

THE DEMAND FOR REPRODUCTIVE HEALTH SERVICES: FRAMEWORKS OF ANALYSIS

by

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Abstract

The paper reviews a unified model of demand for health care inputs and health production, first proposed by Rosenzweig and Schultz (1982), and shows how the model can be applied to design and implement policies to improve reproductive health of the population. Although the focus of the applications is sub-Saharan Africa, the illustrative examples presented are of general interest. The key feature of the model is the link between demand for reproductive health services and the production of health by households and individuals.

The demand for reproductive health services together with the associated health production technology is first analyzed in the context of a unitary model of the household, before positioning the analysis in a more general collective model. In one of the several illustrations presented, the control function approach is used on Kenyan data to estimate the effect of tetanus immunization on birth weight in a unitary-household setting. Vaccinating mothers against tetanus during pregnancy is found to increase birth weight but *indirectly* through complementary behaviors and health care consumption patterns that are induced by vaccination. The effects of unobserved variables on birth weight, such as the knowledge gaps among mothers about health care, are also found to be substantial. An investigation is required on how to extend information to mothers about essential health care during pregnancy. It is argued that if mothers do not possess such information, tetanus vaccination may never induce them to invest in activities that improve birth weight in line with the complementarity hypothesis. More generally, we find a need to implement what we term *immunization plus* interventions to empower women to use reproductive health services effectively. The types of data needed to estimate other models presented in the paper are briefly discussed.

1. INTRODUCTION

Like other welfare indicators, reproductive health is the outcome of consumption of both reproductive health care and other goods and services. In many developing countries, the availability as well as the consumption of reproductive health services is limited by a combination of economic, social and technological factors. As a consequence, low-income countries, especially in Africa have poor indicators of reproductive health such as maternal mortality ratio, infant mortality and total fertility rates. There is need to find ways of expanding provision and consumption of reproductive services in sub-Saharan Africa to improve the general health of the population in the region, which currently remains low because essential reproductive health care is lacking. The key components of reproductive health care include:

- Family planning information and services;
- Safe pregnancy and delivery services;
- Prenatal and postnatal care;
- Prevention of placental malaria, through usage of insecticide treated bed-nets;
- Post-abortion care, in the event of abortion;
- Prevention and treatment of sexually transmitted infections, including HIV/AIDS;
- Information and counselling on sexuality;
- Nutrient supplements during pregnancy;
- Behaviours during pregnancy that are pro-fetal growth;
- Antenatal and neonatal immunization services;
- Elimination of harmful practices against women such as genital mutilation and forced marriage.

Consistent with the literature, the above reproductive health services may be grouped into three categories, namely: (a) market commodities (b) behaviours and (c) information.

The category of reproductive health care that falls under market commodities includes immunization of mothers against tetanus, immunizations of newborns, medical treatments and dietary supplements during pregnancy, family planning products and services, and infrastructural facilities, such as antenatal as well as post-natal clinics. Examples of individual behaviours that promote reproductive health include early initiation of prenatal care usage, exercising, and restraints from unhealthy practices such smoking or drinking during pregnancy. The informational elements of reproductive health care include:

- Knowledge about one's current health status as obtained, for example, via medical check-ups, and routine antenatal screening;
- Knowledge about factors that promote health as acquired through counselling on nutrition, HIV/AIDS, family planning, and sexually transmitted diseases;
- Knowledge about types of reproductive and other services available in local health facilities, as well best practices during pregnancy – information that can be transmitted during routine immunizations sessions.

The policies that increase availability of reproductive health services act on the supply-side of the market for these services, while policies that increase their consumption act on the demand-side. Both sorts of policies need to be implemented to improve reproductive health of the population. However, while the availability of reproductive health services and commodities is a necessary condition for better health, it is by no means sufficient. Reproductive health products and services must be used in order for them to improve health. Thus, an understanding of the demand-side of reproductive health care markets is key to the design and implementation of policies that enhance the health of mothers and newborns. Underlying the demand frameworks developed in this paper is the assumption that reproductive health services are available. The following are the demand-side questions that need to be answered to generate the information required to fully and efficiently utilize reproductive health services:

- a. Which of the existing reproductive health services and products are the households using and why?
- b. What determines the intensity of usage of particular services and commodities and their intra-household allocations?
- c. What types of information do households need in order to make informed decisions about reproductive health care?
- d. What kinds of household behaviors need to be promoted in order to enhance maternal and child health?

The above questions relate to consumption of inputs that enhance reproductive health. As in any demand situation, the utilization of these inputs is constrained by market and non-market environments. The market environment includes availability of reproductive health inputs and their prices, household income and how it is shared among household members. The non-market environment comprises the household residence (a rural or an urban setting), personal characteristics of household members, such as age, education, health status, and the information they possess about the quality of reproductive health inputs.

The purpose of demand analysis is to understand the types of policies that need to be implemented to increase all forms of health care consumption, *reproductive* health care included, in order to *improve* health. In much of the general health economics demand literature, the connection between health consumption and health production is only implied, but is not explicitly made (Akin et al., 1986; Akin et al., 1998); Gertler and Van der Gaag, 1990). This paper contributes to the existing literature by explicitly linking health care consumption to health production with a focus on reproductive health in low-income countries. Like general health, reproductive health is the complete well-being of persons at particular *life cycles*, and not merely the absence of disease or infirmity among such individuals. Examples of such individuals include men and women of reproductive age, infants, and children. The bulk of reproductive health services in all countries are typically targeted to pregnant women, newborns, and children.

2. DEMAND FOR REPRODUCTIVE HEALTH INPUTS

We use a slightly modified version of a model by Rosenzweig and Schultz (1982) in which health is embedded in a utility maximizing behavior of an agent, e.g., a mother, a father, or any other household member. The model is also summarized in Mwabu (2007a,b) and its applications highlighted in Strauss and Thomas (2007). The Rosenzweig-Schultz one-period utility function is of the form:

$$U = U(X, Y, H) \quad (1)$$

where,

X = a health neutral good, i.e., commodity that yields utility, U , to an individual but has no direct effect on reproductive health status of a person; an example of such a good is clothing of men, women and children;

Y = a health-related good or behavior that yields utility to an individual and also affects reproductive health, e.g., smoking, alcohol consumption, or preventive activities;

H = reproductive health status of an individual.

The reproductive health production function is given by

$$H = F(Y, Z, \mu) \quad (2)$$

where,

Z = purchased market inputs such as medical care that affect health directly;

μ = the component of health due either to genetic or environmental conditions uninfluenced by behavior.

An individual maximizes (1) given (2) subject to the budget constraint given by equation (3)

$$I = XP_x + YP_y + ZP_z \quad (3)$$

where,

I is exogenous income;

P_x, P_y, P_z are, respectively, the prices of the health-neutral good, X (such as clothing), health-related consumer good, Y (such as quitting smoking) and health investment good, Z (e.g., immunization). Notice from equations (1) and (2) that the health investment good is purchased only for the purpose of improving reproductive health so that it enters an individual's utility function only through H .

Equation (2) describes an individual's production for health. The health production function has the property that it is imbedded in the constrained utility maximization behavior (equations 1 and 3). Expressions (1)-(3) can be manipulated to yield health input demand functions of the form

$$X = D_x (P_x, P_y, P_z, I, \mu) \quad (4.1)$$

$$Y = D_y (P_x, P_y, P_z, I, \mu) \quad (4.2)$$

$$Z = D_z (P_x, P_y, P_z, I, \mu) \quad (4.3)$$

The effects of changes in prices of the three goods on health can be derived from equations (4.1-4.3) since from equation (2), a change in health can be expressed as

$$dH = F_y \mathcal{C} dY + F_z \mathcal{C} dZ + F_\mu \mathcal{C} d\mu \quad (5)$$

where,

F_y , F_z , F_μ are marginal products of health inputs Y , Z and μ , respectively (see equation (2)).

From the equation (2), the change in health can be related to changes in respective prices of health inputs as follows

$$dH/dP_x = F_y \mathcal{C} dY/dP_x + F_z \mathcal{C} dZ/dP_x + F_\mu \mathcal{C} d\mu/dP_x \quad (6.1)$$

$$dH/dP_y = F_y \mathcal{C} dY/dP_y + F_z \mathcal{C} dZ/dP_y + F_\mu \mathcal{C} d\mu/dP_y \quad (6.2)$$

$$dH/dP_z = F_y \mathcal{C} dY/dP_z + F_z \mathcal{C} dZ/dP_z + F_\mu \mathcal{C} d\mu/dP_z \quad (6.3)$$

where,

$d\mu/dP_i = 0$, for $i = x, y, z$ so that in equation (6), the terms $F_\mu \mathcal{C}(\cdot) = 0$, since μ is a random variable unrelated to commodity prices.

2.1 Effects of prices on reproductive health demands

The above expressions show that commodity prices are correlated with the health status of an individual, i.e., a child or an adult. Specifically, the signs and sizes of effects of commodity prices on health depend on (a) magnitudes of changes in demand for health inputs following price changes and (b) sizes of the marginal products of health inputs. It is interesting to observe from equation (6.1), that changes in prices of health-neutral goods also affect reproductive health via the budget constraint.

The effects of commodity prices on reproductive health (dH/dP_i for $i = x, y, z$) depend on several factors. The first factor is the magnitude of the change in the demand for a reproductive health input following a price change (i.e., dY/dP_i or dZ/dP_i for $i = x, y, z$). The second factor is the magnitude or sign of the marginal product of that health input (F_i for $i = x, y, z$). The change in price of the health-neutral good (X) affects reproductive health status indirectly through the budget constraint. Moreover, although a change in price of good Y might be associated with an

improvement in reproductive health ($F_y \partial Y / \partial P_y > 0$), the effect of the same change on demand for other goods could worsen reproductive health ($F_z \partial Z / \partial P_y < 0$). Thus, the overall impact of own and cross price effects on reproductive health is uncertain. These cross-price effects are absent in demands for reproductive that are not linked to health production.

It is clear from equations (6.1-6.3) that the demand effect of own price of Z can be expressed as $dZ/dP_z = (dH/dP_z - F_y \partial Y / \partial P_z - F_\mu \partial \mu / \partial P_z) / F_z$, which reduces to $(dH/dP_z - F_y \partial Y / \partial P_z) / F_z$, because $F_\mu \partial \mu / \partial P_z = 0$. The term $(F_y \partial Y / \partial P_z)$ is the change in reproductive health status due to a change in usage of a substitute or a complementary health input, Y , following the change in the price of input Z . The difference term, i.e., $(dH/dP_z - F_y \partial Y / \partial P_z)$, is the change in reproductive health status due to the usage of Z following the change in its price.

Thus, the ratio of the change in reproductive health status to the marginal product of Z , i.e., $[(dH/dP_z - F_y \partial Y / \partial P_z) / F_z]$, represents the additional quantity of reproductive health service, Z , that is demanded due to a unit change in its price so that for the entire price change, we have the expression, $dZ = [dP_z \partial (dH/dP_z - F_y \partial Y / \partial P_z) / F_z]$. This expression is of policy interest because it reveals that in order to predict the change in utilization of the reproductive health service, dZ , following a change in its price, information on marginal products of all reproductive health inputs (F_y and F_z) is required. However, on its own, the above expression could convey the misleading information that the demand for reproductive health services is motivated solely by the desire to improve health. Expression (1) indicates that the magnitudes of marginal utilities of reproductive health services determine observed demands for these services.

2.2 Consumer behavior, marginal products and marginal utilities of reproductive health services

Equations (6.1-6.3) depict the role of reproductive health care as an input into health production (equation (2)) while equation (1) depicts its role as a consumer good. As consumer good, reproductive health care yields utility and as an input it improves health. The marginal utilities of Y and Z are available from equation (1), whereas their respective marginal products can be derived from equation (2). Thus, it can be seen from expressions (1) and (6) that a mother would be willing to consume a commodity that has a prospect of harming health (e.g., smoking), because it yields utility. Similarly, a person would be willing to undertake medical treatment that yields disutility if it is expected to improve health. These and other commonly observed behaviors in health care markets are explained by Rosenzweig-Schultz model.

2.3 Estimation of reproductive health care demands and reproductive health production technologies

Policy-makers need to know the parameters of reproductive health care demand functions and the associated health production technologies to plan for provision and utilization of family health services and related goods. Reproductive health services planning is required to achieve commonly agreed health objectives, such the Millennium Development Goal of reducing maternal mortality substantially 2015. To obtain the information required for planning, reproductive health technology and related input demand parameters must be estimated jointly.

This estimation is complicated by the need to identify reproductive health care demand functions from reproductive health production technologies.

The first step in the estimation of a reproductive health production model is the estimation of demands for inputs into that model. In the context of equation (2), these are demands for Y and Z . The demand for X is not of interest, except as a residual, particularly in budget share demand specifications. As inputs into reproductive health production, Y and Z are choice variables and are therefore endogenous to reproductive health. Thus, in order to obtain unbiased and consistent estimates of demand parameters for Y and Z , instrumentation of these variables is required. The instrumental variables for Y and Z are factors that can be used to predict Y and Z , without affecting reproductive health status. Equations (4.1-4.3) indicate that exogenous income such as rent income, and prices of Y , Z and X are valid instruments. Availability of social infrastructure such as roads, and access variables, such as distances or travel time to health facilities are additional instruments (Strauss, 1986; Bound et al., 1995).

3. FUNCTIONAL FORMS AND SPECIFICATION ISSUES

The material here is an adaptation and elaboration of Mwabu (2007a). Following Rosenzweig and Schultz (1983), the translog reproductive health production function can be written as

$$\ln(H) = \left(\frac{1}{2} E_i E_j \beta_{ij} \ln(Y_i) \ln(Y_j) + G_i \beta_i \ln(Y_i) + \beta^* Z + \epsilon \right) + \eta, \quad (7)$$

where,

the term \ln is the natural log operator; β , β^* , β_i , and β_{ij} are technological parameters to be estimated; Y_i is health input i , with $i = \dots, j$; Z is a vector of other control variables such as socioeconomic characteristics of households; η is a random error term.

As an alternative to the translog function, the following generalized linear reproductive health production relationship can be specified (see Diewert, 1971) follows

$$H = \left(\beta_i \beta_j \beta_{ij}^{1/2} \ln(Y_i) \ln(Y_j) + G_i \beta_i \ln(Y_i) + \beta^* Z + \epsilon \right) + \eta, \quad (8)$$

where β_{ij} are health effects of the interaction terms. In the case of four health inputs, the model to be estimated would have sixteen interaction coefficients (including the coefficients on the square root terms). However, symmetry restrictions, i.e., $\beta_{ij} = \beta_{ji}$, considerably reduce the number of the parameters that are actually estimated. As in the case of the translog function, the generalized linear and Leontief specifications (Diewert, 1971) are very useful in providing second-order approximations to an arbitrary function at a given vector of covariates using only a minimal number of parameters, i.e., the coefficients of the interaction terms.

Since ϵ is unobservable, the composite error term in equation (7) is the sum of η and ϵ , which is potentially correlated with the independent variables (Y_i s) so that the OLS estimates of β_i and β_{ij} parameters may be inconsistent.

In a translog, the data determine the correct mathematical form of the production technology. For example, if the estimated β_{ij} s are equal to zero, equation (7) takes the form of a Cobb-Douglas production function. Second, the symmetry restriction, $\beta_{ij} = \beta_{ji}$, significantly reduces the number of β_{ij} parameters to be estimated.

To concretize the usefulness of symmetry restriction, assume that there are four health inputs into a reproductive health production function. Now suppressing the Z covariates and the composite error term, expression (7) can be rewritten out in full as

$$\begin{aligned} \ln(H) = & (\alpha_0 + \beta_1 \ln(Y_1) + \beta_2 \ln(Y_2) + \beta_3 \ln(Y_3) + \beta_4 \ln(Y_4) + \frac{1}{2}\{\beta_{11} \ln(Y_1)\ln(Y_1) + \\ & \beta_{12} \ln(Y_1)\ln(Y_2) + \beta_{13} \ln(Y_1)\ln(Y_3) + \beta_{14} \ln(Y_1)\ln(Y_4)\} + \frac{1}{2}\{\beta_{21} \ln(Y_2)\ln(Y_1) + \\ & \beta_{22} \ln(Y_2)\ln(Y_2) + \beta_{23} \ln(Y_2)\ln(Y_3) + \beta_{24} \ln(Y_2)\ln(Y_4)\} + \frac{1}{2}\{\beta_{31} \ln(Y_3)\ln(Y_1) + \\ & \beta_{32} \ln(Y_3)\ln(Y_2) + \beta_{33} \ln(Y_3)\ln(Y_3) + \beta_{34} \ln(Y_3)\ln(Y_4)\} + \frac{1}{2}\{\beta_{41} \ln(Y_4)\ln(Y_1) + \\ & \beta_{42} \ln(Y_4)\ln(Y_2) + \beta_{43} \ln(Y_4)\ln(Y_3) + \beta_{44} \ln(Y_4)\ln(Y_4)\} \end{aligned} \quad (9)$$

From the symmetry restriction, $\beta_{ij} = \beta_{ji}$, we find

$$\begin{aligned} \beta_{12} &= \beta_{21}, \beta_{13} = \beta_{31}, \beta_{14} = \beta_{41}; \\ \beta_{23} &= \beta_{32}, \beta_{24} = \beta_{42}, \beta_{34} = \beta_{43}. \end{aligned}$$

Thus, ignoring the coefficients of the quadratic terms, i.e., β_{11} , β_{22} , β_{33} , and β_{44} , it can be seen from (9) that out of a total of 12 coefficients of the interaction terms, only 6 need to be estimated, namely, β_{12} , β_{13} , β_{14} , β_{23} , β_{24} , and β_{34} . It is interesting to observe that there is no need to estimate the coefficients of the *interactions* of the fourth (last) input with each of the other inputs. That is, symmetry makes unnecessary the estimation of β_{41} , β_{42} , and β_{43} . More generally, estimation of β_{ij} is not needed when i is indexing the *last* input in the interaction terms. For completeness of the example, notice from (equation 9), that the double summation of parameters ($\sum_i \sum_j \beta_{ij}$) in equation (7) can be fully expanded as

$$\begin{aligned} \text{Inner summation:} \quad \sum_j \beta_{ij} &= (\beta_{11} + \beta_{12} + \beta_{13} + \beta_{14}); (\beta_{21} + \beta_{22} + \beta_{23} + \beta_{24}); \\ & (\beta_{31} + \beta_{32} + \beta_{33} + \beta_{34}); (\beta_{41} + \beta_{42} + \beta_{43} + \beta_{44}) \end{aligned} \quad (10A)$$

$$\text{Outer summation:} \quad \sum_i \beta_{ij} = \sum_j \beta_{1j} + \sum_j \beta_{2j} + \sum_j \beta_{3j} + \sum_j \beta_{4j} \quad (10B)$$

Notice that equation (8) can be expanded similarly. As noted earlier, for expression (7) to simplify to a Cobb-Douglas production function, the sum in (10B) must be equal to zero. Statistically, the sum in (10B) is equal to zero if the parameters in (10A) are jointly not different from zero. This observation is easily checked if (7) is written as

$$H = \exp(\alpha_0) \prod_i Y_i^{\beta_i} \exp\{\frac{1}{2} \sum_i \sum_j \beta_{ij} \ln(Y_i) \ln(Y_j)\} \exp(\sum_j \beta_{4j} Z_j) \exp(\epsilon) \quad (10C)$$

where, as before, Z may contain dummy variables such as gender, race, region of residence. Equation (10) shows that the translog is an augmented form of the Cobb-Douglas function.

The above model specifications concern functional forms for continuous health input demands or for continuous health production functions. In the health economics literature, there are also examples of functional forms for demand and production functions that are discrete. That is, the dependent variables are discrete (see e.g., Gertler and van der Gaag, 1990; Strauss and Thomas, 1995; Dow, 1999; and Sahn et al., 2003).

The above studies discuss and apply nested and non-nested discrete choice models of health care demand using micro data. The models are appropriate for analyzing multiple rather than binary choices. A nested multinomial model for example is appropriate if one is analyzing a mother's decision to use or not to use an immunization service and her subsequent choice of an immunization facility from among multiple alternatives such as government or missionary clinics. If a multinomial model is not nested, a simple version of such a model is adequate. Furthermore, binary probit and logit models are sufficient when analysis is restricted to a dichotomous choice, e.g., whether or not a mother is using family planning.

A convenient specification of a nested logit model that encompasses all the aspects discussed above is in Sahn et al. (2003). Sahn *et al* model selection of a health care provider, given that a person is sick. Since this is a discrete choice, the focus of the analysis is on the probability that one selects a given option. In their model, they specify five options: no care (or self-care), care at a public hospital, care at a private hospital, care at a public clinic, and care at a private clinic. Following Gertler and van der Gaag (1990), they specify an indirect utility function of the form:

$$V_j = f(y-p_j) + Q(\mathbf{X}, \mathbf{Z}_j) + e_j \quad (11A)$$

where,

$(y-p_j)$ is net income (y) after paying a price p for health care at option j ; \mathbf{X} is a set of individual or household variables that do not vary with the discrete alternatives; and \mathbf{Z}_j is a set of choice-specific variables. The function, $Q(\mathbf{X}, \mathbf{Z}_j)$, indicates the quality of alternative j , and is a function of attributes characterizing the alternative, as well as those of the individual making the choice. In this specification, the quality function, $Q(\mathbf{X}, \mathbf{Z}_j)$, is linear in \mathbf{X} and \mathbf{Z} variables. The \mathbf{X} variables include age, education, marital status, duration of illness, and household demographics. In all cases, the coefficients on these attributes vary across alternatives. In equation (11), the benefits obtainable from treatment at a particular facility depend on net income of an individual (signifying the quantity of the service that can be bought) and the quality of service (indicating the efficacy or effectiveness of treatment).

To satisfy certain utility maximization axioms (see Gertler and van der Gaag, 1990), the functional form for prices and income is usually specified as a quadratic in the logs of net income as follows:

$$f(y-p_j) = \beta_1 * \ln(y-p_j) + \beta_2 * [\ln(y-p_j)]^2 \quad (11B)$$

where the β 's are kept equal across the choice alternatives being considered. This constrains the marginal utility of income to be the same across options (see Dow, 1999).

As with all discrete choice models, the logit model in equation (11) identifies only the difference in utilities, $V_j - V_0$, where V_0 is a reference or base utility, which in this case is utility from self-care. Specifically, the quality of self-care is set to zero. In situations where costs of care are small relative to income, the function $f(y-p_j)$ will be similar across alternatives. To simplify estimation, Sahn et al. (2003) work with the following approximate form of equation (11B):

$$f(y-p_j) = \beta_1 * \ln(y-p_j) + \beta_2 * [\ln(y-p_j)]^2 \\ \approx \beta_1 * \{\ln(y) - p_j/y\} + \beta_2 * \{\ln(y)^2 - 2\ln(y) (p_j/y)\} \quad (12)$$

Both $\ln(y)$ and its square are constant across options, so that after taking the difference $V_j - V_0$, only $\beta_1(-p_j/y) - \beta_2\{2\ln(y) (p_j/y)\}$ remains, and thus the two coefficients of interest are identified. Nesting the logit choices allows estimation of the covariances between the e_j 's across options, which in turn allows cross-price elasticities to vary between alternatives. Sahn et al (2003, p.) specify the probability (π) that a person chooses alternative l ($l \neq j$) is given by

$$p_l = \frac{\left[\exp\left(\frac{V_l}{s_{j(l)}}\right) \right] \left[\sum_{i \in j(l)} \exp\left(\frac{V_i}{s_{j(l)}}\right) \right]^{\left(\frac{s_{j(l)}}{\tau_{k(l)}} - 1\right)} \left[\sum_{j \in k(l)} \left[\sum_{i \in j(l)} \exp\left(\frac{V_i}{s_j}\right) \right]^{\left(\frac{s_{j(l)}}{\tau_{k(l)}}\right)} \right]^{\tau_{k(l)}}}{\sum_k \left(\sum_j \left[\sum_{i \in j} \exp\left(\frac{V_i}{s_j}\right) \right]^{\frac{s_j}{\tau_k}} \right)^{\tau_k}} \quad (13)$$

where,

i indexes the individual options (private hospital, etc.); j indexes the lower level nests (hospital care, or non-hospital care); and k indexes the upper level nest (no care or care). V_i is the indirect utility associated with option i ; σ_j is the inclusive value coefficient for the lower level nests; τ_k is the inclusive value coefficient for the upper level nests (the limbs); and $j(l)$ and $k(l)$ indicate the lower and upper level nests to which option l belongs. Note that if all τ_k are constrained to one, equation (13) reduces to one-level nested logit probability; and if the σ_j are also one, it collapses to a multinomial logit model. Furthermore, if the choice set is binary, equation (13) reduces to a binary logit or probit model. Notice that although equation (13) is typically used to estimate discrete choice demands, it can also be used to analyze discrete health outcomes in a production function context. For example, the framework can be used to estimate the probability that a child will be in one of the several mutually exclusive health states after being immunized against a particular illness. In the same vein, analysis can focus on demand for reproductive health itself, as in Grossman (1972), instead of on demand for the inputs required to produce it as in equation (4).

In Grossman's model, the demand for health (reproductive health included) is for investment and consumption purposes (see Mwabu, 2007a). In the spirit of that framework, reproductive health yields direct utility to an individual, and also increases labor income through two channels. The first channel is through a reduction in sick time so that more time is available for production. The second is through the enhancement of work effort.

4. ESTIMATION ISSUES

In order to estimate equations (7), (8) or (13), measurement of all the variables specified in these equations is required. The health outcome variable – the dependent variable, H , in equation (7) for example can be measured using a number of indicators, e.g., birth weight, height, and body mass index.

Because of problems of endogeneity, estimation of equations (7) or (8) via the OLS yields biased results. The IV method addresses the endogeneity problem by purging the correlation between the health inputs and the overall residual in equation (7). As can be seen from equation (7), the overall residual consists of a white noise term and unobservable health endowments. Endogeneity is also an issue in equation (13) and could partially be addressed using the *ivprobit* methods in STATA.

The challenge in using the IV methods is to find valid instruments for the endogenous variables. In general, local commodity prices and measures of community level infrastructure have been shown to be valid instruments for health inputs (Rosenzweig and Schultz, 1983; Strauss, 1986; Strauss and Thomas, 1995); Wooldridge, 2002).

5. INTRA-HOUSEHOLD ALLOCATIONS

5.1 Background

The household provides the environment in which individuals produce and consume health and other goods and services. In addition to providing its members with an environment for production and consumption of private and public goods, the household also provides the mechanism for intra-household allocation of essential commodities such as health care, food, clothing and reproductive health services. This allocation mechanism is important because it determines the well-being of all household members. The presentation and discussion of household models in this section (the whole of Section 5) draws heavily from Mwabu (2007a).

5.2 The unitary model

In Becker's (1981) household model, commonly known as the *unitary* model, the intra-household distribution of commodities occurs automatically. The model predicts that in a household with a caring head, all members will pursue a common goal. It is Becker's (1974, p.

1080) Rotten Kid Theorem that ensures automatic intra-household transfers. In Becker's words, "... sufficient 'love' by one member guarantees that all members act as if they loved other members as much as themselves. As it were, the amount of 'love' required in a family is economized: sufficient 'love' by one member leads all other members by 'an invisible hand' to act as if they too loved everyone."

Bergstrom (1989) provides a simple and clear exposition of the Rotten Kid Theorem. The theorem "asserts that if all family members receive gifts of money income from a benevolent household member, then even if the household does not precommit to an incentive plan for family members, it will be in the interest of selfish family members to maximize total family income" (p. 1138). Bergstrom (1989, pp. 1139-1140) illustrates the theorem as follows.

Let $U(X_1, \dots, X_n)$ be the utility of an altruistic household head, where X_i ($i = 1, \dots, n$) is consumption of a private good X by household member i . Denote I_i as the income of selfish member i before any intra-household transfers occur so that total consumption expenditure of all household members on units of commodity X is equal to total household income, i.e., $\sum_i X_i = \sum_i I_i$, where price of X is unity. After the income transfers by the household head, the distribution of consumption in the household must be the one that maximizes the utility of the household head subject to the restriction that $\sum_i X_i = \sum_i I_i$.

The rational head will not choose an intra-household consumption distribution that does not maximize his utility. Because the transfers are made out of total household income, consumption of each household member depends on that total income. Hence each member has an interest in maximizing total household income, even at the cost of reducing one's *own* income because the head would compensate any such cost through transfers. Furthermore, any gain in personal income unwanted by the head would be similarly offset. Just like the rational head will not choose an intra-household allocation that does not maximize his utility, rational household members would not deviate from such an allocation because they know that the head would offset the income effect of their actions. Thus, the Pareto optimal intra-household consumption allocation is achieved automatically without the head having to use the transfers to enforce it. This is the intuitive proof of the theorem.

The reasons for the failure of the theorem to work as stated include problems in monitoring behavior of household members, information asymmetries within the household, and problems in designing incentives that make household members accomplish the welfare program chosen by the head. Formal analysis of these issues and additional reasons are in Bergstrom (1989). In the context of the theorem, the term "rotten" means selfish, or "not as caring about the well-being of other household members as much as the altruistic head does." Browning et al (1994, p. 1071), distinguish between altruistic preferences where an individual derives utility from a good consumed by another (as in the above case), and caring preferences where a person cares about the good consumed by another only insofar as it gives the other person some utility. The caring

preferences have the advantage of being non-paternalistic because a person does not make transfers that are not beneficial to another.

The unitary household model predicts that household members will pool their resources and that their welfare is unaffected by the identity of the person controlling resource allocation. These predictions are unlikely to apply in the case of vulnerable household members such as women and children.

5.3 The collective model

The collective model is the alternative to the unitary model in the household economics literature. The collective household model (Chiappori, 1988; Alderman, et al., 1995; Haddad et al., 1997) is appropriate for analyzing reproductive health within a household because it accounts for intra-household distribution of market and non-market goods. This model is well known in the household economics literature. Following Thomas (2000) the welfare of a household in a collective model can be written as:

$$\text{Max } W = \sum_m J_m U_m(L, X; A, e), \quad m = 1, \dots, N \quad (14A)$$

Subject to

$$pX = \sum_m (w_m(T_m - L_m) + Y_m) \quad (14B)$$

where

W = Welfare derived from total household consumption;

$J_m U_m(\cdot)$ is an individual utility function, weighted by J_m , the index of bargaining power of individual m in the allocation of consumption within the household, such that $\sum_m J_m$ is equal to 1;

p is a vector of commodity prices;

w is a vector of wages for all household members;

T is total household time;

Y is total non-labor income;

X is a vector of goods consumed by all household members, including medical and health care so that commodity expenditure, pX is equal to total labor and non-labor income;

L is a vector of leisure time for all household members;

A is a vector of household-level demographics such as household size, composition, and personal characteristics such as age, gender, health status and education of all household members;

e is a vector of unobserved heterogeneity in the household, such as attitudes and ability of members or more generally, efficiency parameters (Manser and Brown, 1980, p. 35; Mwabu, 2007a).

5.3.1 The Bargaining version of the collective model

In expression (14A), the household maximizes the weighted sum of utilities that its members derive from their own consumption bundles, given the sharing rule. There is need to clarify that equation (14A) is one of the ways of specifying the welfare function of the household in the collective decision making process context. An alternative specification (Manser and Brown, 1980; McElroy and Horney, 1981) in a two-person household context is

$$\text{Max } W = [U_1(L, X; A, e) - V_{01}]C[U_2(L, X; A, e) - V_{02}] \quad (15)$$

where,

W is household welfare;

$U_1(\cdot)$ is utility for individual 1;

$V_{01}(\cdot)$ is reservation utility for individual 1, i.e., the utility that person 1 can obtain if he is not a member of the household;

$U_1 - V_{01}$ is the net benefit that person 1 gets from being a member of the household; and similarly for person 2.

Following Manser and Brown (1980, p. 38), and assuming an N -person household, equation (17) can be rewritten in logarithmic form as

$$\text{Log}(W) = \sum_m \text{Log}[U_m(L, X; A, e) - V_{0m}], \quad m = 1, \dots, N \text{ and } U_m(\cdot) \dots V_{0m} \quad (16)$$

In equation (16), the household maximizes the *product* of net utilities of its members (rather than the *sum* of weighted utilities as in (14A)) subject to the same budget constraint (equation (14B)).

Notice that equation (16) is restricted to situations where $U_m(\cdot) \dots V_{0m}$ to avoid taking the logarithm of zero. The bargaining power index, J , enters the household objective function through the reservation utility (indirect utility) of the following general form

$$V_{0m} = V_{0m}(p, w; A, J(D(2))) \quad (17)$$

where,

V_{0m} = the maximum indirect utility that a household member m can attain given the market prices, p , the wage rate, w , and his social-economic characteristics, A and bargaining power within the household;

J = is the Pareto weight, the share of m 's utility in total household welfare, and helps aggregate personal utilities to the household level utility;

D = resource sharing rule, which helps decentralize decision making within the household;

2 = is a set of m 's options outside the household, e.g., job and marriage opportunities.

Thus in equation (17) the term, $J(D(2))$, is a proxy for income that person m can command within the household, and generally reflects his consumption possibilities (see Mwabu, 2007a for details).

If the bargaining power index (J) of the household member m is equal to 1, equation (16) converges to a unitary model. This can easily be checked as follows. If $J_m = 1$, the net utility from being a household member for each of the other $m-1$ members is large, i.e., their reservation utilities are small because by definition they have no options outside the household or such options are of limited value. In contrast, the reservation utility for the person with complete bargaining power

($J_m = 1$) is large, and therefore his personal gain from household membership is small or negligible. However, there is more to this. If person m has complete bargaining power, the net gains that the other members derive from the household could *reflect* his preferences. That is, if the other members share person m 's preferences, then their net utilities are also m 's utilities. This is the common preferences model. However, the dominant member could also impose his caring preferences on other household members. This is the benevolent dictator model. Notice that if the net gain of the dominant household member is negative, he would still remain a member, as long as the sum of net gains for all members (him included) is positive.

5.3.2 The separate spheres version of the collective model

It is easy to modify equation (16) to capture non-cooperative behavior within the household (Chen and Woolley, 2001) as follows

$$\text{Log}(W) = \sum_m J_m \{ \text{Log}[U_m(L, X; A, e) - V^*_{0m}], m = 1, \dots, N \text{ and } U_m(\dots) \dots V^*_{0m} \quad (18)$$

where,

V^*_{0m} is the maximum utility that household member m gets without cooperating with other family members, conditional on being part of the family. That is, it is the utility the individual derives by acting strategically to maximize self interest, taking as given the behavior of other household members. These are the utilities derived from what has been termed *separate spheres* of responsibilities within the household (Lundberg and Pollak (1993).

However, since individuals in a household care about one another, i.e., they have caring preferences (Browning et al., 1994; Chen and Woolley, 2001), they also have an incentive to cooperate, particularly in the provision of household public goods. The utility level, V^*_{0m} represents the minimum benefit that m would expect to get if he were to cooperate with other household members. For example, if he were to agree to contribute to a household good, such as cleaning the household compound every week, his utility under the new circumstance cannot be less than V^*_{0m} . Thus, as in equation (16), the V^*_{0m} represents reservation utility or a point of threat to cooperation. In contrast to equation (16), where the threat is about divorce or quitting the household, in equation (18) the threat is about a return to a non-cooperative behavior (Lundberg and Pollak, 1993, 1994). Notice that as in equations (14A) and (16), if the bargaining power index, J_m , is unity, equation (18) collapses to a unitary model.

The formulation of the welfare function in equation (18) is best illustrated with a two-person household, consisting of a husband (m) and a wife (f). Following Chen and Woolley (2001) assume that a household member i has the following utility function, which is separable in private good, x_i , and a household public good x^h as shown in equation (19).

$$W_i = U_i + U_j = [u(x_i) + v(x^h)] + s[u(x_j) + v(x^h)], \text{ for } i, j = m, f \quad (19)$$

where,

W_i is the welfare of person i , a weighted sum of utilities from own consumption and consumption of j (weighted by the parameter, s), where, s is a caring parameter (the share of j 's utility in i 's total utility) so that $0 < s < 1$. Notice that if the caring parameter, s , is equal to zero, then the own utility of i , $u(x_i)$, is weighted by 1.

Chen and Woolley (2001) show that both m and f choose x to maximize W_i subject to a budget constraint, taking as given each other's purchases of public good, x^h . The resulting Cournot equilibrium pair of x and x^h for each spouse is associated with an optimal level of W_i^* . These net utilities are generated by a non-cooperative game within a family. Any cooperative Nash game, like joint provision of a public good, must yield at least W_i^* , $i = m, f$. Denoting W_i^* as V_{01}^* and V_{02}^* respectively (where $01 = m$ and $02 = f$), the expression for maximization of household-level welfare rather than of personal utilities by the spouses is

$$\max W = [U_1(L, X; A, e) - V_{01}^*]^{J_1} [U_2(L, X; A, e) - V_{02}^*]^{J_2} \quad (20)$$

where, the exponents, J_1 and J_2 are the bargaining power indices of the husband and wife, respectively. This expression easily generalizes to equation (18) in the context of an N -person household. The solution to expression (18) is a Cournot-Nash equilibrium because it combines non-cooperative and cooperative behaviors of Cournot and Nash games, respectively.

The caring parameter, s in equation (19) and the Pareto weight, J in equation (20) should be carefully distinguished. We start with exposition of the caring parameter. The caring parameter, s accounts for interdependencies of utilities of persons m and f within a household. It takes account of the fact that the utility level of person m , for example, could depend on the utility level of f , and vice versa.

The caring parameter states that that utility of person 1 (i.e., U_1) is equal to $(1-s)u_1$ plus some fraction, s , of utility of person 2 (u_2); and conversely for person 2's utility. Person 1's utility under the caring preferences assumption can be expressed as:

$$U_1 = (1-s)u_1 + su_2 \quad (21)$$

Notice that if s is equal to zero, $U_1 = u_1$, which means that the preferences are egoistic rather than caring. In that case, an individual's utility is based solely on his or her own consumption. The

extension of this example to the case of an N -person household is straightforward. In the case of an N -person household, s becomes s_{ij} , where, s_{ij} is the share of utility of member j in member i 's utility, where for a given $i, j = 2, 3 \dots N-1$.

In contrast, the Pareto weight, J_1 , is the share of person 1 in the total utility of the household with members whose utilities are interdependent. In a two-person household, if J_1 is equal to zero, the utility of person 1 does not matter; only that of person 2 does. This is the case of a unitary model, where person 2 acts as a dictator. This case is also easily generalizable to an N -person household. As noted earlier, the role of J is to aggregate utilities of individuals to a *household level utility*, taking into account the bargaining power of each member. In contrast, the role of s , is to construct the *utility index of an individual*, taking into account the interdependencies of individuals within a household, as summarized by the caring parameter, s , which expresses the extent to which an particular individual's preferences are caring.

6. EXPERIMENTAL APPROACHES

The demand frameworks described so far rely on survey data and regression analysis to make causal inference. That is, to measure causal effects of variables which affect reproductive health. The effect of a variable (such as tetanus immunization) that improves reproductive health (e.g. reduces maternal mortality) can only be measured correctly if it is varying independently of reproductive health. That is, if tetanus vaccination is exogenous to maternal mortality.

The regression approach to this problem is controversial because the effects of confounding variables are difficult to isolate from the impact of the variable of interest. This particular problem arises because of measurement errors, reverse causality, and omitted variables. From a technical standpoint, the problem is that the explanatory variable of interest is correlated with the disturbance term in a regression equation. Although instrumental variables are widely used to solve this problem, credible instruments are not easy to find (Bound et al., 1995). The ideal solution to the problem of identifying causality in the example given above is to design an experiment, in which "treatment" and "comparison" groups are randomly assigned tetanus vaccination. For example, the treatment group would be vaccinated, and the comparison group would not. Measured differences in maternal mortality between the two groups would in this case be attributed to tetanus vaccination. However, ideal experiments are difficult to design (Rosenzweig and Wolpin, 2000; Culyer and Newhouse, 2000). Experimental and non-experimental methods of identifying causality are thoroughly covered in Schultz and Strauss (2007). The relatively new regression techniques for measuring causal effects in structural models, e.g., the local instrumental variable (LIV) method, and the control function approach are ably presented in Todd (2007).

7. APPLICATIONS OF FRAMEWORKS: SELECTIVE ILLUSTRATIONS

The applications presented in this section pertain only to the unitary version of the general collective household model. Because of data limitations, it is not possible to illustrate other versions of the collective model. Moreover, the unitary model is illustrated using only a few of the available specifications of demand and production functions. It is hoped that the variants of the collective model presented in this paper, as well as the various specifications discussed therein will guide the case studies on reproductive health, growth and poverty at the micro level in Africa and elsewhere.

7.1 Demand for contraceptives and maternal health in Malaysia

Using a budget constraint similar to the one shown in equation (3), Rosenzweig and Schultz (1987) estimated the effects of contraceptives on maternal health using a two-period utility model. The models in equations (22A-B) are helpful in interpreting the estimation results that follow.

$$\text{Max } V = E\{U(n_1, X_{1j}) + \delta U(N_j, H_j, X_{2j}; \alpha_j)\}, \quad i=1,2 \quad (22A)$$

Where,

V = expected utility over the two time periods;

n_1 = number of children ever born in period 1;

X_{1j} = market goods consumed by couple j in period i ($i=1, 2$);

δ = discount rate;

α = household-specific taste parameter;

$N_j = n_{1j} + n_{2j}$ (cumulative fertility) of household j over the two time periods;

H_j = per child human capital input for couple j (e.g., educational attainment);

s_j = per child human capital input (e.g., average years of schooling or birth weight).

Maximization of equation (22A) subject to a budget constraint yields demand functions for fertility, human capital and market goods defined above.

The reproduction function technology of the couple (the couple's fecundity) is given by

$$n_{ij} = n(Z_{ij}; i) + u_i + e_i, \quad n_z < 0, n_{zz} < 0 \quad (22B)$$

Where

Z_s = fertility control inputs (i.e., contraceptives or family planning methods).

u_j = time-invariant, couple specific component of fertility that is unaffected by the couple's behavior;

e_j = independently distributed disturbance term.

In equation (22B) the demand for Z (contraceptive commodities and services) is as shown in equation (4). Clearly, covariates Z in the reproduction function equation (22B) are endogenous.

Thus, to consistently estimate their effects on fertility (n_{ij}), use of IV method is required. The instruments suggested in equations (4) were used for estimation using Malaysian data (1262 households). In equation (22B) n_j measures of the health status of the mother. Table 7.1 presents estimation results of a linear reproduction function (equation (22B)). As argued in section 5, a general flexible form such as the translog is the ideal form to estimate.

Table 7.1: Estimates of a linear reproduction technology of a couple (dependent variable is number of children ever born (t-stat in parentheses))

<i>Variables</i>	<i>Estimation procedure</i>	
	OLS	2SLS
<i>Endogenous Variables</i>		
Pill/IUD	-0.0241 (2.77)	-0.0713 (2.02)
Condom	-0.0233 (1.43)	-0.0291 (0.38)
Ineffective methods/(100)	-0.079 (0.07)	-0.881 (0.17)
Breast feeding, in months ($\times 10^{-2}$)	-.00737 (0.6)	-0.131 (2.91)
<i>Exogenous Variables</i>		
Mother's age, in months ($\times 10^{-3}$)	0.218 (0.71)	0.0418 (0.93)
Mother's age squared ($\times 10^{-6}$)	-0.631 (1.71)	-0.758 (1.52)
Constant	0.0436 (0.71)	0.134 (1.60)
<i>R-squared</i>	0.10	-
<i>F</i>	8.90	8.17

Source: Rosenzweig and Schultz (1987), Table 4, p. 174.

In Table 7.1, results of estimation of demand functions and a health production function in the spirit of equation (1). The 2SLS results show the effects of contraceptives on fertility after purging their correlation with the error term. That is, after making the demand for contraceptives vary independently of fertility. In contrast, the OLS results are obtained without taking into account the endogeneity of contraceptives to fertility. In both cases, the pill reduces fertility, but the IV estimate is larger than the OLS estimate. The negative coefficient on breastfeeding becomes larger and statistically significant when the endogeneity problem is removed, indicating that 2SLS is the appropriate estimation method. Notice that although the first stage regressions (estimations of demands for contraceptives) are not shown, these are routinely reported (see Bound et al., 1995). Notice that inclusion in equation (22B) of variables that capture the control of household assets by various members of the households would yield results that would indicate intra-household variations in the demand for contraceptives and fertility.

7.2 Demand for general health care services in Tanzania

General health services are important determinants of reproductive health. For example, the health of mothers and children in malarious regions is critically dependent on availability and use of effective malaria treatments. Thus, credible policies for promoting reproductive health cannot be designed and implemented without a reliable framework for predicting demand for general health care at health facilities. In designing reproductive health policies, policy makers may want to know why households use or do not use health facilities.

Sahn et al. (2003) analyze the determinants of household choice of health facilities in rural Tanzania using a nested multinomial logit model (see equation (13)). From the estimation results they computed the following demand elasticities.

Table 7.2: Own price elasticities of demand

Facility Type	Own price elasticities of demand	
	(1) At this facility	(2) All
Public hospital	-1.859	-0.0530
Private hospital	-1.639	-0.0420
Public clinic	-0.343	-0.0390
Private clinic	-1.694	-0.0350

Source: Constructed from Sahn et al. (2003), Table 2, p. 11.

Table 7.2 shows own price elasticities of demand for specific facilities (column (1)) and for groups of facilities for which a range of substitute services exist and for groups of facilities which have limited substitutes for the services they provide. The striking finding from the table is that own price elasticities at specific facilities are large (as expected) due to possibilities of service substitution, whereas demand for services at groups of facilities is price inelastic. A similar analysis can be conducted for reproductive health care. The results show the facilities at which service demand is most sensitive to price change, i.e., where demand for example would change substantially due to a small proportional change in prices. This information can be used to target reproductive health services to particular social groups, particularly by region. Notice that elasticities of demand for various contraceptive options such as the pill, the condom, IUD etc (see Table 7.1) can be estimated using a version of equation (13) and applied similarly as the ones just discussed.

7.3 The effect of tetanus immunization on birth weight in Kenya

7.3.1 Context

The unified health care demand model presented in Section 2 was first applied in the United States by Rosenzweig and Schultz (1982, 1983). This section shows the application of the model in a Kenyan context using nationally representative household data collected by the government in 1994 (see also, Mwabu, 2007b,c). The survey data included immunization of mothers during

pregnancy, user charges for health care services, household income and assets, birth weight, whether a child was delivered at home or at a health facility, education of parents, and the time mothers spent on household chores such as collection of water and firewood.

The 1994 Kenyan data permit joint estimation of models of reproductive health care demand and health production. Health is measured by birth weight. Birth weight is a good indicator of health of the child in the womb because the weight is taken immediately after birth. Thus, a malnourished fetus will be born at low birth weight. The key determinants of birth weight include nutritional status and age of the mother, the quantity and quality of ante-natal care services received by the mother, mother's immunization against preventable diseases and behavioral change during pregnancy such as quitting smoking. Other factors such as areas of residence, which are proxies for availability of health care and nutrients, also affect the health of the child in utero.

Immunization against tetanus during pregnancy is used as a proxy for antenatal care services received by a woman. Immunization against tetanus is further assumed to be complementary to other inputs that improve the health of the child in the womb, such as presumptive malaria treatments and avoidance of risky behaviors. A thorough analysis of the complementarity hypothesis (the competing risk model) is in Dow et al. (1999). Dow et al. observe that "...a woman will increase inputs into birthweight when she believes that the EPI will be available to increase the child's chances of surviving..." (p. 1362). Tetanus vaccination for pregnant women is one of the major components of EPI (Expanded Program on Immunization), a world-wide vaccination initiative sponsored by the World Health Organization, which also provides maternal services to women such as safe delivery and post-natal care.

In accordance with the complementarity argument, we assume that expectant women who received tetanus vaccination during the 1994 Kenyan survey were more likely to engage in demand behavior that increased birth weight than women who were not immunized. The key argument is not that tetanus vaccination directly increases birth weight, but that vaccination is strongly correlated with health care consumption and behaviors that increase birth weight.

The general complementarity idea is that when a specific cause of a health problem is removed, other background causes follow suit, because people have incentives to also remove them. For example, a reduction in the risk of child death via immunization against tetanus, automatically reduces the risk of child death due to low birth weight. Stated differently, the adoption of a specific behavior, or the uptake of a specific input that improves health, creates incentives to engage in other health-augmenting behaviors or consumption.

The above complementarities, which are analytically captured by Leontief preferences and technologies, are forms of positive social externalities of an intervention, i.e., large indirect and often unanticipated benefits of an innovation. For example, an intervention that improves obstetric care has a larger benefit than that associated with the reduction in the risk of infant deaths at birth. The obstetric care intervention could also give mothers an incentive to behave in ways that improve birth weight, thus reducing the risk of infants dying due to low birth weight.

However, mother's immunization against tetanus immunization could also induce moral hazard, a form of a negative social externality. For example, knowing that immunization against tetanus protects them and their newborns from a tetanus infection during child-birth, the mothers might choose to deliver at home rather than at clinics. Such a choice could expose the newborn to death risks associated with poor general care during delivery, despite being at good health in utero.

We estimate demand for tetanus vaccination simultaneously with a model of birth weight determination. In the birth weight model, vaccination is assumed to improve child health in line with the complementarity hypothesis. Indeed, a positive empirical relationship between birth weight and tetanus vaccination is consistent with complementarity hypothesis.

7.3.2 Measurement issues

Equation (2) is the appropriate framework for measuring the effect of tetanus vaccination on birth weight when Z is interpreted as tetanus vaccination, and H as birth weight. (The classic paper on the connection between birth weight and general health is Waaler, 1984). In equation (2), tetanus vaccination is endogenous to birth weight because it is a choice variable. Thus, instruments for tetanus vaccination are needed in order to consistently estimate the effect of vaccination on birth weight. The instruments for tetanus vaccination are factors that affect demand for tetanus vaccination without influencing directly the birth weight. These institutional and supply-side factors are household land holdings, household rent income, prices of health care, and the amount of time women spend to collect water.

When estimating equation (2), there is further need to deal with potential sample selection bias because some of the children in the 1994 survey did not have birth weight. In particular, children born at home rather at clinics did not have birth weights. The Heckman procedure (Heckit) is used to deal with the sample selection bias (Wooldridge, 2002). The first step in the application of the Heckit procedure is the identification of the probit equation. That is, specification of factors that influence selection of the unit of study into the estimation sample without directly affecting birth weight. In our case, the unit of analysis is a child. A child was included into the estimation sample only if he or she had a birth weight extracted from a growth-monitoring card. The factors that identify the sample selection equation are the same as those that identify the demand for tetanus vaccination. Moreover, the heterogeneity of birth weight due to non-linear interaction of tetanus vaccination with unobservables and omitted variables could bias the estimated structural coefficients. The control function approach (Garen, 1984; Wooldridge, 1997; and Card, 2001) is used to address this issue.

Following Wooldridge (2002; Mwabu, 2007b) the estimation strategy may be summarized as follows.

$$B = \mathbf{w}_b^* + \beta M + \epsilon_1 \quad (23.1)$$

$$M = \mathbf{w}_m^* + \epsilon_2 \quad (23.2)$$

$$G = \mathbf{1}(\mathbf{w}_g^* + \epsilon_3 > 0) \quad (23.3)$$

where,

B, M, G are birth weight, immunization status of the mother, and an indicator function for selection of the observation into the sample, respectively;
 w_1 = a vector of exogenous covariates;
 w = exogenous variables, consisting of w_1 covariates that belong in the birth weight equation and a vector of instrumental variables, w_2 , that affect immunization status, M , but have no direct influence on birth weight, B ;
 α, β, γ = vectors of parameters to be estimated, and a disturbance term, respectively.

In the recent literature, the endogenous explanatory variables are commonly referred to as “treatment variables” (see Strauss and Thomas, 2007). This terminology stresses the fact that the most credible way to measure the effect of an endogenous variable on the outcome of interest (i.e., to identify *treatment effect*) is to vary the endogenous variable experimentally. In an experimental setting, this variation is achieved through a random assignment of units of study into *treatment* and *control* groups. The word “treatment” is used to indicate that a section of the study sample is “treated” (its characteristic of interest, such as immunization, is varied exogenously). Since this variation occurs when other causal factors are held constant, it is possible to identify the effect of the characteristic on outcome variable of interest, e.g., birth weight. In the absence of an experiment, such a variation is achieved through an econometric procedure, with the aid of a structural model (see Schultz and Strauss, 2007).

Equation (23.1) is the structural equation of interest, i.e., the birth weight production technology whose parameters are to be estimated. Equation (23.2) is the linear projection of the potentially endogenous variable, M , on all the exogenous variables, w , i.e., a reduced form linear probability model of vaccination.

The third equation (23.3) is the probit for sample selection. It is the probability of a mother’s child being included in the estimation sample. It captures the fact that in the household survey, the mothers who did not deliver at the clinics generally did not report birth weights for their children. Since the children without birth weights are excluded from equation (23.1), equation (23.3) helps correct any sample selection bias in the estimated parameters. The correction factor, derived from equation (23.3), is the inverse of the Mills ratio.

To accommodate any non-linear interactions of unobservable variables with the birth weight regressors, and to account for sample selection bias, equation (23.1) is rewritten as

$$B = \alpha_0 + w_1 \cdot \alpha + \beta \cdot M + \gamma_1 \cdot V + (\gamma_2 \cdot (V \cdot M + I \cdot Mills) + u \quad (23.4)$$

where

V = Fitted residual of M (observed value of M minus its fitted value), derived from a linear probability model;

$V \times M$ = Interaction of the fitted immunization residual with the actual value of the immunization status;

$Mills$ = Inverse of the Mills ratio;

u = A composite error term comprising u_1 and a predicted part of u_2 , under the assumption that $E(u_1) = 0$;

$\delta, \beta, \alpha, \gamma$, and Γ = parameters to be estimated.

The exclusion restrictions are imposed in equation (23.4) because the vector of instruments, w_2 (for immunization status, M), is absent from the equation. The terms V , $(V \times M)$, and $Mills$ in equation (23.4) are the control function variables because they control for the effects of unobservable factors that would otherwise contaminate the estimates of structural parameters.

The reduced form immunization residual, V , serves as the control for unobservable variables that are correlated with M . In particular, if an unobserved variable is linear in V , it is only the intercept, α_0 , that is affected by the unobservable, and thus the IV estimates of equation (23.4) are consistent even without the inclusion of the interaction term. The interaction term, $(V \times M)$, controls for the effects of any neglected non-linear interaction of an unobservable variable with the immunization status of the mother. Specifically, if the effect of M on birth weight is influenced by an unobserved variable, say, a (which is correlated with M), this unobserved influence ($a \times M$) is relegated to the structural error term and its source neglected during estimation. The estimated coefficient on M contains this neglected effect of unobserved variables; other structural coefficients may be similarly affected. Inclusion of the interaction term, $(V \times M)$, in equation (23.4) purges the estimated coefficients of the effects of unobservables (see Card, 2001).

Empirically, an unobserved variable, say a , is represented by the reduced form immunization residual. The interaction (multiplication) of V with M captures the idea that the size of a varies non-linearly with M . Thus, its unobserved and neglected effect ($a \times M$) changes in a non-linear way as M changes. The inverse of the Mills ratio holds constant the effects of the non-random sample on structural parameters. Although the polynomials of the fitted residual term, V , and its interactions with exogenous covariates, i.e. w , can also be included in equation (23.4), the practice in the literature is to omit them or include them selectively (see Garen, 1984; Wooldridge, 2005). It is possible to test which of the various versions of equation (23.4) are consistent with data (see Mwabu, 2007b).

The IV estimates of equation (23.4) are unbiased and consistent only when one or the other of the following conditions holds (a) the expected value of the interaction between immunization and its fitted residual ($V \times M$) is zero; (b) the expectation of the interaction between immunization and its fitted residual is linear (see Wooldridge, 1997).

Equation (23.4) can be estimated using the MLE procedure in STATA or similar software. Thus, inclusion of the inverse of the Mills ratio in equation (23.4) as a regressor is redundant, because both its sample value and its coefficient are automatically generated upon convergence of the likelihood function.

7.3.3 Estimation Results: Full sample

Table 7.3 shows how tetanus immunization affects birth weight, controlling for other covariates of interest, notably the age and area of residence of the mother. As noted previously, immunization is a proxy for health care inputs that improve birth weight such as nutrition intake of the mother (Fogel, 2004). Table 1 summarizes estimation results obtained from equation (23.4) under different assumptions.

7.3: Estimation of vaccination demand and birth weight functions under different assumptions

Variables	Estimation Methods				
	<i>OLS</i>	<i>Heckit</i> (ML procedure)		<i>Control Function Approach</i> (Dependent Variable = birthweight)	
Sample Selection Variable (= 1 if birth weight is not missing)	Birth weight equation	Sample Selection Variable (1=if birth weight >0)	Birth weight equation	Linear Interaction of vaccination with unobservables	Non-linear interaction of vaccination with unobservables
Mother's Vaccination Status (1=vaccinated)	.1349 (3.96)		.1273 (3.71)	.2894 (2.19)	.5886 (2.55)
Age of mother, years	.0197 (4.12)	-.0121 (1.24)	.0199 (4.21)	0.0182 (3.69)	.0182 (2.97)
Age of mother squared (x 10 ⁻³)	-.2746 (4.27)	.1374 (1.02)	-.2734 (4.30)	-.2426 (3.49)	-.2450 (2.72)
Sex of the Child (1 = Male)	.0986 (5.67)	.0001 (0.00)	.0981 (5.64)	.0984 (5.66)	.0979 (5.64)
Area of Residence (1 = Rural)	-.3803 (1.73)	-.3307 (5.96)	-.0306 (1.35)	-.0328 (1.46)	-.0328 (1.31)
<i>Identification Variables</i> (affect sample selection but not birth weight)					
Log of household Land Holding		-.1379 (6.97)			
Log of Household Rent Income		.0220 (4.92)			
Mother's education		.0855 (18.5)			
Father's education		.0197 (4.78)			

Minutes spent to fetch water in <i>wet</i> season per day, cluster median ($\times 10^{-3}$)		-2.245 (3.17)			
Minutes spent to fetch water in <i>dry</i> season per day, cluster median ($\times 10^{-3}$)		-2.616 (8.02)			
User charges (KSh) at private health facilities, cluster median ($\times 10^{-3}$)		-.7475 (3.77)			
<i>Control function Variables</i> (account for birthweight effects of unobservables in the error term)					
Reduced form vaccination residual				-.1655 (1.22)	-.5508 (2.16)
Vaccination status x Vaccination residual					.6041 (2.45)
Inverse of the Mills Ratio [s.e]		-.0351 [.0302]			-.0159 [.0457]
Constant	2.705 29.10	.3059 (1.70)	2.719 (29.2)	2.575 (18.1)	2.700 (9.80)
R-squared	0.016				
Wald statistic [<i>p</i> -value]		69.35 [0.000]			
<i>H</i> ₀ : Correlation between reduced form immunization error term and the structural error term = 0 [<i>p</i> -value]					0.24 [0.623]
Sample sizes	4162	7838	4162	4162	4162
Total observations	7838				
Censored obs	3676				

7.3.4 Discussion of Results: Full Sample

Table 7.3 shows the link between the demand for reproductive health care and health status at the earliest stage of the life cycle. The results of demand for tetanus immunization from the full sample (the first-stage regression) are not reported in Table 7.3. Table 7.4 reports these estimates by residence and household income. The results show that age and education of the mother, household land assets and income, and money and time costs of general health care, strongly affect utilization of vaccination services. The results are consistent with previous research in this area (see Ainsworth et al., 1996; Gertler and van der Gaag, 1990; Acton, 1975). It should be noted that the instruments for the selection equation (Table 7.3, middle panel) are the same as the instruments for immunization equation (see Table 7.4 below).

The results in Table 7.3 show that birth-weight is strongly associated with tetanus immunization. The pattern of coefficients on mother's age in all specifications has an inverted U-shape, indicating that younger mothers are more likely than older women to deliver heavier babies. Moreover, in all specifications, males are heavier at birth than females.

It is evident from Table 7.3 that the size of the effect of tetanus vaccination on birth weight depends on estimation method. Thus, it is important to use proper estimation method to avoid misleading policy conclusions. The properly estimated effect of vaccination (the last column) is nearly 5 times greater than the OLS estimate (first column). The problems due to endogeneity and neglected non-linearities are revealed by a comparison of the Heckit estimates with the estimates derived via the control function approach. The Heckit estimate of the effect of immunization on birth weight is 0.1273 (which is close to the OLS estimate of 0.1349), indicating that the coefficient changes very little with the removal of the sample selection bias. However, when immunization status of the mother is endogenized, the coefficient more than doubles to 0.289. Moreover, accounting for non-linear interactions of immunization with unobservables further increases the coefficient to 0.588. This estimate shows that immunization (a proxy for the quality of health care received by the mother during pregnancy) substantially increases birth weight. In particular, tetanus immunization in Kenya increased birth weight by nearly half a kilogram in 1994 (see also Mwabu, 2007b).

The column labeled sample selection variable, presents information on determinants of demand for births at health facilities because in this data set, reporting of a birth weight by mothers is strongly associated with a clinic birth. The probit results associated with the structural parameter estimates shown in the last column of the table are not reported. An interesting finding from the probit estimates is that rural mothers are less likely to deliver at the clinics compared with urban mothers, and that land holding reduces the probability of a clinic birth. These two findings are related because rural settings are associated with large land holdings. Household income and education increase the probability of reporting a birth weight. However, money prices of general health services and the time spent on collecting water reduce this probability.

The coefficient on reduced-form immunization residual (last column) is statistically significant (t -ratio =2.16). However, the coefficient on the inverse of the Mills ratio is insignificant, suggesting that sample selection bias is not a problem in this data set. That is, birth weight is not associated with the demand for clinic birth. The special case of the control function approach (the linear interaction of vaccination with its fitted residual) is interesting because the estimated coefficients of the birth weight technology under this specification are identical to the usual IV estimates. The estimates (except for the standard errors) correspond to those obtained under the strict assumption that the covariance between vaccination (the endogenous variable) and its fitted residual is zero (see Wooldridge, 1997).

The coefficient on the fitted residual without controls for non-linear interactions is .1655 (t -ratio =1.22). However, with the controls for non-linear interactions between vaccination and unobservables, this coefficient increases to 0.5508 (t -ratio = 2.16), indicating that vaccination status is endogenous to birth weight. The control function approach is the appropriate estimation strategy because it takes into account both the endogeneity of vaccination, and the heterogeneity of response of birth weight to vaccination. The heterogeneity arises from non-linear interaction of vaccination with unobserved determinants of birth weight, such as the biological endowment of the mother and her environment. Inclusion of the control function variable, $(V \wedge M)$, in the birth weight equation purges the estimates of any effects of heterogeneity. The descriptive statistics associated with Table 7.3 are in appendix tables A1 and A2.

7.3.5 Estimation Results By Residential Area and Household Income

Tables 7.4 and 7.5 present estimation results by residential area and household income. Household exogenous income is per capita *rent* income per month. The household income is *low* if it is Ksh 700 or below (which was the food poverty line in 1994 (see Republic of Kenya, 1996)), and is *high* if it is more than Ksh 1,500.

Table 7.4: A Linear Probability Model of Demand for Tetanus Vaccination: Dependent Variable Equals One if Mother was Vaccinated During Pregnancy and Equals Zero Otherwise (*t*-statistics in Parentheses)

Variables	Rural and urban sub-samples		Income sub-samples	
	Rural	Urban	Rural Low Income	Rural High Income
Age of mother, years	.0081 (2.63)	.0125 (1.49)	.0080 (2.29)	.0207 (1.95)
Age of mother squared (x 10 ⁻³)	-.1624 (3.81)	-.2208 (1.64)	-.1617 (3.39)	-.3762 (2.28)
Sex of the Child (1 = Male)	-.0034 (0.35)	-.0004 (0.02)	-.007 (0.56)	.0188 (0.91)
Area of Residence (1 = Rural)	--	--	--	--
<i>Identification Variables</i> (affect demand for immunizations but not birth weight)				
Log of household Land Holding	.0243 (3.64)	.0211 (1.45)	.0279 (3.43)	-.0049 (0.34)
Log of Household Rent Income	.0044 (3.16)	-.0005 (0.27)	.0093 (3.59)	-.0117 (0.75)
Mother's education	.0116 (7.52)	.0039 (1.59)	.0131 (7.21)	.0053 (1.44)
Father's education	.0014 (1.06)	.0046 (2.45)	.0025 (1.59)	-.0022 (0.71)
Minutes spent to fetch water in wet season per day, cluster median (x10 ⁻³)	-.9046 (3.28)	-2.293 (2.97)	-.9091 (2.92)	.1835 (0.22)

Minutes spent to fetch water in <i>dry</i> season per day, cluster median ($\times 10^{-3}$)	-.812 (6.16)	.591 (1.40)	-.9577 (5.89)	-.5218 (2.12)
User charges (KSh) at private health facilities, cluster median ($\times 10^{-3}$)	.1546 (1.13)	-.2671 (5.23)	.4085 (2.41)	-.0464 (0.18)
Constant	.7364 (13.43)	.7348 (5.85)	.7150 (11.18)	.7438 (3.67)
R-squared	0.094	0.059	0.118	0.038
Sample sizes	3372	790	2448	602

Table 7.5: Estimation of birth weight production functions using the Control Function Approach; by residential area and household income: dependent variable is birth weight in kg (*t*-statistics in parentheses)

<i>Variables</i>	All	Rural	Urban	Rural Low Income	Rural High Income
Mother's Vaccination Status (1=vaccinated)	.5886 (2.55)	.2982 (1.27)	2.069 (1.76)	.6422 (2.49)	-2.10 (2.57)
Age of mother, years	.0182 (2.97)	.02195 (3.40)	.0135 (0.64)	.0167 (2.36)	.066 (2.68)
Age of mother squared ($\times 10^{-3}$)	-.2450 (2.72)	-.3052 (3.28)	-.1875 (.55)	-.2352 (2.33)	-.9571 (2.50)
Sex of the Child (1 = Male)	.0979 (5.64)	.0856 (4.41)	.1525 (3.92)	.0843 (3.73)	.0714 (1.53)
Area of Residence (1 = Rural)	-.0328 (1.31)	--	--	--	--
<i>Control function Variables</i> (account for birthweight effects of unobservables)					
Reduced form vaccination residual	-.5508 (2.16)	-.2178 (0.82)	-2.38 (1.84)	-.6049 (2.07)	2.46 (2.78)
Vaccination status x Vaccination residual	.6041 (2.45)	.5186 (2.01)	2.49 (1.90)	.6341 (2.24)	-2.11 (2.33)

Inverse of the Mills Ratio [se]	-.0159 [.0457]	-.0594 [.046]	-.0545 [.1060]	-.0077 [.0579]	-.1496 [.0885]
Constant	2.700 (9.80)	2.489 (10.1)	.8491 (0.69)	2.22 (8.15)	4.251 (5.10)
Wald Statistic	58.35 (0.000)	54.69 (.000)	20.15 (.000)	45.34 (.000)	18.58 (.000)
Sample sizes	4162	3372	790	2448	602

7.3.6 Discussion of Results from Various Sub-samples

Tables 7.4 and 7.5 depict estimation results for tetanus vaccination demand and for birth weight production functions by area of residence of the mother and household income. The exclusion restrictions in Table 7.4 identify the immunization equation because the hypothesis that the coefficients on these restrictions are jointly equal to zero can be rejected (test results are available from authors on request). The top panel in Table 7.4 shows that age of the mother affects demand for tetanus vaccination. This effect is evident in all sub-samples. In particular, demand for tetanus vaccination first increases with age of the mother and then falls, indicating that younger mothers are more likely to use tetanus immunization services compared with older women. This finding is mirrored in the upper panel of Table 7.5 where the effect of mother's age on birth weight first rises before it falls, indicating that the mean birth weight among younger mothers is higher than among older women.

In Table 7.4, land and income are shown to be important determinants of demand for tetanus vaccination in rural areas and among low-income mothers in rural areas. However, in urban areas and among high-income rural mothers, these variables have no effect on demand. Restricting attention to demand effects of land and income, it can be seen that rich mothers in rural areas have immunization demand patterns similar to demands for average mothers in urban areas. The correlations of demand with education are quite interesting. In rural areas, a mother's education is positively correlated with utilization of tetanus immunization services. However, in urban areas, a woman's own education is weakly correlated with demand for tetanus immunization. Instead, the main determinant of a woman's demand for vaccination is her spouse's education. Among high-income mothers in rural areas, education is not associated with demand for immunization. In contrast, women's education is strongly correlated with demand for tetanus immunization among poor rural households.

The opportunity cost of time is negatively associated with demand for tetanus vaccination in virtually all specifications. However, the signs of coefficients on the money prices charged for immunization services differ between rural and urban sub-samples. In the rural sub-sample, the coefficient on the money price is positive, which contradicts the law of demand; it is possible that in rural areas service prices are positively associated with service quality.

Table 7.5 shows the control function parameter estimates of the birth weight production function. The table shows estimates of the structural parameters of the birth weight equation using different sub-samples. Except in the case of the high-income rural sub-sample, the effect of tetanus vaccination on birth weight is positive, a finding that is consistent with the complementarity hypothesis (Mwabu, 2007b, Dow et al., 1999). The last column of Table 7.5 suggests that mothers from high-income rural households have consumption or behavioral preferences that negatively affect birth weight. For example, although vaccinated mothers from high-income households have an incentive to invest in better nutrition, in accordance with the complementarity hypothesis, they also have greater opportunities to engage in consumption and behaviors that reduce birth weight, such as smoking and drinking. Grossman (1972) reported a

similar finding in the context of general health. Apart from the negative coefficient on immunization, the magnitude of this coefficient is implausibly large. Another notable finding from Table 7.5 is that male newborns are heavier than females in all sub-samples, which is an indication that this estimate is quite robust.

The coefficients on reduced form immunization residual and on the interaction term, both indicate that the unobservables indeed have an effect on birth weight. See Table 7.5, column 1, which is a repetition of Table 7.3, last column. However, these effects are not stable across sub-samples (see the control function estimates in Table 7.5). As can be seen from Table 7.5, the coefficient on immunization is 0.2982 in the rural sample, but is nearly seven times as large (2.069) in the urban sample. Moreover, the variability of this coefficient is even greater between the high-income rural sub-sample (0.6422) and the low-income sample (-2.10) in the same area. There are many possible sources of this variation. One potential source is the type of information or counseling that mothers receive while at sites of immunization services. High-income rural mothers are more likely to both smoke and/or drink and to use immunization services. That is, immunization in a high-income area is likely to be negatively correlated with birth weight, because of the negative effects of smoking and drinking on birth weight. As already noted, although mothers from such a sample are likely to be better nourished, the positive effect of nutrition on birth weight could easily be outweighed by the negative effects of factors associated with high income. The coefficient on the inverse of the Mills ratio is statistically insignificant in all sub-samples, suggesting that sample selection bias is not a problem in this Kenyan data set.

8. CONCLUSION

The paper has reviewed a variety of demand frameworks, and illustrated how the frameworks can be used to inform policies for improving reproductive health of the population. The frameworks have the following key features. First, they can help identify constraints to utilization of commodities and services that are essential for improving reproductive health. Second, they provide an economic approach to the analysis of individual and household behaviors that promote reproductive health, thereby facilitating an interdisciplinary research on such behaviors, e.g., effects of smoking and breastfeeding on maternal and child health. Third, the very specification of these frameworks is likely to motivate policy makers to take demand estimates to the next stage of examining the effects of service utilization on health. Fourth, intra-household variations in reproductive health and in demands for reproductive health services and commodities can be studied using the frameworks. However, because of data limitations, it was not possible to provide an illustrative application of an intra-household model in this essay. Nonetheless, the theoretical frameworks provide insights of how to formulate policies for addressing inequalities in reproductive health within the household.

Some of the frameworks can be estimated using existing data sets. The Kenyan example presented in this paper demonstrates this feasibility. The control function estimates of the birth weight production function suggest that the information that mothers possess about health-improving technologies plays a critical role in motivating them to invest in behaviors and consumption that complement tetanus immunization in increasing birth weight. A mother's immunization against tetanus while pregnant reduces the risk of a child dying from tetanus infection during delivery. As a consequence, the complementary hypothesis of the competing risk model (Dow et al., 1999) predicts that mothers would be strongly motivated to reduce other risks to child survival, e.g., the risk of a child dying from syndromes associated with a low-birth weight.

The mechanisms through which pregnant mothers reduce this risk include investing in better nutrition, avoiding smoking and drinking, and using prenatal care services. These are elements of a health production technology. Unless mothers possess information about this technology, they are unlikely to adopt behaviors and consumption patterns that are complementary to tetanus immunization in improving child health. For example, mothers could receive vaccination against tetanus, and continue to smoke or consume alcohol because they lack information about harmful effects of these types of consumption on the fetus. Such information can be provided at immunization clinics. The information would reduce or close any knowledge gaps existing among women who receive tetanus immunization at clinics.

We hypothesize that the heterogeneity of information on health-improving practices and technologies among women is the source of variation in birth weight across income levels observed in Table 7.5. There is need therefore to investigate the content of health education extended to mothers in different regions and at different clinics during vaccination days. Standardization of such information would enable women to have access to the same

reproductive health care technology. As a consequence, immunization of mothers against tetanus (or implementation of safe delivery interventions) would be accompanied by behavior and consumption patterns that increase rather than reduce child health.

More generally, the results in Table 7.5 suggest the need for health facilities and health policy makers to do more than simply immunize mothers. They suggest the need for *immunization plus* interventions. Specifically, when receiving immunizations, mothers should be counseled about other things they can do to maintain their health and that of their unborn children. Data on the content of the counseling that occurs during immunization days would help design immunization plus programs. Such data would be particularly germane to the immunization plus campaigns if it captures existing counseling practices in both rural and urban areas.

If the information contents of counseling are exactly the same in rural and urban areas, then there would be a basis for nuanced counseling over space and across income levels, and across other characteristics of mothers such as occupation, education and age. The information on the content of existing immunization programs would also provide a basis for pointing out the imperatives for effective empowerment of women (not giving out doles to them but providing sound education and training especially to young women and promoting remunerative employment for mothers). Indeed, the *immunization plus* interventions provide the link between reproductive health, economic growth and poverty reduction. The unified demand framework presented in the paper helps the policy makers evaluate how participation in *immunization plus* interventions empowers women by improving their health, equipping them with useful skills, and connecting them to productive livelihoods. The collective household model that informs demand analysis can be used to assess whether empowerment of women benefits the whole family.

Because of data limitations, it was possible to illustrate empirically only a few of the frameworks presented in this paper. For example, to implement intra-household models, information is needed on exogenous income or resources that are controlled by various household members. Panel data are also required to analyze why some household members engage in practices that promote reproductive health while other members do not. A case in point is why some mothers deliver at clinics while others consistently choose to deliver at home. In addition to quantitative data of the type analyzed in this paper, qualitative data might be necessary to answer these sorts of questions. Experimental data may also be needed to deal with difficult issues of inference and policy, e.g., why is fertility high in some regions or households? What is the effect on women's health of a fertility decline? Additional data sets are also needed to analyze the relationship between reproductive health and poverty dynamics.

REFERENCES

- Acton, Jan Paul (1975), "Nonmonetary Factors in the Demand for Medical Services: Some Empirical Evidence", *Journal of Political Economy*, 83(3): 595-614.
- Ainsworth, Martha, Kathleen Beegle and Andrew Nyamete (1996), "The Impact of Women's Schooling on Fertility and Contraceptive Use: A study of 14 Sub-Saharan Countries", *World Bank Economic Review* 10(1): 85-122.
- Akin, J., C. Griffin, D.K. Guilkey, and B.M. Popkin (1986), "The Demand for Primary Health Care Services in the Bicol Region of the Philippines", *Economic Development and Cultural Change*, 34(4): 755-82.
- Akin, J., D.K. Guilkey, P. Hutchinson, and M. McIntosh (1998), "Price Elasticities of the Demand for Curative Health Care with Control for Sample Selectivity and Endogenous Illness: An Analysis for Sri Lanka", *Health Economics*, 7(6): 509-31.
- Alderman, Harold, and Jere R. Behrman (2006), "Reducing the Incidence of Low Birth Weight in Low-Income Countries Has Substantial Economic Benefits," *World Bank Research Observer*, 21(1):25-48.
- Becker, Gary S. (1981), *A Treatise on the Family*, Cambridge MA: Harvard University Press.
- Bergstrom, T. C. (1989), "A Fresh Look at the Rotten Kid Theorem – and Other Household Mysteries", *Journal of Political Economy*, 97(5): 1138-1159.
- Bloom, David, and Jeffrey Sachs (1998), "Geography, Demography, and Economic Growth in Africa", *Brookings Papers on Economic Activity*, 1998(2): 207-295.
- Bolduc, Denis, Guy Lacroix, and Christophe Muller (1996), "The Choice of Medical Providers in Rural Benin: A Comparison of Discrete Choice Models", *Journal of Health Economics*, 15(4): 477-98.
- Bound, J., D. Jaeger and R. Baker (1995), "Problems with Instrumental Variables Estimation when the Correlation Between the Instruments and the Endogenous Explanatory Variables is Weak," *Journal of the American Statistical Association*, 90(430): 443-450.
- Browning, Martin, Francois Bourguignon, Pierre-Andre Chiappori and Valerie Lechene (1994), "Incomes and Outcomes: A Structural Model of Intrahousehold Allocations", *Journal of Political Economy*, 102(6): 1067-1096.

- Browning, Martin (2000), "The Saving Behavior of a Two Person Household", *Scandinavian Journal of Economics*, 10(2): 236-251.
- Card, David (2001), "Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems," *Econometrica*, 69(5):1127-1160.
- Central Bureau of Statistics (1996), *Basic Poverty Report*, Ministry of Planning and National Development, Nairobi.
- Chen, Zhiqi and Frances Woolley (2001), "A Cournot-Nash Model of Family Decision Making", *Economic Journal*, 111(474): 722-748.
- Chiappori, Pierre-Andre (1988), "Rational Household Labor Supply", *Econometrica*, 56 (1): 63-90.
- Culyer, A. J. and J. Newhouse (2000), eds, *Handbook of Health Economics, Volumes 1A and 1B*. Amsterdam: Elsevier, North-Holland.
- Dercon, Stefan and Pramila Krishnan (2000), "In Sickness and in Health: Risk Sharing within Households in Ethiopia", *Journal of Political Economy*, 108(4): 688-727.
- Deaton, Angus (1997), *The Analysis of Household Surveys: A Microeconomic Approach to Development Policy*, Baltimore: Johns Hopkins University Press.
- Diewert, W. E. (1971), "An Application of the Shephard Duality Theorem: A Generalized Leontief Production Function", *Journal of Political Economy*, 79(3): 481-507.
- Dow, William H. (1999), "Flexible Discrete Choice Demand Models Consistent with Utility Maximization: An Application to Health Care Demand", *American Journal of Agricultural Economics*, 81(3): 680-685.
- Dow, William H., Philipson, Thomas J., and Sala-i-Martin, Xavier (1999), "Longevity Complementaries Under Competing Risks", *American Economic Review*, 89(5): 1358-1371.
- Fogel, Robert W. (2004), *The Escape from Hunger and Premature Death, 1700-2100: Europe, America and the Third World*, Cambridge: Cambridge University Press.
- Garen, John (1984), "The Returns to Schooling: A Selectivity Bias Approach with a Continuous Choice Variable," *Econometrica*, 52(5): 1199-1218.
- Gertler, P. and van der Gaag (1990), *Health Care Financing in Developing Countries*, Baltimore: Johns Hopkins University Press.

- Grossman, Michael (1972), "On the Concept of Health Capital and the Demand for Health", *Journal of Political Economy*, 80(2): 223-255.
- Haddad, L., J. Hoddinott, and H. Alderman (1997), eds, *Intrahousehold Resources and Allocation in Developing Countries*, Baltimore: Johns Hopkins University Press.
- Heckman, James J. (1979), "Sample Selection Bias as a Specification Error," *Econometrica*, 47(1): 153-162.
- Hunt-McCool, Janet and B.F. Kiker and Ying Chu Ng (1994), "Estimates of the Demand for Medical Care Under Different Functional Forms", *Journal of Applied Econometrics*, 9(2): 201-218.
- Lindelow, M. (2005), "The Utilization of Curative Health Care in Mozambique: Does Income Matter?", *Journal of African Economies*, 14(3): 435-482.
- Lundberg, Shelly and Robert A. Pollak (1993), "Separate Spheres Bargaining Models of Marriage", *Journal of Political Economy*, 106(6): 988-1010.
- Manser, Marilyn and Murray Brown (1980), "Marriage and Household-Making: A Bargaining Analysis", *International Economic Review*, 21(1): 31-44.
- McElroy, Marjorie B., and Mary J. Horney (1981), "Nash-Bargained Decisions: Towards a Generalization of the Theory of Demand", *International Economic Review*, 22(2): 333-349.
- McElroy, Marjorie B.(1990), "The Empirical Content of Nash-Bargained Household Behavior", *Journal of Human Resources*, 25(4): 559-583.
- Mwabu, G. (2007a), "Health Economics for Low-income Countries", in: Schultz, T. Paul and John Strauss, eds, *Handbook of Development Economics, Volume 4*, Amsterdam: Elsevier Science, North-Holland, forthcoming.
- Mwabu, G. (2007b), "The Production of Child Health in Kenya: A Structural Model of Birth Weight." Conference paper on Economic Development in Africa, March 18-19, Centre for the Study of African Economies, University of Oxford, mimeo.
- Mwabu, G. (2007c), "The Demand for Health Care", in: Heggenhougen, K., ed., *Encyclopedia of Public Health*, Amsterdam: Elsevier Science, North-Holland, forthcoming.
- Rosenzweig, Mark R., and Schultz, T. Paul (1982), "The Behavior of Mothers as Inputs to Child Health: The Determinants of Birth Weight, Gestation, and the Rate of Fetal Growth", pp. 53-92, in: Fuchs, Victor R., ed., *Economic Aspects of Health*, Chicago: The University of Chicago Press.

Rosenzweig, Mark R., and T. Paul Schultz (1983). "Estimating a Household Production Function: Heterogeneity, the Demand for Health Inputs, and Their Effects on Birth Weight." *Journal of Political Economy*, 91(5): 723-746.

Rosenzweig, Mark R., and T. Paul Schultz (1987). "Fertility and Investments in Human Capital: Estimates of the Consequences of Imperfect Fertility Control in Malaysia." *Journal of Econometrics*, 36: 163-184.

Sahn, David E., Stephen D. Younger, and Garance Genicot (2003), "The Demand for Health Care Services in Rural Tanzania", *Oxford Bulletin of Economics and Statistics*, 65(2): 241-259.

Schultz, T. Paul (2004), "Health Economics and Applications in Developing Countries", *Journal of Health Economics*, 23(4): 637-641.

Schultz, T. Paul and John Strauss (2007), eds, *Handbook of Development Economics, Volume 4*, Amsterdam: Elsevier Science, North-Holland, forthcoming.

Singh, Inderjit, J., Lyn Squire and John Strauss (1986), eds, *Agricultural Household models: Extension, Application and Policy*, Baltimore, MD: Johns Hopkins University Press.

Strauss, John and Duncan Thomas (1995), "Human Resources: Empirical Modeling of Household and Family Decisions", in: J. Behrman and T. N. Srinivasan, eds, *Handbook of Development Economics, Vol. 3A*. Amsterdam: Elsevier Science, North-Holland, pp. 1883-2023.

Strauss, John, and Duncan Thomas (1998), "Health, Nutrition, and Economic Development", *Journal of Economic Literature*, 36(2): 766-817.

Strauss, John and Thomas, Duncan (2007), "Health over the Life Course", in: Schultz, T. Paul and John Strauss, eds, *Handbook of Development Economics, Volume 4*, Amsterdam: Elsevier Science, North-Holland, forthcoming.

Thomas, Duncan (1990), "Intrahousehold Resource Allocation: An Inferential Approach", *Journal of Human Resources*, 25(4): 635-664.

Thomas, Duncan (2000), "Comments on 'Intrahousehold Allocations'", *Journal of African Economies*, 9 (AERC Supplement 1): 144-149.

Waller, Hans Th. (1984), "Height, Weight and Mortality: The Norwegian Experience", *Acta Medica Scandinavica*, 679(Supplement), pp. 1-56.

World Bank (1993), *World Development Report 1993: Investing in Health*, New York: Oxford University Press.

World Health Organization (2005), *World Health Report 2005*, Geneva: World Health Organization.

Wooldridge, Jeffrey M. (1997), "On Two Stage Least Squares Estimation of the Average Treatment Effect in a Random Coefficient Model," *Economics Letters*, 56, 129-133.

Wooldridge, Jeffrey M. (2000), *Introductory Econometrics: A Modern Approach*, Cincinnati, Ohio: The South-Western College Publishing, Thomson Learning.

Wooldridge, Jeffrey M. (2002), *Econometric Analysis of Cross Section and Panel Data*, Cambridge, MA: MIT Press.

Wooldridge, Jeffrey M. (2005), "Unobserved Heterogeneity and Estimation of Average Partial Effects," in: Donald W. K. Andrews and James H. Stock, eds, *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, Cambridge: Cambridge University Press, pp. 26-55.

Appendix Tables

Appendix Table A1: Descriptive statistics, uncensored sample

Variable	Obs	Mean	Std. Dev.	Min
Max				
Birth weight 5	4162	3.175709	.5653995	1
Immunization 1	4162	.9137434	.2807763	0
Predicted imm 1.114153	4162	.9137434	.082934	-.1094432
Pred residual .8044392	4162	-1.32e-10	.2682486	-1.038387
Mother age 91	4162	29.2852	6.991334	16
Immun x resid .8044392	4162	.07194	.0710595	-.1141534
Mother age sq 8281	4162	906.4899	490.9636	256
Sex (male=1) 1	4162	.5057665	.5000268	0
Rural (=1) 1	4162	.8101874	.3921999	0
Log land 4.61512	4162	.9089697	.7845221	0
Log rent income 11.05091	4162	2.906136	3.586057	0
Mother education 16	4162	6.909178	3.82128	0
Father education 16	4162	6.891567	4.480119	0
Water min, wet 360	4162	17.51562	21.01926	0
Water min., dry 780	4162	26.65017	42.44428	0

User fees, private 4162 35.14031 78.5439 0
1265.83

Appendix Table A2: Descriptive statistics, full sample

Variable	Obs	Mean	Std. Dev.	Min
Max				
Birth weight, kg 5	4174	3.175419	.5649474	1
Immunization (=1) 1	7861	.8252131	.3798089	0
Predicted immuniz 1.114153	7838	.8679894	.1435308	-.1275014
Immuniz residual .9328943	7838	-.0430341	.3395746	-1.044042
Age mother, years 91	7861	30.24539	7.645715	15
Immuniz x resid .9328943	7838	.0840497	.0898886	-.1141534
Age mother square 8281	7861	973.233	554.098	225
Sex child (1=Male) 1	7861	.502735	.5000243	0
Rural (=1) 1	7861	.8707544	.335493	0
Birthweight report 1	7861	.5309757	.4990713	0
Log land 5.303305	7838	.9974064	.8516709	0
Log rent income 11.05091	7861	2.581198	3.441401	0
Mother education 16	7861	5.441547	4.221362	0
Father education 16	7861	5.685116	4.631377	0
Water minutes, Wet 480	7859	26.45731	43.74528	0

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Water minutes, dry |      7859      49.19112      100.1076          0
780
User fees, private |      7861      32.11538      82.32426          0
2389.583

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