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Preference updating in public health risk valuation

Mehmet Kutluay
Institute for Environmental Studies, Vrije Universiteit, Amsterdam
Tinbergen Institute, Amsterdam/Rotterdam
mehmet.kutluay@vu.nl

Roy Brouwer
Department of Economics and The Water Institute, University of Waterloo, Canada
Institute for Environmental Studies, Vrije Universiteit, Amsterdam

Richard S. J. Tol
Institution Department of Economics, University of Sussex
Institute for Environmental Studies, Vrije Universiteit, Amsterdam
Department of Spatial Economics, Vrije Universiteit, Amsterdam
Tinbergen Institute, Amsterdam
CESifo, Munich

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JEL classification: D83, D90, I12, I18

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Preference updating in public health risk valuation

Mehmet Kutluay*[1,2], Roy Brouwer[3,1], and Richard S. J. Tol[4,1,5,2,6]

[1] *Department of Environmental Economics, Institute for Environmental Studies, Vrije Universiteit Amsterdam, the Netherlands*
[2] *Tinbergen Institute, Amsterdam/Rotterdam, the Netherlands*
[3] *Department of Economics and The Water Institute, University of Waterloo, Canada*
[4] *Department of Economics, University of Sussex, Falmer, UK*
[5] *Department of Spatial Economics, Vrije Universiteit, Amsterdam, the Netherlands*
[6] *CESifo, Munich, Germany*

Abstract

Willingness to pay (WTP) for malaria pills, in light of new risk information and probability weighting, is estimated via a discrete choice experiment (CE). A lottery played prior to the CE yields individual-level probability weighting parameters through Bayesian inference. Over-reaction to new malaria risk information is found as marginal WTP for malaria protection increases by 20-33%. The probability weighting parameter helps to explain the observed variation in malaria valuation, while over or under-weighting of probabilities is found to be correlated with malaria knowledge and experience. This is independent of whether or not the information treatment is received. Over-reaction to new information uncovers potential biases, possibly from simply reminding people about being sick, in placing a monetary value on avoiding uncertain public health risks.

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1 Introduction

Many decisions are made under risk and uncertainty. They can range from choosing between career specializations to buying medicine for future use. Many issues on the public agenda also revolve around future scenarios that are probabilistic in nature. Low-probability high-impact events, like epidemic disease outbreaks, prompt concrete policy decisions to be taken in the present even though they concern the near-future. Malaria is one such disease that falls into this category, as it could become more widespread due to climate change. Projections regarding the likelihood of future outbreak occurrences are routinely created, and incoming new information is dispersed amongst policy-makers and, sometimes, the general public. This study focuses on how new information like this influences public preferences and health risk valuation.

Although there is a large literature on how new *qualitative* information affects valuation (Bergstrom *et al.*, 1990; Spash & Hanley, 1995; Lee *et al.*, 1998; Alberini *et al.*, 2005; Johnston *et al.*, 2017), not much is known about the impact of providing *numerical* information, in particular changes in risk levels (e.g. Dekker *et al.*, 2011). Work has been done on how people change subjective beliefs when presented with new information (Cameron, 2005) and experiences (Deryugina, 2013). These findings highlight that people tend to update their subjective beliefs after being given new information, but sometimes not in the direction that rational individuals would be expected to. Updated subjective beliefs reflect public heterogeneity in

*Corresponding author - mehmet.kutluay@vu.nl

approaching objective probabilities, such as adhering to former beliefs and compromising between belief and fact. This makes it important to assess how new risk information can influence public preferences for health risk protection and valuation.

In this study we assess willingness to pay (WTP) to avoid malaria morbidity in the context of new information regarding the diseases prevalence via a choice experiment (CE) in Mumbai, India. In a series of choice tasks, survey participants are presented a menu of malaria prevention pills that differ in terms of suitability, durability, level of protection and price. In the survey leading up to the CE, participants are asked for their beliefs and perception of malaria prevalence. Half of the sample receives extra information on actual malaria prevalence, with the opportunity to revise their previous answer regarding their perception of malaria prevalence. Based on previous findings and health-state dependent utility theory, we hypothesize that respondents who get the extra information, disclosing a low level of malaria prevalence, and find out that it is lower than they previously thought will subsequently also lower their WTP.

A set of utility and probability weighting function parameters are estimated, at the individual level, through lottery choices. Respondent-level parameter estimates are derived from a Bayesian estimation routine. The identified best-fit probability weighting function parameter is treated as a respondent-specific covariate to explain choice behavior in the CE. Since it gauges how respondents evaluate probabilities in making gains, we view this parameter as also indicative of how optimistic or pessimistic a respondent is about making a probable financial gain.

This study contributes to the behavioral economics and valuation literatures in a number of important ways. First of all, this is the first study as far as we know where individual probability weighting parameters are estimated and included in the subsequent choice model analysis. In doing so, potential correlations between respondent characteristics and probability weighting behavior is investigated. There are surprisingly few studies that have analyzed socio-demographic determinants of probability weighting. Secondly, other malaria valuation studies have applied contingent valuation only (Trapero-Bertran *et al.*, 2012). This is the first study to employ a CE to measure public WTP to prevent malaria.

The paper continues as follows: section 2 details the empirical strategy for the inferential models used, section 3 explains the research methodology and presents descriptive survey statistics, section 4 presents the regression results and section 5 provides the conclusions and discussion.

2 Modeling Framework

2.1 Multinomial Logit Specification

A random utility framework is utilized in analyzing CE data. Here the utility function is linear and is used to describe how attributes within the CE options influence the resulting choices (Train, 2009). The random utility for a malaria prevention pill i, from choice set j, chosen by individual n is:

$$\begin{aligned} U_{ijn} &= V_{ijn} + \epsilon_{ijn} \\ V_{ijn} &= \beta X_{ij} + \gamma Z_{ijn} \end{aligned} \tag{1}$$

Where X_{ij} is a matrix containing the attribute levels of the malaria pills in each choice set j, β is a vector of coefficients for the choice attributes corresponding in X_{ij}. They reflect the sample preferences for the attributes. Z_{ijn} is a matrix that contains attribute levels, like X_{ij}, but with interactions of individual-specific covariates (e.g. age, income). γ is the relevant coefficient vector. These coefficients also reflect sample preferences, as opposed to individual ones. From this framework, we extract the marginal WTP (MWTP) for a marginal change in some attribute $K \in X$ as, from equation 1, $-(\frac{\delta V_{ijn}}{\delta X_K})/(\frac{\delta V_{ijn}}{\delta X_{\text{Price}}})$. If V_{ijn} is a linear function in β and γ, then the MWTP for attribute K is simply $-\beta_K/\beta_{\text{Price}}$. Last, but crucial to the

next steps, ϵ_{ijn} is the idiosyncratic error term, distributed i.i.d. of extreme value type 1. This assumption allows us to construct the multinomial logit model.

A simple assumption is made: if individual n chooses option i over all other options in choice set j, then it is because U_{ijn} is higher than U_{kjn} for $k \neq i$. Let P_{ijn} denote the probability of this choice occurring. It follows that:

$$P_{ijn} = \frac{e^{\lambda\beta\tilde{X}_{ij}+\lambda\gamma\tilde{Z}_{ijn}}}{\sum_{k\in J} e^{\lambda\beta\tilde{X}_{kj}+\lambda\gamma\tilde{Z}_{kjn}}} \tag{2}$$

Due to the assumptions on the error term, we have a scale parameter λ appearing in the final step. For the sole purpose of extracting MWTP values, it can be overlooked, since it gets divided out.

A multinomial logit equation can be used to estimate the coefficients β and γ in equation 1 (McFadden, 1974). However this structure imposes the so-called irrelevance of independent alternatives (IIA) rule. The ratio of the probability of choosing any i and k are independent of other choices in the same choice set. Using the above equation, it can be easily seen that $P_{ijn}/P_{kjn} = e^{V_{ijn}}/e^{V_{kjn}}$. This is a strict rule and also ignores the panel structure of the dataset, where individuals make choices from multiple choice sets.

To address both these problems, we fit a mixed logit model (McFadden & Train, 2000) based on the specified random utility model. The mixed logit model allows the β and γ coefficients to have random effects across individuals. Analytically, this means that the probabilities P_{ijn} become:

$$P_{ijn} = \int \frac{e^{\Delta V_{ijn}}}{\sum_{k\in J} e^{\Delta V_{kjn}}} G(d\alpha;\theta) \tag{3}$$

The α vector consists of coefficients from β and γ that we assume to have random effects. The θ vector consists of the random effects, which are usually the associated distribution parameters of the coefficients in α (e.g. standard deviation).

The disadvantage of using this approach is that it relies on the above integral to be simulated. This can become expensive in terms of computation time and different likelihood optimization routines can produce slightly different results. We make use of the mlogit package in R (Croissant, 2013) and utilize it in running the mixed logit models. The number of Halton draws, to improve the statistical efficiency of the estimated parameters, is set to 1000.

2.2 Estimating Probability Weighting Parameters

We observe seven distinct binary lottery choices for each respondent. From these observations we estimate associated utility and probability weighting function parameters, similar to Harrison *et al.* (2010). However we apply a different econometric method. We follow the Bayesian estimation method laid out in Balcombe & Fraser (2015), as opposed to the maximum likelihood estimation (MLE) in Harrison *et al.* (2010).

The Bayesian estimation method finds the posterior density of each parameter of interest, conditional on the dataset. Following Bayes' theorem, the posterior density function is calculated using the following relation:

$$P(\theta|D) \propto P(D|\theta)P(\theta) \tag{4}$$

Parameters are denoted by θ and data by D. $P(D|\theta)$ is the likelihood maximized in MLE routines. $P(\theta)$ is the prior density of θ. The left hand side of Equation (4) is integrated with respect to θ, resulting in the cumulative posterior density. We do this by making use of a Gibbs sampler routine called JAGS (Just Another Gibbs Sampler) within R. Eight thousand random draws are taken from the resulting posterior density to derive any moment/statistic needed from the θ vector.

There are several reasons the Bayesian method is suitable for our objective. The first is overcoming problems related to small-sample size when estimating individual level parameters (MLE methods rely on asymptotic theory for consistent estimates). The second is being able

to extract the distribution of each parameter, making sensitivity analyses possible later on. The third and last reason is the need to define the prior density for each parameter. This allows us to constrain the parameters to their theoretical boundaries, making it impossible for them to acquire theoretically non-sensible values.

The commonly used utility and probability weighting functions, along with the associated priors, are taken from Balcombe & Fraser (2015). We have six candidate utility and six probability weighting functions, making a total of 36 models to parametrize and compare. The functions are outlined below, while parameter priors are detailed in the annex to this paper, along with the estimated model structure.

The utility functions are as follows:

$$\text{POWER-I: } U(x) = x^{\alpha_1} \,:\, \alpha_1 > 0 \tag{5a}$$

$$\text{POWER-II: } U(x) = (x + \alpha_2)^{\alpha_3} \,:\, \alpha_2 > 0,\, \alpha_3 > 0 \tag{5b}$$

$$\text{EXPO-I: } U(x) = 1 - e^{-\alpha_4 x} \,:\, \alpha_4 > 0 \tag{5c}$$

$$\text{EXPO-II: } U(x) = 1 - e^{-\alpha_5 x^{\alpha_6}} \,:\, \alpha_5 > 0,\, 0.5 < \alpha_6 < 1.5 \tag{5d}$$

$$\text{LOG: } U(x) = ln(1 + \alpha_7 x) \,:\, \alpha_7 > 0 \tag{5e}$$

$$\text{QUAD: } U(x) = x - \frac{\alpha_8 x^2}{2} \,:\, 0 < \alpha_8 < \frac{2}{x_{\max}} \tag{5f}$$

The utility and probability weighting functions are treated as candidate data-generating-processes in explaining the lottery choices we have. The probability weighting functions are as follows:

$$\text{PRELEC-I (Prelec, 1998): } w(p) = e^{(-(-ln(p))^{\beta_1})} \,:\, 0 < \beta_1 < 2 \tag{6a}$$

$$\text{PRELEC-II (Prelec, 1998): } w(p) = e^{(-\beta_2(-ln(p))^{\beta_3})} \,:\, 0 < \beta_2 < 2,\, 0 < \beta_3 < 2 \tag{6b}$$

$$\text{K\&T (Tversky \& Kahneman, 1992): } w(p) = \frac{p^{\beta_4}}{(p^{\beta_4} + (1-p)^{\beta_4})^{\frac{1}{\beta_4}}} \,:\, 0.27 < \beta_4 < 1 \tag{6c}$$

$$\text{POWER: } w(p) = p^{\beta_5} \,:\, 0 < \beta_5 < 2 \tag{6d}$$

$$\text{G\&E (Stott, 2006): } w(p) = \frac{\beta_6 p^{\beta_7}}{\beta_6 p^{\beta_7} + (1-p)^{\beta_7}} \,:\, 0 < \beta_6 < 2,\, 0 < \beta_7 < 2 \tag{6e}$$

$$\text{LINEAR: } w(p) = p \tag{6f}$$

The LINEAR function is the probability weighting function used in expected utility theory. Also, the POWER function is a special case of the PRELEC-II function, where $\beta_2 = \beta_3 = 1$. More discussion on the properties, limitations, advantages and disadvantages of each function can be found in Balcombe & Fraser (2015).

Typically, the Bayes ratio is used to compare any two models to each other (when applied to the same dataset). The numerical derivation of the Bayes ratio is nearly impossible to calculate for models with large numbers of parameters (Kruschke, 2014). In our case, we have 1411 to 5644 parameters across 36 different models. The estimated parameters are used to predict lottery choices for each draw of the posterior density. Then the proportion of accurate predictions can be calculated for each draw. The means and 95% credibility intervals are reported in Table 1.

Before selecting the best-fitting model, one can note how poorly some model combinations perform. 20 of the 36 models are no different, or far worse, than tossing a coin (match score = 0.5) in predicting lottery choices. Studies that compare models typically report log-likelihood (Stott, 2006; Harrison *et al.*, 2010) or Bayes' ratios (Balcombe & Fraser, 2015). While these measures are useful for comparing models to each other, they say little about their unexplained variation. In Table 1, we have explained at most 53.4% to 56% of observed variation. This means that the proposed models are not good at explaining more than 40% of the observed lottery choices (underlying causes are beyond the scope of this paper).

Table 1: Fraction of correct predictions by alternative utility/probability-weighting models

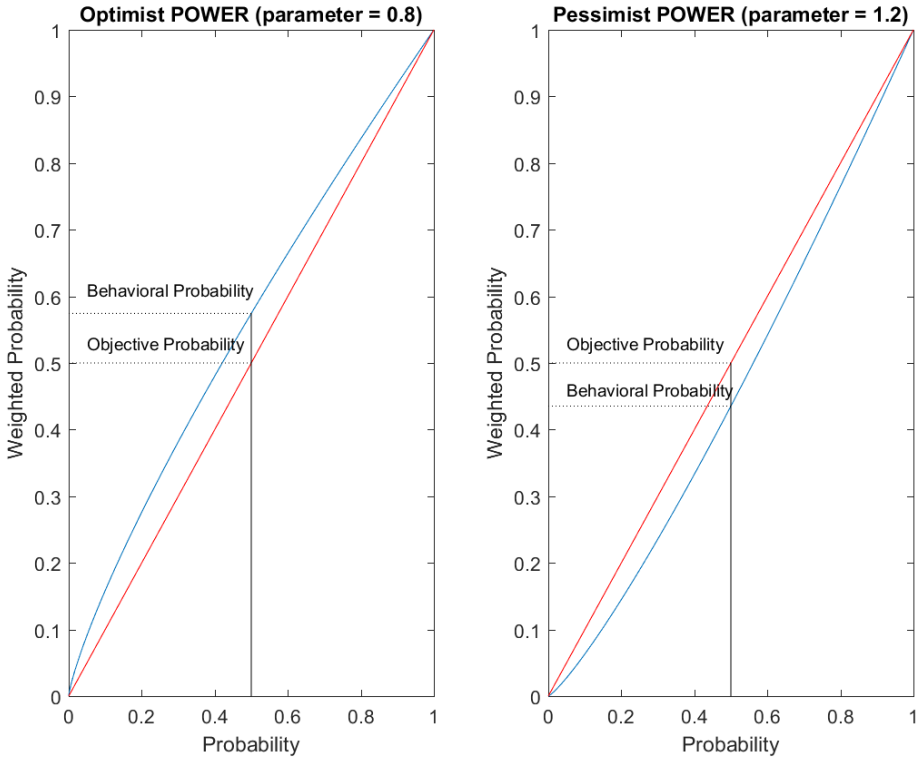
Utility Model \ **Probability Weighting Model**	LINEAR	PRELEC-I	PRELEC-II	POWER	GE	KT
EXPO-I	0.471 0.483 0.494	0.499 0.510 0.521	0.500 0.511 0.523	0.491 0.503 0.516	0.500 0.512 0.524	0.500 0.511 0.522
EXPO-II	0.495 0.508 0.521	0.503 0.515 0.526	0.505 0.517 0.529	0.498 0.512 0.524	0.505 0.516 0.529	0.504 0.516 0.527
POWER-I	0.524 0.537 0.550	0.522 0.535 0.547	0.532 0.543 0.555	**0.534** **0.547** **0.560**	0.525 0.538 0.550	0.518 0.530 0.542
POWER-II	0.450 0.455 0.460	0.474 0.481 0.487	0.456 0.484 0.513	0.461 0.471 0.481	0.487 0.516 0.544	0.477 0.483 0.489
LOG	0.483 0.495 0.507	0.497 0.507 0.517	0.508 0.519 0.530	0.501 0.512 0.525	0.506 0.517 0.528	0.495 0.504 0.512
QUAD	0.449 0.454 0.459	0.474 0.481 0.489	0.482 0.492 0.501	0.465 0.475 0.486	0.483 0.493 0.503	0.477 0.482 0.488

Lower 2.5% quantile, mean and upper 97.5% quantile match statistics for each model

As can be seen, the best-fitting utility model is the POWER-I specification. It was also reported as the best-fitting function at the individual level in Balcombe & Fraser (2015). Many of the probability weighting functions have overlapping credibility intervals. PRELEC-II and the POWER functions stand out by having the highest upper bound credibility interval values (0.555 and 0.560 respectively). We select the POWER probability weighting function parameter, in combination with the POWER-I utility function, as our covariate of choice. It has a similar data fit as the PRELEC-II specification, but with fewer parameters.

For each respondent, we have draws of the β_5 parameter from Equation (6d). The average β_5 for each respondent is calculated, centered around 1 ($\beta_5 = 1$ is the switching point between a concave and convex POWER function) and treated as a respondent-specific covariate. A convex POWER function ($\beta_5 > 1$) implies that the individual under-weighs the objective probability of making a monetary gain, which we refer to here as a pessimistic view. If the POWER function is concave ($\beta_5 < 1$), then the implication is that the individual over-weighs the objective probability of making a monetary gain, which we refer to here as an optimistic view. An illustration is given in Figure 1.

Figure 1: Optimism and Pessimism over Probable Gains



The POWER function with minimum (0.8) and maximum (1.2) estimated average parameter values across the respondents

3 Data Collection and Survey Design

3.1 Questionnaire Design

The survey consisted of a questionnaire followed by a CE regarding a hypothetical pill to prevent malaria. The survey targeted the main decision maker of the household, and is thus administered to one person per household.

The questionnaire consists of four sections. The first section contains standard socio-demographic questions about the respondent and the household. The second section consists of a series of binary lottery choices, where one of the lotteries is randomly selected and played using a real payoff.

Binary lottery choices are included to incentivize the respondents to finish the survey and elicit their attitudes towards financial risks. In the context of a developing country field survey, we follow the setup presented in Harrison *et al.* (2010) to make the payoffs and associated probabilities easy to communicate and understand. Seven choices, consisting of two lotteries each, are presented to the respondents in random order. Table 2 gives an overview of the lottery choices. All payoffs are in Indian Rupees (INR). Note that, at the time, 75 INR was approximately 1 Euro or 1.15 USD.

An example of a lottery choice is given in Figure 2. The design is chosen to clearly communicate the payoffs and probabilities. Each respondent answers test questions to make sure they understand the layout.

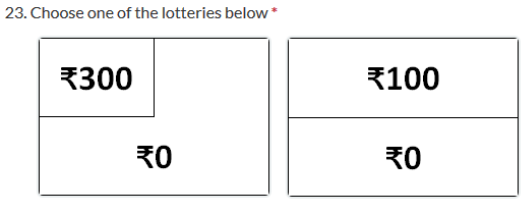
The third section entails questions on knowledge and experience with malaria. The malaria knowledge questions are taken from Dhawan *et al.* (2014), a study that assessed knowledge

Table 2: Lottery Choices, Payoffs and Probabilities

	Left-Hand Lottery			Right-Hand Lottery		
Task Number	Payoff 1	Payoff 2	Payoff 3	Payoff 1	Payoff 2	Payoff 3
1	300; 1/4	100; 1/2	0; 1/2	100; 1		
2	300; 1/4	0; 3/4		100; 1/2	0; 1/2	
3	300; 3/4	0; 1/4		300; 1/2	100; 1/2	
4	600; 1/2	0; 1/2		300; 3/4	0; 1/4	
5	300; 3/4	0; 1/4		300; 1/2	200; 1/4	0; 1/4
6	600; 1/2	0; 1/2		300; 1/2	200; 1/4	0; 1/4
7	500; 1/4	0; 3/4		200; 1/2	0; 1/2	

Payoffs and probabilities denoted as (payoff ; probability). Adapted from Harrison *et al.* (2010)

Figure 2: Example Binary Lottery Choice



English version of a binary lottery choice task

of malaria across different socio-economic groups in Mumbai. The respondents are also asked about their own and household's experience with malaria. These are followed by questions on the perceived severity of their own or other's episodes. If the respondents have no first- or second-hand experience with malaria, then they are asked to rate how severe they think having malaria might be. Respondents are also asked about any malaria prevention pills they have used.

The final section contains information about the objective probability of getting malaria. Past studies done on the impact of providing quantitative information report a high degree of heterogeneity in respondents' reactions. The reactions range from ignoring to not believing, to over-reacting and, on occasion, updating their beliefs to match them with the given information (Cameron, 2005; Deryugina, 2013; Cerroni *et al.*, 2014). In our study the objective malaria prevalence is given to a random 50% of the survey participants. Beforehand, subjective probability of getting malaria is approximated by asking respondents about how many people they think out of 100 in their locality had malaria last year. This number, divided by 100, is the subjective prevalence of malaria in the locality. After this question, any respondent has a 50% chance of finding out the real probability of people getting malaria in Mumbai (1%), based on the municipal's public health report (Porecha, 2015):

> Due to unplanned urbanization in Mumbai, there has been an ongoing malaria epidemic since 2011. [...] At the height of the epidemic, almost 1 out of 100 people in Mumbai was reported to have malaria (76,755 cases). Think of this as, out of 100 people in your street, 1 of them has malaria.
>
> Given this information, would you change your previous answer?

As in Cameron (2005), they then have the opportunity to change their answer on malaria prevalence.

Since malaria is a communicable disease, the likelihood of becoming ill increases as one is surrounded by others with malaria. The respondents are asked how they view their likelihood of getting malaria with respect to everyone else in their locality. Table 3 shows how these answers are used to construct the respondent's subjective probability of getting malaria.

Unlike Cameron (2005), no confidence intervals are asked. This is to keep the questions as

Table 3: Inference of Subjective Malaria Risk

Answer	Inferred Subjective Probability
"I never get malaria"	0
"Less likely than everyone else"	P/2
"Similar to everyone else"	P
"More likely than everyone else"	P + (1-P)/2
"I always get malaria"	1

P is the subjective prevalence of malaria in the locality

clear and simple as possible[1]. If p denotes the subjective probability of getting malaria, we use $p(1-p)$ as its variance[2]. This indicates how uncertain respondents are about their subjective baseline risk.

3.2 Discrete Choice Experiment Design

In the CE, respondents are asked to choose between different types of hypothetical malaria prevention pills. The pills are already on the market, but not widely used due to their side effects. The pills differ in terms of price, who can use it (other than the respondent), level of protection and how long the pills are taken. Attributes and their levels are found in Table 4.

Table 4: Choice Attributes and Levels

Attribute	Levels
Suitability	Child under 5; Child between 5 and 14; Person over 14; Pregnant woman
Protection	25%; 50%; 75%; 100%
Duration	6 weeks; 26 weeks
Price (INR, per pill pack)	100; 200; 300; 500; 750

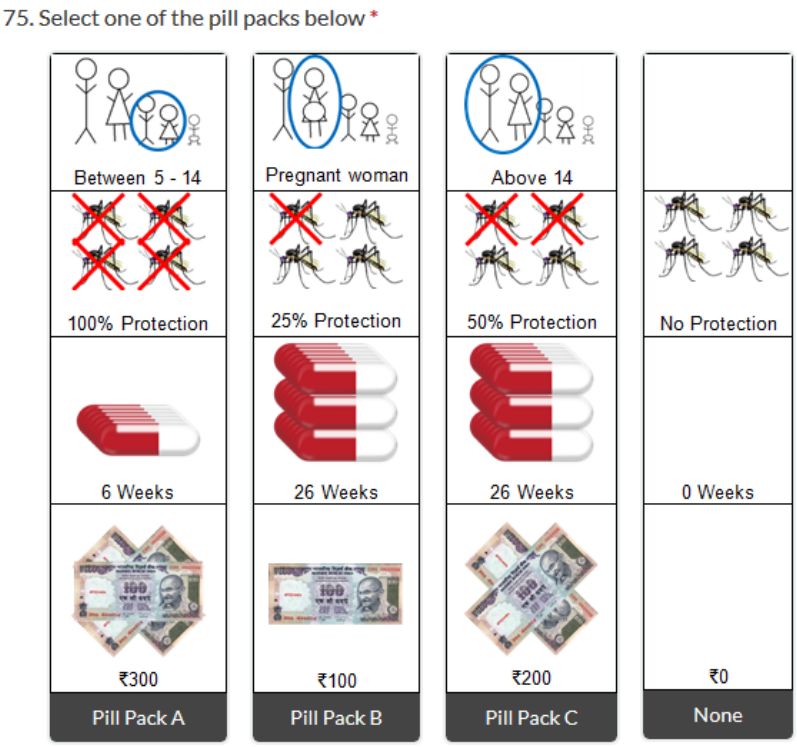
The levels of the attributes are determined using a D-optimal Bayesian design (Bliemer *et al.*, 2008). The protection levels are selected for ease of communication through diagrams (see the example choice card in Figure 3). Also, the respondents play lotteries including the same probabilities, making these specific percentages cognitively accessible. The suitability attribute is included to measure preferences for protecting vulnerable family members and altruism. Malaria is especially dangerous for children under the age of 5 and pregnant women. The age of 14 is when children have, in theory, finished their compulsory education in India and thus we consider above-14's to be adults, from an economic perspective. The levels for the duration attribute are taken from real malaria prevention pills. This is done in order to make the hypothetical pills seem as authentic as possible, especially to those respondents who have already taken them before. The price attribute's levels are based on a bidding game in the pilot surveys, outlined in the appendix.

The utility coefficient priors are determined through a recent meta-analysis on WTP to treat or prevent malaria (Kutluay *et al.*, 2015). A second pilot survey was used to update the priors in the D-optimal Bayesian design and detect potential problems in the CE and questionnaire. The only issue encountered during the pretest was respondent boredom due to

[1] Cameron (2005) had economics undergraduate students as subjects, who could reliably be asked for confidence intervals.

[2] Under the assumption that p is the parameter for the Bernoulli distribution on (not) getting malaria. This means that $p(1-p)$ is the associated variance. See Manski (2004) as an example where a similar measure is utilized.

Figure 3: Example Choice Card



a high number of choice cards (9), which is typical in developing country contexts (Mangham *et al.*, 2009). This was therefore reduced to 6 in the main CE.

In each choice card, the respondents can choose one of three malaria prevention pills or opt out. If they choose a pill that was suitable for them or someone else, they are asked to indicate who this pill is meant for, themselves or others from the household, extended family or charity. If respondents opt out, then the reasons for doing so are asked in a follow-up question.

3.3 Data Collection

The pilot and main surveys took place between April and June of 2016 in Mumbai, India with sample sizes of 94 and 1409 respectively. The main survey took, on average, under 13 minutes to complete.

The survey was translated into Hindi and Marathi. Surveyors were obtained through Nirmana, a local NGO with a focus on public health. The surveyors were trained and supervised by the first author of this study. Apartment buildings were entered upon getting support of the local housing association leader or priests. This led to an average response rate of 81%. Respondents were incentivized by a participation and lottery payout fee.

The survey was framed as a general household survey, with some additional questions regarding their outlook on health. Respondents were never told beforehand that the survey was about malaria. One respondent was interviewed per household, an adult who has a say in how the household budget is spent, preferably the main decision-maker.

4 Results

4.1 Sample Summary Statistics

Descriptive statistics of the respondents and their choices are presented. Table 5 outlines respondents' socio-demographic characteristics, along with their experience, knowledge and subjective risk perception of getting malaria.

Table 5: Sample Summary Statistics

Variable	Mean: Control	Mean: Treatment	Min.	Max.	N	P-value
Female	0.56	0.59	0	1	1411	0.20
Age	36.21	37.37	19.5	79.5	1411	0.13
No Schooling	0.09	0.10	0	1	1411	0.65
Monthly Household Income	24708.33	24270.63	1000	197500	1411	0.91
Had Malaria	0.42	0.41	0	1	1411	0.92
Household Member(s) had Malaria	0.34	0.34	0	1	1411	0.93
Knowledge Score of Malaria Seasonality	0.56	0.54	0	1	1411	0.25
Knowledge Score of Mosquito Breeding Sites	0.65	0.66	0	1	1411	0.75
Knowledge Score of Malaria Transmission	0.77	0.77	0	1	1411	0.77
Knowledge Score of Malaria Symptoms	0.70	0.71	0.25	1	1411	0.31
Subjective Risk of Malaria (%)	20.09	23.21	0	100	1411	0.01
Prior Subjective Malaria Prevalence (per 100)	22.88	20.66	0	100	1411	0.23
Posterior Subjective Malaria Prevalence (per 100)	.	41.76	1	92	138	.
Variance of Prior Subjective Malaria Prevalence	0.10	0.10	0	0.25	1411	0.30
Variance of Posterior Subjective Malaria Prevalence	.	0.17	0	0.25	138	.
Changed Prior Malaria Prevalence Belief	.	0.20	0	1	697	.

"P-value" is the resulting p-value of the Wilcoxon rank-sum test for the variable between control and treatment groups

The respondents were chosen from non-slum residential areas of Mumbai, due to logistical reasons. This is a stricter condition than one might think since more than half of Mumbai's residents are estimated to live in slums (Census, 2011). There are no observable differences between those who did and those who did not receive the information treatment (aside from subjective malaria risk), as shown through a series of Wilcoxon rank-sum tests. We have a relatively high number of female respondents, Mumbai has a female/male ratio of 0.853 (Census, 2011). Female over-representation is, in this case, mainly due to the male household members being available only after working hours for interviews.

Although more then 40% of the respondents have had malaria (with 30% saying they have second-hand experience), the amount of knowledge regarding the disease was not very high. The knowledge scores in Table 5 have ranges between 0 and 1, with 1 denoting that a given respondent answered all questions correctly. Relatively more respondents were better informed about the transmission, source and symptoms of malaria, compared to its seasonality.

A surprising finding is how the belief of malaria prevalence increases, rather than decreases, when new information is given. This drives the result that elicited subjective malaria risk is significantly different for new information receivers than non-receivers (Wilcoxon rank-sum test, p-value = 0.01). The prior belief is, on average, 22% whereas the posterior is 42%. The information given to respondents is that malaria prevalence is 1% (1 in 100 persons). This points to an over-reaction for those who receive the information shock and choose to change their previous answer. However their adjustment of their prior beliefs is such that it almost doubles the average. This is not a large group, since only 20% of those who received the information shock opted to change their answer. Of these 138 respondents, 117 increased their subjective prevalence estimate.

The correlates for changing subjective prevalence are analyzed via a logit regression (Table 6). Two regressions are run: one without malaria knowledge scores and the other with. As can be seen, over-reaction initially seems to be linked to malaria experience, variance of the prior prevalence, age and household income. However once the malaria/mosquito knowledge scores are added, significance shifts from the socio-demographic coefficients to the knowledge coefficients. The more one is exposed to, knows about, and is relatively confident about their

Table 6: Effects of Explanatory Factors on Changing Malaria Prevalence (Logit)

	Socio-Demographics		Include Malaria Knowledge	
No Schooling	0.252	(0.357)	0.349	(0.374)
HH Income (log)	-0.303**	(0.152)	-0.340**	(0.149)
HH Had Malaria	0.276	(0.217)	0.315	(0.223)
Had Malaria	0.527**	(0.209)	0.388*	(0.218)
Age	-0.0148*	(0.00867)	-0.0144	(0.00894)
Male	-0.0432	(0.212)	0.00577	(0.221)
Has Child(ren)	0.0374	(0.267)	-0.00621	(0.270)
Variance of Malaria Prevalence	5.186***	(1.072)	4.097***	(1.156)
Knowledge Score of:				
Malaria Transmission			-1.217***	(0.383)
Mosquito Breeding			-0.126	(0.375)
Malaria Seasonality			-1.176***	(0.292)
Malaria Symptoms			-0.609	(0.626)
Constant	1.105	(1.582)	3.629**	(1.717)
Observations	697		697	
AIC	666.3		647.9	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

answer regarding malaria prevalence, the less likely receiving new information will compel them to revise their answer.

Table 7: Choice Summary Statistics

	Mean	Std. Dev.
Opt-Out in all Choice Cards	12.69%	.333
Opt-Out	24.20%	.238
Reasons for Opt-Out:		
Malaria is Not a Concern	10.90%	.163
Prices are too High	8.63%	.145
Not Interested in Prevention Pills	0.07%	.013
Use Other Protection Methods	4.44%	.105
Choosing Pills for Others:		
Pregnant Women	4.93%	.110
Babies	2.24%	.075
Children	3.45%	.092
Observations	33864	

Table 7 presents choice statistics, specifically the number of opt-outs and choosing pills for others. The opt-out was chosen in 24% of all choice occasions. Just over 12% of the respondents opted out in all of their choices. Around 40% of the latter stated to have no preference for malaria protection, while the rest was mainly due to respondents finding the prices too high and claiming other methods used for malaria protection. Of the pills respondents could have chosen for others (babies, children and pregnant women), most opted to choose for themselves (adults). When respondents chose pills for others, pregnant women and babies were the least chosen, even though they experience malaria more severely.

4.2 Estimated Choice Model

The estimated mixed logit model is presented and analyzed. The alternative specific constant (ASC) dummy variable takes the value 1 for any pill and 0 otherwise. Thus a positive ASC term implies a preference for the pills on offer, ceteris paribus. The subjective risk of getting

malaria is interacted with the protection attribute ("Protection x Own-Risk"). Not accounting for the baseline risk of getting malaria does not yield meaningful coefficient estimates for the protection attribute.[3]

In order to assess the impact of the extra information on resulting MWTP values, the attribute-only and addition of the information shock dummy models are estimated (first and second models of Table 8). All the coefficients, except for price, are assumed to have random effects across respondents. The distributions, except for dummy variables, are assumed to be normal. Dummy variables are assumed to have uniform distributions (Hensher *et al.*, 2005). Since we have included the ASC term, we cannot put in all the categorical variables for the suitability attribute. We omit the adult pills, making all the other suitability attribute levels relative to the adult category.

The protection, own-risk and duration all have the expected positive significant coefficients. It is worth noting that the ASC term is negative, meaning that there is a clear tendency to opt-out of choosing pills at the baseline. However, if the protection attribute is increased to 25% (at the baseline it is 0%), then the tendency to opt-out is nullified. This means that respondents will opt out of choosing pills that do not offer protection, which is an intuitive outcome. The attribute-only model shows that respondents were averse to selecting pills for others, with the highest negative coefficients for pregnant women and babies (the population subgroups that are most severely affected by malaria).

The information shock is included in the model as an interaction variable with the attributes. Since respondents are notified that malaria had a 1% prevalence in Mumbai at the height of the last outbreak, we hypothesize this to have a negative impact. However the difference between prior and posterior expressed probability of getting malaria in Table 5 suggests that MWTP may increase. Indeed, receiving the new information leads to a significant decrease in MWTP for babies getting malaria, but a significant increase in demand for protection. In fact, the MWTP for protection increases, on average, by more than 25% with the information treatment ($\frac{0.017}{0.064} = 0.266$). Other attribute interactions are not significant.

We further the analysis by including the individual-level probability weighting parameter, henceforth POWER, into the mixed logit functions. The formula of MWTP under rank dependent utility suggests that any probability over-weighting can have a significant impact (Bleichrodt & Eeckhoudt, 2006), however no empirical studies to date have verified this. Since POWER is estimated using lottery choices, it reflects optimism/pessimism in the monetary gain domain. Therefore including POWER into the regressions will help to see if behavior in the monetary domain can explain behavior in the health domain.

This inclusion also allows us to investigate if the over-reaction to new information is due to how people process and respond to probabilistic data. The increase in demand for a risk reduction could be driven by respondents who are pessimistic about probable gains. Hence, this might reflect how they evaluate a lower probability of getting malaria. To this end, the POWER parameter is included through attribute and information dummy interactions. It is interacted with the information shock dummy to see if this pessimism/optimism to probable gains influences the pill choices made through the receiving of information. The output can be found in the third and fourth columns of Table 8.

The inclusion of the POWER parameter does not explain away the over-reaction to new information. The effect size of the over-reaction has increased from 25% to over 30%. However, as expected, the POWER parameter explains variation in malaria pill selection. We find higher MWTP for protection as POWER increases, even when accounting for POWER through the information shock. This provides evidence that behavior in the monetary domain can be correlated to behavior in the health domain. Pessimism is correlated to higher valuation of preventing diseases. A 0.1 increase in the POWER parameter, towards the pessimistic direction is associated with a more than 15% increase in MWTP for additional protection. Including the information shock interaction with the POWER parameter results in a higher AIC metric

[3] 50% protection for someone who has a 10% chance of getting malaria is different than for someone else who has a 80% chance of getting malaria. In the first case, the subjective risk reduces by 5%, whereas in the latter case it reduces by 40%.

Table 8: Mixed Logit Results

	Attribute-Only	Information	POWER	Information and POWER
Price	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)
ASC	−1.576*** (0.148)	−1.611*** (0.150)	−1.570*** (0.153)	−1.668*** (0.155)
Pregnant	−11.550*** (0.679)	−10.282*** (0.603)	−9.417*** (0.594)	−10.586*** (0.656)
Baby	−16.838*** (1.008)	−15.390*** (0.881)	−14.339*** (0.849)	−14.039*** (0.789)
Child	−5.011*** (0.339)	−4.959*** (0.370)	−5.041*** (0.376)	−4.873*** (0.395)
Protection	0.073*** (0.003)	0.064*** (0.003)	0.062*** (0.003)	0.067*** (0.003)
Protection x Own-Risk	0.044*** (0.005)	0.097*** (0.007)	0.094*** (0.008)	0.085*** (0.008)
Duration	0.034*** (0.004)	0.033*** (0.005)	0.033*** (0.005)	0.034*** (0.005)
Information Shock:				
Pregnant		−0.495 (0.327)	−1.940*** (0.446)	−1.136*** (0.371)
Child		−0.297 (0.251)	−0.663** (0.324)	−0.699** (0.328)
Baby		−1.976*** (0.390)	−2.343*** (0.408)	−2.013*** (0.396)
Protection		0.017*** (0.004)	0.020*** (0.003)	0.015*** (0.004)
Protection x Own-Risk		−0.061*** (0.008)	−0.045*** (0.009)	−0.029*** (0.009)
Duration		0.005 (0.006)	0.006 (0.007)	0.002 (0.007)
POWER Parameter:				
Pregnant			−6.464*** (1.385)	−8.744*** (2.004)
Child			−3.463*** (1.296)	−4.796** (1.889)
Baby			−9.493*** (1.587)	−7.666*** (2.065)
Protection			0.100*** (0.016)	0.110*** (0.022)
Protection x Own-Risk			−0.003 (0.039)	−0.086 (0.059)
Duration			0.027 (0.032)	−0.002 (0.046)
Info x POWER:				
Pregnant				−1.143 (2.842)
Child				2.196 (2.605)
Baby				−4.551 (3.223)
Protection				0.005 (0.032)
Protection x Own-Risk				0.059 (0.079)
Duration				0.079 (0.065)
Observations	8,400	8,400	8,400	8,400
AIC	10705.24	10678.29	10645.1	10662.18

Note: *p<0.1; **p<0.05; ***p<0.01

compared to including the POWER parameter through the attributes only.

The main take-away from Table 8 is that inferred behavior in the monetary gains domain has explanatory potential for stated behavior in the health risks domain. Additionally, there is a lack of evidence that individual interpretation of probabilities plays a role - since the "Info x POWER" interaction variables in the fourth model are not statistically significant. Instead, it seems that pessimism and optimism about probable gains, on their own, is influential.

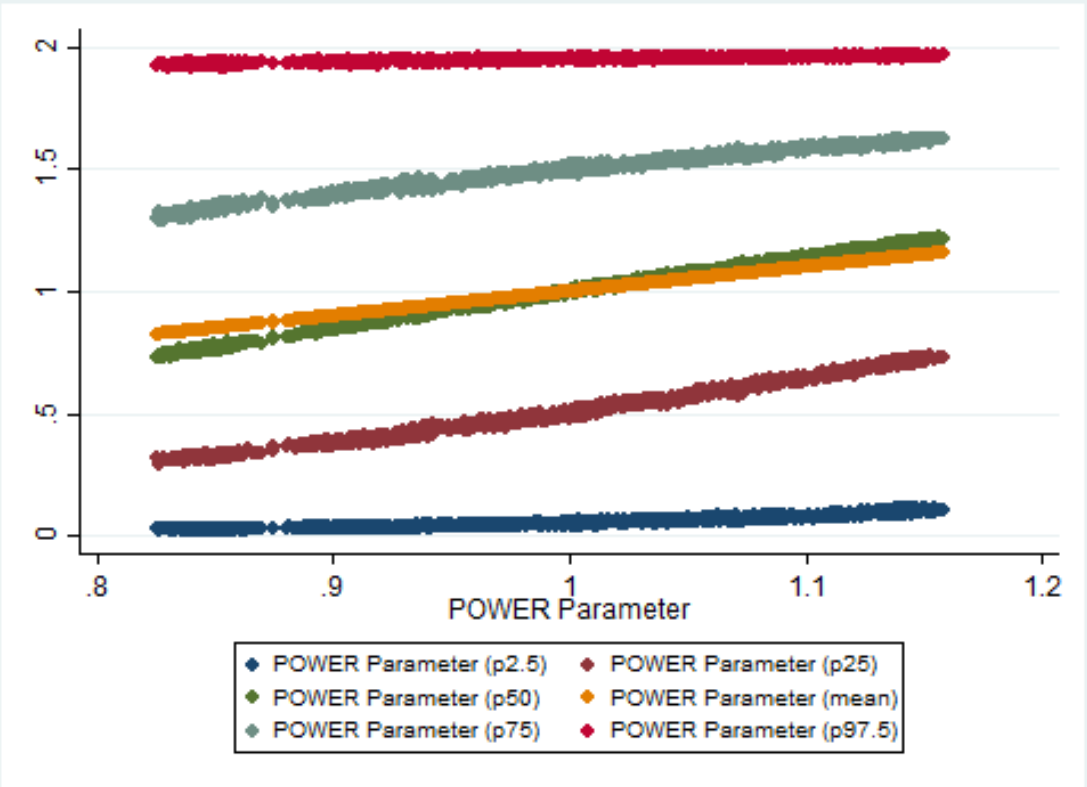
These results warrant extensive sensitivity and robustness checks on the POWER parameter. Only the mean value of the POWER parameter is used in the regressions. Thus, a sensitivity analysis is carried out for the best fit model of Table 8 (third model). Afterwards, the socio-demographic correlates of the POWER parameter are identified and controlled for, again using the third model of Table 8.

4.2.1 Sensitivity Analysis: Credibility Interval of POWER Parameter

For each respondent there are 8,000 draws of the POWER parameter (see section 2.2). The analysis so far has considered the mean value of these draws per respondent. The posterior distributions, where the draws come from, were estimated based on the lottery choices made, i.e. seven choices per respondent. Due to this small sample size, a large spread is present around the mean value (see Figure 4). We look at whether or not this spread affects the main results by re-running the third model in Table 8 with different values of the POWER parameter.

A range of draws from the posterior distribution is considered. In order to capture the potential impact of the spread, a selection of percentiles are used, including the minimum and

Figure 4: Interquartile Range and 95% CI of the POWER Parameter



maximum values. The resulting coefficient values for the variables showing the main results can be found in Table 9.

Table 9: Sensitivity Analysis of the POWER Posterior Density

	Info-Shock x Protection	POWER x Pregnant	POWER x Child	POWER x Baby	POWER x Protection
POWER Posterior Density:					
Average	0.014***(0.003)	-6.701***(1.375)	-3.044**(1.280)	-11.692***(1.586)	0.076***(0.016)
Minimum	0.017***(0.004)	-468.9 (441.1)	-413.7 (375.4)	-85.63 (479.8)	8.535 (5.801)
0.5^{th} Percentile	0.015***(0.004)	-89.81***(23.53)	-72.81***(22.47)	-99.28***(26.84)	1.173***(0.300)
2.5^{th} Percentile	0.017***(0.004)	-19.60***(5.58)	-16.63***(5.296)	-51.51***(6.842)	0.359***(0.069)
5^{th} Percentile	0.016***(0.004)	-12.81***(3.140)	-8.227***(2.883)	-16.70***(3.570)	0.169***(0.038)
25^{th} Percentile	0.015***(0.004)	-5.018***(1.088)	-2.720***(0.976)	-4.232***(1.189)	0.065***(0.013)
50^{th} Percentile	0.020***(0.004)	-4.469***(0.950)	-2.334***(0.883)	-6.342***(1.085)	0.069***(0.011)
75^{th} Percentile	0.015***(0.004)	-8.434***(1.563)	-2.914**(1.363)	-2.088 (1.648)	0.114***(0.017)
95^{th} Percentile	0.021***(0.004)	-35.43***(6.366)	-11.69**(5.834)	-35.26***(6.978)	0.368***(0.070)
97.5^{th} Percentile	0.010***(0.003)	-57.88***(12.12)	-24.52**(11.05)	-73.09***(13.33)	0.757***(0.135)
99.5^{th} Percentile	0.015***(0.004)	-90.56* (48.705)	-98.10**(44.74)	-145.36***(51.97)	1.397**(0.569)
Maximum	0.014***(0.003)	132.1 (593.8)	-548.2 (494.7)	-2,982***(691.5)	0.169 (6.706)

Note: *p<0.1; **p<0.05; ***p<0.01

Most of the coefficients preserve sign and significance across different runs of the model. The exceptions are for the minimum/maximum values of the POWER parameter and POWER

x Baby coefficient in the 75th percentile. However, the main results hold within the bounds of the 99% CI. This indicates that the large spread of the POWER parameter does not seem to be an obstacle in drawing inferences by only using its mean value. In other words, the main results are not sensitive to the dispersion of the POWER parameter.

The main results could be driven by socio-demographic variables that affect MWTP through the estimated probability weighting parameter. To see whether this is the case, correlates of the POWER parameter are identified and controlled for as a robustness check in the next section.

4.2.2 Robustness Check: Controlling for POWER Parameter Correlates

The socio-demographic correlates of risk aversion have been extensively researched, but very limited attention has been paid to probability weighting. Few studies have analyzed what drives probability weighting behavior. Some studies have looked at differences between gender (Fehr-Duda *et al.*, 2006; Croson & Gneezy, 2009), age (Harbaugh *et al.*, 2002) and the amount of experience and knowledge economic agents have with the domain in question (Dimmock *et al.*, 2016). We therefore include these as potential correlates. Knowledge of malaria can furthermore be influenced by schooling, so we include a dummy variable for education level. We also control for covariates used widely in the valuation literature. These include having children, household income and decision-making position in the household (Trapero-Bertran *et al.*, 2012; Kutluay *et al.*, 2015). OLS regressions are run with Huber-White robust standard errors. Table 10 displays the output of these regressions.

Table 10: Explaining the Variation Underlying the Probability Weighting Parameter (OLS)

	Model (1)		Model (2)		Model (3)		Model (4)	
Female	0.00329	(0.56)	0.00377	(0.64)	0.00438	(0.74)	0.00432	(0.72)
Age	0.0000317	(0.13)	-0.00000962	(-0.04)	0.00000120	(0.00)	0.0000364	(0.15)
No Schooling	0.0182*	(1.81)	0.0181*	(1.79)	0.0175*	(1.74)	0.0188*	(1.87)
Has Child(ren)	-0.00875	(-1.28)	-0.00922	(-1.34)	-0.0100	(-1.46)	-0.00923	(-1.34)
Household Income (log)	-0.00724*	(-1.84)	-0.00742*	(-1.88)	-0.00608	(-1.53)	-0.00679*	(-1.70)
Decision Maker of Household:								
Mostly Respondent			0.0355*	(1.95)	0.0391**	(2.16)	0.0445**	(2.29)
Together			0.00161	(0.27)	0.000888	(0.15)	0.00244	(0.40)
Mostly Others			-0.00473	(-0.57)	-0.00481	(-0.58)	-0.00440	(-0.52)
Subjective Malaria Risk					-0.000567***	(-3.29)	-0.000514***	(-2.99)
Variance of Malaria Prevalence					0.0889*	(1.95)	0.0995**	(2.16)
Had Malaria							-0.0111*	(-1.93)
Knowledge Score of:								
Malaria Transmission							-0.00989	(-0.86)
Mosquito Breeding Sites							-0.0257***	(-2.62)
Malaria Seasonality							0.0259***	(3.26)
Malaria Symptoms							-0.0273	(-1.65)
Constant	0.0704*	(1.76)	0.0731*	(1.81)	0.0630	(1.56)	0.0989**	(2.21)
Observations	1411		1411		1411		1411	
Adjusted R^2	0.004		0.005		0.012		0.025	

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Contrary to findings in the literature, age and gender have no significant impact on the POWER parameter. Lack of schooling and household income play a significant role, where having no schooling correlates with pessimism and higher household income correlates with optimism. The role of the respondent in household expenditure decision-making is significant, where respondents who self-report to be the main decision-maker are more likely to be pessimistic.

Experience with and knowledge of malaria have significant impacts on the POWER parameter, giving evidence in support of the competence hypothesis (Heath & Tversky, 1991). Respondents who have had experience with malaria, self-report greater subjective probability of getting it and know about mosquito breeding grounds have lower POWER parameters, im-

plying optimism. In contrast, respondents with higher variances on their prior guess of malaria prevalence in their neighborhood (i.e. people who are not sure about malaria prevalence) have higher POWER parameters, implying pessimism. More knowledge on malaria leads to two different outcomes. Knowing about the seasonality has a positive impact on the POWER parameter, implying pessimism. However, knowledge on mosquito breeding grounds has a negative impact—seasons cannot be controlled, but mosquito breeding grounds in cities (i.e. small puddles of clean water) can easily be cleared.

Despite the significant coefficients on the various explanatory factors, the reported R^2 values in Table 10 are very low. This is in line with the findings of Sutter *et al.* (2013) and Dimmock *et al.* (2016): it is hard to argue that the POWER parameter only acts as a proxy for socio-demographic variables. However, it should be noted that the R^2 increases five-fold when the malaria covariates are included, further adding support to the competence hypothesis.

The significant covariates from Table 10 are included into the third model of Table 8 to see if the main results (over-reaction to information and impact of pessimism) change. These regressions are grouped in terms of knowledge of malaria (Table 11), experience/perception of malaria (Table 12) and socio-demographics (Table 13). The new covariates are treated as fixed terms in the logit models.

Our main results are robust to controlling for respondents' knowledge regarding malaria. The effect size of the information shock on the MWTP for protection is between 24% and 33%. It is also worth noting that results of other-regarding preferences through the POWER parameter (optimists having a higher MWTP for others) are also robust to the addition of new covariates. This indicates that the influence of the POWER parameter on MWTP is not through the information shock. It is rather via the evaluation of attributes by the respondents, regardless of whether or not they were subjected to the information treatment.

Knowledge of mosquito breeding sites and the seasonality of malaria are correlated with optimism and pessimism, respectively. From Table 11 we see that knowing about the seasonality leads to a positive impact on MWTP for protection, which could be interpreted as the expression of additional fear of malaria. The opposite is true for mosquito breeding grounds - there is a negative impact on MWTP for protection, which is indicative of being less concerned. Similar results, where higher WTP values for events that are caused outside of one's control as opposed to events that they can control, have been reported before (Viscusi & Evans, 1990). One cannot control the seasons, but can clear up shallow puddles of water around one's home, the primary cause of malaria in urban settings (Dhawan *et al.*, 2014).

As can be seen in Table 12, our main results are robust when control is included for respondents' experience and perceptions of malaria. The effect size of the information shock on the MWTP for protection is between 20% and 32%. This gives further evidence that the probability weighting behavior of the respondents influences MWTP through the attributes, and not the information shock.

Having experienced malaria before is associated with an increase in MWTP for protection with respect to the subjective baseline risk. There is no increase in MWTP for protection alone - it is statistically the same for people who have had and have not had malaria. Furthermore, having had malaria is correlated with lower MWTP for others. These results are in contrast to when respondents' perceptions of malaria (as opposed to experience) are taken into account.

An increase in subjective malaria risk is positively correlated in MWTP for all attributes, an intuitive result in line with health-dependent utility theory (Viscusi & Evans, 1990). The effects are not as clear for the variance in prior malaria prevalence. An increase in variance is associated with higher MWTP for protection and duration of protection, but lower MWTP when subjective baseline risk increases. The main results are robust to accounting for relevant socio-demographic covariates, shown in Table 13.

The analysis is continued by adding in socio-demographic variables that were found to be significantly correlated to the POWER parameter. Having no schooling and self-reporting to be in charge of consumption decisions in the household are positively correlated to the POWER parameter, implying pessimism. When included in the model, after taking into account the POWER parameter, they have an overall negative impact on MWTP for protection, duration

Table 11: Probability Weighting and Knowledge of Malaria

	Baseline	Seasonality	Mosquitoes
Price	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)
ASC	−1.570*** (0.153)	−1.632*** (0.152)	−1.527*** (0.156)
Pregnant	−9.417*** (0.594)	−11.507*** (0.710)	−7.040*** (0.619)
Baby	−14.339*** (0.849)	−17.461*** (1.090)	−9.854*** (0.756)
Child	−5.041*** (0.376)	−5.301*** (0.475)	−4.813*** (0.450)
Protection	0.062*** (0.003)	0.058*** (0.004)	0.063*** (0.004)
Protection x Own-Risk	0.094*** (0.008)	0.109*** (0.009)	0.080*** (0.012)
Duration	0.033*** (0.005)	0.034*** (0.007)	0.024*** (0.009)
Malaria Seasonality:			
Pregnant		0.131 (0.385)	
Baby		2.036*** (0.465)	
Child		0.798** (0.392)	
Protection		0.018*** (0.005)	
Protection x Own-Risk		−0.059*** (0.011)	
Duration		−0.006 (0.010)	
Mosquito Breeding:			
Pregnant			−2.806*** (0.598)
Baby			−5.975*** (0.624)
Child			−0.523 (0.469)
Protection			−0.001 (0.006)
Protection x Own-Risk			0.022 (0.015)
Duration			0.015 (0.012)
Information Shock:			
Pregnant	−1.940*** (0.446)	−0.160 (0.296)	−3.111*** (0.556)
Child	−0.663** (0.324)	−0.654* (0.390)	−0.335 (0.264)
Baby	−2.343*** (0.408)	−1.906*** (0.395)	−2.644*** (0.441)
Protection	0.020*** (0.003)	0.014*** (0.003)	0.021*** (0.003)
Protection x Own-Risk	−0.045*** (0.009)	−0.036*** (0.008)	−0.044*** (0.008)
Duration	0.006 (0.007)	0.009 (0.007)	0.003 (0.007)
POWER Parameter:			
Pregnant	−6.464*** (1.385)	−5.421*** (1.387)	−7.812*** (1.493)
Child	−3.463*** (1.296)	−4.498*** (1.304)	−3.613*** (1.280)
Baby	−9.493*** (1.587)	−9.242*** (1.589)	−15.549*** (1.737)
Protection	0.100*** (0.016)	0.082*** (0.016)	0.094*** (0.017)
Protection x Own-Risk	−0.003 (0.039)	0.030 (0.038)	0.043 (0.039)
Duration	0.027 (0.032)	0.053* (0.032)	0.040 (0.033)
Observations	8,400	8,400	8,400
AIC	10645.1	10661.51	10632.3
Note:			*p<0.1; **p<0.05; ***p<0.01

and others (except for MWTP for protection in the case of being the main consumption decision maker in the household). This is in contrast to the impact of household income (associated with optimism) on MWTP for others. Note that the household income is centered around the mean, thus we see a positive correlation of MWTP for others through respondents in households that have higher-than-average income. This covariate does not have an impact on other MWTP values.

4.3 Treatment-Driven or Respondent-Driven Over-Reaction

All evidence and analysis supports the robustness of increasing MWTP in the face of new information. Is this an overall treatment effect, or simply how a sub-group of respondents react to the treatment? Of the 715 respondents that were part of the information treatment, only 138 opted to change their initial malaria prevalence guess. Of these 138 respondents, 117 increased their guess. These respondents are labeled here as "Over-Reactors". The others are labeled as "Normal-Reactors". As seen in Table 6, many people who increased their malaria prevalence estimate were less likely to know about malaria transmission mechanisms and its seasonality, have a high variance of their prior prevalence guess and are slightly poorer than

Table 12: Probability Weighting and Malaria Experience/Perception

	Baseline	Own Risk	Variance	Had Malaria
Price	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)
ASC	−1.570*** (0.153)	−1.635*** (0.151)	−1.818*** (0.159)	−1.747*** (0.156)
Pregnant	−9.417*** (0.594)	−11.474*** (0.744)	−12.563*** (0.803)	−10.867*** (0.688)
Baby	−14.339*** (0.849)	−17.279*** (1.099)	−19.626*** (1.219)	−14.560*** (0.848)
Child	−5.041*** (0.376)	−5.269*** (0.418)	−5.156*** (0.455)	−4.701*** (0.407)
Protection	0.062*** (0.003)	0.066*** (0.003)	0.069*** (0.003)	0.065*** (0.003)
Protection x Own-Risk	0.094*** (0.008)		0.039*** (0.011)	0.091*** (0.009)
Duration	0.033*** (0.005)	0.023*** (0.006)	0.016** (0.007)	0.030*** (0.006)
Own (Malaria) Risk:				
Pregnant		0.073*** (0.007)		
Baby		0.012** (0.006)		
Child		0.009* (0.005)		
Protection		0.001*** (0.0001)		
Duration		0.0004*** (0.0001)		
Prior Prevalence Variance:				
Pregnant			19.061*** (1.986)	
Baby			2.694 (1.744)	
Child			3.245** (1.499)	
Protection			0.072*** (0.024)	
Protection x Own-Risk			−0.006 (0.057)	
Duration			0.153*** (0.037)	
Had Malaria:				
Pregnant				−0.933*** (0.301)
Baby				−2.141*** (0.341)
Child				−0.571** (0.261)
Protection				0.008** (0.003)
Protection x Own-Risk				−0.014 (0.008)
Duration				0.010 (0.007)
Information Shock:				
Pregnant	−1.940*** (0.446)	−1.880*** (0.408)	−1.673*** (0.389)	−0.582* (0.344)
Child	−0.663** (0.324)	−0.337 (0.253)	−0.740** (0.310)	−0.686** (0.322)
Baby	−2.343*** (0.408)	−0.646** (0.324)	−1.027*** (0.328)	−1.309*** (0.343)
Protection	0.020*** (0.003)	0.019*** (0.003)	0.014*** (0.003)	0.013*** (0.004)
Protection x Own-Risk	−0.045*** (0.009)	−0.036*** (0.008)	−0.018** (0.009)	−0.034*** (0.008)
Duration	0.006 (0.007)	0.004 (0.007)	0.007 (0.007)	0.003 (0.007)
POWER Parameter:				
Pregnant	−6.464*** (1.385)	−6.250*** (1.413)	−6.154*** (1.407)	−9.770*** (1.481)
Child	−3.463*** (1.296)	−2.803** (1.259)	−4.003*** (1.336)	−3.866*** (1.300)
Baby	−9.493*** (1.587)	−9.299*** (1.580)	−7.037*** (1.599)	−8.165*** (1.563)
Protection	0.100*** (0.016)	0.112*** (0.017)	0.112*** (0.017)	0.101*** (0.016)
Protection x Own-Risk	−0.003 (0.039)	−0.067* (0.039)	−0.092** (0.039)	0.036 (0.039)
Duration	0.027 (0.032)	0.063* (0.032)	0.007 (0.033)	0.048 (0.033)
Observations	8,400	8,400	8,400	8,400
AIC	10645.1	10621.82	10585.16	10641.59

Note: *p<0.1; **p<0.05; ***p<0.01

the average household. These observable characteristics by themselves do not explain the over-reaction seen in Table 8, as the previous regressions show.

Therefore, our main results could be driven by the Over-Reactors, rather than through an overall treatment effect. There is no evidence to show that the increase in MWTP for protection is completely driven by observable respondent characteristics. We therefore examine if unobservable characteristics of these 117 respondents are driving the results. This is done by splitting the sample and estimating the attribute-only mixed logit model for both groups, A Swait and Louviere test (henceforth: SL test) is conducted to see whether the parameter coefficient and scale differences are statistically significant. In the random utility model coupled with the logistic regression, the scale parameter λ is inversely linked to the variance of the error term (Swait & Louviere, 1993).

To this end, the SL test looks at whether the same MNL model, run across two groups,

Table 13: Probability Weighting and Respondent Characteristics

	Baseline	No Schooling	Income	Decision Maker
Price	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)
ASC	−1.570*** (0.153)	−1.755*** (0.152)	−1.700*** (0.152)	−1.735*** (0.155)
Pregnant	−9.417*** (0.594)	−10.383*** (0.653)	−9.111*** (0.588)	−10.918*** (0.676)
Baby	−14.339*** (0.849)	−16.286*** (0.978)	−17.591*** (1.128)	−14.258*** (0.821)
Child	−5.041*** (0.376)	−4.630*** (0.364)	−4.266*** (0.369)	−4.677*** (0.390)
Protection	0.062*** (0.003)	0.069*** (0.003)	0.063*** (0.003)	0.066*** (0.003)
Protection x Own-Risk	0.094*** (0.008)	0.075*** (0.007)	0.076*** (0.007)	0.086*** (0.008)
Duration	0.033*** (0.005)	0.037*** (0.005)	0.034*** (0.005)	0.035*** (0.005)
No Schooling (dummy; 1 = No Schooling):				
Pregnant		−3.413*** (0.680)		
Baby		−1.946*** (0.547)		
Child		−2.003** (0.782)		
Protection		−0.016*** (0.006)		
Protection x Own-Risk		−0.016 (0.020)		
Duration		−0.038*** (0.012)		
Household Income (log):				
Pregnant			2.048*** (0.182)	
Baby			1.425*** (0.214)	
Child			0.557*** (0.173)	
Protection			−0.002 (0.002)	
Protection x Own-Risk			0.002 (0.006)	
Duration			−0.005 (0.005)	
Respondent is Decision-Maker in Household (dummy):				
Pregnant				−6.047*** (1.507)
Baby				−8.545*** (2.392)
Child				−5.288* (2.886)
Protection				0.121*** (0.036)
Protection x Own-Risk				−0.070 (0.047)
Duration				−0.073 (0.051)
Information Shock:				
Pregnant	−1.940*** (0.446)	−1.243*** (0.374)	−2.052*** (0.431)	−0.513 (0.325)
Child	−0.663** (0.324)	−0.951*** (0.328)	−1.131*** (0.367)	−0.749** (0.336)
Baby	−2.343*** (0.408)	−1.307*** (0.324)	−0.866** (0.338)	−1.974*** (0.414)
Protection	0.020*** (0.003)	0.016*** (0.003)	0.018*** (0.004)	0.014*** (0.004)
Protection x Own-Risk	−0.045*** (0.009)	−0.036*** (0.008)	−0.031*** (0.008)	−0.041*** (0.009)
Duration	0.006 (0.007)	0.005 (0.007)	0.004 (0.007)	0.002 (0.007)
POWER Parameter:				
Pregnant	−6.464*** (1.385)	−6.824*** (1.409)	−2.105 (1.373)	−7.308*** (1.410)
Child	−3.463*** (1.296)	−3.308** (1.298)	−2.939** (1.231)	−3.626*** (1.284)
Baby	−9.493*** (1.587)	−10.076*** (1.653)	−9.369*** (1.610)	−6.899*** (1.562)
Protection	0.100*** (0.016)	0.106*** (0.016)	0.068*** (0.016)	0.093*** (0.016)
Protection x Own-Risk	−0.003 (0.039)	−0.023 (0.039)	−0.0002 (0.038)	0.014 (0.038)
Duration	0.027 (0.032)	0.040 (0.033)	0.043 (0.032)	0.045 (0.032)
Observations	8,400	8,400	8,400	8,400
AIC	10645.1	10610.66	10627.72	10640.91

Note: *p<0.1; **p<0.05; ***p<0.01

have equal β and λ estimates. Thus, the null hypothesis is $\beta_0 = \beta_1$ and $\lambda_0 = \lambda_1$ and this is tested in two stages. First, $\beta_0 = \beta_1$ is tested (HA). If HA is not rejected, then $\lambda_0 = \lambda_1$ is tested (HB). This also allows one to estimate the $\frac{\lambda_1}{\lambda_0}$ ratio. However, if HA is rejected, then testing HB is not meaningful, since it assumes $\beta_0 = \beta_1$. λ for the treatment group (i.e. receiving the information shock) is lower than the control group, the treatment has increased the variance of the utility function.

The SL test is executed across four sample divisions, shown in Table 14. HA is not rejected in the first comparison, between the information treatment and control groups. The resulting $\frac{\lambda_1}{\lambda_0}$ ratio of 0.9 shows that giving extra malaria prevalence data influences pill choices, independent of the attributes. Thus the pill choices that the treatment group respondents make are

influenced by factors other than the pill attributes, implying a treatment effect. This indicates that the treatment, independent of respondent characteristics, is driving the over-reaction.

We cannot make as strong a claim about people who change their stated prevalence estimate versus those who do not (comparisons 2 and 3 in Table 14). This is because the attribute coefficients are shown to be statistically different across the two groups. Thus people who change their stated prevalence estimate, value the pill attributes differently than those that did not do so. The same result comes up when we compare the Over-Reactors to the Normal-Reactors, in the last comparison 4.

Table 14: SL Test Results Across Sub-Groups

Run	**Sample**	**Group 0**	**Group 1**	**P-value for HA** ($\beta_0 = \beta_1$)	**P-value for HB** ($\lambda_0 = \lambda_1$)	$\frac{\lambda_1}{\lambda_0}$
1	All	Control	Information Treatment	1	0.0002	0.9
2	All	Non-Changers	Changers	0.003	.	1.05
3	Information	Non-Changers	Changers	<0.0001	.	1.25
4	Information	Normal-Reactors	Over-Reactors	<0.0001	.	2.2

Overall, the main results withstand comprehensive sensitivity and robustness checks. The reaction of information-receivers seems to stem from an overall treatment effect. The effect size stays stable within the 20% - 33% range across all regressions. In analyzing this over-reaction, we also find that perceived pessimism (optimism) in probable gains leads to lower (higher) MWTP for others and higher (lower) MWTP for protection. These findings are robust after accounting for variables that influence the POWER parameter, a metric for pessimism and optimism regarding probable gains. Knowledge, experience and perceptions of malaria, along with some socio-demographic variables, correlate to the POWER parameter and this finding is supportive of the competence hypothesis across health risk and monetary domains. That is, the more experience and knowledge respondents have about a health risk, the more optimistic they are regarding monetary risks.

5 Conclusion and Discussion

5.1 Conclusion

Valuation of malaria outbreaks is investigated under a information treatment condition and probability weighting. We look at how valuation changes when additional quantitative disease prevalence information is presented. We further investigate how public preferences and values are influenced by inferred behavior towards probabilistic gains, via estimates of individual-level probability weighting parameters. The study contributes to the behavioral economics (i.e. analysis of the relationship of probability weighting in the financial domain and WTP for public health risk and the socio-demographic drivers behind probability weighting) and valuation (i.e. first study to analyze valuation of malaria prevention via a CE) literatures. Equally important, our results uncover potential biases from agenda-setting. Merely reminding survey participants of the possible prevalence of malaria made them regard the issue as more important. This is relevant to policy-makers wanting to evaluate preventive disease policies.

We find that respondents update their malaria valuation as a result of getting new information. More specifically, we observe an over-reaction, since the sample receiving the additional information about the relatively low level of malaria prevalence expressed a higher valuation of malaria prevention. Receiving extra information increases public WTP for protection by at least 20% and at most 33%. This result persists when individual pessimism to probable gains and other respondent characteristics are accounted for. It is also not driven by respondents who updated their stated subjective malaria risk upon receiving information. All evidence points to an overall information treatment effect.

We further discuss other results and findings of this paper below.

5.2 Discussion

If respondents were behaving in line with health-dependent utility theory, then we would have seen a decrease in valuation upon getting the information treatment. Reasons why this does not happen in the case of public preferences for the protection from malaria could be related to the framing of the provided information. Despite thorough pre-testing, respondents may have over-reacted to quantitative information in the form of percentages, whereas giving counts could have led to a different result. The importance of the role of risk communication in health valuation is reported, for example, in Dekker *et al.* (2011) or Logar & Brouwer (2017). Due to resource constraints, the study relied on one risk communication approach only in this study.

Valuation of others than the respondents self is also presented. Malaria is most severely experienced by pregnant women and children under the age of 5. Our results show that these two groups were valued the least. Respondents overwhelmingly chose to get pills for themselves rather than for others, including members of their households. This is in line with the lower estimated WTP values found in the literature for malaria prevention policies that also covers others, such as community-wide malaria protection programs (Kutluay *et al.*, 2015). One possible reason for the lower WTP found in this study is that by making survey respondents choose from a menu of pill characteristics, they were effectively put in a shopping aisle setting where they were asked to select their most preferred pills. This may have biased them to mainly choose for themselves.

We find that pessimism and optimism about monetary risks help to explain the variation in valuation of malaria risk, independent of whether or not the information treatment is received. Optimists (pessimists) have higher (lower) valuation for others and lower (higher) valuation for own malaria risk reduction. This suggests that behavior in one risk domain (monetary gains) can be indicative of behavior in another risk domain (health losses). This is robust to the large spread of the estimated probability weighting parameter and select respondent characteristics.

Further arguments for behavioral links between the financial and health risk domains come from running regressions on the probability weighting parameters. Attitudes towards probable financial gains are strongly correlated with knowledge of malaria, experience with malaria and self-reported local malaria prevalence. In contrast, there is almost no correlation with socio-demographic variables. This presents new findings in the behavioral and health economics literatures.

In searching for the probability weighting function that best fits our dataset, we find that many of the utility-probability weighting function models tested worse than flipping a coin in explaining the lottery choices. To the best of our knowledge, this is the first study to re-construct the probability of choosing a lottery given the model parameters. Existing studies tend to compare models merely through log-likelihood or Bayes ratios in order to find the statistically best-fitting model. Out of the 36 models, 25% (9 models) perform significantly worse while 30% (11 models) are statistically not significantly different from flipping a coin. This calls into question the validity of these models in explaining decision-making under uncertainty or of using parametric methods to explain lottery choices.

These findings motivate further research. For instance, more treatment groups can be set up with different framing of the same information to investigate possible framing effects. Another avenue would be to see if individual probability weighting parameters are indicative of behavioral outcomes in other risk domains. In the event that they are, then theories like the competence hypothesis need to be updated to account for the fact that attitudes toward risk in different domains are not necessarily independent. From a policy-maker perspective, additional research is needed to see under which conditions similar increases in valuation are observed. This can help identify bias-inducing mechanisms in communicating risk information, and contribute towards better policy designs.

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Appendix

A Pilot Surveys

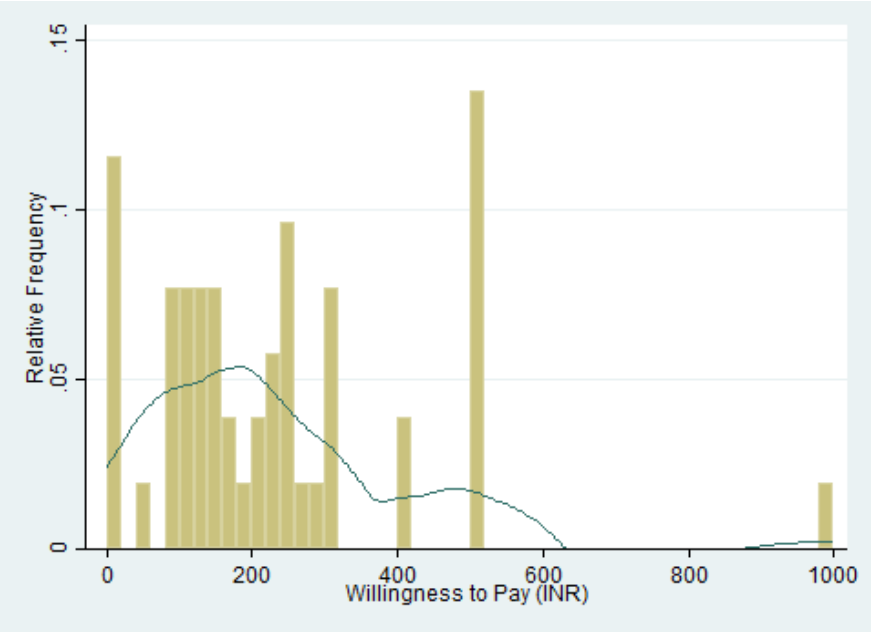
A.1 First Pilot Survey - Bidding Game

A bidding game is used to identify the levels of the price attribute. In the bidding game, the hypothetical malaria prevention pills that respondents are presented have 100% protection, suitable only for the respondent and are used weekly for 26 weeks. The lowest bid is 80 and the highest bid is 240 INR. Half the respondents bid down (up) from 240 (80) INR in increments of 40 INR. This was to control for any anchoring effects. If the minimum (maximum) bidding amount was rejected (accepted), then the respondent was asked an open-ended question on how much they are willing to pay for the pill.

The sample size is 54. No anchoring effects are found, however many respondents ended up answering the open-ended question. This was due to keeping the upper bound of the bidding game too low. A histogram of the resulting WTP can be found in Figure 5. This WTP has quartiles of 105, 195, 300 and 1000 INR[4]. The 90^{th} percentile is 500 INR. Therefore 100, 200, 300 and 500 INR were included into the price attribute. Note The 1000 INR figure is an outlier, but is still incorporated in the levels. Hence an additional level of 750 INR, the middle point between 500 and 1000 INR, is included.

[4]Mean is 226 INR - hence a fairly centered distribution.

Figure 5: Histogram and Fitted Kernel Density of Bidding Game WTP



A.2 Second Pilot Survey - CE

The first CE (for the second pilot survey) is designed using the price vector from the bidding game. The choice design is generated using NGENE, where a D-optimal Bayesian approach is taken. The priors for the utility function coefficients were obtained from Kutluay *et al.* (2015). Since the regression coefficients from that study are fixed point estimates, the first design has fixed priors.

The priors are listed: the adult category pill has a prior coefficient of 1 (the rest are 0), protection is 0.5, length of duration has no priors (hence becomes 0) and the price coefficient has -0.09.

Note that the third pill pack on offer for each choice card is anchored to be suitable only for the respondent. In the eventuality that the respondent is pregnant, they are directed to another CE. Hence, within the same survey there are two alternative CEs - one for pregnant women and the other for non-pregnant adults. Also, for each CE, four blocks of choice cards are calculated. This is to record as much choice variety as possible in the survey.

The sample size for the pilot CE is 43. A mixed logit model, containing only the attributes, is estimated. All the coefficients are assumed to be random across respondents with normal distributions. This is used to put in random priors for the D-optimal design of the final CE.

The random priors for the final CE design are listed: mean 1.3 and standard deviation 0.67 for adult, mean 0 and standard deviation 3.25 for pregnant woman, mean 0.2 and standard deviation 0.2 for protection level, mean 0 and standard deviation 0.05 for duration, mean -0.006 and standard deviation 0.004 for price. The 0 means are given for the attributes that did not have significant coefficients. All estimated random effects are significant.

As mentioned in the main text, the final design of the CE is much shorter than its pilot predecessor. Six choice cards are presented instead of nine.

B Calculating Malaria Knowledge Scores

The questions asked to respondents in Dhawan *et al.* (2014) were also asked in our survey. The questions were multiple choice with one or more than one answers being correct. If a respondent gave the correct answers only, then they receive a 1 for that question category (e.g.

regarding the seasonality of malaria). If a respondent did not select any of the correct answers, then they get 0. In the following sub sections, the algorithm for calculating all the points in between are given per question.

B.1 How Does Malaria Get Transmitted?

The following question, along with the answer options (the correct one indicated in parentheses), was asked:

> In your opinion, how does malaria get transmitted?
>
> - Mosquito bites (correct)
> - Drinking contaminated water
> - Eating contaminated food
> - Standing next to another person with malaria

There are 3 wrong answers. Points are distributed as follows:

- 0 points: The correct answer is not selected
- 0.25 points: The correct answer is selected, along with three wrong answers
- 0.5 points: The correct answer is selected, along with two wrong answers
- 0.75 points: The correct answer is selected, along with one wrong answer
- 1 point: Only the correct answer is selected

B.2 What are the Breeding Grounds of Mosquitoes?

The following question, along with the answer options (the correct ones are indicated in parentheses), was asked:

> In your opinion, what are the breeding grounds of mosquitoes?
>
> - Pond or lake (correct)
> - Stagnant water (correct)
> - Open sewage
> - Dry and clean place

There are 2 right and 2 wrong answers. Points are distributed as follows:

- 0 points: The correct answers are not selected
- 0.1 points: One correct and two wrong answers are selected
- 0.3 points: One correct and one wrong answer is selected
- 0.5 points: One correct and no wrong answers are selected
- 0.6 points: Two correct and two wrong answers are selected
- 0.8 points: Two correct and one wrong answer are selected
- 1 point: Only the correct answers are selected

B.3 In Which Season are you Most Likely to Get Malaria?

Before asking this question, respondents were asked whether or not they thought that there was a relationship between malaria and the weather ("In your opinion, is there a relationship between getting malaria and the weather?"). Those who answered "No" immediately got 0 points for this question category.

For those who answered "Yes", the following question, along with the answer options (the correct one is indicated in parentheses), was asked:

> In your opinion, in which season are you most likely to get malaria?
>
> - Before monsoon
> - Before and during monsoon
> - During monsoon (correct)
> - During and after monsoon (correct)
> - After monsoon (correct)
> - Other:
> - The monsoon does not matter

There are three right answers, but selecting "During and after monsoon" (coded as "correct") is equivalent to selecting the other two correct answers (coded as "weakly correct"). Points are distributed as follows:

- 0 points: The (weakly) correct answers are not selected and the question before is answered "No"
- 0.05 points: One weakly correct and three wrong answers are selected
- 0.2 points: One weakly correct and two wrong answers are selected
- 0.35 points: One weakly correct and one wrong answer is selected
- 0.5 points: One weakly correct answer is selected
- 0.55 points: Two weakly correct and three wrong answers OR one correct, one weakly correct and three wrong answers are selected
- 0.7 points: Two weakly correct and two wrong answers OR one correct, one weakly correct and two wrong answers are selected
- 0.85 points: Two weakly correct and one wrong answers OR one correct, one weakly correct and one wrong answer is selected
- 1 point: Only the correct answers are selected

B.4 What are the Symptoms of Malaria?

The following question, along with the answer options (the correct ones are indicated in parentheses), was asked:

> Please mark the common symptoms of malaria you are aware of
>
> - Fever (correct)
> - Chills (correct)
> - Itching
> - Headache (correct)
> - Sweating (correct)

- Abdominal pain (correct)
- Vomiting (correct)
- Diarrhea
- Rashes

There are 6 right and 3 wrong answers. Points are distributed as follows:

- 0 points: The correct answers are not selected
- 0.025 points: One correct and three wrong answers are selected
- 0.1 points: One correct and two wrong answers are selected
- 0.175 points: One correct and one wrong answer is selected OR two correct and three wrong answers are selected
- 0.25 points: One correct answer is selected OR two correct and two wrong answers are selected
- 0.325 points: Two correct and one wrong answers are selected OR three correct and three wrong answers are selected
- 0.4 points: Two correct answers are selected OR three correct and two wrong answers are selected
- 0.475 points: Three correct and one wrong answers are selected OR four correct and three wrong answers are selected
- 0.55 points: Three correct answers are selected OR four correct and two wrong answers are selected
- 0.625 points: Four correct and one wrong answers are selected OR five correct and three wrong answers are selected
- 0.7 points: Four correct answers are selected OR five correct and two wrong answers are selected
- 0.775 points: Five correct and one wrong answers are selected OR six correct and three wrong answers are selected
- 0.85 points: Five correct answers are selected OR six correct and two wrong answers are selected
- 0.925 points: six correct and one wrong answers are selected
- 1 point: Only the correct answers are selected

C Bayesian Estimation of Parameters

Considering equation 4 in the main text, $P(D|\Theta)$ is the likelihood function. This follows directly from the utility and probability weighting specifications detailed in equations 5 and 6. The priors, $P(\Theta)$ in equation 4, have to be specified by the researcher. The details are in subsection C.1. The model specification is explored in subsection C.2. Issues regarding convergence to the posterior densities, number of draws per distribution and other Bayesian estimation specific technicalities are addressed in subsection C.3.

C.1 Priors

Balcombe & Fraser (2015) is followed for the priors. We outline them in detail below. Refer to equation 5 for the parameters.

For α_1 in the POWER-I function, a log-normal distribution is specified such that $Pr(\alpha_1 < 0.1) = 0.10$ and $Pr(\alpha_1 < 2) = 0.9$. If we consider z to be a standard normal variable, then $\alpha_1 = e^{\mu+\sigma z}$. We find μ and σ:

$$\begin{aligned} Pr(\alpha_1 < 0.1) &= 0.1 \\ \Rightarrow Pr(z < \frac{ln(0.1) - \mu}{\sigma}) &= 0.1 \\ Pr(z < -1.2813) &= 0.1 \\ \Rightarrow \frac{ln(0.1) - \mu}{\sigma} &= -1.2813 \end{aligned}$$

$$\begin{aligned} Pr(\alpha_1 < 2) &= 0.9 \\ \Rightarrow Pr(z < \frac{ln(2) - \mu}{\sigma}) &= 0.9 \\ Pr(z < 1.2813) &= 0.9 \\ \Rightarrow \frac{ln(2) - \mu}{\sigma} &= 1.2813 \end{aligned}$$

This is two equations with two unknowns. The results are $\mu = -0.8047$ and $\sigma = 1.169$. A random variable X is simulated with the $N(-0.8047, (1.169)^2)$ distribution. Then $\alpha_1 = e^X$, which makes α_1 log-normally distributed.

For α_4 in the EXPO-I function, a log-normal distribution is specified such that $Pr(\alpha_4 < 0.1) = 0.1$ and $Pr(\alpha_4 < 10) = 0.9$. The same steps are followed:

$$\begin{aligned} Pr(\alpha_4 < 0.1) &= 0.1 \\ \Rightarrow Pr(z < \frac{ln(0.1) - \mu}{\sigma}) &= 0.1 \\ Pr(z < -1.2813) &= 0.1 \\ \Rightarrow \frac{ln(0.1) - \mu}{\sigma} &= -1.2813 \end{aligned}$$

$$\begin{aligned} Pr(\alpha_4 < 10) &= 0.9 \\ \Rightarrow Pr(z < \frac{ln(10) - \mu}{\sigma}) &= 0.9 \\ Pr(z < 1.2813) &= 0.9 \\ \Rightarrow \frac{ln(10) - \mu}{\sigma} &= 1.2813 \end{aligned}$$

This is two equations with two unknowns. The results are $\mu = 0$ and $\sigma = 1.797$

For α_7 in the LOG function, a log-normal distribution is specified such that $Pr(\alpha_7 < 0.1) = 0.1$ and $Pr(\alpha_7 < 100) = 0.99$. The same steps are followed:

$$
\begin{aligned}
Pr(\alpha_7 < 0.1) &= 0.1 \\
\Rightarrow Pr(z < \frac{ln(0.1) - \mu}{\sigma}) &= 0.1 \\
Pr(z < -1.2813) &= 0.1 \\
\Rightarrow \frac{ln(0.1) - \mu}{\sigma} &= -1.2813
\end{aligned}
$$

$$
\begin{aligned}
Pr(\alpha_7 < 100) &= 0.99 \\
\Rightarrow Pr(z < \frac{ln(100) - \mu}{\sigma}) &= 0.99 \\
Pr(z < 2.325) &= 0.99 \\
\Rightarrow \frac{ln(100) - \mu}{\sigma} &= 2.325
\end{aligned}
$$

This is two equations with two unknowns. The results are $\mu = 0.1528$ and $\sigma = 1.915$

For α_8 in the QUAD model, the normalization of the x input ensures that the function is increasing in x for all α_8 values upper-bounded by 1. A negative α_8 means the utility function is convex, so Balcombe & Fraser (2015) puts 75% of prior distribution mass in the concave (non-negative) region. We take α_8 to be uniformly distributed between $-\frac{1}{3}$ and 1.

For α_2 in the POWER-II function, Balcombe & Fraser (2015) gives it the same prior as α_4 in the EXPO-I function. α_3 on the other hand, takes a log-normal distribution with 50% of probability mass below 0.5 and 10% of probability mass above 1. This translate to as follows:

$$
\begin{aligned}
Pr(\alpha_3 < 0.5) &= 0.5 \\
\Rightarrow Pr(z < \frac{ln(0.5) - \mu}{\sigma}) &= 0.5 \\
Pr(z < 0) &= 0.5 \\
\Rightarrow \frac{ln(0.5) - \mu}{\sigma} &= 0
\end{aligned}
$$

$$
\begin{aligned}
Pr(\alpha_3 < 1) &= 0.9 \\
\Rightarrow Pr(z < \frac{ln(1) - \mu}{\sigma}) &= 0.9 \\
Pr(z < 1.2815) &= 0.9 \\
\Rightarrow \frac{ln(1) - \mu}{\sigma} &= 1.2815
\end{aligned}
$$

This is two equations with two unknowns. The results are $\mu = 0$ and $\sigma = 0.5409$ for α_3. For α_2 they are $\mu = 0$ and $\sigma = 1.797$.

For α_5 in the EXPO-II function, Balcombe & Fraser (2015) uses the same priors as α_7 ($\mu = 0.1528$ and $\sigma = 1.915$). α_6 is constrained between 0.5 and 1.5, with the most probability mass given to the value 1. This means a triangular distribution. This is achieved by adding two variables that are distributed $U(0.5, 1.5)$ and dividing them by 2.

All the probability weighting function parameters are given uniform distribution priors within their theoretical limits as outlined in equation 6.

C.2 Model Specification

In each model, the probability of the right-hand lottery being chosen was assumed to follow a Bernoulli distribution with probability parameter p_i, i being the index for each lottery choice. The logit output of p_i, $log(\frac{p_i}{1-p_i})$, is defined as the difference between the two rank dependent utilities of the right-hand and left-hand lotteries. Thus, $\text{logit}(p_i) = \text{RDU}_R - \text{RDU}_L$. The RDU values are calculated by putting in normalized monetary payoff data for each lottery, along with the relevant model parameters.

Each RDU component that is not part of the dataset is then equated to a constant term that only changes across respondents. These constant terms are the model parameters, referred to as Θ in equation 4. They are then assigned their prior distributions as specified in the previous subsection.

This structure was written in BUGS language, embedded in the overall R script. The packages MCMCpack (Martin *et al.*, 2011), runjags (Denwood, 2016) and rjags (Plummer, 2016)

C.3 Acquiring Reliable Posterior Draws

When numerically deriving the integral for the posterior density, there is no test to prove that the resulting draws are from the converged distribution. There are tests to show whether or not a given draw from a distribution is not converged. Most articles graphically report the densities themselves overlapped upon multiple chains to show convergence. Since we have between 1411 and 5644 parameters across models, this is not feasible.

Instead we make use of the autorun.jags command in the runjags package. This function tests for non-convergence in the final draw automatically. The test utilized for non-convergence is the Gelman-Rubin diagnostic (Gelman & Rubin, 1992). If non-convergence is detected, then the command continues to run the MCMC chain iterations until non-convergence is not detected anymore.

Two chains are run with 4000 final draws each, this means that there are 8000 draws per parameter per respondent. The thinning value is set at 10 in order to avoid autocorrelation across draws. The burn-in number of draws is set at 8000 and the number of adaptive iterations at 1000. This is computationally expensive, which is why the scripts were run through the help of the Dutch national supercomputer cluster, Lisa Computer Cluster. We thank SURFsara (`www.surfsara.nl`) for the support in using the Lisa Computer Cluster.