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The Production of Child Health in Kenya: A Structural Model of Birth Weight

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Abstract

The paper investigates birth weight and its correlates in Kenya using nationally representative data collected by the government in the early 1990s. I find that immunization of the mother against tetanus during pregnancy is strongly associated with improvements in birth weight. Other factors significantly correlated with birth weight include age of the mother at first birth and birth orders of siblings. It is further found that birth weight is positively associated with mother's age at first birth and with higher birth orders, with the first born child being substantially lighter than subsequent children. Newborn infants are heavier in urban than in rural areas and females are born lighter than males. There is evidence suggesting that a baby born at the clinic is heavier than a newborn baby drawn randomly from the general population.

Key words: Health care demand, immunization, health production, birth weight, control function approach, weak instruments, multiple endogenous variables

JEL Codes: C31, C34, I11, I12, J13

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1. INTRODUCTION

We use birth weight as a measure of health status of children in a Kenyan rural setting in which mothers demand market and non-market inputs to produce child health. The health inputs and behaviours determining birth weight that are demanded by women and their households vary according to many factors, including unobserved preferences on health care and unmeasured health endowments of mothers. A demand model is proposed to measure effects on birth weight of potentially endogenous inputs into production of child health in the womb.

Despite the general acceptance of health human capital as a factor of production (see Grossman, 1972a,b; 1982), little empirical analysis exists in developing countries of the processes through which child health *in utero* is produced. Moreover, in developing countries where many children are born at home and are not weighed at birth (see WHO, 2004), analysis of birth weight must be conducted on a selected sample of children so that the results so obtained could suffer from sample selection bias. The objectives of this paper are:

(a) to formulate a structural model of birth weight production that links mothers' demands for market and non-market health inputs to an observed indicator of child health at birth, namely, birth weight;
(b) to estimate birth weight production function taking into account endogeneity of its inputs, unobserved heterogeneity of mothers, and non-random selection of babies into the study sample.

Birth weight is a good measure of health status of a child at birth because it represents the outcome of the gestation period. Since birth weight is a measure of the nutritional status of a baby at birth, it is also a measure of the nutritional status of the fetus during the gestation period. Moreover, since adverse conditions during fetal growth, such as placental malaria, congenital diseases and mother's smoking during pregnancy reduce birth weight (see Rosenzweig and Schultz, 1983; WHO, 2004), it must be the case that birth weight is also an indicator of the overall health of the child in the womb. Thus, the determinants of weight at birth are the same factors that determine the overall health of a baby in utero.

Another measure of infant health is the *Apgar* score, named in honour of Virginia Apgar, an American doctor who first proposed its use in 1953 (CDC, 2005). The Apgar score is a sum of scores on physical tests conducted on a newborn, typically 1 or 5 minutes after birth. After the birth of a child, the doctor assesses the health of the newborn on the basis of five factors, and gives a value from 0 to 2 for each factor, and then finds the total value, the Apgar score, which ranges from 0-10. The five factors used for the assessment are the heart rate, respiratory effort, muscle tone, reflex irritability, and colour (see Apgar, 1953; Almond et al., 2005). When written in upper case letters, APGAR, is an acronym that refers to the five criteria for assessing the health of a new born, namely: Appearance (colour), Pulse rate (heart rate), Grimace (reflex irritability), Activity (muscle tone) and Respiration (respiratory effort).

An Apgar score of 0-3 indicates that the infant is severely physically depressed; a score of 4-6 indicates moderate depression, while a score of 7-10 indicates the baby is in good to excellent condition. Thus, an Apgar score of less than 7 indicates that an infant at birth is in poor health, and roughly corresponds to the health status represented by a low birth weight (i.e., a weight less than 2,500 grams at birth). However, a lower cutoff point for weight at birth could be used to determine low-birth-weight babies, especially in societies with individuals of small body builds. The nutritional standard against which individuals, infants included, are to be compared is not a fixed parameter over time or across societies (see Fogel. 2004, pp. 57-58).

Almond et al. (2005) show that the Apgar score is strongly correlated with birth weight. As the birth weight tends to 2.8 kilograms, the Apgar score gets close to its maximum value of 10 (Almond, 2005, p. 1057). However, the relationship between birth weight and Apgar score is not linear because larger than normal babies typically get low Apgar scores. Moreover, the Apgar score correlates poorly with future neurologic outcomes (CDC, 2005). Like birth weight, the Apgar score is an indicator of the overall health of the baby in utero and at birth, but unlike the birth weight, it is not well correlated with some key dimensions of well-being or with future health indicators (CDC, 1981). Birth weight is a more comprehensive measure of well-being at birth and is the one adopted for this study.

From the life cycle perspective, health conditions in utero have consequences for later life cycles (Fogel, 1997; Victora et al., 2008). Thus, birth weight is not merely a measure of health of an infant, but is also an indicator of the infant's potential for survival both as a child, and as an adult. Previous studies show strong correlations between low-birth weight and infant mortality, high blood pressure, celebral palsy, deafness, and behavioural problems in adult life (Waaler, 1984; Almond et al., 2005; Case et al., 2005; WHO, 2007).

Behrman and Rosenzweig (2004, p. 586-587) cite studies that suggest that female infants born at low-birth weight develop impairments in adult life that increase their probability of having low-birth weight babies. Could birth weight of today's infants then be a predictor of health status of the next generations? The theory of technophysio evolution (Fogel and Costa, 1997) predicts that the health status of several future generations is linked to current birth weight.[1] Behrman and Rosenzweig (2004) and Victora et al. (2008) provide evidence in support of this theory. They show that a mother's birth weight is positively correlated with her first child's birth weight. Specifically, a female offspring of a malnourished mother faces a high risk of delivering a low-birth weight baby at first birth.

In addition to being a metric for measuring health status, birth weight is an indicator of economic and social well-being (Strauss and Thomas, 1995; 1998). Examples of specific economic returns to investments in birth weight have been emphasized in one particular study. Alderman and Behrman (2006) list six economic benefits of increasing birth weight in developing countries, namely: (i) reduced infant mortality, (ii) reduced cost of neonatal care, (iii) reduced cost of childhood illnesses, (iv) productivity gain from increased cognitive ability, (v) reduced cost of chronic diseases in adults, and (vi) better intergenerational health.

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[1] Fogel and Costa (1997, footnote 1, p. 49) explain this theory as follows. "We use the term *technophysio evolution* to refer to changes in human physiology brought about *primarily* by environmental factors. The environmental factors include those influencing chemical and pathogenic conditions of the womb in which the embryo and fetus develop. Such environmental factors may be concurrent with the development of the embryo and fetus or may have occurred before conception of the embryo earlier in the life of the mother or higher up the maternal pedigree. Experimental studies on animal models indicate that environmental insults in a first generation continue to have potency in retarding physiological performance over several generations despite the absence of subsequent insults; the potency of the initial insult, however, declines from one generation to the next..." (Emphasis in the original).

Alderman and Behrman argue that interventions for realizing the above benefits are relatively inexpensive and include investments in antimicrobial and parasitic treatments, insecticide treated bed-nets, maternal records to track gestation weight, iron and food supplements, and family planning campaigns. Another factor that is strongly associated with birth weight, but which is generally neglected in the literature, is the involvement of males in prenatal care of their partners (WHO, 2007).

Although the empirical analysis in this paper is undertaken with Kenyan data, the paper adds value to the existing literature on birth weight determinants and to a wider economic literature in several key respects. First, its findings corroborate those of a similar study conducted using demographic and health and surveys from Malawi, Tanzania, Zambia and Zimbabwe which showed that tetanus immunization of pregnant mothers improves survival chances of infants by inducing health care behaviours of mothers that raise birth weight (see Dow et al., 1999). Second, the paper uses existing econometric techniques in a novel way to illustrate how the common problems of sample selection, endogeneity and heterogeneity can be confronted when estimating a variety of economic models, with the birth weight production function being used as a generic example. Third, the paper shows that despite the difficulties encountered in using cross-section data to estimate structural models, appropriate econometric techniques can nonetheless be applied on such data to generate credible evidence on some critical aspect of health policymaking in a developing country context, such as the association between infant health and immunization of the mother against tetanus. Fourth, the econometric techniques illustrated, particularly the control function approach, can be used to consistently estimate structural models of birth weight production when data from panels or imperfect experiments are available. Fifth, the literature on joint demand for health inputs and health production that are reviewed in the paper is applicable in other economic investigations, such as the analyses of joint demands for agricultural inputs and crop production.

Finally, the paper points to types of data that need to be collected to facilitate the testing of complementarity between tetanus immunization and health care behaviours of mothers in the production of birth weight. Additional data that would be needed for that purpose include the number of tetanus immunizations received from health care delivery systems, and the quality of available reproductive health care services. As shown later in the paper, inclusion of exogenous indicators of the quality of the reproductive health care system in the birth weight production function would drive the size of the coefficient on tetanus immunization towards zero in accordance with the complementarity hypothesis. A referee for this journal correctly pointed out that a birth weight production model of the type formulated by Dow et al. (1999), which is adopted for this study, is internally inconsistent because while claiming that tetanus vaccination has *no* direct effect on birth weight, the estimated coefficient on vaccination status of the mother is nonetheless *positive* and statistically significant. This situation arises due to omission of birth weight-improving behaviours and investments that are *induced* by tetanus vaccination from the birth weight production function. Since birth weight improvements come entirely from such behaviours and investments, complete controls for them in a birth weight production function of the type estimated here would reduce the regression coefficient on tetanus vaccination to zero. However, in the absence of such controls, this regression coefficient would be positive, because it would be capturing the indirect, spillover effects of tetanus vaccination. Controls for indirect or spillover effects were not included in this study due to data limitations.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on birth weight determinants followed by Sections 3 through 5 on data, theory and empirical evidence, respectively. Section 6 concludes the paper.

2. RELATED LITERATURE

The literature on birth weight is enormous (see Rosenzweig and Zhang, 2006; footnote 2, p. 586), but only a handful of economic studies exist in developing countries on this topic. Since the original formulation by Rosenzweig and Schultz (1982, 1983) of a structural production model of birth weight, a number of studies have been conducted along the same lines. Grossman and Joyce (1990) and Joyce (1994) investigate birth weight effects of prenatal care in New York City, with controls for demographics of mothers and for their adverse or favourable self-selection into the study sample.

An instance of adverse self-selection of mothers into the study sample arises when mothers with unobserved problematic pregnancies use prenatal care more intensively than healthy mothers, but end up delivering low-birth weight babies that would otherwise have died. An example of favourable selection is when pregnant mothers with unobservable endowments of good health make the recommended number of visits to prenatal care clinics and end up delivering babies at normal birth weight. These self-selection phenomena into study samples compound the well-known problem of identifying the causal effect of an endogenous variable (Griliches, 1977). In either of these cases, the variable of primary interest, birth weight, may or may not be observed for some of the children. In the case where birth weight is missing for some of the children, the selected sample is said to be censored (Heckman, 1979).

Grossman and Joyce (1990) estimate the effect of prenatal care on birth weight taking into account that prenatal care is endogenous (usage level is affected by unobserved preferences and health endowments of mothers) and recognizing the phenomenon of sample selection (sample is not a random draw from the population of expectant mothers). Using cross-section data from New York City, they find that delay in using prenatal care reduces birth weight, as in the earlier larger study in the United Sates by Rosenzweig and Schultz (1982). Dow et al. (1999) find a strong effect of tetanus toxoid vaccination of mothers during pregnancy on birth weight in Malawi, Tanzania, Zambia and Zimbabwe using data from demographic and health surveys. This is a notable finding because tetanus vaccination has no *direct* effect on birth weight. The positive effect of tetanus vaccination on birth weight comes from the complementarity of tetanus vaccination with prenatal care inputs that enhance birth weight.

Dow et al. (1999) ague that a mother’s consumption of tetanus vaccination increases survival chances of the child after birth, which motivates the mother to further invest in prenatal care. If inputs that complement prenatal care in improving child health are not available, mothers have little incentive to invest in prenatal care. Examples of these inputs include tetanus vaccination of the mother during pregnancy, sanitary obstetric care, and child immunizations. This complementarity hypothesis is best investigated using panel data on mothers as in Dow et al.(1999). In the present study, the hypothesis that tetanus vaccination and prenatal care are complementary in the production of child health is maintained but is not tested due to data limitation.

The present work differs from that of Dow et al. (1999) in three respects. First, actual birth weight is the measure of infant health rather than the probability of an infant being at a particular birth weight that is employed by Dow et al. Second, account is taken of sample selection bias due to censoring of birth weights for children born at home rather than at the clinics. Third, a framework that nests child health production into a utility maximizing behavior of the mother is used, and this nesting permits explanation of a wide range of consumption patterns observed in health care and related markets.

In contrast to previous investigations of the association between tetanus vaccination and birth weight, our data sample is not only selected but also censored. That is, apart from the possibility that selection of mothers and children into the sample is non-random, information on birth weight is available only for 54 percent of the relevant population of children. This is a common problem in developing countries where usually, only the birth weights of children born at clinics are recorded (UNICEF, 2004). Thus, the approach used here is potentially applicable in many settings in low-income countries.

3. DATA

The data we use are derived from a nationally representative sample of over 10,000 households collected by the Kenya National Bureau of Statistics, Ministry of Planning and National Development in 1994 (Government of Kenya, 1996). The analytic sample consists of mothers with children aged 1-5 years, as of the time of the survey in 1994. The unit of observation is a child aged 1-5 years. For each child, information is available on his or her weight and sex, and on his/her parents' characteristics such as age, and education. The data file for each child is linked to household-level characteristics such as land holding and the amount of time women spent per day to collect water or firewood. In addition, we linked information external to the household survey to the analytic sample. The key variables derived from external data include food prices and rainfall. Thus, for each child of age 1-5 years, we compiled information on his/her weight at birth, sex, place of birth, mother's vaccination status during pregnancy, parents' demographics, household characteristics and community-level variables (see Table 1). The community-level variables such as means and medians for various prices were generated using cluster level information.

An important feature of our sample is that birth weight information is missing for 3,444 children, comprising 46% of the total sample. The remaining 4,038 children, or 54% of the sample, have birth weight information. Birth weight is missing mainly for children born at home. In 1994, nearly 52% of the Kenyan children were born at home (Government of Kenya, 1996). Only 17% of the children born at home had birth weight information compared with 75% of the children delivered at the clinics. The reporting or recording of birth weight during the household survey was primarily dependent on where the child was delivered. The birth weights were directly extracted from the growth monitoring cards of children, which also showed where the child was born.

We assume that any child who was born at the clinic and had a missing birth weight had also a missing growth monitoring card at the time of the survey. About 1,011 children in the sample, 25% of whom were born at the clinics, did not have birth weight. Moreover, there were 617 children in the sample who were born at home but still had information on birth weight. We assume that these children were weighed at home after birth or were later taken to a clinic where they were weighed. Reporting of a birth weight in the household sample is assumed to be strongly associated with a mother's contact with a clinic or with the health personnel during or after birth.

If the birth weight production function is estimated using only the sample of children for whom birth weight is available, the estimated parameters would not be applicable to all children, unless birth weight information is missing randomly or the sample selection phenomenon is taken into account during estimation. Since availability of birth weight information in the household survey is related to obstetric care choices of mothers (whether to deliver at the clinic or at home), there is a real possibility that our sample is not random. Estimation issues that arise in non-random samples are discussed in Section 4.

4. MODEL

Demand for market and behavioural inputs into birth weight

We use a slightly modified version of a model by Rosenzweig and Schultz (1982) in which child health production in utero is embedded in a utility maximizing behavior of the mother. We assume the following utility function

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

where

X = a health neutral good, i.e., commodity that yields utility, U, but has no direct effect on the health of a fetus, such as the mother's clothing or school uniforms of the school-age children;
Y = a health-related good or behavior that yields utility to the mother and also affects growth of the fetus, e.g., smoking or alcohol consumption[2];
H = health status of a child in utero.

The child health production function is given by

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

where,

Z = purchased market inputs such as medical care services that affect fetal health directly;
μ = the component of fetal health due to genetic or environmental conditions uninfluenced by parental behaviour and preferences.

[2] The optimizing behaviour of the mother is not necessarily in the best interest of her fetus because the mother might make choices that enhance her utility at the expense of fetal growth.

The mother maximizes (1) given (2) subject to the budget constraint given by equation (3)

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

where I is exogenous income and P_x, P_y, P_z are, respectively, the prices of the health-neutral good, X, health-related consumer good, Y, and child investment good, Z. Notice from equations (1) and (2) that the child investment good is assumed to be purchased only for the purpose of improving child health so that it enters a mother's utility function only through H.

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

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

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

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

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

$$\mathrm{d}H = F_y \bullet \mathrm{d}Y + F_z \bullet \mathrm{dZ} + F_\mu \bullet \mathrm{d}\mu \qquad (5)$$

where,

F_y, F_z, F_μ are marginal products of health inputs Y, Z and μ , respectively.

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

$$\mathrm{d}H/\mathrm{d}P_x = F_y \bullet \mathrm{d}Y/\mathrm{d}P_x + F_z \bullet \mathrm{d}Z/\mathrm{d}P_x + F_\mu \bullet \mathrm{d}\mu/\mathrm{d}P_x \qquad (6.1)$$

$$\mathrm{d}H/\mathrm{d}P_y = F_y \bullet \mathrm{d}Y/\mathrm{d}P_y + F_z \bullet \mathrm{d}Z/\mathrm{d}P_y + F_\mu \bullet \mathrm{d}\mu/\mathrm{d}P_y \qquad (6.2)$$

$$\mathrm{d}H/\mathrm{d}P_z = F_y \bullet \mathrm{d}Y/\mathrm{d}P_z + F_z \bullet \mathrm{d}Z/\mathrm{d}P_z + F_\mu \bullet \mathrm{d}\mu/\mathrm{d}P_z \qquad (6.3)$$

where

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

The above expressions show that commodity prices are correlated with the health status of a child. 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 on (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 child health through the household budget constraint. Thus, policy-makers need to know the parameters of both the child health production technology and the associated health input demands to predict health effects of changes in input prices. To obtain such information, health production and input demand parameters must be estimated simultaneously. Such estimation is complicated by the need to identify input demands from health production technology. In our case, the estimation is further complicated by the need to identify the birth weight effect of the sample selection rule to avoid biases in parameter estimates due to non-random selection of children into the estimation sample.

Model estimation

Since the mother's health endowment, μ, is unobserved, the parameters of child health production technology in equation (2) are not identified. However, equations (4.1) - (4.3) suggest the identifying instruments, i.e., the exclusion restrictions. The instruments in our case, are the input prices (P_x, P_y, and P_z) and the exogenous household income, I. A striking observation about the instruments is that they comprise the same set of variables for each of the inputs in equation (2). The random health endowment, μ, is excluded from the set of instruments because unlike the prices and income, it is correlated both with the child's health and with input demands. Since X is health-neutral, a mother's demand for this input is ignored so that focus is on estimation of equations (4.2) and (4.3). However, the price of X (in our case, the cost of school uniform) is allowed to affect demands for Y and Z through the budget constraint. The set of identifying instruments is shown in table 1.

We estimate equation (2) using a maximum likelihood method that ideally allows for correction of structural parameters for biases due to endogeneity of inputs and the censoring and heterogeneity of birth weight. In particular, the Heckman (1979) sample selection procedure is used to purge the estimates of the biased effects of any non-randomness of a selected sample, while the control function approach (Garen, 1984; Wooldridge, 1997; Card 2001) is used to deal with the bias due to non-linear interactions of the inputs into birth weight with unobservable variables specific to mothers.

Following Wooldridge (2002, p. 567) our estimation approach may be summarized as follows.

$$b = \mathbf{w}_1\delta_b + \Sigma_j\beta_j\boldsymbol{m}_j + \varepsilon_1, \quad j = 1,\ldots 4 \qquad (7.1)$$
$$m_j = \mathbf{w}\delta_{mj} + \varepsilon_{2j} \qquad (7.2)$$
$$g = \mathbf{1}(\mathbf{w}\delta_g + \varepsilon_3 > 0) \qquad (7.3)$$

where, b, m_j, g represent birth weight, endogenous determinants of birth weight, and an indicator function for selection of the observation into the sample, respectively, and where:
$\mathbf{w}_1$ = a vector of exogenous covariates;
$\mathbf{w}$ = exogenous covariates, comprising $\mathbf{w}_1$variables that also belong in the birth weight equation,

plus a vector of instruments, $\mathbf{w}_2$, that affect each of the endogenous inputs, m_j, but have no direct influence on birth weight;
δ, β, ε = vectors of parameters to be estimated, and a disturbance term, respectively.

The disturbance term for equation (7.3) is assumed to have a normal distribution and may be correlated with the error term for equation (7.1). Moreover, we do not make the usual assumption that these disturbance terms (ε_1 and ε_3) are independent of **w** (the entire set of instruments) because non-linear interactions between unobservables, and the endogenous inputs in equation (7.1) may be omitted from this equation. However, we assume that the covariance between **w** and any of the disturbance terms in equation (7.2) is zero.

Equation (7.1) is the structural equation of interest, i.e., the birth weight production function whose parameters are to be estimated. Equation (7.2) is the linear projection of each of the potentially endogenous variables m_j (j = 1,...4) on all the exogenous variables, **w**. The endogenous determinants of birth weight include one market input, i.e., vaccination of the mother against tetanus, and three behavioural inputs, namely: first-order birth, higher-order births, and age of the mother at first birth. The predicted values of these multiple endogenous variables are used to compute the residuals shown in equation (7.1a) below.

The third equation (7.3) is the probit for sample selection. It is the probability of the mother reporting a birth weight for her child in the household survey. That is, 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 (7.1), equation (7.3) helps correct biases in the estimated parameters resulting from any non-randomness of the selected sample. The correction factor from equation (7.3) is the well-known inverse of the Mills ratio (Heckman, 1976, 1979). The ratio was first tabled in Mills (1926), but the expression underlying its derivation has a long history (Ruben, 1964) and is still undergoing refinement (see Withers and McGavin, 2006).

In order to use the inverse of the Mills ratio to adjust the parameters of the birth weight equation (7.1), two tasks are required. The first is the construction of this ratio from the probit estimates of equation (7.3). The second task is estimation of equation (7.1) using the inverse of the Mills ratio as one of the exogenous regressors. These tasks can be accomplished in one step (application of maximum likelihood procedure on equations (7.1) and (7.3)) or in two steps, namely: (1) probit estimation of the selection equation to obtain the inverse of the Mills ratio, and (2) least squares estimation of the birth weight equation, with the inverse of the Mills ratio being treated as one of the regressors. We use the one-step maximum likelihood approach because it is more efficient than the two-step procedure (see Wooldridge, 2002).

To accommodate non-linear interactions of unobservable variables with the observed regressors specified in the birth weight function, and to account for sample selectivity bias, equation (7.1) is extended as follows

$$b = \mathbf{w}_1\delta_b + \Sigma_j\beta_j\boldsymbol{m}_j + \Sigma_j\alpha_j\boldsymbol{V}_j + \Sigma_j\gamma_j(\boldsymbol{V}_j \times \boldsymbol{m}_j) + \tau\boldsymbol{\lambda} + \varepsilon_1,\ j = 1,\ldots4 \qquad (7.1a)$$

where

$\boldsymbol{V}$ = residual of an endogenous input (observed value of m minus its fitted value);
$(\boldsymbol{V}\times \boldsymbol{m})$ = interaction of a residual with an endogenous input;
$\boldsymbol{\lambda}$ = inverse of the Mills ratio;
α, γ, and τ = additional parameters to be estimated.

The terms $\boldsymbol{V}_j$, $(\boldsymbol{V}_j \times \boldsymbol{m}_j)$ and λ in equation (7.1a) are the *control function* variables because they control for the effects of unobservable factors that would otherwise contaminate the estimates of structural parameters of birth weight (see Heckman and Robb, 1985). For example, $\boldsymbol{V}$ serves as a control for unobservable variables that are correlated with $\boldsymbol{m}$, thus allowing these endogenous inputs to be treated as if they were exogenous covariates during estimation. The interaction term, $(\boldsymbol{V}\times \boldsymbol{m})$, controls for the effects of neglected non-linear interactions of unobservable variables with birth weight inputs. Finally, the inverse of the Mills ratio (the pseudo error term) holds constant, in the usual ceteris paribus fashion, the effects of sample non-randomness on structural parameters. Although the polynomials of the residual terms and interactions of unobservables with exogenous covariates, i.e., $\mathbf{w}_1$ can also be included in equation (7.1a), the practice in the literature is to omit them or include them selectively (see Garen, 1984; Petrin and Train, 2003; Wooldridge, 2005). Altonji et al. (2005) propose a general model of the relationship between observables, unobservables and an outcome variable in selection models of the type formulated here.

Equation (7.1a) has some important insights about model specification, testing and estimation.

a. The usual t and F statistics can be used to test whether the estimated coefficients on the controls for unobservables are statistically significant. If for example, all the three coefficients (α, γ, and τ) are statistically insignificant, the parameters of the birth weight equation can be consistently estimated with OLS using a selected sample. That is, endogeneity, heterogeneity and sample selection phenomena are not empirically discernible, despite a strong theoretical case for their existence. Thus, because these estimation problems may still be present even when α, γ, and τ in Equation (7.1a) are all equal to zero, the OLS results should be interpreted with care.

b. If γ and τ are statistically insignificant, the only *control function* variables in the birth weight equation are the predicted residuals of the endogenous inputs. In that case, the structural parameters can be consistently estimated by applying 2SLS on the selected sample. However, the standard errors of the 2SLS estimates need to be adjusted because the generated regressors introduce elements of the error terms from the reduced form equations (first stage regressions) into the disturbance term of the structural equation. Although as desired, the expected mean of the composite structural disturbance term is equal to zero, the associated standard errors of the estimated parameters are not valid because these standard errors incorrectly include elements of the disturbance terms from the first stage regressions (see Wooldridge, 2000, p. 477; Wooldridge, 2002, p. 568).

c. When both γ and τ in equation (7.1a) are equal to zero, the IV method is a special case of the control function approach.

d. If τ is statistically insignificant, the control function approach is the preferred estimation method for equation (7.1a). The method involves application of 2SLS on the selected sample, and a correction for standard errors of the estimated parameters. In this case, IV estimates would be biased and inconsistent because the assumption that γ in equation

(7.1a) is equal to zero is not valid. It is worth stressing that IV estimates are consistent when the mathematical expectation of the interaction between endogenous regressors with unobservables is either equal to zero or is linear (see Wooldridge, 1997; Heckman, 1998; Card, 2001).

e. If τ is statistically significant, estimation of equation (7.1a) should be through Heckit (Wooldridge, 2002, p. 564) to account for sample selectivity bias. The Heckit can be implemented in one-step MLE procedure (Statacorp., 2001), or in a two-step method, where the first step involves ML estimation of probit equation for the sample selection, and the second step applies ordinary least squares (OLS) method on the selected sample to estimate the birth weight equation.

Since, there is no way of telling a priori which of the situations listed in (a) to (e) above prevails before fitting the model to data, the specification shown in equation (7.1a) is the reasonable one to hypothesize. The specification combines features of the control function approach to the modeling of the effects of unobservables on birth weight parameters through medical care choices of mothers, with features of a sample selection model as to how the unobservables affect the same parameters through non-random selection of children into the estimation sample. We estimate equation (7.1a) using the MLE procedure in Stata (Statacorp., 2001). Thus, inclusion of the inverse of the Mills ratio in equation (7.1a) as a regressor is redundant, because both its sample value and its coefficient are automatically generated upon convergence of the log-likelihood function (see Statacorp., 2001).

In Equation (7.1a), tetanus immunization status of the mother is one of the $\boldsymbol{m}_j$ multiple endogenous inputs. However, notice that the factors that complement tetanus immunization in the production of child health are missing from Equation (7.1a). Letting $\boldsymbol{m_1}$ be the immunization status of the mother, and ignoring for the moment the other endogenous inputs, Equation (7.1a) can be reformulated as

$$b = \boldsymbol{w}_1\delta_b + \beta\boldsymbol{m_1} + \alpha\boldsymbol{V_1} + \gamma(\boldsymbol{V_1} \times \boldsymbol{m_1}) + \tau\boldsymbol{\lambda} + \phi Q + \theta(\boldsymbol{m_1} \times Q) + \varepsilon_1 \qquad (7.1b)$$

where,

Q = exogenously supplied health inputs such as the medical equipment and the number of qualified health personnel at a local clinic, which represent the quantity and quality of prenatal care services provided, while ϕ and θ are the new parameters to be estimated. In Equation (7.1b), Q is the input set whose utilization is induced by tetanus vaccination or is complemented by this vaccination.

From equation (7.1b) the effect of tetanus vaccination, $\boldsymbol{m_1}$, on birth weight, b, of an infant is given by the following partial derivative

$$\partial b/\partial \boldsymbol{m_1} = \beta + \theta Q + \gamma V_1 \qquad (7.1c)$$

The first term, β, in equation (7.1c) is the direct effect of $\boldsymbol{m_1}$ on birth weight, which should be zero because biologically, tetanus toxoid has no direct effect on fetal growth. There is need to emphasize that the role of tetanus vaccination is to reduce the risk of the fetus contracting tetanus during birth, an outcome which motivates the mother to invest in better nutrition and behaviours that enhance fetal growth and therefore reduce the risk of her infant dying due to low-birth weight. The reduction in the risk of the child dying from tetanus is assumed to provide the mother with an incentive to reduce the risk of the child dying from complications due to low-birth weight.

The complementarity hypothesis relates to the Leontief relationship between $\boldsymbol{m_1}$ and Q in the production of birth weight. That is, when $\boldsymbol{m_1}$ and Q increase in a fixed proportion fashion, birth weight improves. If for example, the direct effect of $\boldsymbol{m_1}$ on birth weight is zero (i.e., β in Equation (7.1c) is equal to zero), all the increase in birth weight comes from changes in Q, and is equal to $\theta Q + \gamma V_1$; recall here that Q is induced by $\boldsymbol{m_1}$.

The second term, θQ, is the complementarity effect. Ideally, the estimated parameter, θ, is the effect on birth weight of a proportional increase in both $\boldsymbol{m_1}$ and Q, i.e., the effect of a unit increase in the interaction term ($\boldsymbol{m_1} \times Q$) on birth weight. However, the term, θQ, is not actually estimated. Although this complementarity effect is not obvious, it is easily understood by noting that when both $\boldsymbol{m_1}$ and Q are increasing, birth weight is increasing at the rate, θ. As long as $\boldsymbol{m_1}$ is increasing, every unit increase in Q increases birth weight by θ, so that a unit increase in $\boldsymbol{m_1}$ increases birth weight by θQ grams, which is the magnitude of the spillover effect of tetanus vaccination on birth weight. The third term in equation (7.1c), which is interpreted similarly as the θQ, captures the non-linear indirect effects of $\boldsymbol{m_1}$ on birth weight.

From equation (7.1c), it can be seen that if information is not available on Q so that the interaction term ($\boldsymbol{m_1} \times Q$) is not included in equation (7.1b), the estimated indirect effect, θQ, will be absorbed in β. Thus, in this case, the estimated value of β should not be zero, because it captures the spillovers of tetanus vaccination, which can be substantial. Equation (7.1c) shows that even in the absence of data on inputs that complement $\boldsymbol{m_1}$ in improving birth weight, the effects of the complementary inputs can still be measured. In the present application, Equation (7.1a) was estimated without controls for Q and without the interaction term ($\boldsymbol{m_1} \times Q$) due to data limitations.

<u>Model identification</u>

In order to properly interpret the estimated parameters of the model in Equations (7.1-7.3), it is important that birth weight effects of the endogenous inputs and of the sample selection rule be identified. Since there are four endogenous inputs in equation (7.1), identification requires at least five (not four) exclusion restrictions because there are five equations that need to be solved simultaneously. That is, we need at least four instruments for the four endogenous inputs in equation (7.1) and another exogenous variable that determines selection of children into the estimation sample. All the five instruments should be excluded from the birth weight equation (see Wooldridge, 2002, p. 569). Our data set fully satisfies this requirement.

Table 1 (panel 2*A*-*E*) shows the list of variables included in Equations (7.2) and (7.3) but excluded from the structural Equation (7.1). The coefficients on exclusion restrictions and on other exogenous covariates are allowed to differ across equations (7.2) and (7.3). It is unnecessary to apportion exclusion restrictions between the two equations because a restriction that belongs in one equation also belongs in the other (see IV estimation commands in STATA, Stata Corp., 2001). The list of instruments in Table 1 (panel 2*A-E*) corresponds to the implicit vector, $\mathbf{w}_2$ in Equations (7.2) and (7.3) while the list of covariates in panel 3 corresponds to $\mathbf{w}_1$ in Equation (7.1).

Ideally, three types of structural effects may be identified, namely: (a) effects of the endogenous inputs from those of unobservable variables that are correlated with these inputs (b) birth weight impacts of all regressors from the effects of unobservable variables that influence selection of children into the sample and (c) effects of endogenous inputs from those of neglected non-linearities of the structural model. In each case, identification is through a common set of exclusion restrictions. These are variables (Table 1, panel 2*A-E*) that influence both the health inputs (Equation 7.2) and selection of children into the estimation sample (Equation 7.3) without *directly* affecting the birth weight (Equation 7.1). It is important to point out that valid instruments *do* affect the outcome variable, birth weight here, but are constrained in how they do so. There is also need to stress that even with valid instruments it is difficult in practice to separate out the impacts of endogenous variables from the effects of unobservables in a structural model. This is one reason why experimental approaches to identification of structural parameters have become popular in the development economics literature (see Schultz and Strauss, 2008).

5. RESULTS

5.1 Summary Statistics and Preliminary Discussion

Table 1 presents sample statistics for all the variables used in the analysis. To the extent possible, the descriptive statistics for the endogenous variables in Table 1 are compared with related statistics from the literature.

Table 1

Descriptive Statistics

Variables	Mean	Standard Deviation
Outcome Variables		
Birth weight of children in kilogrammes	3.179	0.57
1. Potentially endogenous determinants of birth weight		
Vaccination of the Mother with Tetanus Vaccine During Previous Pregnancy (= 1 if immunized)	0.925	0.26
First Birth Order (First born child =1)	0.179	0.38
Higher Birth Orders, 2, 3, ...	2.73	2.45
Age of Mother at First Birth in Years	19.95	5.84

2. Instruments for endogenous inputs		
A*. *Money Prices		
Cluster Level Mean of Price of Maize Grain per Kilogramme (Ksh)	15.60	0.91
Price of Beans per Kilogramme	29.36	2.53
Price of Milk per Litre	12.25	0.75
Price of Cooking Fat per Kilogramme	86.97	2.17
Price of Green Vegetables per Kilogramme	6.77	1.68
Cluster Level Mean of cost per Visit to a Private Health Facility (Kenya Shillings)	34.57	75.97
Cost per Visit to a Mission Health Facility (Kenya Shillings)	14.88	50.18
Cost per Visit to a Government Health Facility (Kenya Shillings)	10.17	29.89
Cluster Level Mean of School Fees per Pupil per Term (Kenya Shillings)	312.49	451.53
Cost of School Uniform per Pupil (Kenya Shillings)	147.8	120.67
B*. *Time Prices		
Cluster Level Median of the Time used to Fetch Water in Wet Season (Minutes per Day)	17.2	19.27
Time Spent to Collect Water in Dry Season (Minutes per Day)	26.4	42.02
Time Spent to Collect Firewood (Minutes per Day)	50.72	60.97
C*. *Household Assets and Income		
Log Household Cattle	0.61	0.82
Log Household Land in Acres	0.91	0.78
Log Household Rent Income (Kenya Shillings)	2.91	3.59
D*. *Environmental Characteristics		
Cluster Level Long-term Mean of Annual Rainfall (centimeters)	29.06	11.28
Deviation of Cluster Level Rainfall Mean for 1994 from the Long-term Mean	2.90	6.16
E*. *Interaction Terms		
Log Land x Log Mean Long-term Rainfall	27.32	27.2
Log Cattle x Log Mean Long-term Rainfall	18.07	25.63
3. Exogenous demographics		
Residence (Rural = 1)	0.81	0.39
Mother's Education in Completed Years	6.98	3.78

Mother's Education Squared	62.96	48.76
Father's Education	6.93	4.45
Father's Education Squared	68.01	57.62
Father Absent During Survey (1=Absent)	0.13	14.25
Father's Age	31.07	14.25
Father's Age Squared	1168.6	769.8
Mother's Age	28.91	6.18
Mother's Age Squared	874.19	387.48
Sex of the Child (Male =1)	0.51	0.50
4. Controls for unobservable variables		
Immunization Residual (Mother's Immunization Status *minus* its Fitted Value)	3.60e-14	.25
First-Order-Birth Residual	1.24e-10	.33
Higher-Order-Birth Residual	-5.45e-10	1.47
Age at First Birth Residual	-7.45e-10	5.62
Immunization × its Residual	.061	.07
First-Order-Birth × its Residual	.11	.24
Higher-Order-Birth × its Residual	2.15	8.82
Age at First Birth × its Residual	31.60	487.86
Inverse of the Mills Ratio	.589	.333
Sample size with uncensored (non-missing) birth weight (Percent of total observations)	4038 (54)	

It can be seen from Table 1 that the majority of mothers (nearly 93 percent) had been vaccinated against tetanus during their last pregnancy. Previous studies report similarly high rates of tetanus vaccination in low-income countries. Dow et al.(1999) report tetanus vaccination rates of the same orders of magnitude for Malawi, Tanzania, Zambia and Zimbabwe over the period 1986-1994.

The mean age of Kenyan women at first birth in the early 1990s was 20 years (Table 1). Around 18 percent of children were first borns, with the remainder, averaging 3.7 per woman being from higher-order births. The mean birth weight for all children was 3.18 Kg, with a low-birth-weight incidence of 7%.

The demographic and health survey of 2003 (Central Bureau of Statistics, et al. 2004) shows that age of the mother at first birth remained relatively constant throughout the 1990s. Moreover, the sample average of 3.7 children per woman for higher-order births in the 1990s is consistent with the rapid decline in total fertility rate from 8.1 children in late 1970s to 5 children in 2003. The same data set reveals only slight differences in incidences of low-birth weights based on reported and measured weights. In response to birth weight questions, mothers said 13 percent of their newborns were smaller than an average child (perceived to be less than 3 kg but greater than 2.5 kg) and that 3.7 percent were very small (less than 2.5 kg). Among the babies that were weighed (born at the clinics), 8 percent were below 2.5 kg (Table 1). Throughout the 1990s, less than 50% of babies were born at health facilities (Central Bureau of Statistics et al., 2004).

Table 1 (panel 2) shows summary statistics for instruments for endogenous inputs into birth weight. Panel 2*A* depicts district level means of prices of key food items in 1994. We assume that these prices affected the quality and quantity of food intake by households and therefore the nutritional status of mothers during pregnancy. The price of maize grain is particularly important in determining nutritional status because maize is the staple food in most Kenyan provinces (see Greer and Thorbecke, 1986). Beans, maize, milk, cooking oil and green vegetables are widely consumed in Kenya, as in other African countries. The nutrition effects of prices of these food items depend on whether the household is a net buyer or a net seller in the food market. If a household is a net seller of milk, an increase in the price of milk increases the household income through the "profit effect" (Singh et al., 1986, p. 20). An increase in the price of milk increases milk consumption if its income effect is larger than the substitution effect.

The last part of panel 2*A* shows that health care costs are higher at private clinics and lower at government health facilities. All health facilities in Kenya in the 1990s provided curative and preventive care, including family planning and vaccinations, a situation that still prevails. However, preventive care and family planning are provided primarily at government clinics. The school fees and unit values of the school uniforms are a proxy for access to schooling within a cluster. Since income is fixed, the higher the cost of health care and schooling, the lower the mother's consumption of nutrients.

Panel 2*B* shows daily time costs of collecting water and firewood. If more time is allocated to water and firewood, less would be available for health care. Women spent on average, 17.2 minutes per day to collect water during the wet season compared with an average of 26.4 minutes in the dry season.

Panel 2*C* shows three forms of household wealth. We assume that mothers in households with large sizes of land or livestock would tend to have a higher opportunity cost of labor time compared with women in households receiving rent income. Thus, the opportunity cost of time for health care should differ across households by type of dominant asset. For example, tetanus vaccination should be positively correlated with rent income and negatively correlated with livestock holding.

Panels 2*D* and 2*E* show sample means for one environmental variable: long-term annual rainfall and its interactions with cattle and land. These variables are used to capture effects of natural events on demand for vaccination and also embody both income and relative price effects.

Panel 3 depicts sample means for demographic characteristics. About 51 percent of the newborns were male, with the sample of children being predominantly rural (81 percent). The child's parents had primary education or approximately 7 years of completed schooling. The mean age of the child's mother and father were 29 years and 31 years, respectively. Education of the mother is expected to increase both the intake of prenatal care and independently affect the birth weight of the newborn; in contrast, age effects are difficult to predict a priori.

Panel 4 shows sample statistics for control function variables. These variables represent unobserved factors that in theory could affect birth weight in complex ways. They are included in the birth weight equation to ensure that its parameters are consistently estimated.

5.2 Demand for Market and Behavioural Health Inputs

5.2.1 Market inputs: tetanus vaccination

Tetanus vaccination is a dichotomous variable that is equal to one if the mother was immunized against tetanus toxoid during the last pregnancy and zero otherwise. Column 1 of Table 2 presents results of a linear probability model of demand for tetanus vaccination. Evident from the table, are strong correlations of prices, wealth and demographics with demand for tetanus vaccination. The negative coefficient on the price of maize suggests that households were net buyers of maize, whereas the positive coefficient on price of beans suggests that households were net sellers beans.

The positive coefficient on cost per visit at government health facilities is the cross-effect of the price of curative care on demand for tetanus vaccination. In the early 1990s, the government increased the cost of treatment in its clinics through a reform programme known as cost-sharing (Mwabu et al., 1995) but preventive health services were provided free of charge. The positive coefficient on cost per visit suggests that the increased demand for immunizations at government clinics is a result of substituting prevention for more expensive curative care. Tetanus immunization can be viewed as a proxy for other forms of preventive health care.

Table 2

Reduced-form Parameter Estimates for Market and Behavioural Input Demand Functions and for Sample Selection Equation (absolute value of robust *t*-statistics in parentheses)

Explanatory Variables (covariate sets *A* to *E* are the exclusion restrictions)	***Dependent Variables***				
	Market Input[a]	Behavioural Inputs[a]			Sample Selection Variable[b]
	(1) Tetanus Vaccination (1= immunized during last pregnancy)	(2) First Order Births (1 = first child)	(3) Higher Order Births (number)	(4) Age of mother at first birth (years)	(5) Birth weight observed (=1 if birth weight reported during the household survey and = 0 if missing)
A. *Money Prices*					
Cluster Level Mean of Price of Maize Grain (× 10^{-2})	-4.64 (3.45)	-1.38 (.72)	16.51 (2.13)	-67.73 (1.53)	-51.24 (6.42)
Price of Beans per Kilo (× 10^{-2})	1.58 (3.08)	.450 (.65)	-4.09 (1.35)	9.86 (.67)	11.35 (4.39)
Price of Milk per Litre (× 10^{-2})	-.199 (0.22)	-3.44 (3.24)	33.82 (5.42)	-32.32 (1.46)	-13.20 (3.61)
Price of Cooking Fat per Kilo (× 10^{-2})	.598 (2.28)	-.116 (.34)	3.01 (1.66)	-9.51 (1.09)	-3.15 (2.15)
Price of Green Vegetables per kilo (× 10^{-2})	-2.03 (4.13)	.351 (.67)	-6.37 (2.53)	.784 (.09)	3.44 (2.19)
Cluster Level Mean of cost per Visit to a Private Health Facility (× 10^{-2})	-.011 (1.52)	.003 (.32)	.015 (.48)	-.225 (3.23)	-.078 (4.08)
Cost per Visit to a Mission Health Facility (× 10^{-2})	-.007 (.72)	.004 (.32)	-.123 (2.22)	.042 (.39)	.022 (.50)
Cost per Visit to a Government Health Facility (× 10^{-2})	.019 (2.10)	.007 (.59)	.091 (1.22)	-.170 (1.21)	.116 (1.63)

Cluster Level Mean of School Fees per Pupil per Term ($\times 10^{-2}$)	-.001 (.81)	-.0003 (.21)	-.004 (.74)	.038 (2.17)	.009 (2.38)
Cost of School Uniform per Pupil ($\times 10^{-2}$)	-.000 (0.0)	-.012 (2.40)	.021 (1.01)	-.187 (3.00)	.008 (.63)
***B**. Time Prices*					
Cluster Level Median of Time used to Fetch Water in Wet Season ($\times 10^{-2}$)	-.000 (0.0)	.003 (.12)	.146 (.84)	1.86 (1.37)	-.119 (.94)
Time Spent to Collect Water in Dry Season ($\times 10^{-2}$)	-.044 (3.07)	-.002 (.18)	-.016 (.25)	-.307 (1.51)	-.269 (4.46)
Time Spent to Collect Firewood ($\times 10^{-2}$)	-.031 (3.21)	-.021 (2.44)	.107 (2.56)	-.171 (.89)	.013 (.49)
***C**. Household Assets and Income*					
Log Household Cattle	-.063 (3.30)	-.015 (.91)	.030 (.32)	-.420 (1.73)	-.043 (1.15)
Log Household Land	.049 (2.77)	-.039 (2.31)	.189 (1.85)	-.476 (1.52)	.017 (.38)
Log Household Rent Income ($\times 10^{-2}$)	.232 (2.19)	-.009 (.06)	-.278 (.42)	-7.09 (3.23)	2.107 (4.47)
***D**. Environmental Characteristics*					
Cluster Level Long-term Mean Annual Rainfall ($\times 10^{-2}$)	.105 (1.45)	-.251 (2.83)	.210 (.47)	-3.15 (1.55)	.131 (.56)
Deviation of Cluster Level Rainfall Mean for 1994 from the Long-term Mean ($\times 10^{-2}$)	.111 (1.38)	-.057 (.52)	-1.79 (4.21)	3.561 (1.84)	.755 (2.13)
***E** . Interaction Terms*					
Log Land × Log Mean Long-term Rainfall ($\times 10^{-2}$)	-.077 (1.46)	.079 (1.38)	.268 (.76)	.770 (.69)	.619 (4.07)
Log Cattle x Log Mean Long-term Rain($\times 10^{-2}$)	.146 (2.52)	.055 (1.03)	-.017 (.05)	1.72 (1.83)	.44 (3.10)
***F**. Demographics*					
Residence (Rural = 1)	-.012 (0.97)	-.056 (2.92)	.242 (3.36)	-.712 (2.24)	-.332 (5.51)

Mother's Education	.012 (3.04)	-.011 (2.71)	-.049 (2.08)	-.244 (2.30)	.076 (5.61)
Mother's Education Squared (× 10^{-2})	-.042 (1.64)	.145 (4.09)	-.412 (2.57)	2.93 (4.43)	-.138 (1.19)
Father's Education	.010 (2.11)	.001 (.20)	.118 (4.69)	-.147 (1.37)	-.048 (.03)
Father's Education Squared (× 10^{-2})	-.058 (1.75)	.020 (.58)	-.907 (5.71)	1.50 (2.37)	.166 (1.54)
Father Absent During Survey (1=Absent)	.094 (1.06)	-.168 (1.49)	2.125 (5.25)	-3.34 (2.23)	.188 (.66)
Father's Age	.004 (.84)	-.013 (2.64)	.082 (4.16)	-.170 (2.30)	.164 (.13)
Father's Age Squared (× 10^{-2})	-.005 (1.05)	.016 (2.95)	-.623 (2.61)	.166 (1.89)	-.002 (.17)
Mother's Age	.004 (.54)	-.144 (19.82)	.221 (5.44)	.692 (7.43)	-.031 (1.43)
Mother's Age Squared (× 10^{-2})	-.006 (.54)	.200 (18.7)	.041 (.59)	-.832 (1.30)	.038 (1.13)
Sex of the Child (Male =1)	-.002 (.02)	.005 (.52)	.085 (1.83)	.236 (1.30)	.013 (.40)
Constant	.615 (2.22)	3.64 (8.78)	-13.99 (6.73)	32.58 (3.18)	9.56 (5.40)
R^2/(Pseudo-R^2)	0.111	0.271	0.643	0.072	.187
Partial R^2 (on excluded instruments)	.062	.014	.059	.016	.149
Joint F /χ^2 (p-value) test for Ho: coefficients on instruments = 0	9 .81 (.000)	3.39 (.000)	10.64 (.000)	3.44 (.000)	584.8 (0.000)
Fitted Value of Probit Index [Standard Dev]	...	...	...	...	.084 [.82]
Probability Density of Probit Index	....	....	...	...	.320 [.09]
Cumulative Density of Probit Index	...	...	...	...	.540[.24]
Observations	4038				7482

a, b: Estimation methods are OLS and MLE (probit model), respectively.

The negative coefficients on time spent to collect water or firewood indicate that time price is a deterrent to vaccination. However, in order for this time price to be treated as exogenous, we make the strong assumption that women walk to sources of water and firewood so that the time spent to collect water or firewood is a proxy for the *fixed* distance that each woman must travel from her home to sources of these necessities.

Women's demand for tetanus vaccination is affected differently by wealth portfolio of the household. The probability of tetanus vaccination increases with land holding and with rent income but declines with cattle wealth. Land and cattle assets increase the marginal product of woman's time, thereby raising the opportunity cost of seeking vaccination services. However, labor substitution within a household may still allow women to attend vaccination clinics. The positive coefficient on the interaction of cattle with rainfall suggests the presence of the substitution effect because during the wet season grazing can occur near the home and small children can tend cattle as their mothers visit vaccination clinics. A woman's education is positively correlated with the probability of vaccination. The coefficient on husband's education is also positive, but much smaller than the coefficient on the woman's own education.

5.2.2 Behavioural inputs: first birth, subsequent births, and age at first birth

Columns 2-4 of Table 2 present findings on fertility and its correlates. The fertility responses to price and wealth are noteworthy. Schultz (1981; 1997) suggests that education may increase women's market wages, thus increasing the opportunity cost of the time women spend rearing children. Other things equal, demand for children and age at first birth, are negatively correlated with women's schooling. Education of the mother is negatively associated with the probability of first birth (where first birth is viewed as a proxy for a large family size), the number of higher-order births, as well as age at first birth (panel *F*, column 2). In contrast, husband's education is positively correlated with higher-order births.

At first sight, the positive coefficient on sex of the child (1 = male) among higher-order births (statistically significant at 10% level, $t = 1.83$) indicates that the last child in a large family is a male rather than a female. However, as pointed out by a referee, this interpretation could be misleading because if couples are looking for a male child, they are likely to end up with a large family, with the last child being a female rather than a male. More importantly, the interpretation is problematic because if parents have a desire for a male child, gender is endogenous to fertility. We assume instead, that gender of the child is exogenous to fertility so that the positive coefficient on sex of the child in Table 2 indicates that a male child is associated with a large family, due perhaps to genetic endowments of parents.

5.2.3 Sample Selection

The set of factors that affects demand for inputs into birth weight also influences selection of children into the estimation sample. As noted earlier, underlying the selection of children into the estimation sample is the demand for clinic births. The mothers who deliver at the clinics are more likely to report birth weight for their children, and these children are the ones used to estimate the birth weight production function. Table 2 (column 5) presents estimation results of a probit model of birth-weight reporting in a household survey. As in columns (1)-(4), reporting of birth weight is significantly correlated with commodity and time prices, wealth, environmental factors and demographics. Among the demographics, education of the mother is strongly associated with birth weight reporting. The coefficient on mother's education first increases and then falls, suggesting that women with post-primary education deliver at home, but most likely with the help of a qualified medical personnel, such as a professional nurse, who weighs the baby after birth.

The last panel of Table 2 (column 5) presents the probit index (predicted *z*-score, which is the sum of each estimated coefficient multiplied by its respective covariate), the probability density, and the cumulative density of the probit index. It is worth noting that the cumulative probability of the probit index (.54) is precisely the conditional probability of reporting a non-missing birth weight in the sample. This is the predicted probability of selection into the sample. The inverse of the Mills ratio (the variable we use in the birth-weight equation to control for unobservables that are correlated with selection of children into the estimation sample), is equal to the probability density of the probit index divided by the cumulative density of the probit index (see Wooldridge, 2002). The inverse of the Mills ratio in this sample is .59. Similarly, the inverse of the Mills ratio for the sample of non-reported birth weights is .69 (=.32/(1-.54). This information is useful in analyzing effects of selected samples on birth weights. In particular, the ratios can be used to determine how birth weights observed in selected samples differ from birth weights in a random sample.

5.2.4 Relevance, strength and exogeneity of instruments

Three properties of an instrument need to be noted at the outset. First, an instrument is relevant if its effect on a potentially endogenous explanatory variable is statistically significant. Second, an instrument is strong, if the size of its effect is 'large'. Finally, the instrument is exogenous if it is uncorrelated with the structural error term. An instrumental variable that meets all these requirements is a valid instrument, but often very difficult to find (Bound, et al., 1995; see also Rivers and Vuong, 1988).

The *p*-value and the magnitude of the first-stage *F* statistic on excluded instruments in Table 2 suggest that the instruments for this study are valid. The partial R^2 shows the predictive power or strength of the instruments in each of the reduced-form equations. An instrument can be exogenous but weak or exogenous but irrelevant in the statistical sense stated above. Similarly, an instrument may be endogenous (correlated with the structural error term), but this correlation may be insufficient to undermine its validity. For example, the bias of an estimate based on instruments that fail over-identification test might be sufficiently small relative to the bias of an alternative estimate (see Stock, 2002). The first-stage *F* statistic and the partial R^2 convey vital information as to the validity and relevance of instruments in the case of a single endogenous variable (see Shea, 1997). However, as pointed out by a referee, in the case of multiple endogenous variables, the Cragg-Donald statistic is needed to assess the validity of instruments (see below).

The joint *F* and χ^2 tests in Table 2 show that the entire set of instruments in panel 2*A*-*E* (Table 1) is valid both for the input equations and for the selection equation. The first-stage *F* statistic on excluded instruments (Table 2) varies from about 3 to 11 (*p*-value = 0.000), while the χ^2 statistic for the selection (probit) equation is 584.8 (*p*-value = 0.000). However, since there are five endogenous regressors (including the sample selection variable) and twenty instruments, there is need to check whether over-identification restrictions hold (Table 3). That is, it is necessary to test the assumption that the extra instruments are uncorrelated with the structural error term (the disturbance term of the birth weight equation). Diagnostic tests in Table 3 indicate that the inputs into birth weight production function are endogenous (Durbin-Wu-Hausman Chi-square Statistic = 62.8, *p*-value = 0.000), which indicates that the OLS estimates are not reliable for inference.

Although the χ^2 statistic is sufficiently high (Table 2), indicating that the instruments strongly identify the sample selection equation, the *F*-statistics on excluded instruments for the input equations are low, suggesting that the excluded instruments are weak (see Stock et al., 2002). However, in this case, the instruments are weak but relevant. Instruments are irrelevant if their joint effect on an endogenous explanatory variable is zero (Stock et al., 2002, p. 519). Instruments are relevant but weak if their joint effect is statistically significant but at a low *F* statistic, typically less than 10. When the instruments are relevant but weak, the 2SLS estimator is biased toward the OLS estimator, which is known to be inconsistent (Bound et al., 1995). However, if the bias of the 2SLS estimator, $E(\beta^{2SLS} - \beta)$ relative to the inconsistency of the OLS estimator, $\text{plim}(\beta^{OLS} - \beta)$ is small (at most 10%), weak instruments are still reliable for inference (Stock et al., 2002, pp. 521-522).

In the case of a structural model with a single endogenous variable, the *F* statistic on excluded instruments can be used to determine whether or not the relative bias $[E(\beta^{2SLS} - \beta)/\text{plim}(\beta^{OLS} - \beta)]$ of the IV estimates in the presence of weak instruments is sufficiently small. For large samples, the first-stage *F* statistic that is consistent with a small relative bias of the IV estimates can be computed from the expression, $F = \mu^2/K+1$, where, *K* is the number of instruments, and μ^2 is the concentration parameter (Stock et al., 2002, p. 519)[3]. In large samples, the first-stage *F* statistic is a good estimator of μ^2/K (the population analogue to the sample *F* statistic on excluded instruments (Bound et al., 1995)). In a single endogenous variable case, tables exist for smallest values of μ^2/K at which the bias of 2SLS estimates is no more than 10% of the inconsistency of the OLS estimates (see Bound et al., 1995, Table A1; and Stock et al., 2002, Table 1).

If for a given *K*, the first-stage *F* statistic is equal to or greater than μ^2/K, this is evidence that the relative bias of the IV estimates is sufficiently small (i.e., 10% or less). For example, when *K* (number of instruments is equal to 5), the value of μ^2/K (normalized concentration parameter) is 5.82. The value of the *F*-statistic that rejects the hypothesis that $\mu^2/K < 5.82$ at the 5% level is 10.83. See Stock et al (2002, p. 522) for details, and for a related size test requiring that the size of the IV *t*-statistic be no more than 15% of the OLS *t*-ratio.

The conclusion from the literature on weak instruments when the structural model has *one* endogenous variable is that if the first-stage *F*-statistic on excluded instruments is large (at least equal to 10), the over-identifying restrictions generally hold. In a simulation example, Bound et al.(1995, Table A1) show that when $\mu^2/K = 10$, the bias of the IV estimates relative to OLS bias is small (about 9%) for a large number of instruments ($K = 200$).

In Table 2, there are two first-stage *F*-statistics of about 10 (see the vaccination and higher-order birth equations), two *F* statistics of about 3 (see first-order birth and age at first birth equations),

[3] The concentration parameter is a unitless measure of the strength of instruments (see e.g., Basmann, 1963, p. 967; Bound et al., 1995, p. 445). In a linear IV regression model with a single endogenous regressor but without a common set of exogenous covariates ($y = Y\beta + \upsilon$; and $Y = Z\Pi + \nu$), the concentration parameter, μ^2, can be expressed as $\mu^2 = \Pi' Z' Z \Pi / \sigma^2_\nu$ (Stock et al., 2002, p. 519), where *y* and *Y* are T x 1 vectors of observations on endogenous variables, *Z* is a T x K matrix of instruments, υ and ν are T x 1 vectors of disturbance terms and β and Π are parameters to be estimated. In a sample context, the concentration parameter is the first-stage explained sum of squares for the endogenous regressor weighted by its sample variance.

and one sufficiently large first-stage chi-square statistic (the sample selection equation)[4]. Although this is evidence that the instruments are weak but relevant, it is only a rough guide to inference because the structural equation contains multiple endogenous variables. In the case of multiple endogenous variables, the Cragg-Donald statistic for detecting weak instruments should be used (see Stock and Yogo, 2004). If the computed *minimum* eigenvalue of the concentration matrix (matrix of the first-stage *F*-statistics) is less than the tabulated critical value, the instruments are weak (Stock and Yogo, 2004, p. 30). However, to a first approximation, the first-stage *F*-statistics themselves can be compared to the tabulated critical values of the minimum eigenvalues at different values of *K* (number of instruments). The difference between the rule of thumb (comparison of the first-stage *F*-statistic to a value of 10), "and the procedure of this paper is that, instead of comparing the first-stage *F* to ten, it should be compared to the appropriate entry in Table 1…" (Stock and Yogo, 2004, p. 32); that is, the tabulated critical values in Table 1. From Table 1 of Stock and Yogo (2004, p. 39), the critical value at $K = 20$ and $n = 3$ is 10.60, where n is the maximum number of endogenous variables for which critical values are tabulated. Since the critical value has changed only marginally, from 10.0 to 10.6, we uphold the preliminary conclusion that the instruments for this study are weak but relevant.

5.2.5 Child Health Production Technology

<u>Statistical significance and stability of estimated coefficients under different specifications</u>

Is tetanus vaccination correlated with birth weight? Panel *A* of Table 3 presents several approaches to answering this question. Column 1 depicts OLS estimates of child health production technology with endogenous inputs so that the estimates are biased. In Table 3 (column 2), consistent IV estimates of technology parameters are presented. Underlying these estimates are two key assumptions: (a) the unobservable variables are uncorrelated with excluded instruments or that the correlation is linear and (b) the estimation sample is randomly selected from the population of interest (in this case, children age, 0-5 years).

In Table 3 (columns, 3a-c), Maximum Likelihood Heckit/control function estimates are presented. The estimates are obtained controlling for sample selection bias and heterogeneity of the birth weight. In columns (3a-c) the assumptions in column (2) are dropped and replaced with two alternative assumptions: (a) the sample on which birth weight is estimated is non-random, and (b) the interaction between unobservable variables and the correlates of birth weight is non-linear. Accordingly, the usual generated regressor (inverse of the Mills ratio) in censored samples is introduced into the birth weight equation through the Heckit procedure to account for sample selection bias. In addition, eight new generated regressors (residuals of input demand functions) are included via control functions to account for correlations of birth weight with

[4] However, if we ignore the relevance of the instruments and the sample selection feature of the model and conduct the *LM* test (Wooldridge, 2002), the over-identification restrictions are rejected (χ^2 statistic = 38.1 (*p*-value = .002). This is not surprising because some of our instruments, notably the prices of medical care and schooling costs were reported by households and then aggregated in an effort to reduce their dependence on household choices within a cluster. Rejection of over-identifying restrictions indicates that there is a feedback effect from the outcome variable to the explanatory variables so that the IV estimator is biased (see Nelson and Startz, 1990, p. S132) but the size of the bias is unknown. Nelson and Startz show that the size of bias depends on the magnitude of the feedback effect (correlation between the structural error and the instrument) and on the quality or relevance of the instrument (the correlation between the instrument and the endogenous regressor). The instruments may pass the over-identification test and still yield more biased estimates than the benchmark OLS estimates. Similarly, instruments may fail over-identification test and still be reliable for inference.

unobservables.

The results in Table 3 (panel *A*) show that tetanus vaccination is positively associated with birth weight. As argued in Section 1, tetanus vaccination is assumed to be complementary to prenatal care in the production of birth weight (see Dow et al., 1999). Columns (1) and (2) of Table 3 present baseline results of the investigation. The IV estimate (.420) of the coefficient on tetanus vaccination in column (2) is about 4 times as large as the OLS estimate (.103) in column (1).

Table 3

Parameter Estimates of Birth Weight Production Function: Dependent Variable is Birth Weight in Kg (absolute value of robust *t*-statistics in parentheses beneath estimates)

Variables	Estimation Methods				
	OLS (1)	IV (2)	Heckit/Control Function Approach (3a)	(3b)	(3c)
A. ***Potentially endogenous market and behavioral inputs***					
Immunization Status of Mother (=1 if Vaccinated)	.103 (2.74)	.420 (2.35)	.499 (3.12)	.763 (3.72)	.769 (3.76)
First-Order Birth (First Born Child =1)	-.104 (3.83)	-1.405 (2.89)	-1.473 (4.00)	-1.361 (3.64)	-1.466 (4.02)
Higher-Order Births, 2, 3...	.008 (1.22)	.113 (2.27)	.087 (2.00)	.078 (1.74)	.082 (1.86)
Age of Mother at First Birth	-.0002 (0.10)	.049 (1.83)	.051 (2.60)	.045 (2.25)	.048 (2.47)
B. ***Exogenous Covariates***					
Residence (Rural = 1)	-.033 (1.43)	-.135 (3.38)	-.139 (4.71)	-.146 (5.04)	-.148 (5.10)
Mother's Years of Schooling	.001 (0.15)	-.0007 (.05)	-.0009 (0.09)	.004 (.38)	.004 (.37)
Mother's Years of Schooling Squared ($\times 10^{-2}$)	.009 (0.15)	.131 (1.25)	.001 (1.48)	.001 (1.46)	.106 (1.42)
Father's Years of Schooling	.010 (1.01)	.001 (.09)	.004 (.40)	.006 (.57)	.006 (.57)
Father's Years of Schooling Squared ($\times 10^{-2}$)	-.007 (0.11)	.054 (.60)	.035 (0.51)	.030 (.44)	.029 (.42)
Father Not Home During Survey (=1 if Absent)	.287 (1.34)	-.067 (.24)	-.015 (0.06)	-.021 (.10)	-.009 (.04)
Age of Father in Years	.010 (.95)	-.008 (.60)	-.006 (.56)	-.007 (.61)	-.006 (.56)
Age of Father Squared ($\times 10^{-2}$)	-.011 (0.79)	.008 (.5)	.007 (.55)	.008 (.54)	.007 (.50)
Age of Mother	.003 (0.19)	-.250 (3.09)	-.258 (4.18)	-.246 (4.10)	-.254 (4.25)
Age of Mother Squared ($\times 10^{-2}$)	-.010 (0.44)	.292 (2.57)	.311 (3.63)	.298 (3.49)	.308 (3.62)
Sex of Child (Male = 1)	.106 (6.00)	.093 (3.67)	.095 (5.20)	.097 (5.29)	.096 (5.25)
C. ***Predicted/pseudo residuals and interaction terms (control function variables)***					

Immunization Residual	...	...	-.418 (2.58)	-.771 (3.36)	-.775 (6.40)
First-Order-Birth Residual	...	...	1.375 (3.73)	1.394 (3.81)	1.368 (3.74)
Higher-Order-Birth Residual	...	...	-.088 (2.00)	-.085 (1.89)	-.083 (1.87)
Age at First Birth Residual	...	...	-.051 (2.60)	-.051 (2.54)	-.049 (2.46)
Inverse of the Mills Ratio	...	...	.062 (1.48)	.085 (1.98)	.086 (2.00)
Immunization × Predicted Immunization Residual	...	...	...	.668 (2.65)	.665 (6.62)
First-Order-Birth × its Residual	...	...	...	-.205 (1.38)	...
Higher-Order-Birth × its Residual × (10^{-2})	...	...	...	.041 (.19)	...
Age of Mother at First Birth × its Residual × (10^{-2})	...	...	...	.007 (1.25)	...
D. ***Tests of Joint Significance of Coefficients on Linear and Squared Terms for Parents' Education and Age,*** χ^2***/F statistics (p-values)***					
Mother's Education	0.27 (.7630)	7.77 (.0206)	13.34 (.0013)	17.68 (.0001)	16.77 (.0002)
Father's Education	3.22 (.0402)	3.81 (.1487)	7.20 (.0274)	8.77 (.0124)	8.34 (.0154)
Mother's Age	.84 (.4302)	18.14 (.0001)	28.07 (.0000)	25.04 (.0000)	26.74 (.0000)
Father's Age	.800 (.4491)	.530 (.7689)	.390 (.8243)	.450 (.7984)	.380 (.8278
Constant	2.76 (12.28)	6.56 (5.31)	6.47 (7.03)	6.09 (6.55)	6.133 (6.62)
R-Squared/(Log-Likelihood)	0.024	...	-7539.5	-7533.4	-7535.4
ρ (Correlation of Birth-weight Residual with Sample Selection Residual) (s.e)	...	...	.112 (.075)	.153 (.077)	.155 (.077)
σ (Sigma of Birth Weight) (s.e)	...	...	.555 (.008)	.556 (.008)	.556 (.008)
Wald χ^2 test for $\rho = 0$ (*p*-value)	...	...	2.17 (.141)	3.83 (.050)	3.86 (.049)
Durbin-Wu-Hausman χ^2 test for exogeneity of variables in panel *A* (*p*-value)	...	62.8 (.0000)	...	...	...
Uncensored observations	4038				

In both the IV and OLS results, the first born siblings are significantly lighter than their younger siblings, which is consistent with findings from previous studies; see for example Joyce and Grossman (1987) for the United States, and Central Bureau of Statistics and others (2004) for Kenya. The IV coefficients on first-order births and on subsequent births are larger in absolute values than the OLS coefficients. The estimated coefficients on age at first birth differ across specifications. The OLS estimate (column 1) is negative and insignificant (t = .10), while the IV estimate (column 2) is positive and statistically significant (t = 1.83). The IV estimate shows that delaying the age at which the first birth occurs is associated with an increase in birth weight.

Panel *B* of table 3 presents estimates of coefficients on demographics. Focusing on the IV estimates, it can be seen that the birth weight of babies in rural areas is lower than that of urban babies, and that male infants are heavier than female infants.[5] Interestingly, the OLS and IV estimates are quite similar, perhaps due to exogeneity of the sex variable.

A comparison of results in columns (3a) and (2) shows that accounting for sample selection bias increases the coefficient on immunization from .420 to .499 or by 18.8 percent. Remarkably, the coefficients on other regressors and t statistics in column (3a) remain practically the same as in IV results (column 2), except in the case of age at-first-birth coefficient where the t-ratio increases from 1.83 to 2.60. As expected, the Durbin-Wu-Hausman chi-square test rejects exogeneity of all child health inputs (immunization, birth-orders and age of mother at first birth shown in panel *A*), indicating that OLS is not a valid estimation method.

The coefficients on residuals in panel *C* (columns 3a-c) are statistically significant, indicating that the market and behavioural inputs into birth weight are endogenous, so that inclusion of these residual terms in the birth weight equation, as is done here, is required for consistent estimation of structural parameters. The coefficient on the inverse of the Mills ratio is statistically insignificant in column (3a) but increases and assumes significance when account is taken of heterogeneity of birth weight through inclusion (as additional controls) of interaction terms of the residuals with endogenous inputs in the structural equation (columns 3b-c). The interaction of immunization with its residual is revealed to be the main source of heterogeneity in birth weight. That is, in line with complementarity hypothesis, mothers who received tetanus vaccination during pregnancy were more likely to use other inputs such as nutritious foods or to adopt behaviours that increase birth weight.

Panel *D* (columns 1-3) shows results of tests of joint statistical significance of the coefficients on linear and square terms of parents' age and education across different specifications. The coefficients on these terms are jointly significant for parents' education and for age of the mother in specifications (2) and (3a).

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[5] These findings are consistent with a joint report by the United Nation's Children's Fund (UNICEF) and World Health Organization (WHO) which states: "For the same gestation age, girls weigh less than boys, first born infants are lighter than subsequent infants, and twins weigh less than singletons" (UNICEF and WHO, 2004, p. 5). The report further states that a baby's low birth weight is a result of preterm birth (before 37 weeks of gestation) or of restricted fetal (intrauterine) growth, the mother's own fetal growth, and her diet from birth to pregnancy.

The last panel of results in columns (3a-c) contains information about sample selection bias. The results in column (3a) suggest that there is no problem of selection bias in this sample, which is not surprising because estimation there is done under the assumption that there is no heterogeneity in birth weight as defined earlier. Specifically, it is assumed that there are no unobservable variables interacting with the regressors in the birth weight equation or equivalently, any such interaction is linear. This assumption is dropped in columns (3b) and (3c), where the residuals are interacted with market and behavioural inputs to capture potential non-linear correlations between birth weight inputs with unobservables.

Under the new specifications, the estimated coefficient on tetanus vaccination increases by 54% (from 0.499 to 0.769). Panel *C* shows that the coefficient on the interaction of immunization with its residual is statistically significant. In specification (3c), the estimated coefficients on all the four interaction terms are jointly statistically significant (χ^2 = 10.29, *p*-value = .0358).

Inclusion in the birth weight equation of interactions of the birth-weight inputs with their residual terms leads to rejection of the hypothesis that the structural error term is uncorrelated with the error of sample selection equation (χ^2 =3.83, *p*-value =.05). As already noted, the coefficient on the inverse of the Mills ratio (roughly, the influence of non-randomness of the sample on birth weight) also increases by about 38.7% (from .062 to .086) and becomes statistically significant. Notice from Table 3 (panel *C* and the bottom panel of this table) that consistent with the formula for the inverse of the Mills ratio (Heckman, 1979; Wooldridge, 2002), the estimated coefficient on this ratio is simply the estimated value of sigma (σ) times the estimated value of rho (ρ).

The outcomes of the new specification (3c), namely: (a) discernible correlation between the disturbance terms of birth weight and sample selection equations, i.e., correlation between rho and sigma, respectively; and (b) detection of statistical significance of the coefficient on inverse of the Mills ratio, are evidence that the unobservable variables that are associated with selection of children into estimation sample are not separable from unobservables that are correlated with birth weight. These inseparable unobservables are captured by the interaction of immunization with its residual (i.e., Immunization × Predicted Immunization Residual). Since the estimated coefficients are stable between specifications (3b) and (3c), the results from the parsimonious specification (3c) are preferred.

<u>Size and policy relevance of estimated coefficients</u>

As argued in Section 1, tetanus vaccination during pregnancy is assumed to complement prenatal care in the production of birth weight. Consistent with this assumption, the results from specification (3c) show that babies born to immunized mothers were 769 grams heavier than babies of mothers who had not received tetanus vaccination. However, the estimated gain in birth weight in this case cannot be attributed to tetanus immunization because the complementarity hypothesis says that the gain comes from mothers' actions in areas of prenatal and general health care induced by vaccination during pregnancy.

Furthermore, as noted by a referee, the gain in birth weight also contains the supply effect of the health care system because if the quantity demanded of tetanus toxoid is not supplied in required amounts, vaccination would not work. Because of data limitation, it was not possible to investigate the size of complementarity effect, via inclusion in equation (7.1a) of interactions of tetanus toxoid with prenatal care, and with exogenous indicators of the quality of antenatal care at local clinics. In light of this, the coefficient on the tetanus variable (.769) cannot be given a causal interpretation because it also contains birth-weight effects of other inputs. It must be acknowledged that this coefficient is too large. Although it can be reasonably associated with mother's intake of nutrients, and with the prenatal care received during pregnancy, consistent effect of nutrition on birth weight has been difficult to establish in experimental studies. In some cases, zinc supplementation of diet during pregnancy was found to increase birth weight in randomized trials but in other cases it had no effect (see Castillo-Duran and Weisstaub (2003). This point is echoed by Costello and Osrin (2003) when they note that practicalities of increasing birth weight at the population level remain questionable. See also Villar et al. (2003), who argue that few interventions exist that can dramatically influence specific health outcomes such as neonatal mortality or birth weight.

Despite the application of the control function approach, the coefficient on immunization could be overstated because effects of unobservables in the birth weight equation might not have been fully controlled for. The problem posed by unobservables in the estimation of structural models using regression methods and the role that experimental methods can play to overcome it is thoroughly treated in Schultz and Strauss (2008); see also Glewwe, et al., 2004). The potential biases associated with unobservable variables should be kept in mind when interpreting the estimation results in Table 3.

The results in panel *B* indicate that infants in rural areas are about 135-148 grams lighter than infants born in urban areas. The IV and Heckit/control function estimates are nearly four times as large as the OLS estimate. A male infant is heavier than a female infant in all specifications, a result that seems to be driven by biological processes.

The estimated coefficient (.086) on the inverse of the Mills ratio in the last panel of Table 3 (specification 3b) is statistically significant at the 5 percent level. This finding justifies the choice of the Heckit/control function approach in Table 3 because it corrects for sample selectivity bias. Moreover, since selection of children into the estimation sample is assumed to be correlated with being born at the clinic (where infants are weighed at birth), the positive coefficient on the inverse of the Mills ratio suggests that babies of mothers who delivered at the clinics are heavier than the newborns from the general population. Further, since the sample mean of the inverse of Mills ratio is .589 (see Table 2), babies born at the clinics are 50 grams (=.589*.086) heavier than newborn babies in the general population. The birth weight of an infant randomly selected from the population is the average of birth weights of babies born at the clinics and at home. However, this average cannot be computed because information on birth weight of babies born at home is missing. Thus, it is not possible to compare the weights of children born at home with the weights of children born at the clinics.

6. CONCLUSION

A structural model of birth weight for Kenya has been estimated using survey data from the early 1990s on women and their surviving children. In this paper, birth weight has been used as a proxy for child health in utero. It has been argued that birth weight strongly correlates with indicators of social and economic prosperity in adult life. The results show that tetanus vaccination during pregnancy is associated with a large increase in birth weight. This finding strengthens the tetanus complementarity hypothesis reported in the literature on birth weight production functions (see Dow et al., 1999).

Consistent with the literature, the OLS estimate of the coefficient on tetanus vaccination is biased downwards, and is about four times smaller than the IV estimate. This bias is likely due to correlation of tetanus vaccination with unobserved health endowments of mothers. Such unobservables are the sources of endogeneity of tetanus vaccination in the birth weight equation. The IV estimate, which is the preferred estimate according to the literature, is also shown to be understated. The IV estimate is understated because instrumental variables do not fully address the endogeneity of birth weight because unobserved differences in birth weights stemming from biological endowments of mothers are neglected. Because mothers differ in health status, their birth weights respond differently to tetanus vaccination and to other inputs with which the inoculation is correlated; however, the IV estimate is derived under the assumption that this response is uniform. The heterogeneity bias is compounded by sample selection bias, which is also ignored when deriving the IV estimate.

We use the Heckit method (see Heckman, 1979; Wooldridge, 2000, p. 561) to correct for sample selection bias, and the control function approach (see Garen, 1984; Wooldridge, 1997; Heckman and Vytlacil, 1998; Card, 2001) to correct for heterogeneity bias. The corrected estimated coefficient on tetanus vaccination is 83% larger than the IV estimate (.769 versus .420). Since the corrected estimate (.769) can be interpreted as capturing the effect of a variety of health inputs on birth weight, rather than the direct impact of a specific intervention (tetanus inoculation), its size may not be entirely implausible. Even so, there is need to point out that this estimate is unusually large. Moreover, the finding is tentative because it relies on the untested assumption that tetanus vaccination is complementary to prenatal care and to other inputs provided by the health care system in the production of birth weight. The estimation strategy proposed in the paper can be applied to test this hypothesis using better data than were available for this study.

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