A Multilevel Analysis of Prenatal Care and Birth Weight in Kenya

Japheth Osotsi Awiti

Research Paper 423

Bringing Rigour and Evidence to Economic Policy Making in Africa

African Economic Research Consortium
Consortium pour la Recherche Économique en Afrique

A Multilevel Analysis of Prenatal Care and Birth Weight in Kenya

By

Japheth Osotsi Awiti
School of Economics
University of Nairobi, Kenya

AERC Research Paper 423
African Economic Research Consortium, Nairobi
March 2021

THIS RESEARCH STUDY was supported by a grant from the African Economic Research Consortium. The findings, opinions and recommendations are those of the author, however, and do not necessarily reflect the views of the Consortium, its individual members or the AERC Secretariat.

Published by: The African Economic Research Consortium
P.O. Box 62882 - City Square
Nairobi 00200, Kenya

ISBN 978-9966-62-121-5

Contents

List of tables

List of figures

Abstract

The paper investigates the effect of adequate use of prenatal care on birth weight in Kenya. We estimate a multilevel model controlling for potential sample selection bias, potential endogeneity of prenatal care, and potential unobserved heterogeneity. A single–level model is also estimated, for comparison.

In estimating the models, we use data from the Kenya Demographic and Health Survey of 2008–2009 together with additional administrative data. The results indicate that adequate prenatal care increases birth weight, holding other factors constant. We further observe that the single–level model overstates the effect of prenatal care on birth weight by about 88g.

Keywords: Birth weight, Prenatal care, Kenya, Multilevel analysis.

1. Introduction

We can view health as comprising physical, mental and social wellbeing (World Health Organization (WHO), 2006). Good health is an important component of human capital (Becker, 2007; Mwabu, 2008).

The study of infant health is important because many health problems that we observe in adult life originate in the early years of life (Hertzman and Power, 2004).

Infant health can be measured at both the individual and population levels. Examples of indicators of infant health at the population level are neonatal mortality rate, postneonatal mortality rate, infant mortality rate, birth weight distribution, and gestational age distribution (Alves and Belluzzo, 2004; Mwabu, 2009). Examples of infant health indicators at the individual level are child survival, birth weight, Apgar score, gestation, disability, and nutritional indicators (Schultz, 1984; Mwabu, 2008).

Table 1 gives data on some key infant health indicators for selected sub-Saharan African countries and other regions. A closer look at the data shows that most of the sub-Saharan African countries have poor infant health outcomes. For example, Kenya had a neonatal mortality rate of 27 per 1,000 live births in 2009 while Tanzania had an infant mortality rate of 68 per 1,000 live births in 2009. Further, 8% of the infants born in Kenya and 10% of the infants born in Tanzania are of low birth weight. The table also shows that about 13% of the infants born in the African region are of low birth weight as compared to only 5% in Western Pacific, 7% in Europe, and 8% in the Americas. A higher percentage of low birth weight infants are, however, found in South–East Asia and the Eastern Mediterranean as compared to Africa.

Table 2 shows additional indicators of infant and child health for Kenya. The table shows, for example, that 85 of every 1,000 children born alive in Kenya in 2010 were likely to die before reaching their fifth birthday. We also note from Table 2 that 15% of all under-five deaths in Kenya in 2010 were due to premature births. Further, we observe, from the table, that about 16% of children under five years of age in Kenya are underweight. All these indicators point towards a concern over infant and child health in Kenya.

Table 1: Some Key infant health indicators for selected sub-Saharan Africa Countries

Country/RegionNeonatalMortalityRateInfantMortalityRateLowbirthweightNewborns

per1,000livebirths)(per1,000livebirths)(%

1990200020091990200020092000–2009*

Angola5348421531269812

Botswana23322246664313

Cameroon36373791969511

CentralAfricanRepublic45474511511911213

DemocraticRepublicofCongo51515112612612610

Eritrea32231792583914

Ethiopia524335124916720

Gabon30282568615214

Gambia413732104937820

Ghana38352676684713

Kenya3032276466558

Lesotho35423374866113

Liberia5751371651338014

Madagascar413121102654016

Malawi433730129996914

Mauritius1512921161314

Mozambique5347411551239615

Namibia25261949503416

Nigeria4946391251148612

Senegal41363173615119

SierraLeone59564916615012314

Swaziland2426206771529

Togo41363289786412

Uganda383431111947914

UnitedRepublicofTanzania43393499866810

Zambia403935108998611

Zimbabwe27342954695611

WHORegion

African444136109988013

Americas171393322158

South–EastAsia47393180624524

European141072819127

EasternMediterranean40353077655421

WesternPacific2217113628185

*Data is for the latest year available.

Source: World Health Organization (WHO) (2011).

Table 2: Selected infant and child health indicators for Kenya

Indicator	Year	Value
Stillbirth rate (per 1,000 total births)	2009	22
Neonatal mortality rate (per 1,000 live births)	2010	28
Infant mortality rate (per 1,000 live births)	2010	55
Under–five mortality rate (per 1,000 live births)	2010	85
% of under–five deaths due to prematurity	2010	15
Low birth weight newborns (%)	2005–2010	8
Children under 5 years stunted (%)	2005–2011	52.2
Children under 5 years underweight (%)	2005–2011	16.4
Children under 5 years overweight (%)	2005–2011	5

Source: World Health Organization (WHO) (2012).

Although there are many indicators of infant health, this study focuses on birth weight. Since birth weight[2] represents the outcome of the gestation period, it is a good measure of infant health at birth (Mwabu, 2009). Weight at birth of less than 2,500g is termed to be low (Zegers-Hochschild et al, 2009). Low birth weight is associated with various adverse health outcomes such as foetal and neonatal morbidity and mortality, impaired cognitive development, and the advent of chronic diseases in later life (Institute of Medicine, 1985; Kramer, 1987).

This means that efforts to increase the birth weight of children beyond the 2,500g threshold are an effective way of improving infant health. This paper focuses on one way of doing that: adequately using prenatal care.

The literature on the determinants of low birth weight is summarized by the Institute of Medicine (1985), Kramer (1987), Ohlsson and Shah (2008), and Darling and Atav (2012). These studies identify a number of maternal risk factors for low birth weight. The factors are summarized in Table 3.[3]

Table 3 shows that one of the risk factors for low birth weight is absent or inadequate prenatal care. In particular, having fewer than five prenatal care visits and beginning prenatal care after the third month increase the likelihood of delivering a low birth weight infant (Coutinho et al, 2009).

Prenatal care, also called antenatal care, refers to the health care provided to an expectant mother throughout the period of pregnancy, but excluding labour and delivery (Berg, 1995; Gajate-Garido, 2013). In the ideal scenario, prenatal care should involve the following activities: provision of appropriate advice on health matters such as nutrition, hygiene, newborn care and safer sex; identification of expectant women at risk of experiencing pregnancy complications through appropriate screening and diagnosis; and either the treatment of identified pre-existing illnesses and conditions or, where treatment is not available at the particular health facility, referral to an appropriate health facility that can deal with the identified conditions (Berg, 1995). Prenatal care can benefit both expectant mothers and their unborn children through identification of expectant mothers at risk of delivering low birth weight infants or experiencing complications during delivery and providing appropriate psychosocial, nutritional, and medical interventions aimed at reducing such risks (Kramer, 1987; Alexander and Korenbrot, 1995).

Table 3: Maternal risk factors for low birth weight

Factor Type	Detailed breakdown
Historical factors	Short or long birth interval
	Previous history of preterm/low birth weight births
	Maternal history of being low birth weight
Demographic factors	Adolescent mothers
	Minority race
	Acculturation
	Unmarried/cohabiting
	Parity (0 or more than 4)
Nutritional factors	Iron deficiency
	Lack of fish oil in diet
Anthropometric factors	Low body mass index
Medical and pregnancy–related conditions	Anatomical factors
	Uterine factors
	Placental factors
	Infections
	Malaria
	Human Immuno–deficiency Virus (HIV)
	Bacterial vaginosis
	Trichomoniasis
	Syphilis
	Gonorrhea
	Urinary tract infection
	Periodontal infection
	Others
	Multiple pregnancy
Psychosocial factors	Adverse psychosocial factors
Lifestyle–related factors	Tobacco use
	Heavy alcohol use
	Cocaine use
	Narcotic use
Environmental factors	Environmental tobacco exposure
Violence/maternal abuse	Violence/abuse
	Maternal trauma
Infertility and in vitro fertilization (IVF) treatment	
Health care risks	Absent or inadequate prenatal care

Source: Institute of Medicine (1985), Kramer (1987), Ohlsson and Shah (2008).

Several indicators have been used in the literature to measure prenatal care use (Evans and Lien, 2005; Conway and Kutinova, 2006; Nazim and Fan, 2011).

Table 4 gives examples of such indicators.

Table 4: Indicators of prenatal care use

Number of prenatal care visits.
Number of prenatal care visits adjusted for pregnancy length.
Whether prenatal care was ever initiated.
Author–constructed quality index of type of care received.
Timing of first prenatal care visit.
Kessner index of adequacy of prenatal care received.
Adequacy of prenatal care utilization index.
Indexes based on WHO recommendations for developing countries.

The World Health Organization (WHO) recommends a minimum of four prenatal care visits at particular intervals, to skilled health personnel (doctors or nurses), for expectant women in developing countries (Berg, 1995).[4] The recommended timing for each visit is shown in Table 5.

Table 5: WHO recommended minimum prenatal care visits for developing countries

Visit	Recommended timing (pregnancy weeks)
First	≤ 16
Second	24 – 28
Third	32
Fourth	36 – 38

Source: Berg (1995).

According to the table, the first prenatal care visit should occur within the first 16 weeks of pregnancy, while the third visit should occur at 32 weeks of pregnancy. There are further detailed recommendations on what should be done at each visit (Berg, 1995). Gajate-Garido (2013) shows that the recommendations of WHO regarding use of prenatal care in developing countries are appropriate. In this study, we construct a prenatal care utilization index based on WHO's recommendations.

Purpose and objectives of the study

This study investigates the effect of adequate use of prenatal care on birth weight in Kenya. The main objective of the study is, therefore, to show how adequate use of prenatal care affects birth weight in Kenya, holding other determinants of birth weight constant.

Specifically, the study has the following objectives:

i. Constructing a measure of adequacy of prenatal care use in Kenya following the WHO recommendations.
ii. Determining the factors influencing adequate utilization of prenatal care in Kenya.
iii. Establishing the effect of adequate use of prenatal care on birth weight in Kenya, using both single–level and multi–level analysis.
iv. Drawing appropriate policy implications from the study findings.

The rest of the paper is structured as follows: Section 2 reviews the literature. Section 3 discusses the methods of the study. The results are presented in Section 4, and Section 5 presents the conclusion and policy implications.

2. Literature review

In this section, we summarize the literature on the effectiveness of prenatal care in improving birth weight. The literature on the determinants of prenatal care use is also summarized.

The literature linking prenatal care to birth weight is abundant. Since absent or inadequate use of prenatal care is a risk factor for low birth weight (see Table 3), we would expect prenatal care use to improve birth weight.

Although many studies show that this is in fact the case (see, for example, Institute of Medicine, 1985; Evans and Lien, 2005; Jewell and Triunfo, 2006; Wehby et al, 2009; Mwabu, 2009; Nazim and Fan, 2011), Kramer (1987) cites studies that fail to find an effect of prenatal care on reducing the risk of low birth weight. Other studies (see, for example, Currie and Grogger, 2002) only find weak influences of prenatal care on the health of infants. Why is this the case? One answer suggested by Conway and Deb (2005) is that studies that find prenatal care to be ineffective in birth weight determination typically combine "complicated" and "normal" pregnancies. Conway and Deb (2005) proceed to demonstrate the effectiveness of prenatal care on "normal" pregnancies.

The literature also identifies several factors that influence prenatal care use (Wehby et al, 2009; Jewell, 2009). Table 6 summarizes some of these factors.

Table 6: Factors influencing prenatal care use

Type of facility visited (that is, whether private or public).
Maternal demographic, socio-economic, situational, and psychological factors.
Race.
Maternal health status.

Gaps in the literature

A careful look at the literature reveals that there is still controversy over the effectiveness of prenatal care in improving birth weight. This is evidenced by the fact that although there are studies which show that prenatal care improves birth weight, others find prenatal care to be ineffective. A look at the literature further reveals that there are very few studies in sub-Saharan Africa investigating the effect of prenatal care on birth weight. Most of the studies cited in the literature also use the single–level model in their analysis.

Our study contributes to the literature by adding to the studies that find prenatal care to be effective in improving birth weight. Our study also contributes to the literature by studying a sub–Saharan African country, Kenya. Unlike previous studies, our study estimates both the single– and the multi–level models in linking prenatal care use to birth weight.

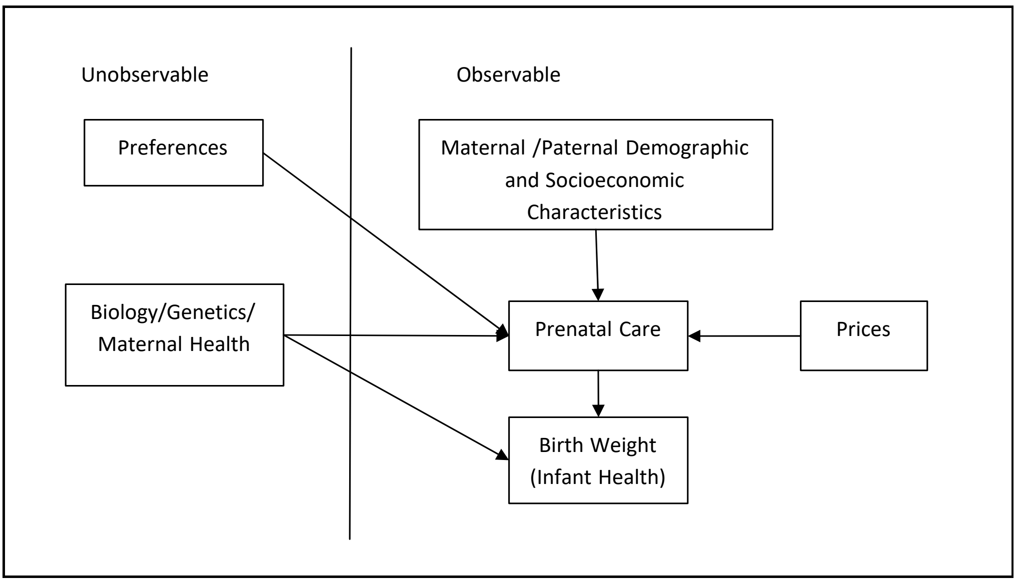
3. Methods

In this section, we present the conceptual model used in the analysis, the theoretical framework, the identification strategy, the empirical model, and a discussion of the data used in the analysis.

Conceptual model

Following Schultz (1984), we can develop the conceptual model shown in Figure 1 for the analysis of the effect of prenatal care use on birth weight.

Figure 1: Conceptual model for analysing the effect of prenatal care on birth weight



Source: Own Construction Based on Schultz (1984).

According to Figure 1, birth weight (a measure of infant health) is influenced by prenatal care use and unobservable biological endowments of both the mother and the child, including true maternal health status.

Prenatal care use, in turn, is influenced by maternal/household demographic and socio–economic characteristics, community characteristics or environmental factors, and unobservable maternal/household preferences.

Theoretical framework

Following Rosenzweig and Schultz (1982; 1983) and Mwabu (2009), we assume that an expectant mother, j, maximizes the utility, U_j, obtained from her consumption of various goods and services that have no impact on the health of her unborn child, X_j, and the health status of her unborn child, H_j. We can represent the expectant mother's utility function as follows:

$$U_j = U(X_j, H_j) \tag{1}$$

We assume that the health status of the unborn child, H_j, is in turn influenced by the adequacy of prenatal care use, Z_j, that affects health directly, other factors, Y_j, and unobservable biological endowments, μ_j. The health production function of the unborn child can, therefore, be represented by the following:

$$H_j = H\,(Z_j, Y_j, \mu_j) \tag{2}$$

The mother is assumed to maximize her utility function subject to the above health production function and a budget constraint given by:

$$I_j = P_x X_j + P_y Y_j + P_z Z_j \tag{3}$$

where, I is the exogenous mother's/household's income, P_x is the unit price of $X_,$ P_y the unit price of Y , and P_z is the unit price of Z.

Mwabu (2009) shows that manipulation of the above equations leads to the following input demand equations, which demonstrate that commodity prices are correlated with infant health:

$$X_j = X(P_x, P_y, P_z, I_j, \mu_j) \tag{4}$$

$$Z_j = Z(P_x, P_y, P_z, I_j, \mu_j) \tag{5}$$

Estimation issues

When estimating our models, we need to worry about potential sample selection bias, potential endogeneity of some of the covariates, and potential unobserved heterogeneity.

Sample selection bias

In general, sample selection bias is likely to occur in situations where the dependent variable is observed only for a restricted, non–random sample (Wooldridge, 2002). It is likely to arise when we examine a subsample in circumstances where the unobservable factors that influence inclusion of individuals in the subsample are correlated with the unobservable factors that influence the variable of primary interest (Vella, 1998). For example, in our case, we only observe the birth weight of a child if it is reported in the dataset. The birth weight information is, however, missing for about 52% of the children.

We are concerned with determining the effect of prenatal care on the birth weight of the children with reported birth weights so as to draw conclusions regarding the effect of prenatal care on the birth weight of all children. Whether we have sample selection bias depends on the difference between children whose birth weights are reported and those for whom birth weights are not reported. If the subsample of children with reported birth weights is randomly drawn from the population of all children, selectivity bias will not arise if we were to just study this particular subsample.

If, however, non–reporting of birth weight is non-random, then the sample of children with reported birth weights is also non-random. This implies that the children with reported birth weights and those whose birth weights are not reported have different characteristics. Sample selection bias will arise when some of the factors influencing the reporting of birth weight also determine birth weight. If these factors are observable, they can be included in the birth weight equation as conditioning variables. In such a case, there will be no sample selection bias.

If, however, the unobservable factors affecting the decision to report the birth weight of the child are correlated with the unobservable factors affecting the birth weight itself, then a relationship exists between reporting of birth weight and the process determining the birth weight (Vella, 1998). In such a case, it is not enough to control for the observable factors when explaining birth weight because the process determining whether birth weight is reported also influences birth weight. If these unobservable factors are correlated with the observable factors then failure to include an estimate of the unobservable factors in the birth weight equation leads to sample selection bias.

Although several approaches to correcting for sample selection bias have been proposed in the literature (see, for example, Heckman, 1979; Olsen, 1980), we use the approach suggested by Olsen (1980). An advantage of the Olsen approach compared to the Heckman (1979) approach is that, unlike the Heckman approach which requires an iterative probit in the first step, the Olsen approach only requires Ordinary Least Squares (OLS) regression techniques in the first step (Olsen, 1980).[5]

The Olsen approach (Olsen, 1980) is implemented as follows:

i. Estimate a linear probability model of the selection equation. There should, however, be at least one regressor in the linear probability model that is not in the main model of interest. These are the exclusion restrictions in our case.
ii. Obtain the predicted probability of selection into the sample. Call this predicted probability, say, $\hat{P}$.
iii. Construct the variable $\left(\hat{P}-1\right)$. This variable, referred to as the selection term, is the additional variable that should be included in the main model of interest as a correction for sample selection bias. If the coefficient of this variable is statistically significantly different from zero, then we reject the null hypothesis of absence of selection bias.

Endogeneity

An econometric model is said to suffer from the problem of endogeneity if there is a correlation between the error term in the model and one or more of the regressors included in the model (Stock and Watson, 2011). Endogeneity can result from the omission of confounder variables from the model, reverse causality between the dependent variable and the endogenous regressor, and measurement errors in the regressors (Cameron and Trivedi, 2010). When a regression model suffers from the problem of endogeneity, the estimated regression coefficients are inconsistent, and we can also not infer causality between the dependent variable and the independent variables in such a model (Cameron and Trivedi, 2010). Zohoori (1997) demonstrates that controlling for endogeneity matters in empirical studies. Terza et al (2008) discuss two Instrumental Variable (IV)—based approaches to correcting for endogeneity bias in nonlinear models: two–stage residual inclusion (2SRI) and two–stage predictor substitution (2SPS), and show that, in non–linear models, the 2SRI approach is consistent while the 2SPS approach is not.

In our model, we suspect that the covariate measuring the adequacy of prenatal care use is endogenous due to mainly the presence of unobservable factors in the infant health equation that are correlated with the adequacy of prenatal care use chosen by the mother. We employ the 2SRI method in an attempt to correct for this endogeneity. For simplicity, we assume that this is the only endogenous covariate in our model. We control for potential endogeneity of prenatal care use by computing the generalized residuals[6] from the adequacy of prenatal care model and including these generalized residuals as an additional regressor in the birth weight model.

Following Bollen et al (1995), we test for the endogeneity of the adequacy of prenatal care use in the birth weight equation by testing for the statistical significance of these residuals in the equation. If the coefficient of the residuals is statistically significantly different from zero, then the adequacy of prenatal care use variable is endogenous; otherwise, it is exogenous.

Unobserved heterogeneity

Unobserved heterogeneity is said to occur if there is a nonlinear interaction between unobservable factors and the endogenous covariate, which causes the effect of the endogenous covariate on the variable of primary interest to differ amongst population subjects (Zohoori and Savitz, 1997). In our case, unobserved heterogeneity will exist if there are some unobservable factors that interact nonlinearly with the adequacy of prenatal care use, causing the effect of prenatal care use on birth weight to differ amongst children in the population.

The standard procedure for controlling for unobserved heterogeneity is the control function approach (Florens et al, 2008; Mwabu, 2009). We employ this approach.

This approach involves including in the birth weight equation interactions between the residuals and the endogenous explanatory variable (in our case, the adequacy of prenatal care use). If the coefficient of the resulting interaction term is statistically significantly different from zero, there is unobserved heterogeneity in our birth weight model. If the coefficient is not statistically significantly different from zero, there is no unobserved heterogeneity in our birth weight model.

Model identification

To properly interpret the estimated parameters of our birth weight model, it is important that birth weight effects of the endogenous covariate (in our case, the adequacy of prenatal care use) and of the sample selection rule be identified (Mwabu, 2009). Because we have one endogenous variable in our model, identification requires at least two exclusion restrictions since we have a situation that requires the simultaneous solution of two equations. A minimum of one excluded instrument is required for the endogenous covariate and another minimum of one exogenous variable is also needed for the determination of the selection of observations into the sub–sample to be used for estimation purposes (Mwabu, 2009).

The variables chosen as excluded instruments should be uncorrelated with the stochastic error term in the birth weight equation (i.e., they should be valid or exogenous), should be correlated with the endogenous variable in the birth weight equation (i.e., they should be relevant, or rather, their effects on the endogenous explanatory variable in the birth weight equation should be statistically significant), and should be excluded from the birth weight equation (Wooldridge, 2002; Murray, 2006; Mwabu, 2009; Brookhart et al, 2010).

In our case, therefore, the variables we use as excluded instruments for prenatal care use should first, affect prenatal care use or be associated with prenatal care use; second, they should be unrelated to mother or household characteristics; and third, they should be related to birth weight only through their association with prenatal care (Brookhart et al, 2010).

Examples of variables that have been used as excluded instruments for prenatal care in the literature include number of prenatal care clinics or providers per capita, distance from residence to prenatal care clinics, population per hospital bed, unemployment rate, rate of uninsured females, price of prenatal care, bus strikes, whether mother cohabits with father of child, and mother's income (Conway and Deb, 2005; Evans and Lien, 2005; Wehby et al, 2009).

We use the "average distance to the nearest health facility" and the "health facilities per 100,000 of population" as excluded instruments in our models. Our models are, therefore, exactly identified (Murray, 2006). These instruments are measured in the years in which the mother was pregnant with the child. We use these instruments both to identify birth weight reporting and also to identify the effect of prenatal care on birth weight.

The choice of distance to the nearest health facility as an excluded instrument is based on the assumption that distances to health facilities are correlated with prenatal care use. Since mothers have other uses for their time (such as engaging in paid work, housework, and child care), they must optimally allocate the time available to them amongst the various uses. The longer the distance to the nearest health facility, the higher the opportunity cost to the mother of visiting the facility for prenatal care. Research actually shows that distance to the health facility significantly influences the utilization of health care services (Qian et al, 2009). We would, therefore, expect a mother's utilization of prenatal care to be limited the longer the distance to the nearest health facility. Consequently, we expect a mother's utilization of prenatal care to be inadequate the longer the distance to the nearest health facility.

One argument in the literature against the use of distance to the nearest health facility as an excluded instrumental variable is that mothers can choose to live near health facilities because of their health status or because of their preferences (Rosenzweig and Schultz, 1982; Gajate-Garido, 2013). This then undermines the argument that the distances are exogenous.

To overcome this possibility, we use provincial[7] level averages for the distance to the nearest health facility in Kenya. This is because, even though an individual mother may choose to live near a health facility because of her health status or simply because she prefers to do so, all the women in a province are unlikely to make this decision simultaneously every time they are pregnant. As such, an individual woman's decision may not immediately affect the average distance to the nearest health facility in a province. Furthermore, if the relocation of a mother is from one area of the province to the other, this does not change the average distance to the nearest health facility in the province.

The health facilities per 100,000 of population is aimed at indicating the overall accessibility and availability of health care in a particular province. We expect that the higher the number of health facilities per 100,000 of population, the more the health care (including prenatal care) is accessible and available for use. Consequently, we expect that the higher the number of health facilities per 100,000 of population, the higher the probability of adequate prenatal care use, and the higher the probability of reporting birth weight.

Empirical model

We formulate both a single–level model and a multilevel model of birth weight.

Single–level model

To formulate the single–level model, we let H_i be the birth weight of the i^{th} infant. The infant's birth weight is linked to prenatal care use via the following equation:

$$H_i = \beta_1 + \beta_2 Z_i + \beta_3 Y + \varepsilon_{1i} \tag{6}$$

where, Z is an indicator of the adequacy of prenatal care use, Y is a vector of controls (or included instruments), and ε_1 is a stochastic error term.

Because Z is potentially endogenous in Equation 6, we have to control for this potential endogeneity. To use the Two–Stage–Residual–Inclusion method to control for this potential endogeneity, we estimate a model for the adequacy of prenatal care use, obtain generalized residuals from the estimated model (Gourieroux et al, 1987), and then include these generalized residuals together with the adequacy of prenatal care variable in our structural equation of interest.

The adequacy of prenatal care use variable is constructed based on the WHO recommendations (Berg, 1995). The adequacy of prenatal care variable is defined as follows:

$$Z_i = \begin{cases} 1 \; if \; mother \; sought \; adequate \; prenatal \; care \; while \; pregnant, \\ 0 \; otherwise. \end{cases} \tag{7}$$

The appropriate model for the adequacy of prenatal care use is, therefore, the binary regression model. An excellent discussion of the binary regression model can be found in Long (1997) and Long and Freese (2006).

Long and Freese (2006) discuss the three methods that can be used to derive the binary regression model: assuming that there is an unobserved (latent) variable that is linked to the observed outcome through a measurement equation, constructing the model as a probability model, and generating the model as a random utility model. We adopt the latent variable method because of its appeal to intuition.

Using the latent variable formulation, we can define a latent variable Z_i^* that is related to Z_i via the following equation:

$$Z_i = \begin{cases} 1 & if\ Z_i^* > 0, \\ 0 & otherwise. \end{cases} \tag{8}$$

This latent variable is linked to the covariates using the equation

$$Z_i^* = \alpha_1 + \alpha_2 Y + \alpha_2 Q + \varepsilon_{2i} \tag{9}$$

where, Y is a vector of controls (or included instruments), Q is a vector of excluded instruments, and ε_2 is a stochastic error term.

Assuming a standard normal distribution for ε_2 leads to a probit model given by:

$$Pr(Z_i = 1) = \Phi(\alpha_1 + \alpha_2 Y + \alpha_2 Q) \tag{10}$$

We estimate this model, obtain its generalized residuals, and include the generalized residuals as an additional variable in the structural equation of interest.

To control for possible non–random selection of individuals into the estimation sample, we also estimate a sample selection equation. Let selection into the sample be given by the following: [SYMBOLS ON THE EQUATION ARE NOT SHOWING]

$$I_i = \begin{cases} 1 & if\ infant\ i'sbirth\ weight\ is\ reported, \\ 0 & otherwise. \end{cases} \tag{11}$$

Following Olsen (1980), we formulate a linear probability sample selection model as:

$$I_i = \gamma_1 + \gamma_2 Y + \gamma_3 Q + \upsilon_{3i} \tag{12}$$

where, Y is a vector of controls (or included instruments), Q is a vector of excluded instruments, and ʊ3 is a stochastic error term.

We estimate this model by Ordinary Least Squares, obtain the predicted probabilities, $\hat{P}$, construct the selection term, $\hat{P}-1$, and include this selection term as an additional regressor in our model of primary interest.[8]

To control for potential unobserved heterogeneity, we include the interaction of the adequacy of prenatal care use with the generalized residuals from the adequacy of prenatal care use equation.

Equation 6 is, therefore, extended as follows:

$$H_i = \beta_1 + \beta_2 Z_i + \beta_3 Y + \beta_4 \hat{\varepsilon}_{2i} + \beta_5 \left(\hat{P}-1\right) + \beta_6 Z \hat{\varepsilon}_{2i} + \varepsilon_{1i} \tag{13}$$

where, Z is an indicator of the adequacy of prenatal care use, Y is a vector of included instruments, $\hat{\varepsilon}_2$ are generalized residuals from the prenatal care model, $\left(\hat{P}-1\right)$ is the selection term, and ε_1 is a stochastic error term. When necessary, Equation 13 is extended by the inclusion of additional higher order interaction terms between the adequacy of prenatal care use and the generalized residuals computed from the adequacy of prenatal care use equation.

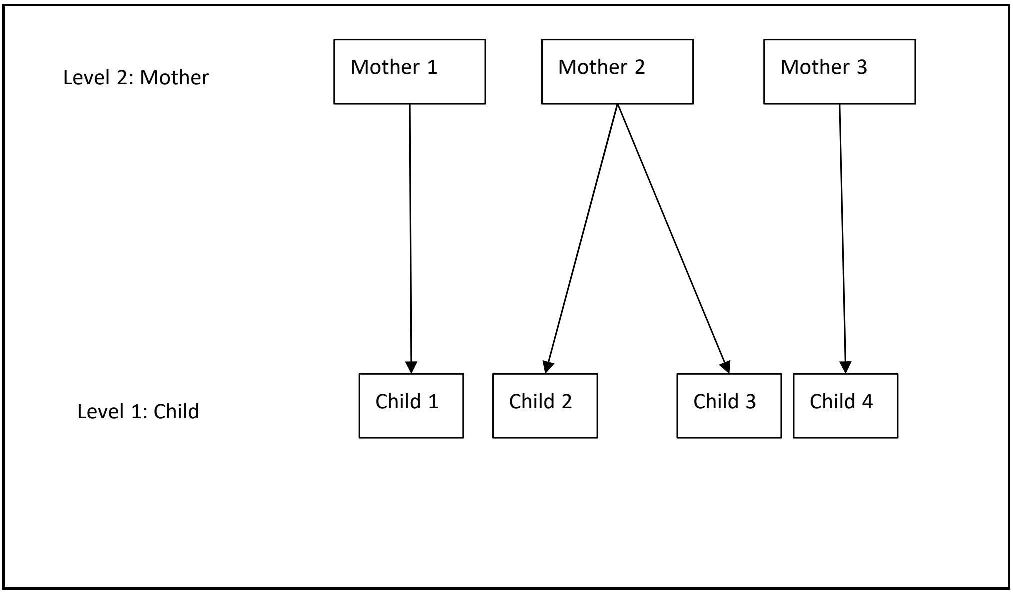
Multilevel model

Economists typically use data collected at different levels of analysis. For example, most household surveys collect data at the individual, household and even community levels. Another example is where we may have data collected on the characteristics of children, their mothers, and the regions they live in. Such data could easily be organized in a hierarchical manner where, for example, an individual is linked to a particular household which is in turn linked to a particular community. Data organized in such a manner, where units at one level are linked to more larger units at a higher level, are referred to as multilevel data (Steenbergen and Jones, 2002)[9]. Steenbergen and Jones (2002) provide a discussion of substantive and statistical motivation for using multilevel analysis.

Further information on multilevel modelling can be obtained from Sniders and Bosker (1999), and Rabe-Hesketh and Skrondal (2008).

Figure 2 shows an example of a multilevel data structure.

Figure 2: An example of a multilevel data structure



In Figure 2, children are the level 1 units while mothers are level 2 units.[10] Children are nested in mothers. Notice from the figure that it is possible for a mother to have more than one child, as is the case with mother 2, but it is not possible for a child to have more than one biological mother.

In multilevel analysis, we aim at explaining the variability in a predicted variable obtained at the lowest level in the data structure based on data gathered at all the levels of nesting (Sniders and Bosker, 1999; Steenbergen and Jones, 2002). For example, for the data structure shown in Figure 2, multilevel analysis would aim at explaining the variability in a predicted variable measured at the child level (such as birth weight) based on data gathered from both children and mothers.

We obtain the multilevel models by breaking the stochastic error terms in our single–level models into two parts: a mother–specific component, ζ, and an infant–specific component, ϵ. The mother–specific component, ζ, controls for unobservable mother–specific characteristics that affect the dependent variable of interest (e.g., birth weight, adequacy of prenatal care use, reporting of birth weight) and is assumed to remain unchanged across infants born to the same mother but to be independent across mothers (Rabe-Hesketh and Skrondal, 2008). The infant–specific component, ϵ, varies between infants as well as mothers but is assumed to be independent across both infants and mothers (Rabe-Hesketh and Skrondal, 2008). It is also further assumed that ζ is independent of ϵ (Rabe-Hesketh and Skrondal, 2008).

The multilevel counterparts of our models are as follows:

$$H_{ij} = \beta_1 + \beta_2 Z_{ij} + \beta_3 Y + \zeta_{1j} + \epsilon_{1ij} \tag{14}$$

$$Z_{ij} = \begin{cases} 1 & if\ mother\ j\ sought\ adequate\ prenatal\ care\ when\ pregnant\ with \\ & infant\ i, \\ 0 & otherwise. \end{cases} \tag{15}$$

$$I_{ij} = \begin{cases} 1 & if\ the\ birth\ weight\ for\ infant\ i\ from\ mother\ j\ is \\ & reported, \\ 0 & otherwise. \end{cases} \tag{16}$$

For the multilevel case, the binary responses are related to the latent continuous responses via the following equations:

$$Z_{ij} = \begin{cases} 1 & if\ Z^*_{ij} > 0, \\ 0 & otherwise. \end{cases} \tag{17}$$

The multilevel latent response for the adequacy of prenatal care use, and the multilevel sample–selection models are given by:

$$Z^*_{ij} = \alpha_1 + \alpha_2 Y + \alpha_2 Q + \zeta_{2j} + \epsilon_{2ij} \tag{18}$$

$$I_{ij} = \gamma_1 + \gamma_2 Y + \gamma_3 Q + \zeta_{3j} + \epsilon_{3ij} \tag{19}$$

where,

Y is a vector of included instruments, Q is a vector of excluded instruments, $\zeta_{1j}, \zeta_{2j}, \zeta_{3j}$ are random intercepts that control for unobservable mother – specific characteristics, $\epsilon_{1ij}, \epsilon_{2ij}, \epsilon_{3ij}$ are infant – specific stochastic error terms.

We assume that $\zeta_{1j} \sim N(0, \psi_1)$, $\zeta_{2j} \sim N(0, \psi_2)$, and $\zeta_{3j} \sim N(0, \psi_3)$. $\epsilon_{1ij} \sim N(0, \theta)$, while ϵ_{2ij} and ϵ_{3ij} are assumed to follow the standard normal distribution.

The corresponding multilevel probit model for the adequacy of prenatal care use is given by:

$$Pr(Z_{ij} = 1) = \Phi(\alpha_1 + \alpha_2 Y + \alpha_3 Q + \zeta_{2j}) \quad (20)$$

To control for potential endogeneity of prenatal care, potential sample selection bias and potential unobserved heterogeneity, we extend Equation 14 as follows:

$$H_{ij} = \beta_1 + \beta_2 Z_{ij} + \beta_3 Y + \beta_4 \hat{\epsilon}_{2ij} + \beta_5 Z_{ij} \hat{\epsilon}_{2ij} + \beta_6 \left(\hat{P} - 1\right) + \zeta_{1j} + \epsilon_{1ij} \quad (21)$$

where, $\hat{\epsilon}_{2ij}$ are generalized residuals from the multilevel prenatal care model, and $\left(\hat{P} - 1\right)$ is the selection term.

For the multilevel models, the dependence among the responses for the same mother can be quantified by the residual intraclass correlation, ρ, of the responses given the covariates (Rabe-Hesketh and Skrondal, 2008). For the multilevel birth weight models, this is given by:

$$\rho = \frac{\psi}{\psi + \theta} \quad (22)$$

while for the multilevel binary models it is given by:

$$\rho = \frac{\psi}{\psi + 1} \quad (23)$$

We estimate our models using Stata 11 software (StataCorp, 2009). The multilevel binary models are estimated using the gllamm command (Rabe-Hesketh and Skrondal, 2008).

Data

The main dataset we use is the Demographic and Health Survey (DHS) data set for Kenya collected in 2008 (Kenya National Bureau of Statistics (KNBS) and ICF Macro, 2010).[11] A good guide to Demographic and Health Survey (DHS) data sets can be found in Rutstein and Rojas (2006). Demographic and Health Surveys are nationally representative household surveys that provide a wide range of household level data on child and maternal health.

Data on average distance to nearest health facilities is obtained from the community dataset of the Kenya Integrated Household Budget Survey that was carried out between 2005 and 2006 (Kenya National Bureau of Statistics (KNBS), 2007). Data on health facilities per 100,000 of population is computed using information obtained from the Kenya National Bureau of Statistics (Kenya National Bureau of Statistics (KNBS), 2011a, b).

Following Berg (1995), prenatal care use is classified as “adequate” if all of the following conditions were met:

a. The mother must have sought the prenatal care from a skilled provider, in particular, from either a doctor or a nurse.
b. The mother must have had at least four prenatal care visits.
c. The first prenatal care visit must have occurred within the first four months of pregnancy.

Table 7 shows the definitions for the various variables found in our models.

Table 7: Variable definitions

Variable	Definition
Birth weight	Birth weight in grams.
Report birth weight	1 if child’s birth weight is reported; 0 otherwise.
Adequate prenatal care	1 if prenatal care is sought from a skilled provider (doctor or nurse), the total number of visits is at least four, and the first prenatal care visit occurs within four months of pregnancy; 0 otherwise.
Mother’s age at birth of child	Mother’s age at time of birth of child in years.
Urban residence	1 if area of residence is urban; 0 otherwise.
No education	1 if mother has no formal schooling; 0 otherwise.
Primary education	1 if mother’s highest education level is primary; 0 otherwise.
Secondary education	1 if mother’s highest education level is secondary; 0 otherwise.
Higher education	1 if mother’s highest education level is higher; 0 otherwise.
First born child	1 if child is first born; 0 otherwise.
Male child	1 if sex of child is male; 0 otherwise.
Wealth index	Household’s wealth index, ranges from 1 to 5.
Average distance to nearest health facility	Provincial level average distance to nearest health facility in kilometres.
Health facilities per 100,000	Number of health facilities per 100,000 of population,
of population	measured at the provincial level.

4. Results

In this section, we present a discussion of the descriptive statistics, the results of the first–stage models, and the results of the birth weight models.

Descriptive statistics

The descriptive statistics are shown in Table 8.

From Table 8, we can observe that the average birth weight in the sample is about 3,320g. We can further observe that about 48% of the children had their birth weights reported, while about 16.9% of the infants were born to mothers who had sought adequate prenatal care when pregnant. Table 8 also shows that the average age at birth for mothers is about 26 years. About 51% of the infants in the sample are males.

First-stage models

We estimate our models in two stages. In the first stage, we estimate sample selection models and prenatal care models. In the second stage, we estimate the birth weight models.

One important question we may want to answer after the estimation of our models is how changes in the explanatory variables affect the probabilities of a positive outcome. This question can be answered by reporting the marginal effects of the respective covariates (Long, 1997). The marginal effect is computed by taking the partial derivative of the estimated probability model with respect to the variable of interest (Long, 1997). As shown by Long (1997), the resulting partial derivative is a function of all the variables and the estimated parameters in the model, and assumes the same sign as the estimated coefficient.

This partial derivative can either be evaluated at the means of the various variables, leading to what is called the marginal effect at the means, or it can be computed for each observation and then averaged over all observations, leading to average marginal effects (Long, 1997). The average marginal effects are preferable to the marginal effects at means (Bartus, 2005). We, therefore, compute and report the average marginal effects for the variables in our models.

For dummy explanatory variables, the marginal effects are given by the differences in the probabilities when the variable assumes the value of 1 and when it assumes the value of 0 (Long, 1997).

Table 8: Descriptive statistics

Variable	Number of Mean Standard Minimum Maximum Observations Deviation
Birthweight	2,7413,320.245682.3658508000
Reportbirthweight	5,7060.4800.50001
Adequateprenatalcare	5,7060.1690.37501
Mother'sageatbirthofchild	5,70626.2456.4961248
Urbanresidence	5,7060.2430.42901
Noeducation	5,7060.2140.4101
Primaryeducation	5,7060.5620.49601
Secondaryeducation	5,7060.1690.37501
Highereducation	5,7060.0550.22801
Firstbornchild	5,7060.2300.42101
Malechild	5,7060.5120.50001
Wealthindex	5,7062.8171.51815
Averagedistancetonearesthealthfacility	5,7068.7095.3813.1122.64
Healthfacilitiesper100,000ofpopulation	5,70613.2252.895821

Table 9 shows the results for the sample selection model and the adequacy of prenatal care model for our sample. In Table 9, the estimates for the sample selection model come from a linear probability model while those of the prenatal care model come from a probit model.

Table 9: Average marginal effects for sample selection and prenatal care models, Robust Z statistics in parentheses

Variable	Report		Adequate	
	(birth weight =1)		(prenatal care =1)	
	(1)	(2)	(3)	(4)
Mother's age at birth of child	0.005	0.009	0.018	0.018
	(0.75)	(1.17)	(2.80)	(2.79)
Square of mother's age at birth of child	-0.00007	-0.0001	-0.0003	-0.0003
	(-0.57)	(-0.95)	(-2.51)	(-2.51)
Urban residence	0.079	0.064	-0.014	-0.014
	(4.18)	(3.09)	(-0.89)	(-0.90)
Primary education	0.142	0.14	0.040	0.040
	(8.05)	(6.64)	(2.47)	(2.46)
Secondary education	0.319	0.306	0.092	0.092
	(14.04)	(11.69)	(4.83)	(4.76)
Higher education	0.386	0.368	0.211	0.211
	(15.34)	(10.25)	(8.75)	(8.67)
First born child	0.099	0.089	0.006	0.006
	(5.92)	(5.86)	(0.45)	(0.45)
Male child	0.011	0.003	0.004	0.004
	(0.96)	(0.34)	(0.38)	(0.38)
Wealth index	0.084	0.091	0.021	0.021
	(14.02)	(14.23)	(4.41)	(4.46)
Average distance to nearest health facility	-0.024	-0.022	-0.011	-0.011
	(-5.10)	(-4.14)	(-2.79)	(-2.76)
Average distance to nearest health facility squared	0.001	0.0009	0.0003	0.0003
	(5.52)	(4.44)	(1.75)	(1.73)
Health facilities per 100,000 of population	0.083	0.070	0.073	0.073
	(4.98)	(4.45)	(5.30)	(5.33)
Health facilities per 100,000 of population squared	-0.002	-0.002	-0.002	-0.002
	(-3.81)	(-3.45)	(-5.08)	(-5.11)
ψ		0.109		3.638 × 10−22
ρ		0.59		3.638 × 10−22
Likelihood Ratio Test for $\psi = 0$: χ^2_1		787.98		4.5 × 10−4
(P-value)		(0.00)		(0.492)
Number of observations	5,706	5,706	5,706	5,706

We show the results for the multilevel model and those for the single-level model, for comparison purposes. The single-level model results are shown in columns 1 and 3 of Table 9, while the multilevel model results are shown in columns 2 and 4 of the table.

We show the results for the sample selection model in columns 1 and 2 of Table 9 and those of the prenatal care model in columns 3 and 4 of the table. From columns 1 and 2 we can conclude that mothers who have formal education, reside in urban areas, or are members of wealthy households are more likely to report the infant's birth weight, holding other factors constant. The birth weight of a first born child is also more likely to be reported than that of a non–first born child, holding other factors constant.

Looking at the results of the prenatal care model, we can observe that, holding other factors constant, the longer the average distance to the nearest health facility, the lower the probability of the mother to seek adequate prenatal care. This is in line with our expectations. We can further observe that more health facilities per 100,000 of population increase the probability of seeking adequate prenatal care, if other factors are held constant.

The results further show that the older the mother at the time of birth of the child, the higher the probability of seeking adequate prenatal care, holding other factors constant. This finding is consistent with the findings from the literature (see, for example, Ribeiro et al, 2009). In conformity with other findings from the literature (see, for example, Celik and Hotchkiss, 2000), we find that highly educated mothers are more likely to seek adequate prenatal care, holding other factors constant.

The likelihood ratio test for $\rho = 0$ shown in Table 9 is a test of the null hypothesis that the variance of the random intercept is zero. From the table, we can observe that while this hypothesis is rejected in the sample selection model, we are unable to reject it in the prenatal care model.

Birth weight models

Table 10 shows the results for the single–level birth weight models. The columns showing the results have been labelled 1, 2, 3 , 4 and 5. Column 1 shows the basic model; column 2 shows the model controlling for sample selection bias. Column 3 shows the model controlling for both sample selection bias and endogeneity of prenatal care use. Column 4 shows the model controlling for sample selection bias, endogeneity of prenatal care use and unobserved heterogeneity while column 5 shows a model that contains the same variables as the model in column 4 together with higher order terms for controlling for unobserved heterogeneity.

Looking at the model in column 2, we notice that the selection term is statistically significant at the 5% level of significance, implying that the model in column 1 does suffer from selection bias. From the model in column 3, we can conclude that prenatal care is not an endogenous determinant of birth weight since the coefficient of the prenatal care residual is not statistically significant. Looking at the model in column 4, we can conclude that there is no unobserved heterogeneity in our model since the coefficient of the interaction of prenatal care with its residual is not statistically significant. The model in column 5 includes higher order terms for controlling for unobserved heterogeneity. Even though these additional terms are not individually statistically significant, we notice that as a result of inclusion of these terms, adequate prenatal care is now statistically significant in this model. Among all the models, we choose the model in column 5 as the most appropriate.

Table 10: Average marginal effects from single-level birth weight models, robust z statistics in parentheses

Variable	(1)	(2)	~~(3)~~	(4)	(5)
Adequate prenatal care	0.288 (0.01)	10.811 (0.37)	417.580 (1.50)	481.284 (1.56)	2222.83 (2.20)
Mother's age at birth of child	-45.85 (-2.49)	-22.239 (-1.21)	-29.071 (-1.51)	-31.199 (-1.57)	-31.250 (-1.57)
Square of mother's age at birth of child	0.724 (2.29)	0.401 (1.28)	0.505 (1.55)	0.538 (1.61)	0.537 (1.61)
Urban residence	-61.525 (-1.81)	105.589 (2.76)	111.197 (2.92)	113.869 (2.99)	114.111 (2.99)
Primary education	141.892 (2.97)	361.887 (6.77)	359.047 (6.70)	358.256 (6.67)	355.757 (6.51)
Secondary education	124.951 (2.34)	651.791 (8.19)	645.269 (8.05)	643.303 (7.97)	649.159 (7.97)
Higher education	77.122 (1.30)	730.977 (7.88)	652.710 (5.86)	636.991 (5.42)	611.188 (5.17)
Firstborn child	-92.331 (-2.58)	111.873 (2.59)	121.202 (2.81)	123.813 (2.88)	126.243 (2.94)
Male child	113.942 (4.41)	134.076 (5.21)	134.177 (5.21)	134.002 (5.20)	135.111 (5.24)
Wealth index	-12.320 (-0.91)	160.887 (6.97)	163.854 (7.09)	164.273 (7.12)	166.415 (7.15)
Selection term		-1880.488 (-9.00)	-2016.01 (-9.04)	-2051.807 (-8.95)	-2072.524 (-8.88)
Prenatal care residual			-232.695 (-1.45)	-319.658 (-1.34)	-357.342 (-1.45)
Interaction of prenatal care with residual				65.518 (0.50)	-4019.095 (-1.68)
Square of interaction of prenatal care with residual					3099.03 (1.65)
Cube of interation of prenatal care with residual					-742.441 (-1.56)
Number of observations	2,741	2,741	2,741	2,741	2,741

Table 11 shows the results for the multilevel birth weight models. The columns of results are also labelled as 1, 2, 3, 4 and 5. Column 1 of the table shows the basic model; column 2 shows the model that controls for sample selection bias; column 3 shows the model that controls for sample selection bias and endogeneity of prenatal care use; while column 4 shows the model that controls for sample selection bias, endogeneity of prenatal care use and unobserved heterogeneity. We include additional higher order terms that control for unobserved heterogeneity in the model in column 4 to obtain the model in column 5.

Table 11: Average marginal effects from multi-level birth weight models, z statistics in parentheses

Variable	(1)	(2)	(3)	(4)	(5)
Adequate prenatal care	-14.419 (-0.48)	0.613 (0.02)	302.974 (1.05)	368.645 (1.12)	2135.395 (1.74)
Mother's age at birth of child	-45.329 (-2.58)	-13.583 (-0.77)	-17.976 (-0.99)	-19,992 (-1.07)	-19.961 (-1.06)
Square of mother's age at birth of child	0.716 (2.38)	0.267 (0.89)	0.334 (1.09)	0.365 (1.16)	0.363 (1.15)
Urban residence	-61.199 (-1.63)	94.433 (2.30)	98.127 (2.39)	100.656 (2.42)	101.048 (2.43)
Primary education	131.329 (2.65)	369.983 (6.61)	369.026 (6.59)	368.889 (6.59)	366.295 (6.46)
Secondary education	114.675 (2.06)	680.206 (7.95)	678.016 (7.92)	677.551 (7.91)	684.169 (7.92)
Higher education	81.703 (1.19)	775.371 (7.37)	719.616 (6.11)	705.913 (5.77)	678.165 (5.38)
Firstborn child	-84.125 (-2.50)	112.732 (2.78)	120.996 (2.93)	122.996 (2.95)	126.016 (3.01)
Male child	117.607 (4.78)	126.414 (5.18)	125.602 (5.15)	125.085 (5.12)	125.888 (5.15)
Wealth index	-13.970 (-1.01)	192.994 (6.97)	197.297 (7.05)	198.539 (7.06)	201.331 (7.07)
Selection term		-2105.303 (-8.56)	-2222.109 (-8.23)	-2263.728 (-7.86)	-2291.842 (-7.80)
Prenatal care residual			-172.803 (-1.05)	-257.543 (-0.98)	-303.14 (-1.10)
Interaction of prenatal care with residual				61.276 (0.41)	-4066.049 (-1.43)
Square of interaction of prenatal care with residual					3138.293 (1.41)
Cube of interation of prenatal care with residual					-752.796 (-1.35)
ψ ρ	203792.024 0.449	181966.913 0.414	181331.785 0.413	181326.42 0.413	181417.132 0.414
LRTest for $\rho = 0$: $\chi^2_1(P\text{ - }value)$	133.70(0.00)	114.94(0.00)	114.04(0.00)	114.03(0.00)	114.290.00)
Number of observations	2,741	2,741	2,741	2,741	2,741

The model in column 5 is the best amongst our models. The results of the likelihood ratio test for ρ = 0 in the model imply that the multilevel model is appropriate for our analysis. We can observe from the model that although we have a selection issue, prenatal care is not endogenous and our models do not suffer from unobserved heterogeneity. We can, however, observe from the model in column 5 that adequate use of prenatal care increases birth weight.

We show the results of both the single–level birth weight model and the multi–level birth weight model in Table 12, for comparison.

Table 12: Average marginal effects for our birth weight models, Z statistics in parentheses

Variable	Birth Weight (grams)	
	Single-level Model	Multilevel Model
Adequate prenatal care	2222.83	2135.395
	(2.20)	(1.74)
Mother's age at birth of child	-31.250	-19.961
	(-1.57)	(-1.06)
Square of mother's age at birth of child	0.537	0.363
	(1.61)	(1.15)
Urban residence	114.111	101.048
	(2.99)	(2.43)
Primary education	355.757	366.295
	(6.51)	(6.46)
Secondary education	649.159	684.169
	(7.97)	(7.92)
Higher education	611.188	678.165
	(5.17)	(5.38)
First born child	126.243	126.016
	(2.94)	(3.01)
Male child	135.111	125.888
	(5.24)	(5.15)
Wealth index	166.415	201.331
	(7.15)	(7.07)
Selection term	-2072.524	-2291.842
	(-8.88)	(-7.80)
Prenatal care residual	-357.342	-303.14
	(-1.45)	(-1.10)
Interaction of prenatal care with residual	-4019.095	-4066.049
	(-1.68)	(-1.43)
Square of interaction of prenatal care with residual	3099.03	3138.293
	(1.65)	(1.41)
Cube of interaction of prenatal care with residual	-742.441	-752.796
	(-1.56)	(-1.35)
ψ		181417.132
ρ		0.414
LR Test for $\rho = 0$: $\chi_1^2(P - value)$		114.29 (0.00)
Number of observations	2,741	2,741

The results in Table 12 show that adequate use of prenatal care increases birth weight, holding other factors constant. This finding is consistent with the findings in the literature (see, for example, Conway and Deb, 2005; Jewell and Triunfo, 2006).

Comparing the results from the multilevel model and those of the single–level model shows that the single–level model overstates the effect of adequate use of prenatal care on birth weight. In the single–level model, holding other factors constant, the birth weight of infants whose mothers sought adequate prenatal care while pregnant is higher than that of the infants whose mothers did not seek adequate prenatal care by about 2223g. This implies that adequate use of prenatal care increases birth weight by about 2223g, holding other factors constant. In the multilevel model, however, the corresponding difference in birth weights between infants whose mothers sought adequate prenatal care and those whose mothers did not seek adequate prenatal care is only about 2135g, holding other factors constant. Consequently, failure to control for unobserved mother–specific characteristics, leads to an overstatement of the effect of adequate prenatal care use on birth weight.

The results further indicate that mothers who reside in urban areas have heavier children compared with those who reside in rural areas, holding other factors constant.

The results also show that mothers with formal schooling have heavier infants compared to those without formal schooling, holding other factors constant. This result is consistent with some of the findings in the literature (see, for example, Muula et al, 2011).

Consistent with the findings in the literature (see, for example, Mwabu, 2009), we find that male infants have higher birth weights compared to female infants, holding other factors constant.

In contrast to the findings in the literature, however, we find that first born infants have higher birth weights than their non–first born counterparts, holding other factors constant.

5. Conclusion and policy implications

In this paper we investigate the effect of adequate use of prenatal care on birth weight in Kenya. We use World Health Organization (WHO) recommendations (Berg, 1995) to construct a variable for adequate use of prenatal care. According to these recommendations, prenatal care is considered adequate if it has been provided by a skilled provider (a doctor or a nurse), it was initiated within the first four months of pregnancy, and the mother made at least four visits. We then estimate our model using data from the Kenya Demographic and Health Survey carried out between 2008 and 2009, and other administrative data. We adopt an estimation strategy that controls for potential endogeneity of prenatal care use, potential sample selection bias, and potential unobserved heterogeneity. We estimate both single–level and multilevel birth weight models. Our results indicate that adequate use of prenatal care increases birth weight, holding other factors constant. Our results also indicate that prenatal care is not endogenous even though sample selection bias is a problem that must be controlled for. The results also indicate that the effect of adequate prenatal care on birth weight is overstated in the single–level model by about 88g.

The main conclusion from our study is that using prenatal care adequately when pregnant leads to higher birth weights amongst infants, and by extension, to better infant health. We can also conclude that there is need for controlling for unobserved mother–specific effects in models that attempt to investigate the effect of prenatal care on birth weight. There is also further need to control for sample selection bias and unobserved heterogeneity in such models.

Because the study shows that adequate use of prenatal care increases birth weight and, by extension, improves infant health, the implication is that policies for promoting adequate use of prenatal care should be pursued. Some of these policies include:

i. Encouraging expectant mothers to only seek prenatal care from skilled providers (i.e., doctors or nurses).
ii. Encouraging the expectant mothers to make at least four visits to their prenatal care providers.
iii. Encouraging the expectant mothers to initiate the prenatal care within the first 16 weeks of pregnancy.
iv. Improving accessibility and availability of prenatal care services by, for ex-ample, ensuring health facilities are not very far from where expectant women live and there are enough nurses and doctors to provide the care when it is sought.

Notes

1. The health of children aged one year and below.

2. This is the weight of the foetus or newborn at birth.

3. These are factors whose possession or presence is associated with an increased probability of giving birth to a low birth weight infant (Institute of Medicine, 1985).

4. Between 2005 and 2011, antenatal care coverage in Kenya was 92% for at least one visit and 47% for at least four visits (World Health Organization (WHO), 2012).

5. Probit models are estimated using the maximum likelihood method. According to Long (1997), maximum likelihood estimation is biased in small samples and relies on numerical methods which could lead in some circumstances to nonconvergence or convergence with a wrong solution. For a further critique of the Heckman procedure, see Puhani (2000).

6. Residuals can generally be viewed as being functionally related to the observed values of the dependent variable and the estimated values of the parameters (Cox and Snell, 1968). For models estimated using maximum likelihood (such as probit), deviance–based definitions of residuals are recommended (Pierce and Schafer, 1986). A detailed discussion on how to compute these residuals for various nonlinear models is provided in Gourieroux et al (1987). Specifically for the probit model, the discussion in Gourieroux et al (1987) implies that for a binary dependent variable y, the ith residual $\hat{u}_i$ can be computed as follows:

$$\hat{u}_i = \begin{cases} \dfrac{\phi(x\hat{\beta})}{\Phi(x\hat{\beta})} & if \quad y_i = 1 \\ \\ \dfrac{-\phi(x\hat{\beta})}{1-\Phi(x\hat{\beta})} & if \quad y_i = 0 \end{cases}$$

   where φ is the probability density function of the standard normal distribution and Φ is the cumulative density function of the standard normal distribution.

7. Provinces have since been abolished in Kenya following the enactment of a new constitution in 2010.

8. Olsen (1980) shows that the equation to be estimated, including a term for correction of sample selection bias is,

$$y_i = X_i\beta + \delta(Z_i\hat{\gamma} - 1) + v_i .$$

This means that $\hat{P}$ - 1= $Z_i\hat{\gamma}$ - 1).

9. In general, multilevel data may consist of several levels of analysis that can be related to one another in some hierarchical order (Steenbergen and Jones, 2002). For simplicity, however, we use only two levels in our study.

10. It is conventional in multilevel analysis to refer to the lowest level of analysis as level 1, the next highest level of analysis as level 2, and so on (Steenbergen and Jones, 2002).

11. More information on Demographic and Health Surveys can be obtained from http://www.measuredhs.com/What-We-Do/Survey-Types/DHS.cfm

References

Alexander, G.R. and C.C. Korenbrot. 1995. "The role of prenatal care in preventing low birth weight". Future of Children, 5: 103–120.

Alves, D. and W. Belluzzo. 2004. "Infant mortality and child health in Brazil". Economics and Human Biology, 2: 391–410.

Bartus, T. 2005. "Estimation of marginal effects using margeff". Stata Journal, 5: 309–29.

Becker, G.S. 2007. "Health as human capital: Synthesis and extensions". Oxford Economic Papers, 59: 379–410.

Berg, C.J. 1995. "Prenatal care in developing countries: The World Health Organization technical working group on antenatal care". Journal of the American Medical Women's Association (1972), 50: 182–86.

Bollen, K.A., D.K. Guilkey and T.A. Mroz. 1995. "Binary outcomes and endogenous explanatory variables: Tests and solutions with an application to the demand for contraceptive use in Tunisia". Demography, 32: 111–31.

Brookhart, M.A., J.A. Rassen and S. Schneeweiss. 2010. "Instrumental variable methods in comparative safety and effectiveness research". Pharmacoepidemiology and Drug Safety, 19: 537–54.

Cameron, A.C. and P.K. Trivedi. 2010. Microeconometrics Using Stata. Revised ed. College Station, Texas: Stata Press.

Celik, Y. and D.R. Hotchkiss. 2000. "The socio–economic determinants of maternal health care utilization in Turkey". Social Science and Medicine, 50: 1797–1806.

Conway, K.S. and P. Deb. 2005. "Is prenatal care really ineffective? Or, is the 'devil' in the distribution?" Journal of Health Economics, 24: 489–513.

Conway, K.S., and A. Kutinova. 2006. "Maternal health: Does prenatal care make a difference?" Health Economics, 15: 461–88.

Coutinho, P.R., J.G. Cecatti, F.G. Surita, J.P. De Souza and S.S. De Morais. 2009. "Factors associated with low birth weight in a historical series of deliveries in Campinas, Brazil". Rev. Assoc. Med. Bras. 55: 692–99.

Cox, D.R., and E.J. Snell, E.J., 1968. "A general definition of residuals". Journal of the Royal Statistical Society. Series B (Methodological), 30:, 248–275.

Currie, J. and J. Grogger. 2002. "Medicaid expansions and welfare contractions: offsetting effects on prenatal care and infant health?" Journal of Health Economics, 21: 313–35.

Darling, R.D. and A.S. Atav. 2012. "Risk factors for low birth weight in New York State counties". Policy, Politics and Nursing Practice, 13: 17–26.

Evans, W.N. and D.S. Lien. 2005. "The benefits of prenatal care: Evidence from the PAT bus strike". Journal of Econometrics, 125: 207–239.

Florens, J.P., J.J. Heckman, C. Meghir and E. Vytlacil. 2008. "Identification of treatment effects using control functions in models with continuous, endogenous treatment and heterogeneous effects". Econometrica, 76: 1191–1206.

Gajate-Garido, G. 2013. "The impact of adequate prenatal care on urban birth outcomes: An analysis in a developing country context". Economic Development and Cultural Change, 62: 95–130.

Gourieroux, C., A. Monfort, E. Renault and A. Trognon. 1987. "Generalized residuals". Journal of Econometrics, 34: 5–32.

Heckman, J. 1979. "Sample selection as a specification error". Econometrica, 47: 153–61.

Hertzman, C. and C. Power. 2004. "Child development as a determinant of health across the life course". Current Paediatrics, 14: 438–43.

Institute of Medicine. 1985. Preventing Low Birthweight. Washington, D.C.: National Academy Press.

Jewell, R.T. 2009. "Demand for prenatal health care in South America". Applied Economics, 41: 469–79.

Jewell, R.T. and P. Triunfo. 2006. The impact of prenatal care on birthweight: The case of Uruguay". Health Economics, 15: 1245–50.

Kenya National Bureau of Statistics (KNBS). 2007. Kenya Integrated Household Budget Survey (KIHBS) 2005/06: Basic Report. Nairobi: Kenya National Bureau of Statistics.

Kenya National Bureau of Statistics (KNBS). 2011a. Economic Survey 2011. Nairobi: Kenya National Bureau of Statistics.

Kenya National Bureau of Statistics (KNBS). 2011b. Statistical Abstract 2011. Nairobi: Kenya National Bureau of Statistics.

Kenya National Bureau of Statistics (KNBS) and ICF Macro. 2010. Kenya Demographic and Health Survey 2008–09. Calverton, Maryland: Kenya National Bureau of Statistics and ICF Macro.

Kramer, M.S. 1987. "Determinants of low birth weight: Methodological assessment and meta–analysis". Bulletin of the World Health Organization, 65: 663–737.

Long, J.S. 1997. Regression Models for Categorical and Limited Dependent Variables. Thousand Oaks, California: SAGE Publications.

Long, J.S. and J. Freese. 2006. Regression Models for Categorical Dependent Variables Using Stata. Second ed. Texas: Stata Press, College Station.

Murray, M.P. 2006. "Avoiding invalid instruments and coping with weak instruments". Journal of Economic Perspectives, 20: 111–32.

Muula, A.S., S. Siziya and E. Rudatsikira. 2011. "Parity and maternal education associated with low birth weight in Malawi". African Health Sciences, 11: 65–71.

Mwabu, G., 2008. "Health economics for low–income countries". In T.P. Schultz and J. Strauss, eds, Handbook of Development Economics. Volume 4. Amsterdam: Elsevier, pp. 3305–3374.

Mwabu, G. 2009. "The production of child health in Kenya: A structural model of birth weight". Journal of African Economies, 18: 212–60.

Nazim, N.H. and L. Fan. 2011. "Does prenatal health care improve child birth weight outcomes in Azerbaijan? Results of the national demographic and health survey". Economics and Human Biology, 9: 56–65.

Ohlsson, A. and P. Shah. 2008. "Determinants and prevention of low birth weight". Institute of Health Economics (IHE) Report. Institute of Health Economics. At http://www.ihe.ca/documents/IHE%20Report%20LowBirthWeight%20final.pdf.

Olsen, R.J. 1980. "A least squares correction for selectivity bias". Econometrica, 48: 1815–20.

Pierce, D.A. and D.W. Schafer. 1986. "Residuals in generalized linear models". Journal of the American Statistical Association, 81: 977–86.

Puhani, P.A. 2000. "The Heckman correction for sample selection and its critique". Journal of Economic Surveys, 14: 53–68.

Qian, D., R.W. Pong, A. Yin, K.V. Nagarajan and Q. Meng. 2009. "Determinants of health care demand in poor rural China: The case of Gansu Province". Health Policy and Planning, 24: 324–34.

Rabe-Hesketh, S. and A. Skrondal. 2008. Multilevel and Longitudinal Modeling Using Stata. Second ed. College Station, Texas: Stata Press.

Ribeiro, E.R., A.M.D.N. Guimar˜aes, H. Bettiol, D.D.F. Lima, M.L.D. Almeida, L. De Souza, A.A.M. Silva and R.Q. Gurgel. 2009. "Risk factors for inadequate prenatal care use in the metropolitan area of Aracaju, Northeast Brazil". BMC Pregnancy and Childbirth, 9: 1–8.

Rosenzweig, M.R. and T.P. Schultz. 1982. "The behaviour of mothers as inputs to child health: The determinants of birth weight, gestation, and rate of fetal growth". In: V.R. Fuchs, ed., Economic Aspects of Health. Chicago: University of Chicago Press, pp. 53–92. At http://www.nber.org/chapters/c6545. pdf.

Rosenzweig, M.R. and T.P. Schultz. 1983. "Estimating a household production function: Heterogeneity, the demand for health inputs, and their effects on birth weight". Journal of Political Economy, 91: 723–46.

Rutstein, S.O. and G. Rojas. 2006. Guide to DHS Statistics. Technical Report. Calverton, Maryland: ORC Macro. At http://www.ophi.org.uk/ wp-content/uploads/OPHI-HDCA-SS2012-Guide_DHS_Statistics.pdf.

Schultz, T.P. 1984. "Studying the impact of household economic and community variables on child mortality". Population and Development Review, 10: 215–35.

Sniders, T.A.B. and R.J. Bosker. 1999. Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling. London: SAGE Publications.

StataCorp. 2009. Stata Statistical Software, Version 11, Special Edition. College Station, Texas: Stata Corporation.

Steenbergen, M.R. and B.S. Jones. 2002. "Modeling multilevel data structures". American Journal of Political Science, 46: 218–37.

Stock, J.H. and M.W. Watson. 2011. Introduction to Econometrics. Third ed. Boston: Addison–Wesley.

Terza, J.V., A. Basu and P.J. Rathouz. 2008. "Two–stage residual inclusion estimation: Addressing endogeneity in health econometric modelling". Journal of Health Economics, 27: 531–43.

Vella, F. 1998. "Estimating models with sample selection bias: aA survey". Journal of Human Resources, 33: 127–69.

Wehby, G.L., J.C. Murray, E.E. Castilla, J.S. Lopez-Camelo and R.L. Ohsfeldt. 2009. "Quantile effects of prenatal care utilization on birth weight in Argentina". Health Economics, 18: 1307–1321.

Wooldridge, J.M. 2002. Econometric Analysis of Cross Section and Panel Data. Cambridge, Massachusetts: MIT Press.

World Health Organization (WHO). 2006. Constitution of the World Health Organization. Geneva: World Health Organization. At http://www.who.int/governance/eb/who_constitution_en.pdf.

World Health Organization (WHO). 2011. World Health Statistics 2011. Geneva: World Health Organization. At http://www.who.int/whosis/ whostat/EN_WHS2011_Full.pdf.

World Health Organization (WHO). 2012. World Health Statistics 2012. Geneva: World Health Organization. At http://www.who.int/gho/ publications/world_health_statistics/EN_WHS2012_Full.pdf.

Zegers-Hochschild, F., G.D. Adamson, J. De Mouzon, O. Ishihara, R. Mansour, R., K. Nygren, E. Sullivan and S. Vanderpoel. 2009. "International committee for monitoring assisted reproductive technology (ICMART) and the World Health Organization revised glossary of ART terminology". Fertility and Sterility, 92: 1520–24.

Zohoori, N. 1997. "Does endogeneity matter? A comparison of empirical analyses with and without control for endogeneity". Annals of Epidemiology, 7: 258–66.

Zohoori, N. and D.A. Savitz. 1997. "Econometric approaches to epidemiologic data: Relating endogeneity and unobserved heterogeneity to confounding". Annals of Epidemiology, 7: 251–57.

Mission

To strengthen local capacity for conducting independent, rigorous inquiry into the problems facing the management of economies in sub-Saharan Africa.

The mission rests on two basic premises: that development is more likely to occur where there is sustained sound management of the economy, and that such management is more likely to happen where there is an active, well-informed group of locally based professional economists to conduct policy-relevant research.

www.aercafrica.org

Learn More

www.facebook.com/aercafrica

twitter.com/aercafrica

www.instagram.com/aercafrica_official/

www.linkedin.com/school/aercafrica/

Contact Us
African Economic Research Consortium
Consortium pour la Recherche Economique en Afrique
Middle East Bank Towers,
3rd Floor, Jakaya Kikwete Road
Nairobi 00200, Kenya
Tel: +254 (0) 20 273 4150
communications@aercafrica.org