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Cross-country Analysis of Maternal Mortality Ratio

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Abstract

Introduction: WHO, UNFPA, and World Bank made a joint statement in 1999 that called for the reduction of maternal mortality ratio by three quarters by 2015, one of the Millennium Development Goals. ***Objectives:*** This paper proposes a regression model to determine if national-level health system indicators corresponding to the interventions identified by the United Nations and other agencies are significantly associated with maternal mortality ratio. ***Method:*** Country-level data on maternal mortality ratio and national-level indicators were accessed and downloaded from the UNICEF webpage. Ordinary least squares (OLS) regression, poisson regression, and negative binomial regression models were used in fitting MMR as a function of total fertility rate (TFR), antenatal care coverage (ANC), contraceptive prevalence rate (CPR), percent skilled birth attendance (SBA), percent institution based deliveries (IBD), gross national income (GNI), total adult literacy rate (ALR), and geographic group variable (GEO). ***Results:*** Using a negative binomial regression model, only the variables percentage of institution-based deliveries (IBD), per capita gross national income (GNI), and geographic cluster (GEO) are found to have statistically significant association with the average maternal mortality ratio. ***Conclusion:*** There is empirical evidence that geographic-cultural clustering has effects on MMR that are not explained by the per capita gross national income and percent of institution-based deliveries. Further studies are needed to unravel these yet unidentified factors that drive Maternal Mortality Ratio. ***Keywords:*** maternal mortality ratio, Poisson regression, negative binomial regression, institutional based delivery.

1. Introduction

The United Nations Maternal Mortality Inter-agency Group defines maternal mortality ratio as the ratio of the number of maternal deaths during a given time period per 100,000 live births during the same time-period (UN Maternal Mortality Estimation Inter-agency Group, 2013). WHO defines maternal death as the death of a woman while pregnant or within 42 days of termination of pregnancy, irrespective of the duration and site of the pregnancy, from any cause related to or aggravated by the pregnancy or its management but not from accidental or incidental causes (WHO, 2008). Furthermore, WHO defines live birth as the complete expulsion or extraction from its mother of a product of conception, irrespective of the duration of the pregnancy, which, after such separation, breathes or shows any other evidence of life - e.g. beating of the heart, pulsation of the umbilical cord or definite movement of voluntary muscles - whether or not the umbilical cord has been cut or the placenta is attached (WHO, 2008).

Maternal mortality ratio (MMR) is an estimate of the likelihood that a pregnant woman will die due to causes related to her pregnancy. It is a development indicator that measures the responsiveness of the health care delivery system to the needs of one of the most vulnerable sectors of the population, the pregnant mother.

From an epidemiological perspective, maternal death is a relatively rare event, and is difficult to measure accurately because it depends on the comprehensive registration of deaths and appropriate determination of the causes of death. MMR is measured using vital registration, health service records, household surveys, and census. But for many low-income countries that have no or very little data, modeling is used to obtain a national estimate (The World Bank, 2006; WHO, UNFPA, UNICEF, and World Bank, 1999). The top causes of maternal deaths globally are severe bleeding/hemorrhage (25%), infections (13%), unsafe abortions (13%), eclampsia (12%), obstructed labor (8%), and other direct

(8%) and indirect causes (20%). The high proportion of unspecified causes of death underlines the difficulty of the current health system to accurately ascertain the causes of maternal deaths.

Various factors are thought to contribute to the magnitude of the maternal mortality ratio. They are broadly classified as patient/medical and health system related (socio-economic) factors. Patient related factors/characteristics include the number of pregnancies, the age of the mother, the presence of co-morbidities, and her level of education. Pregnancy exposes the woman to the risk of dying due to maternal causes. This risk is said to increase as the number of pregnancies increases. Too young or too old mothers also have higher risk compared to pregnant women in the middle age group. Poverty and low education are generally seen as contributory factors to high maternal mortality. The presence of medical conditions that complicate pregnancy like anemia and nutritional disorders are also considered as significant contributors to increased maternal mortality (Hafez, 1998; The World Bank, 2006; WHO, UNFPA, UNICEF, and World Bank, 1999).

Health system characteristics/external characteristics that lead to high maternal mortality ratio include lack of medical care during and after pregnancy (antenatal and post-partum care), unavailability of a skilled birth attendant during delivery, and inaccessibility of properly equipped and staffed birthing institutions (Hafez, 1998; The World Bank, 2006; WHO, UNFPA, UNICEF, and World Bank, 1999).

Recognizing the gravity of the situation, the WHO, the UNFPA, and the World Bank made a joint statement in 1999 that called for the reduction of maternal mortality. In this joint statement, reduction of maternal mortality ratio by three quarters by 2015 has been identified as one of the Millennium Development Goals (United Nations, 2007).

The joint statement identified and recommended the following key interventions to achieve reduction of maternal deaths. These recommendations became the core on which countries based their national initiatives (Hafez, 1998; The World Bank, 2006; WHO, UNFPA, UNICEF, and World Bank, 1999). The major interventions included in their recommendations were:

a) ensuring skilled-birth attendance at delivery and improving health systems to increase availability and accessibility of emergency obstetric care
b) encouraging delayed marriage and first birth for adolescents
c) addressing unwanted and poorly timed pregnancies
d) improving coverage and quality of prenatal and postpartum care

Years after the recommendations were made, several questions of policy importance are: were these interventions effective in lowering maternal mortality? And: which among these interventions were the most effective?

This paper aims to answer these questions through regression modelling with maternal mortality ratio as the outcome variable and health system indicators corresponding to the interventions identified in the joint statement as covariates.

2. Review of Related Literature

It is an innate drive for human beings to ensure that their genes survive (Dawkins, 1989). To this end, they modify their behaviour and, to some extent, their environment to maximize their chances of survival - long enough to ensure that their or their kin's off-springs survive. This strategy necessitates not only awareness but also understanding of the environment, and this understanding can only be achieved by observing and exploring associations between and among phenomena they encounter (Markie, 2013). Human beings, in essence, *model* the world around them through observation and experience.

In that sense, human beings can be regarded as natural scientists and - since statistics is the language and method of science - natural statisticians as well. So it shouldn't come as a surprise that the problems of association, hypothesis testing, and prediction frequent the day to day life of a typical person, much less if that man is a very educated one. Extension of this approach to answer the more abstract and complicated questions should also be a natural consequence.

In the words of H.G. Wells, paraphrased by Samuel Wilks: "Statistical thinking will one day be as necessary for efficient citizenship as the ability to read and write! (Wilks, 1951)"

2.1. Linear Regression Modelling

Understanding associations among phenomena fall under the general realm of statistics called regression modelling (Chatterjee, 2012; Fox, 1997; Montgomery et al, 2012). The phenomena are expressed in mathematical form through equations or models that connect the response variable with one or more explanatory variables through a mathematical function (Chatterjee, 2012; Fox, 1997; Montgomery et al., 2012). The model structure embodies the relationship of the predictor variables to the mean of the response variable. But methods exist that relate the predictors to the median or other quantiles of the outcomes (Koenker and Hallock, 2001).

The true relationship is however often unknown in its entirety, and "truth" is only approximated by extracting information from whatever observed realizations of the phenomena (i.e. the data) can be collected (Montgomery et al., 2012). In its basic form, the regression model can be written as:

$$Y = f\left(X_1, X_2, X_3, \cdots, X_p\right) + \varepsilon$$

where Y is the response variable and $X_1,\ldots,X_p$ are p predictors, f is the function that links the predictors to the response, which in its most familiar form is simply a linear combination of the predictors, and ϵ is the random disturbance or error representing the discrepancy in the approximation (Chatterjee, 2012; Fox, 1997; Montgomery et al., 2012).

In practice, modellers initially specify the structural form of the model that is believed to capture the relationship between the response variable and the predictors. These decisions are generally based on their knowledge or their objective and or subjective judgments. Appropriateness of the *a priori* model is then verified by analysing the empirical data (Chatterjee, 2012).

The number of extensions and sophistications to this basic statistical model has exploded in the past half-decade in response to the constant need to analyze a vast and fast-evolving range of phenomena, which include discrete responses (Hoffmann, 2003; McCullagh and Nelder, 1989; Olsson, 2002), and clustered-longitudinal correlated data (Cressie and Wikle, 2011; Jiang, 2007; Zeger and Liang, 1986), among others.

2.2 Poisson Regression Model

Poisson regression model is a particular member of the generalized linear models where the outcome variable, Y, is assumed to have the distribution of a Poisson random variable with parameter λ (Demidenko, 2007; Jowaheer, 2006). For the Poisson regression model, the link function g is the natural logarithm, and the model takes the form:

$$log\big(E(Y)\big) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_2 X_2 + \cdots + \beta_k X_p$$

The model states that a linear combination of the predictor variables and the parameters is related to the natural logarithm of the mean of the outcome variable. The parameters are estimated using the method of maximum likelihood, and are usually found using numerical methods.

The Poisson distribution is appropriate to model count data especially if the following conditions are met:

1) The logarithm of the mean of the outcome variable changes linearly with equal increment increases in the exposure variable.

2) The changes in the rate from combined effects of different exposures or risk factors are multiplicative.
3) At each level of the covariates, the number of cases has variance equal to the mean.
4) The observations are independent.

2.3 Negative Binomial Regression Model

As a generalized linear regression model, the negative binomial model is an alternative to the Poisson regression model when overdispersion is present, which should be suspected when after the Poisson model is fit, the residuals are already random but variance is larger than what is expected. The negative binomial model includes a dispersion parameter which could be used to adjust the variance independent of the mean (Madsen, 2010).

The negative binomial regression model can also be interpreted as a more general case of Poisson regression. Specifically, it can be derived as a gamma mixture of Poisson model (Demidenko, 2007; Hilbe, 2011; Jowaheer, 2006).

If the overdispersion is due to cluster-correlation, a mixed effects Poisson regression model with clustering variable as a random effect can be used. The random effect and the dispersion parameter are considered nuisance parameters to account for the variability in the data that are brought about by clustering or natural grouping (Madsen, 2010).

3. Methodology

3.1. Source of data and definition of variables

Country-level data on maternal mortality ratio and related country-level indicators were accessed and downloaded from the UNICEF webpage and represent data available as of 1 July 2008. The variables used are described in Table 1.

Table 1. Variables considered in the Analysis

Variable Name	*Variable Label*
ALR	Adult literacy rate (%), 2007
ANC	Antenatal care coverage (%), 2007
CPR	Contraceptive prevalence (%), 2007
GEO	Geographic cluster (UN)
GNI	Gross national income (US $), 2007
IBD	Institutional deliveries (%), 2007
LBR	Annual number of live births, 2007
MMR	Maternal mortality ratio, 2007, reported
SBA	Skilled attendant at delivery (%), 2007
TFR	Total fertility rate, 2007

Maternal mortality ratio is defined as the annual number of deaths of women from pregnancy-related causes per 100,000 live births. Periodically, UNICEF, WHO, UNFPA and the World Bank evaluate these data and make adjustments to account for the well-documented problems of under-reporting and misclassification of maternal deaths and to develop estimates for countries with no data. This paper deals only with country-reported figures that are not adjusted for under-reporting and misclassification, (UNICEF, 2008).

Total fertility rate is the average number of children that would be born to a woman in her lifetime if she were to pass through her childbearing years experiencing the age specific fertility rates for a given period, (UNCSD, 2008b). In theory, higher fertility rates should lead to higher maternal mortality rates as it is directly translated to increase in exposure. The source of basic data is the United Nations Population Division (UNICEF, 2008).

Contraceptive prevalence rate is defined as the percentage of women in union aged 15–49 currently using contraception. Increasing CPR should in theory reduce maternal mortality by reducing the number of unwanted and mistimed pregnancies. This strategy may exert its effect through at least two mechanisms: reducing the fertility rate and avoiding deaths due to unsafe abortion (UNCSD, 2008a). Sources of basic data are DHS, MICS, United Nations Population Division and UNICEF (UNICEF, 2008).

Antenatal care coverage is defined as the percentage of women 15–49 years old attended at least once during pregnancy by skilled health personnel (doctors, nurses or midwives). Increasing antenatal care coverage is expected to contribute to the reduction of maternal deaths since antenatal care provides opportunity to detect and manage complications which can lead to mortality if not detected and managed early on (United Nations, 2007). Sources of data are DHS, MICS and other national household surveys (UNICEF, 2008).

Skilled attendant at delivery and institutional deliveries measures the (1) percentage of births attended by skilled health personnel (doctors, nurses or midwives) and (2) proportion of women 15–49 years old who gave birth during the two years preceding the survey and delivered in a health facility. These efforts could exert their maternal mortality protective effects by providing early management to life threatening conditions that occur during the delivery and immediately after the delivery, the time period when the mother is particularly vulnerable (WHO, UNFPA, UNICEF, and World Bank, 1999). Sources of data are DHS, MICS, WHO and UNICEF (UNICEF, 2008).

Adult literacy rate. Number of literate persons aged 15 and above, expressed as a percentage of the total population in that age group. The source of data is the UNESCO Institute for Statistics (UIS), including the Education for All 2000 (UNICEF, 2008).

Annual number of live births. Source of data is the United Nations Population Division (UNICEF, 2008).

The gross national income per capita (GNI) is the sum of value added by all resident producers, plus any product taxes (less subsidies) not included in the valuation of output, plus net receipts of primary income (compensation of employees and property income) from abroad. GNI per capita is gross national income divided by midyear population. GNI per capita in US dollars is converted using the World Bank Atlas method. The source of data is the World Bank (UNICEF, 2008).

Geographic region clustering variable classifies each country according to the loco-regional geographic clustering used by the United Nations and attached agencies in their reports and analysis (UNICEF, 2008).

3.2. Proposed models

A multiple ordinary least squares regression model (OLS) is included because it is the simplest and most popularly used model to fit data. The OLS model is fitted using all the explanatory variables. Using post-fit plots, the model is checked for homoscedasticity, autocorrelation of errors, normality of errors, outliers, and influential observations. Multicollinearity problems are mitigated through variable selection guided by theory, pre-fit correlation plots of the predictors, and formal measures of collinearity.

A Poisson regression model is included because it is theoretically sound to model maternal mortality ratio that is expressed in counts over a fixed value of denominator. Maternal mortality is a relatively rare event, and the probability of at least 2 events happening at the same unit in time is very small. The death of one woman (due to pregnancy) theoretically does not affect the likelihood that another woman will also die, which implies that each observation can be assumed independent (Cameron, 2013; Hilbe, 2011).

However, the Poisson regression model still assumes that the errors are identically distributed and that the mean should be equal to the variance. But this assumption may not necessarily hold for the maternal mortality data because the countries show natural loco-regional geographic clustering that could give rise to correlation within groups and heterogeneity across groups. This heterogeneity will be reflected as over dispersion, e.g., when the variance is larger than the mean (Cameron, 2013; Hilbe, 2011; Demidenko, 2007; Jowaheer, 2006). When this happens, inference about the estimates may be incorrect, increasing the likelihood for a type I error.

To get around this problem, the loco-regional geographical clustering variable (GEO) is incorporated into the model, first as a fixed intercept. Another way to incorporate overdispersion into the model without being forced to directly attribute the overdispersion to known variables (as the case is in fixed effects poisson modelling), a negative binomial regression model is also proposed. If the overdispersion is not fully accounted for by the negative binomial model itself, the addition of GEO clustering variable as fixed effects is considered.

3.3. Model evaluation

Because the primary aim of the paper is estimation and inference rather than prediction, the acceptability of the models are judged based primarily on the absence of violations of model assumptions. Violations of the model assumptions are evaluated using post-fit plots of the residuals or deviances versus the fitted/in-sample predicted values. Plots are also used to detect presence of outliers and influential observations. Formal methods of evaluation are also included to assist in the model assessment and include the Akaike information criterion (AIC) as the primary basis for judging fit and comparing fit across models, the Shapiro-wilk test for normality, and the studentized Breusch-Pagan test for the detection of heteroskedasticity.

4. Results and Discussion

There are 98 complete cases out of the 196 cases. Furthermore, the number of complete cases render under representation in some geographic cluster of the industrialized countries/territories. To maximize the size of the data, multiple imputations for the missing values of the predictor variables were done using the EM-bootstrap algorithm (Honaker et al., 2013). Multiple imputations yield 174 complete cases, including 9 countries in the industrialized cluster. Table 2 summarizes the number of cases before and after imputation, by geographic clusters.

Table 2. Number of Cases with Complete Data

Geographic cluster	Original Data	After Imputation
East Asia and Pacific (Base region)	9	25
CEE/CIS	13	21
Industrialized countries/territories	0	27
Latin America and Caribbean	19	32
Middle East and North Africa	13	18
South Asia	7	8
Sub-Saharan Africa	37	43
Complete cases	98	174
Total number of cases	196	196

4.1. Ordinary Least Squares Multiple Linear Regression

Several OLS models were analysed, with the GEO variable included as dummy variables ("East Asia and Pacific" category was designated as the base category). This model yields a modest fit with an adjusted R-squared of 0.699. The model provides a significant linear fit ($p< 0.0000$). The Akaike information criterion value is 2297.08. The studentized Breusch-Pagan test for heteroskedasticity is statistically significant ($p<0.00002154$), indicating heteroscedasticity in error variance. The Shapiro-Wilk Normality test statistic W is 0.854 ($p<0.00000$), indicating that the residuals are not normally distributed. Furthermore, large variance inflation factors (VIF) indicates presence of multicollinearity. SBA and IBD are naturally correlated because by definition, all institutionally based deliveries are attended by skilled health professionals. It should not come as a surprise that information contained in the variable SBA is also contained in the variable IBD.

Addition of the interaction between SBA and IBD into the model is considered. The R^2 is 0.730, higher than that of previous model, and the model fit is still statistically significant. The AIC for this model is 2294.87, smaller than the AIC of the first model. However, the studentized Breusch-Pagan test for heteroskedasticity is statistically significant ($p<0.00001345$) and Shapiro-Wilk Normality test statistic W is 0.8491 ($p<0.0000$), indicating that there is still enough evidence to conclude that the residuals are heteroskedastic and not normally distributed.

The square root transformation for the response variable MMR was used while retaining the interaction between IBD and SBA. The Multiple R squared for this model is 0.8186, higher than the first 2 models, indicating that this model provides better fit to the data. The AIC is down to 1009.89, a big drop from the previous 2 models, a big improvement compared to the previous 2 models. There is also an improvement in residuals vs fitted values plot with reducing funnelling pattern seen earlier. However, the studentized Breusch-Pagan test is still significant ($p<0.0008437$), indicating persistence of heteroskedasticity, and the Shapiro-Wilk Normality test is still statistically significant ($p<0.037$), indicating that there is still enough evidence to conclude that the residuals are not normally distributed.

We also investigate whether omitting the variable SBA from the model rather than interacting it with IBD would remedy the multicollinearity problem. This model still considers the square root of the MMR as the response variable, but this time, the variable SBA is omitted from the model. The AIC is a little bit smaller at 1006.3, suggesting a slightly better fit. The studentized Breusch-Pagan test is still statistically significant ($p<0.0002792$), indicating that heteroskedasticity is still present. The Shapiro-Wilk normality test, is no longer significant ($p<0.06516$). All variable now have VIF values < 10. Thus, multicollinearity is already addressed properly in this model. With insignificant predictors removed, estimates for the final OLS model are summarized in Table 3.

Table 3. Estimates of Regression Coefficients in OLS

Coefficients:	Estimate	Std. Error	t value	Pr(>|t|)	sig
(Intercept)	13.565	2.206	6.148	0.000	***
Tfr	1.813	0.410	4.422	0.000	***
Ibd	-0.127	0.017	-7.443	0.000	***
as.factor(geo)CEE/CIS	0.017	1.291	0.013	0.990	
as.factor(geo)Industrialized countries/territories	-2.463	1.224	-2.012	0.046	*
as.factor(geo)Latin America and Caribbean	0.464	1.137	0.408	0.684	
as.factor(geo)Middle East and North Africa	0.414	1.319	0.314	0.754	
as.factor(geo)South Asia	4.784	1.735	2.757	0.007	**
as.factor(geo)Sub-Saharan Africa	6.991	1.304	5.361	0.000	***

Base category for geo: East Asia and the Pacific
Residual standard error: 4.173 on 165 degrees of freedom
Multiple R-squared: 0.8146, Adjusted R-squared: 0.8056
F-statistic: 90.59 on 8 and 165 DF, p-value: < 2.2e-16

4.2. Poisson Regression Models

Table 4 presents the summary of the poisson regression with all the variables included. The residual deviance is larger than the residual degrees of freedom, implying that the conditional variation of the mean MMR is larger than the variance of a Poisson-distributed random variable and is overdispersed. Although all the covariates except ALR were significantly associated with MMR, the standard errors of the estimates are likely to be smaller than they really are and lead to type I errors. The AIC for this model is 11687, several times larger than those for the previous OLS models. Residual plots show an extreme pattern of heteroskedasticity and a mild non-linearity.

Table 3. Estimates of Parameters in a Poisson Model(All Predictors).

Coefficients:	Estimate	Std. Error	z value	Pr(>|z|)	sig
(Intercept)	5.746	0.050	114.082	< 2e-16	***
Tfr	0.100	0.006	15.894	< 2e-16	***
Cpr	-0.006	0.001	-12.391	< 2e-16	***
Anc	-0.002	0.000	-5.688	0.000	***
Sba	0.003	0.001	4.263	0.000	***
Ibd	-0.012	0.001	-18.452	< 2e-16	***
Alr	0.001	0.000	1.771	0.077	.
Gni	0.000	0.000	-25.707	< 2e-16	***
as.factor(geo)CEE/CIS	-0.963	0.047	-20.650	< 2e-16	***
as.factor(geo)Industrialized countries/territories	-0.959	0.085	-11.320	< 2e-16	***
as.factor(geo)Latin America and Caribbean	0.035	0.029	1.178	0.239	
as.factor(geo)Middle East and North Africa	0.092	0.031	2.927	0.003	**
as.factor(geo)South Asia	0.703	0.031	23.033	< 2e-16	***
as.factor(geo)Sub-Saharan Africa	0.869	0.025	34.583	< 2e-16	***

Base category for geo: East Asia and the Pacific
Null deviance: 61445 on 173 degrees of freedom
Residual deviance: 10659 on 160 degrees of freedom
AIC: 11687

An interaction term between SBA and IBD was included. The AIC for this model is 11304, a considerable improvement from the previous one. Heteroskedasticity is still present as indicated in the studentized Breusch-Pagan test (p<0.00001345). The effect of omitting SBA, from the model instead of interacting it with IBD is explored. The model has an AIC of 11703, an increase from the above, and even larger than the AIC of the first poisson regression model.

4.3. Negative Binomial Models

Aiming to address the overdispersion problem, a negative binomial model is fitted, the AIC is 1897.4, lower than some of the OLS models but not with poisson regression models. The residual plots indicates a mild non-linear pattern, but heteroskedasticity practically vanished compared with OLS and poisson regression models. The studentized Breusch-Pagan test however, is still significant ($p<0.00002154$), indicating that heteroskedasticity is still present. The Shapiro-Wilk normality test is still significant ($p<0.00001477$).

A second model is fitted with SBA omitted. The AIC is 1896, a value that is not practically different from the AIC of the previous model. A significant improvement in model fit is considered when the decrease in AIC is at least 2 points (Chatterjee, 2012). The Shapiro-Wilk normality test is significant ($p<0.00001395$) and the studentized Breusch-Pagan test is significant ($p<0.00004816$), indicating that the residuals are still non-normal and heteroskedastic.

With square root transformation applied to the MMR, AIC is 966.7, the smallest AIC so far among the previous models. But the residual plots show essentially the same pattern as that of the two other negative binomial regression models. The Shapiro-Wilk normality test is significant ($p<0.00008855$), indicating non-normality of the residuals, and the studentized Breusch-Pagan test is significant ($p<0.0002792$), indicating the persistence of heteroskedasticity. The variance inflation factors for this model are all less than 10, indicating that multicollinearity is not a problem.

Several other transformations were applied to the predictor variables, but these modifications had negligible effect on improving the model fit characteristics and residual plots. A model without the non-significant predictors is fitted and summarized in Table 5. The AIC for this pre-final model is 961.11, so far the smallest AIC among all the models evaluated in this paper.

Table 5. Estimated Parameters of Negative Binomial Model.

Coefficients:	Estimate	Std. Error	z value	Pr(>|z|)	sig
(Intercept)	2.768	0.187	14.799	< 2e-16	***
Tfr	0.074	0.034	2.182	0.029	*
Ibd	-0.010	0.002	-6.213	0.000	***
Gni	0.000	0.000	-3.000	0.003	**
as.factor(geo)CEE/CIS	-0.294	0.142	-2.067	0.039	*
as.factor(geo)Industrialized countries/territories	-0.541	0.198	-2.728	0.006	**
as.factor(geo)Latin America and Caribbean	-0.022	0.114	-0.197	0.844	
as.factor(geo)Middle East and North Africa	0.100	0.128	0.781	0.435	
as.factor(geo)South Asia	0.306	0.141	2.174	0.030	*
as.factor(geo)Sub-Saharan Africa	0.517	0.113	4.554	0.000	***

Null deviance: 943.89 on 173 degrees of freedom
Residual deviance: 221.86 on 164 degrees of freedom
AIC: 961.11

Table 6 is a summary of the fit characteristics for all the models analysed in this paper. This list is not exhaustive but based on the performance of these models, it appears that the model that best fits the current data is the one presented in Table 5, having the smallest AIC and the most acceptable residual diagnostic plots (among the models analysed) while not demonstrating problems with multicollinearity. Thus, this model is chosen to be the base model upon which the final estimation of the coefficients from all the information. Table 7 summarized the coefficients for the final model.

Table 28. Summary comparison of the models evaluated.

					Residual Plots					Goodness-of-Fit
Model Name	Model Structure	Response variable	predictors	VIFs > 10	Non-linearity (pattern in diagnostic plots)	Heteroskedasticity (With studentized Breusch-Pagan test as formal test)	Non-normality (With Shapiro-Wilk Test as formal test)	Outliers (Scale-location plots)	Influential (Cook's Distance > 1 in Residual-Leverage plots)	Akaike Information Criterion
OLS1	Ordinary Least Squares Multiple Regression	MMR	TFR + CPR + ANC + SBA + IBD + ALR + GNI + GEO(dummy)	Present	mild	severe	Non-normal	Present	None	2297.8
OLS2	Ordinary Least Squares Multiple Regression	MMR	TFR + CPR + ANC + SBA + IBD + ALR + GNI + SBA*IBD + GEO(dummy)	Present	mild	severe	Non-normal	Present	None	2294.9
OLS3	Ordinary Least Squares Multiple Regression	sqrt(MMR)	TFR + CPR + ANC + SBA + IBD + ALR + GNI + SBA*IBD + GEO(dummy)	Present	mild	moderate	Non-normal	None	None	1009.9
OLS4	Ordinary Least Squares Multiple Regression	sqrt(MMR)	TFR + CPR + ANC + IBD + ALR + GNI + GEO(dummy)	None	mild	moderate	normal	None	None	1006.3
OLS5	Ordinary Least Squares Multiple Regression	sqrt(MMR)	TFR + CPR + ANC + IBD + ALR + GNI + GEO(dummy)	None	mild	moderate	normal	None	None	1001.7
Pois1	Poisson GLM	MMR	TFR + CPR + ANC + SBA + IBD + ALR + GNI + GEO(dummy)	Present	mild	severe	Non-normal	None	Present	11687.0
Pois2	Poisson GLM	MMR	TFR + CPR + ANC + SBA + IBD + ALR + GNI + SBA*IBD + GEO(dummy)	Present	mild	severe	Non-normal	None	Present	11304.0
Pois3	Poisson GLM	MMR	TFR + CPR + ANC + IBD + ALR + GNI + GEO(dummy)	None	mild	severe	Non-normal	None	Present	11703.0
Negbin1	Negative binomial GLM	MMR	TFR + CPR + ANC + SBA + IBD + ALR + GNI + GEO(dummy)	Present	mild	mild	Non-normal	None	None	1897.4
Negbin2	Negative binomial GLM	MMR	TFR + CPR + ANC + IBD + ALR + GNI + GEO(dummy)	None	mild	mild	Non-normal	None	None	1895.9
Negbin3	Negative binomial GLM	sqrt(MMR)	TFR + CPR + ANC + IBD + ALR + GNI + GEO(dummy)	None	mild	mild	Non-normal	None	None	966.7
Negbin4	Negative binomial GLM	sqrt(MMR)	TFR + CPR + ANC + IBD + ALR + GNI + GEO(dummy)	None	mild	mild	Non-normal	None	None	961.1

Table 7. Estimates of the Parameters of Final Model

Coefficients:

	Value	Std. Error	t-stat	p-value	sig
(Intercept)	3.08E+00	0.112	27.645	0.000	sig
Ibd	-1.21E-02	0.002	-7.564	0.000	sig
Gni	-1.87E-05	0.000	-2.234	0.028	sig
as.factor(geo)CEE/CIS	-2.91E-01	0.133	-2.187	0.029	sig
as.factor(geo)Industrialized countries/territories	-6.09E-01	0.200	-3.047	0.002	sig
as.factor(geo)Latin America and Caribbean	8.98E-03	0.136	0.066	0.947	
as.factor(geo)Middle East and North Africa	1.69E-01	0.145	1.164	0.245	
as.factor(geo)South Asia	3.31E-01	0.140	2.373	0.018	sig
as.factor(geo)Sub-Saharan Africa	6.74E-01	0.098	6.876	0.000	sig

4.4 Discussion

The final model for maternal mortality ratio (with the East Asia and the Pacific region as the base geographic-cultural category for the dummy variables) is:

$$\begin{aligned} log\left(E\left(\sqrt{Maternal\ mortality\ ratio}\right)\right) \\ &= 3.083081 - 0.012096 * IBD \ - 0.000019 * GNI - 0.290893 * Countries\ in\ Trans. \\ &- 0.608615 * Industrialized\ Countries + 0.331457 * South\ Asia \\ &+ 0.673552 * SubSaharan\ Africa \end{aligned}$$

Controlling for the effects of geographic-cultural clustering (GEO dummies) and gross national income (GNI), and among the other predictors of maternal mortality ratio, only the percentage of women giving birth in health institutions (IBD) yield a statistically significant association with the maternal mortality ratio. A 10 percentage points increase in IBD decreases the mean MMR of any country by 1.3 deaths per 100,000 live births, holding all other variables constant. Much of the differences in the MMRs of the countries are driven by factors related to their geographic and cultural cluster membership. Central European countries/countries in transition have mean MMRs of 1.8 deaths per 100,000 live births less than that of countries in East Asia and the Pacific. Industrialized countries have mean MMRs that are 3.39 deaths per 100,000 live births less than that of countries in East Asia and the Pacific, holding all other variables constant. On the opposite end of the story, countries in South Asia have mean MMRs that are 1.93 deaths per 100,000 live births more than that of countries in East Asia and the Pacific, holding all other variables constant. At the extreme end of the line, countries in the sub-Saharan Africa have mean MMRs that are 3.8 deaths per 100,000 live births more than that of countries in East Asia and the Pacific, holding all other variables constant.

The percentage of institution-based deliveries reflects the degree to which complications related to child-birth and the period directly after, are being detected and appropriately managed. The variables IBD and SBA show the most clear indications of multicollinearity, with IBD having the more statistically significant association when either are entered singly, also suggests that having pregnancies and childbirths attended by skilled health personnel may not be enough to curb maternal deaths, and that appropriate equipment, infrastructure, and support personnel – things that are found in health facilities and not ordinarily in homes – are just as important to effectively reduce maternal mortality ratio (Chowdhury et al., 2007; Fikree et al., 1997; Gupta et al., 2010).

The statistically significant association of per capita gross national income with the average maternal mortality ratio is expected (Buor & Bream, 2004). This association suggests that alleviating poverty may have additional protective effects on the maternal mortality ratio that is over and beyond that of its effects directly attributed to health facility developments.

Based on the final model, the total fertility rate, the contraceptive prevalence rate, the percentage of births attended by skilled health personnel, percentage of pregnancies with at least one ante-natal pregnancy check-up, and adult literacy rate, have no statistically significant associations with the average maternal mortality ratio.

Based on the final model, it appears that policy efforts should focus on increasing the percentage of institution-based deliveries and increasing the per capita gross national income. These results are compatible with current scientific literature (Buor & Bream, 2004; Gupta et al., 2010; Luque

Fernández et al., 2010; McCarthy & Maine, 1992). Furthermore, the final model also suggests that a deeper investigation into the reasons why differences in the Maternal Mortality Ratio are largely driven by factors related to their geographical-cultural membership rather than the purported drivers of MMR, such as total fertility rate, contraceptive prevalence rate, and antenatal care, which were surprisingly not found to have statistically significant associations with MMR.

5. Conclusions

Negative binomial regression model provides better fit to maternal mortality data with overdispersion than the OLS regression and poisson regression models.

Using the best model analysed in this paper, only the variables percentage of institution-based deliveries (IBD), per capita gross national income (GNI), and geographic-cultural location/membership (GEO) are found to have statistically significant association with the average maternal mortality ratio, with the GEO clustering variable explaining more of the variation than either IBD or GNI.

In trying to combat maternal mortality, countries should invest on formal health facilities that can accommodate birth deliveries. Presence of institutional health facilities will somehow protect the mother (who is as vulnerable as the infant), from risks associated with birth delivery.

Further studies on factors related to geographic-cultural clustering is suggested to unravel and yet unidentified factors that drive Maternal Mortality Ratio.

References

Cameron, A. C. (2013). *Regression analysis of count data* (Second edition.). New York: Cambridge University Press.

Chatterjee, S. (2012). *Regression analysis by example* (Fifth edition.). Hoboken, New Jersey: Wiley.

Cressie, N., & Wikle, C. K. (2011). *Statistics for Spatio-Temporal Data*. New York: John Wiley & Sons.

Dawkins, R. (1989). *The Selfish Gene*. Oxford: Oxford University Press.

Demidenko, E. (2007). Poisson Regression for Clustered Data. *International Statistical Review*, *75*(1), 96–113.

Fox, J. (1997). *Applied Regression Analysis, Linear Models, and Related Methods*. Thousand Oaks: SAGE.

Hafez, G. (1998). Maternal mortality: a neglected and socially unjustifiable tragedy - Why WHO selected "Safe motherhood" as the slogan for World Health Day 1998. *Eastern Mediterranean Health Journal*, *4*(1), 7–10.

Hilbe, J. M. (2011). *Negative binomial regression* (2nd ed.). Cambridge, UK ; New York: Cambridge University Press.

Honaker, J., King, G., Blackwell, M. (2011). Amelia II: A program for missing data. *Journal of Statistical Software*, *45*(7), 1-47.

Jiang, J. (2007). *Linear and Generalized Linear Mixed Models and Their Applications*. New York: Springer.

Jowaheer, V. (2006). Model misspecification effects in clustered count data analysis. *Statistics & Probability Letters*, *76*(5), 470–478.

Koenker, R., & Hallock, K. F. (2001). Quantile Regression. *Journal of Economic Perspectives*, *15*(4), 143–156.

Madsen, H. (2010). *Introduction to general and generalized linear models*. Boca Raton: CRC Press.

Markie, P. (2013). Rationalism vs. Empiricism. In E. N. Zalta (Ed.), *The Stanford Encyclopedia of Philosophy* (Summer 2013.). Retrieved from http://plato.stanford.edu/archives/sum2013/entries/rationalism-empiricism/

McCullagh, P., & Nelder, J. A. (1989). *Generalized Linear Models*. London: Chapman and Hall.

Montgomery, D. C., Peck, E. A., & Vining, G. G. (2012). *Introduction to Linear Regression Analysis*. New York: John Wiley & Sons.

Olsson, U. (2002). Generalized linear models: An Applied Approach. Lund : Studentlitteratur.

UN Maternal Mortality Estimation Inter-agency Group. (2013). Definitions. *Maternal Mortality Estimates (UN Maternal Mortality Estimation Inter-agency Group)*. Retrieved December 20, 2013, from http://www.maternalmortalitydata.org/Definitions.html

UNICEF. (2008). *Maternal and newborn health*. New York: UNICEF.

United Nations. (2007). *The millennium development goals report 2007*. New York: United Nations.

United Nations Department for Policy Coordination and Sustainable Development (UN CSD). (2008a). Contraceptive prevalence rate. Retrieved from http://esl.jrc.it/envind/un_meths/UN_ME040.htm

United Nations Department for Policy Coordination and Sustainable Development (UN CSD). (2008b). Total fertility rate. Retrieved from http://esl.jrc.it/envind/un_meths/UN_ME019.htm

United Nations Millennium Development Goals. (n.d.). Retrieved October 17, 2013, from http://www.un.org/millenniumgoals/maternal.shtml

WHO (World Health Organization). (2008). Maternal mortality ratio (per 100,000 livebirths). Retrieved from http://www.who.int/healthinfo/statistics/indmaternalmortality/en/index.html

WHO, UNFPA, UNICEF, and World Bank. (1999). Reduction of maternal mortality. A joint WHO/UNFPA/UNICEF/World Bank statement. Retrieved from http://www3.alliance-hpsr.org/reproductivehealth/publications/reduction_of_maternal_mortality/reduction_of_maternal_mortality_contents.htm

Wilks, S. S. (1951). Undergraduate Statistical Education. *Journal of the American Statistical Association*, *46*(253), 1–18.

Zeger, S. L., & Liang, K.-Y. (1986). Longitudinal Data Analysis for Discrete and Continuous Outcomes. *Biometrics*, *42*(1), 121-130.