

# Measuring Inequality in Early-Life Mortality Within and Between-Groups Over Time: A Bayesian Approach with Application to India.

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# Inequality in Early-Life Mortality

## Gaps between large groups of births

- Usually defined in terms of gaps between large groups of births.
- Precedes other dimensions of social inequality.
- Highly unequally distributed.
- In high income countries, national averages of child mortality are less than 10 deaths per thousand births, while these rates can be higher than 200 deaths per thousand births in low income countries.

# Between-Groups Inequality

## Reducing Inequality by Reducing Gaps

- Sustainable Development Goals calls for "By 2030, end preventable deaths of newborns and 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".

# Between-Groups Inequality

## Within-Countries Disparities

- Within-country disparities can be even larger, with the poor faring worse than the rich.
- Inequities also exist across race, ethnicity and geographic location etc.

# Gaps among wealth groups in India

Richest is 3 times less likely to die than the poorest



- lowest .12; second .11; middle .09; fourth .07; highest .04

## Data Disaggregation and Group Level Heterogeneity

- In India, 70 % of all deaths are not from the poorest quintile.
- Data from other 50 developing countries show similar pattern.
- Births from the same large groups may have very different mortality risk.
- Targeting the poor will lead to inefficient targeting

# Beyond Group Level Averages

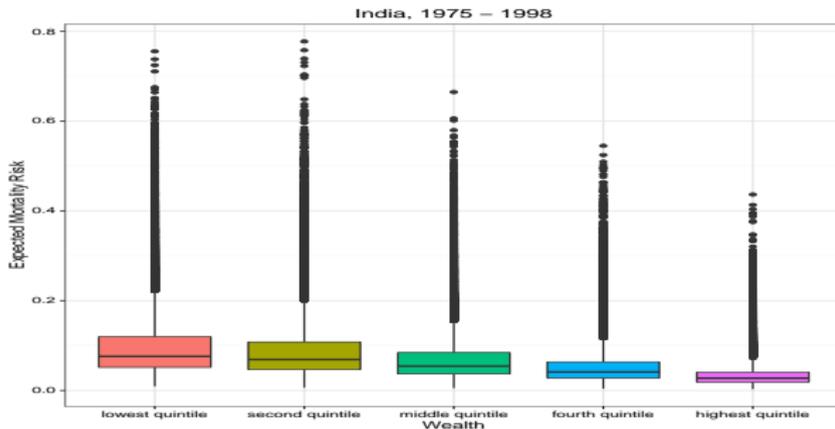
## Estimating Mortality Risk

- Average mortality rates easy to calculate for any group of births but it hides within-group variation.
- Calculating mortality risk for each births is more complex because it is not observable
- but it allows us to investigate within and between-group variation.

# Beyond Group Level Averages

## Estimating Mortality Risk

### Within-Group Variation in India



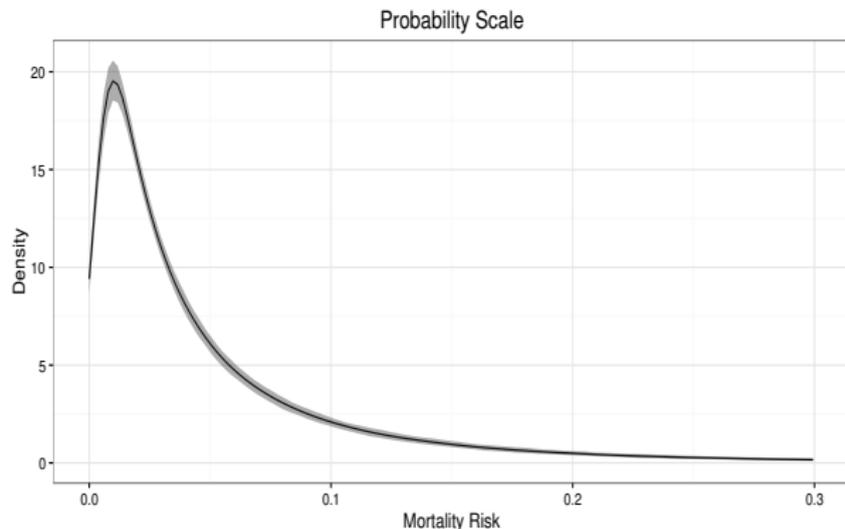
- 10% of births from the lowest quintiles have mortality risk higher than 12% (mean in the raw data).
- 30 % of births from other wealth quintiles have higher mortality risk than the median mortality risk among the poor (.08%).

# Estimating Mortality Risk in India

Two Waves of Demographic and Health Survey from India, 1975-1997.

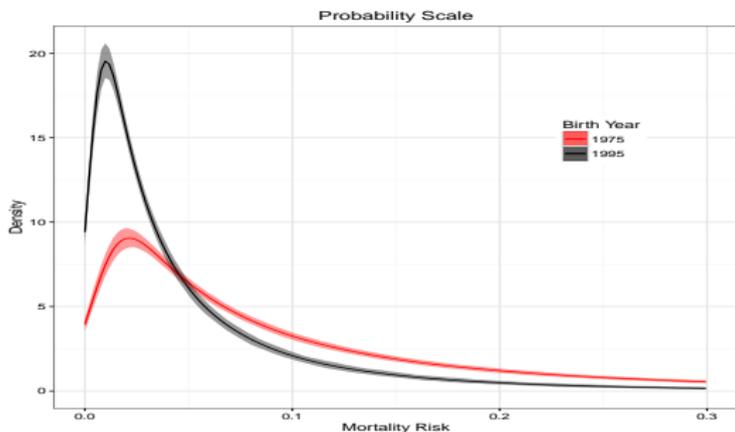
- 408, 706 births from nested in 141, 999 mothers aged 15 to 45, nested in from 3,806 sampling clusters, nested in from 443 districts, nested in from 26 states.
- risk factors: maternal age; maternal education; gender; birth order; wealth; year of the births; caste; and religion.
- Estimate infant mortality risk for each birth  $\hat{\pi}_i$  using a hierarchical Bayesian logit model.

# Distribution of Infant Mortality Risk in India in 1995



- Infant mortality rates (IMR)(based on raw data): 7%;
- Estimated mortality risk: mean: 5%; mode: 1%; median: 3%.
- Estimated proportion of infants with mortality risk higher than IMR: 20%.

# Distribution of Mortality Risk in India



	1975	1997
IMR	11%	7%
mode	2%	1 %
mean	10%	5%
median	5%	3 %
% births with mortality risk higher than IMR in 1975	28%	7 %

## How do we compare distributions of mortality risk?

- Within-group variation is very large and needs to be measured.
- WHO uses inequality measures from the income inequality literature but does it work?
- Mortality risk is a probability and thus defined in the unit interval,  $(0, 1)$ .
- Income is defined on the real line.

## Income Inequality Measures

Most measures of income inequality, such as Gini, Coefficient of Variation, or Theil, have a common formula and are ratio-based measures. For example, consider the coefficient of variation which is the mean,  $\mu$  divided by the standard error,  $\sigma$ :

$$CV = \frac{\sigma}{\mu} \quad (1)$$

where  $\sigma = \sqrt{\sum_i^n (\pi_i - \mu)^2}$  and  $\mu = \frac{1}{n} \sum_1^n \pi_i$ .

## Symmetry Property to investigate whether income inequality measures work for mortality risk

Any inequality measure should produce the same results whether we are measuring mortality ( $\pi_i$  probability of death) or survival ( $1 - \pi_i$ ) because we are measuring the same quantity but using alternative definitions

## Simulation Study

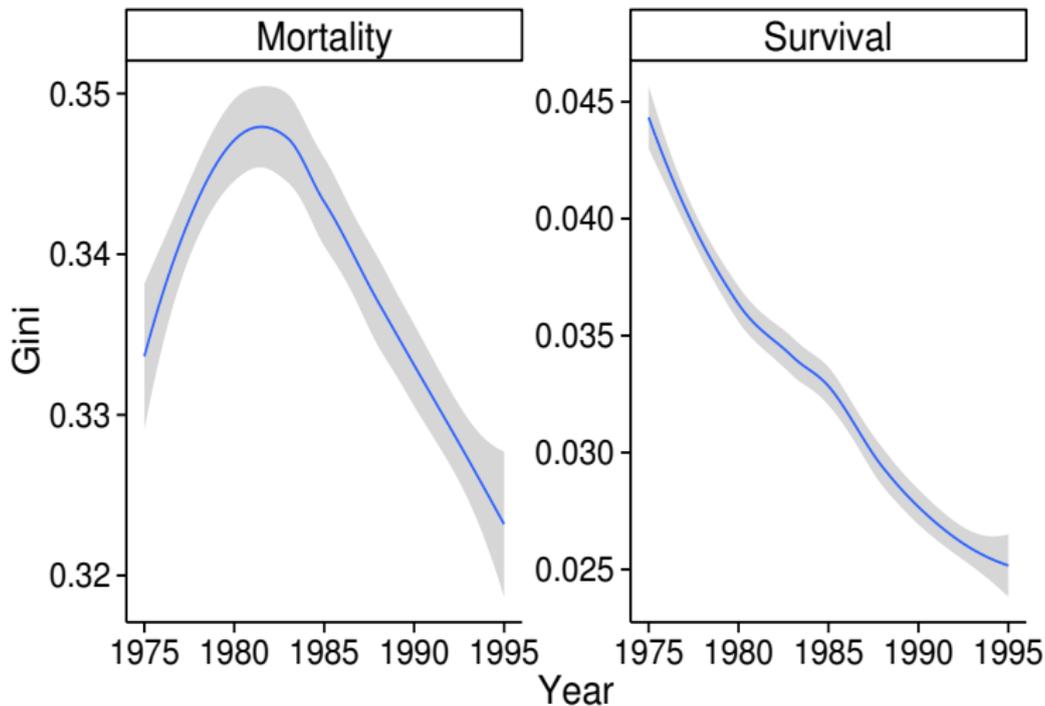
Beta ( $\alpha, \beta$ )	Mean		Sd		CV	
	Mort.	Surv.	Mort.	Surv.	Mort.	Surv.
(1,10)	.089	.91	.084	.084	.9	.09
(.5,10)	.048	.95	.063	.063	1.3	.066
(.3,10)	.029	.98	.05	.05	1.6	.05
(.01,10)	.009	.99	.009	.009	3	.029

Table: Simulated data to test the ratio based measures.

- Income inequality measures are not appropriate for quantifying Mortality Risk.
- Mean and Variances are OK.

# Example using data from India

Overtime trends in Inequality according to Gini



## What have we learned so far?

- Group averages hides within-group variation.
- Estimating mortality risk is useful to quantify variation within and between-groups.
- But income inequality measures are not appropriate for measuring inequality in mortality risk.

# What are we currently developing to quantify mortality risk?

- Paper is coming!
- Graphical and numerical methods that are appropriate to study inequality in mortality.
- Adjustments.
- Anova methods.

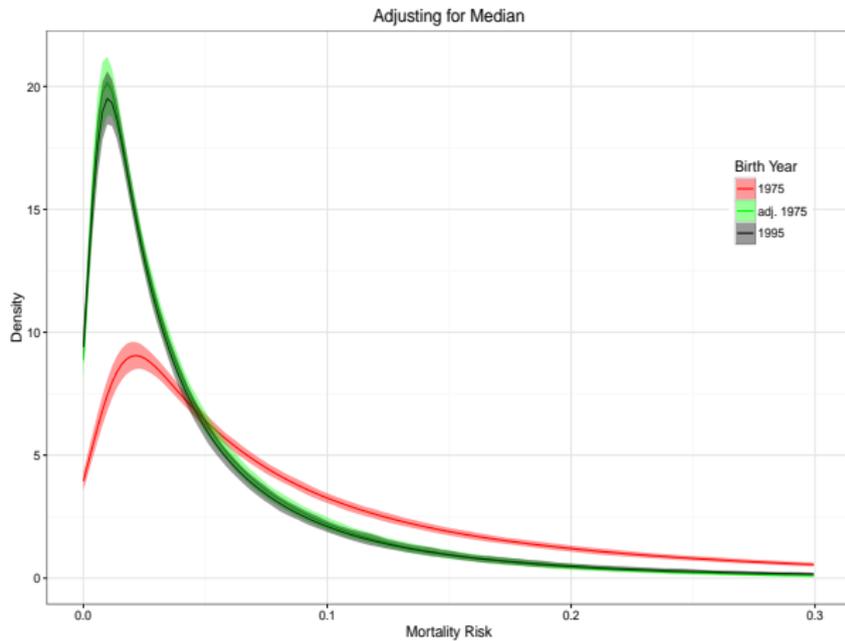
# Adjustments

## Multiplicative Adjustments

- Suppose we want to compare the distribution of mortality risk for two populations, say,  $Y_{1975}$  and  $Y_{1995}$ .
- How to summarize distributional changes by a simple shift?
- Create a third, counterfactual distribution  $Y_{adj}$ .
- $\rho = \text{median}(Y_{1975})/\text{median}(Y_{1995})$ .
- $Y_{adj} = Y_{1975} \times \rho$ .

# Adjustments

## Multiplicative Adjustments



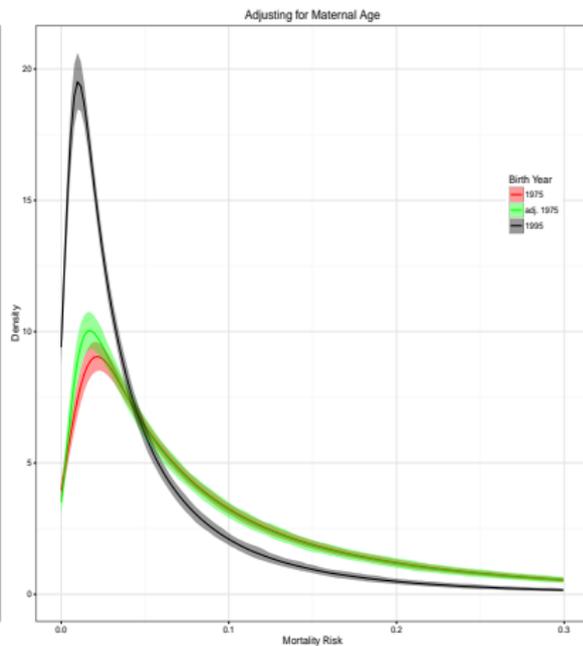
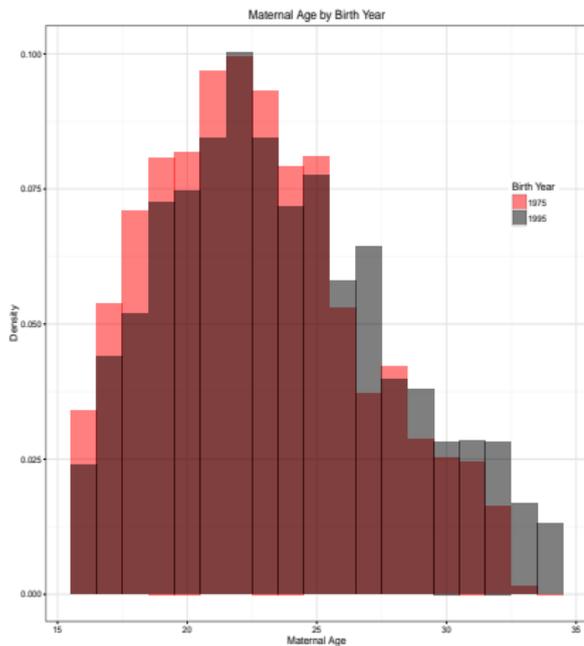
# Covariate Adjustments

## Compositional Changes in the Population

- How much of the differences between distributions of mortality risk are due to difference in the distributions of underlying risk factors (maternal age, maternal education and so forth).
- separate out the effects of the conditional effects  $\beta$ 's from the compositional effects  $X$ 's
- Similar to Oxaaca and Kitagawa decompositions but allow for comparing entire distributions, not only means.

# Covariate Adjustments

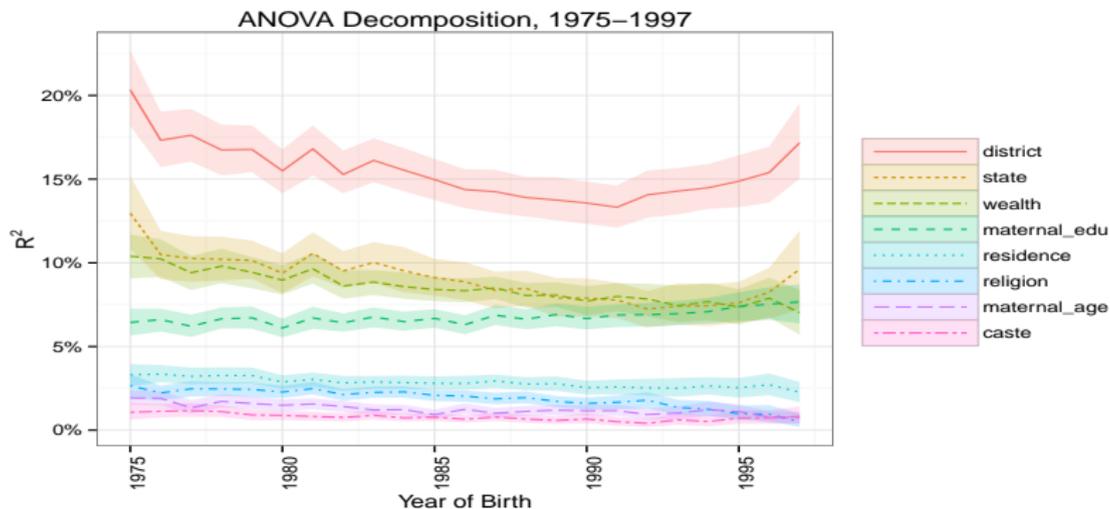
## Maternal Age



# Variance Decomposition

- Variance is a legit quantity for probabilities.
- Using ANOVA to decompose the variance in mortality risk.
- Outcome: mortality risk for each birth,  $\pi_i$ .
- Predictor (categorical): group membership (wealth, caste, district).
- Look at  $R^2$ .

# Variance Decomposition Over Time



**Figure:** Trends in fraction of the mortality risk explained by group level predictors for India, 1975-1998. Each line represents the trend for a particular group, showing how much of the variability in mortality risk is due to between-group sources. The shaded areas represent the 95 % confident regions from the Bayesian estimation.

# Implications and Extensions

## Summaries of Population Health

- Income Inequality measures do not work for mortality.
- Most of the variation in mortality risk is coming from within-group.
- Maybe some combination of variance and means?

# Implications and Extensions

## Sustainable Development Goals

- Sustainable Development Goals set priorities based on averages.
- Tracking average mortality rates may not be enough to describe inequality in mortality risk.

# Implications and Extensions

## Other Health Outcomes

- Other health outcomes are also defined on the probability scale (adult mortality, health life expectancy, GBD).
- Income inequality measures do not apply for them as well.
- Measuring within and between group-variation maybe be useful.

# Implications and Extensions

## Program targeting

- Targeting based on one risk factor is inefficient.
- Using multiple risk factors simultaneously to improve program targeting.
- Working paper from Ramos, Weiss, and Heymann uses data from India to show that using 4 risk factors improves targeting by 30% to 60%.