has twice the damages as health event 1. Figure 1 shows the self-protection on the two risks in the base case. Self-protection increases on health event 2 as damages increase. Figure 1 also compares self-protection for two risks when the initial level of cumulative risk  $\lambda_{01}$  on the health event 1 is higher compared to the base case. This leads to increase in self-protection on health event 2 instead. The intuition behind this behavior is that health event 1, though less damaging, has now a higher chance of occurrence; an additional dollar spent on mitigating health event 2 would yield higher rewards. Figure 2 shows self-insurance on health event 2 increases, whereas self-insurance on health event 1 falls substantially. This highlights how multiple risks affect protection and insurance decisions on one particular risk. Since event 1 has lower damages, it gets even lower attention when the exogenous risks are higher.

[Figure 1] Self-protection over Time



**[Figure 2]** Self-insurance over Time

This result could be sensitive to parameter variations. We assume symmetric insurance and protection costs for the two health events. When the insurance and protection costs of health event 2 exceed those of health event 1, however, insurance and protection on health event 1 are greater than those in the base case. Self-insurance and self-protection for health event 1 are still lower than those on health event 2. When the initial value of cumulative risk parameter,  $\lambda_{02}$ , is raised to 0.5 from its base case level of 0.1, protection effort on health risk 2 falls while self-insurance effort increases. This also allows for an increase in self-insurance and self-protection on health event 1 as compared to the base case. Self-protection on health event 2, however, still remains higher than on health event 1. When  $\lambda_{02}$  is increased to 1, self-protection on health event 2 is now lower than that on health event 1, whereas self-insurance on health event 2 is now higher than that on health event 1. Finally, a higher discount rate does not alter the results found in the base case simulation.

While the presence of multiple risks affects the self-protection and self-insurance of EU maximizing individuals, we now explore their impact on non-EU maximizing agents and on agents that are conservative in revising risks. Considerable effort has been spent towards understanding non-EU maximizing behavior, but the implications on self-protection and

self-insurance have been restricted to static models. We now consider two variations of our dynamic model to include non-EU and conservative agents.

### III. VARIATION I: NON-EXPECTED UTILITY BEHAVIOR

We now add an additional realistic complication to our model. People frequently display biases when evaluating real-world risks (see Tversky and Kahneman, 2002). Based on accumulated evidence in economics and psychology literature (see Hurley and Shogren, 2005), we assume a person assigns higher weights to low probabilities of a health event and lower weights to high probabilities (also see Starmer, 2000).<sup>5</sup>

We add these subjective perceptions through weights placed on the hazard rate  $p(t)$ , which represents the probability of the health event occurring at time  $t$ , given that it did not happen previously. Let the weighting function follow an inverse S-shape. Following Prelec (1998), we use a two-parameter weighting function as:

$$w(p(t)) = \exp(-\theta(-\ln p(t)))^\gamma \quad (27)$$

where  $\theta$  and  $\gamma$  are the *elevation* and *curvature* parameters. *Elevation* reflects the inflection point where a person switches from overestimating low probability events to underestimating high probability events, i.e., the degree of over- and underestimation. *Curvature* captures how people become less sensitive to probability changes the further from the inflection point (Tversky and Kahneman, 1992; Gonzales and Wu, 1999). The inflection point of the inverted s-shaped curve is critical and can only be determined empirically. Weighting of hazard rates implies that predominance is given to the probability of the event happening at time  $t$ , given they would survive until then.

The revised current value Hamiltonian (from equation (22)) is now:

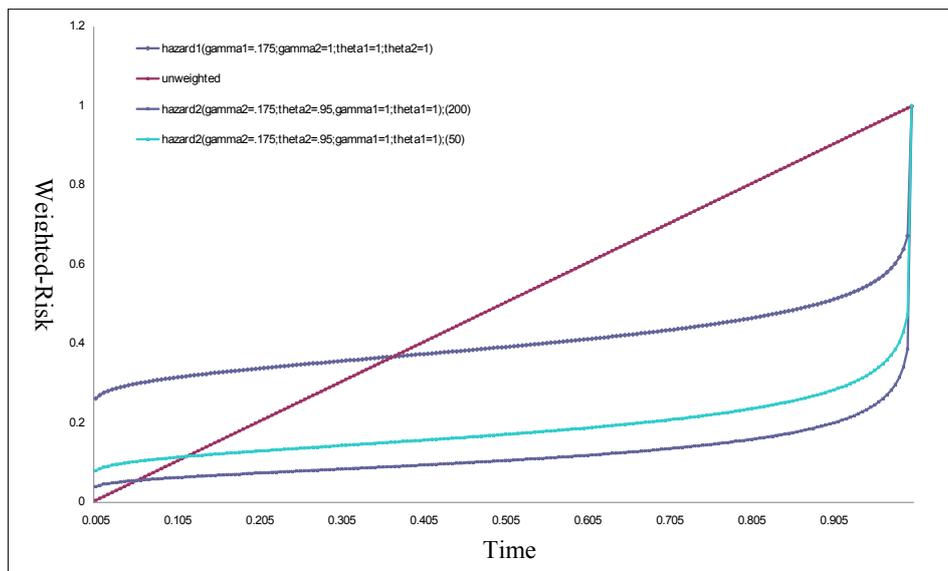
---

<sup>5</sup> Tella et al. (2007) conducted a natural experiment on squatters in Buenos Aires to study the formation of beliefs related to role of markets in ensuring individual success. They found the squatters who were allotted property rights to lands had higher faith in the role of markets than unlucky ones.

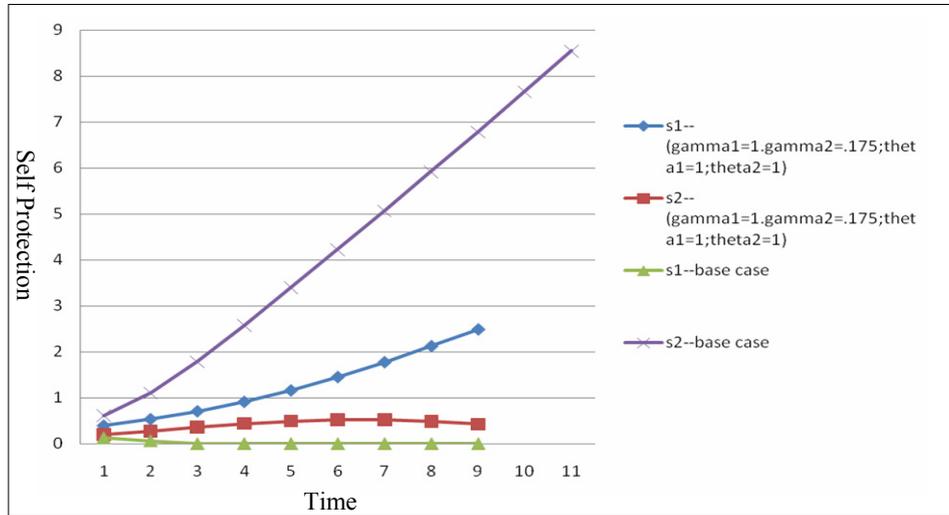
$$\begin{aligned}
& \exp(-\lambda_1(t) - \lambda_2(t)) \cdot (U(w - c(s(t), z(t)))) \\
& + \exp(-\theta_1(-\ln p(t)))^{\gamma_1} \exp(-\lambda_1(t)) \cdot \frac{U(w - d(k_1(t)))}{\rho} \\
& + \exp(-\theta_2(-\ln p(t)))^{\gamma_2} \exp(-\lambda_2(t)) \cdot \frac{U(w - d(k_2(t)))}{\rho} \\
& + m_1(t) \cdot \exp(-\theta_1(-\ln p(t)))^{\gamma_1} + n_1(t) \cdot (z_1(t) - \delta) \\
& + m_2(t) \cdot \exp(-\theta_2(-\ln p(t)))^{\gamma_2} + n_2(t) \cdot (z_2(t) - \delta). \tag{28}
\end{aligned}$$

Continuing with our numerical example, Figure 3 shows the weighing of the hazard function based upon non-expected utility maximization approach. The un-weighted risk is the 45° diagonal line from the origin, whereas the weighted risks intercept the un-weighted risk at varying levels. Figure 4 shows when health event 2 risks are over-weighted, self-protection increases on health event 1 but falls to zero for event 2. Greater risk of health event 2 leads to its discounting which induces less self-protection. This happens even though health event 2 has greater damages. In Figure 5, self-insurance effort on health event 2 increases initially to compensate for the drop in self-protection, but falls in the later stages. Over-weighting of risk leads to its discounting.

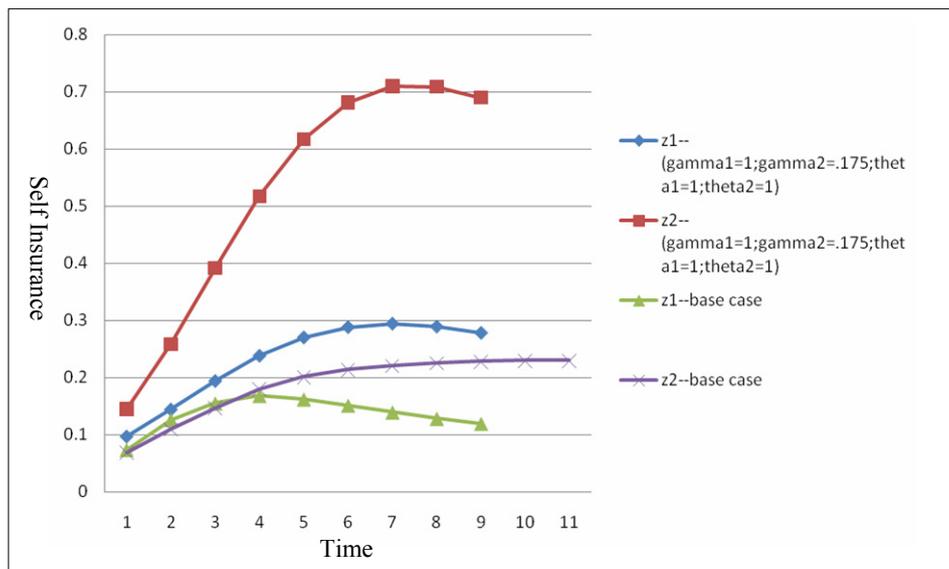
[Figure 3] Weighting of Hazard Function



[Figure 4] Self-protection over Time (Non-EU case)



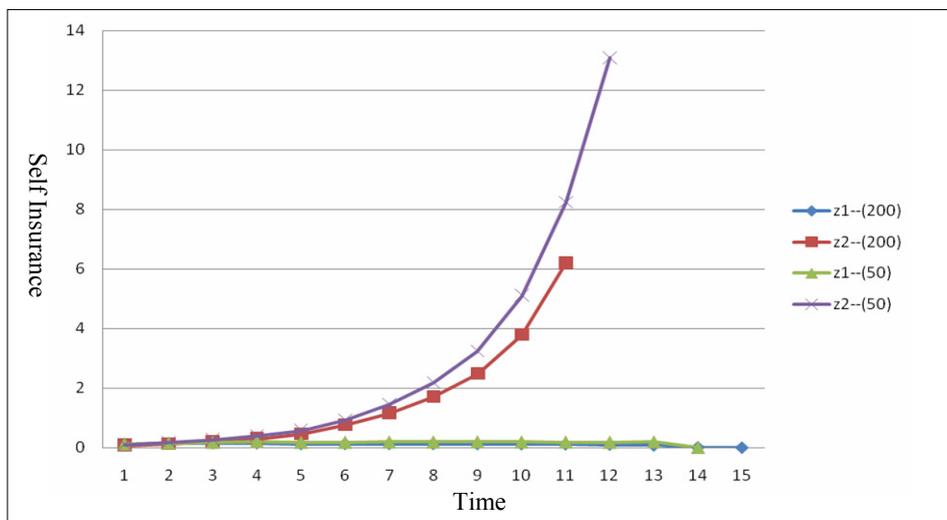
[Figure 5] Self-insurance over Time (Non-EU case)



But this may not always hold. The thresholds at which over-weighting changes to under-weighting also matters in influencing whether higher self-protection will be undertaken for a particular health event. In Figure 3, when threshold of underweighting shifts towards left, it may lead to non-linear changes in self-protection. Two such cases are depicted in Figure 3, in which the hazard rate for health event 2 is weighted by parameters

( $\theta_2 = 1, \gamma_2 = .175$ ) on the function  $\exp(-\theta_2(-\ln p(t)))^{\gamma_2}$ . Further, to shift the threshold for under-weighting to the left, we adjust the power of the log function by scale of 200 and 50 giving rise to  $\exp(-\theta_2(-200 \cdot \ln p(t)))^{\gamma_2}$  and  $\exp(-\theta_2(-50 \cdot \ln p(t)))^{\gamma_2}$ . As shown in the Figure, the threshold for  $\exp(-\theta_2(-200 \cdot \ln p(t)))^{\gamma_2}$  lies farther to the left than the threshold for  $\exp(-\theta_2(-50 \cdot \ln p(t)))^{\gamma_2}$ .

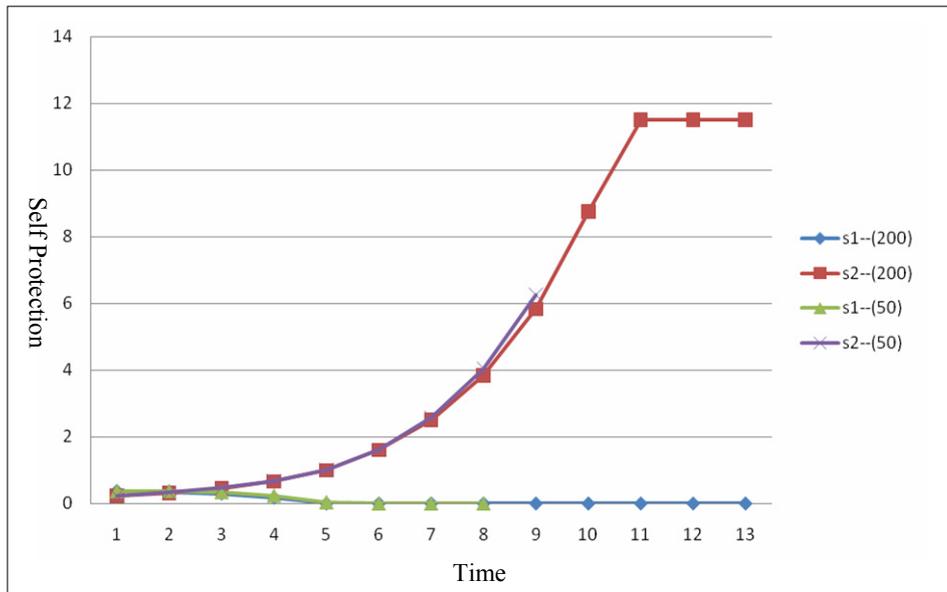
**[Figure 6]** Self-insurance over Time (Lower Thresholds for Underweighting)



An increase in the risk on event 2 leads to greater efforts toward event 1. When under-weighting is significant enough, the results are reversed. Now the higher the underweighting, the lower are self-protection and self-insurance, as illustrated in Figures 6 and 7. A large reduction in perceived risks reduces the need for significant self-protection. As the threshold of underweighting shifts from left to the right, self-protection and self-insurance effort increases. But as illustrated in Figure 4, when the threshold at which underweighting begins is far to the right (i.e., overweight risks), self-protection and self-insurance decline. With subjective risk weightings, self-protection first rises and then declines. This highlights how non-linearities in self-protection arise due to shifting risk perception. Shifting risk perception can exist either with heterogeneous agents or a single agent over time. But the implication is when risks are subjectively weighted, relative self-protection and self-insurance are

further distorted as compared to the case with multiple risks but no weighting.

[Figure 7] Self-protection over Time (Lower Thresholds for Underweighing)



Another related phenomenon—conservatism bias—may further complicate the evaluation of individual allocations of self-protection. Conservatism in revising risks has been found to be at the centre of several contemporary societal problems that involve small risks of catastrophic damages such as those borne out of climate change. We now consider the impact of conservatism bias.

#### IV. VARIATION II: CONSERVATISM BIAS AND ITS TRADEOFFS

Chapman (1973) observed people displayed conservative behavior at low levels of probability but they took more risks at higher levels. In a dynamic context, conservatism makes people *resilient* towards revising their perception of risk. Resilience towards risk revision can arise when poor information or group-adherence cause people to discard preliminary evidence of a particular risk. But as evidence accumulates, resilience to change decreases and people significantly revise the risks. The key

difference exists between a ‘conservative agent’ and ‘non-expected utility maximizing agent’. The conservative person over-weighs large risks after a threshold is crossed, whereas the non-expected utility person under-weighs large risks.

We now consider our dynamic notion of *risk resilience* brought in through belief conservatism. Evidence suggests people tend to be resistant towards upgrading their belief patterns. The resistance level can differ by factors like gender, race, education, and political affiliation. Bleda and Shackley (2005) argue businesses will not change their perceptions towards climate change until affirmative signals are received consistently for a long period of time. They contend businesses perceive reality only after being filtered through a reference frame, which is subjective. Experienced reality differs from actual reality due to perceptions based on their interests. Direct signals of climate change may be subject to misinterpretation as isolated weather-related signals. These signals could be discarded if re-interpretation of these signals requires significant organizational changes (Berhout et al., 2004). The receiver’s frame of reference governs his interpretations of signals or experiences, which can be resilient to objective revisions (Daft and Weick, 1984). The literature on risk perception of climate change confirms the presence of resilience towards risk revisions (e.g., Leiserowitz, 2006, Lorenzoni and Pidgeon, 2006, Viscusi and Zeckhauser, 2006, Oppenheimer and Todorov, 2006).

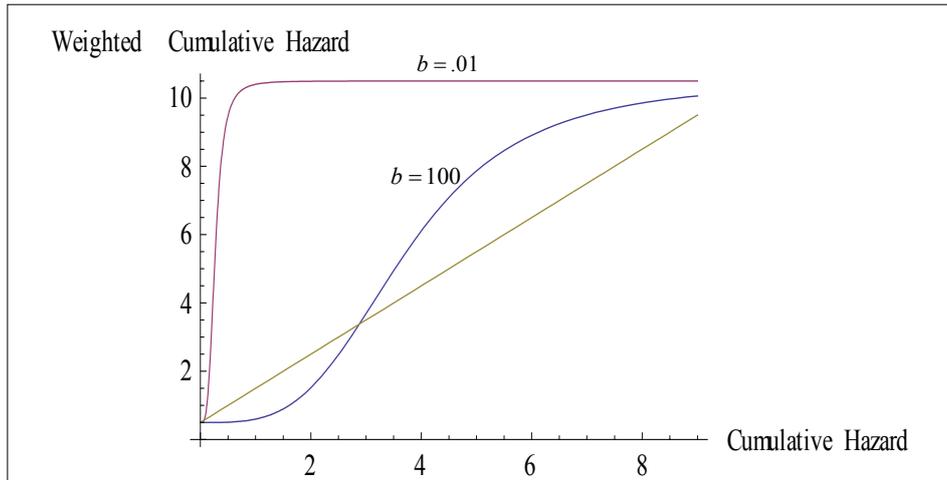
Based on this behavioral pattern, we model conservatism bias as a dynamic process of resilience in beliefs that leads to steep non-linear changes in the perceived hazard rate of the health events. Figure 8 shows this phenomenon. Assume the cumulative risk of health event 2 evolves as

$$\dot{\lambda}_2(t) = p(t) + \zeta \cdot \frac{\lambda^a(t)}{\lambda^a(t) + b} \quad (29)$$

where  $\zeta$ ,  $a$  and  $b$  are parameters which induce a non-linear rise in the cumulate risk of health event 2. As the cumulative stock of risk for health event 2 accumulates, we see a steep increase in the perception of the accumulated stock of risks beyond a particular threshold. Here  $a$

influences the height of the non-linear rise and  $b$  the level of the cumulative stock at which this rise happens. In Figure 8, when  $b$  is .01, the rise in the cumulative hazard happens sooner and is steeper; when  $b$  is 100, the rise is smoother.

**[Figure 8]** Cumulative Hazard and Weighted- Cumulative Hazard

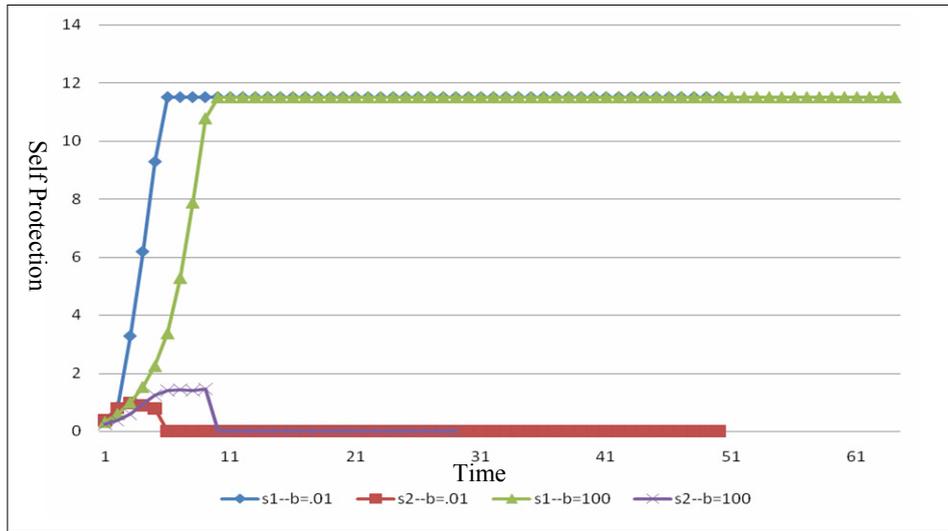


Note: In the Figure, the 45 degree line is the actual cumulative hazard, where as the two other curves depict cumulative hazard exhibiting resilience. Before the point of intersection with the actual cumulative hazard there is under-weighting (which is opposite to the non-EU case where there is over-weighting to the left of the intersection).

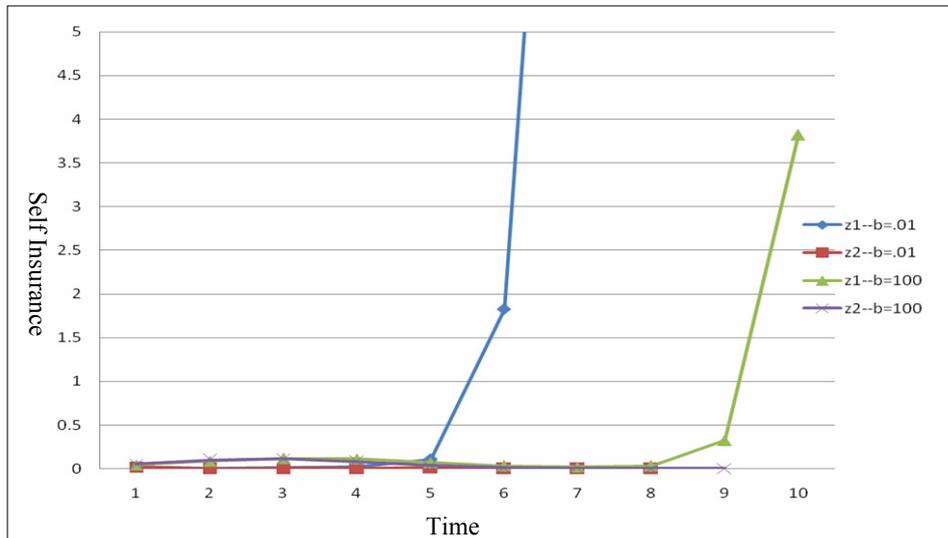
We first assume the two health risks have identical damages ( $d_1 = d_2 = .25$ ). When risks are resilient, the threshold where they undergo sharp upward jumps affects the level of self-protection and self-insurance. In our numerical example we assume health event 2 exhibits resilience in risks, while health event 1 is a normal risk. Figures 9 and 10 show the results. Health event 2 is discounted due to higher risks and most of the attention is focused on mitigating and adapting to event 1. So far the impact of resilience is akin to a discounting effect. But when the threshold for health event 2 comes later ( $b=100$ ), the person self-protects and self-insures more on health event 2 compared to when the thresholds come sooner ( $b=.01$ ). The person who has more time to adjust to non-linear risks discounts risk less. Time to mitigate is the key factor. With less time, self-protection is more expensive since costs are non-linear.

Also, thresholds imply risks increase sooner—so dedicating resources to reduce other risks is a cheaper option.

[Figure 9] Self-protection over Time (Conservatism Bias)



[Figure 10] Self-insurance over Time (Resilient Risk)



In the presence of conservatism bias, this result implies when risks are far off on the horizon, more effort is spent mitigating compared to when they appear suddenly. For instance, if our utility function had preferences

for polar ice caps and polar bears, people would pay to reduce the threats if there was enough time and the risks were manageable. Similarly, stress-related risks or pollution risks receive higher efforts if the risk thresholds were far enough to be manageable.

For conservative agents, when risks are resilient, they may be under-weighted initially (as opposed to over-weighting in non-EU example). The interesting implication when comparing the inverse s-shaped weighing and risk resilience—resilience is the reverse of inverse-s-shaped weighing, which gives rise to non-inverse-s-shaped weighing (or s-shaped weighting). Both influence risk perception behavior; but it is unknown whether some people may exhibit both types of behaviors simultaneously.

## V. CONCLUSION

Risk is endogenous. People expend scarce resources to self-protect and self-insure against the risks posed by poor human and environmental health, both today and into the future (Ehrlich and Becker, 1972). For example, people self-protect by mitigating carbon emissions; we self-insure by adapting to climate change (see Kane and Shogren, 2000). Understanding what factors affect self-protection and self-insurance can help make well-intended public policy better. In that spirit, our extended model of dynamic endogenous risk with non-expected utility agents provides a rationale for why some people do not self-protect, or why certain risks are discounted by a large fraction of the society. We find that self-protection and self-insurance can decrease for any given risk when multiple risks exist, cumulative risks are high, or people are conservative in updating new information about risks. In addition, if people assign non-expected utility weights to the probabilities of good and bad states, self-protection and self-insurance can switch abruptly as cumulative risk increases. We find self-protection can fall as risk aversion increases; multiple risks bring about this reaction.

Given the general policy goal of achieving more risk reduction at fewer costs, our results suggest we need to better understand when these risk thresholds are crossed (for both inverted-s shaped probability weighting functions and resilient risks). Informed policy choices will address these

thresholds, what we know about them and what do not know. The thresholds define the power and limits to public incentives aimed at motivating public perception beyond these thresholds, with the goal of increasing self-protection. For instance, public awareness programs can lead to significant revisions in beliefs related to global warming thereby inducing higher self-protection from society as a whole. The same logic holds true understanding how people balance their self-protection across multiple risks.

### Appendix A: Derivation of Value Functions

The expected value  $E_1[v_0]$  can be split into two parts—expected value when event 1 happens before event 2,  $E_1[v_0]$ , and expected value when event 2 happens before 1,  $E_2[v_0]$ . The expected value when health event 1 happens before 2 ( $E_1[v_0]$ ), is:

$$E_1[v_0] = \left\{ \int_0^{\infty} p_1(t) \cdot \exp(-\lambda_1(t)) \cdot \exp(-\lambda_2(t)) \right. \\ \left. \int_0^t (U(w - c(s(t), z(t)))) \cdot \exp(-\rho \cdot t) ds dt \right\} \quad (14)$$

After integrating by parts, this can be further written as:

$$E_1[v_0] = \left\{ \int_0^{\infty} p_1(t) \cdot \frac{\exp(-\lambda_1(t) - \lambda_2(t))}{p_1(t) + p_2(t)} \right. \\ \left. (U(w - c(s(t), z(t)))) \cdot \exp(-\rho \cdot t) dt \right\} \quad (15)$$

Similarly, expected value  $E_2[v_0]$  when health event 2 happens before 1 can be given as:

$$E_2[v_0] = \left\{ \int_0^{\infty} p_2(t) \cdot \frac{\exp(-\lambda_1(t) - \lambda_2(t))}{p_1(t) + p_2(t)} \right. \\ \left. (U(w - c(s(t), z(t)))) \cdot \exp(-\rho \cdot t) dt \right\} \quad (16)$$

The expected value to the person before either of the two events occurs is given as:

$$E_1[v_0] = \left\{ \int_0^{\infty} p_1(t) \cdot \frac{\exp(-\lambda_1(t) - \lambda_2(t))}{p_1(t) + p_2(t)} \right.$$

$$\begin{aligned}
& \cdot (U(w - c(s(t), z(t)))) \cdot \exp(-\rho \cdot t) dt \Big\} \\
+ E_2[v_0] = & \left\{ \int_0^{\infty} p_2(t) \cdot \frac{\exp(-\lambda_1(t) - \lambda_2(t))}{p_1(t) + p_2(t)} \cdot \right. \\
& \left. \cdot (U(w - c(s(t), z(t)))) \cdot \exp(-\rho \cdot t) dt \right\} \quad (17)
\end{aligned}$$

This equation can be simplified as:

$$\begin{aligned}
E[v_0] = & \left\{ \int_0^{\infty} \exp(-\lambda_1(t) - \lambda_2(t)) \cdot \right. \\
& \left. (U(w - c(s(t), z(t)))) \cdot \exp(-\rho \cdot t) dt \right\} \quad (18)
\end{aligned}$$

Similarly, value function after health event 1 is derived as:

$$E[v_1] = \left\{ \int_0^{\infty} p_1(t) \cdot \exp(-\lambda_1(t)) \cdot \frac{U(w - d(k_1(t)))}{\rho} \cdot \exp(-\rho \cdot t) dt \right\} \quad (19)$$

And the value function after health event 2 is derived as:

$$E[v_2] = \left\{ \int_0^{\infty} p_2(t) \cdot \exp(-\lambda_2(t)) \cdot \frac{U(w - d(k_2(t)))}{\rho} \cdot \exp(-\rho \cdot t) dt \right\} \quad (20)$$

### Appendix B: Base Case Data

[Table 1] Baseline Parameters

$z_1^{\varepsilon_1}$	$\varepsilon_1 = 1.75$	Cost of self-insurance for health event 1
$z_2^{\varepsilon_2}$	$\varepsilon_2 = 1.75$	Cost of self-insurance for health event 2
$s_1^{\beta_1}$	$\beta_1 = 1.75$	Cost of self-protection for health event 1
$s_2^{\beta_2}$	$\beta_2 = 1.75$	Cost of self-protection for health event 2
$\exp(-s_1)$		Hazard function for health event 1
$\exp(-s_2)$		Hazard function for health event 2
$e^{-\theta_1(-\log(-s_1+r))^{\gamma_1}}$	$\theta_1 = 1, \gamma_1 = 1$	Weighted hazard function for health event 1
$e^{-\theta_2(-\log(-s_2+r))^{\gamma_2}}$	$\theta_2 = 1, \gamma_2 = 1$	Weighted hazard function for health event 2
$z_1 - \delta_1$	$\delta_1 = .01$	Effectiveness of self-insurance for health event 1
$z_2 - \delta_2$	$\delta_2 = .01$	Effectiveness of self-insurance for health event 2
$\lambda_1(0)$	0.1	Starting value of risk for event 1
$\lambda_2(0)$	0.1	Starting value of risk for event 2
$\kappa_1(0)$	0.1	Starting value of self-insurance variable for event 1
$\kappa_2(0)$	0.1	Starting value of self-insurance variable for event 1
$\rho$	0.1	Discount rate
$H$	1	Health impact parameter
$\tau$	0.5	Health impact parameter
$\varphi$	3	Health Damage Factor
$a$	3.5	Resilience Parameter
$b$	0.01&100	Resilience Parameter
$\xi$	3	Resilience Parameter
$d_1$	0.25	Damage from health event 1
$d_2$	0.5	Damage from health event 2

## References

- Anderson, H. and P. Lundborg (2007), "Perception of Own Death Risk: An Analysis of Road Traffic and Overall Mortality Risk," *Journal of Risk and Uncertainty*, 34, pp. 67-84.
- Agee, M. D. and T. D. Crocker (2007), "Children's Health Benefits of Reducing Environmental Tobacco Exposure: Evidence from Parents who Smoke," *Empirical Economics*, 32, pp. 217-237.
- Bleda, M. and S. Shackely (2005), "The Formation of Belief in Climate Change in Business Organizations: A Dynamic Simulation Model," Tyndall Center Working paper no. 68.
- Bhattacharya, S., A. Alberini, and M. L. Cropper (2007), "The Value of Mortality Risk Reductions in Delhi, India," *Journal of Risk and Uncertainty*, 34, pp. 21-47.
- Blomquist, G. (2004), "Self-protection and Averting Behavior, Values of Statistical Lives, and Benefit Cost Analysis of Environmental Policy," *Review of Economics of the Household*, 2, pp. 89-110.
- Clarke, R. and W. Reed (1994), "Consumption/Pollution Tradeoffs in an Environment Vulnerable to Pollution Related Catastrophic Collapse," *Journal of Economic Dynamics and Control*, 18, pp. 991-1010.
- Chapman, C. (1973), "Prior Probability Bias in Information Seeking and Opinion Revisions," *American Journal of Psychology*, 86(2), pp. 269-82.
- Dosman, D., W. Adamowicz and S. Hrudey (2001), "Socioeconomic Determinants of Health and Food Safety Related Risk Perceptions," *Risk Analysis*, 21, pp. 307-317.
- Edwards, W. (1968), "Conservatism in Human Information Processing," *Formal Representation of Human Judgment*, B. Kleinmütz (ed.), New York: Wiley & Sons, pp. 17-52.
- Ehrlich, I. and G. Becker (1972), "Market Insurance, Self-insurance, and Self-protection," *Journal of Political Economy*, 80, pp. 623-648.
- Ganderton, P., D. Brookshire, M. McKee, S. Stewart, and H. Thurston (2000), "Buying Insurance for Disaster Type Risks: Experimental Evidence," *Journal of Risk and Uncertainty*, 20, pp. 271-289.
- Gonzalez, R. and G. Wu (1999), "On the Shape of Probability Weighting Function," *Cognitive Psychology*, 38, pp. 129-166.
- Houtven, G., M. Sullivan, and C. Dockins (2008), "Cancer Premiums and Latency Effects: A Risk Tradeoff Approach for Valuing Reductions in Fatal Cancer Risks," *Journal of Risk and Uncertainty*, 36, pp. 179-199.

- Hurley, T. and J. Shogren (2005), "An Experimental Comparison of Induced and Elicited Beliefs," *Journal of Risk and Uncertainty*, 30, pp. 169-188.
- Kane, S. and J. Shogren (2000), "Linking Adaptation and Mitigation in Climate Change Policy," *Climatic Change*, 46, pp. 75-102.
- Konrad, K. and S. Skaperdas (1993), "Self-insurance and Self-Protection: A Non-Expected Utility Analysis," *Geneva Papers on Risk and Insurance Theory*, 18, pp. 131-146.
- Leiserowitz, A. (2006), "Climate Change Risk Perception and Policy Preferences: The Role of Affect, Imagery, and Values," *Climatic Change*, 77, pp. 45-72.
- Lichtenstein, Sarah et al. (1978), "Judged Frequency of Lethal Events," *Journal of Experimental Psychology: Human Learning and Memory*, 4, pp. 551-578.
- Lorenzoni, I. and N. Pidgeon (2006), "Public Views on climate Change: European and USA Perspectives," *Climatic Change*, 77, pp. 73-95.
- Machina, M. (1995), "Non-Expected Utility and Robustness of the Classical Insurance Paradigm," *Geneva Papers on Risk and Insurance Theory*, 20, pp. 9-50.
- Muermann, A. and H. Kunreuther (2008), "Self-protection and Insurance with Interdependencies," *Journal of Risk and Uncertainty*, 36, pp. 103-123.
- New Scientist (2005), "Global Warming may Pump up Hurricane Power," <http://www.newscientist.com/article.ns?id=dn7769>.
- Oppenheimer, M. and A. Todorov (2006), "Global Warming: The Psychology of Long Term Risk," *Climatic Change*, 77, pp. 1-6.
- Pidgeon, N., R. Kasperson, and P. Slovic, eds (2003), *The Social Amplification of Risk*, Cambridge: Cambridge University Press.
- Piketty, T. (1995), "Social Mobility and Redistributive Politics," *Quarterly Journal of Economics*, 110, pp. 551-584.
- Prelec, D. (1998), "The Probability Weighting Function," *Econometrica*, 66, pp. 497-527.
- Protiere, C., C. Donaldson, S. Luchini, J. P. Moatti and P. Shackley (2004), "The Impact of Information on Non-Health Attributes on the willingness to pay for Multiple Health Care Programmes," *Social Science and Medicine*, 58, pp. 1257-1269.
- Reed, W. (1988), "Optimal Harvesting of a Fishery Subject to Random Catastrophic Collapse," *IMA Journal of Mathematics Applied in Medicine and Biology*, 5, pp. 215-235.
- Reed, W. and H. Heras (1992), "The Conservation and Exploitation of Vulnerable Resources," *Bulletin of Mathematical Biology*, 54, pp. 185-207.

- Rott, H. (2000), "The Two Dogmas of Belief Revision," *Journal of Philosophy*, 97, pp. 503-522.
- Shogren, J. and T. Crocker (1991), "Risk, Self-Protection, and Ex Ante Economic Value," *Journal of Environmental Economics and Management*, 20, pp. 1-15.
- Shogren, J. and T. Crocker (1999), "Risk and its Consequences," *Journal of Environmental Economics and Management*, 37, pp. 44-52.
- Rosen, S. (1981), "Valuing Health Risks," *American Economic Review Papers and Proceedings*, 71, pp. 241-45.
- Shavell, S. (1979), "On Moral Hazard and Insurance," *Quarterly Journal of Economics*, 93, pp. 541-562.
- Starmer, C. (2000), "Developments in the Non-Expected Utility Theory: The Hunt for a Descriptive Theory of Choice under Risk," *Journal of Economic Literature*, pp. 331-382.
- Sterman, J., and L. Booth Sweeny (2002), "Cloudy Skies: Assessing Public Understanding of Global Warming," *System Dynamic Review*, 18, pp. 207-240.
- Shackley, P. and C. Donaldson (2002), "Should We Use Willingness to Pay to Elicit Community Preferences for Health Case? New Evidence from using a 'Marginal' Approach," *Journal of Health Economics*, 21, pp. 971-991.
- Sunstein, C. (2002), *Risk and Reason*. Cambridge: Cambridge University Press.
- Tversky, A., and D. Kahneman (1992), "Advances in Prospect Theory: Cumulative Representation of Uncertainty," *Journal of Risk and Uncertainty*, 5, pp. 297-323.
- Tella, R., S. Galiani, and E. Schargrodsky (2007), "The Formation of Beliefs: Evidence from the Allocation of Land Titles to Squatters," *Quarterly Journal of Economics*, 122, pp. 209-241.
- Viscusi, W. and R. Zeckhauser (2006), "The Perception and Valuation of Risks of Climate Change: A Rational and Behavioral Blend," *Climatic Change*, 77, pp. 151-177.