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**Inequality and Child Survival in Kenya: A Probit Model Approach**

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## **Abstract**

In view of the low child survival rates in Kenya, conventional intervention has tended to focus more on the delivery of various clinical and public health technologies to the neglect of economic and psycho-social constraints that may restrict households from using the available health facilities thereby predisposing the child to higher risks of mortality. One such constraint is the distribution of income. But the extent to which income, income distribution or any of the other probable constraints is critical for child survival is not known. This makes it difficult to target financial and other resources appropriately.

The aim of the present study is to estimate welfare weights that can reveal the extent to which household income distribution and other determinants are critical to child survival with a view to facilitating improved targeting of healthcare resources. Using household survey data, the study employs instrumental variable probit model to estimate parameters of an abbreviated social welfare function. The probit index for child survival is computed and used to compare child survival levels by province, given a certain income level, its distribution and the extent to which certain basic needs are met in each province. Child survival probabilities are estimated and reported by sex of the child for each of the provinces. Findings unravel the complex channels through which income inequality is associated with child survival.

## 1.0 INTRODUCTION

Research has shown that generally, survival rates of individuals and their welfare levels are positively related. An important summary measure of the wellbeing of a household is therefore the survival or death of any of its members. Infant and child survival rates are generally considered to be the most sensitive indicators of a household or a nation's health status and by extension, socio-economic development. Caldwell and Ruzicka, (1985) for instance, suggest that child mortality differentials are indicative of the success of the various health interventions and development programs undertaken to improve a people's wellbeing. Data on the levels and determinants of infant and child mortality are therefore essential for planning, resource allocation and even implementation of development programs in a country. A critical developmental concern globally has therefore been the reduction of infant and child mortality rates.

Since World War II, substantial declines in infant and child mortality rates have occurred in most developing countries, resulting both from improvements in standards of living and from national and international public health activity. The declines generated widespread optimism in the 1960s and 70s about the prospects for bringing about a child survival revolution in the developing world. Since the 1980s however, such optimism has been replaced by considerable pessimism about performance in reducing child mortality and about prospects for further reduction. The pessimists identify three areas of concern notably; the slow pace of economic development, the effectiveness of particular health interventions commonly employed and the recent developments in disease patterns in the developing countries, particularly the HIV/AIDS pandemic.

In recognition of these obvious challenges, various economic and social measures have been put in place in Kenya to address problems of poor child health. In this regard, attention has been directed not only at poverty alleviation programs, but also at programs that improve child survival, and early child development. Efforts have also been made to improve preventive medicine and maternal healthcare. It is widely thought that with increased expenditure on healthcare, it is possible to have in place, programs that focus on public health information, behavioural change and health education. Such programs, it has been argued, can serve to promote better initiatives, in areas of reproductive and environmental health, thereby promoting child survival. Increased public expenditure, it has been suggested, can also lead to more facilities and improved access to physicians, improving the accessibility of healthcare to most of the poor.

This focus on a narrow range of interventions has not translated into a sustained reduction in child survival in the country. In fact an upsurge in mortality has been recorded in most regions of the country in the last decade. Republic of Kenya (2004) shows that infant and under-five mortality rates for each of the three five-year periods preceding the 1998 KDHS and the 2003 KDHS were on the increase. The increases were more pronounced during the period between

the mid-1980s and the mid-1990s. The subsequent period showed a slowdown in the increases, with mortality rates nearing stagnation.

In view of the limited success of these conventional interventions, we hypothesize that policy makers could be ignoring the potential economic and psycho-social constraints related to the effective use of health services. Literature documents a number of such factors that may restrict households from using the available health facilities and new health technologies. These include household income and its distribution, levels of maternal and paternal education, parental age, place of residence and poverty among others. Such factors that predispose the child to higher risks of mortality in many parts of the country, particularly the rural areas could as well explain the low uptake of various clinical and public health interventions in the country.

A large body of research exists on the association between child mortality and the various determinants outlined above. We treat all the said determinants as control covariates but emphasize child mortality-income-inequality relationship because compared to the others; it has spawned the most controversial and contradictory research findings.

### **1.1 Research Problem**

The link between child survival on one hand and income inequality and the other determinants on the other has obvious relevance for the design and financing of policies in both health and non-health sectors which have a bearing on child health. At present the extent to which income inequality or any of the other determinants is critical for child survival is however, not known. This explains the popularity of certain clinical and public health interventions that remain the centerpiece of health programs in Kenya. This situation however, makes it difficult to target financial resources to the most deserving areas or even regions. This study proposes to estimate weights that can reveal the key determinants of child survival, in a bid to solve this problem.

### **1.2 Research Objectives**

Using Kenyan household survey data, the study aims at:-

- (a) Constructing a theoretically consistent social welfare index that takes into account the *level* and *distribution* of income, as well as the basic *needs* requirements of the population.
- (b) Using (a) above, to estimate welfare weights of the various determinants

### **1.3 Income, Income Distribution and Child Survival**

Household income is an important variable that affects child survival directly and indirectly. The effect of income on child survival is well documented (see Guo, 1993; Madise et al, 1999 and Alderman et al, 2003) and is reflected in the socio-economic status of family members. Many studies in this area report that an increase in income per adult increases probability of child survival. Besides, a number of studies (see Wolfson et al, 1993; Menchik, 1993 and Hart et al, 1995), bear out the expectation that cumulative measures of lifetime social circumstances such

as wealth, family assets, lifetime earnings and occupational careers are some of the most crucial socio-economic indicators of longevity

The association between child mortality and income distribution, first reported by Rodgers (1979) has been a subject of much debate and controversy. This association has since been confirmed by several other studies including research by Flegg (1982), Le Grand (1987), Waldmann (1992), Wennemo (1993), Kaplan et al (1996), Collinson et al (2007) and Dorling et al (2007). These studies indicate that a full empirical understanding of this nexus is necessary.

Two strands to modern day research in this area stand out. One strand of literature explores the mechanism through which differential fertility affects income distribution. Major studies in this line include Lam (1986), Chu and Koo (1990), Preston and Campbell (1993) and Mare (1997). The other strand explores the reverse feedback mechanism, that higher income inequality raises differential fertility. They include Dahan and Tsiddon (1998), Morand (1999), Kremer and Chen (2002) and De la Croix and Doepke (2003).

Different studies report conflicting results. In some studies, an increase in income inequality is associated with an increase in probability of child survival. This finding might be attributable to positive externality and social learning, since the non-poor, by providing better healthcare and nutrition for their own children, will unintentionally end up protecting the children of the poor from disease epidemics. This is what Deaton and Paxson (2001) call the 'protective effect of higher inequality' However, in some studies, as income inequality increases to higher levels, its coefficient becomes insignificant. Minujin and Delamonica (2000), corroborate this finding.

Using pooled time-series and cross-sectional data from the United States to estimate the protective effect of income across birth cohorts, Deaton and Paxson (2001) found no evidence for the proposition that year and age-specific income inequality is a health hazard. Instead, they report protective effects of higher inequality.

Minujin and Delamonica (2000) on the other hand report that children belonging to families in the bottom income quintile have more than twice the possibilities of dying before reaching age five, than children living in the top income quintile. This position finds support with Wilkinson (1996) who argues that income inequality is a principal determinant of poor health and that income inequality poses a health risk so that at any given age, individuals living in a more unequal society have a higher probability of death. These findings are also corroborated by Rose et al (2000).

## 2.0 METHODOLOGY

### 2.1 Welfare Measurement Model

In order to estimate probabilities of child survival across the various provinces in Kenya, we first formulate a social welfare function (swf) using the concept of *abbreviated social welfare function* (Lambert, 1989). Following Fields (2000), the general form of the abbreviated social welfare function can be expressed as

$$W = f(\text{PCI}, \text{GIN}, \text{POV}, \text{YCO})$$

Where

W = Abbreviated Social Welfare Function

PCI = Per Capita Income

GIN = Gini coefficient

POV = Poverty index or status

YCO = Control covariates, e.g., key demographics, such as, family size, parents' education, age and area of residence, whose welfare effects are uncertain a priori.

Where

$$\frac{\partial W}{\partial \text{PCI}} > 0 ; \frac{\partial W}{\partial \text{GIN}} < 0 ; \text{ and } \frac{\partial W}{\partial \text{POV}} < 0$$

In the literature, the FGT index is used as a measure of poverty (see Kimalu et al, 2002), and the formula for computing it can be expressed as

$$P_{\alpha} = \frac{1}{N} \sum_{i=1}^q \left( 1 - \frac{y_i}{z} \right)^{\alpha}$$

Where,  $P_{\alpha}$  is a measure of absolute poverty, including food poverty;  $y_i$  is the total expenditure of household  $i$ , expressed in per adult equivalent terms ( $i = 1 \dots N$ ),  $Z$  is the poverty line expressed in per adult equivalent,  $N$  is the total number of households,  $q$  is the total number of poor households and  $\alpha$  is the FGT parameter, interpreted as a measure of poverty aversion,  $\alpha > 0$ . For purposes of this study, we estimate and use only one of the three FGT measures, namely, the headcount ratio, for which  $\alpha = 0$ .

### 2.2 A Dichotomous Model of Child Survival

The measure of child survival that we use in this study is the probability of dying by age five (or under-five mortality). This indicator is preferred because it represents cumulative mortality throughout early childhood to an age at which mortality rates are relatively low, and also

because it is generally well estimated by indirect techniques based on the proportion of children who have died among children ever born. Besides, a number of studies (see Deaton and Paxson, 2001) have shown that under-five survival/mortality, is likely to respond more rapidly than adult mortality, to changes in the environment, including effects of income, parental education, place of residence among other factors.

In this study we formulate and use a dichotomous model of determinants of child survival. The probability of a child surviving in a particular household is determined by an underlying response variable that captures the true socioeconomic and environmental conditions that the household faces. Since at a particular point in time, survival of a child is a binary variable (*i.e.*, a child is either alive or dead), let the underlying response variable  $y^*$  be defined by the following regression relationship:

$$y_i^* = \sum \mathbf{x}_i' \beta + u_i \quad (1)$$

where

$$\beta' = [\beta_1, \beta_2 \dots \beta_k] \quad \text{and} \quad \mathbf{x}_i' = [1, x_{i2}, x_{i3} \dots x_{ik}]$$

In equation [1],  $y^*$  is not observable, as it is a latent variable. What is observable is an event represented by a dummy variable  $y$  defined by:

$$y = 1 \quad \text{if } y^* > 0, \text{ if a child survived over a particular time period} \quad (2)$$

and

$$y = 0 \quad \text{otherwise.}$$

From expressions (1) and (2) we can derive the following equation:

$$\begin{aligned} \text{Pr ob}(y_i = 1 | \beta, \mathbf{x}) &= \text{Pr ob}(u_i > -\sum \mathbf{x}_i' \beta) \\ &= 1 - F(-\sum \mathbf{x}_i' \beta) \end{aligned} \quad (3)$$

where  $F$  is the cumulative distribution function for  $u_i$ , and

$$\text{Pr ob}(y_i = 0 | \beta, \mathbf{x}_i) = F(-\sum \mathbf{x}_i' \beta) \quad (4)$$

The observed values of  $y$  are the realization of the binomial variable with probabilities given by equation (3), which varies with  $\mathbf{X}_i$ . Thus, following Maddala (1983), the likelihood function can be given by:

$$L = \prod_{y_i=0} [F(-\sum \mathbf{x}_i' \boldsymbol{\beta})] \prod_{y_i=1} [1 - F(-\sum \mathbf{x}_i' \boldsymbol{\beta})] \quad (5a)$$

Which can be re-written as:

$$L = \prod_{y_i=1} [F(-\sum \mathbf{x}_i' \boldsymbol{\beta})]^{1-y_i} [1 - F(-\sum \mathbf{x}_i' \boldsymbol{\beta})]^{y_i} \quad (5b)$$

The functional form imposed on  $F$  in equation (5)<sup>1</sup> depends on the assumptions made about  $u_i$  in equation (1).<sup>2</sup> The cumulative normal and logistic distributions are very close to each other. Thus, in certain circumstances, using one or the other will basically lead to the same result [Maddala, 1983]. Moreover, following Amemiya [1981], it is possible to derive the estimates of a probit model once we have parameters derived from the logit model.

The logit model assumes a logistic cumulative distribution of  $u_i$  in  $F$  (in equations (5a) and (5b)), so that the relevant logistic expressions are:

$$p(y_i = 1) = 1 - F(-\sum \mathbf{x}_i' \boldsymbol{\beta}) = \frac{e^{\sum \mathbf{x}_i' \boldsymbol{\beta}}}{1 + e^{\sum \mathbf{x}_i' \boldsymbol{\beta}}} \quad (6a)$$

$$F(-\sum \mathbf{x}_i' \boldsymbol{\beta}) = \frac{e^{-\sum \mathbf{x}_i' \boldsymbol{\beta}}}{1 + e^{-\sum \mathbf{x}_i' \boldsymbol{\beta}}} = \frac{1}{1 + e^{\sum \mathbf{x}_i' \boldsymbol{\beta}}} \quad (6b)$$

As before,  $\mathbf{x}_i$  are the characteristics of the households/individuals, and  $\boldsymbol{\beta}_i$  the coefficients for the respective variables in the logit regression. Having estimated equation (5) with maximum likelihood (ML) technique, equation (6a) basically gives us the probability of a child dying [Prob ( $y_i=1$ )] and equations (6b) the probability of a child surviving, i.e., Prob ( $y_i=0$ ).

The underlying response variable ( $y^*$ ) for the probit model [see eq. (1) for the logit model] can be expressed as:

$$y^*_i = \boldsymbol{\beta}' \mathbf{x}_i + u_i \quad (7)$$

<sup>1</sup> The log likelihood function for expressions [5a] and [5b] can be written as,

$$L(\boldsymbol{\beta}) = \log L(\boldsymbol{\beta}) = \sum_{i=0}^n y_i \log (1 - F(-\sum \mathbf{x}_i' \boldsymbol{\beta})) + (1 - y_i) \log F(-\sum \mathbf{x}_i' \boldsymbol{\beta})$$

<sup>2</sup> This basically forms the distinction between *logit* and *probit (normit)* models.



Where, the disturbance term in (7) follows a normal distribution and the dichotomous variables are defined as:

$Z_i = 1$  if  $y_i$  is observed and

$Z_i = 0$  otherwise.

The cumulative probability distribution of the child survival status can now be written as:

$$\Pr ob (Z_{ij} = 1) = \Phi (\alpha_j - \beta' \mathbf{x}_i) - \Phi (\alpha_{j-1} - \beta' \mathbf{x}_i) \quad (8)$$

where,  $\Phi$  is the cumulative distribution function<sup>3</sup>. The likelihood and log-likelihood functions for the model can be given by equations (9) and (10) respectively, as:

$$L = \prod_{i=1}^n \prod_{j=1}^m [\Phi (\alpha_j - \beta' x_i) - \Phi (\alpha_{j-1} - \beta' x_i)]^{Z_{ij}} \quad (9)$$

In log-form, expression (9) becomes

$$L^* = \log L = \sum_{i=1}^n \sum_{j=1}^k Z_{ij} \log \Phi [(\alpha_j - \beta' x_i) - \Phi (\alpha_{j-1} - \beta' x_i)] \quad (10)$$

Equation (10) can be maximized in the usual way, and can be solved iteratively by numerical methods, to yield maximum likelihood estimates of the probit model [see Maddala 1983].

## **2.21 Probit Index as a Welfare Index**

The latent variable expression,  $y^*_i = \beta' \mathbf{x}_i + u_i$ , depicted in equation (7) is the logit or probit index, depending on whether it is the logistic or the normit model of child survival that is estimated. It shows the subjective welfare index that a household attaches to child survival. As is evident from equations (1) and (7), the subjective welfare index  $y^*_i$  depends on income distribution and other socioeconomic and environmental characteristics ( $X$ ) of a household. In other words, the wellbeing of a household in any period depends on whether the household escaped child death in the previous period (this is implicit in the model), and on other control variables such as household income, and education and health of household members. Sen (1988) has argued that survival or death of a household member is the single most important summary measure of the wellbeing of a household at any particular time. Death of a family member, in this case a child, necessarily makes a household worse-off, relative to households

<sup>3</sup> The cumulative density is given by the following expression (see Wooldridge, 2002),

$F=\Phi (z) = (1/\sqrt{2\pi}) \exp (-z^2/2)$ . Moreover, the probit model marginal effects are;

$\partial F_i / \partial x_i = \phi (x'_i \beta) \beta_j = \phi (\Phi^{-1} (F_i)) \beta_j$  where  $F_i = \Phi (x'_i \beta)$

which have not suffered child death. That is, there is nothing that can replace the survival of a family member to keep the household at the same welfare level as before death.

This observation amounts to making a strong non-substitution assumption between survival of a family member *and* other goods that yield utility to the household. In other words, the household has Leontief preferences over *survival probabilities* of its members and other *goods*, e.g.; real income and education. However, since death is eventually inevitable, this assumption applies only in cases of *premature* death. Without this assumption it is possible for a household to be made better-off by a monetary compensation after losing an elderly member, already at the natural end of a lifespan. We focus on child deaths because they are the prime examples of premature deaths in a society.

In Equation (7), the parameters of interest, the  $\beta$ s, are welfare weights. Once estimated, the total welfare that the household derives from child *survival* and from other “goods” can be computed. The weights indicate the contributions of income inequality and the other factors to child survival. That is, they are the ones used to weight the arguments of the welfare function. These weights are optimal, in the sense that they are the ones that maximize child survival and by extension the wellbeing of the household given its environment. Moreover, the weights are consistent and non-arbitrary because they reflect a household’s *preference orderings* of the arguments of the welfare function (i.e., the various determinants of the child survival). The weights here differ sharply from arbitrary welfare weights routinely reported in World Development Reports (UNDP, 1997). Estimation of the welfare weights using equation (10) and computation of the welfare index via equation (7) enables calculation of the child survival probabilities using equation (6) or the normit formula in footnote 4.

From equation (7), or (1),  $y^*_i$  is the logit index and  $\beta$  are parameters to be estimated. In this case,  $y^*_i$  is precisely the abbreviated social welfare index. It shows the level of wellbeing at the household level, conditional on child survival. If the error term  $u$  is normally distributed, the probit model follows and  $y^*_i$  becomes the probit index, which again, measures the wellbeing at the household level, conditional on child survival.

In order to make the idea of abbreviated social welfare empirically operational, it is necessary to specify a particular functional form for a probit index. The abbreviated social welfare function, as proxied by either a probit or a logit index, can be written in linear form as

$$Z = \alpha + \beta_1 Y + \beta_2 G + \beta_3 FGT + \gamma W + \varepsilon$$

Where

$Z$  = Abbreviated social welfare index, the empirical value of a probit index

$Y$  = Household income per adult equivalent

$G$  = Distribution of income in a cluster

*FGT* = Poverty status in a cluster, which shows whether a household falls within a particular income distribution, or the proportion of poor households in that cluster.

*W* = Control variables at the household level, including maternal age, parental education, residence and household size.

As it happens, the probit or the logit index,  $y^*_i$  in equation (7), which can be aggregated at any level, is exactly the abbreviated social welfare index, *Z*, that is needed to rank regions according to the standard of living enjoyed by their populations.

### 3.0 ESTIMATIONS AND DISCUSSION OF RESULTS

#### 3.1 Determinants of Probability of Child Survival

In order to determine the effects of income inequality and the other factors on survival of the child, we carried out estimations of a probit model of child survival. The aim was to explain changes in the probability of child survival in terms of variables such as income distribution, per capita income, mother's age, parental education and place of residence. Finally, we endogenized household size using twins, and included it among the regressors. Both direct and indirect effects of the various variables on the probability of child-survival by gender are reported in Table 3.0 for different survival functions.

The estimation results show that for the boy-child, all the estimated coefficients on covariates are statistically different from zero. In the case of the girl-child, all the effects of the covariates are statistically significant, except for the coefficient on higher level of income inequality. Table 3.0 indicates that mother's age significantly affects a child's chances of survival. The coefficients on age and age squared shows that children born to older mothers are at higher risk of death than those of younger mothers.

An extra year of mother's schooling increases the probability of child survival, with the effect being about the same for both boys and girls. Compared to mother's education, father's education has a far smaller effect on child survival. One year of father's schooling is estimated to increase probability of survival of the boy-child by 0.0016 and that of the girl-child, by 0.0043. This is an indication that father's education has a stronger effect on survival of the girl-child than on that of the boy-child. In a society where the girl-child is discriminated against in terms of economic opportunities, going to school makes fathers want to treat all children the same and to rectify any existing inequalities within the family.

Income per adult is an important variable that affects child survival directly and indirectly. The effect of income on child survival is well documented (see Guo, 1993; Madise et al, 1999 and Alderman et al, 2003) and is reflected in the socio-economic status of family members. An increase in income per adult increases probability of child survival of both the boy and girl child.

It is worth noting that the coefficient on income per adult is statistically significantly different from zero at better than the 5% level in the case of the girl-child, while its significance is at 10% level in the case of the boy-child.

Contrary to expectations, an increase in income inequality first increases chances of child survival and then reduces it. The coefficient for income inequality is statistically significantly different from zero. The effects vary with sex of the child at higher levels of income inequality. For the boy-child, a marginal increase in income inequality leads to a reduction in the survival probability of 0.8388. For the girl-child, the opposite holds. The implication is that for the boy-child, as income inequality increases marginally, the chances of survival increase but only up to a point beyond which any further increase in inequality leads to reduction in the probability of survival. For the girl-child, a marginal increase in inequality leads to an increase in survival probability, but at higher levels of inequality, the survival probabilities fall.

**TABLE 3.0: Marginal Effects of Child Survival: Dependent Variable is Survival Probability (asymptotic t-statistics in parentheses)**

Variables	Survival probabilities			
	Boy-child		Girl-child	
	1	2	1	2
Age of mother, years	0.0196 (24.29)	0.0196 (24.30)	0.0195 (26.04)	0.0195 (26.05)
Age of mother squared	-0.0003 (30.18)	-0.0003 (30.18)	-0.0003 (30.40)	-0.0003 (30.41)
Education of mother, years	0.0165 (20.77)	0.0165 (20.77)	0.0136 (17.98)	0.0136 (17.98)
Education of father, years	0.0017 (2.37)	0.0016 (2.36)	0.0043 (6.38)	0.0043 (6.36)
Residence (rural=1)	-0.0391 (4.45)	-0.0392 (4.46)	-0.0718 (8.54)	-0.0719 (8.55)
Log of per capita income per adult	0.0054 (1.60)	0.0054 (1.60)	0.0120 (3.78)	0.0121 (3.79)
Income inequality (gini)	0.6641 (3.87)	0.6650 (3.87)	0.4316 (2.59)	0.4326 (2.59)
Income Inequality squared	-0.8358 (2.00)	-0.8388 (2.0)	0.0794 (0.18)	0.0751 (0.17)
Twins (1=multiple birth)	---	-0.0133 (0.92)	---	-0.1970 (1.44)
Number of Observations	32083	32083	32083	32083
Percent correctly Predicted	74.38	74.38	77.66	77.67
Log-likelihood function	-17248.90	-17248.48	-16248.46	-16247.44
Pseudo R <sup>2</sup>	0.0781	0.0781	0.0797	0.0797

The coefficient on rural residence is statistically significant for both the boy-child and the girl-child. If a household lives in a rural area, the chances of child survival in that household are reduced. Twins can be used as a proxy for household size. When the twin variable is introduced, it is found to be negatively correlated with child survival, but its coefficient is statistically insignificant.

### **3.2 Instrumental Variable Probit Results**

Using 1994 poverty lines, that is KES 978.27 for rural and KES 1489.60 for urban areas respectively, we estimate the headcount ratio ( $P_{\alpha=0}$ ). We recognise that poverty status is endogenous to child survival and so we correct for endogeneity using instrumental variable probit regression. In the first stage regression, we regress poverty status on the age, education, inequality and place of residence, in addition to a set of instrumental variables, namely; log values of land, cattle, non-agricultural rent, and agricultural rent. Results of the first stage regression are shown in Table 3.1.

**TABLE 3.1: First Stage Regression Results (dependent variable is equal to one if the household head is poor and zero otherwise)**

<b>Variable</b>	<b>Coefficient</b>	<b>t-values</b>
Age of mother, years	0.0126	16.08
Age of mother squared ( $\times 10^{-2}$ )	-0.0001	14.30
Education of mother, years	-0.0194	27.05
Education of father, years	-0.0074	11.47
Residence (rural=1)	0.3158	37.22
Income inequality (gini)	2.2343	14.87
Income Inequality squared	-3.7066	10.94
Total land holding area	0.0051	1.78
Total number of cattle owned	-0.0380	18.15
Non-agricultural rent	-0.0278	12.97
Agricultural rent	-0.0190	9.42
Number of Observations	32,216	
Adjusted R <sup>2</sup>	0.1471	

Results show that all the covariates are significant determinants of poverty status. Mother's age, rural residence, income inequality and land affect poverty. Rural residence has the greatest effect in this regard, implying that poverty is more wide-spread in the rural areas. It is followed

by mother's education, and then age. As mother's age increases, poverty declines, probably owing to the fact that human capital is greater at older ages and therefore the earning potential of women is high. It is also possible that older women are stable in marriage or are supported by spouses. As expected, schooling reduces poverty, as does the ownership of cattle, and rent-generating assets.

In the second stage regression, we use the predicted poverty status as a regressor in a probit model of child survival. We carried out the estimations using four different specifications of the child survival functions. In the first specification, we estimate the basic abbreviated social welfare equation, in which we seek to explain changes in the probability of child survival in terms of per capita income, income distribution and poverty status, in addition to maternal age and father's education as control variables. Results are shown in Table A1 in the appendix. Except for the coefficient on gini squared for the girl-child, all the other variables are statistically significant. Gini squared, poverty status and mother's age are negatively associated with child survival, while per capita income, income distribution and father's education are positively associated with child survival.

In the second specification, we omit household size and twin variables. In the third, we introduce household size, which is endogenous to child survival, and finally, we endogenized household size using twins. The estimation results are shown in Table 3.2. It is evident that probability of survival of both the boy-child and girl-child is largely a function of mother's age, since the coefficient on mother's age is significant for both sexes. A marginal increase in mother's age increases probability of child survival, in all the three specifications. This however, holds only up to a point, beyond which any further increase in mother's age reduces the probability of child survival by an identical proportion for both sexes in all specifications. It is also evident that the coefficients on mother's age and mother's age squared are significant across the specifications for both sexes. These results are consistent with the findings of several other studies such as Madi (2004), Majumder et al (1991), Kim (1988) and Bhuiya and Streatfield (1991).

Findings of these studies suggest that maternal age is one of the most important determinants of infant mortality, indicating that young mothers have the highest probability of losing their infants and that the risk of death in early childhood increases among children born to mothers who are too young or too old. These findings are corroborated by Madi (2004) and Ahmed (1992). Greater child mortality is associated with young mothers (18 years and below) due to limited maternal preparation, ignorance, limited access to proper and adequate healthcare and low incomes. Older mothers (40 years and above) also experience greater child mortality possibly due to the increasing number of children and subsequent demand on the mother's physical strength for child rearing.

As expected, parental education increases the probability of child survival. Save for maternal age, mother's education has a much more significant effect on child survival than any of the other explanatory variables. Although both the coefficients on the mother's and father's

education, respectively, are statistically significant for the girl-child, father's education is not significant across all the specifications in case of the boy-child. The effect of mother's education is therefore shown to be strong in influencing survival of both the boy-child and the girl-child. In contrast, father's education is found to be much stronger in influencing survival of the girl-child.

The evidence on the importance of mother's education for child survival is corroborated by a host of other studies, key among them being Caldwell's (1979) seminal paper on Nigeria. Other studies in this vein include the works of Hobcraft et al (1984), Mensch et al (1984), Lindenbaum (1990), Cleland (1990), Levine (1991), Graham (1991) and Ssewanyana and Younger (2007), the latter of these studies confirms that mother's education has a significant impact on infant survival, and that the impact is larger for mothers with more schooling.

Although the role of mother's education is predominant in much of the literature, it is also of interest to note that father's education, just like mother's education, through its impact on household income, has both direct and indirect effects on child survival. Father's education increases the survival chances of children through the greater knowledge and affluence it brings to the household. Educated fathers are more likely to protect their children from conflicts, famine, and disruptions of the social and physical environment, since such fathers are more likely to have better coping strategies and better economic resources. The observed association between father's education and child survival is corroborated by Toros and Kulu (1988) and Caldwell and Caldwell (1992).

Living in a rural area, is associated with a reduction in the probability of child survival for both the boy-child and girl-child across all the specifications. However, in both cases, the coefficient on rural residence is statistically insignificant. Since there are large differences between the urban and rural areas in Kenya, possible explanations for this correlation can be found in the effect of economic development on child survival. Rural areas in Kenya are much poorer and therefore lack modern social amenities, have poorer sanitary conditions, little or no access to healthcare facilities and mothers lack adequate medical and nutritional information. Besides, the parental levels of education are much lower in the rural areas which, in effect reduces their propensity to use modern medical facilities and to effectively adopt modern health practices. Some studies have indeed shown that children who live in urban areas are slightly more likely to be breastfed earlier than those who live in the rural areas, yet it has long been established that early breastfeeding has a major positive impact on child survival. Further, rural areas in Kenya tend to be associated with extended familial relations. For this reason, large households tend to live in rural areas as already noted, yet household size, on its own, reduces the chances of child survival.

**Table 3.2: IV Probit Results (z-values in parentheses)**

Variables	Maximum Likelihood Coefficient Estimates					
	Boy-child			Girl-child		
	(1)	(2)	(3)	(1)	(2)	(3)
Age of mother, years	0.0186 (19.43)	0.0193 (19.89)	0.0186 (19.44)	0.0196 (21.87)	0.0208 (22.72)	0.0196 (21.89)
Age of mother squared ( $\times 10^{-2}$ )	-0.0003 (25.27)	-0.0003 (25.22)	-0.0003 (25.28)	-0.0003 (26.38)	-0.0003 (26.38)	-0.0003 (26.40)
Education of mother, years	0.0363 (12.40)	0.0350 (11.9)	0.0363 (12.39)	0.0318 (10.82)	0.0300 (10.11)	0.0318 (10.82)
Education of father, years	0.0013 (1.71)	0.0017 (2.26)	0.0013 (1.7)	0.0033 (4.56)	0.0039 (5.42)	0.0033 (4.54)
Residence (rural=1)	-0.0198 (1.26)	-0.0139 (0.88)	-0.0198 (1.26)	-0.0278 (1.85)	-0.0187 (1.23)	-0.0277 (1.84)
Income inequality (gini)	0.3784 (2.07)	0.4857 (2.64)	0.3798 (2.08)	0.3339 (1.89)	0.5051 (2.83)	0.3356 (1.90)
Income inequality squared	0.0385 (0.09)	-0.1345 (0.33)	0.0351 (0.09)	0.5699 (1.35)	0.2850 (0.67)	0.5653 (1.34)
Poverty status	0.0992 (2.27)	0.0700 (1.59)	0.0987 (2.26)	-0.0122 (0.29)	-0.0573 (1.36)	-0.0130 (0.31)
Mother's education $\times$ poverty status	-0.0294 (7.21)	-0.0290 (7.10)	-0.0294 (7.21)	-0.0291 (7.11)	-0.0284 (6.94)	-0.0291 (7.11)
Size of the household	-----	-0.0085 (4.89)	-----	-----	-0.0127 (7.76)	-----
Twins (1=Multiple birth)	-----	-----	-0.0124 (0.86)	-----	-----	-0.0193 (1.41)
Number of Observations	32,216	32,216	32216	32,216	32,216	32216
Percent correctly predicted	74.53	74.55	74.53	77.90	77.94	s77.89
Log-likelihood function	-17275.687	-17263.748	-17275.319	-16256.097	-16226.106	-16255.104
Pseudo R <sup>2</sup>	0.0799	0.0805	0.0799	0.0820	0.0837	0.0821



The association between child mortality and income distribution was first reported by Rodgers (1979). Since then it has been confirmed by several other studies including research by Flegg (1982), Le Grand (1987), Waldmann (1992), Wennemo (1993) and Kaplan et al (1996). From our regression results, it is evident that the distribution of income is a significant determinant of boy-child survival across all the specifications. For the girl-child however, it is significant only in specification two. Contrary to expectations, an increase in income inequality is associated with an increase in probability of survival for the boy-child and girl-child, in all specifications. This finding might be attributable to positive externality and social learning, since the non-poor, by providing better healthcare and nutrition for their own children, will unintentionally end up protecting the children of the poor from disease epidemics.

However, as income inequality increases to higher levels, its coefficient becomes insignificant in all the specifications. Minujin and Delamonica (2000), corroborate this finding. For all the specifications, as income inequality increases, the probability of child survival increases, with the exception of specification (2) for the boy-child. In the latter specification, an increase in income inequality reduces the probability of boy-child survival.

Such an association as reported in Table 3.2 is not entirely unexpected. Total child mortality is influenced by what happens to the larger proportion of the population. A number of studies are in agreement with our findings, that sex of the child is associated with the probability of early child mortality, as mortality is higher among males (Ariunaa and Dashtseren, 2002 ; Madi, 2004; Ssewanyana and Younger, 2007). Total infant mortality in Kenya is influenced heavily by boy-child mortality. A large majority of Kenyans are poor and poverty is associated with lower levels of health and increased mortality.

By raising death rates among the deprived majority, relative deprivation will raise national mortality rates unless the excess mortality can be offset to the same extent, by improvements in mortality in another section of the society. The existence of large numbers of deprived areas with high levels of poverty, crime, and violence is likely to harm health more widely. National mortality rates would then be raised by poorer health in deprived areas as well as by some wider knock-on effects. The larger part of this relation would therefore probably reflect an association between inequalities in income and in health within societies. This suggests that large increases in income inequality would have deleterious effect on population health.

These results further show that an increase in poverty is, paradoxically associated with an increase in the probability of survival of the boy child while being negatively correlated with the chances of survival of the girl-child in all the specifications. In all cases however, the coefficient on poverty is statistically insignificant for the girl-child but fairly significant for the boy-child. These results, although varying in statistical significance, give some support to the observed differences in the probability of early childhood mortality by sex in Kenya and in other regions of the developing world (see also Ssewanyana and Younger, 2007).

Evidence on the relationship between poverty and mortality is controversial. On one hand are the studies that confirm the above observed result for the girl child, that poverty reduces probability of child

survival. They include Persson (2000), Garenne et al (2003), and Deen et al (2002). Friedman et al (2005) also confirm the same for children aged 0-35 months in Western Kenya. On the other hand are studies that confirm the above observed results for the boy child, that some level of poverty can actually enhance chances of child survival through unexpected pathways. Most of these studies suggest that malnourished children are protected to some degree against malaria. Using Nigerian data, Hendrickse et al (1971) found that among children admitted to hospital in Nigeria with clinical malaria, higher parasite density was more frequent among the better nourished children. This finding is also reported by Genton et al (1998) using data from Papua New Guinea.

Nyakeriga et al (2004) used Kenyan data to investigate the association between malaria and malnutrition in a cohort of Kenyan children. In the overall analysis, no difference was noted in the incidence of malaria in malnourished and well-fed children. However, when the data was stratified by age, an association emerged. An elevated incidence of malaria was seen in children below two years of age who were subsequently found to be malnourished. A reduced incidence was however seen in older children. Ahmad et al (1985) confirmed a negative relationship between malnutrition and malarial infection, while Murray et al (1978), noted an increase in the incidence of clinical attacks of malaria, including cerebral complications, when starving refugees were fed.

These studies, in addition to our controversial findings, that male children of the poor are more immune to malarial attacks, suggest that poverty could be protecting children in a highly malaria prone country like Kenya. Since girls are not as predisposed to malarial attacks, they might not be as immune as the boys. This probably explains the decline in girl-child survival probabilities as poverty increases. In Kenya however, most child deaths occur due to malaria. We can therefore hypothesize that poverty could be lowering probability of survival, but through an uncertain and complicated process.

The relationship between education and poverty in Table 3.2 is worthy of note. Lack of education, for instance secondary education, may force poor households to engage in low-productivity activities which may result in poverty. On the other hand, poverty may also lead to low investment in education. The interaction of mother's education and poverty has a coefficient that is statistically different from zero for both the boy-child and the girl-child across all specifications. Our results further suggest that mothers' education interacts with poverty status to reduce probabilities of survival for both sexes. When both the education of the mother and poverty increases, probability of child survival declines. These findings suggest that the beneficial effects of mother's education on child survival are counterbalanced by the negative effects of poverty, such that the effects of the latter eventually prevail.

The intuition behind this result is that high education accompanied by high poverty would force one to seek employment, particularly wage-work, which takes women outside their homes, thus neglecting children, since their low wages do not allow them to employ care-givers while they are away working. There are several reasons to expect women's participation in the labour force to have beneficial effects. A number of studies (Basu and Basu, 1991; Kishor, 1992; Desai and Jain, 1994; Leslie, 1989; and Popkin and Doan, 1990) have, on the other hand, shown that such participation could have detrimental effects on child survival. More direct effects are seen on nutrition of children and shortened breastfeeding among mothers who work. Other effects include reduced availability of time and a consequent

likelihood of increased inability of working women to provide personal and timely care for their children. These negative consequences on health and welfare of children are likely to be exacerbated whenever there is lack of appropriate alternative child care.

Holding constant education while varying poverty status, an educated woman who is also poor, is more likely to have her child die compared to an educated woman who is not poor. Similarly, uneducated woman who is poor is more likely to have her child die, than an uneducated woman who is not poor. If on the other hand, we hold poverty status constant, while varying education, a poor woman who is educated has a better chance of having her child survive, than a poor woman who is not educated. Similarly, a rich woman who is educated has a better chance of having her child survive than a rich woman who is not educated. The overall interaction effect therefore depends on which of the two variables has an overwhelming impact on child survival.

The results further show that the coefficient on household size is statistically significant, and that, large households are negatively associated with child survival for both sexes. Children living in larger households have lower chances of survival than their counterparts living in smaller households. These results confirm the findings of other studies in this area (Mahadevan et al 1985; Manun'ebo et al 1994; Burstrom et al 1999 and Bawa, 2001). One reason that can be advanced to explain this relationship is that, large households may be associated with overcrowding, which could trigger higher child mortality, especially in situations of epidemics such as measles and chicken pox. Besides, large households imply that scarce resources are spread over many heads, a situation that may reduce a household's ability to care for children. However, since household size is endogenous, these results should be interpreted with caution. The presence of twins in a household is found to reduce the probability of survival for both sexes. However, the coefficient on twins variable is insignificant in both cases. This is probably the true effect of household size on child survival, given that the twins variable is a good proxy for the household size, and that this variable is exogenous.

### **3.3 Constructing the Abbreviated Social Welfare Function**

An important way of considering and ranking the distributional implications of alternative social states in a complete and consistent manner is through the formulation of a social welfare function (swf). Sen (1970) defines a social welfare function as a real-valued function that maximizes conceivable, hypothetically feasible welfare measures of members of the society on an ordering of the corresponding social states. In using individual welfare measures as arguments, the social welfare function is individualistic in form. The standard form of this individualistic social welfare function is distinguishable from the 'reduced-form' version that is expressed in terms of inequality measures and mean income. The latter is generally referred to as 'abbreviated social welfare function' (see Fields, 2000).

In order to determine the contribution of income inequality and other covariates to child survival in Kenya, we construct an index of social welfare based on the concept of "abbreviated social welfare function" (aswf), first used by Lambert, (1989). Social welfare is abbreviated if it is expressed as a function of statistics calculated from the income distribution vector (Fields, 2000). Abbreviated social welfare function is one way of studying the contributions of average income and the level of distributive

equality to welfare in an integrated manner. It considers average income and inequality exclusively when evaluating the level of welfare associated with a specific income distribution. This kind of abbreviated social welfare function has the advantage of providing a criterion for ordering income distributions according to their levels of welfare.

Dutta and Esteban (1992) and Lambert (1993), have discussed the conditions that the general form of the abbreviated social welfare function must have for the results to have a natural interpretation with regard to welfare. This is in recognition of the fact that the inequality index and the form of the chosen abbreviated function have a decisive influence on a welfare index. Our interest is to construct a theoretically consistent social welfare function that is based on individual preferences. In particular, aswf uses gini as the inequality index, and cardinal indicators of social welfare, such as the poverty index, household size, parental education, maternal age, area of residence and per capita income. We choose gini index because the use of an *ad hoc* inequality measure begs the question of whether the empirical judgments made using such an *ad hoc* measure will be in accordance with conventional welfare properties. The gini has one property that is particularly appealing, that it is consistent with the monotonicity criterion of ranking welfare levels across individuals.

Under-five mortality rate is useful as a starting point in measuring household welfare, not only because of its place in much of the literature relating income inequality to health, but also because a number of studies have shown that it is likely to respond more rapidly than adult mortality, to changes in the environment, including any effects of income and income inequality (see Deaton and Paxson, 2001). Besides, some studies have confirmed that a striking feature of African mortality is the heavy incidence of deaths in the second and third years of life relative to the first year (Brass, 1975).

To recapitulate, this study uses under-five child survivorship to proxy household welfare, and employs IV probit to estimate the underlying response variable depicted in equation (7), which is also the probit index ( $y_i$ ) as well as the parameters of interest,  $\theta$ s which are the welfare weights captured in Table 3.2. The probit index,  $y_i$  is the total subjective benefit that the household derives from child survival and other factors that enter the welfare function. It can also be interpreted as the abbreviated social welfare index,  $Z$  that can be used to rank regions according to their welfare levels.

In order to rank regions according to the standards of living of their populations, we generate welfare indices ( $Z$ ), by sex and province, using the IV probit estimates in Table 3.2. We also use the same estimates to predict the probability of child survival by province. The two sets of results are the welfare indices and probabilities of child survival that are used to rank the provinces according to their levels of well-being. The results are shown in Table 3.3. The indices generated in Table 3.3, are values of an aswf that are determined by child survival, conditional on a number of covariates, including mother's age, poverty status of the household, parental levels of education, household size, place of residence and the interaction between poverty and mother's education. The resultant welfare indicator is a composite measure that captures the effects of income and its distribution, poverty status, parental education, mother's age and other socio-economic characteristics. This welfare index captures the effects of each of the determinants of child survival, in a well specified and theoretically consistent manner. So, the index proposed here is not arbitrary.

The probability estimates in Table 3.3 can be viewed as non-income measures of wellbeing. The abbreviated social welfare index- Z, combines several dimensions of welfare, including income, survivorship, income distribution and education, among others. It is evident from the table, that welfare ranking obtained using boy-child survival probability is exactly the same as that obtained using girl-child survivorship. It should however, be noted that the probability of survival of the girl-child across all provinces, is uniformly higher than that of the boy-child. This confirms the findings of a number of studies such as Kishor and Parasuraman (1998), Genton et al (1998), and Madi (2004) that, for all early childhood mortality indicators, mortality is consistently higher for males than for females.

It should further be noted that the probability measure of well-being is bounded between zero and unity, whereas the abbreviated welfare measure theoretically stretches from minus infinity to plus infinity. When an abbreviated social welfare measure is negative, it means that the arguments in the welfare function reduce subjective well-being and the vice-versa for a positive welfare index. The estimates in Table 3.3 show that welfare levels are higher in urban areas for both the boy-child and for the girl-child, and once again, survival probability is higher for the girl-child (see Ssewanyana and Younger, 2007) for Uganda.

**Table 3.3: Abbreviated Social Welfare Indices by Province and Sex of the Surviving Child**

Province	Boy-Child			Girl-Child		
	Abbreviated Welfare Index	Probability of survival	Rank	Abbreviated Welfare Index	Probability of survival	Rank
Nairobi	1.0000	0.8041	1	1.2461	0.8474	1
Central	0.8416	0.7867	2	0.9515	0.8139	2
Coast	0.5626	0.7004	7	0.6667	0.7303	7
Eastern	0.6605	0.7315	5	0.7741	0.7624	5
N.Eastern	0.4077	0.6553	8	0.4957	0.6860	8
Nyanza	0.6744	0.7358	3	0.7897	0.7675	3
R. Valley	0.5900	0.7117	6	0.6888	0.7410	6
Western	0.6706	0.7344	4	0.7838	0.7660	4
Rural	0.6225	0.7222		0.7162	0.7502	
Urban	0.9828	0.8092		0.2306	0.8593	
National	0.6604	0.7314		0.7703	0.7617	

In this study, we assume that for each of the characteristics under analysis, the welfare weights (coefficients on arguments of a probit index) remain constant over time and are the same for all the people in the country. The coefficient in this case, serves a benchmark role, much the same way as the

mean income or the poverty line would. The rationale for this is that society is assumed to determine the benefits associated with child survival, or with a unit of education or income. Thus, everyone benefits the same way from each of these units, much the same way that a person benefits after being at a certain threshold level of income, such as the poverty line.

Differences in well-being then arise due to regional differences in probability of child survival or to differences in other endowments and not because one region values an endowment differently. Thus, households with the same levels of characteristics or endowments have the same abbreviated welfare levels. This means that in order to improve the well-being of people or regions, it is necessary to improve their endowments (such as assets, income, education or health).

### **Conclusion**

In conclusion, this study unravels the complex channels through which income inequality is associated with child survival. The findings of this study coincide with a heightened awareness and concern in the country, over the extent of income inequality between the rich and the poor. In our analysis, we attribute the positive association between income inequality and child survival to positive externality and social learning. The latter two pre-suppose that the greater rewards offered to the high income earners and the entrepreneurially successful, makes them even more successful, which in turn leads to higher quality overall economic provisioning for their children, which indirectly benefits the children of the poor.

This, however, does not negate the need for redistributive social policies. Current welfare policy in Kenya (Republic of Kenya, 2007) posits that overall national health can be improved by transferring resources from society's more affluent members to its most vulnerable groups. This position recognizes that there are several ill effects of income inequality. The problem with regard to health is that inequality has a multitude of causes and consequences, and almost all of these could affect health. However, the factors that might cause inequality might also be consequences of inequality. Proponents of income inequality hypothesis for instance, argue that the health effects of income inequality work through social and cognitive processes, rather than by directly affecting material standards. Implication of this is that the psychosocial effects of being at the low end of social ladder are detrimental to health.

The paradoxical positive association between poverty and survival of the boy-child, which suggests that in a high malaria mortality zone, malnourished children are protected to some extent, against malaria, needs further investigation. Even though most child deaths in Kenya are attributable to malaria, it is our contention that the socio-economic status of poor households, adversely affects child health because it limits access to adequate healthcare, safe water, and sanitation.

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**APPENDIX**

**TABLE A1: IV Probit Basic Regression Results (Z-values in parentheses)**

<b>Variables</b>	<b>Survival probabilities</b>	
	<b>Boy-child</b>	<b>Girl-child</b>
Log of per capita income per adult	0.0282 (8.51)	0.0312 (9.90)
Income inequality (gini)	0.8958 (5.09)	0.7743 (4.51)
Income Inequality squared	-1.1424 (2.68)	-0.4562 (1.04)
Poverty status	-0.0993 (4.98)	-0.1436 (7.39)
Age of mother, years	-0.0033 (14.20)	-0.0017 (7.69)
Education of father, years	0.0091 (13.42)	0.0098 (14.91)
Number of Observations	32,083	32, 083
Percent correctly Predicted	73.63	76.07
Log-likelihood function	-18149.12	-17082.50
Pseudo R <sup>2</sup>	0.0300	0.0324