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Abstract

We develop a novel extension of Oaxaca decomposition methods for non-linear random effects models to investigate the decline of infant mortality in 42 low and middle income countries. We analyze micro data from 84 Demographic and Health Surveys where surveys from two time periods were available. We predict mortality at the birth level with a Bayesian hierarchical probit regression models. We use the predictions from these models as input for our new Oaxaca method. Our novel approach accounts for uncertainty in the decompostion results, and allows for point estimates, standard deviations, and posterior distributions of the Oaxaca conclusions. Further, our approach does not depend on assumptions such as matched samples between two surveys and and marginalizes random effects for variables that are not comparable between surveys, such as location effects. For most countries, declines in infant mortality are due to changes in the regression coefficients, not on covariate distributions. However, our decomposition results show that there is considerable heterogeneity between countries and uncertainty on which variable matter the most within countries.

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1 Introduction

Sustainable Development Goals (SDGs) target three for 2030 call for reduction of early-life mortality (ELM). In particular, it calls for all countries to reduce their neonatal mortality to no more than 12 deaths per 1,000 live births and their under-5 mortality to no more than 25 deaths per 1,000 live births (Economic and Commision, 2016). Despite a 44% reduction in child mortality globally from 2000 to 2015, there were still an estimated 5.9 million child deaths in 2015 with a global child mortality rate of 43 deaths per 1,000 live births `https://www.who.int/news-room/fact-sheets/detail/children-reducing-mortality`. Similarly, the neonatal mortality rate declined from 31 deaths per 1,000 live births in 2000 to 19 deaths per 1,000 live births in 2015, still well above SDG goal 3. Progress toward the SDGs has varied widely from country to country (Rajaratnam et al., 2010). Many countries, particularly in sub-Saharan Africa and Southeast Asia still have high infant mortality rates, some as high as 84 deaths per 1,000 live births. To assess whether declines in ELM can be expected to continue and the corresponding SDG-3 targets to be reached requires a better understanding of the determinants of these declines.

Infant and child survival is known to be associated with several parental characteristics, e.g., whether a child's mother has completed her primary education (Desai and Alva, 1998) (Kamal, 2012). Were recent declines to be driven by increases in the proportion of mothers having completed primary school, for instance, future declines might depend on whether future educational gains can be expected or whether this proportion is now approaching 100%. Similarly, ELM has been shown to be associated with younger maternal age at birth (Finlay et al., 2011) and rural parental residence (Van de Poel et al., 2009) (Sastry, 1997). Using data at the national level, Bishai et al. (2016) find that most of the decline of the child mortality was due to improvements in the societal coverage of a broad array of health system, social, economic and environmental determinants of child health. Likewise Van de Poel et al. (2009) use micro data from Sub-Saharan Africa and found that most of the gap in infant mortality between rural and urban populations can be explained by rural household disadvantage in the distribution of risk factors relative to urban households. A similar conclusion as reached by Saikia et al. (2013) that found that most of the rural-urban gap in child mortality in India can be

explained by rural households disadvantage in the distribution of factors. However, to the best of our knowledge, no papers use micro data to analyze the decline of child mortality for a broad range of Low and Middle Income Countries (LMIC).

To our knowledge, no study to date has undertaken a systematic investigation of the role of distributional changes in parental characteristics in recent ELM across Low and Middle Income Countries (LMIC). This may be due to the methodological challenges presented by analyzing individual-level data to determine how much of the difference in average mortality between two populations is due to differences in the distribution of covariates of survival versus differences in the covariate-survival relationship. Decomposition methods have been developed to separate the contribution of differences in distribution (typically referred to as populations' "endowment") and differences in relationship (typically referred to as "propensities"). Kitagawa (1955) introduced a "categorical" form of decomposition for the difference between two aggregate rates using population distribution across groups (categories). Oaxaca (1973) introduced a "statistical" form of decomposition using linear regression models. A number of methodological developments have built on these two seminal contributions, but as discussed in the next section, none of these is fully adapted to take advantage of the wealth of microdata on parental, birth and geographic characteristics that are available in demographic and health surveys and that can used to estimate mortality risk at the individual level using non-linear random effects models.

In this paper, we present new methods to undertake such a decomposition using predictions for infant mortality risk from a non-linear model Bayesian hierarchical random effects model. We then apply these methods to data from 44 LMIC for which micro data is available using. Bayesian hierarchical random effects model with geographic location level random effects. We include countries with a variety of levels of infant mortality and estimate mortality risk using observable parental, individual and geographic characteristics that available in a comparable fashion for 44 developing countries using microdata from Demographic and Health Surveys (DHS).

We show that most of the decline in ELM mortality in LMIC in recent decades has been due to changes in propensities (i.e., changes in the effects of covariates) rather than changes in endowments (i.e., distributional changes. However, there is large heterogeneity between and within countries.

When we look at the effects of the individual covariates in the coefficient by coefficient decomposition within countries, it is difficult to assess which variable mattered the most because of large uncertainty in our estimates. Still, decline in child mortality seems to be associated mostly with changes in the intercept term over time, which suggests that the decline has also been associated with general improvements in health, beyond the covariates that were included in the models. Our results suggest that there is still much room for decline in ELM and that ELM-related SDG 3 might be attainable faster if improvements in health were accompanied by changes in the distribution of important covariates of ELM, such as maternal education and age at birth.

Our paper is organized as follows. Section 2 introduce our new decomposition methods outlining is innovation vis-a-vis current methods.Section 3 introduces the data used in our analyses and describes the statistical model used to estimate mortality risk. Section 4 reports on our empirical findings. Section 5 discusses the methodological and policy implications of our findings.

2 Oaxaca Decomposition

Oaxaca Decomposition methods take two populations under consideration and fit separate regression models to each population to estimate average response for each population. The average difference between populations is decomposed into two parts, one that is due to covariate distribution effects (the distribution of the X's or of the parental, birth and geographic characteristics) and another that is due to differences in the covariate-response relationship (regression coefficients which are the effects of those characteristics on infant mortality). In multivariate models, one can further decompose overall effects into individual X and β effects.

In its original formulation, Oaxaca decomposition methods make use of the fact that in linear models, the average *estimated* response in a population is equal to the response at the average covariate value in the population. However, to take advantage of the parental, individual, and geographic information available in surveys, mortality risk need to be estimated estimated individual levels models. In these models, because of their non-linearity, the average *estimated* response is not equal to the response at the average covariate value. Overcoming this limitation, Fairlie (2005) developed a

Oaxaca decomposition for logit and probit models, assuming matched samples between two population and fitting a model to the pooled data. Bauer and Sinning (2008) built upon this approach and extended the Oaxaca decomposition to a more general class of non-linear models. Van de Poel et al. (2009) extended Oaxaca decompositions to binary response models with random effects for geographic locations (community effects). Van de Poel et al. (2009) also treat random effects as regular regression coefficients for their decomposition procedure but they do not provide uncertainty estimates for their decomposition results.

Despite all these efforts a number of important methodological gaps remain in the application of Oaxaca decomposition methods to the decline in ELM. While it is possible to further decompose the covariate effect into the effects of individual covariates, to our knowledge similar decompositions do not exist for the effect of individual coefficients. Moreover, existing methods require matched samples between the two populations under consideration. This is not generally a reasonable assumption to make when the populations are very different, such as rural versus urban populations, or wealthy versus poor populations. Another undesirable consequence of the assumption of matched samples is that when the samples are of unequal size, it is necessary to over sample the smaller population, which can bias the results.

A related issue arises when we have models with random effects. The method proposed by Van de Poel et al. (2009) has random effects for location, but this assumes that locations are the same in the two populations. While location effects can be of scientific interest, often times we are interested in the unconditional effect of the covariates on ELM, which requires us to marginalize out the random effects.

Most importantly, none of the previous work propagates uncertainty from the estimation of the mortality risk stage to the decomposition analysis stage. This is important because we need to know what decompositions results are statistically significant.

To understand how the outcomes differ between two different surveys, a standard approach is to decompose the difference into two parts using the Oaxaca decomposition. One part is due to the differences in the distribution of covariates and the second is due to the differences in the regression coefficients between two surveys.

2.1 Overall Oaxaca Deomposition

Suppose for subject i in survey k, y_{ik} were a continuous outcome variable defined on the real line with x_{ik} as a covariate vector, and we modeled y_{ik} using a linear regression

$$y_{ik} = \boldsymbol{x}'_{ik}\boldsymbol{\beta}_k + \epsilon_{ik},$$

where $\boldsymbol{\beta}_k$ is a vector of regression coefficients in survey k, and ϵ_{ik} is a normal error term with variance σ_k^2. Letting $\hat{\boldsymbol{\beta}}_k$ be the least squares estimate for $\boldsymbol{\beta}_k$, the mean response in survey k is $\bar{y}_k = \frac{1}{N_k}\sum_{i=1}^{N_k} \boldsymbol{x}'_{ik}\hat{\boldsymbol{\beta}}_k = \bar{\boldsymbol{x}}'_k\hat{\boldsymbol{\beta}}_k$. The decomposition for the difference in two surveys is

$$\bar{y}_1 - \bar{y}_2 = \bar{\boldsymbol{x}}'_1\hat{\boldsymbol{\beta}}_1 - \bar{\boldsymbol{x}}'_2\hat{\boldsymbol{\beta}}_2 \tag{1}$$

$$= \underbrace{(\bar{\boldsymbol{x}}'_1\hat{\boldsymbol{\beta}}_1 - \bar{\boldsymbol{x}}'_2\hat{\boldsymbol{\beta}}_1)}_{\text{X effect}} + \underbrace{(\bar{\boldsymbol{x}}'_2\hat{\boldsymbol{\beta}}_1 - \bar{\boldsymbol{x}}'_2\hat{\boldsymbol{\beta}}_2)}_{\text{coefficient effect}}. \tag{2}$$

The first term in (2) represents the difference due to changes in the distribution of covariates, and the second term represents the difference due to changes in the regression coefficients.

a similar decomposition exists for a general nonlinear model $y_{ik} = F(\boldsymbol{x}_{ik}^T\boldsymbol{\beta}_k)$,

$$\bar{Y}_1 - \bar{Y}_2 = \sum_{i=1}^{N_1} \frac{F\left(\boldsymbol{x}_{i1}^T\boldsymbol{\beta}_1\right)}{N_1} - \sum_{i=1}^{N_2} \frac{F\left(\boldsymbol{x}_{i2}^T\boldsymbol{\beta}_2\right)}{N_2} \tag{3}$$

$$= \underbrace{\left[\sum_{i=1}^{N_1} \frac{F\left(\boldsymbol{x}_{i1}^T\boldsymbol{\beta}_1\right)}{N_1} - \sum_{i=1}^{N_2} \frac{F\left(\boldsymbol{x}_{i2}^T\boldsymbol{\beta}_1\right)}{N_2}\right]}_{\text{X effext}} + \underbrace{\left[\sum_{i=1}^{N_2} \frac{F\left(\boldsymbol{x}_{i2}^T\boldsymbol{\beta}_1\right)}{N_2} - \sum_{i=1}^{N_2} \frac{F\left(\boldsymbol{x}_{i2}^T\boldsymbol{\beta}_2\right)}{N_2}\right]}_{\text{coefficient effect}}, \tag{4}$$

As Fairlie (2005) notes, For a probit model, taking F to be the cumulative distribution function (CDF) of a standard normal random variable, the left hand side of (3) is only approximately equal to the right hand side, but the approximation is generally very close.

2.1.1 Overall Decomposition for the Probit Model with Random Effects

In the study, for each country, we want to decompose the difference in the estimated mortality rates between surveys 1 and 2 into covariate effects and coefficient effects. However, the model (14) and (15)

contains cluster random effects γ_{jk}. The number and location of clusters is not generally comparable between surveys. Therefore, we base our decompositions on the *marginal* model by integrating out the random effects. Let $\tilde{\pi}_{ijk}$ be the probability of death in the marginal model. Then

$$\begin{aligned}
\tilde{\pi}_{ijk} &= \mathrm{P}\left(y_{ijk} = 1 | \boldsymbol{\beta}_k\right) && (5)\\
&= \mathrm{E}\left(y_{ijk} | \boldsymbol{\beta}_k\right) && (6)\\
&= \mathrm{E}\left[\mathrm{E}[y_{ijk} | \boldsymbol{\beta}_k, \gamma_{jk}]\right] && (7)\\
&= \Phi(\boldsymbol{x}_{ijk}^T \tilde{\boldsymbol{\beta}}_k), && (8)
\end{aligned}$$

where $\tilde{\boldsymbol{\beta}}_k = \frac{\boldsymbol{\beta_k}}{\sqrt{1+\sigma_k^2}}$ and (7) follows from iterated expectation formulas. The proof of equation (8) is provided in the appendix. Thus, the marginal model for the probability that $y_{ijk} = 1$ is still a probit model with the regression coefficients multiplied by a correction factor of $\sqrt{1+\sigma_k^2}$.

Substituting (8) for $F(\cdot)$ in (4), the decomposition becomes

$$\mathrm{E}\left[\bar{y}_1 - \bar{y}_2\right] \approx \underbrace{\left[\sum_{j=1}^{n_1}\sum_{i=1}^{N_{j1}} \frac{\Phi\left(\boldsymbol{x}_{ij1}^T \tilde{\boldsymbol{\beta}}_1\right)}{N_1} - \sum_{j=1}^{n_2}\sum_{i=1}^{N_{j2}} \frac{\Phi\left(\boldsymbol{x}_{ij2}^T \tilde{\boldsymbol{\beta}}_1\right)}{N_2}\right]}_{\text{X effect}} + \underbrace{\left[\sum_{j=1}^{n_2}\sum_{i=1}^{N_{j2}} \frac{\Phi\left(\boldsymbol{x}_{ij2}^T \tilde{\boldsymbol{\beta}}_1\right)}{N_2} - \sum_{j=1}^{n_2}\sum_{i=1}^{N_{j2}} \frac{\Phi\left(\boldsymbol{x}_{ij2}^T \tilde{\boldsymbol{\beta}}_2\right)}{N_2}\right]}_{\text{beta effect}} \tag{9}$$

2.1.2 Coefficient By Coefficient Decomposition for the Probit model

Once we have the overall decomposition, it can be of interest to explore the effect of individual regression coefficients on the overall decomposition. Suppose there are two covariates in the model and an intercept term. Then $\boldsymbol{x}_{ijk} = (1, x_{ijk1}, x_{ijk2})^T$ and $\tilde{\boldsymbol{\beta}}_k = (\tilde{\beta}_{k0}, \tilde{\beta}_{k1}, \tilde{\beta}_{k2})^T$. The overall beta effect can be decomposed sequentially into the contributions of each coefficient or set of coefficients

as follows,

$$\text{Overall beta effect} = \left[\sum_{j=1}^{n_2}\sum_{i=1}^{N_{j2}} \frac{\Phi\left(\boldsymbol{x}_{ij2}^T\tilde{\boldsymbol{\beta}}_1\right)}{N_{j2}} - \sum_{j=1}^{n_2}\sum_{i=1}^{N_{j2}} \frac{\Phi\left(\boldsymbol{x}_{ij2}^T\tilde{\boldsymbol{\beta}}_2\right)}{N_{j2}}\right] \tag{10}$$

$$= \underbrace{\left[\sum_{j=1}^{n_2}\sum_{i=1}^{N_{j2}} \frac{\Phi\left(\tilde{\beta}_{10} + x_{ij21}\tilde{\beta}_{11} + x_{ij22}\tilde{\beta}_{12}\right)}{N_{j2}} - \sum_{j=1}^{n_2}\sum_{i=1}^{N_{j2}} \frac{\Phi\left(\tilde{\beta}_{20} + x_{ij21}\tilde{\beta}_{11} + x_{ij22}\tilde{\beta}_{12}\right)}{N_{j2}}\right]}_{\text{the effect of intercept}} \tag{11}$$

$$+ \underbrace{\left[\sum_{j=1}^{n_2}\sum_{i=1}^{N_{j2}} \frac{\Phi\left(\tilde{\beta}_{20} + x_{ij21}\tilde{\beta}_{11} + x_{ij22}\tilde{\beta}_{12}\right)}{N_{j2}} - \sum_{j=1}^{n_2}\sum_{i=1}^{N_{j2}} \frac{\Phi\left(\tilde{\beta}_{20} + x_{ij21}\tilde{\beta}_{21} + x_{ij22}\tilde{\beta}_{12}\right)}{N_{j2}}\right]}_{\text{the effect of first coefficent}} \tag{12}$$

$$+ \underbrace{\left[\sum_{j=1}^{n_2}\sum_{i=1}^{N_{j2}} \frac{\Phi\left(\tilde{\beta}_{20} + x_{ij21}\tilde{\beta}_{21} + x_{ij22}\tilde{\beta}_{12}\right)}{N_{j2}} - \sum_{j=1}^{n_2}\sum_{i=1}^{N_{j2}} \frac{\Phi\left(\tilde{\beta}_{20} + x_{ij21}\tilde{\beta}_{21} + x_{ij22}\tilde{\beta}_{22}\right)}{N_{j2}}\right]}_{\text{the effect of second coefficent}} \tag{13}$$

In the set of equations above, (11) is the portion of the decomposition that is due to differences in the intercept where only β_{j10} in the first term is replaced by β_{j20} in the second term. Then we keep the replacement of intercept in the first term of (12), and only replace β_{j11} by β_{j12} in the second term. Similarly, the replacement of intercept and first coefficient is kept in the first term of (13), and only β_{j21} is substituted by β_{j22} in the second term. As a result, (12) and (13) are the portions of the decomposition that are due to change each of the regression coefficients individiually.

There are 7 covariates in our model, so to do the decomposition, we expand the three equations in (11)-(13) to eight, substituting one coefficient (or set of coefficients for categorical variables) in each equation. In general, the order in which we decompose the overall beta effect into the individual beta effects will matter, and we HOW DID WE DO THIS AGAIN

2.1.3 Accounting for Uncertainty When Evaluating Declines

We estimate mortality risk for subjects with a Bayesian hierarchical probit random effects regression models in (15) using Markov chain Monte Carlo (MCMC). For each iteration $\ell = 1, \ldots, L$ of the MCMC, we have an estimate $\pi_{ijk}^{(\ell)}$ of π_{ijk} for all births which we use to calculate the decomposition in (8) for all L iterations. This gives us a posterior distribution for the decomposition results, which provides a straightforward way to get point and the uncertainty estimates. This allows us to determine which of the declines were significantly different between surveys 1 and 2 for each country.

3 Data and Statistical Model

3.1 Data

To investigate the decline in the incidence of early life mortality over time for infants under 1 year old, we assembled data using two waves of the Demographic and Health Surveys (DHS) from 42 countries. The two waves are between 10 and 20 years apart. For each survey, we include births from mothers aged 15 - 45 years old. We analyze births that occurred between one and five years before the survey to make sure each child was on the study long enough to experience a potential mortality event and to minimize censoring issues. Table 1 shows the survey year, sample size and empirical mortality rate in each wave for all 42 countries. We observe declines in mortality in all countries except Cameroon, which stayed the same from 1991 – 2011.

To estimate the individual mortality risk in each survey within each country, we use a probit model including covariates that have been shown to have an association with child mortality, and are available in all of the surveys and comparable across countries and surveys. We include maternal age in years, mother's education in years, sex of the infant, birth order, place of residence (rural versus urban), and a relative wealth score that indicates how wealthy each individual is. Because wealth is calculated at the household level, we calculate the relative wealth score by taking the percentage of households with wealth less than or equal to that of the household in which the mother for the birth resides in each survey for each country. We also use cluster to indicate the location of household.

3.2 Bayesian Hierarchical Model for Infant Mortality

For each country, let $k \in \{1, 2\}$ index surveys, $j \in \{1, \ldots, n_k\}$ index clusters, and $i \in \{1, \ldots, N_{jk}\}$ index birth, where n_k is the number of clusters in survey k and N_{jk} is the number of births on record in cluster j and survey k. Hence, the total number of infants in each survey $N_k = \sum_{j=1}^{n_k} N_{jk}$. Let y_{ijk} be a binary indicator for whether or not child i died under 1 year old in cluster j and survey k, with $y_{ijk} = 1$ if child i died and $y_{ijk} = 0$ otherwise. We model y_{ijk} as a Bernoulli random variable with mortality probability π_{ijk},

$$y_{ijk}|\pi_{ijk} \sim \text{Bern}(\pi_{ijk}), \tag{14}$$

and a probit model for π_{ijk},

$$\text{P}(y_{ijk} = 1|\boldsymbol{\beta}_k, \gamma_{jk}) = \Phi\left(\boldsymbol{x}_{ijk}^T\boldsymbol{\beta}_k + \gamma_{jk}\right), \tag{15}$$

where $\Phi(\cdot)$ is the standard normal CDF, $\boldsymbol{x}_{ijk}$ is a covariate vector including the 6 covariates mentioned in Section **??** along with an intercept term, and γ_{jk} is a cluster level random effect that is normally distributed with variance σ_k^2,

$$\gamma_{jk} \sim \text{N}(0, \sigma_k^2).$$

For interpretability, we center the continuous variables (maternal age, maternal education, birth order, and wealth) by subtracting off their respective means in the poorest 20% of households in the first survey. We also treat female births from rural places of residence as reference levels, giving the intercept an interpretation in terms of the probability of death for the "average" femal and rural baby in the survey. Finally, to account for potential nonlinear mortality trends in maternal age, maternal education, birth order, and wealth, we fit B-splines of the respective centered variables instead of the raw variables.

4 Results

We fit the Bayesian model to predict infant mortality using Markov Chain Monte Carlo methods the `MCMCglmm` package in `R`, which allows us to get posterior samples of infant mortality π_{ijk}. This allows us to get uncertainty estimates for all parameters of interest including the components of the overall and coefficient-by-coefficient decompositions described above. We ran the model until we obtained 1250 approximately independent posterior samples. We assessed convergence using trace plots and autocorrelation using ACF plots which are also readily available from the MCMC samples.

4.1 Decline of Child Mortality Between Two Surveys

Table 2 plots posterior summaries of the mortality distributions for all countries and surveys. Countries are ordered from top to bottom by estimated yearly decline in infant mortality. Mortality rates are presented as deaths per 1,000 births. The 'Years Between' column denotes the number of years between the two surveys. The 'S1' and 'S2' columns indicate the estimated number of deaths per 1000 births for surveys 1 and 2, respectively. The 'Difference' column refers to the difference in mortality between surveys, and The 'Yearly' column is 'Difference' divided by 'Years between', giving an estimate of how quickly the mortality rate decreased annually. The '95% CI' columns denote posterior intervals.

Comparing the model output with the raw data, we can see that the estimated average mortality rates presented in Table 2 are consistent with the raw mortality rates from Table 1, suggesting that our model fits the data well. The general trend is that there are substantive and significant decreases in the average mortality over time for all countries except Cameroon, Zimbabwe, and Colombia. However, there is heterogeneity between countries in the yearly decline in infant mortality, from more than 5 deaths per 1000 births in Cambodia and Niger to less than one death per 1000 births in Indonesia, Pakistan, Philippines, and Jordan. Yearly declines in child mortality are only weakly correlated with mortality levels in the year of the first survey.

4.2 Decomposition Results

Overall covariate and coefficient effects as well as uncertainty estimates are presented in Table 3 for countries with significant declines in mortality over time. Countries are ordered using the same order as Table 2. The 'Effects' columns denote the actual contribution of the covariate and coefficient effects to the overall decline, and the '%' column denotes the percent of the overall decline that is due to the covariate and coefficient effects, with significant effects in boldface. For example the first row of Table 3 says from survey 1 to survey 2, the mortality rate decreased by about 5% (X effect + beta effect). The reduction due to changes in the covariate distributions was accounted for 18% of the total decline, and the reduction due to changes in the covariate response accounted for 82% of the total decline.

The individual percentages can be more than 100% when for example a beneficial covariate effect is more than offset by deleterious coefficient effect (or vice versa). For example, in Cote d'Ivoire, the mortality rate decreased by about 3%. Covariate effects led to an *increase* in the mortality rate of 0.3%, but this was offset by the coefficient effect, which led to a *decrease* in the mortality rate of 3.4%. Similar trends occur in Tanzania, Senegal, Burkina Faso, Gabon, and the Dominican Republic. For the remaining 35 countries excluding Jordan, Armenia, Ghana and Haiti, the decline in mortality risk is mostly explained by the coefficient effects. For countries with positive overall X effects, Kenya has the largest coefficient effect (99%, 95% CI $48\%, 161\%$.

Table 4 presents the results for the coefficient by coefficient decompositions. Countries are ordered according to the ordering in Tables 2 and 3. Uncertainty is very large for these decompositions and the vast majority of them are not significant. The intercept is significant for only six out of the 39 countries: Mali (155%), Benin (165%), Comoros (117%), Tanzania (155%), Uganda (118%), and Kenya (116%). These are the most important effects in substantive terms.

4.2.1 Statistical Significance in the Beta-by-Beta Decomposition.

We investigate the reasons for the lack of statistical significance in the beta by beta decompositions. Table 2 shows that the posterior interval for the intercept effect is always larger than the variance of

the overall effect, despite the fact that the intercept term is one term in the sum that makes up the overall effect. In fact, because the overall coefficient effect can be written as a collapsing sum of the individual effects, we can examine how the variance of the overall effect changes as more and more terms are incorporated into the sum.

The results of this exercise are plotted in Figure 6. First, the countries generally follow one of two trends: Either the variance starts large and gradually decreases until the final term is added to the model, or the variance decreases until the fifth term, birth order, is added to the model. Then the variance decreases again until the last term is added to the sum. Because the models for each country were fit separately, this suggests that the trends we see are not spurious. Second, the variance *never* reaches its minimum until the final term is added to the model. This suggests that the individual components of the sum are negatively correlated and that is causing the lack of statistical significance in the beta-by-beta decomposition.

5 Discussion and Conclusions

Our analysis confirms that there is large variation in the decline of infant mortality across LMIC. Several countries experienced little or no decline in infant mortality while others have made remarkable progress. Our decomposition results show that, in most countries, the decline in infant mortality in recent decades has been due to actual declines in the propensities of parents with given characteristics to experience an infant death rather than to changes in the distribution of parental and infant characteristics. However, there is substantial variation across countries in the relative contribution to overall infant mortality declines of these declining propensities. Among countries where we are able to reach statistical significance for our decomposition results, the effects of declining propensities on infant mortality amount to a low of 56% of the actual decline in Peru and to a high of 110% of the actual decline in Cote d'Ivoire. (The latter implies that this contribution is counterbalanced by distributional changes in parental characteristics that contributed to increase infant mortality in Cote d'Ivoire.)This is in contrast to previous work which has shown that differences in mortality risk are associated in parental and infant characteristics. For example, Van de Poel et al. (2009) found that

the higher mortality rates in rural areas in India were caused by variation in parental characteristics. Using aggregated data at the country level, (Bishai et al., 2016) found that most of the decline in child mortality rates were due to the over time expansion of health services. Demombynes and Trommlerová (2016), which study the decline in Kenya find that improvements in then distribution of bed nets as the main driver of mortality declines.

Because most of the decline was due to over timechanges in the effects of parental characteristics, we developed a new methodology to isolate the contribution of each characteristic to the overall decline. However, we were unable to find statistically significant effects for most of these individual characteristics due to large uncertainty on in our decomposition estimates. The main reason for that high level of uncertainty was the correlation between the effects of parental characteristics. Nevertheless, some patterns are clear. In general, the intercept tends to have the largest effect, and is the part of the overall coefficient effect that is most likely to be significant. Statistically, the intercept represents the part of the model that captures effects not picked up by the birth and parental characteristics not included in the model. Substantively, we interprete the importance of the intercept as the importance in general improvements in health beyond the parental and infant characteristics included in the statistical model. For example, we know that while some developing have the same income as European countries in the 19th century, they also have mortality rates that are much smaller than Europe in the past, most likely due to the discovery of germ theory and its practical implications. (Cutler et al., 2006; Soares, 2007). While some of this knowledge should be correlated with parental characteristics such wealth and education, not all of it would be.

One important finding from our study is the importance of properly accounting for uncertainty when using Oaxaca methods. The lack of significance for most of the individual effects is consistent with Demombynes and Trommlerová (2016). Similarly, in the study by Van de Poel et al. (2009), decomposition results were presented by no uncertainty estimates were provided. Our results suggest that even large effects might not be statistically significant due to the correlation among parental, geographical and birth characteristics.

Our results is that they do not suggest that improvements in parental characteristics are not worth pursuing. On the contrary, given that we only observed small or no changes on the over time

distribution of these characteristics, our results suggest that the policies designed to help countries to meet the SDGs should increase the promote the improvement of parental characteristics, such as increasing in maternal age of the first birth and increasing maternal education. However, given the large country-to-country heterogeneity in the magnitudes of the decomposition effects, policies should be tailored according to each individual country's needs. For example, higher birth order are more strongly associated with higher risk of death in Zimbabwe than in Mali and Madagascar.

Methodologically, our work can be extended in a number of ways. Currently, we only have random intercepts for geographic location. However, our novel methods allow for more complex random effects structures with several nested random intercepts and slopes and their correlations. That can be useful for situations were the data is nested by several levels (e.g. provinces, districts, neighoods, mothers) and we are interested in explore these nesting levels while estimating mortality risk. Our methodology can also be extended to other types of non-linear random effects models that are useful to study mortality and health. For example, researchers are often interested in investigating the determinants of fertility differences between two populations and would like to apply Oaxaca decomposition methods to this question. Fertility can be estimated with Poisson log-linear models. However, fertility is often modeled using linear regression models, due to the lack of appropriated decomposition methods for more complex Poisson models (Shapiro and Tenikue, 2017). Poisson models are often used to study mortality when the data is aggregated by geographic unit (e.g. number of deaths by district using number of births are an offset). Our methodology can be easily applied to random effects poisson models.

Our work has a number of limitations. First, to make our analysis broad and comparable, we have not included several parental, birth and geographic characteristics that are known to be associated with increased risk of mortality such as sanitation, electricity, and access to clean water.This is because much of the data for these excluded variables have high missing rates for several surveys. Future studies can apply our methodology to country studies, were the comparability of these and other variables are easier. Another limitation is that Oaxaca–Blinder decomposition approach does not identify causal effects with observational data. A causal interpretation of the results relies on the strong assumption that there are no omitted variables, i.e. other factors which determine the

outcome and are correlated with the observed explanatory variables. This assumption does not hold strictly, and thus the coefficients in the regressions should not be interpreted as representing clear causal effects. However, given that the variables included in our analysis have a well-know causal interpretation, we believe that our results can shed some light on the true determinants of mortality in the developing world.

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Table 1. A summary of dataset for two surveys in 42 countries (The last column shows the order of country in Table 2)

Country	Survey 1			Survey 2			
	Year	Sample size	Deaths / 1000	Year	Sample size	Deaths / 1000	Order
Armenia	2000	1453	40	2010	1077	14	13
Bangladesh	2000	5323	69	2014	7733	41	20
Benin	1996	3968	106	2012	10361	48	7
Bolivia	1998	5755	66	2008	6821	45	19
Burkina Faso	1993	4363	103	2010	11701	75	24
Cambodia	2000	6929	103	2014	5590	29	1
Cameroon	1991	2546	67	2011	8937	67	40
Chad	1997	5552	118	2015	13697	72	12
Colombia	1990	2930	23	2005	10975	22	42
Comoros	1996	1607	78	2012	2345	30	9
Cote dIvoire	1999	1367	116	2012	5915	81	11
Dominican Republic	1996	1470	44	2013	3623	31	34
Egypt	1995	7402	71	2014	12043	24	15
Gabon	2000	2525	61	2012	4552	40	26
Ghana	1993	2303	75	2014	4464	51	35
Guatemala	1999	3782	50	2015	9099	28	28
Guinea	1999	4805	109	2012	5367	77	17
Haiti	1994	2215	79	2012	5586	65	33
India	1993	42701	73	2006	40833	52	29
Indonesia	1997	14662	49	2012	14244	36	36
Jordan	1990	6721	32	2012	8585	22	39
Kenya	1993	4833	61	2014	16607	39	32
Kyrgyzstan	1997	1616	59	2012	3197	30	21
Madagascar	1997	4721	104	2009	9294	49	4
Malawi	1992	3365	138	2015	11429	42	5
Mali	1996	7354	134	2012	6823	62	3
Morocco	1992	4171	58	2003	4101	41	27
Mozambique	1997	5614	120	2011	8265	67	8
Namibia	1992	2948	66	2013	3812	46	31
Niger	1998	6152	133	2012	9530	62	2
Nigeria	1990	6005	103	2013	26019	73	30
Pakistan	1991	4614	85	2012	7862	69	37
Peru	1992	6468	62	2012	18988	20	23
Philippines	1993	7315	39	2013	5841	27	38
Rwanda	1992	4454	86	2015	5579	31	14
Senegal	1997	5477	79	2015	7645	38	22
Tanzania	1999	3802	91	2015	6430	41	10
Togo	1998	5497	90	2014	4950	50	18
Turkey	1993	2926	57	2004	3405	34	16
Uganda	1995	5568	90	2011	6178	58	25
Zambia	1996	4335	118	2013	9254	50	6
Zimbabwe	1994	3316	59	2015	4893	55	41

Table 2. A summary of mean mortality probability in two surveys for 42 countries. (Countries are ordered from largest to smallest by the difference per year. Years between is the time interval between the two surveys. S1 and S2 are the mean mortality probability in survey 1 and survey 2 per 1000 people. The difference is S1 probability minus S2 probability, and difference per year is also shown.)

	Years	Mean mortality probability (per 1000)							
Country	between	S1	95% CI	S2	95% CI	Difference	95% CI	Difference per year	95% CI
Cambodia	14	106	[96, 115]	31	[25, 37]	**75**	[63, 87]	**5.4**	[4.5, 5.8]
Niger	14	135	[122, 149]	64	[57, 71]	**71**	[56, 87]	**5.1**	[4.0, 6.2]
Mali	16	141	[129, 154]	64	[56, 73]	**77**	[62, 92]	**4.8**	[3.9, 5.8]
Madagascar	12	107	[93, 121]	51	[45, 57]	**56**	[41, 72]	**4.7**	[3.4, 6.0]
Malawi	23	144	[126, 161]	43	[39, 48]	**100**	[82, 118]	**4.3**	[3.6, 5.1]
Zambia	17	123	[110, 137]	52	[46, 58]	**71**	[57, 86]	**4.2**	[3.4, 5.1]
Benin	16	114	[98, 131]	49	[44, 55]	**65**	[48, 83]	**4.1**	[2.5, 5.2]
Mozambique	14	125	[113, 139]	70	[62, 77]	**56**	[41, 70]	**4.0**	[2.9, 5.0]
Comoros	16	90	[71, 115]	35	[26, 46]	**56**	[33, 81]	**3.5**	[2.1, 5.1]
Tanzania	16	97	[84, 111]	44	[38, 51]	**53**	[37, 68]	**3.3**	[2.3, 4.3]
Cote dIvoire	13	123	[99, 150]	83	[73, 93]	**41**	[14, 69]	**3.2**	[1.1, 5.3]
Chad	18	123	[110, 137]	74	[68, 80]	**50**	[34, 65]	**2.8**	[1.9, 3.6]
Armenia	10	43	[31, 59]	17	[9, 28]	**26**	[9, 43]	**2.6**	[0.9, 4.3]
Rwanda	23	93	[80, 107]	34	[28, 40]	**59**	[44, 74]	**2.6**	[1.9, 3.2]
Egypt	19	72	[65, 79]	25	[22, 28]	**48**	[39, 56]	**2.5**	[2.1, 2.9]
Turkey	11	61	[50, 72]	34	[26, 42]	**27**	[14, 41]	**2.5**	[1.3, 3.7]
Guinea	13	113	[100, 127]	82	[72, 94]	**31**	[14, 49]	**2.4**	[1.1, 3.8]
Togo	16	92	[80, 105]	55	[46, 64]	**37**	[22, 53]	**2.3**	[1.4, 3.3]
Bolivia	10	70	[62, 78]	47	[40, 53]	**23**	[12, 34]	**2.3**	[1.2, 3.4]
Bangladesh	14	73	[64, 83]	43	[38, 50]	**30**	[19, 41]	**2.1**	[1.4, 2.9]
Kyrgyzstan	15	66	[49, 85]	34	[26, 45]	**32**	[13, 52]	**2.1**	[0.9, 3.5]
Senegal	18	82	[72, 93]	44	[37, 52]	**38**	[26, 51]	**2.1**	[1.4, 2.8]
Peru	20	63	[56, 70]	20	[18, 23]	**42**	[34, 50]	**2.1**	[1.7, 2.5]
Burkina Faso	17	110	[96, 127]	76	[70, 83]	**34**	[19, 51]	**2.0**	[1.1, 3.0]
Uganda	16	94	[83, 105]	62	[54, 71]	**32**	[18, 46]	**2.0**	[1.1, 2.9]
Gabon	12	68	[56, 82]	44	[37, 53]	**23**	[8, 39]	**1.9**	[0.7, 3.3]
Morocco	11	63	[51, 77]	44	[36, 53]	**19**	[3, 35]	**1.7**	[0.3, 3.2]
Guatemala	16	54	[44, 65]	30	[26, 34]	**25**	[14, 36]	**1.6**	[0.9, 2.3]
India	13	72	[70, 76]	52	[49, 55]	**20**	[17, 24]	**1.5**	[1.3, 1.8]
Nigeria	23	104	[92, 116]	75	[70, 79]	**29**	[16, 42]	**1.3**	[0.7, 1.8]
Namibia	21	74	[61, 89]	47	[39, 56]	**26**	[11, 44]	**1.2**	[0.5, 2.1]
Kenya	21	65	[56, 75]	40	[37, 43]	**25**	[15, 35]	**1.2**	[0.7, 1.7]
Haiti	18	91	[74, 110]	69	[61, 78]	**21**	[2, 42]	**1.2**	[0.1, 2.3]
Dominican Republic	17	52	[38, 68]	33	[27, 40]	**19**	[4, 36]	**1.1**	[0.2, 2.1]
Ghana	21	78	[65, 94]	56	[47, 66]	**22**	[5, 41]	**1.0**	[0.2, 2.0]
Indonesia	15	50	[46, 54]	37	[33, 40]	**13**	[8, 19]	**0.9**	[0.5, 1.3]
Pakistan	21	90	[79, 101]	72	[64, 79]	**18**	[5, 32]	**0.9**	[0.2, 1.5]
Philippines	20	41	[36, 47]	29	[24, 35]	**12**	[4, 20]	**0.6**	[0.2, 1.0]
Jordan	22	35	[29, 41]	23	[19, 27]	**12**	[4, 19]	**0.5**	[0.2, 0.9]
Cameroon	20	77	[62, 94]	68	[61, 75]	9	[−7, 27]	0.5	[−0.4, 1.4]
Zimbabwe	21	65	[53, 78]	58	[50, 67]	7	[−9, 21]	0.3	[−0.4, 1.0]
Colombia	15	26	[20, 34]	23	[20, 26]	3	[−4, 11]	0.2	[−0.3, 0.7]

Table 1 – Results of the decomposition in the decline of infant mortality risk per 1000 births per year in 42 countries. (Countries are in the same order as Table 2. Bolded results are significant defined as zero not in the 95% confidence interval.)

	Overall X effects				Overall beta effects			
Country	Effects	95% CI	%	95% CI(%)	Effects	95% CI	%	95% CI(%)
Cambodia	**1**	[0.4, 1.5]	**18**	[8, 29]	**4.4**	[3.5, 5.3]	**82**	[65, 100]
Niger	**0.2**	[0.0, 0.4]	**4**	[0, 8]	**4.9**	[3.8, 6.0]	**96**	[75, 119]
Mali	0.2	[−0.2, 0.5]	4	[−3, 10]	**4.6**	[3.6, 5.6]	**96**	[76, 117]
Madagascar	**0.8**	[0.5, 1.2]	**18**	[11, 25]	**3.8**	[2.6, 5.1]	**82**	[55, 108]
Malawi	0.0	[−0.6, 0.5]	0	[−13, 12]	**4.4**	[3.4, 5.3]	**100**	[78, 122]
Zambia	0.2	[−0.2, 0.6]	5	[−5, 14]	**4.0**	[3.1, 4.9]	**95**	[74, 118]
Benin	**0.4**	[0.1, 0.8]	**11**	[2, 20]	**3.6**	[2.6, 4.7]	**89**	[64, 117]
Mozambique	**0.6**	[0.1, 1.1]	**15**	[3, 28]	**3.4**	[2.3, 4.5]	**85**	[57, 114]
Comoros	0.5	[−0.1, 1.1]	16	[−2, 31]	**2.9**	[1.5, 4.6]	**85**	[42, 131]
Tanzania	−0.1	[−0.4, 0.2]	−3	[−12, 6]	**3.4**	[2.4, 4.4]	**103**	[72, 132]
Cote dIvoire	−0.3	[−1.3, 0.6]	−10	[−42, 21]	**3.4**	[1.1, 6.1]	**110**	[35, 196]
Chad	0.5	[−0.4, 1.3]	17	[−14, 46]	**2.3**	[1.1, 3.5]	**83**	[41, 128]
Armenia	**1.1**	[0.4, 2.0]	**44**	[15, 76]	1.5	[−0.1, 3.0]	56	[−4, 113]
Rwanda	0.3	[−0.1, 0.7]	11	[−5, 26]	**2.3**	[1.6, 3.0]	**89**	[61, 119]
Egypt	**0.9**	[0.4, 1.3]	**35**	[16, 51]	**1.6**	[1.1, 2.2]	**65**	[43, 88]
Turkey	0.2	[−0.2, 0.5]	8	[−9, 22]	**2.2**	[1.0, 3.6]	**93**	[42, 148]
Guinea	**0.3**	[0.1, 0.6]	**13**	[3, 24]	**2.1**	[0.8, 3.4]	**87**	[33, 144]
Togo	**0.4**	[0.0, 0.7]	17	[−1, 32]	**1.9**	[1.0, 2.9]	**84**	[43, 127]
Bolivia	0.5	[−0.6, 1.2]	22	[−25, 51]	**1.8**	[0.5, 3.2]	**78**	[23, 137]
Bangladesh	**0.6**	[0.1, 1.1]	**30**	[6, 52]	**1.5**	[0.7, 2.4]	**70**	[31, 113]
Kyrgyzstan	0.2	[−0.7, 1.0]	9	[−34, 46]	**1.9**	[0.5, 3.7]	**91**	[23, 174]
Senegal	−0.1	[−0.4, 0.3]	−4	[−20, 12]	**2.2**	[1.4, 3.0]	**104**	[66, 142]
Peru	**0.9**	[0.6, 1.2]	**44**	[29, 58]	**1.2**	[0.8, 1.6]	**56**	[38, 77]
Burkina Faso	−0.1	[−0.4, 0.1]	−6	[−20, 8]	**2.1**	[1.2, 3.2]	**106**	[58, 158]
Uganda	**0.3**	[0.0, 0.6]	**16**	[2, 29]	**1.7**	[0.8, 2.5]	**84**	[39, 128]
Gabon	−0.1	[−0.5, 0.3]	−5	[−24, 13]	**2.0**	[0.8, 3.5]	**105**	[39, 177]
Morocco	0.3	[−0.2, 0.8]	18	[−14, 47]	**1.4**	[0.0, 2.9]	**82**	[2, 171]
Guatemala	**0.6**	[0.1, 1.0]	**37**	[10, 62]	**1.0**	[0.3, 1.7]	**63**	[18, 113]
India	**0.3**	[0.2, 0.4]	**19**	[10, 28]	**1.3**	[1.0, 1.6]	**81**	[61, 102]
Nigeria	**0.3**	[0.1, 0.6]	**27**	[7, 44]	**0.9**	[0.3, 1.5]	**74**	[28, 120]
Namibia	0.3	[−0.3, 0.8]	26	[−21, 68]	**0.9**	[0.0, 1.9]	**74**	[4, 151]
Kenya	0.0	[−0.5, 0.4]	1	[−43, 36]	**1.2**	[0.6, 1.9]	**99**	[48, 161]
Haiti	0.2	[−0.5, 0.9]	17	[−44, 73]	1.0	[−0.2, 2.3]	84	[−18, 197]
Dominican Republic	−0.3	[−0.9, 0.2]	−29	[−78, 17]	**1.4**	[0.4, 2.6]	**129**	[36, 236]
Ghana	0.3	[0.0, 0.6]	29	[−5, 59]	0.8	[−0.1, 1.6]	71	[−6, 151]
Indonesia	0.1	[−0.5, 0.5]	13	[−58, 60]	**0.8**	[0.2, 1.5]	**87**	[23, 166]
Pakistan	0.1	[−0.2, 0.4]	12	[−24, 44]	**0.8**	[0.1, 1.5]	**88**	[6, 174]
Philippines	0.0	[−0.5, 0.3]	8	[−76, 55]	**0.6**	[0.1, 1.2]	**92**	[11, 198]
Jordan	**0.5**	[0.2, 0.7]	**86**	[30, 134]	0.1	[−0.3, 0.5]	14	[−59, 94]
Cameroon	**0.5**	[0.2, 0.8]	**111**	[41, 181]	−0.1	[−0.8, 0.8]	−11	[−179, 172]
Zimbabwe	0.3	[−0.3, 0.8]	92	[−93, 260]	0.0	[−0.8, 0.9]	8	[−257, 298]
Colombia	**0.3**	[0.0, 0.5]	**131**	[2, 267]	−0.1	[−0.6, 0.5]	−31	[−282, 251]

Table 2 – The coefficient by coefficient decomposition results per 1000 births per year for 42 countries, keeping order the same. Bolded results are significant defined as zero not in the 95% confidence interval.

Country	Overall	95% CI	Intercept	95% CI	Wealth score	95% CI	Maternal edu	95% CI
Cambodia	**4.4**	[3.5, 5.3]	3.9	[−1,2 6.3]	−0.9	[−3.5, 1.8]	0.6	[−0.3, 2.0]
Niger	**4.9**	[3.8, 6.0]	4.4	[−1,4 7.9]	0.1	[−3.0, 4.2]	0.0	[−0.3, 0.2]
Mali	**4.6**	[3.6, 5.6]	**6.2**	[2,6 8.3]	0.2	[−1.5, 2.7]	0.0	[−0.1, 0.1]
Madagascar	**3.8**	[2.6, 5.1]	3.2	[−2,5 6.8]	0.0	[−3.1, 4.2]	−0.3	[−1.3, 0.7]
Malawi	**4.4**	[3.4, 5.3]	2.4	[−2,2 5.3]	0.4	[−1.8, 3.4]	0.4	[−0.6, 1.5]
Zambia	**4.0**	[3.1, 4.9]	−0.8	[−9,5 4.6]	2.3	[−1.5, 7.8]	−0.6	[−2.3, 1.0]
Benin	**3.6**	[2.6, 4.7]	**5.2**	[2,4 7.0]	−0.4	[−1.9, 1.1]	−0.1	[−0.3, 0.1]
Mozambique	**3.4**	[2.3, 4.5]	0.1	[−7,4 5.6]	1.3	[−3.0, 6.9]	0.0	[−1.0, 1.2]
Comoros	**2.9**	[1.5, 4.6]	**3.8**	[0,8 5.7]	0.1	[−1.0, 1.8]	−0.1	[−0.6, 0.4]
Tanzania	**3.4**	[2.4, 4.4]	**4.8**	[1,9 6.4]	−0.3	[−1.6, 1.3]	**−0.9**	[−2.0, −0.2]
Cote dIvoire	**3.4**	[1.1, 6.1]	4.4	[−2,9 9.2]	1.7	[−1.3, 6.7]	−0.1	[−0.6, 0.4]
Chad	**2.3**	[1.1, 3.5]	2.3	[−1,9 5.3]	0.3	[−2.1, 3.6]	**−0.4**	[−0.7, −0.1]
Armenia	1.5	[−0.1, 3.0]	−0.9	[−13,0 3.4]	0.6	[−2.4, 5.1]	1.0	[−2.7, 7.3]
Rwanda	**2.3**	[1.6, 3.0]	0.3	[−4,6 3.2]	1.4	[−0.5, 4.8]	0.0	[−0.8, 0.7]
Egypt	**1.6**	[1.1, 2.2]	1.2	[−2,2 2.7]	0.5	[−0.4, 2.6]	0.1	[−0.3, 0.6]
Turkey	**2.2**	[1.0, 3.6]	2.3	[−3,4 5.2]	0.8	[−1.1, 4.1]	0.0	[−0.8, 0.9]
Guinea	**2.1**	[0.8, 3.4]	0.7	[−7,8 5.8]	0.4	[−3.8, 6.3]	0.1	[−0.3, 0.6]
Togo	**1.9**	[1.0, 2.9]	1.8	[−3,4 4.8]	0.3	[−2.2, 3.4]	0.4	[−0.1, 1.2]
Bolivia	**1.8**	[0.5, 3.2]	−3.0	[−14,8 3.9]	−1.8	[−7.4, 3.9]	**3.6**	[0.0, 8.7]
Bangladesh	**1.5**	[0.7, 2.4]	2.3	[−1,0 4.1]	0.7	[−0.8, 3.1]	−0.3	[−1.1, 0.2]
Kyrgyzstan	**1.9**	[0.5, 3.7]	2.0	[−4,3 5.0]	−0.2	[−2.6, 2.7]	−0.3	[−3.5, 3.9]
Senegal	**2.2**	[1.4, 3.0]	0.3	[−5,4 3.6]	1.4	[−0.9, 5.1]	0.0	[−0.3, 0.3]
Peru	**1.2**	[0.8, 1.6]	0.0	[−3,1 1.7]	**1.1**	[0.1, 3.4]	0.0	[−0.5, 0.6]
Burkina Faso	**2.1**	[1.2, 3.2]	3.8	[−0,6 6.3]	−0.2	[−2.2, 2.2]	0.1	[−0.1, 0.2]
Uganda	**1.7**	[0.8, 2.5]	**3.6**	[0,4 5.4]	0.2	[−1.2, 2.2]	**−0.8**	[−1.7, −0.2]
Gabon	**2.0**	[0.8, 3.5]	0.7	[−7,8 5.0]	1.5	[−1.5, 6.9]	0.3	[−1.6, 3.3]
Morocco	**1.4**	[0.0, 2.9]	0.7	[−7,6 4.9]	0.4	[−3.0, 4.9]	0.2	[−0.3, 1.0]
Guatemala	**1.0**	[0.3, 1.7]	1.8	[−0,2 3.0]	−0.2	[−1.1, 0.9]	−0.1	[−0.6, 0.3]
India	**1.3**	[1.0, 1.6]	1.2	[−1,4 3.3]	0.5	[−0.8, 2.2]	0.0	[−0.3, 0.2]
Nigeria	**0.9**	[0.3, 1.5]	0.8	[−2,7 3.1]	0.3	[−1.4, 2.6]	−0.1	[−0.5, 0.2]
Namibia	**0.9**	[0.0, 1.9]	−0.3	[−5,8 2.7]	0.7	[−1.6, 4.0]	−0.7	[−2.4, 0.9]
Kenya	**1.2**	[0.6, 1.9]	**2.3**	[0,6 3.2]	−0.1	[−0.8, 0.7]	0.1	[−0.2, 0.6]
Haiti	1.0	[−0.2, 2.3]	0.8	[−5,4 4.5]	0.8	[−1.6, 4.7]	0.0	[−1.0, 1.1]
Dominican Republic	**1.4**	[0.4, 2.6]	−4.7	[−14,5 1.7]	1.5	[−2.7, 7.1]	2.0	[−1.3, 6.9]
Ghana	0.8	[−0.1, 1.6]	0.1	[−4,9 2.8]	−0.8	[−3.5, 1.9]	0.5	[−0.4, 1.6]
Indonesia	**0.8**	[0.2, 1.5]	−2.3	[−8,8 1.5]	0.9	[−1.7, 4.7]	0.6	[−0.9, 2.6]
Pakistan	**0.8**	[0.1, 1.5]	1.1	[−3,5 3.5]	1.2	[−0.5, 4.3]	0.0	[−0.3, 0.3]
Philippines	**0.6**	[0.1, 1.2]	0.3	[−3,2 1.9]	0.2	[−1.1, 2.0]	−0.5	[−1.8, 0.8]
Jordan	0.1	[−0.3, 0.5]	−0.2	[−3,0 1.0]	−0.6	[−2.4, 0.6]	−0.9	[−2.8, 0.4]
Cameroon	−0.1	[−0.8, 0.8]	0.4	[−4,3 2.9]	0.8	[−1.0, 3.8]	−0.9	[−1.9, −0.2]
Zimbabwe	0.0	[−0.8, 0.9]	−1.6	[−7,8 1.9]	0.5	[−2.1, 4.6]	0.4	[−1.8, 3.2]
Colombia	−0.1	[−0.6, 0.5]	−1.4	[−7,0 1.1]	−0.5	[−3.3, 1.8]	−0.4	[−2.8, 2.0]

Table 2 – (Continued)

Country	Maternal age	95% CI	Birth order	95% CI	Birth Interval	95% CI	Sex	95% CI	Residence	95% CI
Cambodia	0.5	[−1.6, 4.2]	−0.2	[−1.8, 0.9]	0.0	[−1.1, 1.8]	0.1	[−0.4, 0.6]	**0.4**	[0.1, 0.7]
Niger	0.0	[−2.9, 3.5]	−2.1	[−7.4, 1.6]	2.6	[−1.1, 8.2]	−0.2	[−0.7, 0.3]	0.1	[−0.3, 0.5]
Mali	0.0	[−1.3, 1.9]	−0.1	[−2.0, 1.0]	−0.9	[−2.0, 1.0]	**−0.6**	[−1.0, −0.2]	−0.2	[−0.4, 0.1]
Madagascar	0.0	[−2.9, 3.4]	−1.0	[−5.5, 2.3]	1.8	[−1.2, 6.4]	0.0	[−0.6, 0.6]	0.0	[−0.3, 0.4]
Malawi	1.0	[−0.7, 3.5]	−0.9	[−3.0, 0.7]	1.2	[−0.3, 3.3]	−0.1	[−0.4, 0.2]	0.0	[−0.1, 0.2]
Zambia	1.3	[−2.4, 6.1]	0.4	[−2.6, 3.0]	1.1	[−1.0, 4.5]	0.2	[−0.2, 0.7]	0.1	[−0.5, 0.8]
Benin	0.3	[−1.1, 2.6]	−0.8	[−2.6, 0.4]	−0.3	[−1.5, 1.7]	−0.2	[−0.5, 0.2]	−0.2	[−0.6, 0.2]
Mozambique	2.3	[−0.9, 6.6]	−1.6	[−5.6, 1.2]	1.4	[−1.4, 5.7]	0.0	[−0.5, 0.6]	−0.3	[−0.8, 0.4]
Comoros	−0.7	[−2.2, 0.9]	−0.7	[−3.1, 0.8]	0.4	[−1.0, 3.0]	0.4	[−0.2, 1.1]	−0.2	[−0.6, 0.4]
Tanzania	0.4	[−1.3, 3.3]	−0.7	[−2.8, 0.7]	0.3	[−1.0, 2.6]	−0.3	[−0.7, 0.2]	−0.1	[−0.4, 0.4]
Cote dIvoire	−1.9	[−4.8, 1.6]	−2.0	[−7.2, 1.7]	1.7	[−1.9, 6.9]	−0.8	[−2.0, 0.4]	0.5	[−0.6, 2.1]
Chad	0.4	[−1.5, 2.9]	−0.8	[−4.4, 1.5]	0.6	[−1.7, 4.2]	−0.3	[−0.7, 0.1]	0.2	[−0.2, 0.7]
Armenia	0.0	[−2.4, 3.9]	0.2	[−1.4, 1.8]	0.2	[−0.9, 1.9]	0.3	[−0.6, 1.4]	0.2	[−1.0, 2.1]
Rwanda	0.3	[−1.1, 3.2]	0.2	[−0.9, 1.0]	−0.2	[−0.8, 0.9]	0.2	[−0.1, 0.5]	0.1	[−0.1, 0.4]
Egypt	−0.3	[−1.2, 1.3]	−0.7	[−2.2, 0.3]	**0.9**	[0.0, 2.4]	−0.1	[−0.3, 0.1]	0.0	[−0.2, 0.3]
Turkey	−0.2	[−2.0, 2.7]	0.1	[−1.7, 1.3]	−1.0	[−2.5, 0.9]	0.1	[−0.6, 1.0]	0.1	[−1.0, 1.6]
Guinea	0.1	[−3.4, 4.7]	−1.5	[−7.0, 2.6]	1.9	[−2.0, 7.7]	−0.1	[−0.9, 0.8]	0.3	[−0.5, 1.4]
Togo	−0.8	[−3.0, 2.7]	−1.0	[−4.4, 1.6]	0.8	[−1.6, 4.3]	0.2	[−0.4, 0.7]	0.2	[−0.3, 0.9]
Bolivia	**4.5**	[0.0, 11.7]	−0.4	[−3.6, 1.6]	0.0	[−1.9, 3.2]	−0.4	[−1.0, 0.2]	−0.6	[−1.3, 0.3]
Bangladesh	−0.6	[−1.8, 1.0]	−0.6	[−2.8, 0.8]	0.2	[−1.1, 2.4]	−0.2	[−0.6, 0.3]	0.1	[−0.3, 0.6]
Kyrgyzstan	−0.4	[−2.5, 3.3]	0.0	[−2.1, 1.8]	0.2	[−1.2, 2.4]	0.6	[−0.1, 1.5]	−0.1	[−0.4, 0.4]
Senegal	0.2	[−1.9, 2.9]	−0.4	[−3.1, 1.4]	1.1	[−0.5, 3.9]	**−0.4**	[−0.7, −0.1]	−0.1	[−0.3, 0.2]
Peru	0.2	[−0.6, 1.2]	−0.5	[−1.7, 0.3]	0.5	[−0.3, 1.8]	0.0	[−0.1, 0.2]	−0.1	[−0.3, 0.1]
Burkina Faso	0.1	[−1.8, 3.2]	−0.6	[−3.1, 1.0]	−0.9	[−2.6, 1.6]	0.0	[−0.5, 0.5]	−0.2	[−0.5, 0.1]
Uganda	−0.5	[−2.2, 1.8]	−0.5	[−3.4, 1.5]	0.1	[−1.8, 3.4]	**−0.6**	[−1.0, −0.1]	0.2	[−0.2, 0.6]
Gabon	−0.9	[−3.7, 2.3]	1.0	[−1.4, 3.3]	−1.5	[−3.2, 0.9]	**1.0**	[0.1, 2.1]	−0.1	[−1.3, 1.4]
Morocco	0.0	[−3.2, 5.7]	−0.2	[−3.3, 2.1]	0.2	[−1.8, 3.5]	−0.1	[−0.9, 0.8]	0.1	[−0.7, 1.3]
Guatemala	−0.5	[−1.6, 0.9]	−0.1	[−1.8, 0.9]	0.4	[−0.6, 2.0]	**−0.3**	[−0.6, 0.0]	0.0	[−0.3, 0.4]
India	−0.3	[−1.6, 1.6]	**1.1**	[0.0, 1.9]	**−1.2**	[−1.9, −0.1]	−0.2	[−0.4, 0.1]	0.0	[−0.2, 0.2]
Nigeria	−0.4	[−2.2, 1.7]	−1.8	[−4.9, 0.5]	1.9	[−0.4, 5.0]	**0.3**	[0.0, 0.7]	−0.1	[−0.4, 0.2]
Namibia	0.2	[−2.1, 3.4]	−1.2	[−4.0, 0.9]	1.9	[−0.1, 4.8]	0.0	[−0.5, 0.5]	0.2	[−0.5, 1.0]
Kenya	−0.3	[−1.0, 0.8]	−0.8	[−2.5, 0.2]	0.3	[−0.8, 2.0]	−0.1	[−0.4, 0.2]	−0.1	[−0.4, 0.3]
Haiti	0.0	[−2.3, 3.6]	−0.6	[−3.1, 1.1]	0.4	[−1.2, 3.0]	0.0	[−0.6, 0.6]	−0.4	[−1.1, 0.5]
Dominican Republic	1.4	[−1.5, 5.5]	−0.4	[−2.6, 1.5]	0.9	[−0.7, 3.4]	0.2	[−0.5, 1.0]	0.6	[−0.3, 1.9]
Ghana	0.4	[−2.0, 4.2]	−0.1	[−2.4, 1.9]	0.4	[−1.3, 2.9]	0.4	[−0.1, 1.1]	−0.2	[−0.8, 0.5]
Indonesia	1.1	[−1.3, 5.2]	−0.4	[−2.6, 1.0]	0.8	[−0.6, 3.0]	0.2	[−0.1, 0.5]	0.0	[−0.3, 0.3]
Pakistan	−0.7	[−2.2, 1.6]	−0.4	[−2.8, 1.1]	−0.3	[−1.8, 2.1]	0.2	[−0.2, 0.7]	−0.2	[−0.6, 0.2]
Philippines	0.1	[−1.4, 2.8]	0.7	[−0.2, 1.6]	−0.3	[−0.9, 0.6]	0.1	[−0.2, 0.4]	−0.1	[−0.3, 0.2]
Jordan	1.0	[−1.0, 4.8]	−0.4	[−2.4, 0.9]	**1.3**	[0.1, 3.3]	−0.1	[−0.3, 0.1]	0.0	[−0.3, 0.5]
Cameroon	−0.3	[−2.4, 2.6]	−1.4	[−4.6, 0.8]	0.6	[−1.6, 3.8]	0.3	[−0.4, 1.1]	0.6	[−0.3, 1.7]
Zimbabwe	1.0	[−1.1, 4.4]	−0.6	[−2.7, 0.9]	0.3	[−1.0, 2.6]	0.0	[−0.4, 0.6]	−0.1	[−0.7, 1.0]
Colombia	1.0	[−1.4, 4.9]	−1.4	[−4.6, 0.4]	1.5	[−0.4, 5.0]	0.3	[−0.4, 1.1]	0.9	[−0.3, 2.8]

6 Appendix

6.1 Summary of Categorical Covariates

Table 5. Proportion of Male and Urban in each survey for 42 countries

	Survey1		Survey2	
Country	Male	Urban	Male	Urban
Armenia	0.54	0.54	0.43	0.67
Bangladesh	0.51	0.51	0.24	0.32
Benin	0.51	0.51	0.27	0.35
Bolivia	0.51	0.52	0.52	0.51
Burkina Faso	0.51	0.51	0.31	0.21
Cambodia	0.51	0.50	0.14	0.27
Cameroon	0.51	0.50	0.53	0.40
Chad	0.51	0.51	0.37	0.20
Colombia	0.49	0.51	0.82	0.69
Comoros	0.51	0.50	0.24	0.33
Cote dIvoire	0.50	0.50	0.54	0.32
Dominican Republic	0.51	0.51	0.52	0.56
Egypt	0.52	0.52	0.34	0.41
Gabon	0.52	0.50	0.60	0.61
Ghana	0.51	0.52	0.27	0.40
Guatemala	0.51	0.52	0.23	0.35
Guinea	0.52	0.52	0.27	0.29
Haiti	0.50	0.51	0.38	0.34
India	0.52	0.52	0.28	0.38
Indonesia	0.51	0.52	0.26	0.46
Jordan	0.52	0.51	0.66	0.70
Kenya	0.50	0.51	0.11	0.33
Kyrgyzstan	0.50	0.51	0.28	0.26
Madagascar	0.51	0.52	0.23	0.17
Malawi	0.51	0.50	0.26	0.17
Mali	0.51	0.52	0.30	0.23
Morocco	0.51	0.51	0.35	0.43
Mozambique	0.50	0.51	0.26	0.33
Namibia	0.48	0.50	0.30	0.47
Niger	0.50	0.51	0.25	0.22
Nigeria	0.51	0.51	0.35	0.33
Pakistan	0.51	0.51	0.52	0.42
Peru	0.52	0.51	0.58	0.56
Philippines	0.51	0.52	0.45	0.41
Rwanda	0.50	0.51	0.14	0.22
Senegal	0.52	0.50	0.27	0.28
Tanzania	0.51	0.51	0.24	0.22
Togo	0.51	0.50	0.22	0.27
Turkey	0.51	0.51	0.61	0.67
Uganda	0.49	0.51	0.28	0.21
Zambia	0.49	0.51	0.34	0.37
Zimbabwe	0.50	0.50	0.22	0.40

6.2 The Distribution of Five Continous Covariates

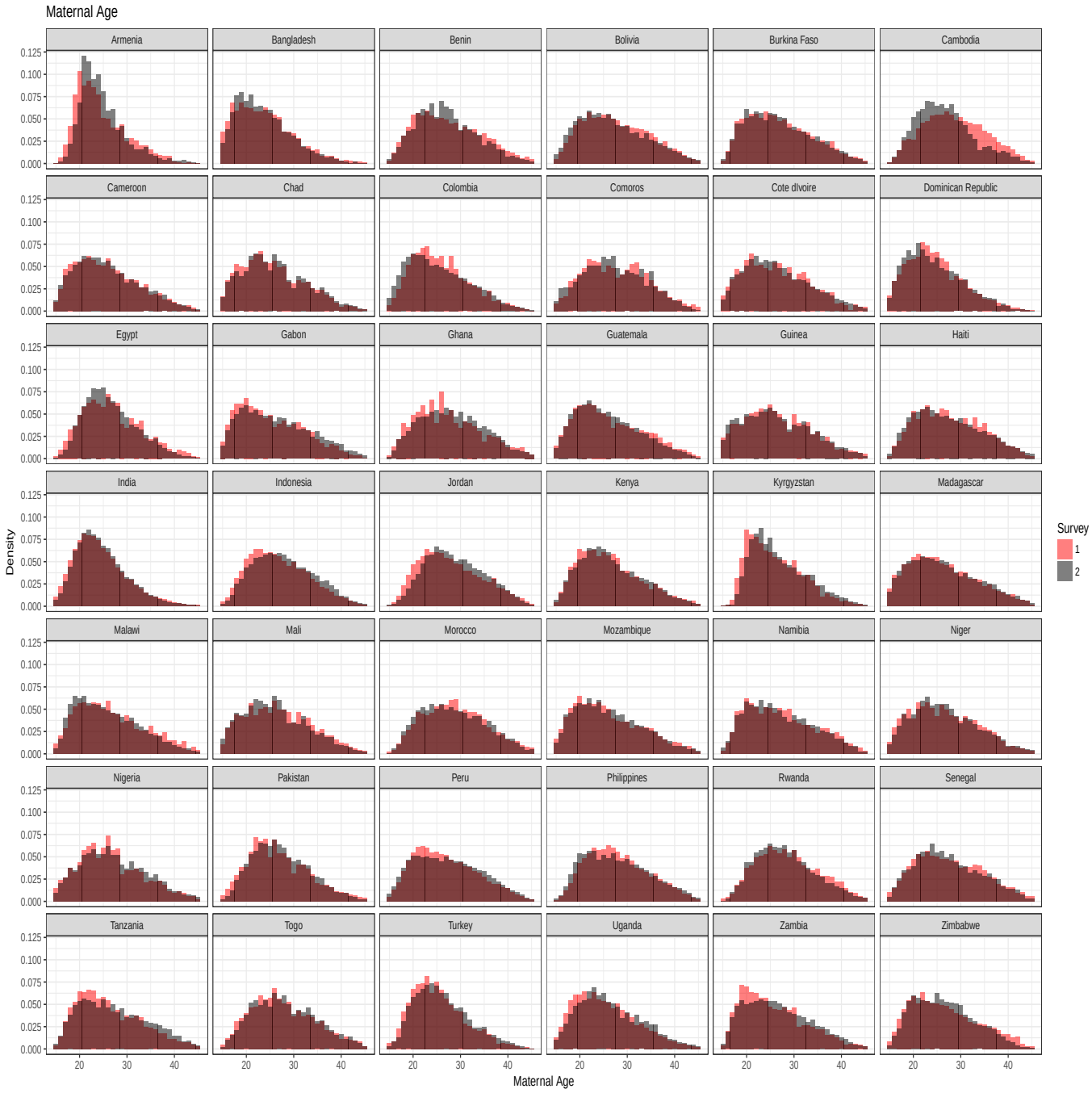

Figure 1 – Histogram of maternal age in two surveys for 42 countries

Figure 2 – Histogram of weath CDF in two surveys for 42 countries

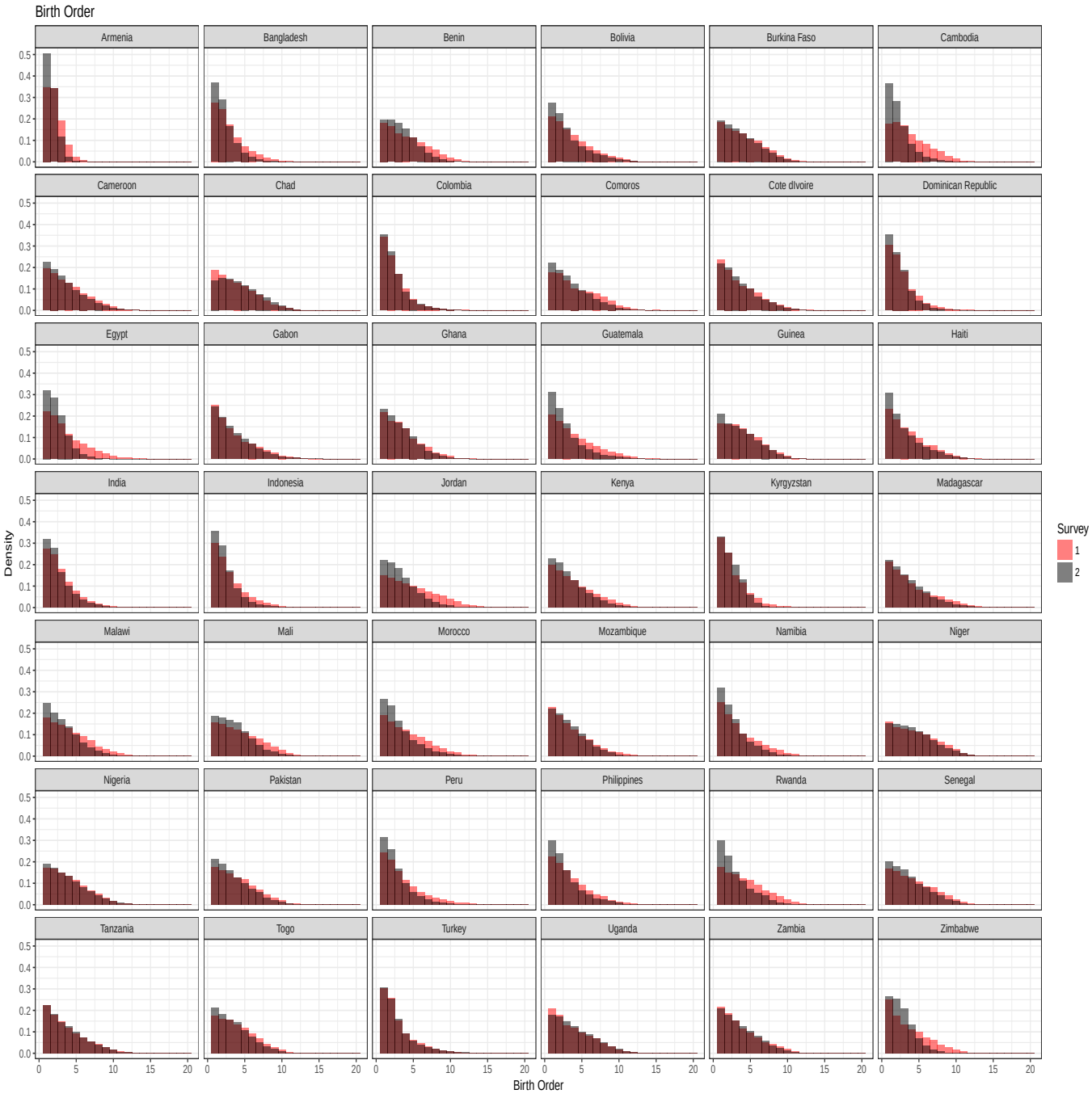

Figure 3 – Histogram of birth order in two surveys for 42 countries

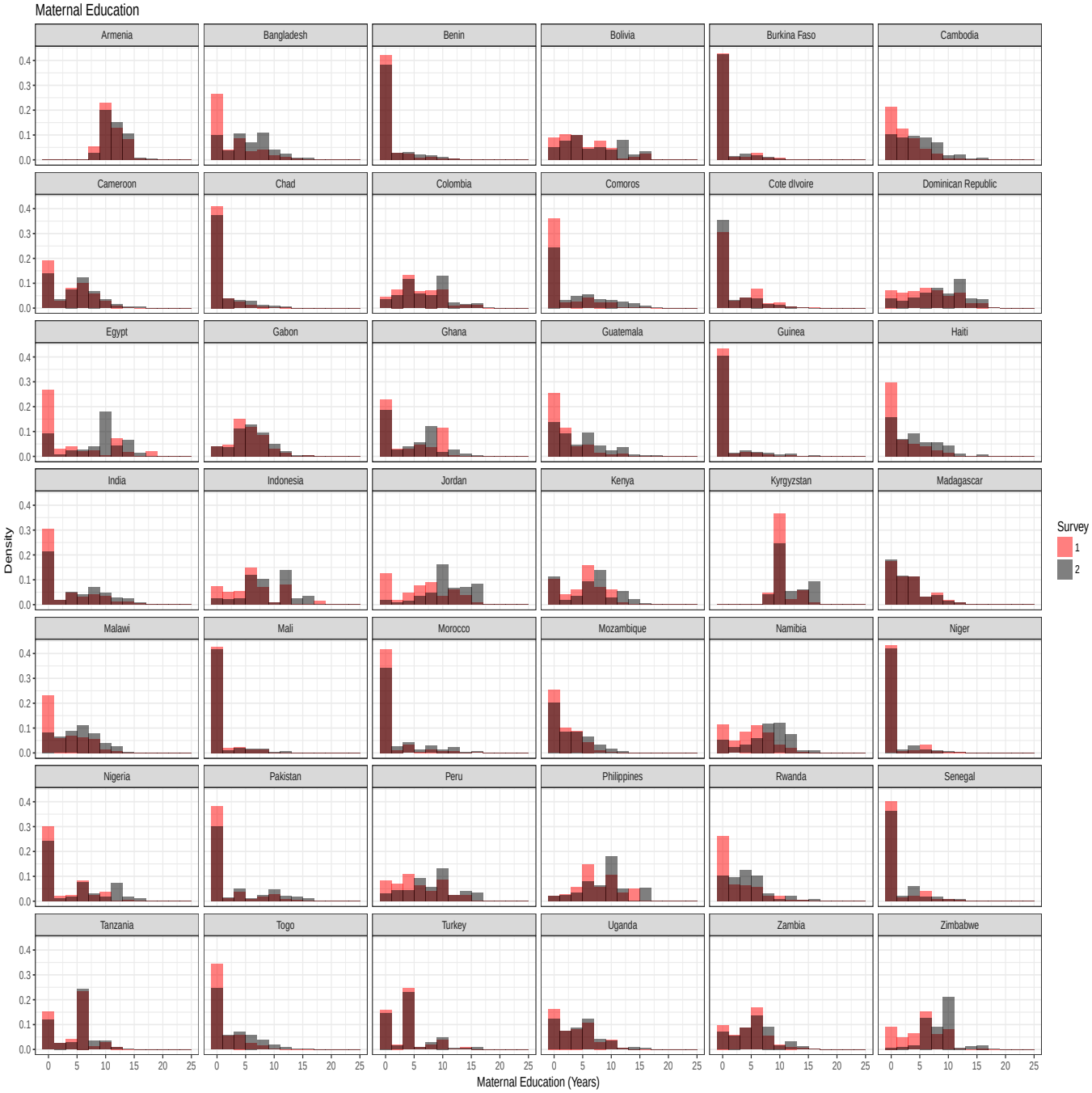

Figure 4 – Histogram of maternal education in two surveys for 42 countries

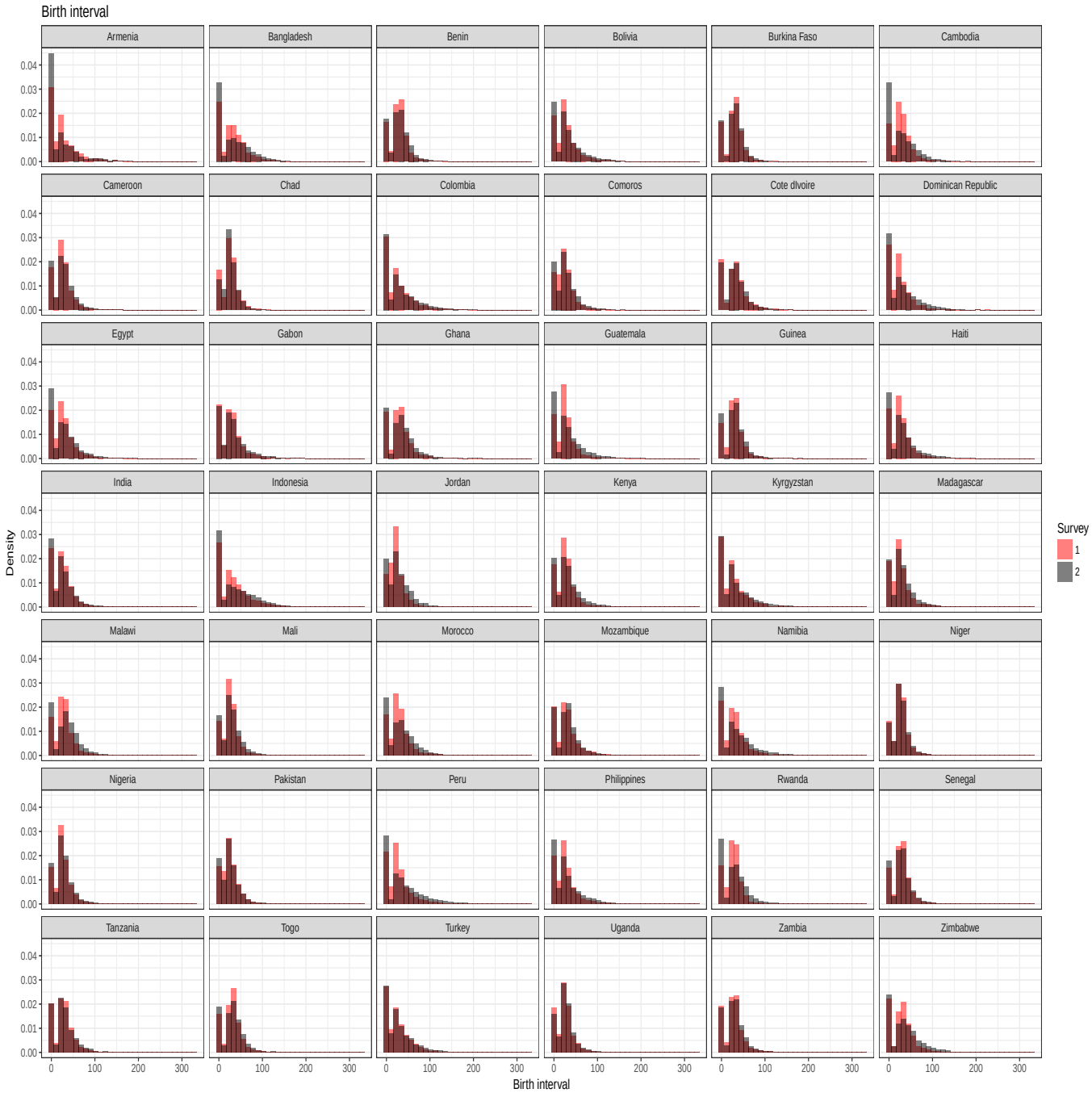

Figure 5 – Histogram of birth interval in two surveys for 42 countries

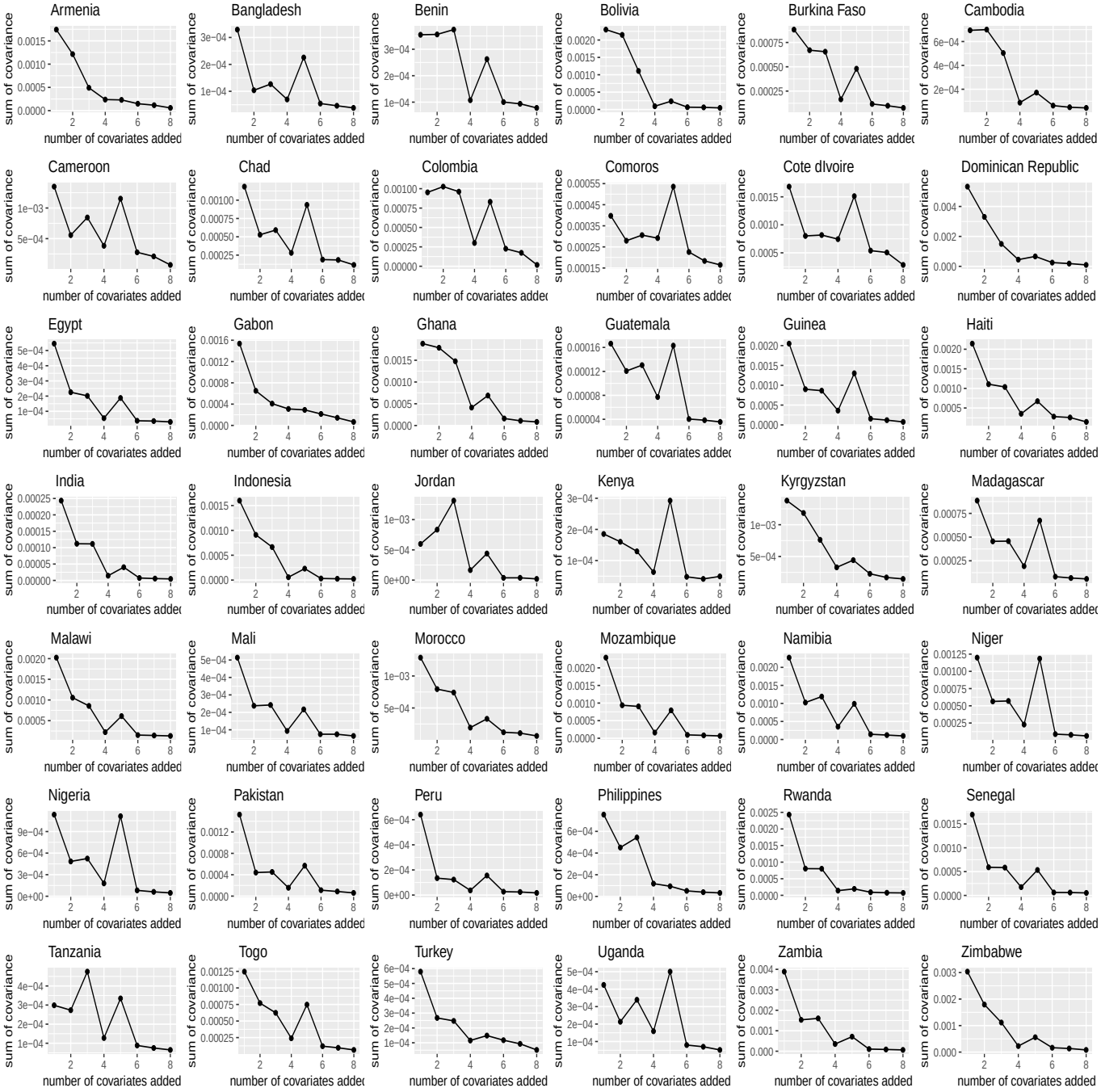

Figure 6 – The overall coefficient effect (9) can be written as a collapsing sum of the individual coefficients. The above figure plots the variance as more terms are added to the sum. The variance of the sum remains larger than the variance of the overall coefficient effect until the last coefficient is added into the sum.

Appendix

In equations (5) – (8) we integrated out the cluster level random effects γ_{jk} to do the Oaxaca decomposition, allowing us to calculate the marginal expected values of the y_{ijk}. For a derivation of this result, we start with the iterated expectation formula. Let Z be a standard normal random variable. Then

$$
\begin{aligned}
E[y_{ijk}] &= E[E(y_{ijk}|\gamma_{jk})] && (16)\\
&= E\Big[\Phi(\boldsymbol{x}_{ijk}^T\boldsymbol{\beta}_k + \gamma_{jk})\Big] && (17)\\
&= E\Big[P(Z < \boldsymbol{x}_{ijk}^T\boldsymbol{\beta}_k + \gamma_{jk}|\gamma_{jk})\Big] && (18)\\
&= P(Z < \boldsymbol{x}_{ijk}^T\boldsymbol{\beta}_k + \gamma_{jk}) && (19)\\
&= P(Z - \gamma_{jk} < \boldsymbol{x}_{ijk}^T\boldsymbol{\beta}_k) && (20)\\
&= P\Big(\frac{Z - \gamma_{jk}}{\sqrt{1+\sigma_k^2}} < \frac{\boldsymbol{x}_{ijk}^T\boldsymbol{\beta}_k}{\sqrt{1+\sigma_k^2}}\Big) && (21)\\
&= \Phi\Big(\frac{\boldsymbol{x}_{ijk}^T\boldsymbol{\beta}_k}{\sqrt{1+\sigma_k^2}}\Big) && (22)\\
&= \Phi(\boldsymbol{x}_{ijk}^T\tilde{\boldsymbol{\beta}}_k), && (23)
\end{aligned}
$$

where $\tilde{\boldsymbol{\beta}}_k = \frac{\boldsymbol{\beta_k}}{\sqrt{1+\sigma_k^2}}$.