Estimating Pigovian subsidies for household participation in mosquito control programs to prevent malaria

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Abstract

Many situations arise in which an individual may benefit others through private efforts to avoid infectious diseases. These situations create positive externalities which can in theory be offset with appropriate Pigovian incentives. Here, I focus on one such situation arising in the case of malaria prevention via government-sponsored insecticide spraying programs in northern Uganda. The private effort in this case is straightforward: Deciding whether or not to participate in such programs when they are offered. Using data from a stated-preference discrete choice experiment concerning these programs, conducted during late 2009, I illustrate an approach to applying this theory, and estimate the magnitude of such an externality and associated monetary transfers for offsetting it. Under reasonable assumptions concerning the biophysical relationship between insecticide spraying and reductions in malaria risk, my analysis suggests that optimal levels of such incentives are significantly positive, but also plausible in magntiude: For a DDT-based program spraying twice per year, the optimal incentive is a subsidy of around $15 per household per round, with a potential decrease in average malaria risk of 5%.

Keywords: positive externalities, Pigovian subsidy, malaria, insecticides

JEL codes: D13, H23, O15

1 Introduction

Economic theory has illustrated a variety of cases in public and environmental health where the aggregation of individually rational behaviors may not be optimal from a societal standpoint. One such case arises when incentives faced by private agents for the prevention of an infectious disease may not lead to an outcome which is efficient from the perspective of a social planner. In theory a rational self-interested agent would not consider the effect of her disease prevention efforts on reducing the spread of infection to other agents. As is well known, this generates the potential for a positive externality arising from dynamics which are peculiar to infectious diseases (Gersovitz and Hammer 2004a; Gersovitz and Hammer 2004b; Althouse, Bergstrom et al. 2010). A social planner who recognizes that one individual's prevention decisions have implications for everybody's risk of infection, and who is concerned with the welfare of all agents, would seek to induce higher levels of individual preventative effort. The standard policy prescription in this case is a subsidy rewarding preventative effort (Pigou 1920).

Even though there is a substantial amount of financing mobilized for public health programs in both high- and low-income countries, explicitly Pigovian incentives arise in a relatively small number of cases, albeit important ones. Moreover, even when incentives are justified in terms of externality theory, I am aware of no cases in which the magnitude of the incentive – the "raw dollar" amount – is based on empirical estimates of the external benefits or damages in question.

In high-income countries, government support for vaccinations is usually provided for a range of childhood diseases, with subsidies for adult immunization typically restricted to influenza and – in the USA – pneumococcal vaccination (Hinman, Orenstein et al. 2004; Ohkusa 2005; Thomas, Russell et al. 2010). In low-income countries, private donors and international organizations, in particular the World Health Organization (WHO), provide funding to countries

for a range of services and tools for infectious disease prevention, many of which amount to subsidized provision of preventative services to at-risk populations. The Global Fund to Fight Aids Malaria and Tuberculosis (GFATM) and the Roll Back Malaria partnership fund a range of malaria prevention activities, including the free distribution in many areas of insecticide-treated bednets and the indoor residual spraying (IRS) of insecticides in homes (the latter intervention being the focus of this paper). In addition, the specific mission of the GAVI Alliance is to provide freely available childhood immunization in low-income countries.

While each of the incentives mentioned above – all subsidies – can be argued to have a Pigovian rationale underlying them, it is unclear whether the declared *level* of support is based on the estimated public benefits from private preventative action, as theory suggests it should. Indeed, in low-income settings financing can be volatile (as recent macroeconomic events have demonstrated) and is more properly understood within the context of international political economy. Not surprisingly, global economic recessions tended to be mirrored by drop-offs in funding for global health programs (Cohen, Smith et al. 2012).

Recognizing the political forces that shape funding streams for infectious disease programs provides an even greater motive for rationalizing the level of support provided for end-user services, by explicitly estimating the benefits and damages involved. Political conversations about global health funding have become increasingly focused on economic efficiency, as is evidenced through the frequent and often explicit focus on cost-effectiveness, and the emphasis of 'value for money' criteria adopted by the Global Fund (GFATM 2011).

In the case of Pigovian incentives for disease prevention, estimating the social benefits of disease prevention requires some knowledge of disease transmission dynamics, a model of human *behavior* with respect to the relevant preventative actions, and a measure of *welfare*. In

economics, utility theory typically provides both the behavioral model (assuming rational agents) and the measure of welfare, and that is the approach I take here (with caveats discussed at the end).

The application I focus on is indoor residual spraying (IRS) for malaria control. In short, this tool consists of government teams visiting homes in malarial areas and spraying the interiors with insecticides which both kill and repel malaria-transmitting mosquitoes and often other insects. Modern IRS programs, almost all of them being deployed in low-income regions, are provided free-of-charge to households. However, in most IRS programs, there is some inconvenience and time-cost imposed on households who decide to participate. Furthermore, there is also a potential cost to household members associated with the risks – real or perceived – of intimate and prolonged exposure to low levels of insecticides. The net impact of these nonmonetary costs and benefits of IRS is likely to vary significantly across households.

Using survey data from a face-to-face discrete choice experiment I conducted in northern Uganda in 2009, I analyze the factors contributing to participation in these IRS programs, estimate the welfare gains from associated malaria risk reductions, and illustrate an empirical approach for analyzing the potential efficiency gains from subsidizing participation in these programs. Given the potential nonmonetary burden as well as 'cobenefits' from IRS (e.g. reduction in nuisance insects), efficient levels of support could in principle amount to more or less than free provision of this service; my analysis implies that the efficient level of these subsidies far exceeds the costs of service provision. Furthermore, the analysis suggests that, for reasonable values of the biological/epidemiological parameters, the implementation of such incentives could decrease malaria cases by between 5% and 10% in this region.

My aim of computing efficient incentives to correct a positive externality from infectious disease prevention also contributes to current research in development economics on using

conditional cash transfers (CCTs) to promote public welfare (Fiszbein, Schady et al. 2009). The proposed Pigovian subsidy/tax discussed here can be viewed as one type of CCT. While some researchers in this area have highlighted the potential efficiency gains from subsidizing malaria prevention (Dupas 2009), attempts to estimate the magnitude of infectious disease externalities (Miguel and Kremer 2004)—and the size of CCTs designed to correct them—have remained essentially divorced from the biological processes which determine the extent to which prevention efforts can reduce disease at the level of the community and the individual. The analysis here aims to use information on these biological processes in order to compute reasonable approximations of efficient Pigovian incentives for IRS participation.

Because this paper proceeds in a somewhat unconventional format (albeit with the aim of improving readability), I provide a roadmap here: The next section provides contextual background on malaria and indoor residual spraying in northern Uganda. After that, a theoretical model of the disease prevention externality and corresponding Pigovian incentive is presented. Then the household survey and implementation of the discrete choice experiment are described, before presenting the econometric model and estimation results from this model. Finally, the theoretical model is applied – in combination with calibrated values for the epidemiological parameters – to the econometric results in order to compute the Pigovian incentives that are the subject of this paper. A discussion of the results concludes.

2 Background on malaria and indoor residual spraying in northern Uganda

Due to climatic and ecological factors, northern Uganda has been and remains a region with some of the highest malaria transmission potential on the planet. Exposure rates have been measured

to reach as high as 300 infectious mosquito bites per person per month (Okello, van Bortel et al. 2006). A recent study found that in one district of northern Uganda, nearly half of children under five years of age had malaria parasites in their blood (Steinhardt, Yeka et al. 2013).

To combat these high levels of malaria, the Ugandan government has partnered with the WHO, the US Agency for International Development (USAID), and the GFATM to expand coverage of a variety of malaria control services. In northern Uganda – which is more rural and less developed than the south (where the capital city Kampala is located) – IRS has been more heavily relied on.[1] Prior to our study, one round of IRS had been conducted between February and April 2008 in Gulu and Oyam districts of northern Uganda, led by USAID contractors in cooperation with the Ugandan National Malaria Control Program. Gulu was sprayed with the pyrethroid insecticide lambda-cyhalothrin (commonly referred to by its trade name ICON), and Oyam was sprayed using DDT (PMI 2009).

The 2008 IRS round proceeded as follows:[2] After radio advertising and consultation with village leaders and local health workers, IRS teams would arrive in villages at designated times. Households were expected to have their homes unlocked with all belongings removed, and to have retrieved 10 liters of water. IRS workers would then inspect homes to ensure that they were empty before dissolving a sachet of insecticide in their spray tanks using water provided by households. Spraying of the surfaces of the residential structures, usually consisting of one- to three-room mud huts, took less than one hour to complete. Spraying was typically conducted in the morning, and households were expected to remain outside of their homes for much of the day.

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[1] While tangential to the focus of this paper, it should be noted that a rebel insurgency that began in the 1980s and persisted into the 2000s demolished much of the infrastructure in northern Uganda, and resulted in the displacement of a number of inhabitants in the north. These "internally displaced persons" (IDPs) were relocated into IDP camps. IRS was used extensively in these camps because the high population densities made it a relatively cost-effective control strategy. However, once the IDPs returned to their home-sites (a process that occupied a period between 2008 and 2009), IRS services continued intermittently, though their frequency was reduced due to increased cost.

[2] This information is based off of an in-person interview with a field manager of the USAID-funded spray teams at the time.

Households were given the choice of whether or not to participate in the IRS program. Based on interviews with IRS workers and focus group participants, nonparticipation was uncommon. Anecdotal reports suggested that nonparticipation usually occurred because household members were absent and their homes were locked.

3 Theoretical model

I present a version of the theoretical framework developed by Althouse, Bergstrom et al. (2010), adapted for the present case. An individual is assumed have indirect expected utility u over personal disease risk ρ, preventative effort q, and money Y. Effort is assumed to be binary: Either an individual participates in IRS ($q = 1$) or not ($q = 0$).

Suppose that participating in IRS carries with it an associated, nonmonetary utility impact of η, independent of any malaria risk reductions. This effect η captures the perceived side-effects and cobenefits of IRS, e.g. human exposure to insecticides (a presumably negative effect) as well as reductions in nuisance insects (a presumably positive effect). In the absence of any monetary expenses associated with IRS, η captures the net benefits and costs of IRS participation, independent of malaria risk reductions. Furthermore, assume that there is some monetary transfer C to each household that participates in IRS. For each level of effort $q \in \{0,1\}$, the associated level of utility is therefore $u_q = \theta\rho_q + \alpha(Y + Cq) + \eta q$. Writing each of these utilities out explicitly, we have:

$$u_1 \equiv \theta\rho_1 + \alpha(Y + C) + \eta$$
$$u_0 \equiv \theta\rho_0 + \alpha Y \quad (1)$$

The parameters θ and α are the associated marginal utilities of malaria risk and wealth, respectively. Obviously, $\theta < 0$ (malaria risk is bad) and $\alpha > 0$ (money is good). These

parameters, along with the net side effects of IRS participation η, are to be estimated econometrically.

Define the overall level of IRS participation in the relevant population as Q, which is simply the mean level of effort q in the population. The malaria risk levels ρ_1 and ρ_0 are assumed to depend on Q, which is the key assumption giving rise to the externality examined here: In particular, households in the community are assumed to benefit from others' participation (for an example of this effect, see Zhou, Githeko et al. 2010). That is, $d\rho_1/dQ < 0$ and $d\rho_0/dQ < 0$.

A rational household participates in IRS whenever $u_1 > u_0$. To allow for interior levels of IRS participation (i.e. neither 100% nor 0% participation) it is necessary in this framework to assume heterogeneous preferences among households (Althouse, Bergstrom et al. 2010). Here we assume that the net IRS side-effects η are distributed across the population according to a continuous probability density function $f(\eta)$. Then the level of participation in IRS implied by this model satisfies $Q = \int_{u_1 > u_0} f(\eta)d\eta$, which can be written as:

$$Q = \int_{\underline{\eta}}^{\infty} f(\eta)d\eta \text{ such that } \underline{\eta} = -\theta[\rho_1(Q) - \rho_0(Q)] - \alpha C \quad (2)$$

Note that an individual with an IRS taste parameter η taking a value of $\underline{\eta}$ is a marginal participant, i.e. one who is indifferent between participating or not, with $u_1|_{\eta=\underline{\eta}} = u_0$. Note that $\underline{\eta} < 0$ for $C \geq 0$: The marginal participant finds the malaria reduction benefits net of the monetary transfers to be exactly offset by what she perceives as negative side-effects ($\underline{\eta} < 0$) of IRS participation. The status quo equilibrium of this model has $C = 0$, and we define this equilibrium in terms of the participation level $Q^* = Q|_{C=0}$ and $\eta^* = \underline{\eta}|_{C=0}$. The indifference condition for this equilibrium can be expressed as follows:

$$0 = \underbrace{\theta[\rho_1(Q^*) - \rho_0(Q^*)] + \eta^*}_{u_1|_{\eta=\eta^*} - u_0} \tag{3}$$

The remainder of the theoretical analysis consists in comparing this equilibrium to a socially optimal one, which we now define.

Social welfare (SW) is assumed to be the total utility of those participating and not participating in IRS in a population of size N, i.e. $SW \equiv N\left[\int_{\underline{\eta}}^{\infty} u_1 f(\eta) d\delta + u_0(1-Q)\right]$. Here we account for any direct costs of IRS service provision (usually borne by the government or donors) as k.

We can thus investigate the socially optimal threshold η^o and participation level Q^o by looking at the first-order condition $dSW/d\underline{\delta} = 0$. Using equations (1) and (2), with some simple manipulation,[3] this condition can be expressed as follows:

$$0 = \underbrace{\theta[\rho_1(Q^o) - \rho_0(Q^o)] + \eta^o - \alpha k}_{u_1|_{\eta=\eta^o} - u_0} + \underbrace{\theta\left[Q^o \frac{d\rho_1}{dQ} + (1-Q^o)\frac{d\rho_0}{dQ}\right]}_{\text{"Indirect marginal SW"}} \tag{4}$$

This first-order condition is composed of two terms. The first term is the direct marginal net benefit to households from participating in IRS: If this were the only term in the first-order condition, then the social optimum would coincide with the status quo equilibrium. The second term is the indirect marginal effect on welfare of increasing IRS coverage. This term is positive, and arises from the protective effects a household gains from overall community-level participation, regardless of its own participation decision. If no such protective effects were to arise ($d\rho_1/dQ = d\rho_0/dQ = 0$), then this indirect effect would be zero, the first-order condition in (4) reduces to indifference condition in equation (3), and there would be no imperative for

[3] To complete this calculation, observe that $\partial Q/\partial\underline{\eta} = -f(\underline{\eta})$.

Pigovian incentives. However, IRS normally imparts community-level protection, and therefore the appropriate Pigovian incentive, expressed as a proportion of household wealth, becomes:

$$C^o = \frac{\theta}{\alpha}\left[Q^o \frac{d\rho_1}{dQ} + (1 - Q^o)\frac{d\rho_0}{dQ}\right] - k \quad (5)$$

Substituting the expression for C^o in equation (5) for C in equation (2) results in a participation level that coincides with the social optimum Q^o in equation (4).

The empirical application of this theory relies on the estimation of the quantities on the right-hand side of this equation. The taste parameters α and θ are estimated econometrically, and IRS cost k is obtained through available estimates. The malaria risk functions ρ_1 and ρ_0 are dictated by the epidemiology and transmission dynamics of malaria in northern Uganda, and are estimated by formulating a transmission model for this purpose and calibrating to published epidemiological studies.

4 Data collection

A face-to-face household survey, containing a discrete choice experiment (DCE), was conducted between June and December of 2009. The survey was designed to assess households' perceptions of malaria burden and the effectiveness of government IRS programs at reducing the risk of contracting the disease. In June, participants in 6 focus group discussions (FGDs) were recruited via convenience sampling from around the headquarters of Gulu in northern Uganda. FGD participants provided qualitative data on their household's experience with malaria, and with the previous IRS round that had been conducted in the area. Participants were also asked to consider a simplified version of the choice task that randomly sampled respondents later faced in the DCE. A prototype questionnaire was drafted, and locally-recruited interviewers were trained for one

week, before pre-testing the survey. The finalized questionnaire was administered to a clustered random sample of 612 households in Gulu and Oyam during November.

TABLE 1: SUMMARY STATISTICS FOR SAMPLE. *** *denotes a significant difference between the Gulu and Oyam statistics of less than 1%. Notes:*

[a]Asset value is calculated as the sum-product of an inventory of items owned by the household, excluding land, and multiplied by respondents' subjective valuations of those items (i.e. what amount could they raise by selling the items).

[b]Fraction of respondents reporting their participation in the single, 2008 IRS round in Gulu and Oyam districts.

[c]This is the estimated percentage of the population who, within the month preceding the interview, were diagnosed at a health facility as having malaria, either via a blood test or presumptively (e.g. presence of fever).

[d] These are subjective probabilities elicited from the respondent that any person in the household would get malaria in the next month.

Variable	*Full Sample*	*Gulu District*	*Oyam District*
Households sampled	578	345	233
Mean household size	6.1	6.0	6.3
Standard deviation	3.2	3.2	2.8
Value of household assets[a]			
Mean	$163	$181	$125
Median	$75	$70	$82
Interquartile range	($29 - $197)	($25 - $255)	($37 - $150)
Money income in past month			
Mean	$37	$40***	$33***
Median	$20	$22	$17
Interquartile range	($7 - $56)	($9 - $65)	($6 - $40)
Percent participating in IRS [b]	80%	78%	84%
Monthly malaria incidence [c]	26%	27%	24%
Perceived malaria risk [d]	29%	30%	26%

Table I summarizes the sample of households, four fifths of whom reported participating in the actual 2008 IRS round. In terms of perceived malaria burden, around a quarter of the people covered by the survey (i.e. all people in the surveyed households) reportedly were diagnosed with malaria at a health facility (clinic, drug shop, etc.) either via a blood test or – most likely – presumptively based on symptoms such as fever. A subjective probability instrument was also

implemented in the questionnaire, adapted from methods described by Delavande, Giné et al. (2011). Responses from this instrument imply that, on average, household heads thought that there was between a 25% and 30% chance that somebody in their household would fall ill with malaria over the course of the next month.

4.1 Description of the discrete choice experiment

The DCE presented survey respondents with three choice tasks. Each choice task consisted of the household selecting the most preferred of three alternatives: (a) an IRS program consisting of one of two insecticides (DDT or ICON) sprayed at a given frequency (between one and 4 times per year) which would yield a given level of malaria risk, (b) another IRS program with different levels for the same attributes, and (c) a one-shot amount of monetary compensation and a higher level of malaria risk that would prevail without any program. The attributes and their levels in the DCE are summarized in Table 1. Within a given choice task, the level of malaria risk associated with the money option was always higher than the level of risk under the IRS options. This type of choice experiment can thus be viewed as providing an estimate of respondents' willingness-to-accept (WTA) a permanent forfeiture of IRS services (and the resulting increases in malaria risk) in exchange for one-shot monetary compensation.

Because most stated preference studies of this type elicit willingness-to-pay (WTP) rather than WTA, readers may find this approach surprising. The main reason for this was that local partners were concerned that linking either a charge or a subsidy to IRS directly would raise concerns/hopes in the communities that IRS services would either no longer be free-of-charge or would carry with them a cash reward. To avoid this problem, we simply asked respondents to weigh the net gains from two hypothetical IRS program against a given amount of cash.

TABLE 2: DESCRIPTION OF THE ATTRIBUTES AND THEIR LEVELS IN THE CHOICE EXPERIMENT.
[1]Compenastion amounts were described to respondents in local currency (Ugandan shillings), but are presented here in USD 2009 for ease of interpretation.

Attribute	*Description*	*Levels and values*
Malaria risk	Average fraction of people out of 10 getting sick with malaria in an average month.	1/10 to 9/10, increments of 1/10
Compensation	One-time payment offered to respondent (in place of IRS).[1]	$0, $4, $22, $43, $65, $217
DDT	Frequency that DDT is sprayed (for IRS programs)	0,1,2, or 4 times per year
ICON	Frequency that ICON is sprayed (for IRS programs), mutually exclusive with DDT.	0,1,2, or 4 times per year

A. Script

In the 1st option, your house would be sprayed with **the chemical *DDT*** in such a way that **2 in 10** people will get malaria in an average month. In order to maintain the malaria-prevention effect of the insecticide, the spray teams would have to return every ***6 months*** in order to spray your home again.

In the 2nd option, your house would also be sprayed but with **the chemical ICON** in such a way that **4 in 10** people will get malaria in an average month. In order to maintain the malaria-prevention effect of the insecticide, the spray teams would have to return every **3 months** in order to spray your home again.

In the 3rd option, you would be given a ONE-TIME payment of **100,000 Ugandan shillings** to use for anything you liked, including things to prevent malaria (sprays, bednets, etc.). Since there would be no insecticide spraying in this case, the risk of malaria would be higher, with 6 in 10 people getting malaria in an average month.

Which option would you choose?

B. Response card

	CIRCLE ONE NUMBER FOR EACH TASK	*i. Insecticide*	*ii. Number of Re-sprayings per year*	*iii. Malaria risk PER MONTH*	*iv. Compensation*
TASK A	*1*	*DDT*	*1*	*8 people sick out of 10*	*0*
	2	*DDT*	*4*	*7 people sick out of 10*	*0*
	3	*--*	*0*	*9 people sick out of 10*	*10,000 UGX*
	-10	*Would not participate*			
TASK B	*1*	*--*	*0*	*9 people sick out of 10*	*100,000 UGX*
	2	*DDT*	*4*	*5 people sick out of 10*	*0*
	3	*DDT*	*1*	*6 people sick out of 10*	*0*
	-10	*Would not participate*			
TASK C	*1*	*DDT*	*1*	*3 people sick out of 10*	*0*
	2	*--*	*0*	*8 people sick out of 10*	*100,000 UGX*
	3	*ICON*	*4*	*2 people sick out of 10*	*0*
	-10	*Would not participate*			

FIGURE 1: DISCRETE CHOICE EXPERIMENT SCRIPT AND RESPONSE CARD.

In order to acclimate respondents with probability concepts, the DCE was immediately preceded by a series of "warm-up" subjective probability elicitations about various events (Delavande, Giné et al. 2011), and a short gambling game designed by Loomes (1991) implemented with a real (albeit trivial) payout of locally popular candies. The DCE began with the interviewer conveying a list of facts about IRS programs, and about the insecticides DDT and ICON, to respondents. After presenting this information to respondents, the interviewer posed the choice tasks to the respondent and recorded their answers according to the script and response card in Figure 1.

Ten different versions of the questionnaire were utilized, each with three different choice tasks, resulting in a total of 30 different choice tasks. The ten questionnaires were evenly distributed through the 15 surveyed villages, and each of the ten interviewers was randomly assigned a random mix of these survey versions at the beginning of each day of fieldwork. The definition and arrangement of alternatives within each choice task were determined using a constrained D-optimal design algorithm (Louviere, Hensher et al. 2000).[4]

5 Econometric specification and estimation

For econometric estimation using the DCE data, we use a mixed-logit model for discrete choice data (Revelt and Train 1998). The unobserved utility u that respondent h perceives from alternative i in choice task t is specified as:

[4] The algorithm was implemented by the author by pre-defining the levels for the relevant attributes and maximizing the determinant of the Fischer information matrix assuming a multinomial probit model estimated on the set of 30 choice tasks, and subject to the constraint that in each choice task IRS alternatives were always associated with a lower level of malaria risk than in the money-only option. While the probit model was not an ideal choice for this procedure, this does not threaten the consistency of the econometric estimates (since respondents were randomly assigned to one of the ten versions of the questionnaire), only their efficiency.

$$U_{ith} = \Theta v_{it} + \alpha C_{it} + \mathrm{H}_h^{ICON} ICON_{ith} + \mathrm{H}_h^{DDT} DDT_{ith} + \epsilon_{ith} \quad (6)$$

where v_{it}, C_{it}, $ICON_{ith}$, and DDT_{ith} are the attributes of the alternatives in the choice experiment—respectively, malaria risk (monthly probability of infection), alternative-specific money transfers, and the frequency of DDT/ICON application. The coefficients Θ, α, H_h^{ICON}, and H_h^{DDT} are taste parameters associated with their corresponding attributes. As per the theoretical model developed above, Θ and α are assumed to be fixed, and H_h^{ICON} and H_h^{DDT} are allowed to vary across the population. We assume these parameters vary according to a bivariate normal distribution.

5.1 Mixed logit estimation results

Table 3 shows the econometric estimates using the specification described above. The last column in the table (column c) corresponds to the specification in equation (6). The other columns show variations of this model, for comparison. In addition to the DCE attributes described above, some respondent characteristics – namely, whether or not the respondent participated in the previous 2008 IRS round (Partic=1) or were located in Oyam district (Oyam=1) – were also included in the regression, to check robustness.[5]

The main parameter estimates are all significant and of the expected sign. Furthermore, they are robust to the inclusion in the regression of respondent characteristics. The latter are significant in the conditional logit model (in which the taste parameters are all fixed and which

[5] See Brown (2011) for additional econometric specifications with estimates. In general, respondent characteristics were not significant in any estimations (with the exception of the variables included above), and most importantly the estimated coefficients on the attributes were robust to the inclusion of respondent characteristics.

does not allow correlated respondent behavior across choice tasks), but they lose their significance when random, correlated parameters are permitted (i.e. columns b and c).

TABLE 3: MIXED LOGIT REGRESSION ESTIMATES FOR DISCRETE CHOICE DATA. *Results obtained from the* mixlogit *add-on for Stata (Hole 2007), with 200 Halton draws per respondent. Clustered standard errors in parentheses. * = 10% significance, ** =5%, ***=1%. Sampling weights applied in estimation.*

	Conditional	Mixed logit		
Variables	logit	(a)	(b)	(c)
Fixed coefficients				
Θ (malaria risk)	-0.984***	-1.088**	-1.383***	-1.381***
	(0.350)	(0.432)	(0.437)	(0.438)
α (money)	0.000897***	0.00148***	0.00110***	0.00106***
	(0.000183)	(0.000333)	(0.000286)	(0.000295)
(DDT+ICON)×Partic	0.108**	0.131	0.0943	
	(0.0515)	(0.120)	(0.126)	
(DDT+ICON)×Oyam	-0.0844*	-0.185*	-0.109	
	(0.0433)	(0.0984)	(0.112)	
Random coefficients				
μ_{DDT}	0.389***	0.945***	1.186***	1.242***
	(0.0728)	(0.173)	(0.217)	(0.155)
μ_{ICON}	0.391***	0.769***	0.745***	0.789***
	(0.0606)	(0.184)	(0.180)	(0.147)
σ_{DDT}		1.219***	1.703***	1.732***
		(0.176)	(0.301)	(0.296)
σ_{ICON}		0.821***	0.805***	0.811***
		(0.207)	(0.230)	(0.230)
$\sigma_{ICON,DDT}$			1.153**	1.189**
			(0.465)	(0.465)
Tasks × Respondents	1,732	1,732	1,732	1,732
Pseudo R-squared	0.294	0.357	0.391	0.391
Degrees of freedom	6	6	6	4
Log-likelihood	-2.998e+06	-2.732e+06	-2.588e+06	-2.590e+06
BIC	5.996e+06	5.464e+06	5.176e+06	5.180e+06

The estimated distribution of the marginal utility from each DDT or ICON application implies that tastes preferences for DDT are highly correlated with those for ICON, and there seems to be a general preference for IRS (in comparison to the money-only alternative). However, there are some important differences between the insecticide types: DDT is more

favorable received on average than ICON (looking at the difference between μ_{DDT} and μ_{ICON}, which is significant). On the other hand, there is more variation in the marginal utility of DDT applications, compared to ICON: The standard deviation of the DDT coefficient is 2.1 times the size of the ICON coefficient's standard deviation.

To aid interpretation of the coefficients, the value of malaria risk reductions can be computed by computing the ratio $(\Theta/\alpha) \times 0.01$. This statistic, which can be viewed as a marginal WTA a permanent (or at least indefinite) increase of 1 percentage point in the monthly probability of malaria illness (which, again, is approximately equal to the expected number of episodes per person per month). For the preferred specification (column c of Table 3), the marginal WTA is estimated to be 12.97 USD, with a 95% confidence interval of ($1.45 - $24.50).

6 Estimation of Pigovian incentives

In the econometric specification in equation (6), capital letters are used for the parameters Θ and H in order to emphasize an important difference between the choices captured in the theoretical model in section 3 – whether or not to participate for a single round of a given IRS program – and the choices reflected in the DCE – whether or not to accept a one-shot money offer or participate in an IRS program, with an associated level of malaria risk which will continue indefinitely. This notation is intended to make clear the necessity of converting from Θ (the marginal "stock" utility from a permanent change in malaria risk) to θ (the marginal "flow" utility from a temporary change in risk). Similarly, H is the marginal "stock" utility from an increase in spray frequency for an IRS program of indefinite length, while η is the utility per IRS application round.

A detailed structural model to convert from these stocks and flows is beyond the scope of this paper (and the data). Instead, a simple discounting formula is applied to accomplish this

conversion, in which I simply take some discount rate r as given. I present results for $r = 10\%$, the results are not sensitive to reasonable changes in the discount rate. The conversion formulae used are:

$$\theta = \Theta[1 - \exp(-r\Delta)]$$
$$\eta = \mathrm{H}[1 - \exp(-r\Delta)] \tag{7}$$

where Δ is the interval of time (in years) between spray rounds (the inverse of the application frequency). The conversion formula for θ can be obtained by assuming that a reduction in the rate of risk v (as was considered in the experiment) for a duration of Δ carries with it a utility of $\theta v[1 - \exp(-r\Delta)] = \theta\rho$. The conversion formula for η is obtained by $H = \sum_{j=0}^{\infty} \eta \exp(-jr\Delta)$, i.e. each round of IRS (applied at intervals of Δ) incurs a discrete utility of η, and H is the present value of the stream of these utilities. The utility parameter α on money remains unchanged.

Expressing the utility specification in (1) in terms of the econometric parameters, using the conversions in (7), we therefore have:

$$u_{h1} = \Theta[1 - \exp(-r\Delta)]\rho_1 + \alpha(Y + C) + \underbrace{\mathrm{H}_h[1 - \exp(-r\Delta)]}_{\eta_h}$$
$$u_{h0} = \Theta[1 - \exp(-r\Delta)]\rho_0 + \alpha Y \tag{8}$$

Here, we explicitly subscript by household h in order to clarify which taste coefficients are heterogeneous.

As noted in the theoretical model, the distribution of the heterogeneous taste parameter – here, H_h – determines equilibrium IRS participation levels. The econometric specification implies a mixture of a normal and a logistic distribution:

$$\mathrm{H}_h|_j = \mathrm{H}_h^j + (\epsilon_{1h} - \epsilon_{0h}) \quad \text{where } j = DDT, ICON$$

$$\text{with } \begin{bmatrix} \mathrm{H}_h^{DDT} \\ \mathrm{H}_h^{ICON} \end{bmatrix} \sim MVN\left\{ \underbrace{\begin{bmatrix} \mu^{DDT} \\ \mu^{ICON} \end{bmatrix}}_{\boldsymbol{\mu}}, \underbrace{\begin{bmatrix} \sigma_{DDT}^2 & \sigma_{DDT,ICON} \\ \sigma_{DDT,ICON} & \sigma_{ICON}^2 \end{bmatrix}}_{\boldsymbol{\Sigma}} \right\} \tag{9}$$

where $MVN\{\boldsymbol{\mu}, \boldsymbol{\Sigma}\}$ is the multivariate normal distribution with mean vector $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$. The term $(\epsilon_{1h} - \epsilon_{0h})$ is a difference in Type I Extreme Value random variables and therefore follows a logistic distribution (e.g. Train 2003).

As per the theoretical model, for the equilibrium calculation we require a function $G_j(x)$ such that $G_j(x) = \Pr[\mathrm{H}_h|_j \geq x\,]$, where j indexes the insecticide type. Using the properties of the logistic distribution, it is straightforward to show that this function can be written as:

$$G_j(x) = \frac{1}{\sigma_j}\int_{-\infty}^{\infty} \frac{1}{1+\exp(w-x)}\,\phi\left(\frac{w-\mu^j}{\sigma_j}\right)dw \tag{10}$$

where $\phi(\cdot)$ is the standard normal probability density function. This formula is convenient for estimation, because the integral can be quickly and accurately computed through simulation with the standard normal distribution (e.g. Train 2003).

Applying the indifference condition in equation (3), and given the malaria risk functions $\rho_1(Q)$ and $\rho_0(Q)$, we can compute the status quo equilibrium $Q^*_{j,\Delta}$ for a given insecticide type j and spray interval Δ in terms of the econometric estimates:

$$\begin{aligned} 0 = {} & \Theta[1-\exp(-r\Delta)]\left[\rho_1\left(Q^*_{j,\Delta}\right) - \rho_0\left(Q^*_{j,\Delta}\right)\right] + \mathrm{H}^*_{j,\Delta}[1-\exp(-r\Delta)] \\ & \text{where} \quad Q^*_{j,\Delta} = G_j\left(\mathrm{H}^*_{j,\Delta}\right) \end{aligned} \tag{11}$$

And similarly from equation (4) we can obtain the socially optimal level of coverage $Q^o_{j,\Delta}$ as:

$$\begin{aligned} 0 = {} & \Theta[1-\exp(-r\Delta)]\left[\rho_1\left(Q^o_{j,\Delta}\right) - \rho_0\left(Q^o_{j,\Delta}\right)\right] + \mathrm{H}^o_{j,\Delta}[1-\exp(-r\Delta)] \\ & + \Theta[1-\exp(-r\Delta)]\left[Q^o_{j,\Delta}\frac{\partial\rho_1}{\partial Q} + \left(1-Q^o_{j,\Delta}\right)\frac{\partial\rho_1}{\partial Q}\right] - \alpha k \\ & \text{where} \quad Q^o_{j,\Delta} = G_j\left(\mathrm{H}^o_{j,\Delta}\right) \end{aligned} \tag{12}$$

The efficient Pigovian incentive to achieve the optimal coverage level is therefore:

$$C^{o}_{j,\Delta} = \frac{\Theta[1-\exp(-r\Delta)]}{\alpha}\left[Q^{o}_{j,\Delta}\frac{\partial \rho_1}{\partial Q} + \left(1-Q^{o}_{j,\Delta}\right)\frac{\partial \rho_1}{\partial Q}\right] - k \tag{13}$$

It is also of interest to examine the potential health impacts of using such incentives to "move" from the status quo to the optimal equilibrium. One such measure is the average risk level at the status quo ($\bar{\rho}^{*}_{j,\Delta}$) and at the optimum ($\bar{\rho}^{o}_{j,\Delta}$):

$$\begin{aligned}\bar{\rho}^{*}_{j,\Delta} &= Q^{*}_{j,\Delta}\rho_1\left(Q^{*}_{j,\Delta}\right) + \left(1-Q^{*}_{j,\Delta}\right)\rho_0\left(Q^{*}_{j,\Delta}\right)\\ \bar{\rho}^{o}_{j,\Delta} &= Q^{o}_{j,\Delta}\rho_1\left(Q^{o}_{j,\Delta}\right) + \left(1-Q^{o}_{j,\Delta}\right)\rho_0\left(Q^{o}_{j,\Delta}\right)\end{aligned} \tag{14}$$

Of course, at this point it should be clear that estimation of Pigovian incentives depends crucially on the nature of the malaria risk functions $\rho_1(Q)$ and $\rho_0(Q)$. The next subsection describes the parameterization of these functions.

6.1 Calibrating malaria risk reduction functions

To get reasonable values for the malaria risk functions, I use some simple estimates from an agent-based model developed and calibrated to published epidemiological studies regarding malaria exposure rates in northern Uganda (Okello, van Bortel et al. 2006), the impact of IRS on mosquito vectors (Shaukat, Breman et al. 2010), and the dispersion behaviour of mosquitoes (Kaufmann and Briegel 2004), which permits a distinction between individual-level and community-level participation in IRS programs. The full specification and sensitivity anlayssis of this model is contained in my dissertation (Brown 2011). For the present paper, the main conclusions from that analysis are that what matters most for the economic model is that IRS is actually effective at reducing malaria episodes in the community.[6]

A great methodological advantage of my model for the purpose at hand is that the risk reduction functions over IRS coverage Q turn out to be well-approximated by a linear function.

[6] There are a large number of reasons that IRS may fail to be effective at reducing malaria burden in various settings (e.g. vector ecology aspects, insecticide resistance, as well as nonlinear dynamics produced by the acquisition and decay of human immunity).

This is quite helpful, because it reduces these functions to four simple parameters, two intercepts and two slope parameters:

$$\rho_0(Q) \approx \beta_{00} - \beta_{01}Q$$
$$\rho_1(Q) \approx \beta_{10} - \beta_{11}Q \quad (15)$$

The linear specification, besides being simple to apply, is also useful for intuition: The intercepts β_{00} is baseline malaria risk (in terms of episodes per person per month) in the absence of any IRS. The (positive) difference $(\beta_{00} - \beta_{10})$ is the amount of risk reduction a household can expect by deciding to participate in IRS, when no one else participates. The slope parameters β_{01} and β_{11} determine the magnitude of the externality; these quantities are the amount of risk reduction that a household can expect from others' participation decisions.

To focus on the broader approach used here, I do not systematically conduct a sensitivity analysis of these epidemiological parameters. Instead, I focus on a single "reasonable" case, that is within the estimates found in my dissertation as well as other published studies (e.g. Chitnis, Schapira, et al. 2010). This scenario specifies the risk parameters as $\beta_{00} = 0.7,\ \beta_{10} = 0.6,\ \beta_{01} = 0.1,\ \beta_{11} = 0.4$. Note that this specification implies that the indirect, community-level benefits from IRS coverage accrue mostly to those households who participate in IRS ($\beta_{01} = 0.1$ and $\beta_{11} = 0.4$).

6.2 Results

Applying the above framework permits estimation of incentives for a range of scenarios. I focus on two spray scenarios, one in which ICON is applied three times per year and another where DDT is applied twice per year. These two scenarios are roughly in keeping with WHO guidelines for two of the most common insecticides used in IRS (WHO 2009). The cost per household per

round for both insecticides is set equal, at 5 USD (e.g. Walker 2000). Note that the assumptions regarding malaria risk reductions are applied to both of these scenarios, i.e. I am agnostic here with regard to whether DDT or ICON performs better in terms of reduced malaria burden.

TABLE 4: ESTIMATED PIGOVIAN INCENTIVES TO INTERNALIZE IRS EXTERNALITIES. *Numbers in parentheses are 95% confidence intervals, calculated using Monte Carlo sampling (N=500) from a multivariate normal distribution using the point estimates and covariance matrix from the econometric estimates (Table 3, column c).*

	DDT sprayed twice per year	*ICON sprayed three times per year*
Equilibrium IRS participation levels		
Status quo $\left(Q^*_{j,\Delta}\right)$	56%	82%
	(52% - 60%)	(77% - 87%)
Welfare-maximizing $\left(Q^o_{j,\Delta}\right)$	60%	86%
	(52% - 71%)	(77% - 93%)
Pigovian incentive $\left(C^o_{j,\Delta}\right)$	$15.23	$12.34
(per IRS round)	($0.47 - $43.21)	($0.25 - $41.59)
Equilibrium risk levels (cases per person per month)		
Status quo $\left(\bar{\rho}^*_{j,\Delta}\right)$	0.5	0.33
	(0.47 - 0.52)	(0.3 - 0.37)
Welfare-maximizing $\left(\bar{\rho}^o_{j,\Delta}\right)$	0.47	0.30
	(0.40 - 0.51)	(0.26 - 0.37)
Percent reduction in risk from Pigovian incentives	5.4%	8.8%
	(0.1% - 13.6%)	(0.3% - 16.5%)

The point estimates for the Pigovian incentive for both the DDT and ICON scenarios are quite close, at $15 and $12 per household per round respectively. These subsidies are net of the costs of IRS service provision (which, recall, I set to $5). It is also important to consider the fact that the ICON subsidies would actually be more costly to provide, because they are provided more frequently in the model: three times per year rather than twice for DDT. In both scenarios, the implied impact of such incentives is a four percentage point increase in equilibrium IRS participation rates. This increased participation translates into an average 5.4% and 8.8%

reduction in malaria cases in the DDT and ICON scenarios respectively. The major difference between the DDT and ICON scenarios lies in their absolute levels of IRS participation and corresponding malaria risk. IRS participation (both status quo and welfare-maximizing) is 26 percentage points higher in the ICON scenario, which translates into an over 30% less malaria risk in the ICON scenario.

7 Discussion

My analysis suggests that implementation of the appropriate Pigovian incentives could reduce malaria risk – measured as average monthly cases per person – by between 5% and 10%. While this potential health impact is modest, it is not insignificant, and the efficiency gains from such incentives would likely outweigh transactions costs associated with them (e.g. if the spray teams offer these cash transfers to households when they visit).

It is important to emphasize, however, that the main objective of this analysis is to illustrate an approach to estimating efficient incentives for an infectious disease externality. I have found the approach used here to be quite tractable. Obtaining more precise statistical estimates of these incentives and their potential impacts would require additional information on how IRS participation directly and indirectly affects malaria risk.

Some caveats are warranted to avoid drawing overly strong conclusions from the results. First, there is an implicit assumption in the above models that agents' perceptions of malaria risks are accurate. This assumption is necessary for connecting econometric parameter estimates, obtained from posing hypothetical risk levels to respondents in surveys, with information about actual, scientifically measured risk levels. While the descriptive statistics in Table I suggest that respondents' perceptions of malaria risk may be sensitive to actual risk, there is not enough

evidence in the present analysis to warrant this conclusion. An even so, these perceptions are likely to be biased by a host of factors, e.g. the overweighting of small probabilities and the overweighting of larger ones, as suggested by Prospect Theory (Kahneman and Tversky 1979). This caveat highlights an area for future research that could yield broad dividends beyond the present context: Risk sensitivity is likely to underlie many decisions regarding the adoption of new technologies or health practices.

Of course, the largest caveat (and topic for future research) is that this paper focuses on a policy instrument which does not yet exist (to my knowledge): the direct subsidization of households' participation in IRS programs. While the costs of provision – being absorbed by the government and donors normally – may be viewed as an implicit subsidy, the estimation here suggests that the efficient level of such a subsidy should far exceed the costs of service provision. Depending on the transactions costs associated the implementation of a such a policy instrument, results from the present analysis suggest that an experimental trial of this instrument would be an appropriate next step to investigate.

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