Method Article

EVALUATING THE ROLE OF MATERNAL INCOME IN MEDIATING THE EFFECT OF MOTHER'S EDUCATION ON UNDER FIVE CHILD MORTALITY IN KENYA

Abstract

Globally millions of children aged below 5 years die every year and some of these deaths could have been prevented. Though a global problem Under-Five Child Mortality (UFCM) is also a major public health problem in Kenya with 52 deaths per 1000 live births in the 2014 Kenya Health Demographic Survey (KHDS). Maternal education is widely regarded as a core social determinant of child health though there are controversies around its beneficial effect.The objective of this study is to identify the role of maternal income in mediating the effect of mother's education level on UFCM. A secondary data set from the Nation wide 2014 Kenya Health Demographic Health Survey (KHDS) data was analysed to determine mortality among the under five children.

Regression with mediation was conducted to access the effect of mother's education on UFCM in the presence of a mediator,in this case "mothers income". Direct,indirect and total effects of the independent variable in the presence of mediation were determined. Maternal education was shown to have a significant direct effect on UFCM .Maternal education level also channelled its effects through maternal income. Change from no education level to primary education level would reduce the the number of deaths by 1.9 deaths per 1000 children.Of this decrease 0.5 fewer deaths were attributed to maternal income pathway representing 26 percent of the total effect. If an intervention could improve maternal income of mother's in no education level to that of mother's in higher education level without affecting other aspects of social deprivation 26% of the education level effect could be eliminated.

Key words: Mediation, Aalen additive model, Child mortality, Total effect

1 Introduction

Under-five child mortality rate is one of the health indicators of great importance for any country. Kenya is among those nations in the Sub-Saharan part of Africa which has high under -five deaths.The Sustainable Development Goal(SDG) number 3,target 3.2 has not been achieved in Kenya,with 43.2 deaths per 1000 live births being reported in the year 2019(UNICEF,2019)which is way above the 25 deaths per 1000 that is expected. This work therefore aims at evaluating determinants of Under Five Child Mortality(UFCM) using appropriate statistical models and assumptions. We have in this case applied regression with mediation and appropriate survival analysis models to conduct this analysis,taking into account the rarely considered aspect of a possibility of mediators on some useful UFCM determinants.

Tremendous achievements have been made worldwide in reducing deaths in the past two decades[21]. Globally, low and middle income countries(LMICs) account for about 99 % of the under five deaths registered and Sub-Saharan African(SSA) alone, accounts for about 50 % of the under five deaths registered in the LMICs annually[21]. More efforts are still needed to realize the sustainable development goal of preventing neonatal child mortality and achieving below 25/1000 child deaths in every nation [21]. Child mortality is a fundamental measurement of a country's level of socio–economic development as well as the quality of life especially of mothers[19].

DHS are a series of national representative surveys that collect data on demographic and child health indicators. These data sets provide a good source to understand some of the social, economic, demographic, environmental, community and health risk –factors.They collect data on a broad scope of risk factors of UFCM.

Several studies[12, 1, 15] have previously used DHS data sets to study the risk factors of under-five mortality in SSA. It is clear that Several risk factors such as residing in rural areas, short preceding birth intervals, high parity, male children, high number of births and low mother's education were indicated as significant predictors of child survival.

A study on determinants of under five child mortality on rural and urban Kenya used the 2008-2009 KHDS data and found out that determinants of UFCM differ in rural and urban areas in Kenya. Poverty was also identified as a key predictor for mortality in rural areas.[6].

Education is a social determinant of health. More education is associated with longer life expectancy, greater likelihood of engaging in health promoting behavior's and better health outcomes. Improved mother's education raises child survival through complex mechanisms[13].

Amongst other things, it raises the skills and self-confidence, increases exposure to information; and alters the way in which others responds to them. Mother's education also improves child care and child survival even after controlling for social class and economic status. Education helps women to overcome barriers set by low autonomy, low social status and low income status. Education levels can be altered fairly easily through policy intervention. Women's education is one of the most effective ways of reducing child mortality. [5].

Mothers education improves child care practices and that this is one of the major pathways through which it helps reduce child mortality. Education improves the mother's basic child- care skills: her domestic management of ill health; efforts at preventive care and use of modern medical services[10]. There is need to increase contraceptive coverage due to the positive benefits associated with it such as reduction of unplanned pregnancies and high risk-births as well as under-five mortality. Increasing access to education and subsequent economic opportunities for women in sub-Saharan Africa could help achieve multiple improved health benefits [3].

Understanding under-five mortality in Uganda, the determinants/risk factors were found to be; mother's educational level, mother's age group, type of residence, education level of partner, birth status ,gender of child, wealth index, children ever born, birth order ,religion, type of toilet facility, mothers occupation, births in the past one year, children below five years in household, gender of head of the household, source of drinking water and age of mother at first birth [15].It is clear that such factors affect UFCM.

Mother's characteristics play a role in some of the variable effects.Parental socio economic position plays a significant role in health-seeking decision making for common childhood illnesses[2].

A study in Kenya [8]sought to understand the determinants of UFCM from 1990 to 2015 towards accelerating Kenya's progress to 2030.Hierarchical multivariate linear regression was used in the analysis. KHDS data from 1989 to 2014 were analyzed.Household wealth,maternal literacy,reproductive health of mother and nutrition were found to be some of the determinants.

Daniel et al[14] studied determinants of infant and child mortality in Kenya using Cox-Proportional hazards model with reference to 2008/09 KHDS data.The study found child mortality as related to education,occupation of mother,age among others

There are limited studies examining mediation among risk factors associated with under-five mortality in Kenya.Most of these methods do not consider other factors effects. These various studies on UFCM mortality leave a question on how factors are mathematically associated to the mortality rate in the presence of mediation.The incidence of relatively higher rate in SSA justify the need to identify and analyze mathematically the major factors affecting infant mortality in the presence of mediation.

Investigations of this kind are especially valuable in epidemiological research as they help understand the causal pathways from exposure to the outcome. It is a widely held belief in public health and clinical decision making that interventions or preventive strategies should be aimed at patients or population subgroups where most cases could potentially be prevented [18]. Several studies on under five child mortality proposed using different modelling tools. Majority of those methods are not applied on survival data.

To assess the magnitude of the pathway from mother's education through maternal income to child mortality the traditional approach estimates hazard ratios of mother's education from Cox models both with or without adjusting for maternal income (the potential mediator) can be obtained. A change in hazard ratios is taken as evidence of mediation through education, however such analysis of mediation has severe shortcomings[4]. Most importantly the observed changes in hazard ratios cannot be given a causal interpretation and the important assumption of proportional hazards can never be satisfied for both models with or without the mediator.

Additive models complements the familiar proportional hazards model in that it describes the association between covariates and failure times in terms of risk difference rather than risk ratio.Mediation analysis can be performed with a univariate or multivariate approach. Univariate analysis means that each mediator is analyzed separately[9]. Multivariate analysis means that the mediation effects are not analyzed separately, but including the consideration of other variables [17]. The Aalen additive model is commonly used in mediation analysis and extensively used in survival data.The Aalen additive model do not assume proportional hazards that are used in most classical survival analysis tools, or more so the influence of time varying co variates.The Aalen additive model has its strength on its ability to yield an estimate of the absolute change in the rate when comparing a given exposure group to the reference group. Thus in this study we propose to use linear regression and Aalen additive model to evaluate mediation in exposure –disease associations. Mediators of critical risk factors associated with under –five mortality will be identified using a nationally representative data on children aged below five years. The main objective is to evaluate the role of maternal income in mediating the effect of mother's education on under-five child mortality in Kenya. A univariate mediation analysis using the example of the role of maternal income in mediating the effects of education on mortality in the KHDS survival data is used.An Aalen additive model is used to determine the effect of maternal education on UFCM and decomposition on additive hazards scale to estimate total,direct and indirect effects is done. This study has three main contributions

- Run a regression of maternal income on education
- To formulate an Aalen additive model determining how maternal income mediates the effect of maternal education on under five child mortality.
- Decomposition on additive hazards scale to estimate total, direct and indirect effects is done.

[9] published a paper on direct and indirect effects in a survival context which is related to this study.

The goal is to use the findings from this study to inform and strengthen appropriate national policies and intervention strategies aimed at reducing under-five mortality in the country. The rest of the paper is outlined as follows: Section 2 presents the methods.Section 3 presents data analysis,findings and results. Section 4 discusses the results and the findings. Section 5 presents a conclusion of the research.

2 Methods

The mediation model offers an explanation for how, or why, two variables are related. An intervening or mediating variable, M, is hypothesized to be intermediate in the relation between an independent variable, X, and an outcome, Y. More recent research has supported tests for statistical mediation based on coefficients from two or more of the following regression equations:

$$Y = i_1 + cx + e_1 \tag{1}$$
$$Y = i_2 + c'x + bm + e_2 \tag{2}$$
$$M = i_3 + ax + e_3 \tag{3}$$

Mediation analysis is an approach to investigate the effect of an exposure on an outcome through a mediator. A vast discussion on mediation analysis can be found in Martinussen and Sheike by[11].The Aalen additive model being additive ,is directly suitable to incorporating the role of mediation as opposed to other forms of survival regression models. Besides the additive models allows for the effect of covariates to vary with time which is not the case for basic forms of multiplicative survival regression models,such as the CoxPH model.The method helps in obtaining a simple and intuitively understandable measure of mediation, namely the number of additional cases per unit time[9].In comparison to relative measures absolute effect measures are particularly relevant for policy making and public health interventions[18] as they more clearly indicate the potential public health impact of intervening on the exposure and mediator of interest.

A lot of different methods for mediation analysis have been developed and published and some of them are listed in [22].[9] proposed a univariate method for mediation analysis in a survival context. The model framework contains T, the survival time, either r the time of interest or the time of censoring and a binary exposure X, equal to 1 if the exposure is present and 0 otherwise. The potential mediators are represented by M and Z represents other baseline covariates.

2.1 Aalen additive model

This is a semi-parametric model that estimates the hazard time t as a linear function of covariates and unspecified baseline hazard[18]. In this semi-parametric model the effects of covariates(constant or variable effect) upon baseline hazard

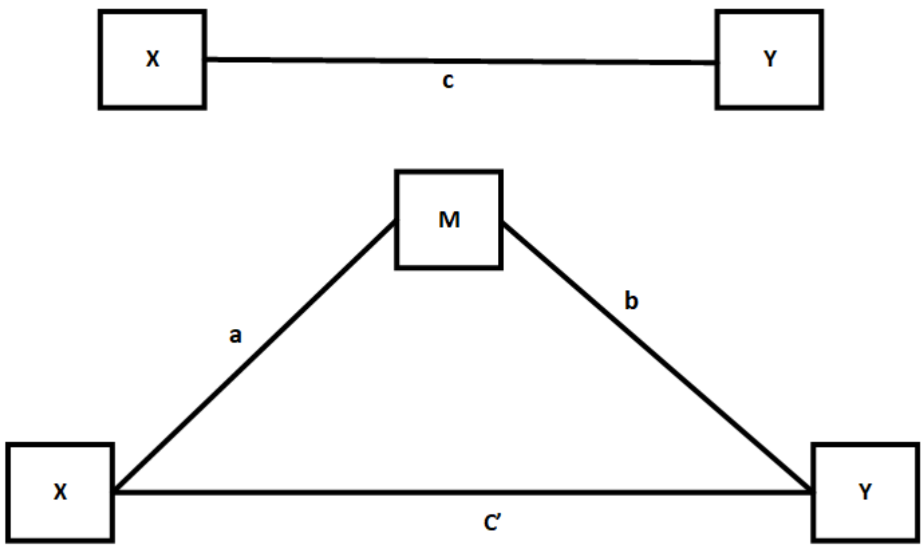

Figure 1: Where X= the independent variable, Y= the dependent variable, and M= the mediating variable. c is the overall effect of the independent variable on Y; c' is the effect of the independent variable on Y controlling for M; b is the effect of the mediating variable on Y; a is the effect of the independent variable on the mediator; i_1, i_2, and i_3 are the intercepts for each equation; and e_1, e_2, and e_3 are the corresponding residuals in each equation.

is additive. According to this model ,the relation between hazard function and failure time T_i with p-dimensional vector X(covariates) is determined.

The aalen additive hazards model expresses the hazards rate at time t of the ith of n individuals with vector of covariates $X_i(t) = (X_{i_1}, X_{i_2}, ...X_{i_p})'$,that is given by

$$h(t|X_i(t)) = \beta_0(t) + \beta_1(t)X_{i1}(t) + ...\beta_p(t)X_{ip}(t) \tag{4}$$

where $\beta_i(t) = (\beta_0(t), \beta_1(t), ...\beta_p(t))'$ is the vector of parameter functions that may be estimated and $\beta_0(t)$ is the base line hazard(Aalen 1989).

2.2 Aalen additive model with mediation

Decomposition estimates will be derived based on Aalen additive hazard model. By adapting the model, we obtain a simple and intuitively understandable measure of mediation, namely the number of additional cases per unit time [9]. The measure is based on counterfactuals and measures the natural direct and indirect effects. The method allows a casual interpretation of mediated effect (in terms of additional cases per unit of time).

The rate at time t measures the probability of experiencing an event within the next unit of time, given that a person has not experienced an event before time t [9, p. 576]. Using Cox regression, it is possible to estimate how many times greater the rate is, in case the exposure X is present relative to the reference X = 0 (hazard ratio). However, [9] suggest using an Aalen additive hazard model for estimating the rate as the ratio modeled by Cox cannot be related to an absolute number of events. The Aalen additive hazard model though “yields an estimate of the absolute change in the rate when comparing a given exposure group to the reference group” [9, p. 576] . It does not assume the hazards to be proportional and it can include time-varying covariate effects. Those are huge advantages compared to the Cox model.

In the Aalen model the rate as a function of exposure (x),mediator (m),and other baseline covariates (z) can be written as

$$\gamma(t; x, m, z) = \lambda_0(t) + \lambda_1(t)x + \lambda_2(t)z + \lambda(t)m \tag{5}$$

Where$\gamma(t; x, m, z)$ is the rate as a function of exposure(x),mediator(m) and other baseline covariates(z). $\lambda_j(t)$ are potentially time –dependent functions. Assuming that the mediator is a normal variable that can be modeled by simple linear regression. Thus, give exposure (x) and other covariates (z),the mediator can be written as

$$M = \alpha_0 + \alpha_1 x + \alpha_2 z + e \tag{6}$$

Where e is a mean zero normally distributed error with variance σ^2 .The ”timereg “package is used to estimate the parameters $\alpha_0, \alpha_1, \alpha_2, \sigma^2$ and the collection of functions $\lambda_0(t), ..., \lambda_3(t)$ Let $\gamma(t; x, m, c)$ denote the counterfactual rate for the event when the exposure is set to X and the mediator to M in the presence of other baseline covariates. The total casual effect of changing the exposure from x^* to x ,measured on the rate difference scale at time can be expressed as

$$\gamma(t;x,M^x)-\gamma(t;x*,M^{x^*}) = \tag{7}$$

$$\gamma(t;x,M^x)-\gamma(t;x*,M^{x^*})+\gamma(t;x*,M^x)-\gamma(t;x*,M^{x^*})$$

$$=\lambda_1(t)(x-x^*)+\lambda_3\alpha_1(t)(x-x^*) \tag{8}$$

i.e $TE(t) = DE(t)+IE(t)$ with TE, DE and IE denote total effect, natural direct effect and natural indirect effect respectively.

The indirect effect is the number of deaths that can be attributed to mediation through the mediator, whereas the direct effect is the number of deaths that can be attributed to the direct path (or to the mediators not included in the analysis). The total effect is the number of deaths caused by changing the exposure. It is equal to the sum of the direct and indirect effects [9].

Confidence intervals for the direct effects are available directly from the Aalen additive model whereas Confidence intervals for the indirect and total effects are constructed by combining the covariance matrices for parameter estimates of the regression and the Aalen model using simulation. The assumptions of the model is that there are no confounding of the relationship between

- Exposure and mediator
- Mediator and outcome
- Exposure and outcome upon conditioning pre-exposure con founders[16]

2.3 Data

A secondary data set from the nationwide2014 Kenya Demographic health survey (KHDS) was used for this analysis. KHDS data obtained from a random sample of 20964 respondents collected as part of the KHDS was analyzed. The data set provides information on every under-five child in the household including sex of the child, survival status of the child, birth interval, birth status and child's weight at birth. The data also provides information on household and community characteristics, health coverage, maternal and antenatal care, infant feeding practices and immunization coverage among others. The dependent variable will be time until child mortality,while the status will be dead within 0-59 months(coded 1) or alive at 5 years (coded 0)and representing censoring status. Right censored data is vastly discussed by[7].Survival data concepts have been widely presented by numerous scholars.

2.4 Variables

The risk factors examined in the study were selected based on results from already published articles. They include sex of child,age of mother,mother's level of education and maternal income. Mother's education level is the exposure and maternal income is the mediator. Education is grouped in four categories;no education,primary education,secondary education and higher education.Household wealth level was used for maternal income. The wealth level was derived from an index computed using data on ownership. The outcome variable is mortality status and month of death. Status was recorded and subsequently coded according to whether the child is alive or not,with 0 for being alive while 1 for being dead within the first 5 years. Age at death is given in months.The covariates included in the model were sex of child and age. One exposure,one mediator and two covariates were considered. To investigate whether the total effect of mother's education level and the effect of mother's education level through maternal income varied by mother's education level, we repeat the analysis stratified by mother's education level. (according to the data). In assessing mediation, we estimate natural direct effects or pure direct effects which is the change in the predicted number of deaths per 1000 children-months per unit level change in mother's education level when the mediator maternal income is set at a value it would take at the reference level of mother's education level. Natural indirect effect is the change in predicted number of deaths per 1000 children-months when the exposure mother's education level is not changed but the mediator is changed.

The first step is to run a regression of maternal income on education adjusted for age and sex of child. This is used to examine associations of maternal income and education. The next step is to fit the Aalen additive model on mortality with sex of child, age, maternal income and education as covariates.This is to explore potential underlying mechanisms in these associations. The difference between the two is the effect of the mediator.

Confidence intervals are also provided for the mediated proportion and the effect measure can be directly interpreted as the number of additional cases of mortality due to different education levels and the number due to direct effects.Absence of maternal income is a data limitation of our study but we note that there is a strong reason to believe that wealth index shows the socio economic position. Descriptive statistics are presented in table 1. All analysis was conducted in R.

3 Results

The general technique adopted in this paper is the ordinary least squares(OLS) to estimate the parameters. This was achieved via R-programming using the package 'timereg'. [9] discusses this technique widely. Descriptive statistics on mortality ,mother's education ,maternal income and covariates are presented in table 1.

3.1 Descriptive characteristics

Table 1: Descriptive characteristics of demographic and variables determining under five child mortality in Kenya,2014

	0 (N = 20093)	1 (N = 871)	TRUE (N = 20964)
Residence			
Urban	6532(32.5%)	296(34.0%)	6828(32.6%)
Rural	13561(67.5%)	575(66.0%)	14136(67.4%)
Education level			
No Education	4406(21.9%)	179(20.6%)	4585(21.9%)
Primary Education	10551(52.5%)	504(57.9%)	11055(52.7%)
Secondary Education	3857(19.2%)	146(16.8%)	4003(19.1%)
Higher education	1279(6.4%)	42(4.8%)	1321(6.3%)
Religion			
Roman Catholic	3706(18.4%)	139(16.0%)	3845(18.3%)
Protestant	12405(61.7%)	553(63.5%)	12958(61.8%)
Muslim	3364(16.7%)	156(17.9%)	3520(16.8%)
No religion	521(2.6%)	20(2.3%)	541(2.6%)
Other	59(0.3%)	3(0.3%)	62(0.3%)
Missing	38(0.2%)	0(0%)	38(0.2%)
Wealth index			
Poorest	6893(34.3%)	285(32.7%)	7178(34.2%)
Poorer	4154(20.7%)	194(22.3%)	4348(20.7%)
Middle	3334(16.6%)	163(18.7%)	3497(16.7%)
Richer	3001(14.9%)	130(14.9%)	3131(14.9%)
Richest	2711(13.5%)	99(11.4%)	2810(13.4%)
Sex			
Male	10157(50.6%)	476(54.6%)	10633(50.7%)
Female	9936(49.5%)	395(45.4%)	10331(49.3%)
Age group			
15-19	1024(5.1%)	28(3.2%)	1052(5.0%)
20-24	4773(23.8%)	210(24.1%)	4983(23.8%)
25-29	6143(30.6%)	250(28.7%)	6393(30.5%)
30-34	4009(20.0%)	179(20.6%)	4188(20.0%)
35-39	2659(13.2%)	117(13.4%)	2776(13.2%)
40-44	1164(5.8%)	69(7.9%)	1233(5.9%)
45-49	321(1.6%)	18(2.1%)	339(1.6%)
Birth type			
Single Birth	19596(97.5%)	784(90.0%)	20380(97.2%)
1st of multiple	240(1.2%)	52(6.0%)	292(1.4%)
2nd of multiple	257(1.3%)	35(4.0%)	292(1.4%)
No of children			
0	586(2.9%)	251(28.8%)	837(4.0%)
1	7415(36.9%)	372(42.7%)	7787(37.1%)
2	8314(41.4%)	198(22.7%)	8512(40.6%)
3	3086(15.4%)	38(4.4%)	3124(14.9%)
4	570(2.8%)	8(0.9%)	578(2.8%)
5	98(0.5%)	3(0.3%)	101(0.5%)
6	19(0.1%)	1(0.1%)	20(0.1%)
7	5(0.0%)	0(0%)	5(0.0%)

A total of 20964 children were identified in the 2014 KHDS data.Of these 871 had died and 20,093 were alive. Table 1 shows the descriptive characteristics of some the variables included in the study. Around 34 per cent of those dead were living in urban areas and 66 percent in rural areas. Among the dead children 54.6 percent were male and 45.4 percent were female.

3.2 Regression of maternal income on education adjusting for age and sex

Table 2: Parameter Estimates and Standard Errors fSES for the regression of maternal income on education adjusting for Age and sex

Coefficients	Estimate	Std. Error	t value	$Pr(>\|t\|)$
(Intercept)	1.281	0.048	26.565	$< 2e-16^{***}$
Age	0.005	0.001	3.942	$8.09e-05^{***}$
Sex	0.013	0.016	0.810	0.418
Primary education	0.987	0.021	47.064	$< 2e-16^{***}$
Secondary education	1.980	0.026	76.482	$< 2e-16^{***}$
Higher education	2.896	0.037	77.901	$< 2e-16^{***}$

Signif. codes: $0^{***}, 0.001^{**}, 0.01^{*}, 0.05^{\cdot}, 0.11$

Table 2 suggests that on average mothers in higher education level have an income of 2.9 units higher than mothers in no education level, when adjusted for age and sex. Mothers in secondary education level have an income of 1.98units higher than mothers in no education level. Mothers in primary level have an income of 0.99 units higher than mothers in no education level .

3.3 Aalen additive model adjusting for maternal income, education level, age and sex.

Table 3: Parameter Estimates and Standard Errors from the Aalen additive model adjusting for maternal income , Education level, age and Sex.

Education level	Estimate(S.E) $x10^{-3}$
No education	0.00(0.00)
Primary education	-1.45(0.057)
Secondary education	-2.30(0.812)
Higher education	-2.75(0.26)
Maternal income	-2.16(0.728)

Table 3 shows that children born of mother's in higher education level have a mortality rate that is $2.75X10^{-3}$ units lower than those of mothers in no education level adjusted for age and sex. Children born of mothers in secondary education level have a mortality rate that is $2.30X10^{-3}$units lower than those of mothers in no education level. Children born of mothers in primary education level have a mortality rate that is $1.45X10^{-3}$ units lower than those of mothers in no education level .

3.4 Mediation Analysis

Table 4: Mediation analysis of maternal income on mothers education level for Under Five Child Mortality

Outcomes	Total effect	Direct effect	Indirect effect
$0-1$	-1.9	-1.4	-0.5
0-II	-2.5	-2.3	-0.2
0-III	-3.5	-2.8	-0.7

As expected[3] high education level leads to a lower rate of child mortality.The effect of mothers education level has two components,direct effect without maternal income and mediation effect of maternal income.

Change from no education level to higher education level would reduce the number of deaths by 3.5 per 1000children$\beta = -3.5$ of this decrease 0.7 fewer deaths ($\beta = -0.7$)were attributed to maternal income pathway(natural indirect effect)representing 20 percent of the total effect . In other words, if an intervention could improve maternal income of no education level one to higher education level without affecting other aspects of social deprivation 20% of the education level effect could be eliminated.

Change from no education level to secondary level, would reduce the number of deaths by 2.5 per 1000children$\beta = -2.5$ of this decrease 0.1 fewer deaths($\beta = -0.1$)were attributed to maternal income pathway(natural indirect effect)representing 4% percent of the total effect . In other words, if an intervention could improve maternal income of education level one to secondary level without affecting other aspects of social deprivation 4% of the education level effect could be eliminated.

Change from no education level to primary level would reduce the number of deaths by 1.9 per 1000children$\beta = -1.9$ of this decrease 0.5 fewer deaths($\beta = -0.5$)were attributed to maternal income pathway(natural indirect effect)representing 26% percent of the total effect . In other words, if an intervention could improve maternal income of no education level 0 to primary level without affecting other aspects of social deprivation 26% of the education level effect could be eliminated.

4 Discussion

Kenya is one of the countries in the region with high UFCM rates. Identification of drivers of mortality among children aged below 5years is an important problem that needs to be addressed. This could help inform health and intervention strategies. The objective if this study was to identify the role of maternal income in mediating the effect of mothers education level on UFCM. This work adds to a limited body of research on how to determine the effects of mediators in epidemiological literature.

The proposed study has used statistical modelling tools specifically linear regression and Aalen additive model to evaluate the role of maternal income in mediating the effect of mother's education on under five child mortality in Kenya. By adapting Aalen's additive model, we obtain a simple and intuitively understandable measure of deviation from risk additivity in survival analysis ,with direct estimation of the absolute deviation from additivity of effects in terms of incidence rates with corresponding confidence intervals. In the analysis the choice of covariates is similar to those in the study of[20].

The analysis indicated that maternal income is a mediator between maternal education and under five child mortality. Our study found out that education was inversely associated with UFCM and maternal income was a partial mediator of the relationship. For the regression model mothers in higher education level have an income of 2.58 units higher than mothers in no education level when adjusted for age and sex. The Aalen additive model shows that children born of mother's in higher education level have a mortality rate that is $2.75X10^{-3}$units lower than those of mothers in no education level adjusted for age and sex. From the confidence intervals high education level leads to a lower rate of child mortality. Change from no education level to primary education level would reduce the number of deaths by 1.9 per week per 1000 children.Of these cases 0.5 can be attributed to pathway through maternal income(natural indirect) as expected. Change from no education level to secondary level would reduce the number of deaths by 2.4 per week per 1000 children.Of these cases 0.1 can be attributed to pathway through maternal income as expected. Change from no education level to higher education level would reduce the number of deaths by 3.5 per week per 1000 children. Of these cases 0.7 can be attributed to pathway through maternal income as expected. In other words, if an intervention could improve maternal income of no education level to higher education level without affecting other aspects of social deprivation 20% of the education level effect could be eliminated.Likewise if an intervention that could improve maternal income of no education level to secondary level without affecting other aspects of social deprivation 4% of the education level effect could be eliminated. An intervention that could improve maternal income of no education level to primary level without affecting other aspects of social deprivation would eliminate 26% of the education level effect.

Similarly Studies in the sub saharan Africa and India indicated that socio economic position plays a significant role in health seeking decision making for common childhood illnesses. Education is a social determinant of health.More education is associated with greater likelihood of engaging in health promoting behaviours and better health outcomes. Kenya is among those nations in the sub-Saharan part of Africa which has high under -five deaths.The need to reduce under five child mortality which lies under one of the Social development Goals ,has promoted use of modelling to understand effects of variables and their mediators. The Sustainable Development Goal(SDG) number 3,target 3.2 has not been achieved in Kenya,with 43.2 deaths per 1000 live births being reported in the year 2019(most recent world bank data). More efforts are still needed to realize the sustainable development goal of preventing neonatal child mortality and achieving below 25/1000 child deaths in every nation(Unicef,2015).

Evaluation of mediators and interactions is important to guide public health interventions ,clinical decision making and health planning policy. The interventions are designed to change mediating variables that are hypothesized to be casually related to the outcome variable.Trying different approaches ,one may get more insight into the data and develop a more critical attitude to the whole analysis.

5 Conclusion

The study involves quantifying mediation in a survival context. The method provides a simple and straight forwardly interpret able measure of both natural and indirect effects along their confidence intervals. Effects are calculated on the additive hazard scale and can therefore be directly translated to expected number of additional cases per unit of time.The method is illustrated by analyzing the relationship between education, maternal income and under-five mortality previously examined in the study of[20]. As in the original analysis we found out that a substantial part of the effect of education on child mortality is mediated through maternal income. Our analysis also provides confidence intervals for mediated proportion and the effect measure can be directly interpreted as the number of reduced cases due to differences in maternal income and the number due to direct effects. If an intervention could improve maternal income of mother's without affecting other aspects of social deprivation the education level effect could be reduced.This means that if the interventions improve maternal income,then the rate of UFCM could be reduced.

The results of this study may contribute to improve relevant interventions for UFCM among children in Kenya. It will help Kenya government ,non governmental organizations and other partners in health sector to know and understand the important areas they need to focus on in order to develop policies and programmed projects to reduce UFCM,which is part of the SDGs and Presidents Big Four Agenda. Major issue for future research is to extend the approach to incorporate interactions among covariates.

References

[1] Aristide R Bado, A Sathiya Susuman, and Eric I Nebie. Trends and risk factors for childhood diarrhea in sub-saharan countries (1990–2013): assessing the neighborhood inequalities. *Global health action*, 9(1):30166, 2016.

[2] Lenka Benova, Oona MR Campbell, and George B Ploubidis. Socio-economic gradients in maternal and child health-seeking behaviours in egypt: systematic literature review and evidence synthesis. *PloS one*, 9(3):e93032, 2014.

[3] Admire Chikandiwa, Emma Burgess, Kennedy Otwombe, and Lucy Chimoyi. Use of contraceptives, high risk births and under-five mortality in sub saharan africa: evidence from kenyan (2014) and zimbabwean (2011) demographic health surveys. *BMC women's health*, 18(1):1–13, 2018.

[4] Stephen R Cole and Miguel A Hernán. Fallibility in estimating direct effects. *International journal of epidemiology*, 31(1):163–165, 2002.

[5] Monica Das Gupta. Death clustering, mothers' education and the determinants of child mortality in rural punjab, india. *Population studies*, 44(3):489–505, 1990.

[6] RR Ettarh and James Kimani. Determinants of under-five mortality in rural and urban kenya. *Rural and Remote Health*, 12(1):3–11, 2012.

[7] Philip Hougaard. Fundamentals of survival data. *Biometrics*, 55(1):13–22, 1999.

[8] Emily C Keats, William Macharia, Neha S Singh, Nadia Akseer, Nirmala Ravishankar, Anthony K Ngugi, Arjumand Rizvi, Emma Nelima Khaemba, John Tole, and Zulfiqar A Bhutta. Accelerating kenya's progress to 2030: understanding the determinants of under-five mortality from 1990 to 2015. *BMJ global health*, 3(3):e000655, 2018.

[9] Theis Lange and Jørgen V Hansen. Direct and indirect effects in a survival context. *Epidemiology*, pages 575–581, 2011.

[10] Robert A LeVine. Women's schooling, patterns of fertility, and child survival. *Educational Researcher*, 16(9):21–27, 1987.

[11] Torben Martinussen and Thomas H Scheike. *Dynamic regression models for survival data*. Springer Science & Business Media, 2007.

[12] Honorati Masanja, Don de Savigny, Paul Smithson, Joanna Schellenberg, Theopista John, Conrad Mbuya, Gabriel Upunda, Ties Boerma, Cesar Victora, Tom Smith, et al. Child survival gains in tanzania: analysis of data from demographic and health surveys. *The Lancet*, 371(9620):1276–1283, 2008.

[13] W Henry Mosley and Lincoln C Chen. An analytical framework for the study of child survival in developing countries. *Population and development review*, 10:25–45, 1984.

[14] Daniel Mwangi Muriithi and Dennis K Muriithi. Determination of infant and child mortality in kenya using cox-proportional hazard model. *American Journal of Theoretical and Applied Statistics*, 4(5):404–413, 2015.

[15] Justine B Nasejje, Henry G Mwambi, and Thomas NO Achia. Understanding the determinants of under-five child mortality in uganda including the estimation of unobserved household and community effects using both frequentist and bayesian survival analysis approaches. *BMC public health*, 15(1):1–12, 2015.

[16] Thu T Nguyen, Eric J Tchetgen Tchetgen, Ichiro Kawachi, Stephen E Gilman, Stefan Walter, and Maria Glymour. Comparing alternative effect decomposition methods: the role of literacy in mediating educational effects on mortality. *Epidemiology (Cambridge, Mass.)*, 27(5):670, 2016.

[17] Carina Rein. *Identification of Mediators in High Dimensional Survival Data in the Presence of Confounding*. PhD thesis, Ludwig maximilian university of munich, 2017.

[18] Naja Hulvej Rod, Theis Lange, Ingelise Andersen, Jacob Louis Marott, and Finn Diderichsen. Additive interaction in survival analysis: use of the additive hazards model. *Epidemiology*, 23(5):733–737, 2012.

[19] Gbemisola W Samuel and Emmanuel O Amoo. A statistical analysis of child mortality: Evidence from nigeria. *Journal of Demography and Social Statistics*, 1(1):110–120, 2014.

[20] Khaing Soe. *What is the association between maternal education and childhood mortality, childhood illnesses and utilisation of child health services in Myanmar?* Lancaster University (United Kingdom), 2019.

[21] Unicef et al. Who; world bank; un-desa population division. levels and trends in child mortality: report 2015: estimates developed by the un inter-agency group for child mortality estimation. new york: United nations children's fund; 2015 [cited 2018 jan 19], 2015.

[22] Haixiang Zhang, Yinan Zheng, Zhou Zhang, Tao Gao, Brian Joyce, Grace Yoon, Wei Zhang, Joel Schwartz, Allan Just, Elena Colicino, et al. Estimating and testing high-dimensional mediation effects in epigenetic studies. *Bioinformatics*, 32(20):3150–3154, 2016.