Seventh Framework Programme

Theme 6

Environment

Project: 603864 – HELIX

Full project title:

High-**E**nd c**L**imate **I**mpacts and e**X**tremes

Deliverable: 5.3

Global assessment of impacts on human health

Version 1.0

Original Due date of deliverable: 31/04/17

Actual date of submission: 31/07/17

Global Assessment of Impacts on Human Health

July

2017

1 Executive Summary

The socio-economic impacts of changing risks to human health, due to climate change, are presented. Climate change is projected to bring about heightened prevalence in many vector and water borne diseases. Many of these diseases are expected to appear in regions where they have been long eradicated or never experienced before. Designing policies to mitigate or adapt to these scenarios requires calibrating the monetized impacts. Multiple economic impact assessment models exist in order to calculate, amongst others, this figure – known commonly as the social cost of carbon. The monetary impacts of diseases are used as inputs into these impact assessment models. They are estimates of populations' willingness to pay to avoid morbidity and mortality. In their current form, none of the models take into account the added impact of these diseases being experienced for the first time.

To this end FUND, an impact assessment model, is re-run with updated disease valuation (willingness to pay) figures. Since obtaining disease valuation requires doing surveys, only one disease was chosen as a case study – malaria. The willingness to pay to avoid malaria, in a setting where it is non-endemic but present (Mumbai, India), was estimated. The difference in willingness to pay between malaria naïve and non-naïve groups was measured and used in the re-run of FUND. It should be noted that other parameters in the FUND model were updated as per the literature. Hence, this deliverable is made up of two parts. Part A is the resulting study from measuring malaria valuation in Mumbai, India. Part B is the resulting study from the re-run of the FUND model.

Part A: Malaria naïve populations have just above 15% higher willingness to pay to avoid the disease than non-naïve populations, indicating an "unfamiliarity premium".

Part B: Including this unfamiliarity premium, amongst other parameter updates, leads to the social cost of carbon barely bulge. The previous model calculated a social cost of carbon of $24.03/tC, while the new model gives an output of $23.52/tC. This is slight dip is largely due to the decrease in malaria prevalence observed worldwide since the previous calibration of the model.

This result is the outcome of two opposing effects on the social cost of carbon: the positive impact of the unfamiliarity premium and the negative impact of less-than-previously thought number of malaria cases in recent year. The fact that these effects almost cancel each other out show that the prospect of an increase in malaria prevalence due to climate change is enough, in valuation terms, to offset the gains made towards eradication of the disease.

Moreover, the existence of a positive unfamiliarity premium for one disease suggests that similar premiums exist for other climate change sensitive diseases. Thus the final social cost of carbon presented in this deliverable is (still) relatively conservative.

Part A: NEW MALARIA RISK AND VALUATION

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

[1]*Institute for Environmental Studies, Vrije Universiteit, Amsterdam, The Netherlands*

[2]*Tinbergen Institute, Amsterdam, The Netherlands*

[3]*Department of Economics, University of Waterloo, Canada*

[4]*Department of Economics, University of Sussex, Jubilee Building, Falmer, BN1 9SL, UK, r.tol@sussex.ac.uk*

[5]*Department of Spatial Economics, Vrije Universiteit, Amsterdam, The Netherlands*

[6]*CESifo, Munich, Germany*

Abstract

After years of decline, malaria prevalence may increase in the future due to climate change, especially in areas that have not experienced the disease. 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 to avoid malaria). 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-naive and experienced respondents. This indicates an unfamiliarity premium for populations unaccustomed to malaria, but at risk of outbreaks. These findings indicate substantially higher returns to climate change mitigation policies than previously thought.

1.1 Introduction

Since 2000, the world has seen a general decline in the rate of malaria transmission. Through benchmarks, such as the Millennium Development Goals, and programs, such as Roll Back Malaria (RBM), mortality rates dropped by 42 percent between 2000 and 2012. 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). This implies that the risk of malaria transmission may increase due to climate change in certain regions (Patz, et al., 2002; McMichael, Woodruff, & Hales, 2006; IPCC, 2014)

Said regions have little to no recent experience with the disease. Any policy to prevent/mitigate this increase in prevalence requires the monetary benefits of avoiding malaria be measured. These monetary benefits, measured as willingness to pay (WTP), have been extensively measured and researched. However, no studies have considered WTP when malaria risk increases (Trapero-Bertran, Mistry, Shen, & Fox-Rushby, 2012; Kutluay, Brouwer, & Tol, 2015). Equally important, in the climate change context, is finding out the difference in WTP between those who have and have not experienced malaria.

There is clearly a premium for avoiding malaria, especially when it is a new disease (as opposed to being endemic). We look at what happens to WTP between 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 terms of malaria risk. Mumbai is a relatively malaria-free city, but is subject to sporadic outbreaks of malaria. This is from construction booms. Construction sites tend to become suitable environments for mosquito

breeding and, thus, the spreading of malaria. People living within one kilometer of a construction site are at more risk of getting malaria than others (Stoler, Weeks, Getis, & Hill, 2009). We look at the WTP differences between these two groups.

A DCE allows one to break the total WTP for malaria prevention down into several attributes. Making use of this, we look at multiple attributes of WTP for malaria prevention. These are valuation for others(pregnant women, 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 others-regarding preferences for policy design purposes.

WTP is a theoretical construct, deriving from health state dependent utility theory (Viscusi & Evans, 1990). 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 heightened malaria risk.

This paper continues as follows: section 2 reviews the existing literature on valuation and DCE, section 3 outlines the theoretical and empirical models used, section 4 gives details about the data collected, section 5 presents descriptive and inferential results and section 6 provides the conclusions and discussion.

1.2 Literature Review

DCEs have been used extensively since the late 1990s in health economics. 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 (de Bekker-Grob, Ryan, & Gerard, 2012). As DCEs have become a widely-accepted tool for measuring stated preferences, guidelines have emerged about using them in developing country contexts (Mangham, Hanson, & McPake, 2009).

Despite their popularity, DCEs have not been used to measure malaria valuation, although some papers have come close. Hanson et al (2005) looks at what attributes people find important regarding hospital care for childhood disease and cranial malaria. More recently, Lagarde (2013) investigates how much healthcare workers would like, in pay raises, to implement different malaria management procedures. Both studies, though having the opportunity, did not measure WTP to avoid malaria.

WTP for malaria has been measured through other survey methods. At least 50 published papers have been identified as measuring WTP to prevent/treat malaria from 1993 (Weaver, et al., 1993) onwards. These papers have all used contingent valuation methods. Two meta-analyses summarize the findings of this literature (Trapero-Bertran, Mistry, Shen, & Fox-Rushby, 2012; Kutluay, Brouwer, & Tol, 2015). One of the common aspects of these studies is that they have measured malaria valuation in locations where malaria is endemic. Therefore what happens to malaria valuation when the risk of getting ill increases has not been investigated.

1.3 Modelling Framework

1.3.1 Exogenous and Endogenous Risk

Many environmental and health related risks like malaria can be mitigated, to a certain extent, through individual decisions. Since WTP is a function of the probability of becoming ill, any change on this should be accounted for. \citet{Shogren1991} proposes 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 likewise risks in environmental and health economics (Bateman, 2005; Brouwer, Akter, Brander, & Haque, 2009; Tonin, Alberini, & Turvani, 2009; Khan, Brouwer, & Yang, Household's willingness to pay for arsenic safe drinking water in Bangladesh,

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. This is assuming that everyone has the same likelihood of getting bitten by a mosquito. People who protect themselves against mosquitoes are less likely to get sick than those who don't. This 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 an individual i faces of getting malaria is divided into two components: exogenous (EX_i) and endogenous (EN_i). 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-tolerances (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 in the next section.

1.3.2 Multinomial Logit Specification

To estimate the MWTP values from the DCE data, we utilize 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 for a malaria prevention pill i, from choice set j, chosen by individual n is:

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

Where X_{ij} is a matrix containing attribute levels of choices in each choice set j and subsequent option i, β is a vector of coefficients for each attribute corresponding in X_{ij}. They reflect the sample 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 relevant coefficient vector. These coefficients also reflect sample 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, $-\left(\frac{\delta V_{ijn}}{\delta X_K}\right) \Big/ \left(\frac{\delta V_{ijn}}{\delta X_{Price}}\right)$. If V_{ijn} is a linear function in β and γ, then the MWTP for attribute K is simply $-\beta_K / \beta_{Price}$. Last, but 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 k different than i. Let P_{ijn} denote the probability of this choice occurring. 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, 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.

The second to last step assumes a logit structure, making use of the fact that the ε_{ijn} terms are extreme value and i.i.d. distributed (McFadden, Conditional logit analysis of qualitative choice behavior, 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 and also ignores the panel structure of the dataset, where individuals make choices from multiple choice sets.

To address both these problems, we impose the mixed logit model (McFadden & Train, Mixed MNL Models for Discrete Response, 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:

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

The α vector consists of coefficients from β and σ 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 $\sum_{k \epsilon J} e^{V_{kjn}}$ term (in general), relaxing the IIA assumption. We have also accounted for individual random effects across choices.

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.

1.4 Data

1.4.1 Questionnaire Design

A survey was designed and carried out in Mumbai, India between April and June 2016. The survey consisted of a questionnaire followed by a DCE regarding a hypothetical pill to prevent malaria. The survey targeted the main decision maker of the household, therefore administered to one person per household.

The questionnaire consists of three sections relevant to this paper. The first section contains standard socio-demographic questions about the respondent and the household. The third 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 and their household's experience with malaria. These are followed by questions on perceived severity of their own or other's episodes. If the respondents have no first or secondhand 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 communicative 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 1 shows how these two answers are used to construct the respondent's subjective probability of getting malaria.

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

P is the subjective prevalence of malaria in the locality

No confidence intervals are asked. This is to keep the questions as clear and simple as possible. If p denotes the subjective probability of getting malaria, we use p(1-p) as its variance[1]. This indicates how uncertain respondents are about their subjective baseline risk.

1.4.2 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 found in Table 2.

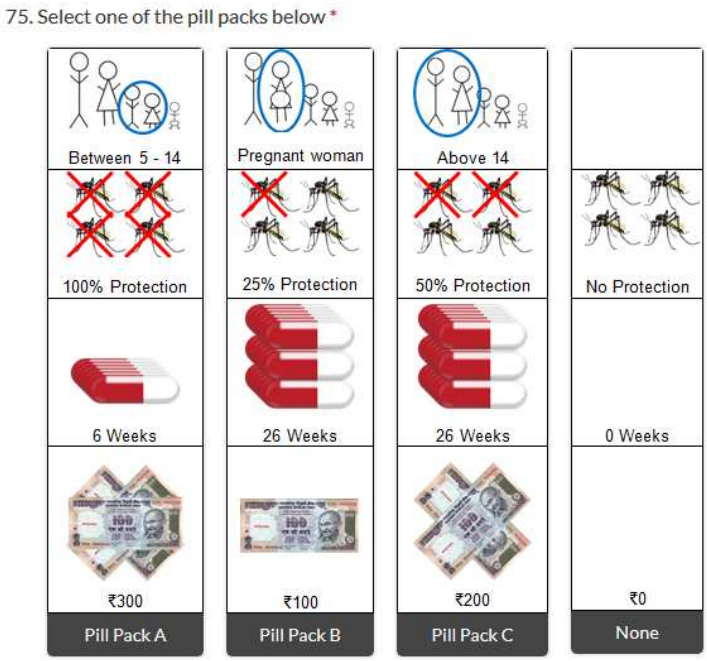
[1] Under the assumption that p is the parameter for the Bernoulli distribution on (not) getting malaria. This means that p(1-p) is the associated variance. See Manski (2004) as an example where a similar measure is utilized

Table 2: 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	100; 200; 300; 500; 750

The levels of the attributes are determined using a D-optimal Bayesian design (Bliemer, Rose, & Hess, 2008). The protection levels are selected in order to be easy to communicate through diagrams (see Figure 1 as an example). 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. Thus we consider above-14's to be adults, from an economic perspective (they can participate in the labor market). Levels for the duration attribute are from real malaria prevention pills. This is in order 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 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, Brouwer, & Tol, 2015). A second pilot survey was used to update the priors in the D-optimal Bayesian design and detect potential faults in the DCE and questionnaire (Mangham, Hanson, & McPake, 2009). 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 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 (e.g. a child under the age of 5), then they are asked 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.

1.4.3 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, a local NGO. The surveyors were trained by the authors of this study and supervised during all survey sessions. 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 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.

1.5 Results

1.5.1 Summary Statistics

Some 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 choose pills for others.

The respondents were chosen from non-slum residential areas of Mumbai, a stricter condition than one might think - more than half of Mumbai's residents are estimated to live in slums (Census, 2011). We have a relatively high number of female respondents, whereas 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 than 40% of respondents have had malaria (with 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 given respondent answered all questions correctly. A detailed description of the scores can be found in the appendix (section \ref{app_scores}). More respondents were better informed about the transmission, source and symptoms of malaria, compared to its seasonality.

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. This explains the higher number of survey areas that are within 1 kilometer of a construction site.

Table 3: Sample Summary Statistics

	Mean	Std Dev	Min	Median	Max
Socio-Demographics:					
Male	.4223955	.4941159	0	0	1
Age	36.79979	14.16249	19.5	29.5	79.5
No Schooling	.0985117	.2981109	0	0	1
Finished 10th Grade	.6286322	.4833418	0	1	1
HH Income	24486.53	20138.87	1000	19750	197500
Has Child(ren)	.6343019	.4817961	0	1	1
Finished University	.1984408	.3989673	0	0	1
Knowledge:					
Malaria Seasonality Score	.5540397	.3383439	0	.5	1
Mosquito Breeding Score	.6526577	.2772938	0	.5	1
Malaria Symptoms Score	.7064848	.1761903	.25	.7	1
Malaria Transmission Score	.7670092	.2307739	0	.75	1
Malaria Risk and Experience:					
No of Prevention Measures	2.88377	2.138293	0	3	9
Within 1-km of Construction	.7002126	.4583272	0	1	1
Had Malaria	.4138909	.492704	0	0	1
HH Had Malaria	.3373494	.4729729	0	0	1
Subjective Malaria Risk (%)	21.66903	25.04345	0	9.5	100
Survey Area (Within 1 km of Construction):					
Khar	.1438696	.3510819	0	0	1
Goregaon	.1389086	.3459737	0	0	1
Byculla	.1169383	.3214607	0	0	1
Worli (Apartment)	.1112686	.314576	0	0	1
Wadala	.0985117	.2981109	0	0	1
Worli	.0708717	.2567014	0	0	1
Wadala (Apartment)	.0198441	.1395138	0	0	1
Survey Area (Outside 1 km of Construction):					
Kanjur Marg	.2572644	.4372813	0	0	1
Goregaon (Outskirts)	.0283487	.1660258	0	0	1
Govandi	.0141743	.1182512	0	0	1
Observations	1411				

Given 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 non-risky areas. However the average number of prevention measures used in households in risky areas is 3.01 while for non-risky areas this is 2.58. The difference is significant (Rank-sum test p-value = 0.025). Even if one relaxes the assumption that number of prevention measures is continuous, evidence is against random dispersion of prevention measures across risky and non-risky areas (chi-squared test p-value is below software\footnote{Stata 14 is used for descriptive and initial inferential statistics} precision).

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 2/5th of the latter can be classified as constituting 0 WTP, while the rest was mainly due to respondents finding the prices too high and claiming other methods used for malaria protection. There were no protest responses. Of the pills respondents could have chosen for others (babies, children and pregnant women), most opted to choose for themselves. When respondents chose pills for others, pregnant women and babies were the least chosen, even though they experience malaria more severely.

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

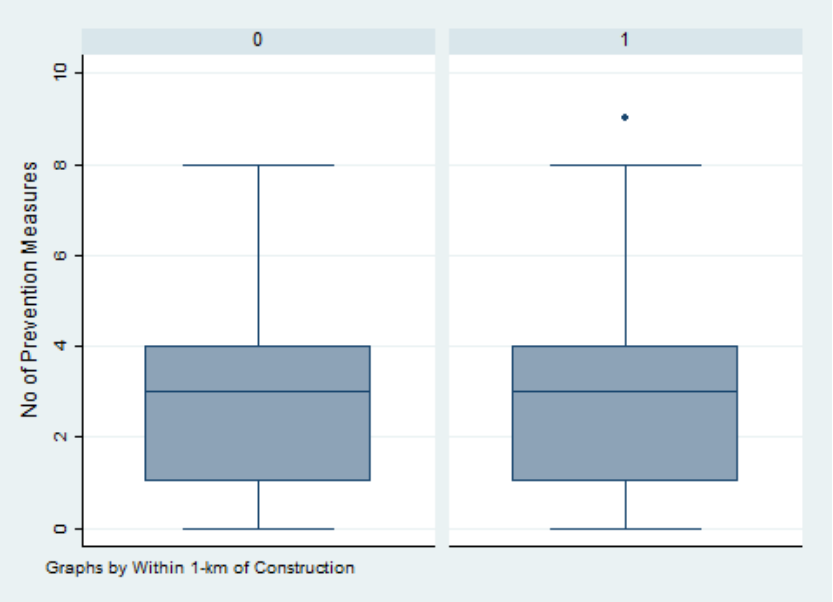


Table 4: Choice Summary Statistics

	Mean	Std. Dev.	Min	Median	Max
Always Opt-Out	12.69%	.3328214	0	0	1
Opt-Out	24.20%	.2384268	0	0	1
Opt-Out: Malaria is Not a Concern	10.90%	.1628311	0	0	1
Opt-Out: Prices are too High	8.63%	.1453307	0	0	1
Opt-Out: Not Interested in Prevention Pills	0.07%	.0133099	0	0	1
Opt-Out: Use Other Protection Methods	4.44%	.1047868	0	0	1
Pills for Others: Pregnant Women	4.93%	.1102846	0	0	1
Pills for Others: Babies	2.24%	.0746951	0	0	1
Pills for Others: Children	3.45%	.0924588	0	0	1
Observations	33864				

1.5.2 Main Regression Results

Following the framework provided in Section 3, relationships between the MWTP for malaria prevention and exogenous/endogenous risk are explored. This can be found in column 3 of Table 5. In order to give a simple overview of which attributes respondents found appealing and unappealing, we build up to the model output in column 3.

The attribute-only estimation and inclusion of exogenous risk are given in columns 1 and 2, respectively. Malaria risk mitigation behavior is included in model 3. The attribute-only variables, except for price, have random parameters, distributed over respondents. Dummy variables are assumed uniform and continuous variables are assumed normally distributed (Hensher, Rose, & Greene, 2005). When respondent-specific covariates are introduced to the model, they are included as fixed parameters.

The alternative specific constant (ASC) variable takes the value 1 if the respondent did not opt out. For estimation to be possible, we select "adult" as the reference category for the suitability 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, Weeks, Getis, & Hill, 2009).

Table 5: Forming the Baseline

	Dependent variable:		
	Pill Choice		
	multinomial logistic		
	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
Log Likelihood	-5,337.621	-5,311.077	-5,200.445
Note:			*p<0.1; **p<0.05; ***p<0.01

The negative ASC coefficient, found in all specifications, indicates that when all other attribute levels are at zero, then the average respondent chooses to opt out. This is hardly surprising. However, when the protection attribute reaches its minimum level (refer to Table 2), the resulting positive impact on the utility function outweighs the negative impact of the ASC term.

The results show a general tendency to be selfish when malaria risk is not controlled for. This is inferred from a combination of relatively negative MWTP for attributes affecting others (pregnant, baby, child) and positive MWTP for attributes affecting one's self (protection, duration) in model 1 of Table 5. When we account for living in higher-risk areas, as in model 2, this selfish behavior gets dampened. MWTP for others increases if the respondents live in these areas. However, 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. When endogenous risk mitigation is accounted for, as in model 3, MWTP for protection increases for people living 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 using.

People in risky areas have higher MWTP for babies (+3.70%), children (+25.98%) and protection (+10.61%) than those in non-risky areas. They care less about how long they have malaria protection for (-36.73%). MWTP for women seems to be no different between the two areas. These constitute our main results.

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

1.5.2.1 Malaria Risk: Experience and Knowledge

While living close to a construction site may increase the value people put on avoiding malaria, this could be driven by respondents' prior experience with the disease. Since people living close to construction sites are more likely to have experienced malaria, firsthand or secondhand, this could be driving the increase in MWTP evident in Table 5.

Firsthand and secondhand (defined as someone in the household having had malaria) are controlled for in Table 6. The main results do not change, except for MWTP for babies. When secondhand malaria experience is accounted for, the babies and km-construction coefficient is no longer significant. This indicates that secondhand malaria experience most likely positively correlates with preferences to protect babies. If so, this impact is diffused between the km-construction and secondhand malaria interactions, as both coefficients are non-significant.

Having first or secondhand 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 can be considered as a malaria unfamiliarity premium.

Table 6: Impact of First/Secondhand Malaria

	Dependent variable:		
	Pill Choice		
	multinomial logistic		
	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
Log Likelihood	-5,200.445	-5,194.056	-5,181.794
Note:			*p<0.1; **p<0.05; ***p<0.01

One's malaria risk can be influenced by one's knowledge of malaria, specifically knowledge that can be used to avoid the disease. 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. The outputs are shown in Table 7.

By looking at the prevention and km-construction interaction variables, we see that accounting for malaria knowledge does not discernibly change the perceived effect sizes. However, when controlling for malaria knowledge makes the MWTP for babies in risky areas not different from the ones in non-risky areas. The more one knows, the more they are likely to not buy pills for babies.

Table 7: Impact of Malaria Spread Knowledge

	Dependent variable:		
	Pill Choice		
	multinomial logistic		
	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:			
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:			
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
Log Likelihood	-5,200.445	-5,180.369	-5,189.416
Note:			*p<0.1; **p<0.05; ***p<0.01

1.5.2.2 Location Fixed Effects

Mumbai is a relatively segregated city at the neighborhood level, thus there might be neighborhood-specific impacts on respondents decisions in selecting pills. All the attribute coefficients are interacted with survey region dummies. Tables 8 and 9 contain the mixed logit outputs. Figure 3 depicts the impact of region fixed effects across attributes. Survey areas that were away from construction sites are taken as the reference group.

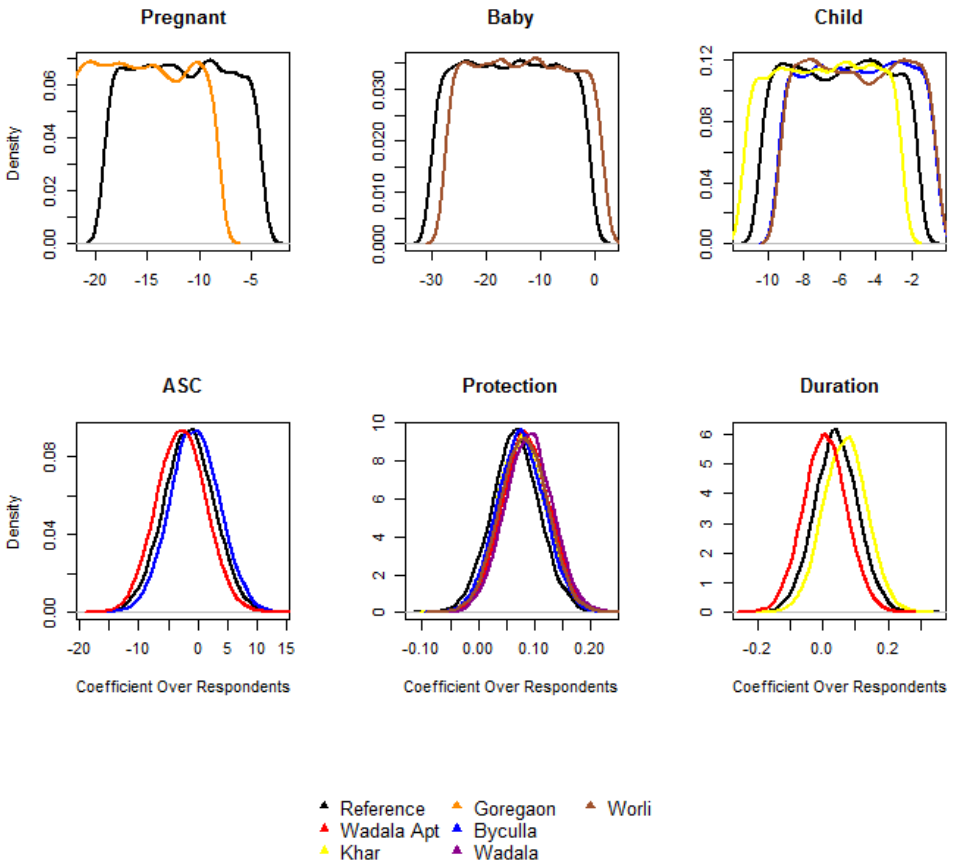
Seen in Figure 3, there are not many differences across regions. Tables 8 and 9, on the other hand, show that the main results were subject to change. The km-construction and pregnant coefficient becomes positive significant when area fixed effects are accounted for, with an effect size just under +10%. 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 model 3 of Table 9, the protection and km-construction interaction variable is non-significant. However, as can be seen in Figure 3, the protection attribute's interaction with the survey area dummy variables is positive. Thus, it is clear that living in risky areas leads to an increase in demand for malaria protection. 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.

While people's approach to the protection attribute changes with respect to their subjective malaria risk across survey locations, accounting for this does not alter the main results.

Figure 3:Area Fixed Effects Across Attributes



1.5.2.3 Correlates of Risk Mitigation

Characteristics driving the number of prevention measures a household has may be driving the main results. A household's decision on the number of prevention measures to take, in theory, should only depend on the amount of perceived malaria risk they are facing. In practice, the theory may not be able to explain the entirety of the household's consumption decisions, hence we run an OLS model to find correlates. Table 10 displays the output.

Table 8: Area Fixed Effects: Others-Regarding Preferences

	Dependent variable:			
	Pill Choice			
	multinomial logistic			
	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
Log Likelihood	-5,200.445	-5,171.361	-5,198.006	-5,178.815

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

Table 9: Area Fixed Effects: Own Preferences

	Dependent variable:			
	Pill Choice			
	multinomial logistic			
	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
Log Likelihood	-5,200.445	-5,181.894	-5,194.602	-5,184.530

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

Table 10: Correlates of Number of Prevention Measures

	(1) Respondent Characateristics		(2) Malaria Knowledge		(3) 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	
R^2	0.060		0.106		0.118	
Adjusted R^2	0.055		0.099		0.109	

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

As can be seen, many respondent characteristics are significant in explaining the number of prevention measures utilized by the household. Their impact do not diminish when we control for malaria experience and knowledge. The significant covariates in Table 10 are included in the mixed logit model and estimates are obtained. The regression tables can be found in the appendix:

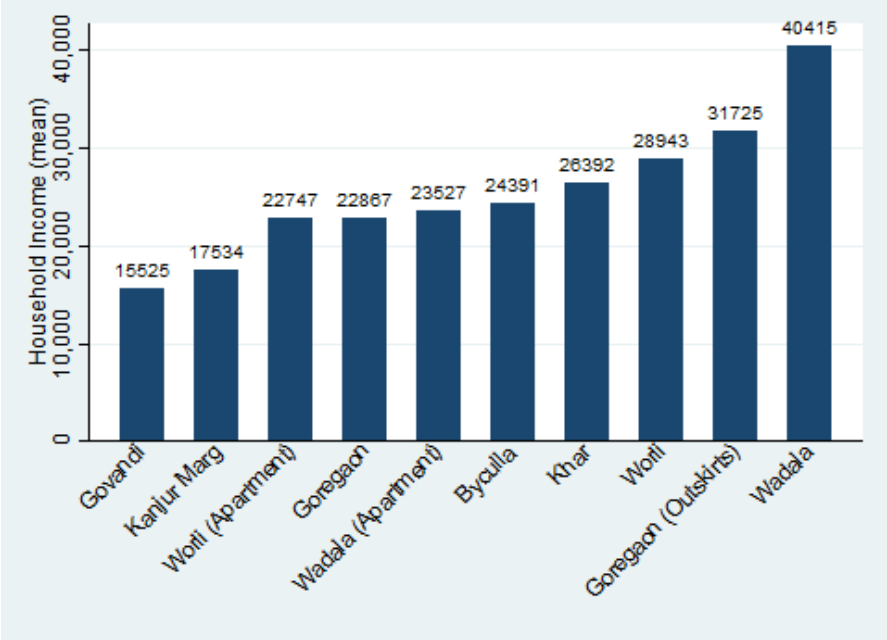
- Malaria general knowledge - Table C1
- Education - Table C2
- Household income and having children - Table C3
- Gender and being married - Table C4

Most of the main results hold when the various covariates are controlled for. The positive significant impact of km-construction x baby does not hold for most of the regressions in Tables C1 to C4. Even in the baseline regression, this coefficient's resulting effect size on MWTP is marginal (3%). Thus the baseline regression result may be due to somewhat low standard errors in those models, as opposed to reflecting a robust finding.

Additionally, The pregnant attribute interaction becomes negative significant, albeit with a small effect size (5%), when household income (logarithmic, centered around the mean) is controlled for (model 2, Table C3). 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. This is an extension of the regional fixed effects, as average household income also varies across the survey regions, seen in Figure 4. Thus, the regional effects seen previously in section 5.2.2 are arguably due to differences in income across households.

Finally, the protection attribute's interaction with the km-construction variable is not always significant (Tables C1, C2 and C4). The significance in these cases becomes conditional on the stated subjective risk of the respondent. This shows that the MWTP for protection still increases in the face of heightened malaria risk, but is also influenced by stated individual likelihood of getting malaria. Thus, we still consider positive MWTP for protection a robust result.

Figure 4: Household Income Across Survey Regions



Overall, we find that MWTP across many attributes increase in the face of heightened malaria risk. MWTP for children increases by 25.98% (between 22.62% - 27.70% 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 10.61% (between 7.07% - 15.52% 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 36.73% (between 25% - 54.76% in all regressions) decrease in MWTP for duration.

1.6 Conclusion and Discussion

In conclusion, we find some significant changes in MWTP for certain attributes of malaria prevention in the face of heightened disease risk. People living in risky areas are willing to spend more on malaria protection and preventing children from becoming sick, compared to others living in non-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. The model where these findings come from, controls for observable factors in subjective malaria risk mitigation. It also takes into account individual random effects across each attribute, except for price. Robustness checks are run, controlling for experience and knowledge of malaria, location fixed effects, and select socio-demographic variables.

The likelihood of getting malaria is taken to be five times larger in risky areas than in non-risky areas (Stoler, Weeks, Getis, & Hill, 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 non-risky areas. Assuming equal populations in both areas, residents face 0.33% chance in non-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, and considering 75 INR = 1 Euro, a 1% increase in malaria risk leads to respondents willing to pay an extra, on average:

- 131.25 INR for full personal protection (i.e. pill with 100\% protection)
- 288 INR to protect children, as opposed to adults (i.e. pill for children)
- 27.75 INR 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 worrying result, as these groups are highly vulnerable too 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 INR to protect children, the average respondent still prefers to protect adults than children. We find almost no evidence of others regarding preferences.

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 others regarding preferences could have arisen because pills are usually for personal consumption. Had the policy 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.

Also, further research is needed on time preferences and how these can affect the valuation of new disease in the future. Heightened malaria prevalence due to climate change is not projected to occur immediately. Moreover, any effective policy to mitigate these scenarios must be adopted in the present. Research carried out in this area will help policymakers have a better understanding of the potential benefits of such policies.

Acknowledgments

The research leading to these results has received funding from the European Union Seventh Framework Programme *FP7/2007-2013* under grant agreement nº 603864.

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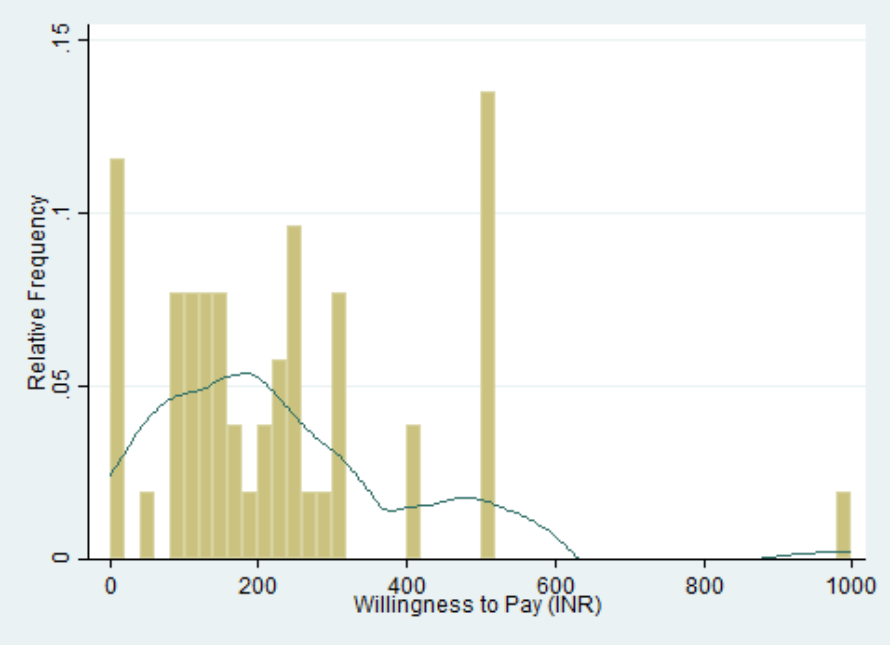
1.7 Pilot Surveys

1.7.1 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[2]. The 90th percentile is 500 INR. Therefore 100, 200, 300 and 500 INR were included into the price attribute. 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.

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



1.7.2 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, Brouwer, & Tol (2015). Since the regression coefficients from that study are fixed point estimates, the first design has fixed priors.

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

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.

1.8 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.

1.8.1 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 point}: The correct answer is selected, along with one wrong answer
- 1 point: Only the correct answer is selected

1.8.2 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

1.8.3 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

1.8.4 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

1.9 Robustness Check Tables

1.9.1 Socio-Demographics

Table C1: Impact of Malaria General Knowledge

	Dependent variable:		
	Pill Choice		
	multinomial logistic		
	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:			
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:			
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
Log Likelihood	-5,200.445	-5,172.304	-5,179.365
Note:			*p<0.1; **p<0.05; ***p<0.01

Table C2: Impact of Education

	Dependent variable:		
		Pill Choice	
		multinomial logistic	
	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
Log Likelihood	-5,200.445	-5,170.324	-5,184.967
Note:			*p<0.1; **p<0.05; ***p<0.01

Table C3: Impact of Household Income and Having Child(ren)

	Dependent variable:		
	Pill Choice		
	multinomial logistic		
	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
Log Likelihood	-5,200.445	-5,162.410	-5,189.123
Note:			*p<0.1; **p<0.05; ***p<0.01

Table C4: Impact of Respondent Characateristics

	Dependent variable:		
	Pill Choice		
	multinomial logistic		
	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			0.006 (0.006)
Observations	8,400	8,400	8,400
Log Likelihood	-5,200.445	-5,182.792	-5,171.012
Note:			*p<0.1; **p<0.05; ***p<0.01

Part B: CLIMATE CHANGE, MALARIA, AND THE SOCIAL COST OF CARBON

Richard S.J. Tol

Department of Economics, University of Sussex, Jubilee Building, Falmer, BN1 9SL, UK, r.tol@sussex.ac.uk

Institute for Environmental Studies, Vrije Universiteit, Amsterdam, The Netherlands

Department of Spatial Economics, Vrije Universiteit, Amsterdam, The Netherlands

Tinbergen Institute, Amsterdam, The Netherlands

CESifo, Munich, Germany

Abstract

I revise the malaria module of FUND, an integrated assessment model, and re-estimate the social cost of carbon. I update the base year, reflecting recent progress in rolling back malaria. I add recently developed scenarios, include an exogenous trend in health care, and change the income elasticity of health care. I alter the sensitivity of malaria to climate change. I update the value of a statistical life, and introduce a premium for populations not previously exposed to malaria. I change the income elasticity of the value of a statistical life, and make it a function of per capita income and the curvature of the utility function. These extensive changes notwithstanding, the social cost of carbon hardly changes. For a 1% pure of time preference, the social cost of carbon is $24.03/tC in the original model, and $23.52/tC in the revised model.

Key words social cost of carbon; climate change; malaria

JEL Classification Q54

1.10 Introduction

Vector-borne diseases have always been a major reason for concern on climate change (Martens et al. 1995). Differences in monetary valuation of health risks due to income differences sparked interest in equity weights (Fankhauser, Tol, and Pearce 1997). Progress in health care (Tol and Dowlatabadi 2001) was first used to illustrate the Schelling Conjecture that greenhouse gas emission reduction is not the only, and not necessarily the best way to reduce the impacts of climate change (Schelling 1992). Vector-borne diseases are also a key component of the social cost of carbon (Anthoff and Tol 2013). In this paper, I update FUND, one of the three models regularly used to estimate the social cost of carbon (IAWGSCC 2010, 2013, 2015), with regard to malaria.

Specifically, the paper does the following things. I update the base year. This may seem like a trivial thing, but much has changed in recent years. The Gates Malaria Partnership, the President's Malaria Initiative, and the WHO Roll Back Malaria programme have led to a rapid reduction in malaria (Breman 2009). Global incidence fell by 6.6% per year between 2005 and 2013 (Roser 2016). This is unlikely to stop, as malaria vaccines are now in late stage trials (Christensen 2017) with, to date, encouraging results (Mordmüller et al. 2017). The second innovation of the paper is

therefore an update of the scenarios, with a particular focus on the future of malaria. The understanding of the impact of climate change on the disease has changed since FUND was last recalibrated, and this is the third contribution of the paper. The fourth lies in the monetary valuation of mortality risks. Climate change would not only change the incidence of malaria in currently endemic or epidemic areas, but also introduce the disease to new areas. Naïve populations attach a premium to unfamiliar afflictions, which I here introduce to FUND. The fifth contribution of the paper is a novel parameterization of the income elasticity of the value of a statistical life. In previous versions of FUND, and indeed other integrated assessment models, parameters are assumed independent. Health risks are risks, however, and their valuation reflects attitudes towards risk. Following recent developments in economic theory, I let the income elasticity depend on the curvature of the utility function.

I study the implications of the above revisions to the model for the social cost of carbon. This is the key indicator for the seriousness of climate change (Boehringer, Loeschel, and Rutherford 2007). It measures the incremental damage done by emitting an extra tonne of carbon dioxide, and the benefit of reducing emissions by one tonne (Tol 2011). If imposed on all greenhouse gas emissions, the social cost of carbon is that tax that restores economic efficiency. Because of this, the social cost of carbon is also a key point of discussion in the debate on climate policy (Pearce 2003, Rose 2012, Greenstone, Kopits, and Wolverton 2013, Pizer et al. 2014, Sunstein 2014, Hahn and Ritz 2015, Guivarch et al. 2016, Heyes, Morgan, and Rivers 2013) and hence a subject of active research (Hope 2008, Foley, Rezai, and Taylor 2013, Newbold et al. 2013, Otto et al. 2013, Weitzman 2013, Howarth, Gerst, and Borsuk 2014, Nordhaus 2014, Pycroft, Vergano, and Hope 2014, Van der Ploeg 2014, Weitzman 2014, Havranek et al. 2015, Rezai and van der Ploeg 2015, van den Bijgaart, Gerlagh, and Liski 2016, Nordhaus 1992, 1993b, a, Tol 1999, Moore and Diaz 2015, Golosov et al. 2014, Rose, Diaz, and Blanford 2017, Pindyck 2017, Nordhaus 2017, Metcalf and Stock 2017, Lemoine and Traeger 2016, Dayaratna, McKitrick, and Kreutzer 2017, Adler et al. 2017).

There are five innovations in this paper, plus variations and sensitivity analyses on the innovations. The innovations are discussed in more detail in Section 3. The results are discussed, one innovation at a time, in Section 4. Section 2 presents the model. Section 5 concludes.

1.11 FUND and the social cost of carbon

This paper uses version 4.0 of the Climate Framework for Uncertainty, Negotiation and Distribution (FUND). FUND is an integrated assessment model of climate change (Tol 1997, 1998, 1999, 2008, Guo et al. 2006, Anthoff, Hepburn, and Tol 2009, Anthoff, Tol, and Yohe 2009, Waldhoff et al. 2014). The source code, data, and a technical description of the model can be found at http://www.fund-model.org.

The model is specified for sixteen regions of the world, viz. the United States of America, Canada, Western Europe, Japan and South Korea, Australia and New Zealand, Central and Eastern Europe, the former Soviet Union, the Middle East, Central America, South America, South Asia, Southeast Asia, China, North Africa, Sub-Saharan Africa, and Small Island States. The model runs from 1950 to 3000 in time steps of one year. The prime reason for starting in 1950 is to initialize the climate change impact module (Tol 2002b, a). The centuries after the 21st are included to assess the long-term implications of climate change.

Scenarios are defined by the rates of population growth, economic growth, autonomous energy efficiency improvements as well as the rate of decarbonization of the energy use, and emissions of carbon dioxide from land use change, methane and nitrous oxide. The scenarios of economic and population growth are perturbed by the impact of climatic change. Market impacts are a deadweight loss to the economy. Population decreases with increasing climate change related deaths that result from changes in heat stress, cold stress, malaria, and storms. Heat and cold stress are assumed to have an effect only on the elderly, non-reproductive population. In contrast, the

other sources of mortality also affect the reproductive population. Heat stress only affects the urban population. Climate-induced migration between the regions of the world also causes the population sizes to change. Immigrants are assumed to assimilate immediately and completely with the respective host population.

The endogenous parts of FUND consist of the atmospheric concentrations of carbon dioxide, methane, nitrous oxide and sulphur hexafluoride, the global mean temperature, the impact of carbon dioxide emission reductions on the economy and on emissions, and the impact of the damages to the economy and the population caused by climate change. Methane and nitrous oxide are taken up in the atmosphere, and then geometrically depleted. The atmospheric concentration of carbon dioxide, measured in parts per million by volume, is represented by a five-box model (Maier-Reimer and Hasselmann 1987). The model also contains sulphur emissions (Tol 2006). Radiative forcing is as in the IPCC. The global mean temperature T is governed by a geometric build-up to its equilibrium. In the base case, the global mean temperature rises in equilibrium by 3.0°C for a doubling of ambient carbon dioxide. The dynamics of the global mean sea level are also geometric. Both temperature and sea level are calibrated to correspond to the best guess temperature and sea level for the IS92a scenario (Kattenberg et al. 1996).

The climate impact module includes agriculture, forestry, sea level rise, cardiovascular and respiratory disorders related to cold and heat stress, malaria, dengue fever, schistosomiasis, energy consumption, water resources, unmanaged ecosystems, diarrhoea, and tropical and extra tropical storms. Climate change related damages can be attributed to either the rate of change (where damages are calibrated at 0.04 °C/yr) or the level of change (with damage functions calibrated at 1.0 °C). Damages from the rate of temperature change slowly fade, reflecting adaptation. FUND is unique in its class of integrated assessment models by explicitly modelling changes in vulnerability due to e.g. changes in socio economic circumstances. FUND's damage functions are calibrated to match studies that assume optimal adaptation and report residual damages and adaptation costs.

People can die prematurely due to climate change, or they can migrate because of sea level rise. Like all impacts of climate change in FUND, these effects are monetized. Other impact categories, such as agriculture, forestry, energy, water, storm damage, and ecosystems, are directly expressed in monetary values without first estimating impacts in 'natural' units. Impacts of climate change on energy consumption, agriculture, and cardiovascular and respiratory diseases explicitly recognize that there is a climatic optimum, which is determined by a variety of factors, including plant physiology and the behaviour of farmers. Impacts are positive or negative depending on whether the actual climate conditions are moving closer to or away from that optimum climate. Impacts are larger if the initial climate conditions are further away from the optimum climate. The optimum climate is of importance with regard to the potential impacts. The actual impacts lag behind the potential impacts, depending on the speed of adaptation. The impacts of not being fully adapted to new climate conditions are always negative.

The impacts of climate change on coastal zones, forestry, tropical and extratropical storm damage, unmanaged ecosystems, water resources, diarrhoea, malaria, dengue fever, and schistosomiasis are modelled as power functions. Impacts are either negative or positive with greater climate change, and they do not change sign. The level of coastal protection is based on an internal cost-benefit analysis that includes the value of additional wetland lost due to the construction of dikes and subsequent coastal squeeze.

Vulnerability to a given climate change is a function of population growth, economic growth, and technological progress. Some systems are expected to become more vulnerable with increases in these factors, such as water resources (with population growth), heat-related disorders (with urbanization), and ecosystems and health (with higher per capita incomes). Other systems such as energy consumption (with technological progress), agriculture (with economic growth) and vector- and water-borne diseases (with improved health care) are projected to become less vulnerable at least over the long term.

The social cost of carbon is computed as the difference between damages along a business as usual path and along a path with an incremental increase in emissions between 2010 and 2019. The differences in damages are discounted back to the year 2015, and normalised by the difference in emissions.

1.12 FUND and the social cost of carbon

1.12.1 Baseline

Previously, FUND was calibrated to the year 1990 (Anthoff and Tol 2014). Much has changed since then. Notably, malaria is much less common. Some 860,000 people died of malaria in 1990. This fell to about 466,000 malaria deaths in 2013. Over the same period, the world population grew from 5.3 billion to 7.2 billion people. The fall in malaria incidence is partly explained by economic growth. Richer people can afford malaria medicine, and reduce mosquito habitat as they houses and yards are better maintained. The ban on DDT was lifted, at least for mosquito control. The supply of bed nets increased rapidly through targeted programmes sponsored by the US government, the Gates Foundation and the World Health Organization (Breman 2009).

In the previous version of FUND, malaria incidence fell only because of income growth. In the current version, I add a trend in health care, which cuts malaria incidence by 1.6% per year between 1990 and 2013.

1.12.2 Scenarios

Previously, FUND's scenario library had five core scenarios: FUND (a variant of EMF22), and SRES A1b, A2, B1 and B2 (Nakicenovic and Swart 2001). Four early versions of the SSP scenarios were also available, viz. IMAGE, MERGE, MESSAGE, and MiniCAM (IAWGSCC 2013). I here add the five SSP scenarios (Riahi et al. 2017), taken as the average of the models available in the IIASA database.

For malaria, I extrapolate the trend observed between 1990 and 2013: Malaria falls by 1.6% per year. This is credible as the demand for bed nets is not yet saturated and as malaria vaccines are about to be available.

Previously, the income elasticity of the incidence of malaria was set at -2.65, with a standard error of 0.69 (Link and Tol 2004). That is, for every 1% increase in per capita income, malaria falls by 2.65%. This elasticity was estimated on regional data. National data are now available from the WHO.1 I re-estimated the income elasticity for the years 2000, 2005, 2010 and 2013. The new elasticity is -1.52, with a standard error of 0.12. This requires a recalibration of the trend in medical technology, which is set to 3.0% per year.

1.12.3 Malaria sensitivity

Previously, FUND assumed that the incidence of malaria increase by 7.9% per degree Celsius of global warming (with a standard error of 5.8%/°C). This was based on model results published in the mid-1990s (Martin and Lefebvre 1995, Martens et al. 1995, Martens, Jetten, and Focks 1997, Morita, Kainuma, Harasawa, Kai, and Matsuoka 1994, Morita, Kainuma, Harasawa, Kai, Dong-Kun, et al. 1994). Estimates of the impact of climate change on malaria have changed since, with recent studies showing little change and even decreases in malaria (due to reduced rainfall). I here follow Peterson (2009) who shows that malaria falls by 17.1% per degree Celsius (with a standard error of 13.2%/°C, derived from the standard deviation between his results for two cases and two scenarios).

1.12.4 Value of a statistical life

Previously, FUND assumed that the value of a statistical life is some $5 mln in 1990, or 200 times per capita income, based on Cline (1992). Viscusi and Masterman (2017) show that the value of a statistical life is somewhat lower at 170 times per capita income.

Kutluay, Brouwer, and Tol (2017) show that people who have not been previously exposed to malaria, are willing to pay more for prevention. They estimate an unfamiliarity premium of 15.9% with a standard error of 4.9%. Peterson (2009) distinguishes between people no longer exposed to malaria and people newly exposed to malaria. If the latter count 16% more, malaria falls by 16.5% per degree Celsius.

1.12.5 Income elasticity

Previously, FUND assumed that the income elasticity of the value of a statistical life is unity. That is, the value of health risks is proportional to per capita income. Recent studies point to a lower income elasticity. The meta-analysis by Doucouliagos, Stanley, and Viscusi (2014) report a range of 0.25 to 0.63, with most estimates greater than 0.50. I therefore use an income elasticity of 0.55. This implies that future health risks are valued less, relative to today, than in previous versions of FUND, but that health risks in poorer countries are valued higher.

Kaplow (2005) argues that the income elasticity of the value of a statistical life is related to the rate of risk aversion; see also Evans and Smith (2010) . For a CRRA utility function, the approximate relationship is

$$\varepsilon = \begin{cases} \dfrac{1}{\ln(y)} + \eta & \eta = 1 \\ \dfrac{y^{1-\eta}}{y^{1-\eta}-1}(1-\eta) + \eta & \eta \neq 1 \end{cases}$$

where ε is the income elasticity of the value of a statistical life, y is per capita income, and η is the rate of relative risk aversion.

1.13 Results

1.13.1 Baseline

The top row of Table 1 shows the social cost of carbon for three alternative pure rates of time preference, viz. 0.1%, 1% and 3% per year. As expected, the lower the pure rate of time preference, the more we care about the future, the more we care about climate change, and the higher the social cost of carbon.

The next row shows the social cost of carbon without the impact of climate change on malaria. The social cost of carbon falls – malaria is a concern – but only by a little bit – malaria is a small concern.

Table 1 shows the social cost of carbon for the 2013 baseline malaria incidence. As malaria fell between 1990 (the old baseline) and 2013, the results for the updated baseline lie in between the old baseline and the no malaria case. Differences are small as malaria is not that important for the social cost of carbon.

1.13.2 Scenarios

The second panel of Table 1 shows that the social cost of carbon is very sensitive to the scenario used. For a 0.1% PRTP, the social cost of carbon ranges from $47/tC to $114/tC. For a 3% PRTP, the social cost of carbon may even be negative, primarily because the short-term benefits of carbon dioxide fertilization dominate the long-term impacts of climate change. The baseline scenario is relatively poor and relatively hot, and thus has a high social costs of carbon relative to the other scenarios.

The third panel of Table 1 shows the sensitivity of the social cost of carbon to the parameters that govern the future evolution of malaria. First, the trend in health care is extrapolated from 1990-2013 to the entire scenario. There is less malaria in the future, and the impact of climate change on malaria consequently falls. Second, the income elasticity of health care is updated to -1.52 (and the exogenous trend increased to 3.0% per year). This slightly increases the social cost of carbon as projected income growth in Sub-Saharan Africa outpaces improvements in health care. Third, as a sensitivity analysis, the income elasticity and the trend are set to nought (but the trend in malaria equals -5.1% per year between 1990 and 2013). There is more malaria in this future, and the social cost of carbon increases. This increase is relatively large compared to other changes in malaria-specific parameterizations, reminding us that, in the baseline specification, malaria rapidly ceases to be a problem.

1.13.3 Malaria sensitivity

The fourth panel of Table 1 shows what happens if malaria does not increase with climate change, but rather falls. The social cost of carbon falls, as expected, but only slightly as malaria is not that influential.

1.13.4 Value of a statistical life

The fifth panel of Table 1 shows the effect of a lower value of a statistical life. Although it affects all health risks, the effect is not that large as positive impacts (cold-related deaths, schistosomiasis, and now malaria) offset negative ones (heat-related deaths, dengue fever, diarrhoea).

The unfamiliarity premium on malaria affecting hitherto malaria-free populations has a minimal effect on the social cost of carbon: It increases by ¢1/tC.

1.13.5 Income elasticity

The sixth and last panel of Table 1 shows the effect of a lower income elasticity of the value of a statistical life. Future lives are valued less and lives in poorer countries are valued more. The latter effect dominates and the social cost of carbon increases.

Table 1 also shows the impact of Kaplow's income elasticity. As this is strictly greater than one, and more so in poorer countries and times, the social cost of carbon falls again.

1.14 Discussion and conclusion

There are regular complaints that the models used to estimate the social cost of carbon are updated only infrequently (Ackerman and Munitz 2016, Ackerman et al. 2009, Ackerman and Munitz 2012, Burke et al. 2016, Pindyck 2013, Cropper et al. 2017). This paper addresses that problem for the impact of climate change on malaria. Five groups of changes are made to FUND: The baseline and scenarios are updated, the sensitivity of malaria is changed, and the value of a statistical life and its income elasticity are altered. The rather extensive changes notwithstanding, the effect on the social cost of carbon is small. The reason is simple: The incidence of malaria has fallen rapidly, and is likely to continue to fall.

There are many caveats to the research presented here. The model is a reduced form. Malaria changes with climate, but there is little geographical detail and no distinction between endemic, seasonal and epidemic malaria, or between different species of malaria-transmitting mosquito. Health care improves as people grow richer, but there is no separation between prevention and cure, or between public and private provision. There is an exogenous trend in health care rather than investment in specific technologies. Valuation of health risks is uniform, rather than age, sex, and status specific. Valuation ignores that decisions on protection against malaria are, in most cases, decisions made by parents on behalf of their children. Refinements can be made, data permitting, but are unlikely to change the bottom line conclusion that the prevalence of malaria is, fortunately, falling for reasons other than climate change, and that climate change will therefore impact a shrinking base.

Acknowledgements

The research leading to these results has received funding from the European Union Seventh Framework Programme FP7/2007-2013 under grant agreement no 603864. David Anthoff and Mehmet Kutluay have been of great help in the preparing the paper.

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Table 1

Case \ PRTP	0.1%	1%	3%
Baseline			
Original model	101.88	24.03	1.14
No malaria	101.71	23.90	1.05
New baseline	101.83	23.99	1.11
Scenarios			
SRES A1b	47.49	9.99	-1.32
SRES A2	114.74	23.61	-0.36
SRES B1	46.26	7.21	-2.16
SRES B2	92.26	20.45	-0.09
IAWGSCC IMAGE	63.17	13.33	-1.04
IAWGSCC MERGE	89.11	21.83	0.74
IAWGSCC MESSAGE	75.13	14.59	-1.21
IAWGSCC MiniCAM	58.82	13.89	-0.38
SSP1	52.51	14.14	0.58
SSP2	71.73	22.08	2.58
SSP3	112.50	35.82	5.29
SSP4	70.99	20.82	2.10
SSP5	53.86	16.56	1.61
Scenario parameters			
Malaria falls by 1.6% per year	101.79	23.96	1.09
Income elasticity of malaria -1.52	101.80	23.97	1.10
Income elasticity of malaria 0	105.57	25.06	1.38
Malaria sensitivity			
Malaria falls with climate change	101.51	23.73	0.94
Value of a statistical life			
Value of a statistical life $4.2 mln	101.24	23.57	0.87
Including unfamiliarity premium	101.25	23.58	0.87
Income elasticity			
Income elasticity of VOSL 0.55	101.98	24.18	1.23
Kaplow income elasticity	101.19	23.52	0.83