Explaining the Decline of Child Mortality in 44 Developing Countries: An Bayesian extension of Oaxaca Decomposition for Probit Random Effects Models

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Abstract

This paper investigates the decline of infant mortality in 42 low and middle income countries. We use micro data from 84 Demographic and Health Surveys, a Bayesian hierarchical model, and a new extension of the Oaxaca decomposition method to study the factors associated with over time reductions in infant mortality rates. We estimate mortality risk for each one of the births in our data and decompose reductions in infant mortality rates into differences in the distribution of the factors versus the differences due to their effects. We found that most of the decline is explained by changes in effects of the factors, not their distributions. However, there is a a considerable heterogeneity between countries. Our results suggest that increasing the coverage of basic factors, such as increasing maternal education and reducing the age of the first birth can greatly reduce infant mortality.

1 Introduction

Sustainable Development Goals (SDG) for the year of 2030, that replaced the Millennium Development Goals (MDG) for 2015, call for reduction of early-life mortality. In particular, the Goal 3 of SDG aim to end preventable deaths of children under 5 years of age, with all countries aiming to reduce neonatal mortality to at least as low as 12 per 1,000 live births and under-5 mortality to at least as low as 25 per 1,000 live births. Under-five mortality rates fell rapidly from 2000 to 2015, declining by 44 per cent globally. Nevertheless, an estimated 5.9 million children under the age of 5 died in 2015, with a global under-five mortality rate of 43 per 1,000 live births. The neonatal mortality rate, that is, the likelihood of dying in the first 28 days of life, declined from 31 deaths per 1,000 live births in 2000 to 19 deaths per 1,000 live births in 2015. However, there is large variation in average levels of early-life mortality and also progress in their over time reduction from countries to countries (Rajaratnam et al., 2010). For example, Mortality among children under 5 years of age remains high in sub-Saharan Africa, with a rate of 84 deaths per 1,000 live births in 2015.

Mortality declines have been paralleled by progress in the coverage of most health determinants as well as progress in health and behavioral changes that impact early-life mortality. Infant mortality has been shown to be associated with parental characteristics, in particular, maternal age at birth (Finlay et al., 2011) (Fall et al., 2015), maternal education (Desai and Alva, 1998) (Kamal, 2012) and urban/rural residence (Van de Poel et al., 2009) (Sastry, 1997). Previous literature suggest that most of the reduction in child mortality is due to the expansion of health determinants. Using data at the national level, Bishai et al. (2016) find that 100% of the decline in child mortality is due to the expansion of the national coverage of the its health determinants, not by change in their effects. Likewise Van de Poel et al. (2009) use micro date and found that most of the gap in infant mortality between rural and urban infants can be explained by rural household disadvantage in the distribution of factors relative to urban household. To the best of our knowledge, no study use micro data for a large group of Low and Middle countries (LMIC) to investigate the factors associated with its decline. We ask whether it is possible that the declines in child mortality reviewed above are due to changes in the distribution of such factors (delayed fertility, increased female education, urbanization) rather than "real" gains in reducing child mortality given maternal characteristics - the effects of the factors.

In this paper we investigate the factors behind the recent decline of infant mortality for countries among 44 LMIC where micro data were available. Micro data allow us to have detailed information at the birth level and thus a higher resolution picture of the factors associated with the decline of infant mortality versus its distributions. We first estimate mortality risk for each one of the infants in our data. We do so using a Bayesian hierarchical probit model with random effects at the community level. We fit a model for each survey to allow for heterogeneous effects, where the same variables may have different effects in different surveys. We then quantify the decline in child mortality between surveys separately for each country by extending Oaxaca type decomposition to non-linear random effects models, based on methods developed by Ramos and Weiss (2018) but also on Fairlie (2005) and Van de Poel et al. (2009).

2 Data Description

2.1 Sample Selection

To investigate the decline of mortality risk for infants under 1 year old between years, we assembled data using two waves of the Demographic and Health Surveys (DHS) from 42 countries. The time intervals between two surveys are various and at least 10 years. For each survey, samples are selected according to maternal ages and the birth year of infants. In terms of the common childbearing age, we included samples with marternal age 15 - 45 years old (including 15 and 45 years old) to eliminate the extreme situation due to abnormal maternal ages. Meanwhile, we only keep children born one to five years before each survey to make sure each subject has more than one-year observation and data are close to the survey year. Table 1 gives a summary of the dataset, illustrating the survey year, sample size and mortality rate in each wave for all 42 countries. The proportion of deaths here refers to the proportion of deaths for live-born infants before they reach 1-year old. It declines in the later survey compared to the earlier one for all countries except for Cameroon which has same proportion in two surveys.

2.2 Variables

The variables considered in the study includes maternal factors, children status, wealth level and sampling cluster. Maternal factors refers to maternal age and mother's education level which is devided into four categories in the raw data, "no education", "primary", "secondary" and "higher education". However, maternal education level is imputed into education years, which is used as continous variable in our study. Children status is represented by sex, birth order of the child and residence. Residence is a dummy variable indicating whether the child lives in rural or urban area. The wealth level is measured by cumulative index with a range from 0 to 1. For those who are in the highest wealth level, they have a value of 1 for wealth cumulative level, while it is set to be 0 for those in the lowest level.

3 Methods

3.1 Bayesian Hierarchical Probit Model with Random Effects

For each country, let y_i denote whether or not child i experienced mortality within the first year of life in kth survey,

$$y_{ik}|\pi_{ik} \sim \text{Bern}(\pi_{ik}), \tag{1}$$

where π_{ik} is the probability of death for child i in survey k, $k \in 1, 2$, $i \in 1, \ldots, N_{jk}$, and N_k is the total number of observations in country j for survey k. Then, we are modeling y_{ik} using a probit model

$$P(y_{ik} = 1|\gamma_{ik}) = \Phi\left(\boldsymbol{x}_{ik}^T \boldsymbol{\beta}_k + \gamma_{ik}\right), \tag{2}$$

where $\Phi(\cdot)$ is the standard normal CDF, and $\boldsymbol{x}_{ik}$ is the covariate vector for birth i at time k. The cluster level random effect γ_{ik} is assumed to be normally distributed with variance σ_k^2,

$$\gamma_{ik}|\sigma_k^2 \sim N(0, \sigma_k^2).$$

The individual covariates we include in the model are a maternal age B-spline, wealth CDF B-spline, birth order B-spline, maternal education in years B-spline, gender of the birth and residence (rural versus urban). In order to interpret the intercept, we center covariates by subtracting the corresponding means in the poorest quintile. Therefore, the intercept implies the probability of death for infant at the mean status in the poorest quintile. We also include two-way interactions in the model.

3.2 Decomposition

In order to understand the difference in outcomes between different surveys, a standard approach is to decompose the difference into two parts, the part due to the difference in the distribution of covariates and another part due to the difference in covariate effects.

3.2.1 Oaxaca's Decomposition for Linear Model

Oaxaca's decomposition proposed by Oaxaca (1973) is applied to a linear regression model in O'Donnell et al. (2008). Suppose Y_{ik} is an outcome variable with covariates vector x_{ik} for subject i in group k, and the linear regression model is

$$Y_{ik} = \boldsymbol{x}_{ik}^T \boldsymbol{\beta_k} + \epsilon_{ik},$$

where $\boldsymbol{\beta}_k$ is the vector of effect parameters including intercept and ϵ_{ik} is the error term. The decomposition for the difference in two groups can be written as

$$\bar{Y}_1 - \bar{Y}_2 = \bar{\boldsymbol{x}}_1^T \boldsymbol{\beta_1} - \bar{\boldsymbol{x}}_2^T \boldsymbol{\beta_2} \tag{3}$$

$$= \underbrace{(\bar{\boldsymbol{x}}_1^T \boldsymbol{\beta_1} - \bar{\boldsymbol{x}}_2^T \boldsymbol{\beta_1})}_{\text{x effect}} + \underbrace{(\bar{\boldsymbol{x}}_2^T \boldsymbol{\beta_1} - \bar{\boldsymbol{x}}_2^T \boldsymbol{\beta_2})}_{\text{beta effect}}. \tag{4}$$

where $\bar{Y}_1$ and $\bar{Y}_2$ denote the mean outcomes in two groups, and $\bar{\boldsymbol{x}}_1$ and $\bar{\boldsymbol{x}}_2$ refer to the vectors of mean covariates in two groups. The first term in (4) represents the difference due to changes in the distribution of covariates, and the second term represents the difference due to changes in the covariate effects.

3.2.2 Decomposition for Non-linear Model

However, since the outcomes in our study are binary and modelled with a probit model, Oaxaca's decomposition for linear model cannot be applied as is. Fairlie (2005) extended the

Oaxaca's decomposition to a non-linear model,

$$Y_{ik} = F(\boldsymbol{x}_{ik}^T \boldsymbol{\beta_k}), \tag{5}$$

and the decomposition is

$$\begin{aligned}
\bar{Y}_1 - \bar{Y}_2 &= \sum_{i=1}^{N_1} \frac{F\left(\boldsymbol{x}_{i1}^T \boldsymbol{\beta}_1\right)}{N_1} - \sum_{i=1}^{N_2} \frac{F\left(\boldsymbol{x}_{i2}^T \boldsymbol{\beta}_2\right)}{N_2} &(6)\\
&= \underbrace{\left[\sum_{i=1}^{N_1} \frac{F\left(\boldsymbol{x}_{i1}^T \boldsymbol{\beta}_1\right)}{N_1} - \sum_{i=1}^{N_2} \frac{F\left(\boldsymbol{x}_{i2}^T \boldsymbol{\beta}_1\right)}{N_2}\right]}_{\text{x effext}} + \underbrace{\left[\sum_{i=1}^{N_2} \frac{F\left(\boldsymbol{x}_{i2}^T \boldsymbol{\beta}_1\right)}{N_2} - \sum_{i=1}^{N_2} \frac{F\left(\boldsymbol{x}_{i2}^T \boldsymbol{\beta}_2\right)}{N_2}\right]}_{\text{beta effect}}, &(7)
\end{aligned}$$

where N_1 and N_2 are total number of subjects in group 1 and group 2.

3.2.3 Overall Decomposition for the probit model

In the study, for each country, we want to decompose the difference in the estimated mortality rates between surveys 1 and 2 into effects due to changes in the distribution of covariates and effects due to changes in the covariate response. If we do not include the random effects in the model, the probit model in (2) can be written as

$$\mathrm{P}(y_{ik} = 1) = \Phi\left(\boldsymbol{x}_{ik}^T \boldsymbol{\beta}_k\right). \tag{8}$$

Combined with (1), we have $E(y_{ik}) = \pi_{ik} = \Phi\left(\boldsymbol{x}_{ik}^T \boldsymbol{\beta}_k\right)$. In this occasion, Y_{ik} in (5) is replace by $\mathrm{P}(y_{ik} = 1)$, and the non-linear function $F(\cdot) = \Phi(\cdot)$. Therefore, the decomposition for the difference between two surveys can be written as

$$\bar{P}_1 - \bar{P}_2 = \sum_{i=1}^{N_1} \frac{E(y_{i1})}{N_1} - \sum_{i=1}^{N_2} \frac{E(y_{i2})}{N_2}, \tag{9}$$

$$= \Big[\sum_{i=1}^{N_1} \frac{\Phi(\boldsymbol{x}_{i1}^T \boldsymbol{\beta}_1)}{N_1} - \sum_{i=1}^{N_2} \frac{\Phi(\boldsymbol{x}_{i2}^T \boldsymbol{\beta}_1)}{N_2} \Big] + \Big[\sum_{i=1}^{N_2} \frac{\Phi(\boldsymbol{x}_{i2}^T \boldsymbol{\beta}_1)}{N_2} - \sum_{i=1}^{N_2} \frac{\Phi(\boldsymbol{x}_{i2}^T \boldsymbol{\beta}_2)}{N_2} \Big], \tag{10}$$

where $\bar{P}_k$ denotes the mean mortality probability in for survey k. The first term in (10) represents the difference due to the changes in the overall distribution of covariates, and the second term represents the difference due to the changes in the overall coefficients.

However, when random effects γ_{ik} are included in the model as (2), given $E(y_{ik}|\gamma_{ik}) = \pi_{ik} = \Phi\left(\boldsymbol{x}_{ik}^T \boldsymbol{\beta}_k + \gamma_{ik}\right)$, we can replace the left hand side of (9) with its expectation to get

$$\mathrm{E}\left[\bar{P}_1 - \bar{P}_2\right] = \sum_{i=1}^{N_1} \frac{\mathrm{E}\left[\mathrm{E}[y_{i1}|\gamma_{i1}]\right]}{N_1} - \sum_{i=1}^{N_2} \frac{\mathrm{E}\left[\mathrm{E}[y_{i2}|\gamma_{i2}]\right]}{N_2} \tag{11}$$

$$= \sum_{i=1}^{N_1} \frac{\mathrm{E}[y_{i1}]}{N_1} - \sum_{i=1}^{N_2} \frac{\mathrm{E}[y_{i2}]}{N_2}, \tag{12}$$

which is equivalent in form to (9). Thus, to do the decomposition, we need to calculate the marginal expected values of the y_{ik}, which is developed in McCulloch (2008). Let Z be a standard normal random variable, given $\Phi(x) = P(Z < x|x)$,

$$\begin{aligned}
E(y_{ik}) &= E[E(y_{ik}|\gamma_{ik})] && (13)\\
&= E\Big[P(Z < \boldsymbol{x}_{ik}^T\boldsymbol{\beta}_k + \gamma_{ik}|\gamma_{ik})\Big] && (14)\\
&= P(Z < \boldsymbol{x}_{ik}^T\boldsymbol{\beta}_k + \gamma_{ik}) && (15)\\
&= \Phi\Big(\frac{\boldsymbol{x}_{ik}^T\boldsymbol{\beta}_k}{\sqrt{1+\sigma_k^2}}\Big) && (16)\\
&= \Phi(\boldsymbol{x}_{ik}^T\tilde{\boldsymbol{\beta}}_k), && (17)
\end{aligned}$$

where $\tilde{\boldsymbol{\beta}}_k = \frac{\boldsymbol{\beta}_k}{\sqrt{1+\sigma_k^2}}$. Thus, the marginal model for the probability that $y_{ik} = 1$ is a probit model with the regression coefficients multiplied by a correction factor of $\sqrt{1+\sigma_k^2}$. Thus, we can replace the coefficients in (10) to write the decomposition as

$$\mathrm{E}\left[\bar{P}_1 - \bar{P}_2\right] = \underbrace{\left[\sum_{i=1}^{N_1} \frac{\Phi\left(\boldsymbol{x}_{i1}^T\tilde{\boldsymbol{\beta}}_1\right)}{N_1} - \sum_{i=1}^{N_2} \frac{\Phi\left(\boldsymbol{x}_{i2}^T\tilde{\boldsymbol{\beta}}_1\right)}{N_2}\right]}_{\text{x effect}} + \underbrace{\left[\sum_{i=1}^{N_2} \frac{\Phi\left(\boldsymbol{x}_{i2}^T\tilde{\boldsymbol{\beta}}_1\right)}{N_2} - \sum_{i=1}^{N_2} \frac{\Phi\left(\boldsymbol{x}_{i2}^T\tilde{\boldsymbol{\beta}}_2\right)}{N_2}\right]}_{\text{beta effect}} \quad (18)$$

4 Preliminary Results and Conclusions

Our decomposition results suggest that most of the decline in infant mortality in recent decades were due to the change in the effects of factors, not on the distribution of the factors. For all countries, more than 60% of the decline can be explained by effect of the factors. However, there is considerable heterogeneity on the effect of the factors.

These results are surprisingly compared with the previous literature that mostly attributed most mortality reductions to change in the distribution of the factors Van de Poel et al. (2009). However, our results are robust, based on detailed micro data and also consistent with the raw micro data.

However, the distribution of the factors are far from ideal. For example, many mothers are poorly educated and have births at the very young age. Thus the main policy implication is that changes in the distribution of factors can further reduce mortality, as they have important effects on the mortality. They can accelerate progress toward SDG.

Given the heterogeneity into these effects, policies should be tailored according to countries needs. Priorities vary between countries. For example, higher birth order are more strongly associated with higher risk of death in Zimbabwe than in Mali and Madagascar.

In terms of comparison with the previous literature, one limitation of our work is that we investigate reduction in infant mortality risk, which is not exactly reduction on national averages of infant mortality. However, this limitation is inherent to the fact we are using micro data to estimate mortality risk at the birth level. And this limitation is also one of the major strength of our research as provide individual level informational that be very relevant for policy

Our study did not include several important variables that are linked to child mortality, such as vaccination breastfeeding and knowledge of Oral Rehydration Solution. However, most the factors we include in the study are similar to those excluded variables. For example, increasing maternal education is consistent with higher contraception use and delayed fertility.

In the next stage of analysis we hope to 1) include additional variables:access to clean water, access to toilet, floor type and access to electricity at home. 2) decompose the effects of the factors, one at the time (for each beta in the regression model) ; 3) simulate what would have been the decline in child mortality have the distribution of important factors, such as maternal age, increased in coverage.

Table 1. A summary of dataset for two surveys in 42 countries

Country	Survey 1			Survey 2		
	Year	Sample size	Proportion of deaths	Year	Sample size	Proportion of deaths
Philippines	1993	7315	0.039	2013	5841	0.027
Indonesia	1997	14662	0.049	2012	14244	0.036
Colombia	1990	2930	0.023	2005	10975	0.022
India	1993	42701	0.073	2006	40833	0.052
Jordan	1990	6721	0.032	2012	8585	0.022
Zimbabwe	1994	3316	0.059	2015	4893	0.055
Bolivia	1998	5755	0.066	2008	6821	0.045
Dominican Republic	1996	1470	0.044	2013	3623	0.031
Pakistan	1991	4614	0.085	2012	7862	0.069
Armenia	2000	1453	0.040	2010	1077	0.014
Ghana	1993	2303	0.075	2014	4464	0.051
Morocco	1992	4171	0.058	2003	4101	0.041
Turkey	1993	2926	0.057	2004	3405	0.034
Senegal	1997	5477	0.079	2015	7645	0.038
Gabon	2000	2525	0.061	2012	4552	0.040
Guinea	1999	4805	0.109	2012	5367	0.077
Bangladesh	2000	5323	0.069	2014	7733	0.041
Kenya	1993	4833	0.061	2014	16607	0.039
Guatemala	1999	3782	0.050	2015	9099	0.028
Uganda	1995	5568	0.090	2011	6178	0.058
Egypt	1995	7402	0.071	2014	12043	0.024
Togo	1998	5497	0.090	2014	4950	0.050
Peru	1992	6468	0.062	2012	18988	0.020
Kyrgyzstan	1997	1616	0.059	2012	3197	0.030
Namibia	1992	2948	0.066	2013	3812	0.046
Cameroon	1991	2546	0.067	2011	8937	0.067
Nigeria	1990	6005	0.103	2013	26019	0.073
Haiti	1994	2215	0.079	2012	5586	0.065
Tanzania	1999	3802	0.091	2015	6430	0.041
Burkina Faso	1993	4363	0.103	2010	11701	0.075
Cambodia	2000	6929	0.103	2014	5590	0.029
Mozambique	1997	5614	0.120	2011	8265	0.067
Madagascar	1997	4721	0.104	2009	9294	0.049
Cote dIvoire	1999	1367	0.116	2012	5915	0.081
Rwanda	1992	4454	0.086	2015	5579	0.031
Chad	1997	5552	0.118	2015	13697	0.072
Comoros	1996	1607	0.078	2012	2345	0.030
Zambia	1996	4335	0.118	2013	9254	0.050
Niger	1998	6152	0.133	2012	9530	0.062
Mali	1996	7354	0.134	2012	6823	0.062
Benin	1996	3968	0.106	2012	10361	0.048
Malawi	1992	3365	0.138	2015	11429	0.042

Table 2. A summary of mean mortality probability in two surveys for 42 countries. (Countries are ordered by the mean of difference from smallest to largest.)

		Mean mortality probability		
Country	Time interval (years)	Survey 1	Survey 2	Difference
Philippines	20	0.030 (0.024, 0.037)	0.022 (0.017, 0.029)	0.008 (-0.002, 0.017)
Indonesia	15	0.028 (0.024, 0.032)	0.019 (0.016, 0.023)	0.008 (0.003, 0.014)
Colombia	15	0.025 (0.017, 0.034)	0.013 (0.010, 0.016)	0.012 (0.004, 0.023)
India	13	0.034 (0.031, 0.037)	0.022 (0.020, 0.024)	0.012 (0.008, 0.015)
Jordan	22	0.031 (0.022, 0.043)	0.017 (0.012, 0.022)	0.014 (0.004, 0.028)
Zimbabwe	21	0.067 (0.048, 0.089)	0.048 (0.037, 0.061)	0.019 (-0.003, 0.044)
Bolivia	10	0.053 (0.043, 0.063)	0.032 (0.026, 0.040)	0.020 (0.007, 0.033)
Dominican Republic	17	0.052 (0.037, 0.072)	0.029 (0.021, 0.040)	0.023 (0.004, 0.044)
Pakistan	21	0.076 (0.061, 0.093)	0.053 (0.043, 0.063)	0.023 (0.004, 0.043)
Armenia	10	0.044 (0.028, 0.065)	0.020 (0.010, 0.034)	0.024 (0.002, 0.047)
Ghana	21	0.072 (0.054, 0.091)	0.048 (0.036, 0.062)	0.024 (0.002, 0.048)
Morocco	11	0.063 (0.044, 0.086)	0.038 (0.028, 0.051)	0.024 (0.002, 0.050)
Turkey	11	0.052 (0.039, 0.067)	0.027 (0.019, 0.037)	0.024 (0.008, 0.042)
Senegal	18	0.069 (0.055, 0.087)	0.044 (0.032, 0.060)	0.025 (0.004, 0.047)
Gabon	12	0.069 (0.050, 0.093)	0.042 (0.030, 0.056)	0.027 (0.003, 0.055)
Guinea	13	0.098 (0.078, 0.121)	0.071 (0.055, 0.088)	0.027 (0.002, 0.056)
Bangladesh	14	0.060 (0.048, 0.074)	0.030 (0.023, 0.038)	0.030 (0.015, 0.045)
Kenya	21	0.053 (0.041, 0.066)	0.021 (0.017, 0.025)	0.032 (0.020, 0.046)
Guatemala	16	0.052 (0.037, 0.070)	0.019 (0.015, 0.025)	0.033 (0.017, 0.051)
Uganda	16	0.082 (0.067, 0.100)	0.050 (0.039, 0.062)	0.033 (0.011, 0.054)
Egypt	19	0.049 (0.041, 0.059)	0.015 (0.012, 0.019)	0.034 (0.025, 0.045)
Togo	16	0.082 (0.063, 0.104)	0.048 (0.036, 0.061)	0.034 (0.011, 0.058)
Peru	20	0.045 (0.036, 0.054)	0.010 (0.008, 0.012)	0.035 (0.026, 0.045)
Kyrgyzstan	15	0.075 (0.050, 0.103)	0.034 (0.023, 0.049)	0.040 (0.012, 0.072)
Namibia	11	0.081 (0.058, 0.111)	0.039 (0.030, 0.050)	0.042 (0.016, 0.074)
Cameroon	20	0.092 (0.065, 0.125)	0.047 (0.039, 0.057)	0.044 (0.015, 0.078)
Nigeria	23	0.087 (0.070, 0.106)	0.042 (0.037, 0.048)	0.045 (0.026, 0.065)
Haiti	18	0.103 (0.073, 0.139)	0.055 (0.044, 0.067)	0.048 (0.016, 0.086)
Tanzania	16	0.087 (0.068, 0.107)	0.034 (0.027, 0.043)	0.052 (0.033, 0.075)
Burkina Faso	17	0.106 (0.083, 0.136)	0.051 (0.043, 0.060)	0.055 (0.030, 0.085)
Cambodia	14	0.082 (0.069, 0.098)	0.025 (0.018, 0.032)	0.058 (0.042, 0.074)
Mozambique	14	0.107 (0.090, 0.126)	0.048 (0.040, 0.057)	0.059 (0.040, 0.079)
Madagascar	12	0.097 (0.076, 0.120)	0.034 (0.027, 0.042)	0.062 (0.039, 0.086)
Cote dIvoire	13	0.133 (0.099, 0.176)	0.069 (0.055, 0.086)	0.064 (0.026, 0.109)
Rwanda	23	0.092 (0.071, 0.119)	0.027 (0.020, 0.036)	0.065 (0.042, 0.094)
Chad	18	0.114 (0.093, 0.140)	0.047 (0.040, 0.055)	0.067 (0.044, 0.094)
Comoros	16	0.109 (0.073, 0.156)	0.039 (0.025, 0.056)	0.070 (0.030, 0.120)
Zambia	17	0.107 (0.088, 0.129)	0.035 (0.028, 0.042)	0.072 (0.052, 0.096)
Niger	14	0.119 (0.097, 0.142)	0.046 (0.037, 0.057)	0.073 (0.049, 0.098)
Mali	16	0.125 (0.105, 0.147)	0.050 (0.040, 0.062)	0.075 (0.051, 0.099)
Benin	16	0.112 (0.087, 0.141)	0.032 (0.026, 0.039)	0.080 (0.055, 0.110)
Malawi	23	0.137 (0.111, 0.168)	0.026 (0.021, 0.032)	0.111 (0.084, 0.142)

Table 3. A summary of decomposition results for the decline of child mortality risk in 42 countries. (Countries are in the same order as Table 2.)

	X effects		Beta effects	
Country	Contribution	%	Contribution	%
Philippines	0.000 (-0.006, 0.005)	5.145 (-76.944, 65.217)	0.007 (-0.003, 0.018)	94.855 (-36.868, 236.295)
Indonesia	0.001 (-0.003, 0.005)	16.827 (-29.987, 55.121)	0.007 (0.001, 0.013)	83.173 (8.398, 158.152)
Colombia	0.003 (-0.001, 0.006)	21.850 (-9.887, 51.951)	0.009 (0.000, 0.020)	78.150 (3.747, 170.688)
India	0.002 (0.001, 0.004)	21.136 (9.594, 31.994)	0.009 (0.006, 0.013)	78.864 (49.215, 109.482)
Jordan	0.005 (-0.002, 0.010)	31.832 (-12.831, 72.124)	0.01 (-0.001, 0.023)	68.168 (-6.427, 156.537)
Zimbabwe	0.005 (-0.007, 0.015)	26.024 (-37.013, 78.420)	0.014 (-0.009, 0.041)	73.976 (-47.094, 213.012)
Bolivia	-0.001 (-0.010, 0.006)	-2.898 (-51.144, 28.609)	0.021 (0.007, 0.037)	102.898 (33.826, 185.552)
Dominican Republic	0.000 (-0.005, 0.005)	1.428 (-21.152, 22.326)	0.023 (0.004, 0.044)	98.572 (16.772, 189.704)
Pakistan	0.004 (-0.002, 0.010)	15.759 (-10.026, 44.481)	0.019 (0.000, 0.041)	84.241 (1.011, 181.945)
Armenia	0.007 (0.001, 0.014)	28.382 (2.628, 57.753)	0.017 (-0.004, 0.038)	71.618 (-16.863, 161.365)
Ghana	-0.003 (-0.012, 0.005)	-12.077 (-49.450, 22.107)	0.027 (0.003, 0.053)	112.077 (11.895, 218.521)
Morocco	-0.004 (-0.011, 0.002)	-16.256 (-43.782, 9.319)	0.028 (0.006, 0.054)	116.256 (25.749, 222.379)
Turkey	-0.001 (-0.006, 0.003)	-4.637 (-26.518, 13.771)	0.025 (0.008, 0.044)	104.637 (33.254, 181.505)
Senegal	-0.004 (-0.011, 0.003)	-16.053 (-45.237, 11.244)	0.029 (0.007, 0.054)	116.053 (28.355, 215.158)
Gabon	0.001 (-0.003, 0.005)	4.291 (-10.450, 18.059)	0.026 (0.003, 0.053)	95.709 (10.205, 193.496)
Guinea	0.003 (0.000, 0.005)	9.541 (-1.079, 19.780)	0.025 (0.000, 0.053)	90.459 (0.023, 191.824)
Bangladesh	0.000 (-0.007, 0.007)	1.329 (-23.408, 23.915)	0.029 (0.014, 0.047)	98.671 (46.413, 157.79)
Kenya	0.000 (-0.009, 0.007)	0.030 (-28.992, 23.399)	0.032 (0.019, 0.048)	99.970 (58.081, 150.197)
Guatemala	0.006 (0.001, 0.011)	18.668 (1.595, 34.843)	0.027 (0.011, 0.046)	81.332 (34.595, 138.475)
Uganda	0.006 (0.001, 0.01)	17.053 (4.587, 30.487)	0.027 (0.005, 0.049)	82.947 (16.811, 149.603)
Egypt	0.005 (-0.005, 0.013)	14.487 (-13.077, 38.030)	0.029 (0.018, 0.043)	85.513 (51.246, 123.726)
Togo	0.005 (0.000, 0.011)	15.72 (-0.980, 31.353)	0.029 (0.006, 0.053)	84.28 (18.495, 155.290)
Peru	0.009 (0.003, 0.014)	25.542 (8.010, 40.319)	0.026 (0.017, 0.036)	74.458 (48.315, 105.317)
Kyrgyzstan	-0.001 (-0.013, 0.010)	-2.499 (-33.316, 24.832)	0.041 (0.011, 0.076)	102.499 (28.466, 189.711)
Namibia	0.002 (-0.013, 0.014)	4.000 (-31.156, 33.869)	0.040 (0.013, 0.075)	96.000 (31.308, 178.601)
Cameroon	0.016 (0.008, 0.026)	37.241 (17.831, 58.514)	0.028 (0.001, 0.060)	62.759 (2.629, 134.737)
Nigeria	-0.002 (-0.010, 0.005)	-4.525 (-21.597, 10.312)	0.047 (0.027, 0.068)	104.525 (59.423, 151.612)
Haiti	-0.006 (-0.024, 0.010)	-11.532 (-49.817, 21.236)	0.054 (0.019, 0.097)	111.532 (39.426, 200.300)
Tanzania	-0.003 (-0.008, 0.001)	-6.653 (-15.854, 1.753)	0.056 (0.035, 0.078)	106.653 (66.948, 147.864)
Burkina Faso	-0.005 (-0.011, 0.001)	-8.267 (-20.616, 2.712)	0.059 (0.033, 0.093)	108.267 (59.778, 168.796)
Cambodia	0.002 (-0.007, 0.010)	3.102 (-12.063, 16.647)	0.056 (0.039, 0.075)	96.898 (66.879, 130.276)
Mozambique	0.003 (-0.005, 0.010)	5.024 (-8.096, 16.496)	0.056 (0.036, 0.078)	94.976 (60.820, 131.876)
Madagascar	0.002 (-0.002, 0.006)	3.294 (-3.329, 9.807)	0.060 (0.037, 0.085)	96.706 (59.104, 135.615)
Cote dIvoire	-0.005 (-0.019, 0.009)	-7.731 (-30.160, 14.037)	0.069 (0.027, 0.120)	107.731 (42.851, 186.904)
Rwanda	0.005 (-0.003, 0.013)	7.481 (-5.036, 20.075)	0.060 (0.036, 0.088)	92.519 (55.687, 135.062)
Chad	0.017 (-0.003, 0.033)	24.869 (-5.124, 49.701)	0.050 (0.024, 0.08)	75.131 (36.394, 119.58)
Comoros	-0.002 (-0.013, 0.008)	-2.481 (-19.004, 11.122)	0.072 (0.03, 0.123)	102.481 (43.017, 174.038)
Zambia	0.001 (-0.006, 0.008)	2.017 (-8.507, 11.638)	0.071 (0.05, 0.095)	97.983 (69.526, 131.098)
Niger	0.002 (-0.001, 0.005)	2.511 (-1.998, 6.650)	0.071 (0.047, 0.096)	97.489 (64.659, 131.226)
Mali	-0.007 (-0.014, 0.000)	-8.723 (-18.771, 0.388)	0.081 (0.057, 0.107)	108.723 (75.664, 143.561)
Benin	0.003 (-0.004, 0.010)	4.068 (-4.648, 12.431)	0.077 (0.051, 0.106)	95.932 (64.177, 132.090)
Malawi	-0.010 (-0.022, 0.003)	-8.742 (-20.215, 2.535)	0.120 (0.091, 0.154)	108.742 (82.505, 138.757)

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