Risk Attitude towards On-Demand Insurance (Proposal)

February 15, 2019

Abstract

As the technology advanced, on-demand insurance products are developed to cover risk in extremely short-term period. This proposal exams the change in the risk attitude as the period of the focused risk is cut. We run an experiment and shows that individuals become extremely risk averse when on-demand insurance is offered. This extreme risk aversion, or a decision anomaly, can be explained by two behavior biases: myopic bias and loss probability miscalculation.

Keywords: On-Demand insurance · Insurance demand anomaly · Behavior finance

1 Introduction

The cornerstone of insurance market is based on the risk aversion assumption. This risk aversion is typically modeled by the concavity of the underlying utility function. As people are risk averse, they are willing to pay a risk premium to transfer a certain event (risk). This utility function however faces criticism when voluminous literature records the anomalies which this utility function does not explain. For example, Hershey and Schoemaker (1980) conduct a lab experiment in the loss domain and Baker et al. (1988) in both the profit and loss domains. Both studies show an incompatible result concluded by the expected utility function. This incompatibility indicates the individual's systematic irrationality in the real world instead of the rational homo economics under the economist theoretical assumption.

The inconsistency of the expected utility function can also be found in the insurance market. Kunreuther and Pauly (2006) discusses the anomalies from both the demand and supply sides of insurance market, such as the limited demand in catastrophe insurance. Some of these anomalies (especially in the insurance demand side) can be explained by people's misperception of risks. Schwarcz (2010) states the irrational preference of sub-optimal insurance decision leads to a systemically over-insured (e.g. the popularity in mobile insurance and flight insurance) and under-insured status (e.g. the unpopularity in catastrophe insurance). When individuals face insurance choices, they are not merely risk averse. Instead, it involved fairly complex decision-making process, subject to various behavior biases.

Tversky and Kahneman (1974) name four biases, i.e. representativeness, availability, adjustment and anchoring. Myopic loss aversion, discussed in Thaler (1999), relates to the loss aversion and mental accounting. With these biases, people assess the risk improperly. Availability especially explains one of the demand anomalis discussed in Kunreuther and Pauly (2006): the popularity of overcharged insurance against "named events", such as flight accidents, or cancer exclusively.

Individual purchases these insurance contracts even though the term life insurance or health insurance are relatively cheaper according to the price with respect to their expected benefits. Rabin and Thaler (2001) asserts that individuals are loss averse, subject to numerous small risks. Hence, it would be a lucrative business to offer one insurance policy, covering a collection of all these small risks, sold at an exorbitant price. However, as individuals are myopically loss averse, this pricy insurance contract is only attractive if they are presented separately as many micro contracts. Otherwise, the risk is combined and we are less loss averse. Rabin and Thaler (2001) believes this condition is hard to achieve due to the high transaction cost.

A traditional insurance policy covers certain risk in a given time period, usually with minimum one year. As technology advances, on-demand insurance provides an innovative solution especially for the non-life insurance market. For example, Slice offers home insurance policies sold per day. Cuvva provides short-term auto insurance available to be purchased per hour. Trov allows clients to choose when to insure their electronic gadget, such as mobile and photography equipment. This type of insurance services can usually be easily acquired on-line or through mobile applications. It allows customers to obtain insurance only when they need it.

This on-demand insurance grants consumers a choice when to be insured. Individuals logically take out insurance only during the risky period. In such a case, insurers would suffer from an adverse selection problem. To deal with this problem, on-demand insurance is usually charged with a higher price. According to KPMG (2017), on-demand insurance's unit rate is generally higher than it would be in case of annual contract. From the demand side, how much riskier a risky period is compared to the rest "safe" period can justify the relatively expensive unit price? Can customers assess the risk in this risky period appropriately? What kind of behavior bias will they suffer from to misjudge the risk? When insurance can be acquired and so considered separately along the time line, will the "money pump" opportunity discussed in Rabin and Thaler (2001) arise as consumers face each small but pricey insurance contract once at a time?

The money pomp opportunity according to Rabin and Thaler (2001) appears when individual confronting with numerous risk with tiny occurrence probability. In such situation, they tend to buy insurance to protect themselves from separate extremely unlikely events. However, Kunreuther and Pauly (2004) explains the underinsurance of catastrophe as the occurrence rate is extremely low, or lower than a certain threshold. Contrary to the "money pomp" theory, to boost the catastrophe insurance demand, they suggest to bundle many small-probability risk. Therefore, how does the insurance demand change when the concerning risk is viewed either separately or combined?

The rest of the paper is structured as follows: The second part introduces the extended CPT Model. We briefly describe the experiment design in the third part. The fourth part demonstrates the model results and the last part concludes this paper.

2 Extended CPT Model

Cumulative Prospect Theory (CPT) (cf. Tversky and Kahneman (1992)) suggests that people's risk appetite differs according to the reference point. In addition, this appetite is influenced by both the distorted probability through a probability weighting function (π) and the sensitivity of the variation through a value function (v). The weighting function is an inverse-sigmoid curve with which people tend to overestimate/underestimate the probabilities when they are small/large. The value function is strictly increasing with the first derivative positive. Nevertheless, with the second derivative negative when the value is above the reference point and positive when the value is below the point, people are risk averse in the gain domain while risk seeking in the loss domain. In addition, the loss aversion is demonstrated with v steeper in the loss domain. These two functions, v and π, lead to a fourfold patter of risk, with the following features: People are risk-averse when facing gains with high probabilities but risk-seeking with low probabilities. On the contrary, in the loss domain, people are risk-seeking with high probabilities and risk-averse with low probabilities.

In CPT, the weighting function, π is formed as

$$\pi(p) = p^{\gamma}/(p^{\gamma} + (1-p)^{\gamma})^{(1/\gamma)}. \tag{1}$$

Thereby, γ controls the weighting function shape. With $\gamma = 0.69$ estimated in Tversky and Kahneman (1992) in the loss domain, the red curve in Figure (1) demonstrates the inverse-sigmoid curve. This curve over-weights the low probabilities while under-weights the high probabilities.

The value function v in CPT is suggested as

$$v(x) = \begin{cases} (x)^{\alpha} & x > 0 \\ \lambda^{CPT}(-x)^{\alpha} & x < 0, \end{cases} \tag{2}$$

where α determines the sensitivity of variation and λ^{CPT}, $\lambda^{CPT} > 1$ represents the loss aversion degree. For $\alpha = 0.88$ and $\lambda^{CPT} = 2.24$ estimated in Tversky and Kahneman (1992), Figure (2) shows that the value curve is concave while $x > 0$. When $x < 0$, the red curve becomes convex and steeper. At the reference point, $v(0) = 0$.

A decision regarding insurance consumption, unlike investment and gambling including prospects of both gain and loss, is a trade-off between a certain small loss (a premium payment) and a severe but rare loss. As both prospects are in the loss domain, loss aversion λ^{CPT} does not play a role in this decision framework. With risk-seeking attitude in the loss domain suggested in $v(x)$, no one would ever purchase insurance if a loss probability is considered fairly ($\gamma = 0$ in Equation (1)). However, individuals take out insurance to protect themselves from a rare but dreadful loss because the fairly small loss probability is enlarged through $\pi(x)$.

For wealth loss, L with a loss probability p, the subjective value of this prospect (V^L) if not taking any insurance is:

$$V^L = \pi(1-p)v(0) + \pi(p)v(L) = \pi(p)v(L).$$

An full insurance contract is assumed to be priced with a proportional loading, $(1+c)Lp$. The prospect value, V^c, with this insurance contract can be shown as:

$$V^c = v((1+c)Lp).$$

People would only obtain this contract if

$$V^c = v((1+c)Lp) \geq \pi(p)v(L) = V^L. \tag{3}$$

The maximum loading individuals are willing to pay (c^{WTP}) can be derived as:

$$c^{WTP}(p) = \pi(p)^{(1/\alpha)}/p - 1. \tag{4}$$

Thereby, $c^{WTP}(p)$ is determined by the parameters α and γ from the CPT model. Figure (3) shows the loading with respect to different loss probability. Due to a higher degree of probability overestimation in π, there exists a negative correlation between c^{WTP} and p.

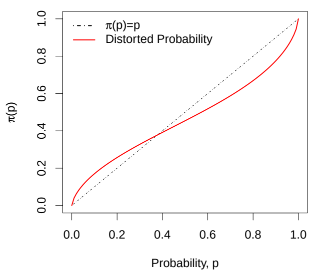


Figure 1: Distorted weighting function ($\gamma = 0.69$)

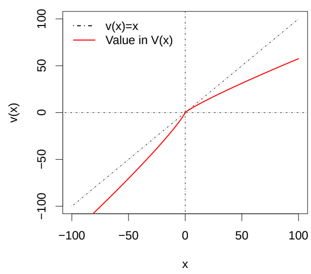


Figure 2: Value function ($\alpha = 0.88$)

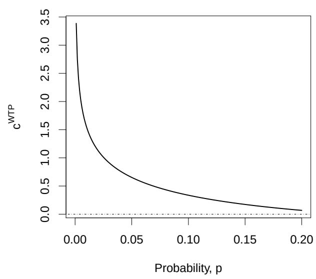


Figure 3: WTP with different p ($\alpha = 0.88$ and $\gamma = 0.69$)

With on-demand insurance offered, individuals are granted with the third choice/prospect, except for taking insurance for the whole period or bearing the risk completely by themselves. Following we extend the CPT model to value the prospect of the on-demand insurance:

2.1 Myopic Bias and Future Discounting

In Samuelson (1963), Samuelson asked his colleague whether to take the bet: 50% chance to gain 200 and 50% to lose 100. Despite the positive expected value, his colleague turned it down. His colleague however suggested he would take it if the bet is played for 100 times. This classic myopic example is mentioned and discussed in Thaler (1999) and other articles as myopic loss aversion. Myopic loss aversion combines narrow braking and loss aversion: people are more loss averse when the risk is presented separately, or braked narrowly (cf. Thaler (1999)). Rabin and Thaler (2001) believes as myopic-loss-aversion agents, we are willing to pay more against each small-scale risk if these risks are offered and thus viewed separately.

On-demand insurance offers insurance covering risk divided into small units along the time line. At each time point, individuals make insurance purchase decision against each tiny risk. Accordingly, the risk in focus is divided and bracketed narrowly. Namely, when individuals decide whether to purchase a daily insurance today, they disregard the tomorrow's risk. With this narrowly-bracketed risk, $c^{WTP}(p)$ increases significantly as the focused loss probability decreases (the negative correlation in Figure (4)).

A traditional insurance contract period is valid for one year, covering a potential loss L with the loss probability in one year p. Assuming each loss event is independent and occurs randomly at a fixed rate, the occurrence of the loss event can be modeled with a Poisson process with the occurrence rate $\Lambda = -\ln(1-p)$. For a different contract period, t, the loss probability within this period becomes $p^D = 1 - \exp(-\Lambda \cdot t)$. For on-demand insurance, $t < 1$. Figure (4) demonstrates that $c^{WTP}(p^D)$ increases substantially when the risk is viewed per month ($t = 1/12$) or even per day ($t = 1/365$).

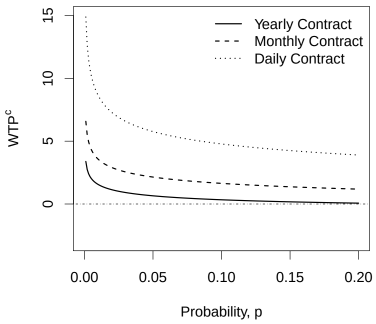


Figure 4: WTP for different period ($\alpha = 0.88$ and $\gamma = 0.69$)

c^{WTP} is elevated as individuals subject to myopic bias and narrowly bracket the risk. However, several factors influence how the risk is bracketed. For example, with both traditional and on-demand insurance products on the market, to compare these two offers, insurance consumers may consider risk not covered by on-demand insurance but by traditional insurance. Namely, a traditional insurance reminds insurance consumers of the risk outside of daily insurance coverage term (after today). Thereby, the on-demand insurance separates the risk while the existence of traditional insurance market aggregates the risk back.

Depended on the insurance products or on individuals' own experience, the risk is considered within a certain risk period. If this period is the same as the insurance period, the maximum c^{WTP} is determined as $V^L = V^c$ in Equation (3). However, if the insurance period is shorter than their risk periods, individuals encounter two prospects with distinct time points. To compare these two prospects, individuals discount the prospect value with a longer period back to the end of the short period of the other prospect. Insurance period is generally shorter than the risk period. Thereby, the prospect value in the risk period is discounted back to the end of the insurance period as :

$$V_D^L = \pi(p)v(L \cdot \delta_m). \tag{5}$$

Risk period is set 1. δ_m denotes a discount function for m period, $m = 1 - t$ with t, the insurance-period fraction of the risk period (cf. Figure (5)). When the insurance period is consistent with individuals' risk period, $t = 1$, $m = 0$, $\delta_0 = 1$ and $L\delta_0 = L$. In such case, they suffer from myopic bias and consider narrowly the risk which insurance is covered. Hence, they are willing to pay a higher loading, which describes the money pump opportunity in Thaler (1999). Otherwise, if $t < 1$ and $m > 0$, c^{WTP} decreases as loss ($L\delta_m$) is discounted along the period where insurance contract provides no coverage. Hence, while the myopic bias pushes c^{WTP} upwards, this willingness declines with the period, where the risk is not covered by the insurance. c^{WTP} for the insurance with coverage period (t) against the risk within the period 1 is extended as:

$$c^{WTP}(p) = \pi(p)^{(1/\alpha)\cdot}\delta_m/p - 1 \tag{6}$$

with $m = 1 - t$.

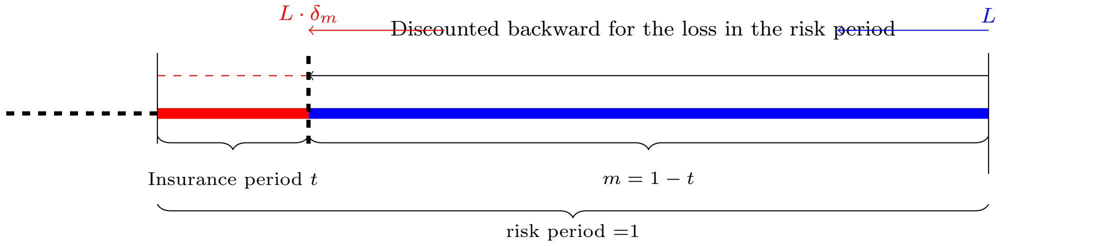
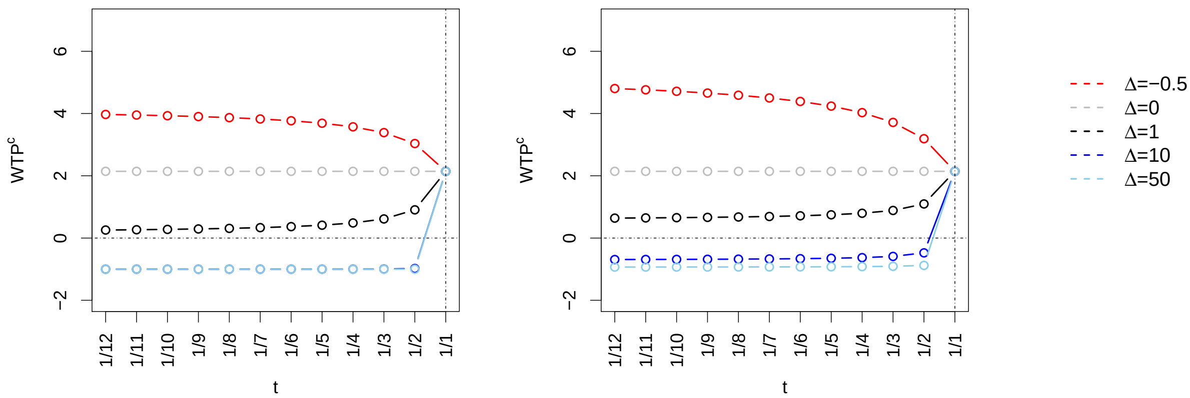


Figure 5

Figure (6) demonstrates the c^{WTP} for the insurance with t, $t \leq 1$. For an exponential discount function, $\delta^e_m = \exp(\Delta^e \cdot m)$ with $-\infty < \Delta^e <$ inf. For a hyperbolic discount function, $\delta^h_m = 1/(1 + \Delta^h \cdot m)$ with $-1/m < \Delta^h$. If $\Delta^e = 0$ or $\Delta^h = 0$, individuals are indifferent along the time line. For $\Delta^e < 0$ or $-1/m < \Delta^h < 0$, individuals prefer positive utility in the future, contradict to the normal economic setting. Only when $\Delta^e > 0$ or $\Delta^h > 1$, individuals discount future loss. In addition, with a larger Δ, individuals discount future loss more severely, thus leading to a even lower c^{WTP}. However, the marginal effect decreases substantially when $\Delta > 10$. As shown in Figure (6), $\Delta = 10$ and $\Delta = 50$ overlap with the exponential discount assumption and are fairly close in the hyperbolic discount assumption.



(a) Loading with different t with exponential discount function, δ^e_m

(b) c^{WTP} with different t with hyperbolic discount function, δ^h_m

Figure 6: c^{WTP} with insurance period shorter than the risk period

2.2 Bias in Loss Probability Miscalculation:

Individuals tend to acquire on-demand insurance to protect themselves in the risky period. This behavior causes information asymmetry problem for insurers. However, insurers could charge a higher loading c. c^{WTP} for the on-demand insurance is influenced by the individuals perception on the risk, especially the loss probability during the risky period. Despite the probability distortion effect captured in CPT model, this loss probability can be easily miscalculated resulted from the representativeness and the availability bias.

Poisson process assumes each accident occurs randomly at a fixed rate. However, the loss probability fluctuates, and so does the occurrence rate. For example, individuals are more likely to break their legs when spending one week in a ski resort than at home for the same one week. Assume one year is separated into a risky period t ($0 < t \leq 1$) and a normal period $1 - t$. The occurrence rate for the risky period is n ($n \geq 1$) times the occurrence rate for the normal period. With the loss probability per year, $p = 1 - \exp(\Lambda)$, the loss probability for the risky period is $p^R = 1 - \exp(-\Lambda^R)$ with the occurrence rate $\Lambda^R = \Lambda \cdot nt/(nt + (1 - t))$.

This loss probability in the risky period can be rewritten as:

$$p^R = 1 - exp(\Lambda^R) = 1 - exp(\lambda \cdot R),$$

with $R = \dfrac{nt}{nt + 1 - t}$ depended on n, the relative risky degree and t, the relative length of the period. This calculation of R can be counter-intuitive, subject to the following biases:

1. Representativeness bias discussed in Tversky and Kahneman (1974) includes the insensitivity of sample size. People are insensitive to sample size when judging posterior probability, conditional probability assigned within a certain state. Accordingly, customers calculate $\lambda^R = \lambda \cdot R$ while neglecting the power of the time length difference. For example, individuals are generally subject to higher risk outside of ski resorts as they spend only a few days per year in the resort. As the sample sizes (here the time length) are different, the posterior probability can be higher outside of the resort than in the resort. If individuals do not consider the time difference (t on R), they overvalue the risk for the skiing holidays and undervalue the same risk while staying at seemly-extremely-safe home.

2. Availability is another bias mentioned in Tversky and Kahneman (1974). This bias arises when people assess loss probabilities by the easiness of recalling such events. Salience is one of the factors influencing this easiness. With several skiing accidents reported, people overevaluate the skiing risk. Kunreuther and Pauly (2006) records this bias to explain a few demand anomalis: insurance demand rises after a disaster, as the tragedy becomes salient. Insurance against certain named events, such as flight accidents, is rather popular since people are easy to recall this specific event.

These two behavior biases lead to miscalculation of p^R, caused by a systematic difference between R and the estimated $\hat{R}$. β represents the degree of this miscalculation with $\beta = \hat{R}/R$. The miscalculated probability p^* is hence formulated as:

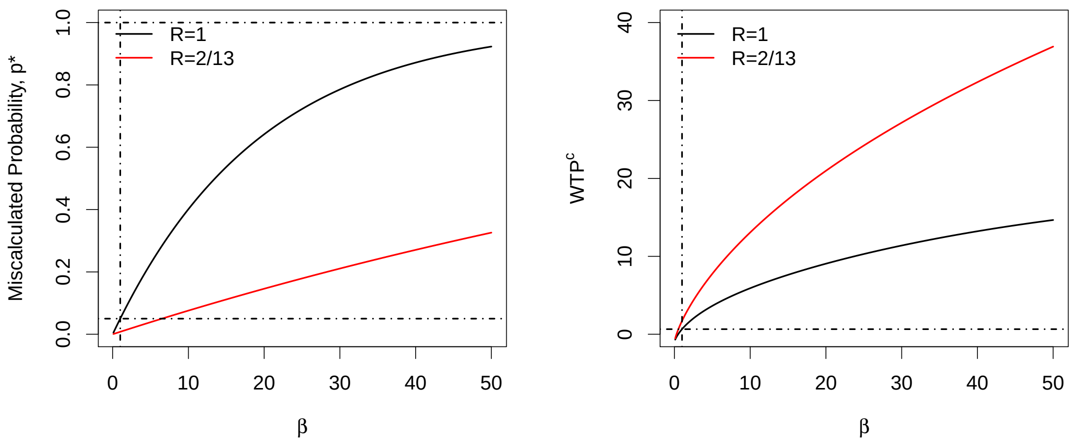
$$p^* = 1 - \exp(\lambda \cdot R \cdot \beta). \tag{7}$$

p^* is overestimated when $\beta > 1$. With p^*, V_D^L and c^{WTP} in Equation (5) and (6) are extended into

$$V_D^L = \pi(p^*)v(L \cdot \delta_m), \text{ and } c^{WTP} = \pi(p^*)^{(1/\alpha)\cdot}\delta_m/p - 1.$$

Figure (7(a)) demonstrates the impact of this bias. $R = 2/13$ presents the risk in the one-month risky period where the occurrence rate is twice the occurrence rate in the normal period ($t = 1/12$, $n = 2$). $R = 1$ signifies the normal year where the occurrence rate remains the same for the whole year ($t = 1$ and $n = 1$). A higher β leads to a higher p^* and thus a higher c^{WTP}.

With smaller R, individual narrowly bracketed the risk. Thus, c^{WTP} for $R = 2/13$ is higher than that for $R = 1$.



(a) Biased probability comparison with respect to different β for $p = 0.05$

(b) WTP with respect to different β ($p = 0.05$, $n = 2$, $t = 1/12$, $\alpha = 0.88$ and $\gamma = 0.69$)

Figure 7

3 Experiment

This experiment recruits 99 students (40 male and 59 female) from University of St.Gallen with the described rewards as "Maximum CHF 31.9, with expected value CHF 28.5." The experiment lasts around 45 minutes, consisting of two sessions with 16 scenarios (decisions) in total, together with a questionnaire recording students' basic information.. The first session is done through an on-line questionnaire, while subjects participate a computer-based game in the second session. The rewards of the experiment depend on the result of the game in the second session.

Session I

Three scenarios are included in Session I where subjects are asked to specify their WTP[1] for a full-coverage mobile phone insurance for a certain period. The hypothetical mobile phone costs CHF 1,000 and the annual loss probability is assumed 5%. In contrast with Session II, in this session, subjects' decisions on the scenarios do not influence their final rewards:

Scenario A: WTP for a one-year insurance;

Scenario M: WTP for the insurance valid for one single month in which month the loss probability is double the probability for the rest 11 months;

[1]We elicit WTP through multiple pairwise choices, as choice answers generate less noise (cf.Hey et al. (2009))

Scenario Mp: WTP for the insurance valid for one single month in which month the loss probability is 0.78%, doubling the probability for the rest 11 months;

Compared to the Scenario M, Scenario Mp provides additional information as the specified loss probability.

Some questions regarding risk attitudes, numeracy and other basic information are asked after these three scenarios. By the end of the session, subjects are told to receive CHF 32 minus certain amount[2] for their effort in fulfilling this questionnaire. This statement reinforces the subjects' perception that they earned their rewards.

Session II

Session II requires subjects to make a series of decisions in a crossing-bridge game, results of which influence their earned rewards:

Tommy (a comic figure in the game) is delivering their rewards through a bridge. The subjects receive their rewards when Tommy crosses the bridge. This bridge consists of 12 blocks. The probability that the bridge breaks down is 5%. If the bridge breaks and Tommy falls, their earned rewards are gone.

Scenario W: before the game begins, a whole bridge insurance is offered with CHF 22. Hence, instead of taking risk, the subjects can choose to receive CHF 10 directly.

Scenario B_i ($i = 1...12$): If subjects choose to take risk, the game begins. At each block i, subjects decide whether to buy an insurance. Each block insurance costs CHF 3. The third block ($i = 3$) is a risky block, with breaking probability twice the rest of eleven blocks. Hence, Scenario B_3 can be considered as the risky period, while Scenario B_i, for $i \neq 3$ are the normal periods.

In Session I, no special framing is deployed as the subjects are presented with the scenarios consecutively. Thus, in each scenario, the risk period is adjusted according to the insurance offered. Therefore, the risk period is one year for Scenario A, and one month for Scenario M and Mp. Namely, $t = 1$ and $m = 0$ for all these tree scenarios.

In Session II, the subjects receive the rewards only after Tommy crosses the whole bridge. In addition, with the monetary motivation, the subjects' risk period can be different from the insurance period.

For Scenario B_i, at each block, subjects compare two prospects, getting insured and giving up CHF 3 or taking risk to gain the full final rewards (CHF 32 minus the premium spent on the previous blocks). As this final rewards are not secured until Tommy crosses the bridge successfully, subjects discount back the rewards to the block on which they are focusing. Namely, the risk period becomes the remaining blocks that Tommy is yet to cross. For i^{th} block, the

[2]To extract each participant's risk attitude, as the lottery choices in Holt and Laury (2002) but in a loss domain, subjects are asked to choose between two prospects: losing CHF 0.1/CHF1.6 with probability p and CHF 3.85/CHF 2 with probability $1 - p$. p ranges from 10% to 100%. By the end of the experiment, one of the choices will be randomly selected, and the rewards determined in Session II will be deducted accordingly.

insurance period related to the risk period, t and the rest of the uninsured period m become:

$$\begin{aligned} t =& 1/(13-i) \\ m =& 1-1/(13-i) \end{aligned} \tag{8}$$

B_3 is a special block, representing the risky period. As a special scenario, subjects may or may not concentrate on this period and narrowly bracket this single block. Therefore, for $i=3$, m may be either 0.9 according to Equation (8) or 0 if subjects narrowly bracket the scenario.

Figure 8 is the screen shot of this computer-based game. At each block, subjects make decisions whether to insure themselves for the next one. Figure (8(a)) shows that when subjects are making decisions for Scenario B_3, extra warning is shown on the screen to intensify ris salience. Table 1 and 2 list and summarize all the scenarios.

(a) Screen shot for Tommy passing the risky block

(b) Screen shot for Tommy passing the bridge other than the risky block

Figure 8: Screen shot for crossing-bridge game

Session I: Hypothetical Loss Amount: CHF 1000

s : Scenario	t, m	Probability Specified	Loss Probability
A : Annual Insurance	$t=1$, $m=0$	Yes	5%
M : Monthly Insurance	$t=1$, $m=0$	No	0.78%
Mp : Monthly Insurance with probability specified	$t=1$, $m=0$	Yes	0.78%

Table 1: Summary of experiment scenarios: Session I

Session II: Monetary Loss Amount: CHF 32 minus premium paid in the previous blocks

s : Scenario	t, m	Probability Specified	Loss Probability	Premium
W : Whole bridge insurance	$t = 1$, $m = 0$	Yes	5%	CHF 22
B_i : $i = 1...12$, $i \neq 3$ Normal period the ith block insurance	$t = \frac{1}{13-i}$ $m = 1 - t$	No	0.39%	CHF 3
B_3 : Risky period the 3rd block insurance	$t = 1$, $m = 0$, or $t = 0.1$, $m = 0.9$	No	0.78%	CHF 3

Table 2: Summary of experiment scenarios: Session II

4 Baysian Model

We apply Bayesian model to calibrate the parameters. This model allows us to combine the prior assumption with the data collected. The output of Bayesian model is a posterior distribution integrating the prior distribution with observated data through a likelihood function. According to Nilsson et al. (2011), parameters in CPT extracted from the Bayesian model is more stable with lower standard deviation than MLE method. In addition, the hierarchy structure within Bayesian model also improves the estimated parameters' stability especially when the data is limited (cf. e.g. Scheibehenne and Pachur (2015)). Furthermore, the posterior distribution, as the combination of joint probabilities of each parameter grants us the flexibility to analyze parameters separately.

Considering the probabilitstic nature of human choice behavior, an error terms ϕ, suggested by Rieskamp (2008) is added into the model. With the Luce choice rule, (cf. Luce et al. (1963)), the probability of purchasing insurance with premium loading instead of bearing the risk by themselves becomes:

$$\frac{1}{1 + \exp^{-\phi(V^c - V^L)}} = \frac{1}{1 + \exp^{\phi'((1+c)Lp)^\alpha - \pi(p^*)(L\delta_m)^\alpha)}}.$$

Thereby p^* is the estimated probability in Equation (7). Within this equation, with s represents a certain scenario set, $\beta_s \neq 1$ when the probability miscalculation bias is prominent. We first take the exponential discount function $\delta^e_m = \exp(\Delta \cdot m)$. $\Delta > 0$ if the risk period is longer than the insurance period and thus individuals discount the loss amount. For Scenario B_3, we first assume $m = 0$, meaning subjects narrowly bracketed this special period. We run another model assuming $m = 0.9$ for Scenario B_3 in the subsequent section. Both prospects: premium payment and the future potential loss are in the loss domain. Here we estimate $\phi' = \phi \cdot \lambda^{CPT}$ instead of ϕ and λ^{CPT} exclusively. Table (3) summarizes all the free parameters.

Parameters		Range
α	Senstivity of variation in CPT	$0 < \alpha \leq 1$ Risk neutral if $\alpha = 1$
γ	Shape of probability weighting function in CPT	$0 < \gamma \leq 1$ Risk neutral if $\gamma = 1$
β	Parameters of probability miscalculation bias	$\beta > 0$ No probability bias exists if $\beta = 1$
Δ	Future discount factor: $\delta^e_m = \exp(\Delta \cdot m)$	$-\infty < \Delta < \infty$ Risk neutral if $\Delta = 0$ Myopic bias exists if $\Delta > 0$
ϕ'	with $\phi' = \phi \cdot \lambda^{CPT}$: error terms times loss aversion in CPT	$\phi' > 0$

Table 3: Sumamry of free parameters

With our main focus on the bias parameters β_s and discount factor Δ, all subjects are assumed to possess identical α and γ. Following Nilsson et al. (2011), we apply weak assumption for α and γ, with uniform distribution, ranging from 0 to 1. Error terms $\phi'_s > 0$, with s denoting various scenarios as the noises differ over the focused scnarios: ϕ'_Q represents the error terms in Session I including hypothetical questions with the risk period equal the insurance period or $t = 1$. ϕ'_B controls the error terms in B_i, $(i = 2...12)$ where monetary motivation is given and special framing is deployed so that $t \leq 1$. It is fairly unlikely to acquire insurance for the first block (B_1) as the subjects have just rejected a much-cheaper full insurance in Scenario W. With this rareness, the noise term is small and we set $\phi'_{B_1} = 20$ (a fairly large number). ϕ'_W in Scenario W is influenced by both the monetary motivation and the feature that $t = 1$. We build a hierarchy structure in which ϕ'_B and ϕ'_Q follow a log normal distribution with $\mu_{\phi'}$ and $\sigma_{\phi'}$, controled by two uniform distributions with the range of (-4.6,3.2) for $\mu_{\phi'}$ and (0,1.13)$\sigma_{\phi'}$.[3] As ϕ'_W share mutual features with both ϕ'_Q and ϕ'_{B_i}, we assume $\phi'_W = \exp(\mu_{\phi'})$), or the expected ϕ' in the group level.

In terms of the bias parameters β_s and discount factor Δ, the loss probability is given in Scenario A, Mp and W. Therefore, subjects suffer no bias in probability calculation and $\beta_A = \beta_{Mp} = \beta_W = 1$. For other scenarios, the loss probability is not specified. We estimate β_M for Scenario M, β_R for Scenario B_3, the risky period in Session II and β_N for Scenario β_i, $i \neq 3$, the normal period in Session II. As $\beta_s > 0$, we set β_s following a Log-normal distribution with $\mu_\beta = \sigma_\beta = B$, where B is with a uniform distribution ranging between 0 and 2[4]. With this prior distribution, the mode of β_s is 1. This assumption underlies that no bias exists leading to loss probability miscalculation. Δ ranges between $-\infty$ and $+\infty$ while subjects discount future value only if $\Delta > 0$. Δ's marginal impact decreases when $\Delta > 10$. Hence, we set the prior distribution for Δ a uniform distribution between -10 and 10.

The Bayesian model is implemented with Markov Chain Monte Carlo algorithms (MCMC) in Denwood (2016) and Kruschke (2014)) with a total of 500,000 MCMC samples, generated from

[3]Based on the CPT experience, plausible value for ϕ lies in an interval between 0.1 to 5 or $\log(-2.3)$ and $\log(1.6)$. We double the range to consider the impact of λ^{CPT} on ϕ'_t. The value 1.13 represents a reasonable upper bound for $\sigma_{\phi'}$(cf.Nilsson et al. (2011)).

[4]$\sigma_\beta > 0$. Based on the experience, the value 2 is considered as a reasonable upper bound.

three chains after a burn-in of 1000 samples.

Generally, it takes at least 25 questions/prospects with a wide range of risk probabilities to estimate α, γ (considering the loss domain only, Tversky and Kahneman (1992) includes 28 prospects and Rieskamp (2008) includes 60 prospects). Here we estimate α and γ with merely three probability points (5% in Scenario A and W, 0.78% in Scenario M, Mp and B_3, and 0.39% in Scenario B_i, $i \neq 3$)). This limited points lead to a strong correlation between α and γ. Figure (9) shows this correlation between α and γ. Hence, these two parameter results do not converge perfectly until MCMC samples increase to 500,000. With 500,000 MCMC samples, α and γ are estimated with effective sample size (ESS) around 10^4.[5] Both of these CPT parameters, $\alpha = 0.67$ and $\gamma = 0.59$, are lower than those computed in Tversky and Kahneman (1992) where $\alpha = 0.88$ and $\gamma = 0.69$. Figure (10) shows that the lower α leads to a lower c^{WTP} while the lower γ pushes c^{WTP} upwards. Overall, c^{WTP} generated by our estimated parameters is lower than by parameters computed in Tversky and Kahneman (1992). Figure (11) exams the correlation between the CPT parameters (α and γ), the error terms (ϕ'_t), the bias parameters (β_s) and the discount factor (Δ). ϕ'_t is negatively correlated with both α and γ. Nevertheless, no strong correlation is shown between CPT parameters and the parameters in focus (β_s and Δ) except for a slight negative correlation between α and β_R.

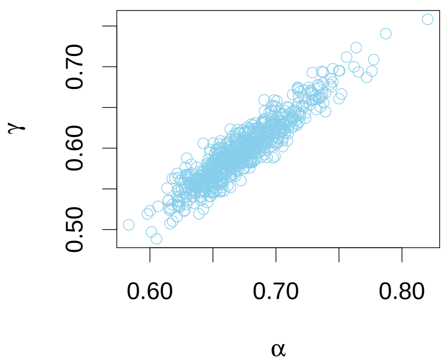


Figure 9: Correlation between α and γ

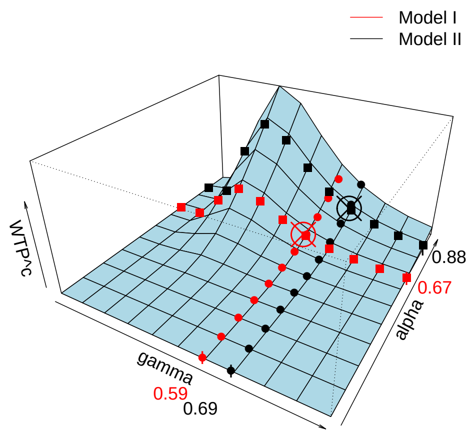
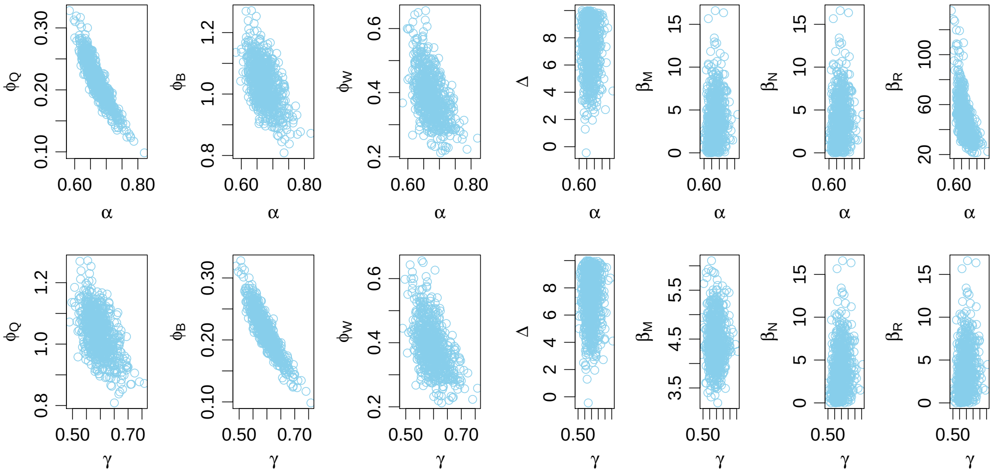


Figure 10: α and γ impacts on c^{WTP} ($p = 0.05$)

[5]Generally, ESS are recommended to achieve at least 10^4 to come out with stable results. (cf. Kruschke (2014))



(a) Correlation between α, γ and ϕ'_t

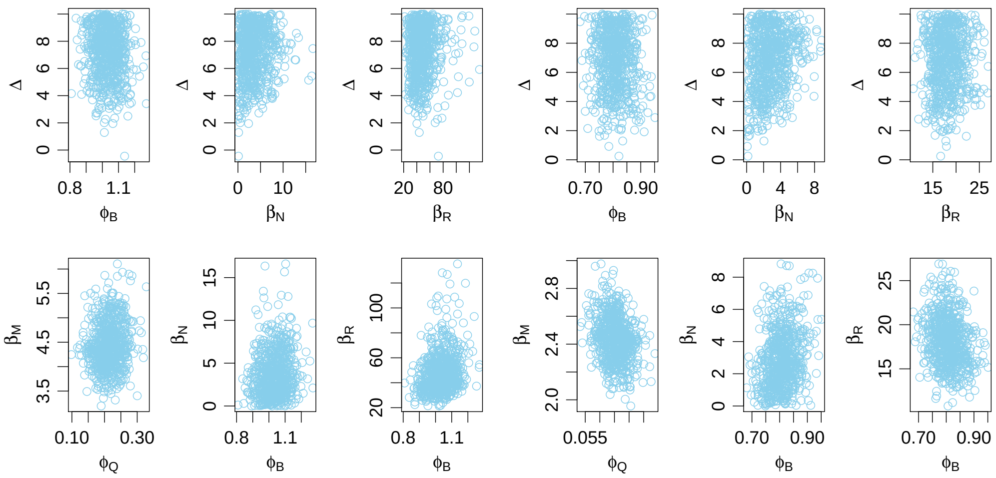
(b) Correlation between α, γ and bias parameters Δ and β_s

Figure 11: Correlation among parameters in Model I

To tackle this collinearity issue among CPT parameters and error terms, Model II is applied where subjects are assumed to behave as if $\alpha = 0.88$ and $\gamma = 0.69$, the parameter values extracted from Tversky and Kahneman (1992). Hence, in Model II, ϕ'_t, Δ, and β_s are the only free parameters. Table (4) summarizes each model with the results of the estimated free parameters and the respective prior distributions. As shown in Figure (12), no strong correlation exists among ϕ'_t, β_s and Δ in both Model I and Model II.

Parameters		Model I	Model II
α	mode, CV, ESS	0.67, 0.05, $\mathbf{9.5 \cdot 10^3}$	α is fixed at 0.88
	prior	$\sim \mathcal{U}(0,1)$	NA
γ	mode, CV, ESS	0.59, 0.07, 10^4	γ is fiexed at 0.69
	prior	$\sim \mathcal{U}(0,1)$	NA
ϕ'_t	mode, CV, ESS	ϕ'_Q : 1.03, 0.07, $2.8 \cdot 10^5$ ϕ'_B : 0.22, 0.17, 10^4 ϕ'_W : 0.37, 0.19, $2.7 \cdot 10^4$ $\phi'_{B'}$ is fixed at 20	ϕ'_Q : 0.06, 0.06, $4.0 \cdot 10^5$ ϕ'_B : 0.81, 0.06, $3.6 \cdot 10^5$ ϕ'_W : 0.20, 0.16, $3.9 \cdot 10^5$ $\phi'_{B'}$ is fixed at 20
	prior	ϕ'_Q, ϕ'_B ~Lognormal($\mu_{\phi'}$,$\sigma_{\phi'}$) $\phi'_W = \mu_{\phi'}$ $\mu_{\phi'} \sim \mathcal{U}(-4.6, 3.2)$ $\sigma_{\phi'} \sim \mathcal{U}(0, 1.13)$	
β_s	mode, CV, ESS	β_M: 4.34, 0.1, $9.6 \cdot 10^4$ β_N: 2.44, 0.7, $1.4 \cdot 10^5$ β_R: 40.38, 0.34, $1.8 \cdot 10^4$ β_A, β_{Mp} and β_W are fixed at 1	β_M: 2.42, 0.07, $4.0 \cdot 10^5$ β_N: 2.24, 0.58, $2.5 \cdot 10^5$ β_R: 17.74, 0.15, $4.0 \cdot 10^5$ β_A, β_{Mp} and β_W are fixed at 1
	prior	$\beta_M, \beta_N, \beta_R$ ~Lognormal(B, B) $B \sim \mathcal{U}(0, 2)$	
Δ	mode, CV, ESS	9.62, 0.28, $2.6 \cdot 10^5$	9.49, 0.29, $3.9 \cdot 10^5$
	prior	$\sim \mathcal{U}(-10, 10)$	$\sim \mathcal{U}(-10, 10)$

Table 4: Two models with parameters results and prior distribution

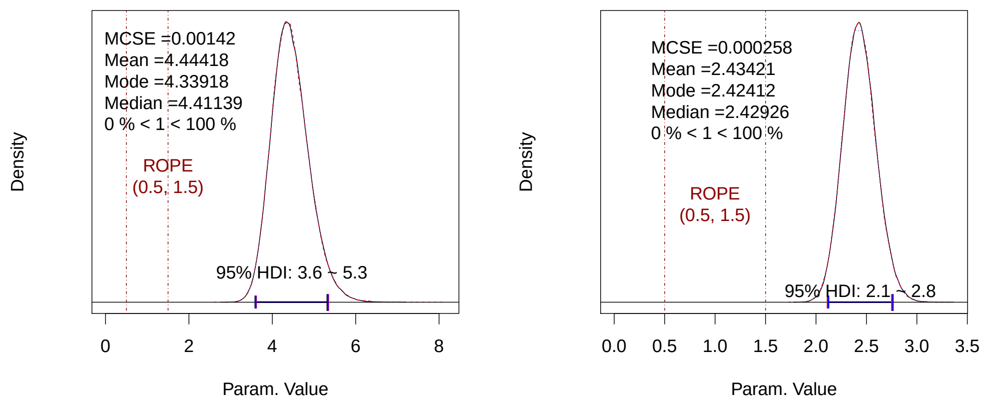


(a) Correlation in Model 1

(b) Correlation in Model II

Figure 12: Correlation among ϕ_t' Δ and β_s

Figure (13) demonstrates the posterior distribution of β_M in both Model I and II. The 95% highest density interval (HDI) and the region of practical equivalence (ROPE) between 0.5 and 1.5 do not overlap. Hence it confirms the existence of probability calculation bias in Scenario M. As β_M is significantly higher than 1, subjects overestimate the loss probability when making decision on this hypothetical situation. With mode of $\beta_M = 4.34$ in Model I and $\beta_M = 2.42$ in Model II, subjects make decisions as if $p^* = 3.4\%$ in Model I or $p^* = 1.9\%$ in Model II, substantially higher than the real loss probability, $p = 0.78\%$.

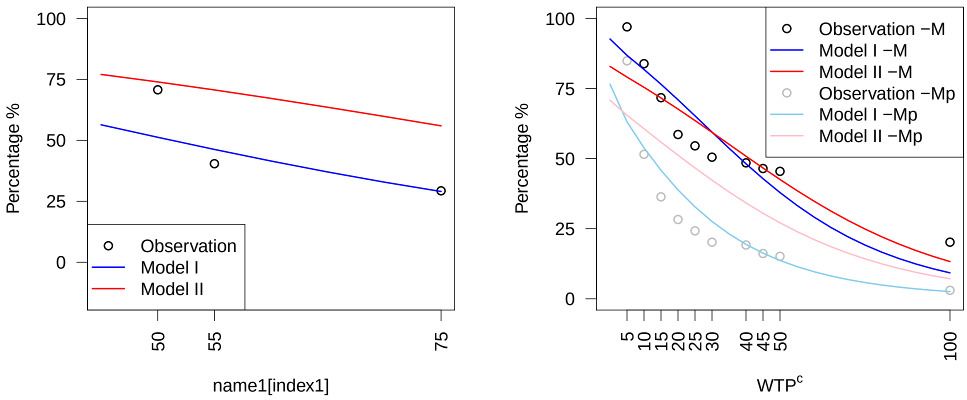


(a) β_M in Model I

(b) β_M in Model II

Figure 13: Distribution of parameter β_M

Figure (14) compares the observation and the predictions (calculated with the mode value of parameters' posterior distribution) from both models. As $\beta_M > 1$, participants are more willing to pay a higher loading when the probability is not specified. Figure (14(b)) shows that the percentage line for Scenario M is shifted towards right compared to that in Scenario Mp.



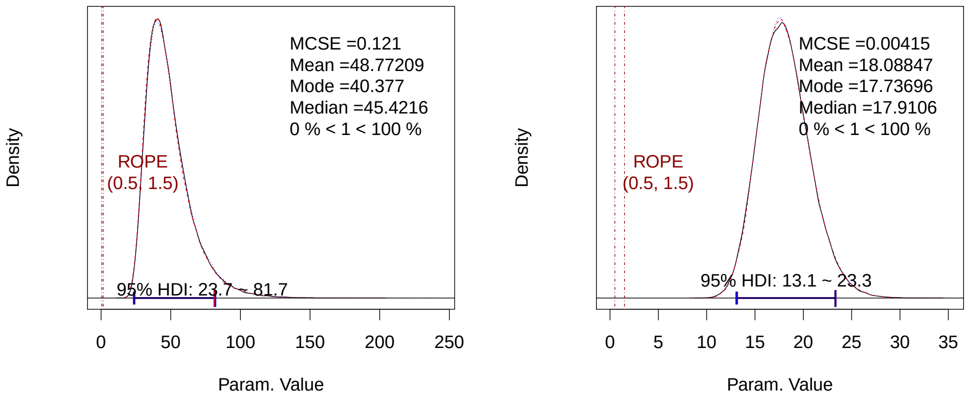
(a) Comparison between model prediction and the collected data in Scenario A

(b) Comparison between model prediction and the collected data in Scenario M and Mp

Figure 14: Comparison between model prediction and observations

The decisions made in Session II are monetarily motivated. The availability bias in this Session is thus even stronger but rather unstable: with the monetary motivation, subjects are easy to imagine either losing some (the insurance premium) or all the rewards for participating this experiment. Hence, cv of both β_N and β_R are larger than that of β_M.

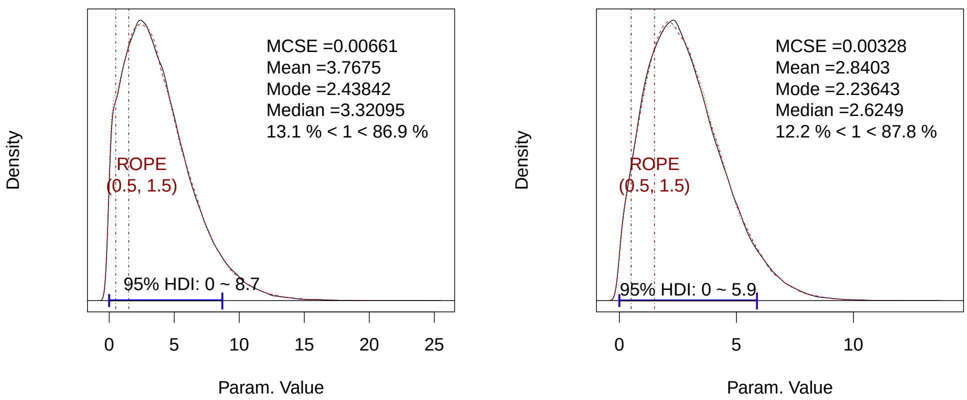
During the risky period (Scenario B_3), this probability-miscalculation bias enlarges as the risk is relatively salient. With mode of $\beta_M = 40.38$ in Model I and $\beta_M = 17.74$ in Model II, subjects act as if $p^* = 27.3\%$ in Model I or $p^* = 13.1\%$ in Model II, extremely larger than the objective probability $p = 0.78\%$. Regarding β_N for the normal Scenario (B_i, $i \neq 3$) subjects do not miscalculate the probability systematically. Due to the larger cv, 95% HDI is rather wide, between 0 and 8.7 in Model I and between 0 and 5.9 in Model II, both of which overlap with the respective ROPE (cf. Figure (16)). It suggests that subjects neither overestimate nor underestimate systematically during the normal period even though the probability is not specified.



(a) β_R in Model I

(b) β_R in Model II

Figure 15: Distribution of β_R

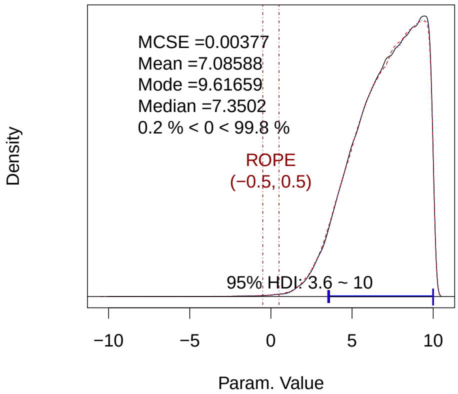


(a) β_N in Model I

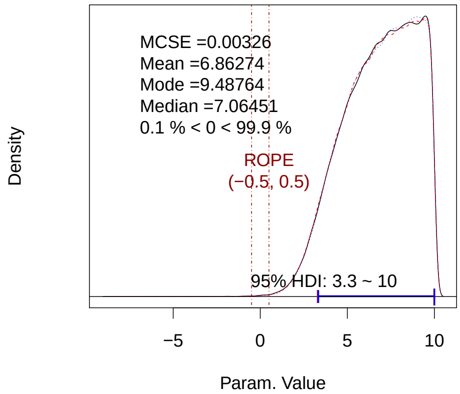
(b) β_N in Model II

Figure 16: Distribution of β_N

The posterior distribution in Figure (17) shows that Δ is higher than 0 in both models with more than 99.5% probability. It confirms that when individuals compares two prospects with different time periods, they discount the value of which possesses longer term. The insurance period is shorter and subjects discount the loss value to compare with the value provided in insurance prospect. Due to this future discount effect, c^{WTP} decreases as the time difference increases.



(a) Δ in Model I



(b) Δ in Model II

Figure 17: Distribution of parameter Δ

Figure (18) compares the model predictions and the observation. Both model I and model II generate similar result. None of the subjects purchase insurance for the first block, as they have just rejected a much-cheaper whole-bridge insurance. Due to the myopic bias, more than 20% of subjects purchase insurance at B_{12}, while Only around 10% of participants purchase insurance for B_i, $i \neq 3, 12$, even though the loss probability is the same. Nearly 80% of subjects purchase insurance at B_3. This high portion is explained by both the myopic ($m = 0$ for B_3) and miscalculation bias. As a result, from Figure (19), insurance for B_3 can be sold with the premium 20 times more than the expected loss. Insurance for B_{12} can be sold higher with a loading $c^{WTP} = 3$. However, for the rest of blocks, if their risk period is longer and $m > 0$, caused by the future discount effect, their c^{WTP} is reduced to even lower than the fair price.

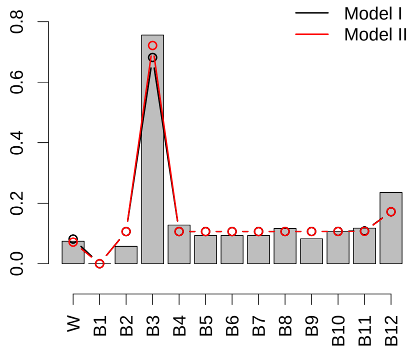


Figure 18: Comparison between model prediction and observations in Session II

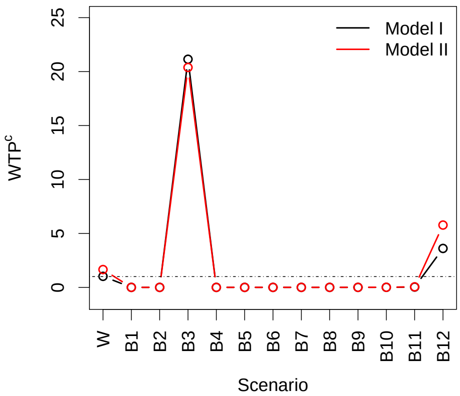


Figure 19: Predicted c^{WTP} in each scenario in Session II

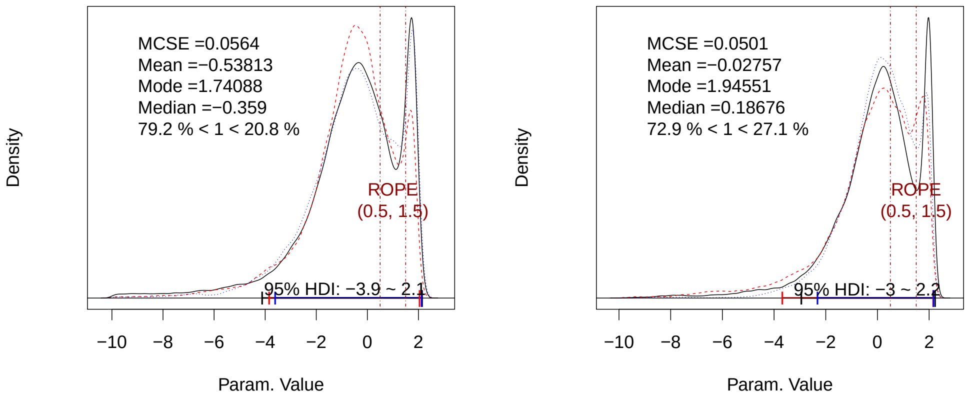
4.1 Myopic Attitudes towards Risky Period

Previous section assumes that when crossing B_3, the subjects' risk period is reduced to one block. Since B_3 has a different loss probability, they concentrate on this block and thus narrowly bracket this risky period. Hence, $m = 0$ at B_3. In this section, we revise the assumption that the subjects' risk period stays the same (the length of the remaining bridge) for all blocks B_i. Hence, from Equation (8), $m = 0.9$ at B_3. From Table (5), the bias parameters and the discount factors for the experiment's Session II (β_N, β_R and Δ) are generated by less than 1000 ESS even with 500,000 samples. Hence, the posterior distributions of Δ from three separate chains do not converge (cf. Figure (20). Figure (**??**) shows that c^{WTP} for B_3 is significantly underestimated. This is clearly not a fitting model, confirming that subjects treat the risky block individually with $m = 0$ when facing a period with a unique loss probability.

Moreover, these results show that both models are fairly robust. Despite the significant change in λ, β_R, and β_N, all parameters related to Session I are rather close to that discussed in the previous section.

Parameters		Model I	Model II
α	mode, CV, ESS	0.67, 0.05, $\mathbf{9.2 \cdot 10^3}$	α is fixed at 0.88
	prior	$\sim \mathcal{U}(0,1)$	NA
γ	mode, CV, ESS	0.59, 0.07, $\mathbf{9.3 \cdot 10^3}$	γ is fiexed at 0.69
	prior	$\sim \mathcal{U}(0,1)$	NA
ϕ'_t	mode, CV, ESS	ϕ'_Q : 0.22, 0.17, 10^4 ϕ'_B: 1.01, 0.07, $2.1 \cdot 10^4$ ϕ'_W : 0.36, 0.19, $2.5 \cdot 10^4$ $\phi'_{B'}$ is fixed at 20	ϕ'_Q : 0.07, 0.06, $4.0 \cdot 10^5$ ϕ'_B: 0.79, 0.06, $8.3 \cdot 10^4$ ϕ'_W : 0.19, 0.16, $4.0 \cdot 10^5$ $\phi'_{B'}$ is fixed at 20
	prior	ϕ'_Q, ϕ'_B ~Lognormal(μ_ϕ,σ_ϕ) $\phi'_W = \mu_\phi$ $\mu_\phi \sim \mathcal{U}(-2.3, 1.6)$ $\sigma_\phi \sim \mathcal{U}(0, 1.13)$	
β_s	mode, CV, ESS	β_M: 4.46, 0.1, $8.4 \cdot 10^5$ β_N: 2.10, 0, **1102** β_R: 6.51, 2.08, **106** β_A, β_{Mp} and β_W are fixed at 1	β_M: 2.41, 0.07, $4.0 \cdot 10^5$ β_N: 0, 2.05, **6643** β_R: 13.28, 2.78, **202** β_A, β_{Mp} and β_W are fixed at 1
	prior	$\beta_M, \beta_N, \beta_R$ ~Lognormal(B, B) $B \sim \mathcal{U}(0, 2)$	
Δ	mode, CV, ESS	1.74, -3.35, **917**	1.95, -58.33, **838**
	prior	$\sim \mathcal{U}(-10, 10)$	$\sim \mathcal{U}(-10, 10)$

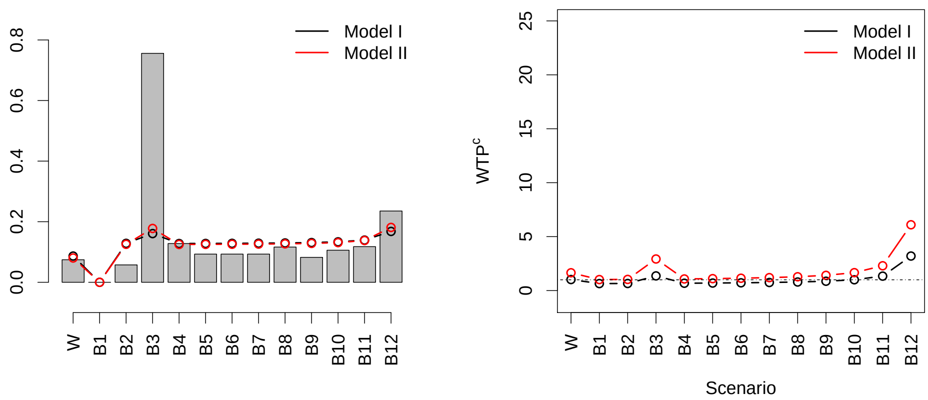
Table 5: Two models with parameters results and prior distribution, where subjects are assumed widely bracket the risky period ($m = 0.9$ at B_3)



(a) Model II

(b) Model II

Figure 20: The posterior distribution of Δ with assumption that subjects widely bracket the risky period ($m = 0.9$ at B_3)



(a) Comparison between model prediction and observations in Session

(b) Predicted WTP in each scenario in Session II

Figure 21: Model predictions with assumption that subjects widely bracket the risky period ($m = 0.9$ at B_3)

5 Conclusion

Tversky and Kahneman (1992) constructs CPT model and explains the coexistence of lottery and insurance with fourfold patter of risk attitudes. In the insurance context, people buy insurance as they overweight the fairly small loss probability. On-demand insurance is offered along the time line, covering even rarer loss. The insurance demand changes as individuals view the risk separately, or modify their risk period due to the insurance product. Namely, the risk period determines how people bracket these risks along the time line, and the length of the risk period influences the WTP for the on-demand insurance.

Longer risk period leads to a lower discount loss amount. Hence, individuals are rather reluctant to purchase insurance against a risk with period much shorter than their long-term risk period. In the experiment, we show that subjects tend to buy more insurance for the last block even though the expected loss is the same for all the blocks except for the third one. The experiment subjects receive their promised rewards after the whole bridge. Therefore, their risk period is the remaining bridge blocks they have not yet crossed. The further they proceed, the shorter their risk period, and the more risk averse they become. Moreover, a scenario with a relatively higher loss probability makes the risk much salient. As a result, subjects also shorten their risk period when making an insurance purchase decision on B_3.

In the real world, several factors may also influence our risk periods. For example, since we usually change our phones or other electronic gadgets rather frequently, the risk periods for these items are rather short. Hence, these insurance contracts or warranty are fairly popular even with an exorbitant price. On the contrary, people view catastrophe as risk for the whole life time. Even with annual catastrophe insurance on the market does not shorten individuals' risk period. With this much long-term risk period, the longer the insurance contract leads to a shorter discount period, and the loss amount will be less discounted. Hence, multi-year hurricane insurance is preferred to the annual insurance as suggested in Kunreuther and Michel-Kerjan (2015).

The risk period can be even reduced when people encounter a special period. For example, if they focus on the time spent on holiday, their value is cut into few weeks, or even few days as B_3 in our experiment. During this risky period, subjects' high risk aversion attitude are caused by both the bias in probability miscalculation and the myopic impact. This combined bias reflects the popularity of "named-event" insurance: the flight crash tragedy makes the risk salient. Moreover, insured focus only on one single journey instead of multiple flight insurance. Traditionally, this "named-event" insurance contract is designed by insurers. The popularity of this contract is then depended on how salient this event is to the customers. With on-demand insurance, individuals can freely choose whichever period to focus on according to their specific experience, memory or even their superstitious belief.

Except for the myopic loss aversion, consumption categories in budgeting discussed in Thaler (1999) may make on-demand insurance even more appealing. Individuals divide spending into budget categories as corporations do for the budget planning and managing. When we do the bookkeeping, small and routine expenses are generally ignored, or spent as "petty cash" in corporation practice. In practice, marketing activities exploit this bias and frame an annual fee as "pennies-a-day". In insurance, on-demand insurance divides the risk into several units. Despite high unit premium, the absolute payout amount for the risk per hour or even per day is trivial and can be categorized as negligible "petty cash." In addition, Kunreuther and Pauly (2006) indicates that individuals focus more on the coverage-premium ratio rather than the loss probability. With lower loss probability, on-demand policy is offered with a much better coverage-premium ratio. Moreover, on-demand insurance is easy to acquire, customers may be more prone to all the mentioned behaviour bias by using heuristics or "system 1"[6] to make decisions.

However, on-demand insurance does not promise a sure success. Following factors hinder this

[6]Kahneman and Patrick (2011) describes two modes of thoughts: "System 1" is instinctive and fast but subject to cognitive biases. "System 2" is slow, but more deliberative and logical.

insurances' "money-pump" opportunities:

To begin with the payment decoupling,Thaler (1999) suggests that one integrated loss is usually better tolerated than several small expenses. It explains the popularity of "flat rate" in telecommunication industry. Though more expensive, the flat rate makes the payment less salient. Therefore, if the on-demand insurance's premium is not small enough to get ignored, customers suffer every time when making premium payments. In this case, traditional insurance will be preferred.

Secondly, the tiny loss probability could not a certain threshold. Though the absolute premium amount of on-demand is small, the loss probability is also divided and becomes insignificant. The threshold model suggests that individuals treat small probability lower than a certain threshold zero (cf. Kunreuther and Pauly (2006)). Namely, individuals may not consider getting insured at all as the loss probability is negligible.

Thirdly, the issues regarding adverse selection, moral hazard or even fraud issues could be much more serious. As on-demand insurance is designed to be convenient and user-friendly, this insurance is easily acquired on-line or through mobile app. How to underwrite and detect fraud while keeping its convenient trait become a crucial point. Therefore, so far only small and rather easy insurance contracts are offered on the market.

Last but not least, currently there are only limited on-demand insurers on the market, providing relatively unique products. As monopolies in each segmented market, these insurtechs can take the money-pump opportunity, selling their unique products with inflated prices. As more insurers join this market, this market will becomes more competitive, and the premium will then decrease substantially to an equivalent point.

References

Baker, J. R., Lattimore, P. K., and Witte, A. D. (1988). An empirical assessment of alternative models of risky decision making. *National bureau of economic research Cambridge, Mass., USA*, 2717.

Denwood, M. J. (2016). runjags : An R Package Providing Interface Utilities, Model Templates, Parallel Computing Methods and Additional Distributions for MCMC Models in JAGS. *Journal of Statistical Software*, 71(9):1–25.

Hershey, J. C. and Schoemaker, P. J. H. (1980). Risk taking and problem context in the domain of losses: An expected utility analysis. *Journal of Risk and Insurance*, 47(1):111–132.

Hey, J. D., Morone, A., and Schmidt, U. (2009). Noise and bias in eliciting preferences. *Journal of Risk and Uncertainty*, 39(3):213–235.

Holt, C. A. and Laury, S. K. (2002). Risk Aversion and Incentive Effects. *American Economic Review*, 92:1644–1655.

Kahneman, D. and Patrick, E. (2011). *Thinking, Fast and slow.* New York: Farrar, Straus and Giroux.

KPMG (2017). Will on-demand insurance become mainstream?

Kruschke, J. K. (2014). *Doing Bayesian data analysis : a tutorial with R, JAGS, and Stan.* Academic Press.

Kunreuther, H. and Michel-Kerjan, E. (2015). Demand for fixed-price multi-year contracts: Experimental evidence from insurance decisions. *Journal of Risk and Uncertainty*, 51(2):171—-194.

Kunreuther, H. and Pauly, M. (2004). Neglecting Disaster: Why Don't People Insure Against Large Losses? *Journal of Risk and Uncertainty*, 28(1):5–21.

Kunreuther, H. and Pauly, M. (2006). Insurance Decision-Making and Market Behavior. *Foundations and Trends in Microeconomics*, 1(2):63–127.

Luce, R. D., Bush, R. R., and Eugene, G. (1963). *Handbook of mathematical psychology.*

Nilsson, H., Rieskamp, J., and Wagenmakers, E. J. (2011). Hierarchical Bayesian parameter estimation for cumulative prospect theory. *Journal of Mathematical Psychology*, 55(1):84–93.

Rabin, M. and Thaler, R. H. (2001). Anomalies: risk aversion. *Journal of Economic Perspectives*, 15(1):219–232.

Rieskamp, J. (2008). The Probabilistic Nature of Preferential Choice. *Journal of Experimental Psychology: Learning Memory and Cognition*, 34(6):1446–1465.

Samuelson, P. A. (1963). Risk and Uncertainty: A Fallacy of Large Numbers. *Scientia*, 98:108–113.

Scheibehenne, B. and Pachur, T. (2015). Using Bayesian hierarchical parameter estimation to assess the generalizability of cognitive models of choice. *Psychonomic Bulletin and Review*, 22(2):391–407.

Schwarcz, D. (2010). Insurance demand anomalies and regulation. *Journal of Consumer Affairs*, 44(3):557–577.

Thaler, R. H. (1999). Mental Accounting Matters. *Journal of Behavioral Decision Making*, 12(3):183–206.

Tversky, A. and Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, 185(4157):1124–1131.

Tversky, A. and Kahneman, D. (1992). Advances in Prospect Theory Cumulative Representation of Uncertainty. *Journal of Risk and Uncertainty*, 5(4):297–323.