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Public preferences and valuation of new malaria risk

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JEL classification: I12; Q51

Key words: malaria; willingness to pay; discrete choice experiment

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Abstract

After years of decline, malaria prevalence may increase in the future due to climate change, and spread to areas that have not experienced the disease before. Any policy that aims to mitigate or adapt to this scenario needs to take into account the economic benefits of avoided malaria (willingness to pay - WTP). Much work has been done on WTP, but not much is known about how WTP changes with the probability of becoming ill. To this end a survey is carried out in Mumbai, India, to compare respondents' WTP to avoid malaria across risky and less-risky areas. We find WTP to be 10% higher in risky areas than in less-risky areas. We also observe WTP to increase by more than 15% between malaria-experienced and naive respondents, indicating a familiarity premium. These findings indicate higher welfare returns to climate change mitigation policies than previously thought.

1 Introduction

Since 2000, the world has seen a general decline in malaria mortality and morbidity. Through benchmarks, such as the Millennium Development Goals, and programs, such as Roll Back Malaria, mortality rates due to the incidence of malaria dropped by 42 percent between 2000 and 2012 (Breman, 2009). However, recent developments are threatening to undo this progress. For example, it has been shown that malaria is sensitive to weather variations and climate change (Bouma & Kaay, 1996) and risk of malaria transmission may increase due to climate change in certain regions (Patz *et al.*, 2002; McMichael *et al.*, 2006; IPCC, 2014). Malaria may also spread to regions with little to no recent experience with the disease (Peterson, 2009).

In this context, malaria infection imposes a cost on society. Thus estimates of the social cost of carbon, the impact of emitting one additional tonne of carbon dioxide (Tol, 2011), require quantification and monetization of malaria risks. Monetary benefits are measured in terms of willingness to pay (WTP) to avoid malaria, since these reflect stated/inferred subjective welfare loss due to disease. This WTP to avoid malaria has been extensively assessed and researched. However, no studies to date have considered WTP when malaria risk *increases* (Trapero-Bertran *et al.*, 2012; Kutluay *et al.*, 2015), even though we know that respondents value increases and

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decreases differently (Horowitz & McConnell, 2003). Equally important, in the climate change context, is finding out the difference in WTP between those who have and those who have not previously experienced malaria.

People pay to avoid malaria. Because of risk aversion (Brouwer *et al.*, 2009) and hedonic adaptation (Oswald & Powdthavee, 2008), we expect differences in WTP between malaria-naive and experienced people. Hedonic adaptation predicts that people with prior experience of malaria should be less troubled by the prospect of contracting the disease (Oswald & Powdthavee, 2008), and thus have a lower WTP for prevention measures. However, Zhao & Tsai (2011) show that knowledge of the duration of an episode increases the intensity of the affective experience, whether they are negative or positive experiences. Respondents with prior experience of malaria (a negative experience) know its typical length better than the unexperienced. Hence, we expect experience with malaria to result in higher WTP estimates.

Since the probability of becoming ill has a positive impact on the WTP to avoid it, we expect WTP for one's own protection to increase in the face of higher malaria risk. We estimate the WTP for malaria medication for comparable populations when malaria risk increases fivefold from a negligible baseline. To this end, a discrete choice experiment (DCE) is carried out between residents across areas differing in malaria risk exposure.

DCEs have been used extensively since the late 1990s in studies focused on health and environmental valuation. Many changes have occurred regarding the implementation of DCEs, including more statistically efficient choice designs, flexible multinomial regression models for subsequent analyses and an increasing emphasis on including changes in probabilities as attributes to measure environmental and health risks (de Bekker-Grob *et al.*, 2012). As DCEs have become a widely-accepted tool for measuring stated preferences, guidelines have emerged about using them in developing country contexts (Mangham *et al.*, 2009).

WTP for malaria, though, has been measured primarily through contingent valuation methods[1]. DCEs, on the other hand, have not been used for malaria valuation[2]. These studies have looked at WTP to prevent/treat malaria where the disease is endemic. In contrast, we analyze WTP in a non-endemic setting, where respondents differ in their prior experience and likelihood of getting ill.

Until the early 1990s Mumbai was relatively malaria-free, but has since been subject to sporadic outbreaks[3](Kshirsagar, 2006). The reasons have been linked to an increase in migrant populations and constructions sites. Construction sites tend to be suitable for mosquito breeding and thus spread malaria (Limaye *et al.*, 2012). People living within one kilometer of mosquito-breeding grounds are more at risk of getting malaria than others (Stoler *et al.*, 2009). We estimate WTP differences between these two groups. Furthermore, we ask respondents about previous experience with malaria and again estimate WTP differences between those with and without prior malaria experience.

We look at multiple attributes of WTP for malaria prevention for different groups of people (non-pregnant adults, expecting mothers, babies, children), length of protection (duration) and the percentage of risk reduction (protection). Malaria is especially dangerous for babies (children under the age of 5) and pregnant women, making it important to take into account these groups for policy design purposes.

This paper continues as follows: Section 2 outlines the theoretical and empirical models used,

[1]This valuation literature has been summed up in two meta-analyses (Trapero-Bertran *et al.*, 2012; Kutluay *et al.*, 2015)

[2]Some papers have come close. Hanson *et al.* (2005) look at what attributes people find important regarding hospital care for childhood disease and cranial malaria. Lagarde (2013) investigates how much healthcare workers would like, in pay raises, to implement different malaria management procedures. Neither study measures, however, WTP to avoid malaria.

[3]An extensive overview regarding the current situation of malaria and other diseases in Mumbai can be found in Praja (2017)

Section 3 gives details about the data collected, Section 4 presents descriptive and inferential results and Section 5 provides the conclusions and discussion.

2 Modeling Framework

2.1 Exogenous and Endogenous Risk

Risks like malaria can be mitigated, to a certain extent, through individual decisions. WTP is a function of the probability of becoming ill. Shogren & Crocker (1991) propose a model of WTP where the risk of illness is exogenously given but managed by the individual. This framework has become useful in modeling and analyzing WTP for avoiding similar risks in environmental and health economics (Bateman *et al.*, 2005; Brouwer *et al.*, 2009; Tonin *et al.*, 2009; Khan *et al.*, 2014). Thus, we use the framework in Shogren & Crocker (1991) to explain the relationship between increased levels of exogenous risk and valuation.

Personal risk mitigation in the case of malaria is relatively straightforward. Malaria spreads via mosquitoes that have fed off of infected people. Therefore, any increase in the number of malaria-infected mosquitoes will lead to an increase in the likelihood of some person becoming ill. People who protect themselves against mosquitoes are less likely to get sick than those who do not. Some examples of protection from mosquitoes include using insect-repellents, sleeping under insecticide treated nets and putting up mosquito coils. Protection against mosquitoes allows any person to manage a given exogenous risk, thus we can label this as the endogenous component of the total likelihood of getting malaria.

The total risk of getting malaria an individual i faces is divided into two components: exogenous (EX_i) and endogenous (EN_i) risk. WTP is a function of these risks, along with a vector of socio-demographics (Z_i), including individual's ability to pay (i.e. income, Y_i) and risk-tolerance (R_i):

$$WTP_i = f(EX_i, EN_i, Y_i, R_i, Z_i) \tag{1}$$

Given the DCE framework, we control for all of these factors in a multinomial logit model. The model, and the random utility theory it is motivated by, is outlined below.

2.2 Multinomial Logit Specification

In order to estimate the *marginal* WTP (MWTP) values from the DCE data, we use a random utility framework. Here, the utility function is a linear function that is used as a tool to describe how attributes within the DCE options influence the resulting choices (Train, 2009). The utility of a malaria prevention pill i, from choice set j, chosen by individual n is:

$$\begin{aligned} U_{ijn} &= V_{ijn} + \epsilon_{ijn} \\ V_{ijn} &= \beta X_{ij} + \gamma Z_{ijn} \end{aligned} \tag{2}$$

where X_{ij} is a matrix containing the attribute levels of the alternative malaria pills in each choice set j and the chosen pill option i, while β is a vector of coefficients for each attribute corresponding in X_{ij}. These reflect the respondents' average preferences over 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 associated coefficient vector. These coefficients also reflect average preferences, as opposed to individual ones. From this framework, we extract the MWTP for a marginal change in some attribute $K \in X$ as, from Equation (2), $-(\frac{\delta V_{ijn}}{\delta X_K})/(\frac{\delta V_{ijn}}{\delta X_{\text{Price}}})$. If V_{ijn} is a linear function in β and γ, then the MWTP for attribute K is simply $-\beta_K/\beta_{\text{Price}}$. Finally, crucial to the next steps, ϵ_{ijn} is the idiosyncratic error term, distributed i.i.d. 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 all $k \neq i$. Let P_{ijn} denote the probability of observing this choice. It follows that:

$$\begin{aligned} P_{ijn} &= \text{Prob}(U_{ijn} \geq U_{kjn}, \forall i \neq k) \\ &= \text{Prob}(V_{ijn} + \epsilon_{ijn} \geq V_{kjn} + \epsilon_{kjn}, \forall i \neq k) \\ &= \text{Prob}(\epsilon_{ijn} - \epsilon_{kjn} \geq V_{kjn} - V_{ijn}, \forall i \neq k) \\ &= \text{Prob}(\epsilon_{ijn} - \epsilon_{kjn} \geq \Delta V_{ijn}, \forall i \neq k) \\ &= \frac{e^{\Delta V_{ijn}}}{\sum_{k \in J} e^{\Delta V_{kjn}}} \\ &= \frac{e^{\lambda \beta \tilde{X}_{ij} + \lambda \gamma \tilde{Z}_{ijn}}}{\sum_{k \in J} e^{\lambda \beta \tilde{X}_{kj} + \lambda \gamma \tilde{Z}_{kjn}}} \end{aligned} \tag{3}$$

Due to the assumptions on the error term, the scale parameter λ appears in the final step. When extracting MWTP values it gets divided out.

The second to last step in Equation (3) assumes a logit structure, making use of the fact that the ϵ_{ijn} terms are extreme value and i.i.d. distributed (McFadden, 1974). This means that a multinomial logit equation can be used to estimate the coefficients β and γ in Equation (2). However this structure imposes the so-called irrelevance of independent alternatives (IIA) assumption. 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 assumption. It also ignores the panel structure of the dataset, where individuals make choices from multiple choice sets.

To address both these problems, we use the mixed logit model (McFadden & Train, 2000) onto 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:

$$P_{ijn} = \int \frac{e^{\Delta V_{ijn}}}{\sum_{k \in J} e^{\Delta V_{kjn}}} G(d\alpha; \theta) \tag{4}$$

where $G(.)$ is a mixing distribution, typically chosen by the researcher. The α vector consists of coefficients from β and γ that we can 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). As can be seen, the ratio P_{ijn}/P_{kjn} no longer cancels out the $\sum_{k \in J} e^{V_{kjn}}$ term (in general), relaxing the IIA assumption. We have also accounted for individual random effects across choices.

The disadvantage of this approach is that the above integral has to be evaluated. This is computationally expensive and different likelihood optimization routines can produce slightly different results. We use the mlogit package in R (Croissant, 2013). The number of Halton draws, to improve the statistical efficiency of the estimated parameters, is set to 1000.

3 Data

3.1 Questionnaire Design

The survey consisted of a questionnaire followed by a DCE focusing on the purchase of a hypothetical pill to prevent malaria. The survey targeted the main decision maker of the household, and was therefore administered to one person per household.

The questionnaire consists of two sections relevant to this paper. The first section contains standard socio-demographic questions about the respondent and the household. The second section entails questions on knowledge and experience with malaria.

Malaria knowledge and experience is recorded through a series of questions. The malaria knowledge questions are taken from Dhawan *et al.* (2014), a study that assessed knowledge of malaria across different socio-economic groups in Mumbai. The respondents are also asked about their own and their household's experience with malaria. These are followed by questions on perceived severity of their own and 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 prior malaria prevention pills they have used.

Since malaria is a communicable disease, the likelihood of becoming ill increases as one is surrounded by others with malaria. The respondents are therefore asked how they view their likelihood of getting malaria with respect to everyone else in their locality. Table 1 shows how these two answers are used to construct the respondent's subjective probability of getting malaria, where P is the subjective prevalence (%) of malaria in the locality.

Table 1: 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

3.2 Discrete Choice Experiment Design

Respondents are asked to choose between different types of hypothetical malaria prevention pills. These pills are readily available in stores, but not widely used due to their side effects. The (hypothetical) pills differ in terms of price, who can use it (other than the respondent), level of protection and how long the pills are taken for. The attributes and their levels are presented in Table 2.

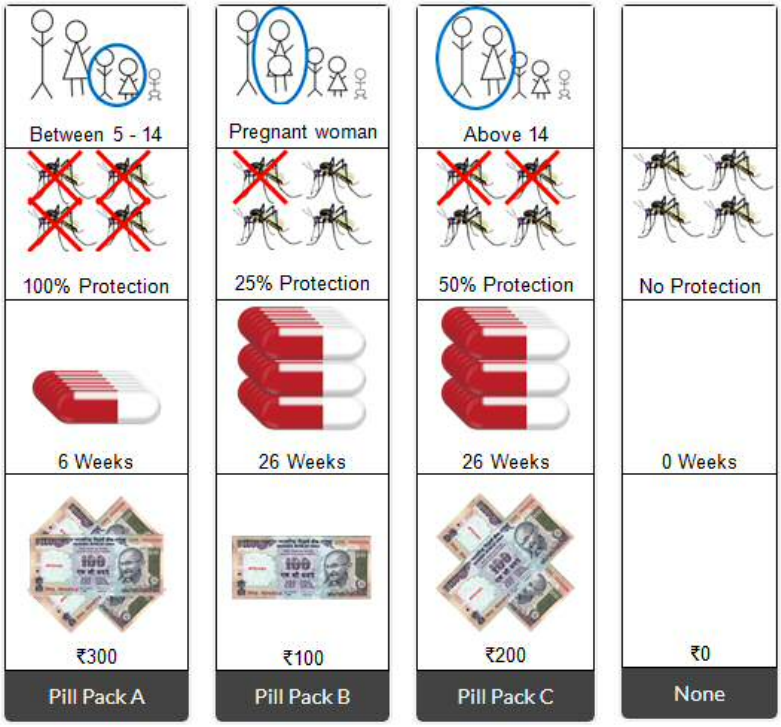
Table 2: Choice Attributes and Levels per Pill Pack

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 (₹ per 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 in order to facilitate easy communication through diagrams (see Figure 1 as an example). 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. Thus we consider above-14's to be adults, from a labor market perspective. Levels for the duration attribute are based on real malaria prevention pills. This is to make the hypothetical pills resemble the real pills, especially to those respondents who have already taken them before. The price attribute's levels are selected based on a bidding game in the pilot surveys.

Figure 1: Example Choice Card



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. The only issue encountered during the pretest was respondent boredom due to a high initial number of choice cards (9). This was therefore reduced to 6 in the main DCE.

In each choice task, 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 (e.g. a child under the age of 5), they are asked who this pill is meant for, themselves or others in the household, extended family or charity. If respondents opt out consistently, then the reasons for doing so are asked in a follow-up question after the DCE.

3.3 Data Collection

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

The survey was translated into Hindi and Marathi. Surveyors were obtained through Nirmana[4], a local NGO. The surveyors were trained by the authors of this study and supervised during all survey sessions. Residents of apartment buildings were surveyed upon getting support of the local housing association secretaries or neighborhood priests. This led to an average response rate of 81%.

Respondents were not told beforehand that the survey was about malaria. It was framed as a household survey, with some additional questions regarding respondent's outlook on health. One respondent was interviewed per household, an adult who has a say in how the household budget is spent.

4 Results

4.1 Summary Statistics

The descriptive statistics of the respondents and their choices are presented in this section. Table 3 outlines respondents socio-demographic characteristics, along with their experience, knowledge, perception and subjective risk perception of getting malaria. Table 4 presents choice statistics, specifically the number of opt-outs and pills chosen for others.

The respondents were chosen from non-slum residential areas of Mumbai, a stricter condition than one might think, since more than half of Mumbai's residents are estimated to live in slums (Census of India, 2011). We have a relatively high number of female respondents, particularly considering Mumbai's female/male ratio of 0.853 (Census of India, 2011). Female over-representation is, in this case, mainly due to the male household members being available only after working hours for interviews.

More than half of our responses came from risky areas. Since 2011, Mumbai has been undergoing a construction boom. This boom was underway during the collection of survey responses, and explains the higher number of survey areas that are within 1 kilometer of a construction site.

Although more then 40% of the respondents have had malaria (with another 30% saying they have second-hand experience of it), the amount of knowledge regarding the disease was not very high. The scores in Table 3 have ranges between 0 and 1, with 1 denoting that a respondent answered all questions correctly. A detailed description of the scores can be found in the appendix (section B). Respondents were better informed about the transmission, source and symptoms of malaria, than about its seasonality.

Considering the framework of Shogren & Crocker (1991), one expects households living in at-risk areas to invest more in malaria prevention measures. Figure 2 shows plenty of overlap in the distribution of prevention measures between risky and less-risky areas, with the boxes covering the interquartile range. The average number of prevention measures used in households in risky areas is 3.01, while for less-risky areas this is 2.58. Despite the overlap in Figure 2, the difference in means is statistically significant at the 5% level (Rank-sum test p-value = 0.025). Even if one relaxes the assumption that the number of prevention measures is continuous, evidence is against random dispersion of prevention measures across risky and less-risky areas (the chi-squared test p-value is below 1%)[5].

[4] `http://www.nirmana.org/index.php`

[5] Stata 14 is used for descriptive and initial inferential statistics

Table 3: Sample Summary Statistics

	Mean	Std Dev	Min	Median	Max
Socio-Demographics:					
Male	.42	.49	0	0	1
Age	36.80	14.16	19.5	29.5	79.5
No Schooling	.10	.30	0	0	1
Finished 10th Grade	.63	.48	0	1	1
HH Income	24486.53	20138.87	1000	19750	197500
Has Child(ren)	.63	.48	0	1	1
Finished University	.20	.40	0	0	1
Knowledge:					
Malaria Seasonality Score	.55	.34	0	.5	1
Mosquito Breeding Score	.65	.28	0	.5	1
Malaria Symptoms Score	.71	.18	.25	.7	1
Malaria Transmission Score	.77	.23	0	.75	1
Malaria Risk and Experience:					
No of Prevention Measures	2.88	2.14	0	3	9
Within 1-km of Construction	.70	.46	0	1	1
Had Malaria	.41	.49	0	0	1
HH Had Malaria	.34	.47	0	0	1
Subjective Malaria Risk (%)	21.67	25.04	0	9.5	100
Survey Area (Within 1 km of Construction):					
Khar	.14	.35	0	0	1
Goregaon	.14	.35	0	0	1
Byculla	.12	.32	0	0	1
Worli (Apartment)	.11	.32	0	0	1
Wadala	.10	.30	0	0	1
Worli	.07	.26	0	0	1
Wadala (Apartment)	.02	.14	0	0	1
Survey Area (Outside 1 km of Construction):					
Kanjur Marg	.26	.44	0	0	1
Goregaon (Outskirts)	.03	.17	0	0	1
Govandi	.01	.12	0	0	1
Observations	1411				

The opt-out was chosen in 24% of all choice occasions (Table 4). Just over 12% of the respondents opted-out in all of their choices. Around $2/5^{\text{th}}$ of the latter can be classified as legitimate zero WTP values as a result of having no interest in purchasing the hypothetical malaria pills, while the rest was mainly due to respondents finding the prices too high and claiming other methods used for malaria protection. The most frequently selected methods of protection were using mosquito coils (57 %), keeping doors closed (50%) and cleaning dark corners of the house (46%). There were no protest responses. Respondents chose mostly pills 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 Main Regression Results

The model in Shogren & Crocker (1991) is taken as a guide in setting up the regression models. Socio-demographic variables in equation 1 are controlled for via the respondent random effects in the mixed logit estimations. Hence, we focus on the impacts of exogenous and endogenous malaria risk on WTP.

Table 5 shows the regression results for the β and γ coefficient estimates of equation 2. The results for the attribute-only (with adjustment to subjective malaria risk) model and the exogenous risk model are given in columns 1 and 2, respectively. Malaria risk mitigation behav-

Figure 2: Number of Prevention Measures Used vs Living in Risky Area

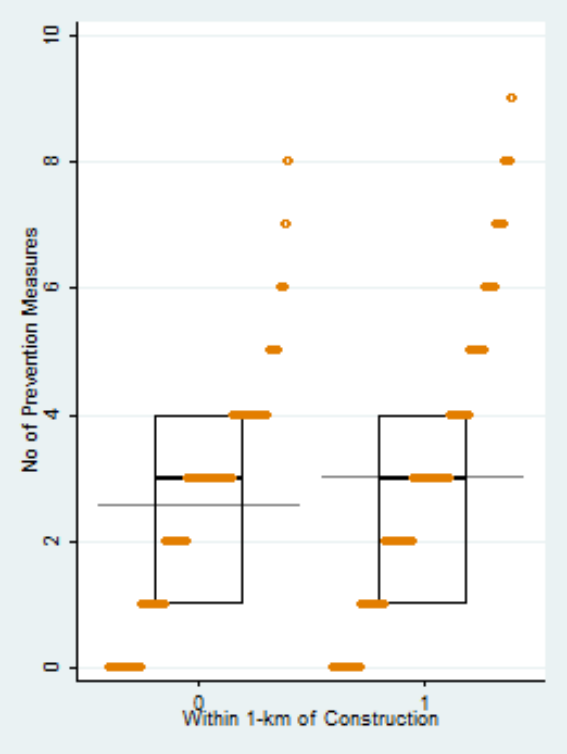


Table 4: Choice Summary Statistics

	Mean	Std. Dev.
Opt-Out	24.20%	.238
Opt-Out in all Choice Cards	12.69%	.333
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	

ior—endogenous risk—is included in model 3. The attribute-only variables, except for price, have random parameters, distributed over respondents. Dummy variables are assumed to be uniform distributed and continuous variables are assumed normally distributed (Hensher *et al.*, 2005). Respondent-specific covariates are introduced to the model as fixed parameters. We select "adult" as the reference category for the "suitable for" attribute. Recall that being within a one kilometer radius of a construction site increases the likelihood of getting malaria by up to five-fold (Stoler *et al.*, 2009).

The alternative specific constant (ASC) variable takes the value 0 if the respondent opts out. The negative ASC coefficient, found in all model specifications, indicates that when all other at-

tribute levels (including protection offered) are at zero, then the average respondent unsurprisingly chooses to opt out. However, when the protection attribute reaches its minimum level of 25%, the resulting positive impact on the utility function outweighs the negative impact of the ASC term, meaning that the average respondent would already buy the malaria pill.

Table 5: Baseline regression results

	Model 1	Model 2	Model 3
	Attribute-Only	Exogenous Risk	Endogenous Risk
Price	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)
ASC	−1.576*** (0.148)	−1.493*** (0.148)	−1.291*** (0.144)
Pregnant	−11.550*** (0.679)	−12.147*** (0.769)	−11.358*** (0.641)
Baby	−16.838*** (1.008)	−17.944*** (1.129)	−15.324*** (1.006)
Child	−5.011*** (0.339)	−6.308*** (0.428)	−5.913*** (0.403)
Protection	0.073*** (0.003)	0.067*** (0.004)	0.066*** (0.004)
Protection x Own-Risk	0.044*** (0.005)	0.048*** (0.008)	0.015 (0.009)
Duration	0.034*** (0.004)	0.047*** (0.006)	0.049*** (0.007)
Km-Construction:			
Pregnant		1.142*** (0.327)	0.015 (0.288)
Baby		1.473*** (0.346)	0.567* (0.320)
Child		2.063*** (0.297)	1.536*** (0.285)
Protection		0.005 (0.004)	0.007** (0.003)
Protection x Own-Risk		0.007 (0.009)	0.010 (0.008)
Duration		−0.017** (0.007)	−0.018** (0.007)
Prevention Measures:			
Pregnant			1.196*** (0.079)
Baby			0.830*** (0.078)
Child			0.278*** (0.050)
Protection			−0.002*** (0.001)
Protection x Own-Risk			0.009*** (0.002)
Duration			0.0004 (0.002)
Observations	8,400	8,400	8,400
AIC	10705.24	10664.15	10454.89
Pseudo R-squared	0.488	0.491	0.502

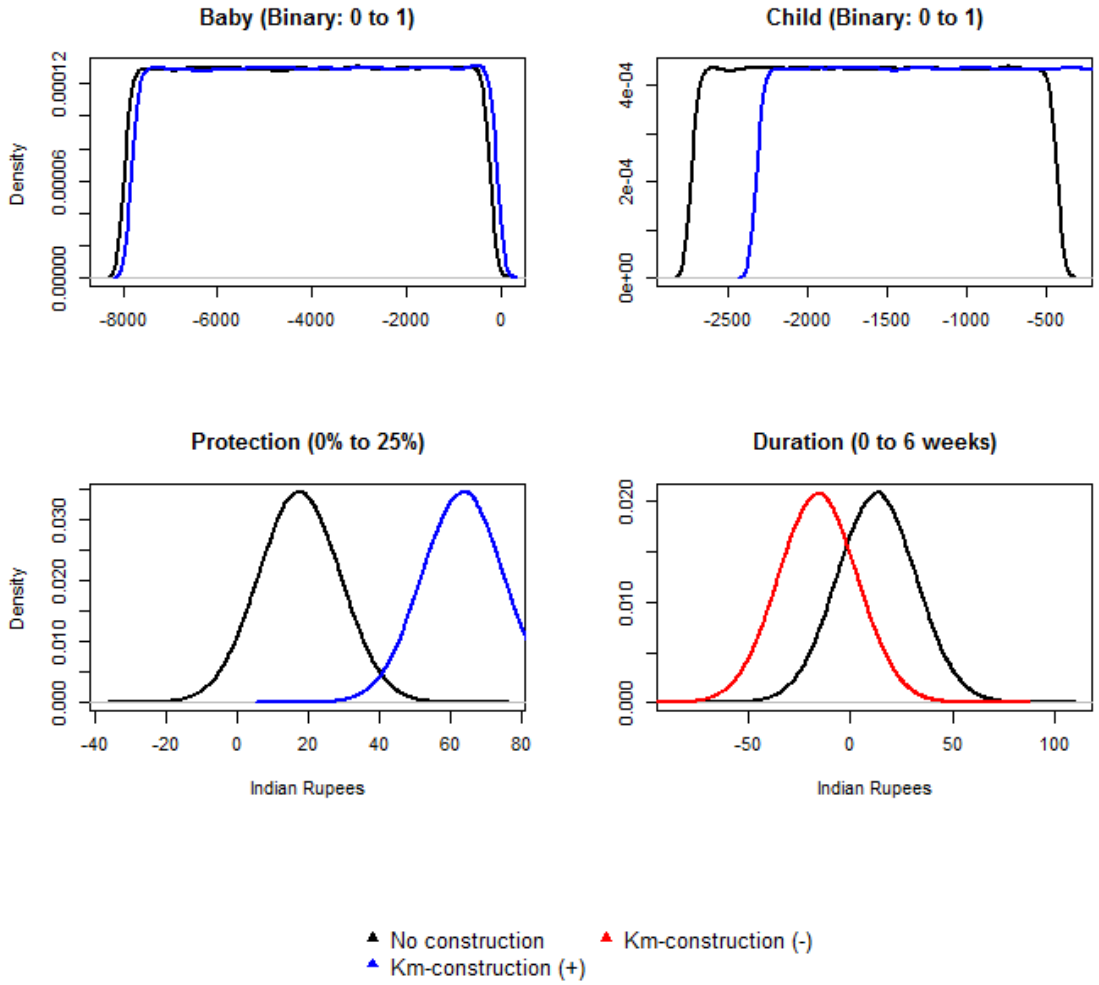
Note: *p<0.1; **p<0.05; ***p<0.01

The respondents show a general tendency to be selfish when malaria risk is not controlled for. This is inferred from the negative MWTP for attributes affecting others (pregnant, baby, child) and positive MWTP for attributes affecting one's self (protection, duration) in column 1 of Table 5. Here, it is important to note that we account for subjective malaria risk by multiplying the protection attribute with one's own malaria risk, as calculated in Table 1. When we account for living in higher-risk areas, as in model 2, this selfish behavior is dampened. MWTP for others increases if the respondents live in these areas as can be seen from the significant positive coefficient estimates for the interaction terms. When endogenous risk mitigation is accounted for, as in model 3, MWTP for self-protection increases significantly for people living in high malaria risk areas. This indicates that there are differences between how respondents value protection from malaria contingent on the number of mitigation measures they are taking already.

Our key results can be found in model 3 of Table 5. People in risky areas ("Km-Construction") have higher MWTP for babies (+3.70%), children (+25.98%) and protection (+10.61%) than those in less-risky areas. MWTP for pregnant women seems to be no different between the two areas. People in risky areas care less about how long they have malaria protection for (-36.73%). MWTP for an additional week of protection is negative. This indicates that people in risky areas care more about being protected than about how long they are protected for.

An illustration of these differences in MWTP terms can be found in Figure 3, where the MWTP differences are in steps of the DCE attribute levels (e.g. protection increases in steps of 25%). The

Figure 3: Key Results



distributions are across respondents. For instance, a number of respondents are willing to pay for an extra week of protection when living in less-risky areas (black curve). However this number is smaller for the sample that lives in risky areas (red curve). Figure 3 underlines the relatively small MWTP differential for babies as opposed to the other attributes, also from a monetary perspective.

Individual random effects, and hence preference heterogeneity across the choice attributes, are controlled for via the mixed logit specification. However additional robustness checks are run to see under what conditions the main results hold or not. This also allows one to discuss potential mechanisms behind the main results of increased MWTP in the face of higher disease risk. Experience with malaria, survey location fixed effects and correlates of risk mitigation behavior are added into the model in the following sections.

4.3 Robustness Checks

4.3.1 Experience with Malaria

Living close to a construction site increases the value people put on avoiding malaria for themselves, children and babies. This could be driven by respondents' prior experience with the disease, since they are more likely to have experienced malaria, first-hand or second-hand. Second-hand experience of malaria is defined as a member of the respondent's household having had malaria.

Prior malaria experience is controlled for in Table 6. The main results do not change, except for the interaction between babies and km-construction. When second-hand malaria experience is accounted for, the babies and km-construction coefficient is no longer significant. This indicates that second-hand malaria experience most likely positively correlates with preferences to protect babies. If so, this impact is diffused between the km-construction and second-hand malaria interactions, as both coefficients are non-significant.

Having first- or second-hand malaria experience is correlated with an increase in MWTP for protection and duration, but a decrease in MWTP for others. Having experienced malaria before leads to a 15.87% increase in MWTP for protection. This increase supports the argument that, potentially due to remembering the length of previous bouts of illness, people who have experienced malaria have a higher WTP. The increase in MWTP for protection here is regarded as a familiarity premium. Our result is consistent with the duration knowledge effect dominating the hedonic adaptation effect.

One's malaria risk can be influenced by one's knowledge of malaria, specifically knowledge that can be used to avoid the disease. Previous valuation research has shown that a perceived locus of control tends to influence WTP (Viscusi & Evans, 1990). This could lead to a dampening of the overall WTP for malaria protection through pills. To see if the main results are affected by this, respondent's answer scores on questions regarding mosquito breeding grounds and malaria seasonality are introduced into the mixed logit models. Knowledge about mosquito breeding grounds can be utilized to prevent mosquito bites (i.e. by clearing out pools of shallow water around the residence). However knowing about malaria outbreaks being seasonal is not easily applicable to preventing becoming ill. The outputs are shown in Table 7.

We see MWTP for self-protection decreasing as one knows more about mosquito breeding sites - knowledge which can be used to mitigate morbidity risk. On the other hand, knowing about malaria seasonality - knowledge which cannot be used to mitigate morbidity risk - leads to an increase in MWTP for self-protection. Accounting for malaria knowledge does not discernibly change the perceived effect sizes as revealed by the prevention and km-construction interaction variables. However, when controlling for malaria knowledge makes the MWTP for babies in risky areas not different from the ones in less-risky areas. The more they know, the less likely they are to buy pills for babies.

4.3.2 Location Fixed Effects

Mumbai's neighborhoods are relatively segregated so there might be neighborhood-specific impacts on respondents decisions in selecting pills. All the attribute coefficients are interacted with survey region dummies. Tables C1.1 and C1.2, in the appendix, contain the mixed logit outputs. Survey areas that were away from construction sites are taken as the reference group.

Tables C1.1 and C1.2, on the other hand, reveal that the main results do change. The km-construction and pregnant coefficient becomes positive significant when area fixed effects are included, with an effect size just under +10%. This shows that there is a preference to get pregnant women protected from malaria in risky areas, but it is subject to regional effects.

In the third model of Table C1.2, the protection and km-construction interaction variable is insignificant. However, the protection attribute's interaction with the survey area dummy variables is positive. That is, living in risky areas leads to an increase in demand for malaria protection.

Table 6: Impact of First/Secondhand Malaria

	Model 1	Model 2	Model 3
	Baseline	Firsthand Malaria	Secondhand Malaria
Price	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)
ASC	−1.291*** (0.144)	−1.307*** (0.145)	−1.364*** (0.144)
Pregnant	−11.358*** (0.641)	−11.120*** (0.658)	−11.545*** (0.635)
Baby	−15.324*** (1.006)	−15.240*** (1.024)	−16.019*** (1.050)
Child	−5.913*** (0.403)	−5.683*** (0.401)	−5.887*** (0.407)
Protection	0.066*** (0.004)	0.063*** (0.004)	0.064*** (0.004)
Protection x Own-Risk	0.015 (0.009)	0.012 (0.010)	0.022** (0.010)
Duration	0.049*** (0.007)	0.045*** (0.008)	0.039*** (0.007)
Km-Construction:			
Pregnant	0.015 (0.288)	0.052 (0.290)	0.228 (0.293)
Baby	0.567* (0.320)	0.674** (0.328)	0.325 (0.325)
Child	1.536*** (0.285)	1.564*** (0.295)	1.581*** (0.290)
Protection	0.007** (0.003)	0.007* (0.003)	0.008** (0.003)
Protection x Own-Risk	0.010 (0.008)	0.011 (0.008)	0.006 (0.008)
Duration	−0.018** (0.007)	−0.017** (0.007)	−0.016** (0.007)
Prevention Measures:			
Pregnant	1.196*** (0.079)	1.199*** (0.080)	1.277*** (0.078)
Baby	0.830*** (0.078)	0.836*** (0.079)	0.862*** (0.083)
Child	0.278*** (0.050)	0.279*** (0.050)	0.262*** (0.051)
Protection	−0.002*** (0.001)	−0.002*** (0.001)	−0.003*** (0.001)
Protection x Own-Risk	0.009*** (0.002)	0.009*** (0.002)	0.010*** (0.002)
Duration	0.0004 (0.002)	0.0001 (0.002)	0.001 (0.002)
Firsthand Malaria:			
Pregnant		−0.561** (0.268)	
Baby		−0.418 (0.296)	
Child		−0.598** (0.238)	
Protection		0.010*** (0.003)	
Protection x Own-Risk		−0.003 (0.008)	
Duration		0.009 (0.006)	
Secondhand Malaria:			
Pregnant			−0.090 (0.281)
Baby			−0.314 (0.315)
Child			−0.605** (0.245)
Protection			0.013*** (0.003)
Protection x Own-Risk			−0.018** (0.008)
Duration			0.014** (0.007)
Observations	8,400	8,400	8,400
AIC	10454.89	10454.11	10429.59
Pseudo R-squared	0.502	0.502	0.503

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

The lack of significance in the km-construction and protection coefficient could be because all the variation is explained by the protection variable's interaction with the survey region dummies.

4.3.3 Household and Individual Correlates of Risk Mitigation

Household characteristics may drive the main results. A household's decision on the number of prevention measures to take, in theory, should only depend on their perceived malaria risk. In practice, the theory may not be able to fully explain a household's consumption decisions, so we run an OLS model to find correlates. Table 8 displays the results.

Many respondent characteristics are significant in explaining the number of prevention measures

Table 7: Impact of Malaria Knowledge

	Model 1	Model 2	Model 3
	Baseline	Mosquito Breeding	Malaria Seasonality
Price	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)
ASC	−1.291*** (0.144)	−1.405*** (0.144)	−1.394*** (0.142)
Pregnant	−11.358*** (0.641)	−10.667*** (0.686)	−10.844*** (0.609)
Baby	−15.324*** (1.006)	−12.807*** (0.888)	−15.533*** (0.984)
Child	−5.913*** (0.403)	−6.009*** (0.476)	−6.057*** (0.422)
Protection	0.066*** (0.004)	0.075*** (0.005)	0.058*** (0.004)
Protection x Own-Risk	0.015 (0.009)	0.005 (0.013)	0.040*** (0.010)
Duration	0.049*** (0.007)	0.037*** (0.010)	0.050*** (0.008)
Km-Construction:			
Pregnant	0.015 (0.288)	0.026 (0.297)	0.083 (0.293)
Baby	0.567* (0.320)	0.488 (0.324)	0.364 (0.321)
Child	1.536*** (0.285)	1.546*** (0.289)	1.614*** (0.289)
Protection	0.007** (0.003)	0.009*** (0.003)	0.009*** (0.003)
Protection x Own-Risk	0.010 (0.008)	0.006 (0.008)	0.003 (0.008)
Duration	−0.018** (0.007)	−0.020*** (0.007)	−0.018** (0.007)
Prevention Measures:			
Pregnant	1.196*** (0.079)	1.276*** (0.081)	1.281*** (0.078)
Baby	0.830*** (0.078)	0.854*** (0.080)	0.845*** (0.079)
Child	0.278*** (0.050)	0.252*** (0.050)	0.254*** (0.050)
Protection	−0.002*** (0.001)	−0.003*** (0.001)	−0.003*** (0.001)
Protection x Own-Risk	0.009*** (0.002)	0.010*** (0.002)	0.009*** (0.002)
Duration	0.0004 (0.002)	0.001 (0.002)	0.001 (0.002)
Mosquito Breeding Knowledge:			
Pregnant		−1.376*** (0.494)	
Baby		−4.261*** (0.584)	
Child		0.113 (0.402)	
Protection		−0.014** (0.005)	
Protection x Own-Risk		0.022* (0.013)	
Duration		0.017 (0.011)	
Malaria Seasonality Knowledge:			
Pregnant			−1.116*** (0.350)
Baby			−0.095 (0.419)
Child			0.042 (0.366)
Protection			0.015*** (0.005)
Protection x Own-Risk			−0.040*** (0.011)
Duration			−0.006 (0.009)
Observations	8,400	8,400	8,400
AIC	10454.89	10426.74	10444.83
Pseudo R-squared	0.502	0.503	0.503

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

used by the household, also when we control for malaria experience and knowledge. The significant covariates in Table 8 are included in the mixed logit model and estimates are obtained. The regression tables can be found in the appendix, Tables C2.1, C2.2, C2.3, and C2.4. Most of the main results hold when the various covariates are controlled for, except for km-construction x baby. Even in the baseline regression, this coefficient's resulting effect size on MWTP is small (3%).

Additionally, the pregnant attribute interaction becomes significant negative, albeit with a small effect size (5%), when household income (logarithmic, centered around the mean) is controlled for (second model, Table C2.3). The attribute's interaction with the income covariate is positive significant, indicating that respondents from richer-than-average households are more willing to protect pregnant women.

Finally, the protection attribute's interaction with the km-construction variable is not always significant (Tables C2.1, C2.2 and C2.4). The significance in these cases becomes conditional on

Table 8: Correlates of Number of Prevention Measures

	(1)		(2)		(3)	
	Respondent Characateristics		Malaria Knowledge		Malaria Experience	
HH Income (log)	0.599***	(7.14)	0.639***	(7.66)	0.619***	(7.39)
Age	-0.00448	(-0.92)	-0.00351	(-0.73)	-0.00547	(-1.12)
Male	-0.374***	(-3.12)	-0.279**	(-2.34)	-0.354***	(-2.95)
Married	0.359**	(2.30)	0.348**	(2.30)	0.338**	(2.24)
Has Child(ren)	0.178	(1.10)	0.201	(1.28)	0.200	(1.28)
No Schooling	-0.0867	(-0.48)	-0.287	(-1.60)	-0.252	(-1.35)
Finished 10th Grade	0.315**	(2.17)	0.319**	(2.23)	0.309**	(2.19)
Finished University	-0.223	(-1.40)	-0.231	(-1.46)	-0.229	(-1.44)
Malaria Seasonality Score			0.309*	(1.84)	0.349**	(2.09)
Mosquito Breeding Score			-1.031***	(-5.74)	-1.112***	(-6.22)
Malaria Symptoms Score			1.666***	(5.05)	1.689***	(5.12)
Malaria Transmission Score			0.585***	(2.62)	0.595***	(2.62)
Had Malaria					0.361***	(3.30)
HH Had Malaria					0.238**	(2.18)
Within 1-km of Construction					0.207*	(1.75)
Constant	-3.080***	(-3.83)	-4.666***	(-4.89)	-4.724***	(-4.94)
Observations	1411		1411		1411	
Adjusted R^2	0.055		0.099		0.109	

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

the stated subjective risk of the respondent. This shows that the MWTP for protection increases in the face of heightened malaria risk, but is also influenced by stated individual likelihood of getting malaria. Thus, the positive MWTP for protection is a robust result.

Overall, we find that MWTP across many attributes increase in the face of heightened malaria risk. MWTP for children increases by 26.0% (between 22.6% - 27.7% in all regressions) compared to adults. For pregnant women, a significant effect is found only when household income or regional fixed effects are controlled for. Thus, it is not a robust result by itself. An extra percentage of malaria protection increases by 10.6% (between 7.1% - 15.5% in all regressions) in value. Respondents expressed a higher preference for protection than duration in the face of higher malaria risk. This is reflected in the 36.7% (between 25.0% - 54.8% in all regressions) decrease in MWTP for duration.

5 Conclusion and Discussion

In conclusion, we find some significant changes in MWTP for certain attributes of malaria prevention in the face of heightened risk exposure. People living in risky areas are willing to spend more on malaria protection and preventing children from becoming sick, compared to others living in less-risky areas. They are also less concerned about how long they are protected for, hence willing to pay less for the duration of the hypothetical prevention pills. These findings come after controlling for observable factors in subjective malaria risk mitigation. Individual random effects across each attribute, except for price, are also taken into account. Robustness checks are run, controlling for experience and knowledge of malaria, location fixed effects, and selected socio-demographic variables. In controlling for malaria experience, we find that respondents who have had malaria before have over 15% higher WTP than others. We call this difference a unfamiliarity premium.

The likelihood of getting malaria is taken to be five times larger in risky areas than in less-risky areas (Stoler *et al.*, 2009). Considering that about 1% of the population of Mumbai had malaria at the peak of the last outbreak (Porecha, 2015), one can guesstimate the probabilities of becoming ill in risky and less-risky areas. Assuming equal populations in both areas, residents face 0.33%

chance in less-risky and 1.67% chance in risky areas of getting malaria. Thus, the changes in MWTP discussed in this paper are regarding a 1.33% rise in the likelihood of getting malaria.

Given our results a 1% increase in malaria risk leads to respondents willing to pay an extra, on average:

- Around 2 USD for full personal protection (i.e. pill with 100% protection)[6]
- 4.36 USD to protect children, as opposed to adults (i.e. pill for children)
- 0.4 USD less for six weeks of protection (i.e. pill that lasts for six weeks)

No robust MWTP increases/decreases are found for protecting pregnant women and babies against malaria. This is a particular result, as these groups are highly vulnerable to malaria, especially pregnant women in unstable transmission areas (Newman *et al.*, 2003; Barcus *et al.*, 2007). While a 1% increase in malaria risk leads to a jump of ₹288 to protect children, the average respondent still prefers to protect adults than children. We find almost no evidence of others regarding preferences.

Our survey design allows a test for hedonic adaptation, by testing for WTP differences between malaria-naive and malaria-experienced respondents. Hedonic adaptation dictates that malaria-naive respondents would have a higher WTP. We find the opposite, which we hypothesize is due to duration knowledge. We call the difference in WTP, at more than 15%, between naive and experienced respondents as a familiarity premium. However, we did not survey the respondents knowledge about the duration of malaria episodes. Future surveys should include that.

Since this is the first DCE to measure malaria valuation, it is not clear how the usage of hypothetical pills affects our results. A lack of other-regarding preferences could have arisen because pills are usually for personal consumption. Had the choice cards been framed for the household (e.g. mosquito-proofing the house, insecticide treated bed-nets etc.) then there might have been different results regarding MWTP for others. This requires further research.

Further research is also needed on time preferences and how these can affect the valuation of new diseases emerging in the future. Any effective policy to mitigate climate change and its impact of infectious diseases such as malaria must be adopted in the present. Research carried out in this area will help policymakers to understand the potential benefits of such policies.

For now, it is clear that the results presented here put an upward pressure on the social cost of carbon. We have seen that WTP to prevent malaria is positively correlated to overall risk and occurrence. Climate change scenarios show both these parameters increasing in regions with little to no experience of prior malaria (Peterson, 2009), making the cost of mitigation/adaptation policies easier to justify.

Acknowledgments

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[6] At the time of the survey, 1 Euro = ₹75 and 1 USD = ₹66

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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.

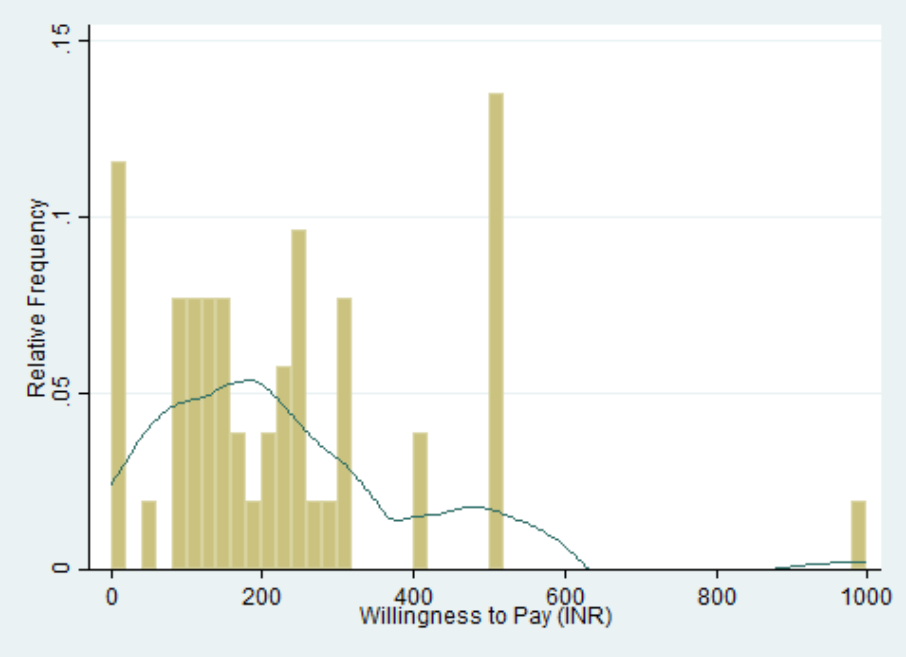
The sample size is 54. No anchoring effects are found, however many respondents ended up answering the open-ended question. This was due to keeping the upper bound of the bidding game too low. A histogram of the resulting WTP can be found in Figure 4. This WTP has quartiles of 105, 195, 300 and 1000 INR[7]. 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.

A.2 Second Pilot Survey - DCE

The first DCE (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.

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

Figure 4: Histogram and Fitted Kernel Density of Bidding Game WTP



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 DCE. Hence, within the same survey there are two alternative DCEs - one for pregnant women and the other for non-pregnant adults. Also, for each DCE, 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 DCE 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 DCE.

The random priors for the final DCE 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 DCE 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 Robustness Check Tables

C.1 Area Fixed Effects

Table C1.1: Area Fixed Effects: Others-Regarding Preferences

	Model 1	Model 2	Model 3	Model 4
	Baseline	Pregnant	Baby	Child
Price	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)
ASC	−1.291*** (0.144)	−1.387*** (0.145)	−1.295*** (0.145)	−1.379*** (0.144)
Pregnant	−11.358*** (0.641)	−11.536*** (0.631)	−11.364*** (0.639)	−11.859*** (0.638)
Baby	−15.324*** (1.006)	−16.238*** (1.050)	−15.284*** (1.032)	−16.163*** (1.045)
Child	−5.913*** (0.403)	−6.147*** (0.409)	−5.930*** (0.404)	−6.021*** (0.394)
Protection	0.066*** (0.004)	0.068*** (0.004)	0.066*** (0.004)	0.068*** (0.004)
Protection x Own-Risk	0.015 (0.009)	0.017* (0.010)	0.016* (0.009)	0.019** (0.010)
Duration	0.049*** (0.007)	0.044*** (0.007)	0.048*** (0.007)	0.043*** (0.007)
Km-Construction:				
Pregnant	0.015 (0.288)	1.107** (0.520)	−0.006 (0.289)	0.215 (0.293)
Baby	0.567* (0.320)	0.291 (0.323)	0.580 (0.486)	0.345 (0.323)
Child	1.536*** (0.285)	1.606*** (0.292)	1.539*** (0.287)	1.372*** (0.442)
Protection	0.007** (0.003)	0.009** (0.003)	0.007** (0.003)	0.008** (0.003)
Protection x Own-Risk	0.010 (0.008)	0.005 (0.008)	0.013 (0.008)	0.005 (0.008)
Duration	−0.018** (0.007)	−0.016** (0.007)	−0.018*** (0.007)	−0.017** (0.007)
Prevention Measures:				
Pregnant	1.196*** (0.079)	1.254*** (0.083)	1.196*** (0.079)	1.322*** (0.081)
Baby	0.830*** (0.078)	0.849*** (0.081)	0.823*** (0.085)	0.851*** (0.081)
Child	0.278*** (0.050)	0.257*** (0.050)	0.275*** (0.050)	0.272*** (0.053)
Protection	−0.002*** (0.001)	−0.003*** (0.001)	−0.002*** (0.001)	−0.003*** (0.001)
Protection x Own-Risk	0.009*** (0.002)	0.010*** (0.002)	0.008*** (0.002)	0.010*** (0.002)
Duration	0.0004 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
Observations	8,400	8,400	8,400	8,400
AIC	10454.89	10408.72	10462.01	10423.63
Pseudo R-squared	0.502	0.504	0.502	0.504

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

Table C1.2: Area Fixed Effects: Own Preferences

	Model 1	Model 2	Model 3	Model 4
	Baseline	ASC	Protection	Duration
Price	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)
ASC	−1.291*** (0.144)	−1.491*** (0.190)	−1.280*** (0.145)	−1.379*** (0.144)
Pregnant	−11.358*** (0.641)	−11.495*** (0.608)	−11.360*** (0.639)	−11.726*** (0.631)
Baby	−15.324*** (1.006)	−15.534*** (0.986)	−15.109*** (0.989)	−16.252*** (1.047)
Child	−5.913*** (0.403)	−5.999*** (0.398)	−5.904*** (0.403)	−6.057*** (0.397)
Protection	0.066*** (0.004)	0.068*** (0.004)	0.067*** (0.004)	0.067*** (0.004)
Protection x Own-Risk	0.015 (0.009)	0.018* (0.010)	0.018* (0.010)	0.019* (0.010)
Duration	0.049*** (0.007)	0.046*** (0.007)	0.049*** (0.007)	0.044*** (0.007)
Km-Construction:				
Pregnant	0.015 (0.288)	0.052 (0.289)	0.039 (0.288)	0.190 (0.293)
Baby	0.567* (0.320)	0.560* (0.325)	0.627* (0.321)	0.320 (0.323)
Child	1.536*** (0.285)	1.491*** (0.286)	1.526*** (0.286)	1.618*** (0.291)
Protection	0.007** (0.003)	0.006* (0.004)	−0.003 (0.004)	0.008** (0.003)
Protection x Own-Risk	0.010 (0.008)	0.013 (0.008)	0.011 (0.008)	0.008 (0.008)
Duration	−0.018** (0.007)	−0.015** (0.007)	−0.018*** (0.007)	−0.022** (0.011)
Prevention Measures:				
Pregnant	1.196*** (0.079)	1.258*** (0.079)	1.217*** (0.080)	1.298*** (0.080)
Baby	0.830*** (0.078)	0.776*** (0.078)	0.828*** (0.078)	0.864*** (0.081)
Child	0.278*** (0.050)	0.284*** (0.050)	0.281*** (0.050)	0.247*** (0.049)
Protection	−0.002*** (0.001)	−0.002*** (0.001)	−0.002*** (0.001)	−0.003*** (0.001)
Protection x Own-Risk	0.009*** (0.002)	0.008*** (0.002)	0.008*** (0.002)	0.010*** (0.002)
Duration	0.0004 (0.002)	0.001 (0.002)	0.0003 (0.002)	0.001 (0.002)
Observations	8,400	8,400	8,400	8,400
AIC	10454.89	10429.79	10455.20	10435.06
Pseudo R-squared	0.502	0.503	0.502	0.503

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

C.2 Socio-Demographics

Table C2.1: Impact of Malaria General Knowledge

	Model 1	Model 2	Model 3
	Baseline	Transmission Method	Symptoms
Price	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)
ASC	−1.291*** (0.144)	−1.502*** (0.146)	−1.335*** (0.145)
Pregnant	−11.358*** (0.641)	−9.686*** (0.657)	−11.109*** (0.749)
Baby	−15.324*** (1.006)	−17.782*** (1.168)	−17.701*** (1.150)
Child	−5.913*** (0.403)	−6.293*** (0.549)	−6.323*** (0.620)
Protection	0.066*** (0.004)	0.056*** (0.006)	0.099*** (0.008)
Protection x Own-Risk	0.015 (0.009)	−0.018 (0.014)	0.028 (0.018)
Duration	0.049*** (0.007)	0.041*** (0.013)	0.084*** (0.015)
Km-Construction:			
Pregnant	0.015 (0.288)	0.201 (0.294)	0.359 (0.304)
Baby	0.567* (0.320)	0.498 (0.334)	0.623* (0.324)
Child	1.536*** (0.285)	1.523*** (0.291)	1.560*** (0.290)
Protection	0.007** (0.003)	0.005 (0.003)	0.007* (0.003)
Protection x Own-Risk	0.010 (0.008)	0.014* (0.009)	0.007 (0.008)
Duration	−0.018** (0.007)	−0.016** (0.007)	−0.021*** (0.007)
Prevention Measures:			
Pregnant	1.196*** (0.079)	1.336*** (0.082)	1.269*** (0.081)
Baby	0.830*** (0.078)	0.767*** (0.080)	0.786*** (0.071)
Child	0.278*** (0.050)	0.281*** (0.051)	0.267*** (0.051)
Protection	−0.002*** (0.001)	−0.003*** (0.001)	−0.002** (0.001)
Protection x Own-Risk	0.009*** (0.002)	0.008*** (0.002)	0.008*** (0.002)
Duration	0.0004 (0.002)	0.001 (0.002)	0.001 (0.002)
Malaria Transmission Knowledge:			
Pregnant		−3.157*** (0.583)	
Baby		1.914*** (0.555)	
Child		0.250 (0.492)	
Protection		0.018** (0.007)	
Protection x Own-Risk		0.049*** (0.017)	
Duration		0.007 (0.014)	
Malaria Symptoms Knowledge:			
Pregnant			−0.581 (0.769)
Baby			3.468*** (0.838)
Child			0.369 (0.723)
Protection			−0.045*** (0.009)
Protection x Own-Risk			−0.025 (0.023)
Duration			−0.050*** (0.018)
Observations	8,400	8,400	8,400
AIC	10454.89	10410.61	10424.73
Pseudo R-squared	0.502	0.504	0.504

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

Table C2.2: Impact of Education

	Model 1	Model 2	Model 3
	Baseline	No Schooling	Completed 10th Grade
Price	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)
ASC	−1.291*** (0.144)	−1.461*** (0.144)	−1.418*** (0.143)
Pregnant	−11.358*** (0.641)	−11.326*** (0.606)	−11.345*** (0.645)
Baby	−15.324*** (1.006)	−15.053*** (0.979)	−15.241*** (0.960)
Child	−5.913*** (0.403)	−5.879*** (0.398)	−6.327*** (0.420)
Protection	0.066*** (0.004)	0.071*** (0.004)	0.066*** (0.004)
Protection x Own-Risk	0.015 (0.009)	0.015 (0.010)	0.017* (0.010)
Duration	0.049*** (0.007)	0.057*** (0.008)	0.042*** (0.008)
Km-Construction:			
Pregnant	0.015 (0.288)	−0.104 (0.292)	0.232 (0.294)
Baby	0.567* (0.320)	0.402 (0.329)	0.365 (0.322)
Child	1.536*** (0.285)	1.389*** (0.297)	1.431*** (0.294)
Protection	0.007** (0.003)	0.003 (0.004)	0.009** (0.004)
Protection x Own-Risk	0.010 (0.008)	0.017** (0.009)	0.006 (0.008)
Duration	−0.018** (0.007)	−0.024*** (0.007)	−0.023*** (0.007)
Prevention Measures:			
Pregnant	1.196*** (0.079)	1.256*** (0.081)	1.326*** (0.082)
Baby	0.830*** (0.078)	0.751*** (0.078)	0.841*** (0.077)
Child	0.278*** (0.050)	0.290*** (0.050)	0.234*** (0.050)
Protection	−0.002*** (0.001)	−0.003*** (0.001)	−0.003*** (0.001)
Protection x Own-Risk	0.009*** (0.002)	0.008*** (0.002)	0.009*** (0.002)
Duration	0.0004 (0.002)	0.001 (0.002)	0.00002 (0.002)
No Schooling:			
Pregnant		−1.127** (0.550)	
Baby		−1.728*** (0.534)	
Child		−0.879 (0.752)	
Protection		−0.009* (0.006)	
Protection x Own-Risk		−0.005 (0.019)	
Duration		−0.053*** (0.012)	
Completed 10th Grade:			
Pregnant			−0.827*** (0.294)
Baby			−0.087 (0.311)
Child			0.755*** (0.275)
Protection			0.003 (0.003)
Protection x Own-Risk			0.006 (0.008)
Duration			0.016** (0.007)
Observations	8,400	8,400	8,400
AIC	10454.89	10406.65	10435.93
Pseudo R-squared	0.502	0.504	0.503

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

Table C2.3: Impact of Household Income and Having Child(ren)

	Model 1	Model 2	Model 3
	Baseline	Household Income	Having Child(ren)
Price	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)
ASC	−1.291*** (0.144)	−1.454*** (0.146)	−1.303*** (0.145)
Pregnant	−11.358*** (0.641)	−10.886*** (0.577)	−11.600*** (0.653)
Baby	−15.324*** (1.006)	−16.249*** (1.056)	−15.019*** (1.025)
Child	−5.913*** (0.403)	−5.917*** (0.397)	−6.223*** (0.449)
Protection	0.066*** (0.004)	0.067*** (0.004)	0.069*** (0.005)
Protection x Own-Risk	0.015 (0.009)	0.018* (0.010)	0.012 (0.012)
Duration	0.049*** (0.007)	0.045*** (0.007)	0.072*** (0.009)
Km-Construction:			
Pregnant	0.015 (0.288)	−0.550* (0.296)	0.022 (0.293)
Baby	0.567* (0.320)	0.156 (0.333)	0.362 (0.322)
Child	1.536*** (0.285)	1.454*** (0.288)	1.564*** (0.287)
Protection	0.007** (0.003)	0.007* (0.004)	0.007** (0.003)
Protection x Own-Risk	0.010 (0.008)	0.012 (0.008)	0.009 (0.008)
Duration	−0.018** (0.007)	−0.015** (0.007)	−0.022*** (0.007)
Prevention Measures:			
Pregnant	1.196*** (0.079)	1.195*** (0.078)	1.202*** (0.079)
Baby	0.830*** (0.078)	0.735*** (0.078)	0.817*** (0.079)
Child	0.278*** (0.050)	0.276*** (0.050)	0.291*** (0.051)
Protection	−0.002*** (0.001)	−0.002*** (0.001)	−0.002*** (0.001)
Protection x Own-Risk	0.009*** (0.002)	0.008*** (0.002)	0.009*** (0.002)
Duration	0.0004 (0.002)	0.001 (0.002)	0.0002 (0.002)
Log Household Income			
Pregnant		1.625*** (0.175)	
Baby		1.339*** (0.196)	
Child		0.269* (0.164)	
Protection		−0.004* (0.002)	
Protection x Own-Risk		0.0001 (0.005)	
Duration		−0.002 (0.004)	
Having Child(ren):			
Pregnant			0.255 (0.276)
Baby			−1.047*** (0.302)
Child			0.349 (0.239)
Protection			−0.003 (0.003)
Protection x Own-Risk			0.006 (0.008)
Duration			−0.032*** (0.007)
Observations	8,400	8,400	8,400
AIC	10454.89	10390.82	10444.25
Pseudo R-squared	0.502	0.505	0.503

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

Table C2.4: Impact of Respondent Characateristics

	Model 1	Model 2	Model 3
	Baseline	Married	Male
Price	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.004*** (0.0002)
ASC	−1.291*** (0.144)	−1.424*** (0.143)	−1.470*** (0.145)
Pregnant	−11.358*** (0.641)	−11.708*** (0.630)	−11.329*** (0.617)
Baby	−15.324*** (1.006)	−15.482*** (0.984)	−15.027*** (0.946)
Child	−5.913*** (0.403)	−5.938*** (0.394)	−6.043*** (0.403)
Protection	0.066*** (0.004)	0.064*** (0.004)	0.064*** (0.004)
Protection x Own-Risk	0.015 (0.009)	0.013 (0.010)	0.008 (0.010)
Duration	0.049*** (0.007)	0.045*** (0.007)	0.043*** (0.007)
Km-Construction:			
Pregnant	0.015 (0.288)	0.203 (0.309)	0.288 (0.299)
Baby	0.567* (0.320)	0.359 (0.323)	0.723** (0.336)
Child	1.536*** (0.285)	1.645*** (0.291)	1.490*** (0.295)
Protection	0.007** (0.003)	0.007** (0.004)	0.004 (0.004)
Protection x Own-Risk	0.010 (0.008)	0.006 (0.008)	0.014* (0.008)
Duration	−0.018** (0.007)	−0.020*** (0.007)	−0.017** (0.007)
Prevention Measures:			
Pregnant	1.196*** (0.079)	1.282*** (0.079)	1.259*** (0.081)
Baby	0.830*** (0.078)	0.834*** (0.077)	0.790*** (0.078)
Child	0.278*** (0.050)	0.260*** (0.051)	0.279*** (0.050)
Protection	−0.002*** (0.001)	−0.003*** (0.001)	−0.002*** (0.001)
Protection x Own-Risk	0.009*** (0.002)	0.009*** (0.002)	0.008*** (0.002)
Duration	0.0004 (0.002)	0.0004 (0.002)	0.001 (0.002)
Married:			
Pregnant		−0.179 (0.305)	
Baby		0.371 (0.329)	
Child		−0.399 (0.257)	
Protection		0.014*** (0.003)	
Protection x Own-Risk		0.006 (0.008)	
Duration		0.010 (0.007)	
Male:			
Pregnant			−1.306*** (0.300)
Baby			−0.871*** (0.315)
Child			0.012 (0.235)
Protection			0.013*** (0.003)
Protection x Own-Risk			0.016** (0.008)
Duration			0.005 (0.006)
Observations	8,400	8,400	8,400
AIC	10454.89	10431.58	10408.02
Pseudo R-squared	0.502	0.503	0.504

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