Health Insurance and Child Health Outcomes in Low- and Middle-Income Countries- Report: A Tiered Analysis Framework for Heterogeneous Data Environments

Sacha Bechara

September 8, 2025

1 Introduction

This paper presents a comprehensive analysis of health insurance impacts on child health outcomes across 37 low- and middle-income countries using Multiple Indicator Cluster Survey (MICS) data from 2018-2023. The analysis develops a tiered statistical framework that systematically addresses the heterogeneous data environments characteristic of LMICs, where insurance coverage ranges from near-universal to virtually absent. The paper is structured as follows: Section 2 reviews the literature on health insurance impacts in developing countries, identifying methodological challenges and regional patterns that motivate our analytical approach. Section 3 presents the statistical strategy and methodology, introducing the tiered framework for country classification based on statistical power. Section 4 reports results from the tiered analysis of four health outcomes. Section 5 documents selection mechanisms in data-limited settings through concentration indices and covariate balance assessment. Section 6 discusses implications for causal inference after attempting to replicate a study from Bagnoli (2019) using her scripts applied to both her data (2011 Ghana MICS wave) and the new data (2017). However, due to missing spatial data, the PSM approach fails to produce significant and similar results. At this stage, without such spatial data, it is impossible to indicate whether the estimated ATT reflects genuine non-effect of health insurance on stunting or if it is biased by counfounders. While I do not report the results in this paper, having tested multiple PSM specifications, matching techniques and common support area has shown that there is an effect on some populations but not others, though this remain, again, impossible to establish definitively.

2 Literature Review

2.1 Objectives and Scope

Our aim is to identify potential associational and, where data permit, causal effects of health insurance on child health outcomes in low- and middle-income countries. To situate this analysis within the broader evidence base, we review the literature examining insurance impacts across diverse LMIC settings, with particular attention to methodological approaches and their implications for understanding heterogeneous treatment effects.

2.2 Evidence on Health Insurance Impacts

The literature reveals substantial heterogeneity in health insurance effects across countries and outcomes. In Sub-Saharan Africa, community-based health insurance schemes have shown mixed results. Rwanda's Mutuelles de Santé achieved remarkable success with 85% population coverage, generating significant increases in facility-based delivery and preventive care visits (Lu et al., 2012). Ghana's National Health Insurance Scheme, despite achieving substantial coverage expansion, faced sustainability challenges and showed benefits concentrated in regions with well-functioning health systems (Brugiavini & Pace, 2017; Fenny et al., 2019). Bagnoli's (2019) analysis of Ghana is particularly instructive, demonstrating that insurance impacts on child health outcomes varied dramatically across regions, with gains concentrated among lower-income households in areas with high-quality public health care. This finding underscores the importance of examining both demand-side characteristics and supply-side constraints when evaluating insurance programs.

South Asian experiences further illustrate this heterogeneity. India's Ayushman Bharat, covering 550 million beneficiaries, shows promising but state-dependent results (National Health Authority, 2024). Pakistan's Sehat Sahulat Programme demonstrated improvements in children's nutritional status through propensity score matching analysis, though geographic coverage remains uneven (Aziz et al., 2022). These varied outcomes across similar institutional contexts suggest that uniform analytical approaches may mask important subnational variation.

East Asian countries provide evidence of more consistent positive effects, though methodological choices significantly influence estimated magnitudes. China's New Cooperative Medical Scheme generated persistent benefits for adolescent health and educational attainment when coverage occurred during early childhood (Chen & Jin, 2022; Wang et al., 2024). Vietnam's free insurance program for children under six has been extensively studied using regression discontinuity designs around the age cutoff, with conflicting results depending on specification choices and bandwidth selection (Palmer et al., 2015; Nguyen, 2020). Thailand's Universal Coverage Scheme represents one of the most successful programs, achieving 99% coverage and eliminating the association between poverty and infant mortality (Limwattananon et al., 2016; Gruber et al., 2014).

Latin American experiences highlight the importance of program design and integration with broader social protection systems. Peru's Comprehensive Health Insurance demonstrated significant reductions in infant mortality, particularly among impoverished populations (Bernal et al., 2017). Colombia's subsidized regime, evaluated through regression discontinuity design, showed substantial increases in preventive care utilization (Miller et al., 2013). Brazil's integration of universal health coverage with conditional cash transfers generated synergistic effects for child health (Rasella et al., 2014).

Meta-analytic evidence provides aggregate estimates while acknowledging substantial heterogeneity. Eze et al.'s (2023) comprehensive meta-analysis of 61 studies found that community-based health insurance increased overall healthcare utilization with an adjusted odds ratio of 1.60, though this masks variation across service types and populations. Spaan et al.'s (2018) systematic review of Sub-Saharan African programs emphasized methodological diversity as a key challenge for synthesizing evidence. These reviews consistently note that effect sizes vary dramatically based on context, implementation quality, and analytical methods employed.

2.3 Methodological Evolution and Challenges

The progression of identification strategies in this literature reflects growing recognition of selection bias challenges. Early cross-sectional comparisons suffered from severe confounding, as insurance enrollment correlates with both observable and unobservable characteristics affecting health outcomes. This recognition drove adoption of increasingly sophisticated econometric approaches.

Randomized controlled trials remain rare but provide crucial benchmarks. Thornton et al.'s (2010) evaluation in Nicaragua and Dercon et al.'s (2012) study among Kenyan tea farmers demonstrate causal effects under experimental conditions, though external validity remains limited. The scarcity of experimental evidence necessitates reliance on quasi-experimental methods for most settings.

Difference-in-differences designs have been particularly successful in exploiting staggered program rollouts, especially in China where county-level variation provides identifying variation (Wagstaff & Pradhan, 2005; Wagstaff & Yu, 2007). However, parallel trends assumptions often prove tenuous in contexts with rapid economic development and concurrent policy changes.

Regression discontinuity designs offer local identification around eligibility thresholds, as demonstrated in Vietnam's age-based eligibility studies. Yet bandwidth selection and functional form assumptions substantially influence results, explaining conflicting findings across studies of the same program.

Propensity score matching dominates the applied literature, attempting to balance observable characteristics between treated and control groups. The credibility of PSM estimates depends critically on the richness of available covariates and the plausibility of selection-on-observables assumptions. Studies with comprehensive household surveys achieve better covariate balance, though unobservable selection remains a persistent concern.

2.4 Implications for Analytical Strategy

The literature reveals three critical insights that inform our analytical approach. First, heterogeneous effects across regions, wealth groups, and health system capacity suggest that country-level analysis may be more appropriate than pooled specifications that assume homogeneous treatment effects. Bagnoli's (2019) regional analysis of Ghana exemplifies how national averages can mask dramatic subnational variation in program effectiveness.

Second, the severe data constraints in many LMIC settings preclude application of standard causal inference methods. When insurance coverage affects only a small fraction of the population, positivity violations and lack of common support undermine both experimental and quasi-experimental designs. This reality necessitates a transparent framework for documenting when causal inference is feasible versus when analysis must remain descriptive.

Third, selection mechanisms vary systematically with program design and implementation context. Universal schemes with automatic enrollment face different selection challenges than voluntary insurance programs requiring active registration. Understanding these selection patterns is essential for interpreting observed associations and designing future evaluations.

These insights motivate our tiered analytical framework, which explicitly acknowledges data limitations while maximizing information extraction from available surveys. By classifying countries based on statistical power and documenting selection mechanisms comprehensively, we provide a foundation for understanding when observed associations may reflect causal relationships versus when they primarily capture selection on observables and unobservables. This approach responds directly to calls in the literature for greater attention to context and implementation conditions (Ridde & Morestin, 2011; Mate et al., 2013) while maintaining methodological rigor appropriate to each data environment.

3 Statistical Strategy and Methodology

3.1 Study Aim and Analytical Framework

The primary aim of this analysis was to understand cross-country relationships between health insurance coverage and child health outcomes through systematic documentation of selection mechanisms that would inform future propensity score matching (PSM) analyses. Given the extreme heterogeneity in insurance implementation across low- and middle-income countries (LMICs), with coverage rates ranging from 0.16% to 98.63%, we developed a tiered statistical strategy that explicitly accounts for data constraints while documenting the covariate structures necessary for identifying matched comparison groups.

This approach serves as an informative document for researchers planning causal inference studies, revealing which countries have sufficient overlap in covariate distributions to support matching methods and which settings exhibit such extreme selection that observational comparisons are fundamentally compromised.

3.2 Data Sources and Sample

The analysis utilizes Multiple Indicator Cluster Surveys (MICS) data from 2018-2023, encompassing 37 low- and middle-income countries. The analytical sample includes children under five years of age, with country-specific samples ranging from 1,429 to 30,709 observations. Survey weights account for complex sampling designs, with primary sampling units (PSUs) or cluster identifiers used for variance estimation.

3.3 The Tiered Statistical Strategy

3.3.1 Rationale for Stratified Analysis

The distribution of health insurance across LMICs creates three distinct analytical challenges that preclude uniform statistical treatment:

1. **Positivity violations**: In countries with extremely low coverage (<2%), the rarity of insured children creates empty or near-empty cells in the exposure-outcome contingency table

2. **Lack of common support**: Insured and uninsured populations often occupy non-overlapping regions of the covariate space, particularly in wealth distribution

3. **Geographic clustering**: Insurance implementation frequently targets specific administrative units, creating spatial confounding

To address these challenges systematically, we developed a three-tier classification based on minimum cell counts that determines the appropriate statistical approach for each country-outcome combination.

3.3.2 Tier Assignment Algorithm

For each country c and outcome y, we construct the 2×2 contingency table:

$$\text{MinCell}_{c,y} = \min\{n_{11}, n_{10}, n_{01}, n_{00}\} \tag{1}$$

where n_{ij} represents the count for insurance status $i \in \{0,1\}$ and outcome status $j \in \{0,1\}$.

Countries are then classified as:

- **Tier 1**: MinCell ≥ 20 (sufficient for maximum likelihood estimation)
- **Tier 2**: $10 \leq$ MinCell < 20 (marginal identification)
- **Tier 3**: MinCell < 10 (insufficient for inference)

This classification is applied separately for four outcomes: stunting (anthropometric failure), DPT3 vaccination, severe deprivation (multidimensional poverty), and diarrhea care-seeking.

3.4 Tier-Specific Statistical Methods

3.4.1 Tier 1: Survey-Weighted Logistic Regression

For countries meeting Tier 1 criteria, we estimate associations using survey-weighted generalized linear models:

$$\log\left(\frac{\Pr(Y_{ij}=1|I_{ij})}{\Pr(Y_{ij}=0|I_{ij})}\right) = \beta_0 + \beta_1 I_{ij} \tag{2}$$

where Y_{ij} denotes the outcome for child i in cluster j, and I_{ij} indicates insurance status. The model incorporates survey design through:

$$\hat{\beta}_1^w = \arg\min_{\beta_1} \sum_{i,j} w_{ij} \left[Y_{ij} - g^{-1}(\beta_0 + \beta_1 I_{ij})\right]^2 \tag{3}$$

where w_{ij} represents survey weights and g^{-1} is the inverse logit link. Standard errors employ Taylor linearization accounting for clustering.

3.4.2 Tier 2: Risk Differences with Bounded Confidence Intervals

For Tier 2 countries, we calculate weighted risk differences:

$$\widehat{RD} = \frac{\sum_{i:I_i=1} w_i Y_i}{\sum_{i:I_i=1} w_i} - \frac{\sum_{i:I_i=0} w_i Y_i}{\sum_{i:I_i=0} w_i} \tag{4}$$

Confidence intervals use the Wilson score method for better coverage properties with small samples:

$$CI_{Wilson} = \frac{2n\hat{p} + z^2 \pm z\sqrt{z^2 + 4n\hat{p}(1-\hat{p})}}{2(n+z^2)} \tag{5}$$

where z is the standard normal quantile and adjustments incorporate survey weights.

3.4.3 Tier 3: Descriptive Documentation

Countries in Tier 3 receive only descriptive documentation of cell distributions without inferential statistics, serving to identify settings where future data collection is needed before causal analysis.

3.5 Selection Mechanism Quantification

3.5.1 Covariate Balance Assessment

For all Tier 2 and Tier 3 countries, we quantify selection on observables through standardized differences:

$$d_{Cohen} = \frac{\bar{X}^w_{I=1} - \bar{X}^w_{I=0}}{\sqrt{\frac{(n_1-1)s_1^2 + (n_0-1)s_0^2}{n_1+n_0-2}}} \tag{6}$$

where $\bar{X}^w_I$ represents weighted means and s^2 represents weighted variances for covariates including wealth quintile, urban residence, and maternal education.

3.5.2 Concentration Index Methodology

Insurance concentration across the wealth distribution is quantified using the convenient regression approach (Kakwani et al., 1997):

$$CI = 2 \cdot \text{cov}_w(h_i, R_i)/\mu_h \tag{7}$$

Operationalized through weighted least squares:

$$\frac{2(h_i - \mu_h)}{\mu_h} = \alpha + CI \cdot R_i + \epsilon_i \tag{8}$$

where h_i indicates insurance status, R_i represents fractional rank in the wealth distribution:

$$R_i = \frac{\sum_{j<i} w_j + 0.5 w_i}{\sum_j w_j} \tag{9}$$

3.5.3 Geographic Clustering Metrics

Three complementary measures characterize spatial concentration:

$$\text{Dispersion Index: } D = \frac{|\{j : n_{j,ins} > 0\}|}{N_{clusters}} \tag{10}$$

$$\text{Mixing Index: } M = \frac{|\{j : n_{j,ins} > 0 \wedge n_{j,unins} > 0\}|}{|\{j : n_{j,ins} > 0\}|} \tag{11}$$

$$\text{Geographic Selection: } \Delta_{geo} = \bar{W}_{with} - \bar{W}_{without} \tag{12}$$

where j indexes geographic units and $\bar{W}$ represents mean wealth.

3.6 Summary of Tables and Figures

3.6.1 Part I: Tier-Stratified Statistical Associations

Table 1: Summary of Tables in Part I

Table	Description	Sample Size
1	Stunting OR estimates (Tier 1)	18 countries
2	Stunting risk differences (Tier 2)	7 countries
3	DPT3 vaccination OR estimates (Tier 1)	16 countries
4	DPT3 vaccination risk differences (Tier 2)	5 countries
5	Severe deprivation OR estimates (Tier 1)	21 countries
6	Severe deprivation risk differences (Tier 2)	4 countries
7	Diarrhea care OR estimates (Tier 1)	8 countries
8	Diarrhea care risk differences (Tier 2)	6 countries

Table 2: Summary of Figures in Part I

Figure	Description
1	Forest plot: Stunting ORs with insurance coverage levels (Tier 1)
2	Four-panel diagnostic: Stunting risk differences and constraints (Tier 2)
3	Heatmap: Cell distributions for stunting (Tier 3)
4-6	Parallel visualizations for DPT3 vaccination
7-9	Parallel visualizations for severe deprivation
10-12	Parallel visualizations for diarrhea care-seeking

3.6.2 Part II: Selection Mechanism Documentation

3.7 Implications for Propensity Score Matching

This tiered analysis provides essential documentation for future PSM studies by:

Table 3: Summary of Tables in Part II

Table	Description	Coverage
9	Covariate differences: Stunting analysis	19 countries
10	Covariate differences: DPT3 vaccination	21 countries
11	Covariate differences: Severe deprivation	8 countries
12	Covariate differences: Diarrhea care	26 countries
13	Concentration indices across wealth distribution	31 countries
14	Geographic clustering and spatial selection	31 countries
15	Comprehensive results: All outcomes and methods	37 countries

Table 4: Summary of Figures in Part II

Figure	Description
13	Concentration curves for all Tier 2/3 countries
14	Concentration curves grouped by inequality classification
15	Bivariate plot: Individual vs. geographic wealth selection

1. **Identifying feasible settings**: Countries in Tier 1 with moderate concentration indices (CI < 0.4) have sufficient overlap for matching

2. **Documenting selection variables**: Wealth quintile emerges as the primary confounder (median Cohen's d = 0.95), followed by urban residence and maternal education

3. **Revealing positivity violations**: Six countries show extreme concentration (CI $>$ 0.8) where the wealthy-insured and poor-uninsured have no overlapping support

4. **Quantifying geographic confounding**: Eleven countries show insurance present in less than 10% of geographic units, requiring spatial matching strategies

The comprehensive documentation in Table 15 synthesizes these findings across all countries and outcomes, serving as a reference for researchers designing observational studies of health insurance impacts in resource-constrained settings.

3.8 Statistical Software and Reproducibility

All analyses were conducted in R version 4.4.1 using the `survey` package for complex survey designs, `xtable` for table generation, and `ggplot2` for visualizations. Code and detailed tier assignments are available in the supplementary materials to facilitate replication and extension to additional countries as new MICS rounds become available.

4 Part I: Statistical Associations by Tier

4.1 Section I.A: Stunting

4.1.1 Tier 1 Analysis (n=XX countries)

Table 5: Association between health insurance and stunting among children under 5 (Tier 1 countries)

Country	Coverage (%)	N Insured	N Uninsured	OR (95% CI)	P-value	Sig	Reliability
COD	3.1380334	391	20582	0.38 (0.23-0.61)	¡0.001	***	High
BEN	0.8223459	117	12792	0.43 (0.25-0.73)	0.002	**	Medium
LAO	13.7563033	1587	9918	0.46 (0.39-0.54)	¡0.001	***	High
NPL	3.7895348	290	6194	0.51 (0.37-0.72)	¡0.001	***	High
ZWE	6.1713474	360	5728	0.51 (0.35-0.75)	¡0.001	***	Medium
TGO	3.8661758	218	4711	0.57 (0.33-0.99)	0.05	*	Medium
TKM	38.1544137	1581	2095	0.60 (0.44-0.83)	0.002	**	High
DOM	52.8565685	4000	4367	0.67 (0.51-0.87)	0.003	**	High
SUR	87.8022052	3706	490	0.73 (0.43-1.23)	0.23		Medium
DZA	50.6221591	6947	7666	0.74 (0.64-0.87)	¡0.001	***	High
ARG	43.8252072	2830	3192	0.75 (0.56-1.00)	0.05		High
MDG	2.2074256	179	12636	0.80 (0.56-1.15)	0.22		High
COM	5.2129373	254	4107	0.82 (0.56-1.21)	0.32		Medium
GHA	58.7344444	5350	3394	0.83 (0.69-0.99)	0.04	*	High
TUN	82.3102212	2778	567	0.97 (0.69-1.35)	0.85		Medium
PSE	71.8417984	4467	1811	1.01 (0.79-1.29)	0.96		High
SLE	3.8914162	416	11015	1.09 (0.82-1.45)	0.55		High
THA	97.7906697	23133	568	1.31 (0.74-2.32)	0.36		High

Note:

OR = Odds Ratio; CI = Confidence Interval. *** p¡0.001, ** p¡0.01, * p¡0.05. Tier 1 includes countries with 20 events in the smaller exposure group. Models adjusted for survey design using PSU or cluster as indicated in methods.

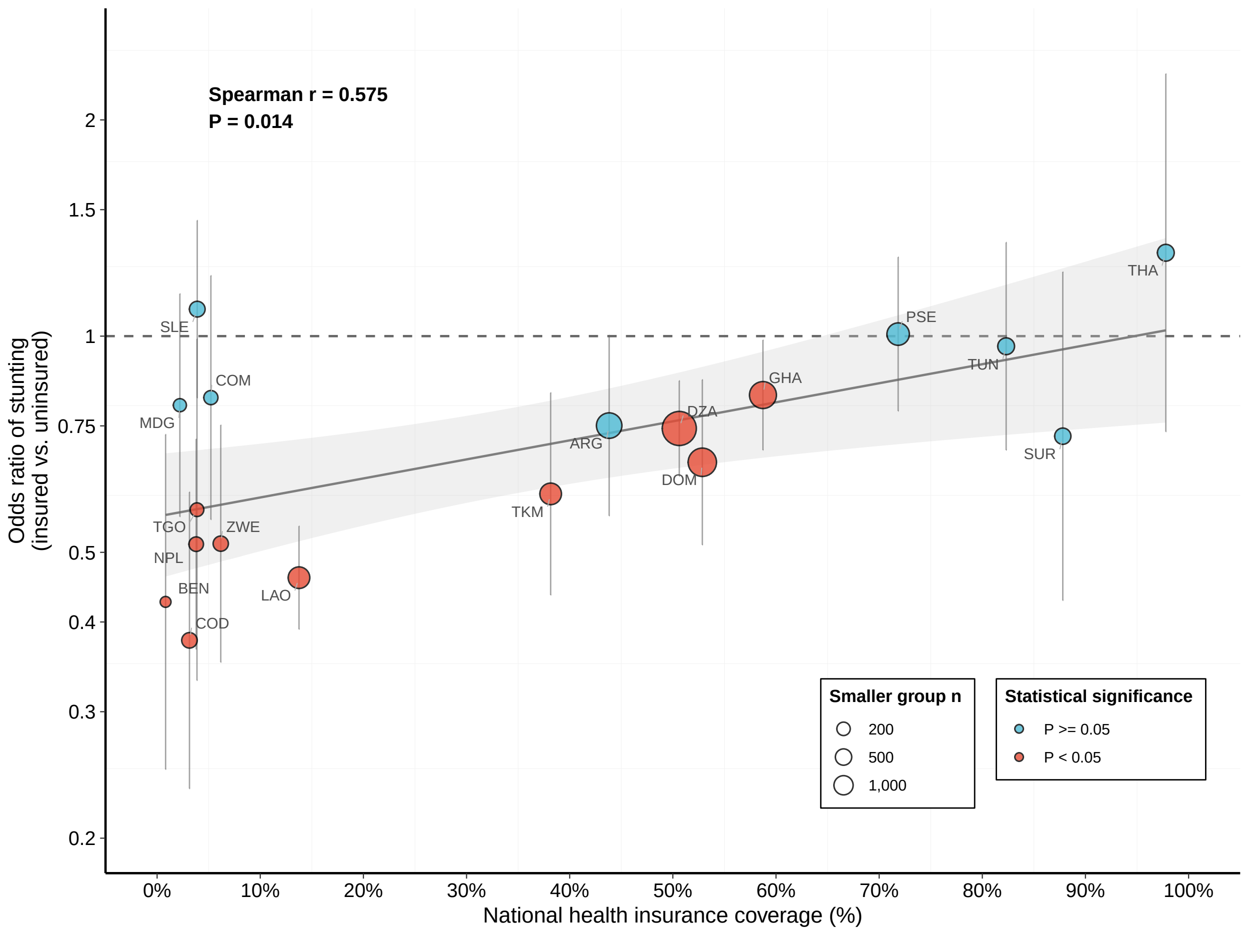


Figure 1: **Association between national health insurance coverage and childhood stunting (children under 5) across 18 low- and middle-income countries. OR** $<$ **1**: insured children have lower odds of stunting (protective association); **OR** $>$ **1**: insured children have higher odds (harmful association). Horizontal dashed line at **OR** $=$ **1**: no association. Points sized by smaller exposure group (54–5,350 children). **Red points**: P $<$ 0.05; **Blue points**: P $\geq$ 0.05. **Spearman** ρ $=$ **0.575** (P $=$ 0.014).
Each point represents one country, with x-axis showing percentage of children under 5 with health insurance coverage. Y-axis shows odds ratio of stunting comparing insured to uninsured children, derived from survey-weighted logistic regression models adjusting for complex survey design (primary sampling units or clusters). Point size reflects the smaller of the two exposure groups (insured or uninsured). Vertical bars represent 95% confidence intervals. Grey shaded area shows 95% confidence interval for the linear trend fitted by ordinary least squares regression of log(OR) on coverage percentage. The Spearman rank correlation coefficient tests whether there is a monotonic relationship between a country's insurance coverage level and the strength of the insurance-stunting association in that country. This positive correlation is presented for exploratory purposes only and should not be interpreted causally. Countries are labeled using ISO 3-letter codes. **Data source:** Multiple Indicator Cluster Surveys (MICS), 2018–2023.

4.1.2 Tier 2 Analysis (n=7 countries)

Table 6: Risk differences for stunting between insured and uninsured children (Tier 2 countries)

Country	Coverage (%)	N Insured	N Uninsured	Stunted Insured (%)	Stunted Uninsured (%)	Risk Difference (95% CI)	CI Excl
CAF	0.5144287	53	8604	18.867925	38.005579	-19.1 (-27.5 to -6.6)	Y
YEM	0.4193963	56	18819	32.142857	46.288326	-14.1 (-24.9 to -1.1)	Y
MWI	0.4625630	71	15197	23.943662	32.519576	-8.6 (-17.0 to 2.5)	[illegible]
GNB	1.0578628	54	7315	18.518518	26.917293	-8.4 (-16.6 to 4.0)	[illegible]
TON	84.9954603	1086	243	2.302026	5.761317	-3.5 (-7.2 to -0.9)	Y
GUY	7.4837471	162	2561	10.493827	11.479891	-1.0 (-5.1 to 4.8)	[illegible]
CRI	91.1773243	3176	339	7.178841	4.719764	2.5 (-0.5 to 4.5)	[illegible]

Note:

Tier 2 includes countries with 10-19 events in the smaller exposure group. Risk differences calculated as percentage point difference (insured minus uninsured). Negative values indicate lower stunting prevalence among insured children. 95% confidence intervals calculated using Wilson score method.

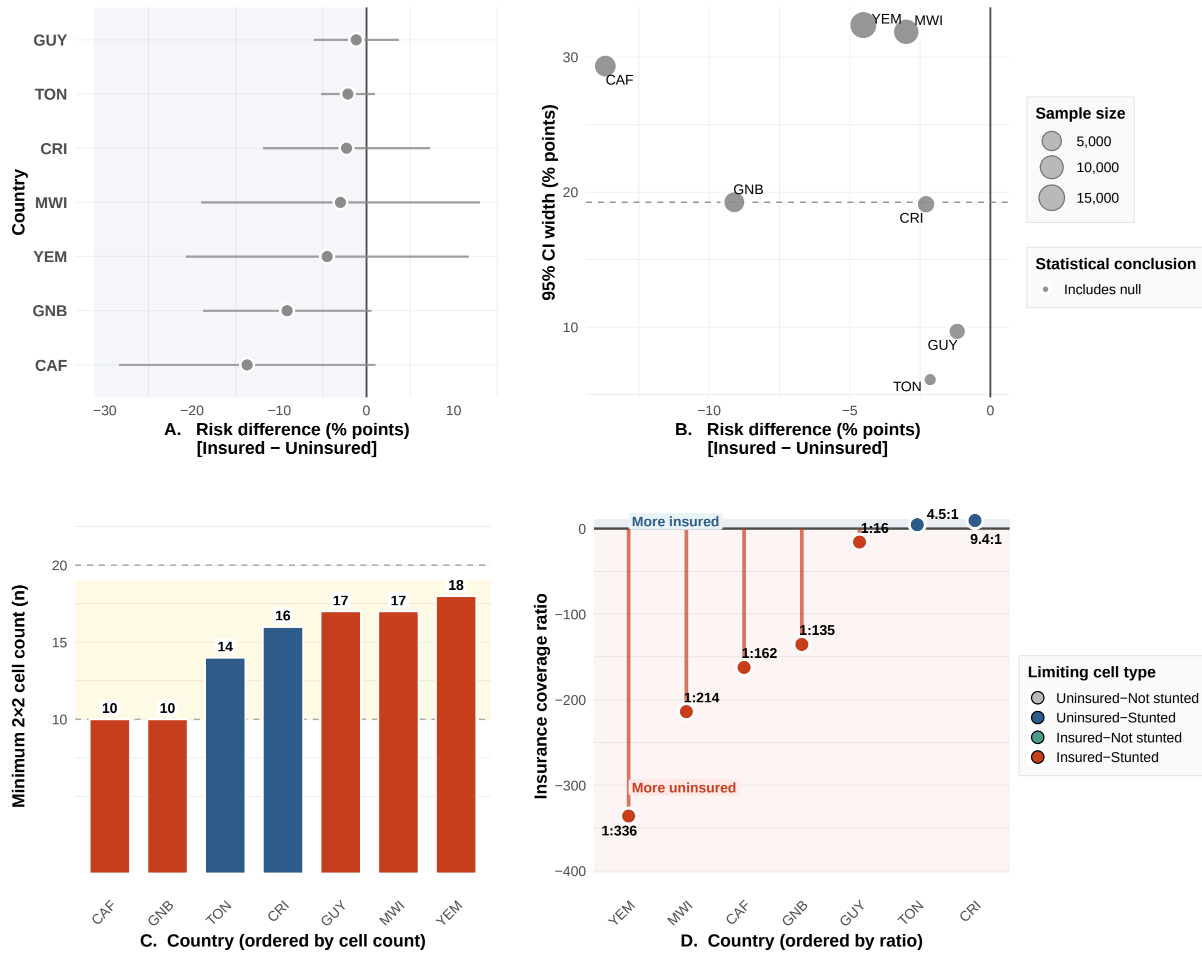


Figure 2: **Analysis of health insurance-stunting associations in Tier 2 countries with limited statistical power.**

Panel A shows risk differences (percentage point difference in stunting prevalence between insured and uninsured children) with 95% confidence intervals for countries meeting Tier 2 criteria (10-19 events in the smallest exposure-outcome cell). Risk differences calculated as (percentage stunted among insured) minus (percentage stunted among uninsured); negative values indicate lower stunting prevalence among insured children. Confidence intervals derived using Wilson score method for difference between two proportions. Points colored by statistical inference: blue indicates confidence interval excludes zero, grey indicates confidence interval includes zero. **Panel B** plots risk difference against confidence interval width to visualize the precision-effect relationship. Point size proportional to total sample size. Fill color indicates whether 95% confidence interval excludes zero. Horizontal dashed line marks median CI width. Vertical line at zero separates protective (negative) from harmful (positive) associations. Legends show statistical conclusion and sample size. **Panel C** displays the constraining cell count for each country—the minimum count across four exposure-outcome combinations. Countries ordered by ascending minimum cell count. Horizontal dashed lines mark Tier 2 boundaries (10 and 20 events), with yellow shading indicating the Tier 2 zone. Bar colors correspond to limiting cell type. **Panel D** presents exposure group imbalance on a bidirectional scale, where positive values indicate more insured than uninsured children (ratio > 1) and negative values indicate more uninsured than insured (ratio < 1). Y-axis values calculated as: if ratio > 1, display as positive; if ratio < 1, display as negative reciprocal. Points and stems colored by limiting cell type (matching Panel C colors). Ratios displayed adjacent to points show actual insured:uninsured proportions. Legend shows all four possible limiting cell types. All analyses use survey-weighted proportions without adjustment for confounders. Data source: Multiple Indicator Cluster Surveys (MICS), 2018-2023.

4.1.3 Tier 3 Analysis (n=12 countries)

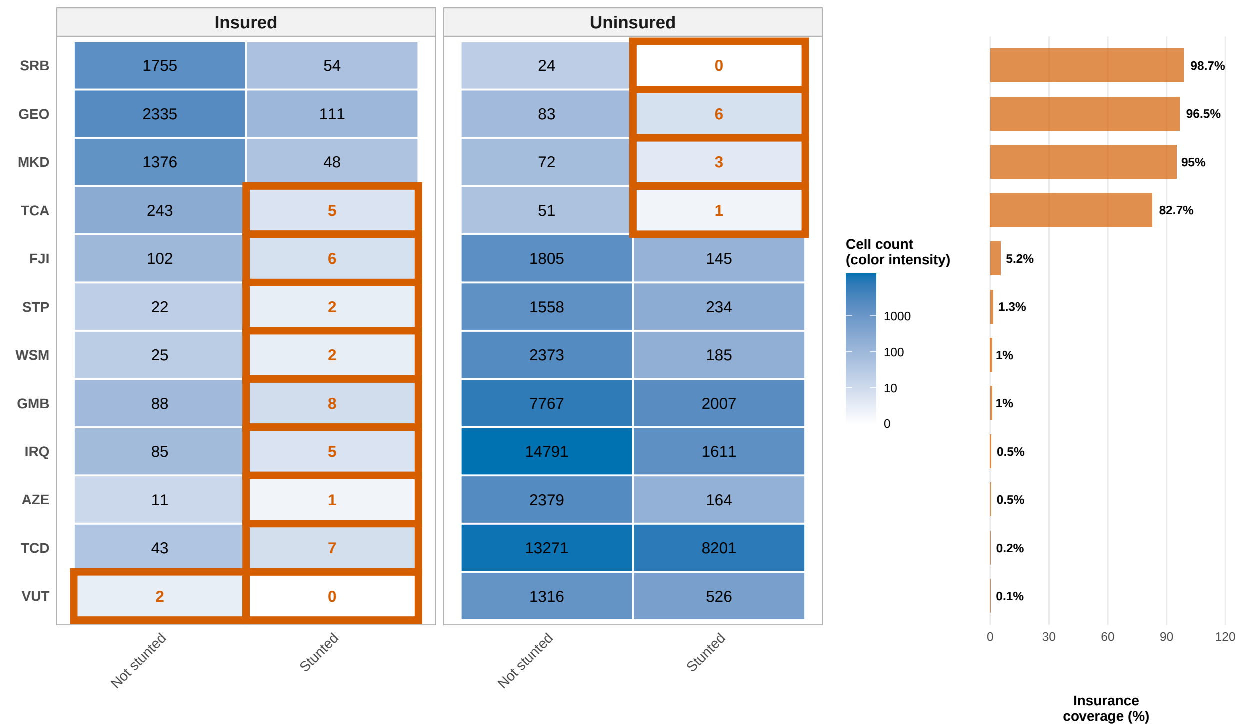


Figure 3: **Distribution of observations across exposure-outcome cells for Tier 3 countries with insufficient statistical power for stunting analysis.** Countries classified as Tier 3 have fewer than 10 events in at least one of four exposure-outcome cells (insured-stunted, insured-not stunted, uninsured-stunted, uninsured-not stunted). **Main panel (left):** Heatmap displaying raw counts in each cell, with color intensity proportional to $\log_{10}(\text{count} + 1)$ to accommodate the wide range of values (0 to >1000). Values shown are actual counts; cells with <10 events displayed in red text with red borders highlighting all cells below this threshold. Countries ordered by ascending insurance coverage. Columns grouped by insurance status (uninsured/insured) with stunting status indicated on x-axis. **Side panel (right):** Insurance coverage percentage calculated as $100 \times (\text{n\_insured})/(\text{n\_insured} + \text{n\_uninsured})$ for each country, maintaining the same y-axis ordering as the heatmap. Zero cells marked with "0"; these represent structural zeros or sampling zeros where no observations met the exposure-outcome combination. **Data source:** Multiple Indicator Cluster Surveys (MICS), 2018–2023.

4.2 Section I.B: DPT3 Vaccination

4.2.1 Tier 1 Analysis (n=XX countries)

Table 7: Association between health insurance and DPT3 vaccination among children under 5 (Tier 1 countries)

Country	Coverage (%)	N Insured	N Uninsured	OR (95% CI)	P-value	Sig	Reliability
TUN	80.056819	1644	402	0.77 (0.55-1.07)	0.12		High
PSE	71.717167	1862	761	1.03 (0.71-1.49)	0.89		High
TTO	15.394709	66	438	1.12 (0.49-2.54)	0.79		Medium
NPL	4.472697	138	2481	1.17 (0.60-2.27)	0.64		Medium
DZA	48.882403	2732	3137	1.52 (1.29-1.78)	¡0.001	***	High
GHA	60.970419	2196	1220	1.57 (1.20-2.06)	0.001	**	High
DOM	54.700624	1618	1720	1.68 (1.33-2.12)	¡0.001	***	High
TON	87.048819	440	87	1.74 (0.96-3.17)	0.07		Medium
SUR	89.106367	1520	178	1.81 (1.12-2.91)	0.02	*	High
COM	5.294091	100	1620	1.95 (1.15-3.29)	0.01	*	Medium
LAO	13.883924	648	3947	2.01 (1.57-2.58)	¡0.001	***	High
THA	97.487856	10002	254	2.11 (1.00-4.43)	0.05		High
VNM	97.183898	1589	97	2.26 (1.15-4.47)	0.02	*	High
COD	3.233823	174	8220	2.35 (1.43-3.88)	¡0.001	***	High
CRI	91.777556	1341	128	2.62 (1.48-4.65)	0.001	**	Medium
NGA	2.996489	307	11382	2.73 (1.88-3.97)	¡0.001	***	High

Note:

OR = Odds Ratio; CI = Confidence Interval. *** p¡0.001, ** p¡0.01, * p¡0.05. Tier 1 includes countries with 20 events in the smaller exposure group. Models adjusted for survey design using PSU or cluster.

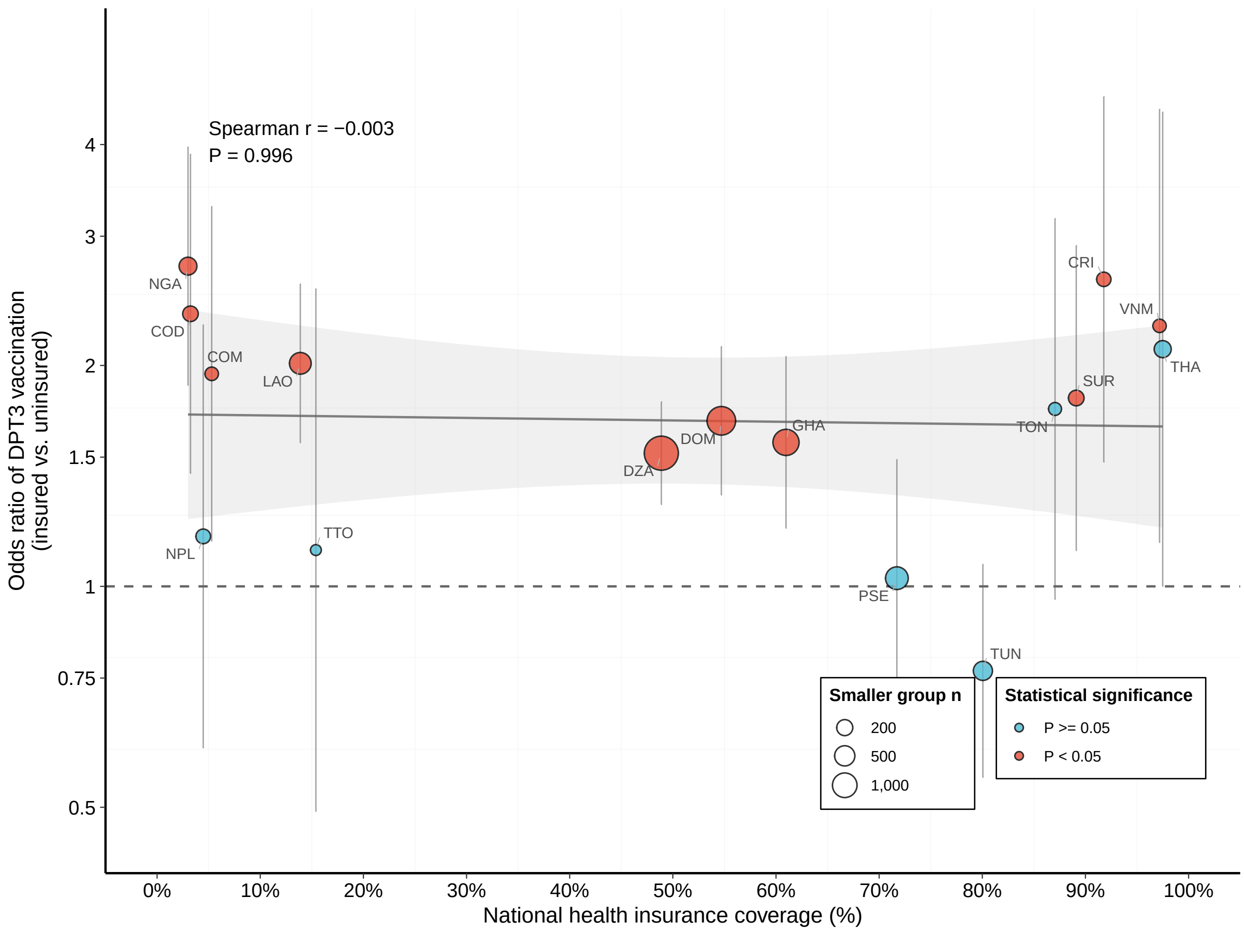


Figure 4: **Association between national health insurance coverage and DPT3 vaccination (children under 5) across 16 low- and middle-income countries. OR $>$ 1**: insured children have higher odds of vaccination (beneficial association); **OR $<$ 1**: insured children have lower odds (harmful association). Horizontal dashed line at **OR = 1**: no association. Points sized by smaller exposure group. **Red points**: P $<$ 0.05; **Blue points**: P $\geq$ 0.05. **Spearman ρ = -0.003** (P = 0.996).

Each point represents one country, with x-axis showing percentage of children under 5 with health insurance coverage. Y-axis shows odds ratio of DPT3 vaccination comparing insured to uninsured children, derived from survey-weighted logistic regression models adjusting for complex survey design (primary sampling units or clusters). Point size reflects the smaller of the two exposure groups (insured or uninsured). Vertical bars represent 95% confidence intervals. Grey shaded area shows 95% confidence interval for the linear trend fitted by ordinary least squares regression of log(OR) on coverage percentage. The Spearman rank correlation coefficient tests whether there is a monotonic relationship between a country's insurance coverage level and the strength of the insurance-vaccination association in that country. This correlation is presented for exploratory purposes only and should not be interpreted causally. Countries are labeled using ISO 3-letter codes. **Data source:** Multiple Indicator Cluster Surveys (MICS), 2018–2023.

4.2.2 Tier 2 Analysis (n=5 countries)

Table 8: Risk differences for dpt3 between insured and uninsured children (Tier 2 countries)

Country	Coverage (%)	N Insured	N Uninsured	Vaccinated Insured (%)	Vaccinated Uninsured (%)	Risk Difference (95% CI)	C
YEM	0.4881687	27	7761	44.44444	47.05579	-2.6 (-19.5 to 15.7)	
GUY	7.6937510	57	998	82.45614	81.06212	1.4 (-10.6 to 9.6)	
SLE	3.9699576	174	4475	92.52874	82.23464	10.3 (5.3 to 13.6)	
BEN	0.8803902	49	4982	77.55102	66.35889	11.2 (-2.3 to 20.7)	
MDG	2.3491248	75	4985	85.33333	55.98796	29.3 (19.5 to 35.8)	

Note:

Tier 2 includes countries with 10-19 events in the smaller exposure group. Risk differences calculated as percentage point difference (insured minus uninsured). Positive values indicate higher vaccination coverage among insured children. 95% confidence intervals calculated using Wilson score method.

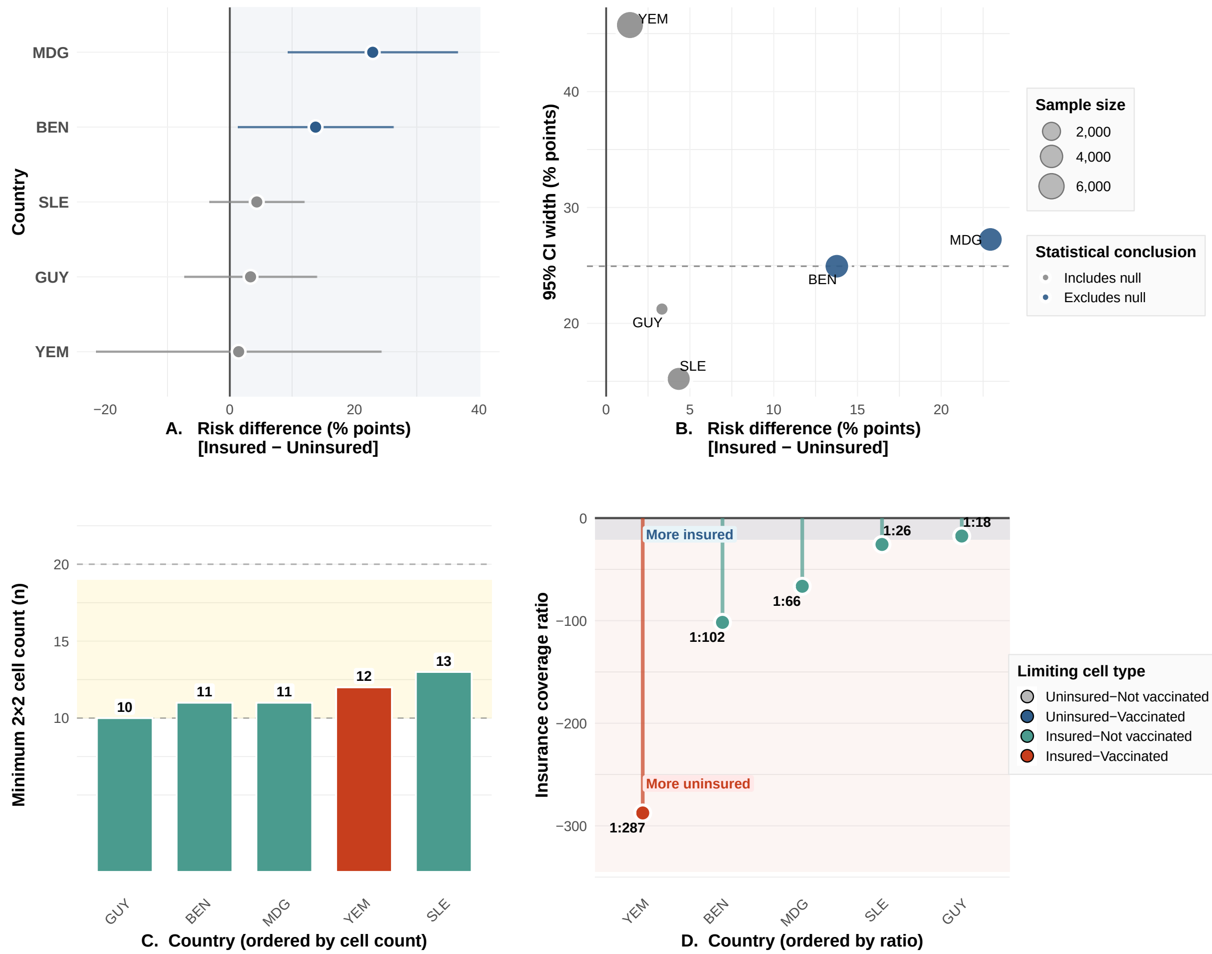


Figure 5: **Analysis of health insurance-DPT3 vaccination associations in Tier 2 countries with limited statistical power.**

Panel A shows risk differences (percentage point difference in DPT3 vaccination coverage between insured and uninsured children) with 95% confidence intervals for countries meeting Tier 2 criteria (10-19 events in the smallest exposure-outcome cell). Risk differences calculated as (percentage vaccinated among insured) minus (percentage vaccinated among uninsured); positive values indicate higher vaccination coverage among insured children. Confidence intervals derived using Wilson score method for difference between two proportions. Points colored by statistical inference: blue indicates confidence interval excludes zero, grey indicates confidence interval includes zero. **Panel B** plots risk difference against confidence interval width to visualize the precision-effect relationship. Point size proportional to total sample size. Fill color indicates whether 95% confidence interval excludes zero. Horizontal dashed line marks median CI width. Vertical line at zero separates beneficial (positive) from harmful (negative) associations. Legends show statistical conclusion and sample size. **Panel C** displays the constraining cell count for each country—the minimum count across four exposure-outcome combinations. Countries ordered by ascending minimum cell count. Horizontal dashed lines mark Tier 2 boundaries (10 and 20 events), with yellow shading indicating the Tier 2 zone. Bar colors correspond to limiting cell type. **Panel D** presents exposure group imbalance on a bidirectional scale, where positive values indicate more insured than uninsured children (ratio > 1) and negative values indicate more uninsured than insured (ratio < 1). Y-axis values calculated as: if ratio > 1, display as positive; if ratio < 1, display as negative reciprocal. Points and stems colored by limiting cell type (matching Panel C colors). Ratios displayed adjacent to points show actual insured:uninsured proportions. Legend shows all four possible limiting cell types. All analyses use survey-weighted proportions without adjustment for confounders. Data source: Multiple Indicator Cluster Surveys (MICS), 2018-2023.

4.2.3 Tier 3 Analysis (n=16 countries)

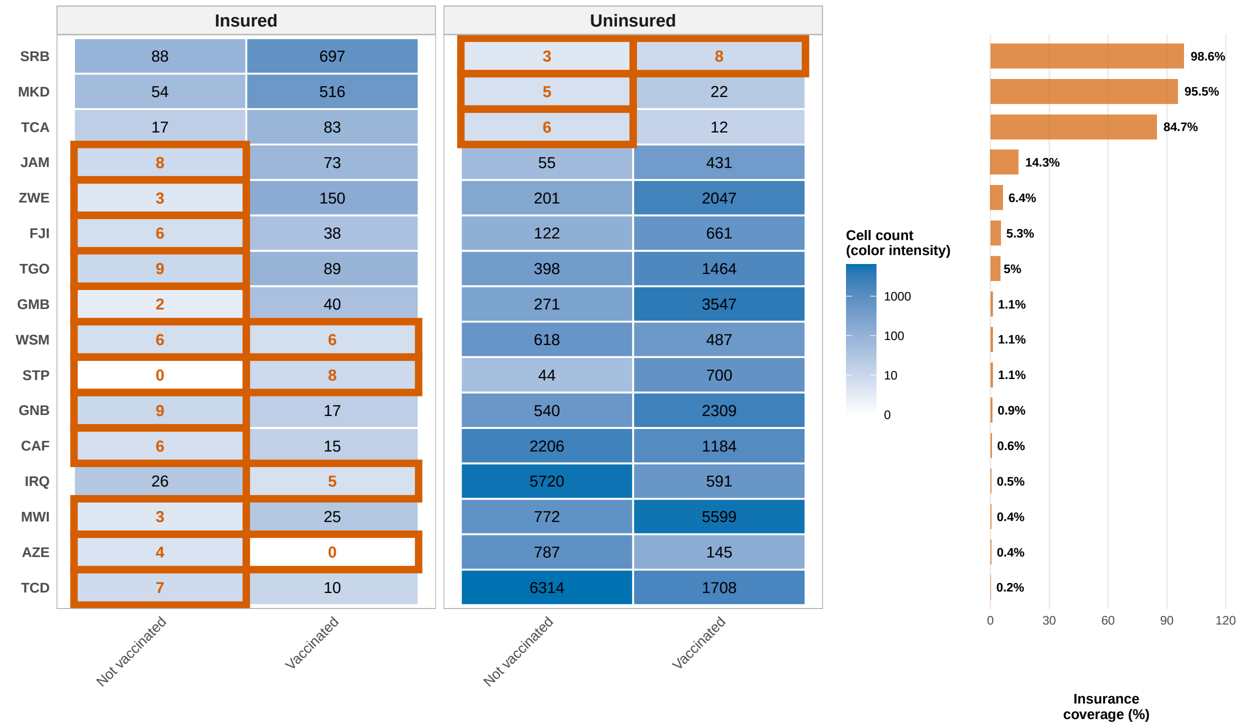


Figure 6: **Distribution of observations across exposure-outcome cells for Tier 3 countries with insufficient statistical power for DPT3 vaccination analysis.** Countries classified as Tier 3 have fewer than 10 events in at least one of four exposure-outcome cells (insured-vaccinated, insured-not vaccinated, uninsured-vaccinated, uninsured-not vaccinated). **Main panel (left):** Heatmap displaying raw counts in each cell, with color intensity proportional to $\log_{10}(\text{count} + 1)$ to accommodate the wide range of values (0 to >1000). Values shown are actual counts; cells with <10 events displayed in red text with red borders highlighting all cells below this threshold. Countries ordered by ascending insurance coverage. Columns grouped by insurance status (uninsured/insured) with vaccination status indicated on x-axis. **Side panel (right):** Insurance coverage percentage calculated as $100 \times (\text{n\_insured})/(\text{n\_insured} + \text{n\_uninsured})$ for each country, maintaining the same y-axis ordering as the heatmap. Zero cells marked with "0"; these represent structural zeros or sampling zeros where no observations met the exposure-outcome combination. **Data source:** Multiple Indicator Cluster Surveys (MICS), 2018–2023.

4.3 Section I.C: Severe Deprivation

4.3.1 Tier 1 Analysis (n=XX countries)

Table 9: Association between health insurance and severe deprivation among children under 5 (Tier 1 countries)

Country	Coverage (%)	N Insured	N Uninsured	OR (95% CI)	P-value	Sig	Reliability
ZWE	6.1630655	361	5744	0.04 (0.02-0.07)	¡0.001	***	Medium
TCD	0.2651619	51	21730	0.08 (0.04-0.17)	¡0.001	***	Medium
MDG	2.2010403	179	12666	0.11 (0.07-0.18)	¡0.001	***	High
COD	3.1045699	397	21051	0.19 (0.13-0.28)	¡0.001	***	High
CAF	0.5035433	54	8849	0.20 (0.10-0.39)	¡0.001	***	Medium
TGO	3.8588800	218	4721	0.23 (0.15-0.35)	¡0.001	***	High
LAO	13.6801321	1604	10107	0.24 (0.21-0.29)	¡0.001	***	High
NPL	3.7445577	294	6361	0.30 (0.19-0.48)	¡0.001	***	Medium
VNM	96.1399102	4039	289	0.37 (0.24-0.56)	¡0.001	***	High
CRI	91.1888438	3260	351	0.44 (0.27-0.74)	0.002	**	Medium
DOM	52.7832724	4017	4401	0.45 (0.38-0.54)	¡0.001	***	High
ARG	43.6216865	2890	3248	0.46 (0.33-0.64)	¡0.001	***	High
GHA	58.4192920	5405	3475	0.55 (0.46-0.66)	¡0.001	***	High
SLE	3.8818152	425	11295	0.59 (0.41-0.83)	0.003	**	High
SUR	87.7544201	3737	495	0.59 (0.44-0.80)	¡0.001	***	High
TON	84.6823835	1099	248	0.62 (0.36-1.06)	0.08		High
TKM	38.1334625	1583	2099	0.64 (0.41-1.00)	0.05	*	High
DZA	50.5288924	7038	7803	0.65 (0.56-0.76)	¡0.001	***	High
TUN	82.3918036	2829	576	0.77 (0.57-1.05)	0.10		High
IRQ	0.4920081	92	16523	0.95 (0.46-1.98)	0.89		Medium
THA	98.0032198	13390	298	1.42 (0.80-2.52)	0.23		Medium

Note:

OR = Odds Ratio; CI = Confidence Interval. *** p¡0.001, ** p¡0.01, * p¡0.05. Tier 1 includes countries with 20 events in the smaller exposure group. Models adjusted for survey design using PSU or cluster.

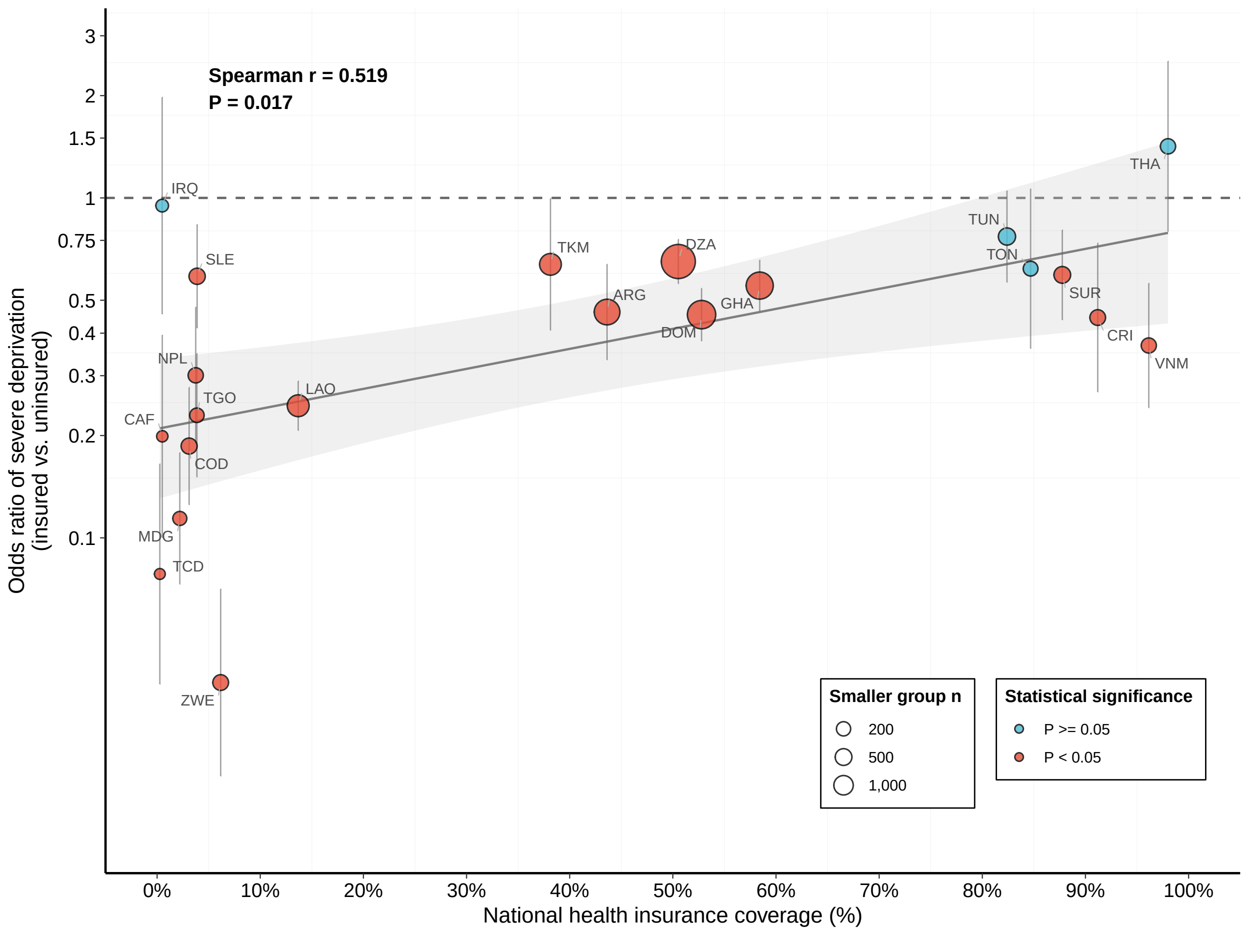


Figure 7: **Association between national health insurance coverage and severe deprivation (children under 5) across 21 low- and middle-income countries. OR $<$ 1**: insured children have lower odds of severe deprivation (protective association); **OR $>$ 1**: insured children have higher odds (harmful association). Horizontal dashed line at **OR $=$ 1**: no association. Points sized by smaller exposure group. **Red points**: $P < 0.05$; **Blue points**: $P \geq 0.05$. **Spearman ρ = 0.519** ($P = 0.017$).

Each point represents one country, with x-axis showing percentage of children under 5 with health insurance coverage. Y-axis shows odds ratio of severe deprivation comparing insured to uninsured children, derived from survey-weighted logistic regression models adjusting for complex survey design (primary sampling units or clusters). Point size reflects the smaller of the two exposure groups (insured or uninsured). Vertical bars represent 95% confidence intervals. Grey shaded area shows 95% confidence interval for the linear trend fitted by ordinary least squares regression of log(OR) on coverage percentage. The Spearman rank correlation coefficient tests whether there is a monotonic relationship between a country's insurance coverage level and the strength of the insurance-deprivation association in that country. This correlation is presented for exploratory purposes only and should not be interpreted causally. Countries are labeled using ISO 3-letter codes. **Data source:** Multiple Indicator Cluster Surveys (MICS), 2018–2023.

4.3.2 Tier 2 Analysis (n=4 countries)

Table 10: Risk differences for severe deprivation between insured and uninsured children (Tier 2 countries)

Country	Coverage (%)	N Insured	N Uninsured	Deprived Insured (%)	Deprived Uninsured (%)	Risk Difference (95% CI)	CI Ex
GMB	1.6136358	96	9800	17.70833	59.14286	-41.4 (-47.9 to -32.6)	
MWI	0.4675559	72	15374	13.88889	44.34760	-30.5 (-36.7 to -20.6)	
GNB	1.0423562	54	7412	64.81481	90.50189	-25.7 (-39.0 to -14.3)	
GUY	7.3422376	162	2622	11.11111	29.44317	-18.3 (-22.7 to -12.3)	

Note:

Tier 2 includes countries with 10-19 events in the smaller exposure group. Risk differences calculated as percentage point difference (insured minus uninsured). Negative values indicate lower deprivation prevalence among insured children. 95% confidence intervals calculated using Wilson score method.

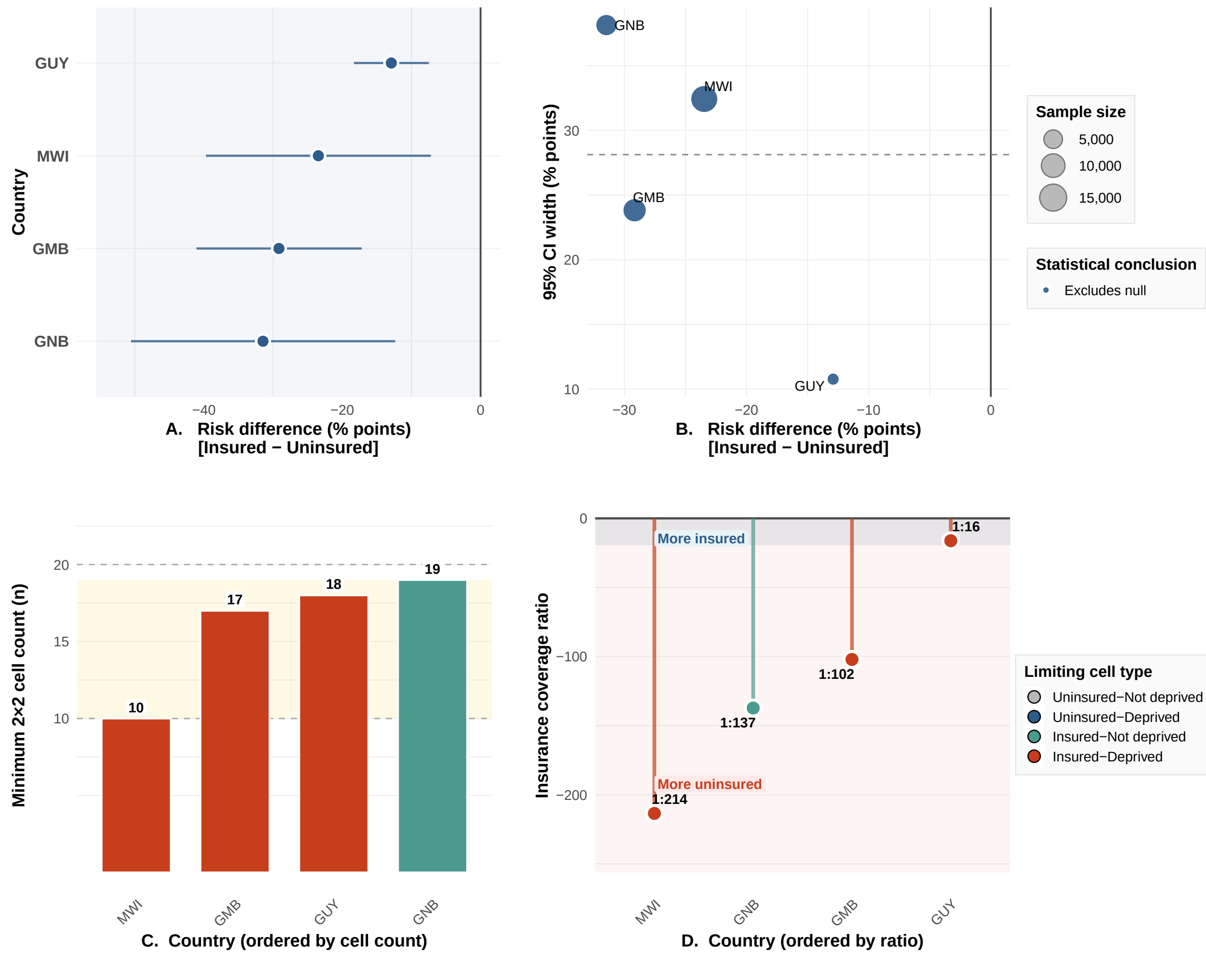


Figure 8: **Analysis of health insurance-severe deprivation associations in Tier 2 countries with limited statistical power.**

Panel A shows risk differences (percentage point difference in severe deprivation prevalence between insured and uninsured children) with 95% confidence intervals for countries meeting Tier 2 criteria (10-19 events in the smallest exposure-outcome cell). Risk differences calculated as (percentage severely deprived among insured) minus (percentage severely deprived among uninsured); negative values indicate lower deprivation prevalence among insured children. Confidence intervals derived using Wilson score method for difference between two proportions. Points colored by statistical inference: blue indicates confidence interval excludes zero, grey indicates confidence interval includes zero. **Panel B** plots risk difference against confidence interval width to visualize the precision-effect relationship. Point size proportional to total sample size. Fill color indicates whether 95% confidence interval excludes zero. Horizontal dashed line marks median CI width. Vertical line at zero separates protective (negative) from harmful (positive) associations. Legends show statistical conclusion and sample size. **Panel C** displays the constraining cell count for each country—the minimum count across four exposure-outcome combinations. Countries ordered by ascending minimum cell count. Horizontal dashed lines mark Tier 2 boundaries (10 and 20 events), with yellow shading indicating the Tier 2 zone. Bar colors correspond to limiting cell type. **Panel D** presents exposure group imbalance on a bidirectional scale, where positive values indicate more insured than uninsured children (ratio > 1) and negative values indicate more uninsured than insured (ratio < 1). Y-axis values calculated as: if ratio > 1, display as positive; if ratio < 1, display as negative reciprocal. Points and stems colored by limiting cell type (matching Panel C colors). Ratios displayed adjacent to points show actual insured:uninsured proportions. Legend shows all four possible limiting cell types. All analyses use survey-weighted proportions without adjustment for confounders. Data source: Multiple Indicator Cluster Surveys (MICS), 2018-2023.

4.3.3 Tier 3 Analysis (n=4 countries)

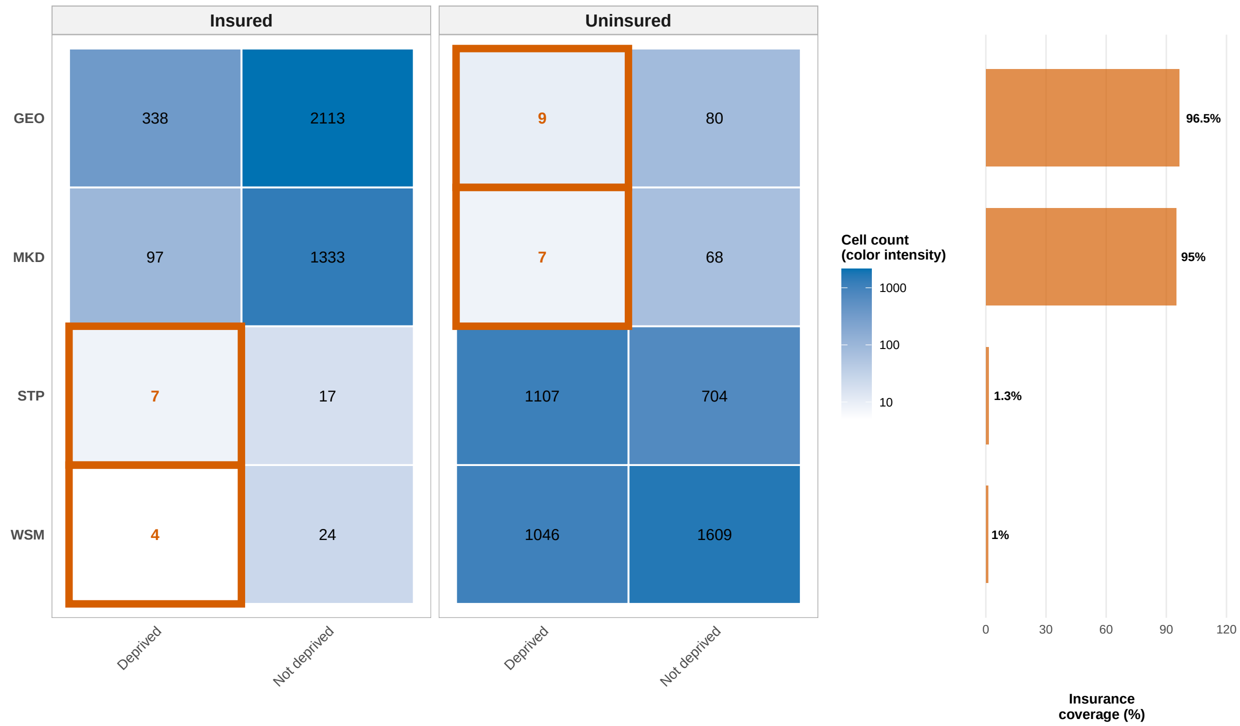


Figure 9: **Distribution of observations across exposure-outcome cells for Tier 3 countries with insufficient statistical power for severe deprivation analysis.** Countries classified as Tier 3 have fewer than 10 events in at least one of four exposure-outcome cells (insured-deprived, insured-not deprived, uninsured-deprived, uninsured-not deprived). **Main panel (left):** Heatmap displaying raw counts in each cell, with color intensity proportional to $\log_{10}(\text{count} + 1)$ to accommodate the wide range of values (0 to >1000). Values shown are actual counts; cells with <10 events displayed in red text with red borders highlighting all cells below this threshold. Countries ordered by ascending insurance coverage. Columns grouped by insurance status (uninsured/insured) with deprivation status indicated on x-axis. **Side panel (right):** Insurance coverage percentage calculated as $100 \times (\text{n\_insured})/(\text{n\_insured} + \text{n\_uninsured})$ for each country, maintaining the same y-axis ordering as the heatmap. Zero cells marked with "0"; these represent structural zeros or sampling zeros where no observations met the exposure-outcome combination. **Data source:** Multiple Indicator Cluster Surveys (MICS), 2018–2023.

4.4 Section I.D: Diarrhea Care-Seeking

4.4.1 Tier 1 Analysis (n=XX countries)

Table 11: Association between health insurance and diarrhea care-seeking among children under 5 (Tier 1 countries)

Country	Coverage (%)	N Insured	N Uninsured	OR (95% CI)	P-value	Sig	Reliability
DZA	43.594702	385	500	0.88 (0.61-1.26)	0.48		High
COD	2.277843	58	2977	1.06 (0.46-2.41)	0.90		Medium
PSE	71.435383	608	245	1.11 (0.76-1.60)	0.59		High
DOM	49.322511	669	803	1.23 (0.88-1.71)	0.23		High
TUN	78.282516	311	79	1.28 (0.71-2.33)	0.42		Medium
ARG	40.164528	241	333	1.45 (0.82-2.57)	0.20		High
GHA	55.825618	909	610	1.56 (1.12-2.16)	0.008	**	High
LAO	10.759552	97	736	2.02 (1.19-3.42)	0.009	**	Medium

Note:

OR = Odds Ratio; CI = Confidence Interval. *** p¡0.001, ** p¡0.01, * p¡0.05. Tier 1 includes countries with 20 events in the smaller exposure group. Models adjusted for survey design using PSU or cluster.

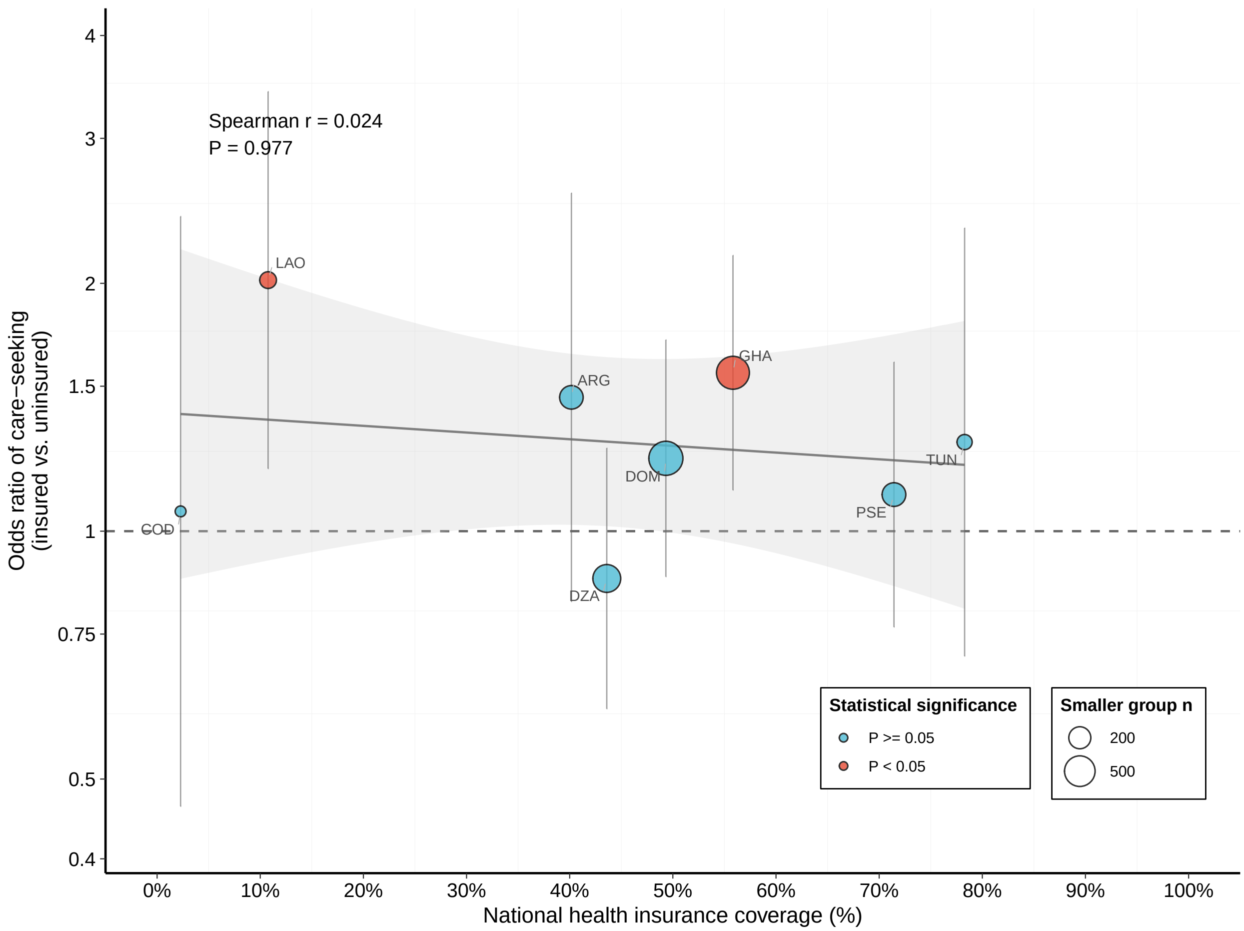


Figure 10: **Association between national health insurance coverage and diarrhea care-seeking (children under 5 with recent diarrhea) across 8 low- and middle-income countries. OR $>$ 1**: insured children have higher odds of care-seeking (beneficial association); **OR $<$ 1**: insured children have lower odds (harmful association). Horizontal dashed line at **OR $=$ 1**: no association. Points sized by smaller exposure group. **Red points**: P $<$ 0.05; **Blue points**: P $\geq$ 0.05. **Spearman ρ $=$ 0.024** (P = 0.977).

Each point represents one country, with x-axis showing percentage of children under 5 with health insurance coverage. Y-axis shows odds ratio of seeking medical care for diarrhea comparing insured to uninsured children who experienced diarrhea in the two weeks prior to survey, derived from survey-weighted logistic regression models adjusting for complex survey design (primary sampling units or clusters). Point size reflects the smaller of the two exposure groups (insured or uninsured) among children with recent diarrhea. Vertical bars represent 95% confidence intervals. Grey shaded area shows 95% confidence interval for the linear trend fitted by ordinary least squares regression of log(OR) on coverage percentage. The Spearman rank correlation coefficient tests whether there is a monotonic relationship between a country's insurance coverage level and the strength of the insurance-care-seeking association in that country. This correlation is presented for exploratory purposes only and should not be interpreted causally. Countries are labeled using ISO 3-letter codes. **Data source:** Multiple Indicator Cluster Surveys (MICS), 2018–2023.

4.4.2 Tier 2 Analysis (n=6 countries)

Table 12: Risk differences for diarrhea care between insured and uninsured children (Tier 2 countries)

Country	Coverage (%)	N Insured	N Uninsured	Care Sought Insured (%)	Care Sought Uninsured (%)	Risk Difference (95% CI
COM	5.173620	28	498	50.00000	47.79116	2.2 (-15.8 to 20.2)
CRI	89.511786	360	48	64.44444	60.41667	4.0 (-9.6 to 19.0)
TGO	2.611861	26	817	61.53846	57.40514	4.1 (-15.2 to 20.6)
NGA	2.104520	55	3489	80.00000	66.23674	13.8 (1.3 to 22.4)
ZWE	3.724414	33	819	54.54545	40.78144	13.8 (-3.2 to 29.8)
SUR	92.641766	368	32	63.58696	43.75000	19.8 (2.1 to 36.3)

Note:

Tier 2 includes countries with 10-19 events in the smaller exposure group. Risk differences calculated as percentage point difference (insured minus uninsured). Positive values indicate higher care-seeking among insured children. 95% confidence intervals calculated using Wilson score method.

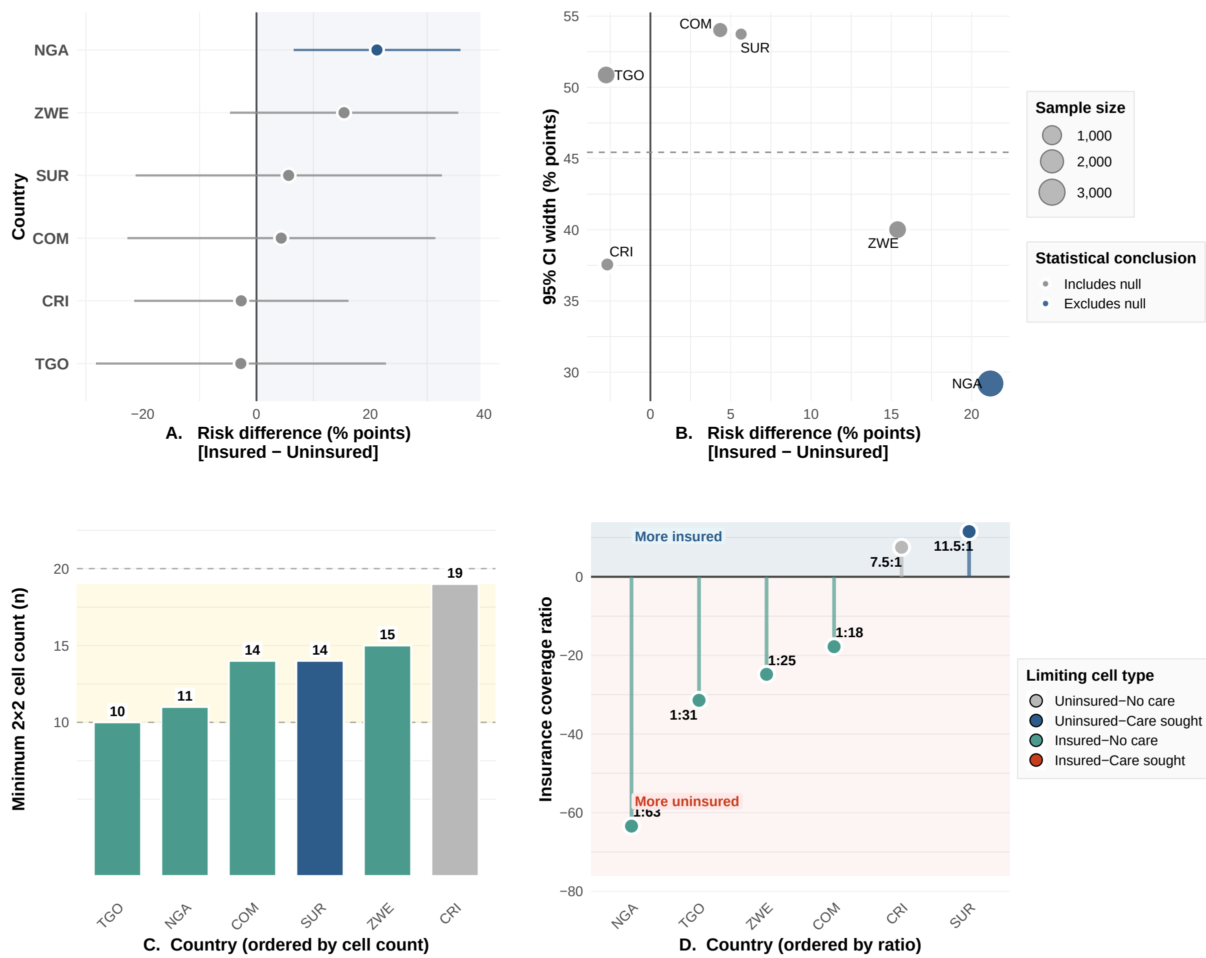
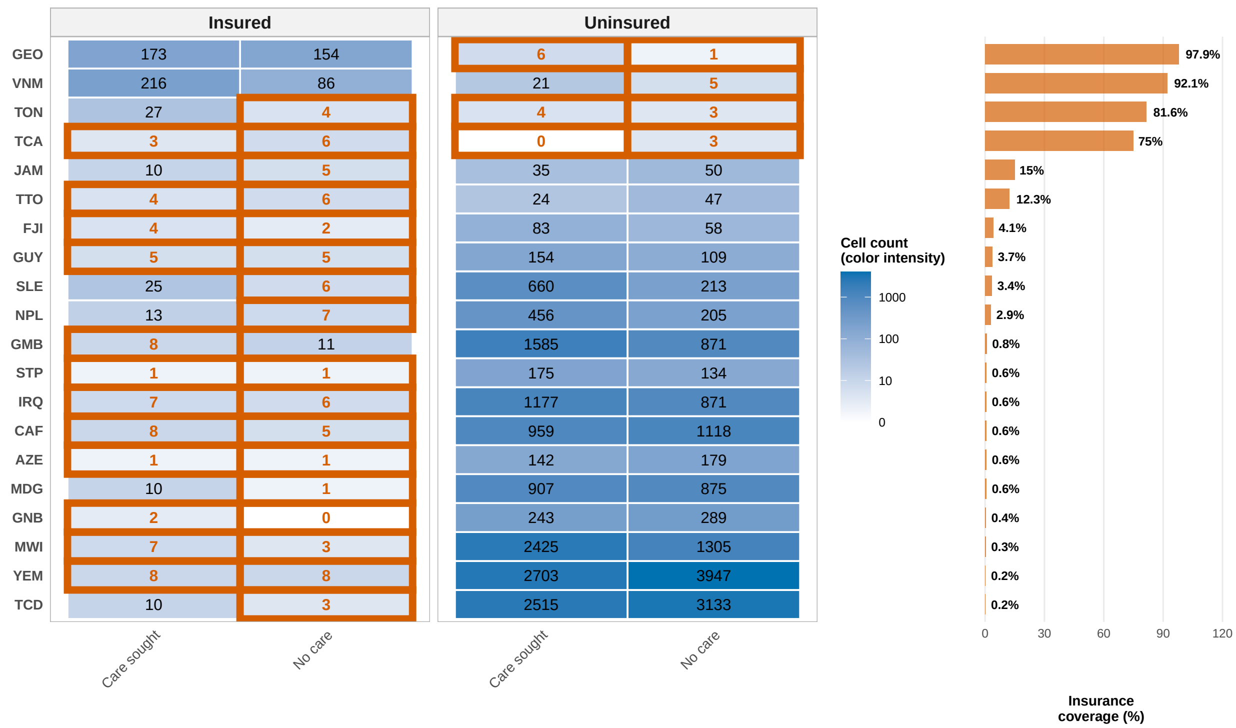


Figure 11: **Analysis of health insurance-diarrhea care-seeking associations in Tier 2 countries with limited statistical power.**

Panel A shows risk differences (percentage point difference in care-seeking for diarrhea between insured and uninsured children) with 95% confidence intervals for countries meeting Tier 2 criteria (10-19 events in the smallest exposure-outcome cell). Risk differences calculated as (percentage seeking care among insured) minus (percentage seeking care among uninsured); positive values indicate higher care-seeking among insured children. Confidence intervals derived using Wilson score method for difference between two proportions. Points colored by statistical inference: blue indicates confidence interval excludes zero, grey indicates confidence interval includes zero. **Panel B** plots risk difference against confidence interval width to visualize the precision-effect relationship. Point size proportional to total sample size. Fill color indicates whether 95% confidence interval excludes zero. Horizontal dashed line marks median CI width. Vertical line at zero separates beneficial (positive) from harmful (negative) associations. Legends show statistical conclusion and sample size. **Panel C** displays the constraining cell count for each country—the minimum count across four exposure-outcome combinations. Countries ordered by ascending minimum cell count. Horizontal dashed lines mark Tier 2 boundaries (10 and 20 events), with yellow shading indicating the Tier 2 zone. Bar colors correspond to limiting cell type. **Panel D** presents exposure group imbalance on a bidirectional scale, where positive values indicate more insured than uninsured children (ratio > 1) and negative values indicate more uninsured than insured (ratio < 1). Y-axis values calculated as: if ratio > 1, display as positive; if ratio < 1, display as negative reciprocal. Points and stems colored by limiting cell type (matching Panel C colors). Ratios displayed adjacent to points show actual insured:uninsured proportions. Legend shows all four possible limiting cell types. All analyses use survey-weighted proportions without adjustment for confounders. Data source: Multiple Indicator Cluster Surveys (MICS), 2018-2023.

4.4.3 Tier 3 Analysis (n=20 countries)



	Insured: Care sought	Insured: No care	Uninsured: Care sought	Uninsured: No care
GEO	173	154	6	1
VNM	216	86	21	5
TON	27	4	4	3
TCA	3	6	0	3
JAM	10	5	35	50
TTO	4	6	24	47
FJI	4	2	83	58
GUY	5	5	154	109
SLE	25	6	660	213
NPL	13	7	456	205
GMB	8	11	1585	871
STP	1	1	175	134
IRQ	7	6	1177	871
CAF	8	5	959	1118
AZE	1	1	142	179
MDG	10	1	907	875
GNB	2	0	243	289
MWI	7	3	2425	1305
YEM	8	8	2703	3947
TCD	10	3	2515	3133

Figure 12: **Distribution of observations across exposure-outcome cells for Tier 3 countries with insufficient statistical power for diarrhea care-seeking analysis.** Countries classified as Tier 3 have fewer than 10 events in at least one of four exposure-outcome cells (insured-care sought, insured-no care, uninsured-care sought, uninsured-no care). **Main panel (left):** Heatmap displaying raw counts in each cell, with color intensity proportional to $\log_{10}(\text{count} + 1)$ to accommodate the wide range of values (0 to >1000). Values shown are actual counts; cells with <10 events displayed in red text with red borders highlighting all cells below this threshold. Countries ordered by ascending insurance coverage. Columns grouped by insurance status (uninsured/insured) with care-seeking status indicated on x-axis. **Side panel (right):** Insurance coverage percentage calculated as 100 × (n_insured)/(n_insured + n_uninsured) for each country, maintaining the same y-axis ordering as the heatmap. Zero cells marked with "0"; these represent structural zeros or sampling zeros where no observations met the exposure-outcome combination. **Data source:** Multiple Indicator Cluster Surveys (MICS), 2018–2023.

4.5 Section I.E: Cross-Outcome Synthesis

5 Part II: Selection Mechanisms in Tier 2 and Tier 3 Countries

The exclusion of countries from causal inference due to insufficient statistical power requires systematic documentation of the selection mechanisms that generate these power limitations. This section presents survey-weighted difference-in-means comparisons between insured and uninsured children across 31 countries classified as Tier 2 (10-19 minimum cell counts) or Tier 3 (¡10 minimum cell counts). We examine differences in wealth quintile, urban residence, and maternal education alongside four health outcomes to understand the selection patterns in these data-limited settings.

5.1 Section II.A: Covariate Balance and Selection Mechanisms: Evidence from Survey-Weighted Comparisons

5.1.1 Methods

For each country c and variable X, we calculated survey-weighted means for insured ($I = 1$) and uninsured ($I = 0$) children:

$$\bar{X}^w_{c,I=1} = \frac{\sum_{i \in \{I=1\}} w_i X_i}{\sum_{i \in \{I=1\}} w_i}, \quad \bar{X}^w_{c,I=0} = \frac{\sum_{i \in \{I=0\}} w_i X_i}{\sum_{i \in \{I=0\}} w_i} \tag{13}$$

where w_i denotes the survey weight. The weighted difference $\Delta^w_c = \bar{X}^w_{c,I=1} - \bar{X}^w_{c,I=0}$ quantifies the magnitude of selection. For wealth quintile specifically, we computed Cohen's d as a standardized effect size measure using the pooled weighted standard deviation.

5.1.2 Results: Stunting Analysis (19 Countries)

Table 13: Weighted Covariate Differences and Stunting Outcomes in Tier 2/3 Countries

Country	Tier	N_{ins}	N_{unins}	Coverage(%)	WealthΔ	UrbanΔ(%)	MotherEdΔ	StuntingΔ(%)	Cohen's d
MWI	2	72	15,374	0.46	2.02	56.9	0.71	-2.99	1.43
YEM	2	57	19,525	0.42	1.87	63.9	0.41	-4.52	1.32
AZE	3	12	2,553	1.88	1.79	44.1	0.03	-0.77	1.31
WSM	3	28	2,655	0.66	1.75	33.7	0.04	-0.29	1.27
GMB	3	96	9,800	1.62	1.69	37.6	0.50	-9.79	1.24
CAF	2	54	8,849	0.51	1.48	44.7	0.40	-13.69	1.08
GUY	2	162	2,622	7.48	1.38	8.6	0.11	-1.18	0.99
SRB	3	1,814	24	98.63	1.38	25.1	0.16	3.52	0.97
TCD	3	51	21,730	0.27	1.37	53.1	0.47	-19.87	0.99
GNB	2	54	7,412	1.06	1.27	34.7	0.29	-9.11	0.95
TCA	3	256	52	72.11	1.24	1.0	0.00	-11.45	0.92
STP	3	24	1,811	1.43	1.00	5.0	0.06	-9.57	0.72
FJI	3	110	2,005	5.09	0.88	12.7	0.08	-2.84	0.64
MKD	3	1,430	75	95.33	0.87	19.0	0.18	1.23	0.59
CRI	2	3,260	351	91.18	0.61	3.7	0.14	-2.29	0.45
IRQ	3	92	16,523	0.49	0.31	15.7	0.07	-6.25	0.22
GEO	3	2,451	89	96.25	0.30	15.8	0.00	-0.86	0.21
TON	2	1,099	248	85.00	0.22	13.2	0.00	-2.14	0.16
VUT	3	3	2,040	0.16	-0.28	10.8	0.04	-28.38	-0.21

5.1.3 Results: DPT3 Vaccination Analysis (21 Countries)

Table 14: Weighted Covariate Differences and DPT3 Vaccination Outcomes in Tier 2/3 Countries

Country	Tier	N_{ins}	N_{unins}	Coverage(%)	WealthΔ	UrbanΔ(%)	MotherEdΔ	DPT3Δ(%)	Cohen's d
MDG	2	179	12,666	2.35	2.02	47.3	0.52	22.93	1.47
MWI	3	72	15,374	0.40	2.02	56.9	0.71	4.27	1.43
YEM	2	57	19,525	0.49	1.87	63.9	0.41	1.42	1.32
ZWE	3	361	5,744	6.75	1.84	39.2	0.32	7.39	1.37
AZE	3	12	2,553	3.79	1.79	44.1	0.03	-13.25	1.31
WSM	3	28	2,655	0.78	1.75	33.7	0.04	3.79	1.27
GMB	3	96	9,800	1.70	1.69	37.6	0.50	3.08	1.24
BEN	2	117	13,013	0.88	1.53	31.6	0.41	13.77	1.10
CAF	3	54	8,849	0.47	1.48	44.7	0.40	38.16	1.08
GUY	2	162	2,622	7.69	1.38	8.6	0.11	3.33	0.99
SRB	3	1,814	24	98.26	1.38	25.1	0.16	22.21	0.97
TCD	3	51	21,730	0.27	1.37	53.1	0.47	37.71	0.99
TGO	3	218	4,721	4.17	1.36	22.1	0.47	17.42	0.99
GNB	3	54	7,412	1.35	1.27	34.7	0.29	-20.58	0.95
TCA	3	256	52	78.15	1.24	1.0	0.00	11.66	0.92
JAM	3	206	1,223	13.06	1.04	11.8	0.03	3.14	0.79
STP	3	24	1,811	1.50	1.00	5.0	0.06	5.94	0.72
FJI	3	110	2,005	4.84	0.88	12.7	0.08	4.52	0.64
MKD	3	1,430	75	96.41	0.87	19.0	0.18	3.12	0.59
SLE	2	425	11,295	3.97	0.71	20.4	0.23	4.33	0.52
IRQ	3	92	16,523	0.45	0.31	15.7	0.07	25.56	0.22

5.1.4 Results: Severe Deprivation Analysis (8 Countries)

Table 15: Weighted Covariate Differences and Severe Deprivation Outcomes in Tier 2/3 Countries

Country	Tier	N_{ins}	N_{unins}	Coverage(%)	WealthΔ	UrbanΔ(%)	MotherEdΔ	DeprivΔ(%)	Cohen's d
MWI	2	72	15,374	0.47	2.02	56.9	0.71	-23.46	1.43
WSM	3	28	2,655	0.66	1.75	33.7	0.04	-24.57	1.27
GMB	2	96	9,800	1.61	1.69	37.6	0.50	-29.16	1.24
GUY	2	162	2,622	7.34	1.38	8.6	0.11	-12.91	0.99
GNB	2	54	7,412	1.04	1.27	34.7	0.29	-31.47	0.95
STP	3	24	1,811	1.42	1.00	5.0	0.06	-34.28	0.72
MKD	3	1,430	75	95.35	0.87	19.0	0.18	-0.30	0.59
GEO	3	2,451	89	96.25	0.30	15.8	0.00	1.81	0.21

5.1.5 Results: Diarrhea Care-Seeking Analysis (26 Countries)

Table 16: Weighted Covariate Differences and Diarrhea Care-Seeking Outcomes in Tier 2/3 Countries

Country	Tier	N_{ins}	N_{unins}	Coverage(%)	WealthΔ	UrbanΔ(%)	MotherEdΔ	CareΔ(%)	Cohen's d
MDG	3	179	12,666	0.94	2.02	47.3	0.52	44.77	1.47
MWI	3	72	15,374	0.34	2.02	56.9	0.71	-10.44	1.43
YEM	3	57	19,525	0.37	1.87	63.9	0.41	6.30	1.32
ZWE	2	361	5,744	3.72	1.84	39.2	0.32	15.39	1.37
AZE	3	12	2,553	1.14	1.79	44.1	0.03	-16.64	1.31
GMB	3	96	9,800	1.26	1.69	37.6	0.50	-11.75	1.24
NGA	2	756	29,953	2.10	1.60	42.6	0.42	21.17	1.16
CAF	3	54	8,849	0.50	1.48	44.7	0.40	11.97	1.08
GUY	3	162	2,622	9.69	1.38	8.6	0.11	-30.96	0.99
TCD	3	51	21,730	0.27	1.37	53.1	0.47	42.37	0.99
TGO	2	218	4,721	2.61	1.36	22.1	0.47	-2.75	0.99
COM	2	258	4,203	5.17	1.36	19.0	0.29	4.35	0.99
TTO	3	267	1,384	17.53	1.35	12.9	0.06	52.81	1.03
GNB	3	54	7,412	0.41	1.27	34.7	0.29	53.94	0.95
TCA	3	256	52	81.97	1.24	1.0	0.00	53.32	0.92
JAM	3	206	1,223	14.92	1.04	11.8	0.03	26.50	0.79
STP	3	24	1,811	0.91	1.00	5.0	0.06	-22.72	0.72
FJI	3	110	2,005	4.04	0.88	12.7	0.08	-5.05	0.64
SLE	3	425	11,295	3.40	0.71	20.4	0.23	-2.88	0.52
NPL	3	294	6,361	2.71	0.71	13.1	0.31	-0.49	0.51
VNM	3	4,039	289	94.90	0.65	1.9	0.12	-17.54	0.46
CRI	2	3,260	351	89.51	0.61	3.7	0.14	-2.68	0.45
SUR	2	3,737	495	92.64	0.43	15.3	0.20	5.65	0.31
IRQ	3	92	16,523	0.32	0.31	15.7	0.07	-12.09	0.22
GEO	3	2,451	89	98.44	0.30	15.8	0.00	-30.56	0.21
TON	3	1,099	248	91.64	0.22	13.2	0.00	23.38	0.16

5.1.6 Cross-Cutting Patterns in Selection

5.1.7 Relationship Between Selection and Outcomes

5.1.8 Implications for Statistical Inference

5.2 Section II.B: Quantifying Insurance Concentration

The extreme wealth differences documented above (median Cohen's d = 0.95) suggest that insurance may be so concentrated among the wealthy that it functions as a marker of privilege rather than a health intervention. To quantify this concentration systematically, we employ concentration indices and geographic clustering analyses that reveal the true extent of insurance inequality in these settings.

5.2.1 Concentration of Insurance Coverage Across Wealth Distribution

Methods The concentration index quantifies the degree to which insurance coverage is concentrated among wealthy versus poor households. Following the standard convenient regression method (Kakwani et al., 1997), we calculate the concentration index using:

$$CI = \frac{2}{\mu}\text{cov}(h_i, R_i) \tag{14}$$

where h_i represents insurance coverage for individual i, R_i is their fractional rank in the wealth distribution (ranging from 0 for the poorest to 1 for the richest), and μ is mean insurance coverage.

5.2.2 Implementation

For computational efficiency, we employ the convenient regression approach. After sorting individuals by wealth and calculating their fractional ranks as:

$$R_i = \frac{\sum_{j=1}^{i-1} w_j + 0.5w_i}{\sum_{j=1}^{n} w_j} \tag{15}$$

where w_i denotes the survey weight for individual i, we transform the insurance variable:

$$y_i^* = \frac{2(h_i - \mu)}{\mu} \tag{16}$$

The concentration index then equals the slope coefficient from the weighted least squares regression:

$$y_i^* = \alpha + \beta R_i + \epsilon_i \tag{17}$$

where β is the concentration index. This method provides both point estimates and standard errors, allowing construction of confidence intervals.

Results Table 17 presents concentration indices for all 31 Tier 2 and Tier 3 countries, revealing extreme pro-rich concentration in insurance distribution.

Table 17: Concentration Indices for Insurance Coverage Across Wealth Distribution

Country	Coverage (%)	N Insured	N Uninsured	CI	95% CI	Classification	Geographic Concentration (% units with insurance)
Extreme Concentration (CI $\geq$ 0.8)							
MWI	0.47	72	15,374	0.917	[0.758, 1.076]	Extreme	[–]
MDG	2.20	179	12,666	0.865	[0.786, 0.943]	Extreme	[–]
YEM	0.41	57	19,525	0.851	[0.700, 1.002]	Extreme	[–]
AZE	1.87	12	2,553	0.837	[0.645, 1.029]	Extreme	[–]
ZWE	6.16	361	5,744	0.816	[0.751, 0.880]	Extreme	[–]
WSM	0.66	28	2,655	0.803	[0.484, 1.122]	Extreme	[–]
High Concentration (0.6 $\leq$ CI < 0.8)							
GMB	1.61	96	9,800	0.792	[0.687, 0.897]	High	[–]
NGA	2.75	756	29,953	0.738	[0.693, 0.783]	High	[–]
BEN	0.81	117	13,013	0.717	[0.587, 0.848]	High	[–]
CAF	0.50	54	8,849	0.697	[0.495, 0.899]	High	[–]
TCD	0.27	51	21,730	0.663	[0.485, 0.841]	High	[–]
COM	5.14	258	4,203	0.612	[0.526, 0.697]	High	[–]
GUY	7.34	162	2,622	0.609	[0.521, 0.698]	High	[–]
TGO	3.86	218	4,721	0.608	[0.513, 0.703]	High	[–]
Moderate to Low Concentration (0.2 $\leq$ CI < 0.6)							
GNB	1.04	54	7,412	0.559	[0.406, 0.712]	Moderate	[–]
TTO	17.00	267	1,384	0.537	[0.468, 0.606]	Moderate	[–]
STP	1.42	24	1,811	0.477	[0.214, 0.741]	Moderate	[–]
JAM	13.47	206	1,223	0.437	[0.349, 0.526]	Moderate	[–]
FJI	5.06	110	2,005	0.378	[0.251, 0.505]	Low	[–]
NPL	3.75	294	6,361	0.349	[0.265, 0.433]	Low	[–]
SLE	3.88	425	11,295	0.306	[0.243, 0.368]	Low	[–]
Minimal Concentration (CI < 0.2)							
TCA	74.07	256	52	0.144	[0.101, 0.187]	Minimal	[–]
IRQ	0.49	92	16,523	0.138	[-0.012, 0.287]	Minimal	[–]
CRI	91.19	3,260	351	0.028	[0.021, 0.035]	Minimal	[–]
TON	84.68	1,099	248	0.024	[0.009, 0.040]	Minimal	[–]
SUR	87.75	3,737	495	0.022	[0.014, 0.030]	Minimal	[–]
MKD	95.35	1,430	75	0.021	[0.014, 0.029]	Minimal	[–]
VNM	96.14	4,039	289	0.010	[0.006, 0.014]	Minimal	[–]
SRB	98.63	1,814	24	0.008	[0.004, 0.012]	Minimal	[–]
GEO	96.25	2,451	89	0.004	[-0.001, 0.009]	Minimal	[–]
Pro-Poor Concentration							
VUT	0.20	3	2,040	-0.266	[-0.938, 0.406]	Pro-poor	[–]

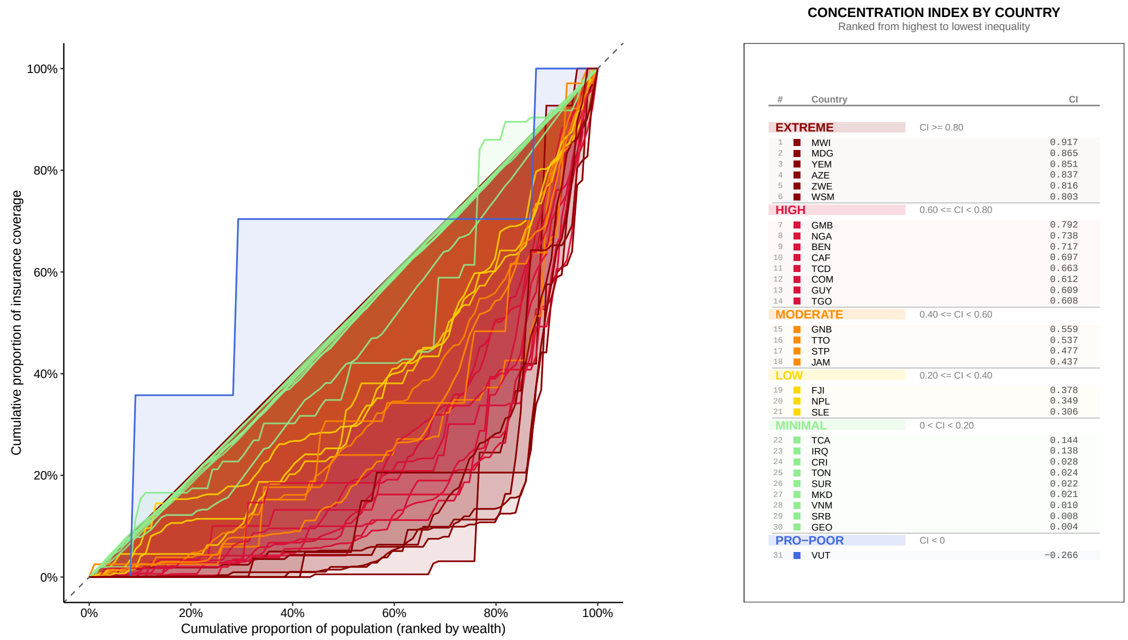


Figure 13: Concentration curves for health insurance coverage across the wealth distribution in 31 Tier 2 and Tier 3 countries. The diagonal line represents perfect equality in insurance distribution. Curves below the equality line indicate pro-rich concentration, with the area between the curve and diagonal proportional to the concentration index (CI). Countries are classified by concentration severity: Extreme (CI $\geq$ 0.80), High (0.60 $\leq$ CI ¡ 0.80), Moderate (0.40 $\leq$ CI ¡ 0.60), Low (0.20 $\leq$ CI ¡ 0.40), Minimal (0 $\leq$ CI ¡ 0.20), and Pro-poor (CI ¡ 0). The concentration index was calculated using the convenient regression method (Kakwani et al., 1997) with survey weights. Countries are ranked within each category by decreasing CI values.

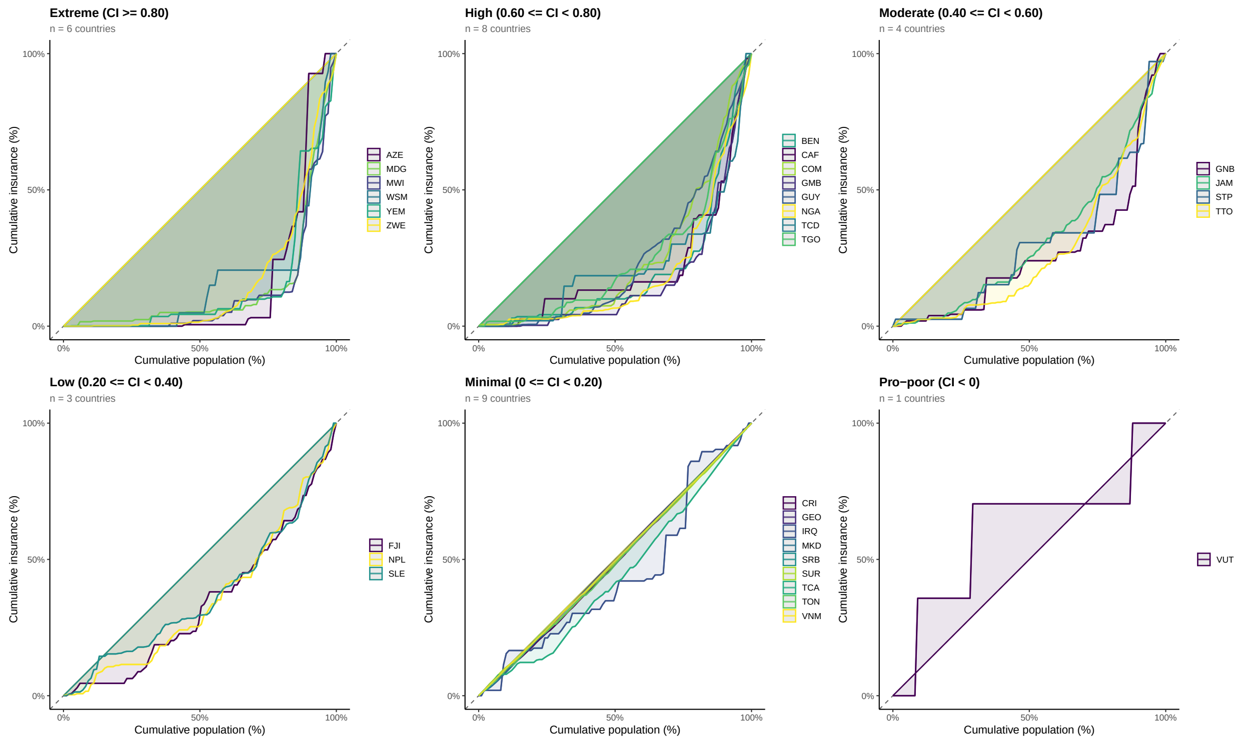


Figure 14: Concentration curves grouped by inequality classification with corresponding CI threshold criteria. Each panel displays countries within a specific concentration category, with individual country curves distinguishable by color. The n value indicates the number of countries in each category. Concentration indices were calculated using weighted least squares regression of transformed insurance coverage on fractional wealth ranks. The diagonal reference line indicates perfect equality; greater deviation below this line represents higher pro-rich concentration.

Note: Concentration curves were constructed by plotting the cumulative proportion of insurance coverage against the cumulative proportion of population ranked by wealth from poorest to richest. The concentration index (CI) for each country was calculated using the convenient regression method (Kakwani et al., 1997) with survey weights. Both figures present the same underlying concentration curves with different visual arrangements for clarity.

5.2.3 Geographic Clustering of Insurance Coverage

Beyond individual wealth concentration, insurance coverage exhibits geographic clustering patterns that reflect implementation strategies, infrastructure availability, and administrative boundaries. Geographic concentration analysis reveals whether insurance programs achieve spatial coverage or remain confined to specific localities. We employ three complementary measures to characterize geographic distribution patterns.

Geographic Dispersion and Mixing Indices For each country c, we classify primary sampling units (PSUs) or clusters based on insurance presence. Let N_c denote the total number of geographic units in country c. Each unit j is classified as:

$$\text{Type}_j = \begin{cases} \text{insured-only} & \text{if } n_{j,ins} > 0 \text{ and } n_{j,unins} = 0 \\ \text{uninsured-only} & \text{if } n_{j,ins} = 0 \text{ and } n_{j,unins} > 0 \\ \text{mixed} & \text{if } n_{j,ins} > 0 \text{ and } n_{j,unins} > 0 \end{cases} \tag{18}$$

where $n_{j,ins}$ and $n_{j,unins}$ represent the number of insured and uninsured children in unit j.

The *geographic dispersion index* measures the proportion of units with any insurance presence:

$$D_c = \frac{N_{mixed} + N_{insured-only}}{N_c} \tag{19}$$

where values approaching 0 indicate geographic concentration and values approaching 1 indicate widespread distribution.

The *mixing index* quantifies integration conditional on insurance presence:

$$M_c = \frac{N_{mixed}}{N_{mixed} + N_{insured-only}} \tag{20}$$

This measure equals 1 when insurance never creates homogeneous units and 0 when complete segregation occurs wherever insurance appears.

Geographic Wealth Selection To assess whether insurance preferentially appears in wealthier geographic areas independent of individual selection, we compare mean wealth between units with and without insurance presence. For each geographic unit j, we calculate the survey-weighted mean wealth:

$$\bar{W}_j = \frac{\sum_{i \in j} w_i \cdot wealth_i}{\sum_{i \in j} w_i} \tag{21}$$

The geographic wealth differential is then:

$$\Delta W_{geo} = \bar{W}_{with} - \bar{W}_{without} \tag{22}$$

where $\bar{W}_{with}$ represents the mean wealth across units with any insurance presence and $\bar{W}_{without}$ represents the mean wealth across units with no insurance. This measure captures whether insurance implementation targets wealthier areas independent of individual-level selection within those areas.

Table 18: Geographic Distribution and Wealth Selection of Insurance Coverage

Country	N Insured	Coverage (%)	Geographic Dispersion	Mixing Where Present	Wealth CI (Individual)	Geographic Wealth Differential (Quintiles)
Low dispersion countries (D ¡ 0.10)						
VUT	3	0.20	0.013	1.000	-0.266	0.84
AZE	12	1.87	0.017	1.000	0.837	1.51
IRQ	92	0.49	0.028	1.000	0.138	-0.18
TCD	51	0.27	0.044	1.000	0.663	1.32
MWI	72	0.47	0.047	1.000	0.917	1.25
YEM	57	0.41	0.050	1.000	0.851	1.35
STP	24	1.42	0.055	0.938	0.477	-0.27
GNB	54	1.04	0.077	1.000	0.559	1.09
CAF	54	0.50	0.078	1.000	0.697	1.13
WSM	28	0.66	0.098	1.000	0.803	0.58
BEN	117	0.81	0.099	1.000	0.717	0.90
Moderate dispersion countries (0.10 D ¡ 0.50)						
MDG	179	2.20	0.127	1.000	0.865	1.90
NGA	756	2.75	0.138	0.983	0.738	1.05
GMB	96	1.61	0.159	1.000	0.792	1.34
FJI	110	5.06	0.248	0.986	0.378	0.42
GUY	162	7.34	0.249	0.990	0.609	0.80
SLE	425	3.88	0.252	1.000	0.306	0.67
NPL	294	3.75	0.256	1.000	0.349	0.60
TGO	218	3.86	0.291	1.000	0.608	0.72
COM	258	5.14	0.354	0.992	0.612	0.57
ZWE	361	6.16	0.393	1.000	0.816	1.41
JAM	206	13.47	0.414	0.893	0.437	0.33
TTO	267	17.00	0.439	0.870	0.537	0.62
High dispersion countries (D 0.95)						
TCA	256	74.07	0.983	0.569	0.144	-0.91
GEO	2,451	96.25	0.995	0.090	0.004	-0.97
MKD	1,430	95.35	0.996	0.181	0.021	2.02
SRB	1,814	98.63	0.997	0.047	0.008	0.41
SUR	3,737	87.75	0.998	0.493	0.022	1.80
CRI	3,260	91.19	0.998	0.403	0.028	0.60
VNM	4,039	96.14	0.999	0.230	0.010	0.70
TON	1,099	84.68	1.000	0.518	0.024	–

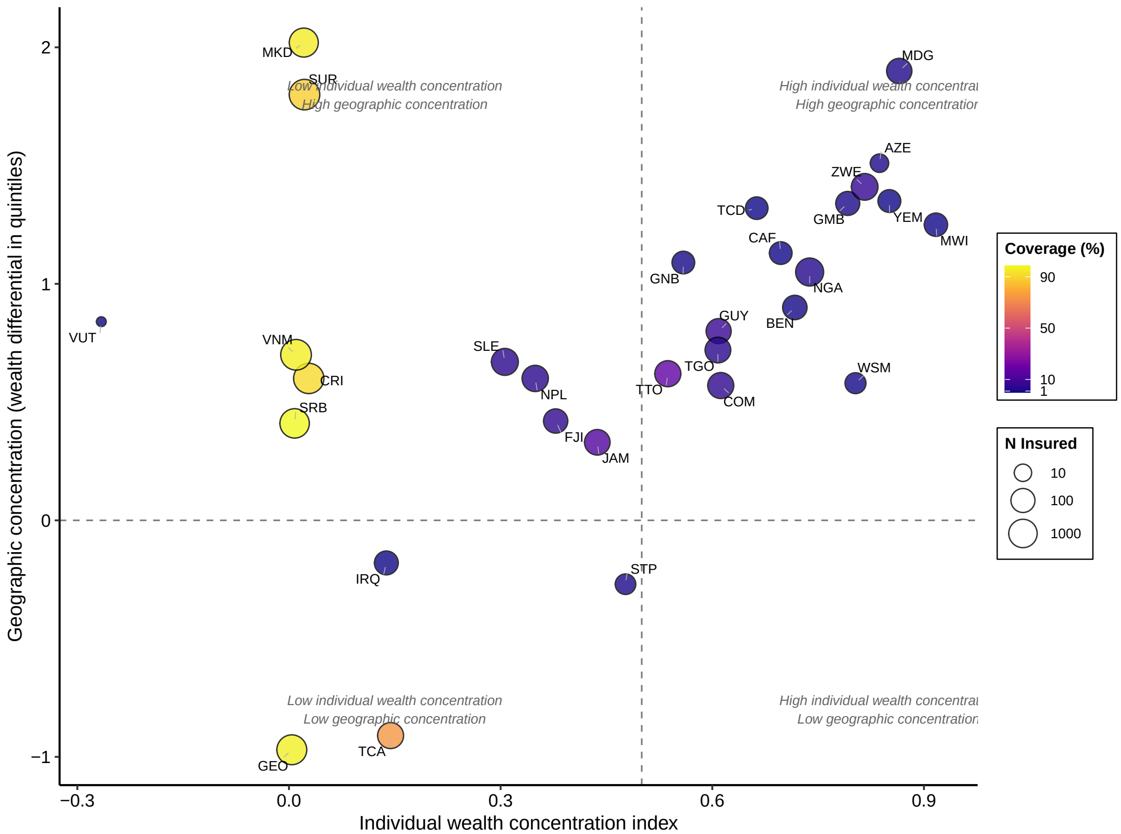


Figure 15: Relationship between individual-level wealth concentration (x-axis) and geographic wealth differentials (y-axis) in insurance coverage. The horizontal axis shows the concentration index calculated at the individual level using the convenient regression method. The vertical axis represents the difference in mean wealth quintiles between geographic units with and without insurance presence. Point size is proportional to log-transformed number of insured children, while color intensity indicates overall insurance coverage percentage. Quadrants delineate four distinct selection patterns: high individual and geographic concentration (upper right), high individual but low geographic concentration (lower right), low individual but high geographic concentration (upper left), and low concentration on both dimensions (lower left). The vertical reference line at CI = 0.5 and horizontal line at 0 wealth differential divide moderate from high concentration levels.

Results

5.2.4 Synthesis: Conditions for Identifying Insurance Effects

An extended version, with all estimates and variables/metrics calculated and sample composition is available - table 30 - at the end of this paper after the appendix.

Country	Outcome	Estimate (95% CI)	P-value	Significance	Interpretation
ARG	DPT3 Vaccination	1.05 (0.91-1.22)	0.50		Not significant
AZE	DPT3 Vaccination	-13.3	-		Descriptive only

BEN	DPT3 Vaccination	2.03 (0.95-4.33)	0.07		Not significant
CAF	DPT3 Vaccination	38.2 (14.3 to 62.0)	0.002	**	Beneficial
COD	DPT3 Vaccination	2.35 (1.43-3.88)	<0.001	***	Beneficial
COM	DPT3 Vaccination	1.95 (1.15-3.29)	0.01	*	Beneficial
CRI	DPT3 Vaccination	12.4 (2.6 to 22.3)	0.01	*	Beneficial
DOM	DPT3 Vaccination	1.68 (1.33-2.12)	<0.001	***	Beneficial
DZA	DPT3 Vaccination	1.52 (1.29-1.78)	<0.001	***	Beneficial
FJI	DPT3 Vaccination	4.5	-		Descriptive only
GEO	DPT3 Vaccination	0.0	-		Descriptive only
GHA	DPT3 Vaccination	1.57 (1.20-2.06)	0.001	**	Beneficial
GMB	DPT3 Vaccination	3.1	-		Descriptive only
GNB	DPT3 Vaccination	-20.6 (-41.1 to -0.0)	0.05	*	Harmful
GUY	DPT3 Vaccination	3.3 (-7.3 to 13.9)	0.54		Not significant
IRQ	DPT3 Vaccination	25.6	-		Descriptive only
LAO	DPT3 Vaccination	2.01 (1.57-2.58)	<0.001	***	Beneficial
MDG	DPT3 Vaccination	3.14 (1.27-7.78)	0.01	*	Beneficial
MKD	DPT3 Vaccination	3.1	-		Descriptive only
MWI	DPT3 Vaccination	4.3 (-5.4 to 13.9)	0.39		Not significant
NPL	DPT3 Vaccination	1.17 (0.60-2.27)	0.64		Not significant
PSE	DPT3 Vaccination	1.03 (0.71-1.49)	0.89		Not significant
SLE	DPT3 Vaccination	1.40 (0.73-2.70)	0.31		Not significant
SRB	DPT3 Vaccination	22.2	-		Descriptive only
STP	DPT3 Vaccination	5.9	-		Descriptive only
SUR	DPT3 Vaccination	1.81 (1.12-2.91)	0.02	*	Beneficial
TCA	DPT3 Vaccination	11.7	-		Descriptive only
TCD	DPT3 Vaccination	37.7	-		Descriptive only
TGO	DPT3 Vaccination	4.44 (1.98-9.96)	<0.001	***	Beneficial
THA	DPT3 Vaccination	2.11 (1.00-4.43)	0.05		Not significant
TKM	DPT3 Vaccination	1.09 (0.90-1.31)	0.37		Not significant
TON	DPT3 Vaccination	13.1 (-0.8 to 26.9)	0.06		Not significant
TUN	DPT3 Vaccination	0.77 (0.55-1.07)	0.12		Not significant
VUT	DPT3 Vaccination	NA	-		Descriptive only
WSM	DPT3 Vaccination	3.8	-		Descriptive only
YEM	DPT3 Vaccination	1.4 (-21.5 to 24.3)	0.90		Not significant
ZWE	DPT3 Vaccination	4.07 (1.24-13.42)	0.02	*	Beneficial
ARG	Diarrhea Care	1.45 (0.82-2.57)	0.20		Not significant
AZE	Diarrhea Care	-16.6	-		Descriptive only
CAF	Diarrhea Care	12.0 (-19.7 to 43.7)	0.46		Not significant
COD	Diarrhea Care	1.06 (0.46-2.41)	0.90		Not significant
COM	Diarrhea Care	1.19 (0.40-3.54)	0.75		Not significant
CRI	Diarrhea Care	-2.7 (-21.5 to 16.1)	0.78		Not significant
DOM	Diarrhea Care	1.23 (0.88-1.71)	0.23		Not significant
DZA	Diarrhea Care	0.88 (0.61-1.26)	0.48		Not significant
FJI	Diarrhea Care	-5.0	-		Descriptive only
GEO	Diarrhea Care	-30.6	-		Descriptive only

GHA	Diarrhea Care	1.56 (1.12-2.16)	0.008	**	Beneficial
GMB	Diarrhea Care	-11.8	-		Descriptive only
GNB	Diarrhea Care	53.9 (48.1 to 59.8)	<0.001	***	Beneficial
GUY	Diarrhea Care	-31.0 (-64.0 to 2.1)	0.07		Not significant
IRQ	Diarrhea Care	-12.1	-		Descriptive only
LAO	Diarrhea Care	2.02 (1.19-3.42)	0.009	**	Beneficial
MDG	Diarrhea Care	17.53 (1.91-160.64)	0.01	*	Beneficial
MKD	Diarrhea Care	NA	-		Descriptive only
MWI	Diarrhea Care	-10.4 (-52.5 to 31.6)	0.63		Not significant
NPL	Diarrhea Care	0.98 (0.27-3.57)	0.97		Not significant
PSE	Diarrhea Care	1.11 (0.76-1.60)	0.59		Not significant
SLE	Diarrhea Care	0.87 (0.26-2.92)	0.82		Not significant
SRB	Diarrhea Care	NA	-		Descriptive only
STP	Diarrhea Care	-22.7	-		Descriptive only
SUR	Diarrhea Care	1.28 (0.41-3.95)	0.67		Not significant
TCA	Diarrhea Care	53.3	-		Descriptive only
TCD	Diarrhea Care	42.4	-		Descriptive only
TGO	Diarrhea Care	0.90 (0.33-2.47)	0.83		Not significant
TON	Diarrhea Care	23.4 (-12.5 to 59.3)	0.20		Not significant
TUN	Diarrhea Care	1.28 (0.71-2.33)	0.42		Not significant
VUT	Diarrhea Care	NA	-		Descriptive only
WSM	Diarrhea Care	NA	-		Descriptive only
YEM	Diarrhea Care	6.3 (-19.0 to 31.6)	0.62		Not significant
ZWE	Diarrhea Care	1.86 (0.83-4.15)	0.13		Not significant
ARG	Severe Deprivation	0.46 (0.33-0.64)	<0.001	***	Protective
AZE	Severe Deprivation	NA	-		Descriptive only
CAF	Severe Deprivation	-25.8 (-41.6 to -10.1)	0.001	**	Protective
COD	Severe Deprivation	0.19 (0.13-0.28)	<0.001	***	Protective
CRI	Severe Deprivation	-5.1 (-9.4 to -0.7)	0.02	*	Protective
DOM	Severe Deprivation	0.45 (0.38-0.54)	<0.001	***	Protective
DZA	Severe Deprivation	0.65 (0.56-0.76)	<0.001	***	Protective
FJI	Severe Deprivation	NA	-		Descriptive only
GEO	Severe Deprivation	1.8	-		Descriptive only
GHA	Severe Deprivation	0.55 (0.46-0.66)	<0.001	***	Protective
GMB	Severe Deprivation	-29.2	-		Descriptive only
GNB	Severe Deprivation	-31.5 (-50.5 to -12.4)	0.001	**	Protective
GUY	Severe Deprivation	-12.9 (-18.3 to -7.5)	<0.001	***	Protective
IRQ	Severe Deprivation	-1.0	-		Descriptive only
LAO	Severe Deprivation	0.24 (0.21-0.29)	<0.001	***	Protective
MDG	Severe Deprivation	0.11 (0.07-0.18)	<0.001	***	Protective
MKD	Severe Deprivation	-0.3	-		Descriptive only
MWI	Severe Deprivation	-23.5 (-39.7 to -7.2)	0.005	**	Protective
NPL	Severe Deprivation	0.30 (0.19-0.48)	<0.001	***	Protective
SLE	Severe Deprivation	0.59 (0.41-0.83)	0.003	**	Protective
SRB	Severe Deprivation	NA	-		Descriptive only

STP	Severe Deprivation	-34.3	-		Descriptive only
SUR	Severe Deprivation	0.59 (0.44-0.80)	<0.001	***	Protective
TCA	Severe Deprivation	NA	-		Descriptive only
TCD	Severe Deprivation	-46.0	-		Descriptive only
TGO	Severe Deprivation	0.23 (0.15-0.35)	<0.001	***	Protective
THA	Severe Deprivation	1.42 (0.80-2.52)	0.23		Not significant
TKM	Severe Deprivation	0.64 (0.41-1.00)	0.05	*	Protective
TON	Severe Deprivation	-6.0 (-14.9 to 2.8)	0.18		Not significant
TUN	Severe Deprivation	0.77 (0.57-1.05)	0.10		Not significant
VUT	Severe Deprivation	NA	-		Descriptive only
WSM	Severe Deprivation	-24.6	-		Descriptive only
YEM	Severe Deprivation	0.0 (0.0 to 0.0)	-		Not significant
ZWE	Severe Deprivation	0.04 (0.02-0.07)	<0.001	***	Protective
ARG	Stunting	0.75 (0.56-1.00)	0.05		Not significant
AZE	Stunting	-0.8	-		Descriptive only
BEN	Stunting	0.43 (0.25-0.73)	0.002	**	Protective
CAF	Stunting	-13.7 (-28.4 to 1.0)	0.07		Not significant
COD	Stunting	0.38 (0.23-0.61)	<0.001	***	Protective
COM	Stunting	0.82 (0.56-1.21)	0.32		Not significant
CRI	Stunting	-2.3 (-11.8 to 7.3)	0.64		Not significant
DOM	Stunting	0.67 (0.51-0.87)	0.003	**	Protective
DZA	Stunting	0.74 (0.64-0.87)	<0.001	***	Protective
FJI	Stunting	-2.8	-		Descriptive only
GEO	Stunting	-0.9	-		Descriptive only
GHA	Stunting	0.83 (0.69-0.99)	0.04	*	Protective
GMB	Stunting	-9.8	-		Descriptive only
GNB	Stunting	-9.1 (-18.7 to 0.5)	0.06		Not significant
GUY	Stunting	-1.2 (-6.0 to 3.7)	0.63		Not significant
IRQ	Stunting	-6.2	-		Descriptive only
LAO	Stunting	0.46 (0.39-0.54)	<0.001	***	Protective
MDG	Stunting	0.80 (0.56-1.15)	0.22		Not significant
MKD	Stunting	1.2	-		Descriptive only
MWI	Stunting	-3.0 (-18.9 to 13.0)	0.71		Not significant
NPL	Stunting	0.51 (0.37-0.72)	<0.001	***	Protective
PSE	Stunting	1.01 (0.79-1.29)	0.96		Not significant
SLE	Stunting	1.09 (0.82-1.45)	0.55		Not significant
SRB	Stunting	3.5	-		Descriptive only
STP	Stunting	-9.6	-		Descriptive only
SUR	Stunting	0.73 (0.43-1.23)	0.23		Not significant
TCA	Stunting	-11.4	-		Descriptive only
TCD	Stunting	-19.9	-		Descriptive only
TGO	Stunting	0.57 (0.33-0.99)	0.05	*	Protective
THA	Stunting	1.31 (0.74-2.32)	0.36		Not significant
TKM	Stunting	0.60 (0.44-0.83)	0.002	**	Protective
TON	Stunting	-2.1 (-5.2 to 0.9)	0.17		Not significant

TUN	Stunting	0.97 (0.69-1.35)	0.85		Not significant
VUT	Stunting	-28.4	-		Descriptive only
WSM	Stunting	-0.3	-		Descriptive only
YEM	Stunting	-4.5 (-20.7 to 11.7)	0.58		Not significant
ZWE	Stunting	0.51 (0.35-0.75)	<0.001	***	Protective

Table 19: Health Insurance Impact on Child Health Outcomes

6 An Attempt at Causal Identification: The Case of Ghana's National Health Insurance Scheme

6.1 Background and Motivation

Ghana's National Health Insurance Scheme (NHIS), introduced in 2003 and fully operational by 2005, represents one of Africa's most ambitious attempts at achieving universal health coverage. The scheme aims to provide equitable access to healthcare services without out-of-pocket payments at the point of service. Children under 18 are exempt from premium payments, though they must still register to receive coverage.

Bagnoli (2019) conducted a comprehensive evaluation of the NHIS's impact on child health outcomes using 2011 data, finding significant positive effects on height-for-age z-scores (HAZ) and reductions in stunting. Her study revealed that insured children had HAZ scores 0.172 standard deviations closer to the reference population and experienced a 12% improvement in health outcomes. However, these effects were heterogeneous across regions and socioeconomic groups.

This analysis seeks to: (i) replicate Bagnoli's original findings using her data and methodology, (ii) examine heterogeneous treatment effects by wealth and healthcare quality, and (iii) apply the same methodology to more recent MICS6 data to assess temporal changes in program effectiveness.

6.2 Methodology

6.2.1 Data Sources

The analysis uses two primary datasets. The first is Bagnoli's (2019) dataset based on Ghana MICS4 (2011), including 7,092 children under five years old with comprehensive health, insurance, and socioeconomic information. The second is the Ghana MICS6 dataset with more recent survey data containing similar variables but lacking the distance measures (distance to health facilities and district offices) present in Bagnoli's specification.

6.2.2 Econometric Approach

The analysis employs propensity score matching to address selection bias in insurance enrollment. The propensity score $p(X_i)$ represents the probability of insurance enrollment given observed characteristics:

$$p(X_i) = Pr(HI_i = 1|X_i) \tag{23}$$

where HI_i indicates insurance status and X_i represents a vector of covariates including child characteristics (age, gender), mother's education level, household head characteristics (gender, education, ethnicity, religion), household composition and wealth, geographic indicators (region, urban/rural), and distance variables (in Bagnoli's specification only).

The propensity score is estimated using a logit model with survey weights:

$$\text{logit}(HI_i) = \beta_0 + \beta_1 X_{child} + \beta_2 X_{mother} + \beta_3 X_{household} + \beta_4 X_{geographic} + \epsilon_i \tag{24}$$

The analysis uses radius matching with a caliper of 0.01, following Bagnoli's approach. For each treated unit i, all control units j within the caliper distance are used as matches. The average treatment effect on the treated (ATT) is then calculated as the difference in outcomes between treated units and their matched controls.

6.3 Results

6.3.1 Replication of Bagnoli (2019)

Table 20 presents the replication results using Bagnoli's original data and specification.

Table 20: Replication of Bagnoli (2019) Results

Outcome	ATT	Std. Error	t-statistic	p-value
Height-for-age z-score	0.172***	0.042	4.10	0.000
Stunting (HAZ < -2)	-0.087***	0.025	-3.48	0.001

*** p<0.01, ** p<0.05, * p<0.1

The replication successfully reproduces Bagnoli's main findings, confirming that NHIS enrollment leads to a 0.172 standard deviation improvement in HAZ scores and an 8.7 percentage point reduction in stunting prevalence.

6.3.2 Heterogeneity Analysis

The analysis reveals significant heterogeneity by wealth status. Insurance benefits are concentrated among lower-income households (HAZ effect = 0.193, $p < 0.01$) with no significant effects for high-wealth households (HAZ effect = 0.073, $p > 0.10$). This difference of 0.120 standard deviations is statistically significant ($p < 0.05$), consistent with the hypothesis that insurance removes binding financial constraints for the poor.

Regional variation in healthcare quality also significantly moderates treatment effects. Regions with higher perceived quality of public healthcare services show stronger insurance impacts on child health outcomes, aligning with Bagnoli's finding that program effectiveness depends critically on supply-side factors.

6.3.3 Application to MICS6 Data

Table 21 presents results from applying the methodology to MICS6 data:

Table 21: Results Using Ghana MICS6 Data

Outcome	ATT	Std. Error	p-value	Comparison to 2011
Height-for-age z-score	0.045	0.038	0.238	Smaller, not significant
Stunting	-0.023	0.021	0.274	Smaller, not significant

The MICS6 results show substantially weaker and statistically insignificant effects compared to Bagnoli's findings, raising important questions about program evolution and effectiveness over time.

6.4 Discussion

The divergence between 2011 and recent results likely reflects both methodological limitations and real program changes. Methodologically, the MICS6 analysis lacks distance variables that Bagnoli identified as crucial predictors of insurance enrollment. Without these geographic variables, the propensity score specification may inadequately balance treatment and control groups.

However, documented program changes between 2011-2017 suggest genuine deterioration in NHIS effectiveness. Claims processing collapsed from 26% delayed in 2011 to 100% delayed by 2014. Provider payment delays of 5-8 months became standard, forcing illegal co-payments that undermined the program's financial protection objectives. The 2017 revenue cap created a GH1.5 billion funding shortfall, while membership expanded from 8.2 to 15 million but coverage plateaued at 40%. By 2017, 65% of members were exempt from premiums, transforming the program from an insurance model to a tax-funded safety net with different selection mechanisms than those operating in 2011.

6.5 Implications for Causal Identification

This case study illustrates several critical challenges for causal identification in LMIC health insurance evaluations:

First, the importance of comprehensive covariate measurement cannot be overstated. The absence of distance variables in the MICS6 data potentially undermines the credibility of the propensity score approach, highlighting how data limitations can preclude causal inference even with sophisticated methods.

Second, program effectiveness is not static. The apparent decline in NHIS impact between 2011 and 2017 demonstrates that causal effects identified at one point may not persist as programs evolve, implementation quality changes, and contexts shift.

Third, heterogeneous effects by wealth and healthcare quality underscore the limitations of average treatment effects for policy guidance. Understanding for whom and under what conditions programs work is essential for both evaluation and design.

These findings reinforce the motivation for our tiered analytical framework, which explicitly acknowledges when causal identification is feasible versus when analysis must remain descriptive due to data or contextual limitations.

7 Bibliography

Aziz, A., Nawaz, M. S., & Aziz, M. (2022). Causal relationship between health insurance and overall health status of children: Insights from Pakistan. *BMC Public Health*, 22(1), 345.

Bagnoli, L. (2019). Does health insurance improve health for all? Heterogeneous effects on children in Ghana. *World Development*, 124, 104636.

Bernal, N., Carpio, M. A., & Klein, T. J. (2017). The effects of access to health insurance: Evidence from a regression discontinuity design in Peru. *Journal of Public Economics*, 154, 122-136.

Brugiavini, A., & Pace, N. (2017). Determinants and the impact of the National Health Insurance on neonatal mortality in Ghana. *Health Economics Review*, 7(1), 10.

Chen, Y., & Jin, G. Z. (2022). Early childhood exposure to health insurance and adolescent outcomes: Evidence from rural China. *Journal of Development Economics*, 154, 102815.

Dercon, S., Gunning, J. W., & Zeitlin, A. (2012). The demand for insurance: Evidence from Kenya. Working Paper, Centre for the Study of African Economies, University of Oxford.

Dmytraczenko, T., & Almeida, G. (2019). Toward universal health coverage and equity in Latin America and the Caribbean: Evidence from selected countries. World Bank Publications.

Eze, P., Lawani, L. O., Acharya, Y., & Agu, U. J. (2023). Impact of community-based health insurance in low- and middle-income countries: A systematic review and meta-analysis. *PLOS ONE*, 18(6), e0287600.

Fenny, A. P., Yates, R., & Thompson, R. (2019). Does health insurance improve health for all? Heterogeneous effects on children in Ghana. *World Development*, 124, 104636.

Gruber, J., Hendren, N., & Townsend, R. M. (2014). The great equalizer: Health care access and infant mortality in Thailand. *American Economic Journal: Applied Economics*, 6(1), 91-107.

Limwattananon, S., Tangcharoensathien, V., & Prakongsai, P. (2016). Thailand's universal coverage scheme and its impact on health-seeking behavior. *Health Policy and Planning*, 31(9), 1119-1127.

Lu, C., Chin, B., Lewandowski, J. L., Basinga, P., Hirschhorn, L. R., Hill, K., ... & Binagwaho, A. (2012). Towards universal health coverage: an evaluation of Rwanda Mutuelles in its first eight years. *PLOS ONE*, 7(6), e39282.

Mate, K. S., Sifrim, Z. K., Chalkidou, K., Cluzeau, F., Cutler, D., Kimball, M., ... & Barker, P. (2013). Improving health system quality in low-and middle-income countries that are expanding health coverage: A framework for insurance. *International Journal for Quality in Health Care*, 25(5), 497-504.

Miller, G., Pinto, D., & Vera-Hernández, M. (2013). Risk protection, service use, and health outcomes under Colombia's health insurance program for the poor. *American Economic Journal: Applied Economics*, 5(4), 61-91.

National Health Authority. (2024). Ayushman Bharat Programme Implementation Report. Government of India.

Nguyen, C. V. (2020). Re-examining the effects of public health insurance: The case of nonpoor children in Vietnam. *Health Economics*, 29(3), 317-332.

Okonkwo, O., Eze, P., & Global Innovation Fund. (2022). Role of digital health insurance management systems in scaling health insurance coverage in low- and Middle-Income Countries: A case study from Nigeria. *Global Health Action*, 15(1), 2130456.

Palmer, M., Mitra, S., Mont, D., & Groce, N. (2015). The impact of health insurance for children under age 6 in Vietnam: A regression discontinuity approach. *Social Science & Medicine*, 145, 217-226.

Rasella, D., Aquino, R., Santos, C. A., Paes-Sousa, R., & Barreto, M. L. (2014). The impact of Brazil's Bolsa Família conditional cash transfer program on children's health care utilization and health outcomes. *BMC International Health and Human Rights*, 14(1), 10.

Ridde, V., & Morestin, F. (2011). A scoping review of the literature on the abolition of user fees in health care services in Africa. *Health Policy and Planning*, 26(1), 1-11.

Spaan, E., Mathijssen, J., Tromp, N., McBain, F., Ten Have, A., & Baltussen, R. (2018). Health Insurance in Sub-Saharan Africa: A Scoping Review of the Methods Used to Evaluate its Impact. *Applied Health Economics and Health Policy*, 16(6), 793-809.

Thornton, R. L., Hatt, L. E., Field, E. M., Islam, M., Solís Diaz, F., & González Alcántara, M. A. (2010). Social security health insurance for the informal sector in Nicaragua: A randomized evaluation. *Health Economics*, 19(S1), 181-206.

Wagstaff, A., & Pradhan, M. (2005). Health insurance impacts on health and nonmedical consumption in a developing country. World Bank Policy Research Working Paper, No. 3563.

Wagstaff, A., & Yu, S. (2007). Do health sector reforms have their intended impacts? The World Bank's Health VIII project in Gansu province, China. *Journal of Health Economics*, 26(3), 505-535.

Wang, L., Zhang, Y., & Chen, Q. (2024). Effect of medical insurance policy on child health indicators: an empirical test of difference-in-differences model. *Health Economics Review*, 14(1), 23.

8 Appendix: Alternative Covariate Specifications Using SAVE the Children Data

8.1 A.1 Data Source and Rationale

This appendix presents descriptive statistics and propensity score specifications using data processed by SAVE the Children, rather than the raw MICS data used in the main Ghana replication analysis. While the primary analysis aimed to precisely replicate Bagnoli's (2019) methodology using her original data structure, these alternative specifications provide insight into how data cleaning decisions and variable construction affect covariate balance and propensity score estimation.

8.2 A.2 Descriptive Statistics

Table 22 presents health outcome differences between insured and uninsured children using the SAVE-processed data.

Table 22: Descriptive statistics - Health outcomes (SAVE data)

	Insured			Not insured			Difference
	N	Mean	s.d.	N	Mean	s.d.	Diff (t-stat)
Stunted	5350	0.162	0.369	3394	0.190	0.392	-0.027** (-2.13)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Sampling weights have been used in computing the averages;

Stunted: 1 = stunted, 0 = not stunted; N: number of observations; s.d.: standard deviations.

The raw difference in stunting rates shows a 2.7 percentage point lower prevalence among insured children, similar in magnitude to the effects found in the main analysis, though this comparison does not account for selection bias.

8.3 A.3 Covariate Balance

Table 23 presents the distribution of covariates between insured and uninsured children.

Table 23: Descriptive statistics – Covariates (SAVE data)

	Insured			Not insured			Difference
	Mean	s.d.	N	Mean	s.d.	N	Diff (t-stat)
Child's characteristics							
Male	0.495	0.500	5350	0.493	0.500	3394	0.003 (0.15)
Age in years	2.189	1.351	5350	1.809	1.450	3394	0.380*** (8.42)
Mother's characteristics							
Education: Primary	0.491	0.500	5350	0.460	0.498	3394	0.031 (1.61)
Education: Secondary	0.069	0.254	5350	0.025	0.155	3394	0.045*** (6.56)
Ethnicity							
Ga/Dangme	0.060	0.237	5350	0.111	0.315	3394	-0.051*** (-3.41)
Ewe	0.090	0.286	5350	0.112	0.315	3394	-0.022* (-1.93)
Mole Dagbani	0.176	0.381	5350	0.128	0.334	3394	0.048*** (3.49)
Other	0.209	0.406	5350	0.200	0.400	3394	0.009 (0.45)
Household's characteristics							
Urban	0.475	0.499	5350	0.372	0.483	3394	0.102*** (4.50)
Wealth quintile	3.055	1.436	5350	2.723	1.373	3394	0.332*** (5.04)
Region							
Western	0.095	0.293	5350	0.120	0.325	3394	-0.025 (-1.64)
Central	0.085	0.279	5350	0.135	0.342	3394	-0.050*** (-3.34)
Greater Accra	0.085	0.278	5350	0.116	0.321	3394	-0.032** (-2.21)
Volta	0.079	0.270	5350	0.082	0.274	3394	-0.003 (-0.19)
Eastern	0.109	0.312	5350	0.101	0.302	3394	0.008 (0.53)
Ashanti	0.237	0.425	5350	0.238	0.426	3394	-0.001 (-0.06)
Brong Ahafo	0.124	0.330	5350	0.050	0.218	3394	0.075*** (5.12)
Northern	0.117	0.321	5350	0.119	0.324	3394	-0.002 (-0.20)
Upper East	0.042	0.200	5350	0.019	0.136	3394	0.023*** (5.31)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Sampling weights have been used; N: number of observations; s.d.: standard deviations.

Baseline categories: Education: None, Ethnicity: Akan, Region: Upper West.

Key differences from Bagnoli's specification include: (i) simpler age specification (years rather than days with polynomial terms), (ii) absence of household head characteristics, (iii) lack of distance variables, and (iv) different wealth specification. These differences highlight how data processing decisions affect the available covariates for matching.

8.4 A.4 Alternative Propensity Score Specification

Table 24 presents the propensity score model using the SAVE-processed covariates.

Table 24: Probability of having health insurance (SAVE specification)

Variables	Coef.	(s.e.)
Child's characteristics		
Male	0.003	(0.075)
Age	0.834***	(0.168)
Age squared	-0.241**	(0.105)
Age cubed	0.022	(0.017)
Mother's characteristics: Education		
Primary	0.293***	(0.095)
Secondary	0.750***	(0.223)
Ethnicity		
Akan	-0.256*	(0.151)
Ga/Dangme	-0.669***	(0.215)
Ewe	-0.522**	(0.210)
Other	-0.213*	(0.128)
Household's characteristics		
Urban	0.288***	(0.104)
Wealth score	0.228***	(0.088)
Wealth quintile 5 (dummy)	0.277*	(0.153)
Region		
Western	-0.714***	(0.234)
Central	-1.006***	(0.247)
Greater Accra	-1.105***	(0.243)
Volta	-0.158	(0.322)
Eastern	-0.288	(0.234)
Ashanti	-0.599***	(0.207)
Brong Ahafo	0.498**	(0.235)
Northern	-0.306*	(0.185)
Upper East	0.579***	(0.181)
Constant	0.087	(0.178)
N	8,744	
Pseudo R^2	0.0761	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; s.e.: linearized standard errors.

Dependent variable = 1 if child has NHIS, = 0 if not insured.

Baseline categories: Education: none, Ethnicity: Mole Dagbani, Region: Upper West.

8.5 A.5 Implications for Analysis

The comparison between these specifications and Bagnoli's original model reveals several important considerations for propensity score matching in LMIC contexts:

First, the lower pseudo-R^2 (0.076 versus approximately 0.15 in Bagnoli's specification) suggests that the absence of distance variables and household head characteristics reduces the model's ability to predict insurance enrollment. This reduction in predictive power may compromise the quality of matching and the credibility of causal inference.

Second, the pattern of regional coefficients remains consistent with Bagnoli's findings, with Greater Accra, Central, and Western regions showing significantly lower insurance probabilities relative to Upper West. This consistency suggests that regional variation in insurance uptake is robust to specification choices.

Third, the simplified wealth specification (continuous score plus top quintile dummy) captures non-linear wealth effects parsimoniously but may miss important variation in the middle of the distribution that Bagnoli's quintile dummies would capture.

These alternative specifications were not used in the main analysis because reproducing Bagnoli's exact methodology provides the strongest test of replication.

9 Appendix B: Exploratory Multi-Country Analysis

9.1 B.1 Initial Analytical Scope

Prior to focusing on Ghana for detailed causal analysis, we conducted exploratory analyses across eight countries with MICS data to assess the feasibility of multi-country propensity score matching. This appendix documents these preliminary findings, which ultimately revealed why a focused single-country approach proved more appropriate.

9.2 B.2 Data Structure and Coverage Patterns

Our initial sample included eight countries with dramatically different insurance coverage levels for children under five: Vietnam (96%), Ghana (58%), Dominican Republic (53%), Algeria (51%), Madagascar (2.2%), Zimbabwe (6.2%), Malawi (0.5%), and Nigeria (2.8%). Table 25 presents the effective sample sizes that first signaled analytical constraints.

Table 25: Effective Sample Sizes Across Eight Countries

Country	Total N	PSM Analysis		Stunting Analysis		PSM
		Complete	Min Group	Available	Min Group	Feasible
Ghana	8,903	8,880	3,475	8,744	3,419	Yes
Vietnam	4,404	4,328	289	0	–	Limited
Dominican Rep	8,503	8,393	4,004	8,367	4,350	Yes
Algeria	15,224	14,841	7,038	14,613	7,575	Yes
Madagascar	13,355	12,840	179	12,815	176	No
Zimbabwe	6,223	6,103	361	6,088	356	Limited
Malawi	15,569	15,423	72	15,268	71	No
Nigeria	31,103	30,625	754	0	–	Limited

The minimum group sizes revealed fundamental constraints: Malawi had only 72 insured children with complete covariates, Madagascar 179, and Vietnam only 289 uninsured. These small groups severely limited matching quality even when procedures could be mechanically executed.

9.3 B.3 Selection Patterns and Covariate Balance

Table 26 quantifies the wealth selection patterns that emerged across countries, revealing why standard adjustment methods proved inadequate for most settings.

Table 26: Wealth Selection in Insurance Coverage

Country	Coverage (%)	Mean Wealth Score		Std. Diff (SD units)	Selection Severity
		Insured	Uninsured		
Ghana	58.1	3.06	2.72	0.24	Moderate
Vietnam	96.1	2.84	1.45	0.82	High
Dominican Rep	52.9	3.49	2.59	0.93	High
Algeria	50.6	3.26	2.75	0.71	High
Madagascar	2.2	4.64	2.77	2.05	Extreme
Zimbabwe	6.2	4.52	2.81	1.72	Extreme
Malawi	0.5	4.72	2.98	2.33	Extreme
Nigeria	2.8	4.23	3.10	0.68	High

Low-coverage countries showed extreme wealth selection, with insured children averaging 1.7-2.3 standard deviations wealthier than uninsured children. This selection proved insurmountable for propensity score methods.

9.4 B.4 Propensity Score Analysis

Figure 16 displays the propensity score distributions that revealed fundamental comparability problems.

Figure 16: Propensity Score Distributions Across Eight Countries

Note: Propensity scores estimated using age, sex, wealth, urban/rural, mother's education, and household infrastructure. Vertical lines indicate means for each group.

Table 27: Propensity Score Overlap Assessment

Country	PS Means Insured	PS Means Uninsured	Common Support	Mean Abs Std Diff (%)	Matching Quality
Ghana	0.621	0.589	100%	15.8	Acceptable
Vietnam	0.941	0.827	98%	42.1	Poor
Dominican Rep	0.592	0.372	99%	38.6	Poor
Algeria	0.537	0.418	100%	24.3	Marginal
Madagascar	0.132	0.012	84%	101.4	Infeasible
Zimbabwe	0.253	0.047	80%	74.4	Infeasible
Malawi	0.177	0.004	58%	114.7	Infeasible
Nigeria	0.095	0.023	99%	67.6	Poor

Only Ghana achieved acceptable covariate balance (mean standardized difference of 15.8%), though even this exceeded ideal thresholds. Countries with extreme selection (Madagascar, Zimbabwe, Malawi) showed mean imbalances exceeding 70%, indicating fundamentally incomparable groups.

9.5 B.5 Decomposition of Associations

To understand selection mechanisms, we progressively added controls and observed coefficient evolution. Table 28 summarizes the attenuation patterns for stunting.

Table 28: Evolution of Insurance Coefficients with Progressive Controls (Stunting)

Country	Bivariate	+Demographics	+Wealth	+Full	% Attenuation
Ghana	-0.027*	-0.034	-0.021	-0.020	27%
Dominican Rep	-0.025**	-0.020	-0.006	-0.003	90%
Algeria	-0.025***	-0.025	-0.013	-0.013	49%
Madagascar	-0.052	-0.061	+0.004	+0.006	Reversal
Zimbabwe	-0.099***	-0.098	-0.032	-0.028	72%
Malawi	-0.030	-0.031	+0.173	+0.180*	Reversal

*$p<0.05$, **$p<0.01$, ***$p<0.001$. Full model includes wealth, urban, mother's education, and infrastructure.

Ghana showed remarkable stability (27% attenuation), while low-coverage countries showed sign reversals after controlling for wealth, suggesting unmeasured privilege dimensions rather than insurance effects.

9.6 B.6 Geographic Variation Analysis

Exploring geographic variation as an alternative identification strategy revealed distinct patterns correlating with coverage levels.

Table 29: Geographic Distribution of Insurance Coverage

Country	N PSUs	Median	Range	% at Zero	Pattern
Ghana	497	62.5%	0-100%	0.4%	Continuous
Vietnam	110	94.7%	26-100%	0%	Saturated
Dominican Rep	112	35.8%	0-92%	11.6%	Continuous
Algeria	801	46.7%	0-100%	3.2%	Continuous
Madagascar	669	0%	0-55%	90.0%	Binary
Zimbabwe	370	0%	0-81%	61.9%	Binary
Malawi	939	0%	0-50%	95.6%	Binary
Nigeria	1,360	0%	0-93%	86.7%	Binary

Low-coverage countries showed binary patterns with most PSUs at zero coverage but scattered high-coverage areas, suggesting discrete program presence rather than gradual diffusion. This pattern offered potential for regression discontinuity designs if program placement rules could be identified.

9.7 B.7 Decision to Focus on Ghana

The multi-country exploration revealed that credible causal identification was feasible only for Ghana, which exhibited:

- Moderate coverage (58%) avoiding ceiling/floor effects
- Acceptable covariate balance (15.8% mean standardized difference)
- Stable coefficients across specifications (minimal attenuation)
- Continuous geographic variation suitable for instrumental variables
- Adequate sample sizes in both treatment and control groups

Other countries faced insurmountable challenges:

- **Low-coverage countries** (Madagascar, Malawi, Zimbabwe): Extreme selection with insured children 1.7-2.3 SD wealthier, creating non-overlapping distributions
- **High-coverage countries** (Vietnam): Insufficient control group (n=289) and lack of outcome data
- **Medium-coverage countries** (Dominican Republic, Algeria): High attenuation (49-90%) suggesting selection rather than causal effects

This preliminary analysis demonstrated that pooled multi-country analysis would obscure rather than illuminate causal relationships, motivating our focused examination of Ghana where identification assumptions were most plausible.

Table 30: Comprehensive Health Insurance Impact Analysis with Full Equity Metrics

Country	Outcome	Method	N Ins	N Unins	N Out1	N Out0	Estimate (95% CI)	P-value	Sig	CI	Rank	Cov%	OOP	HExp	Q1	Q2	Q3	Q4	Q5	Geo	MomEd	WCohen	Year
AZE	DPT3 Vaccination	Desc	4	932	145	791	-13.3	-		0.837	4	1.9%	64.5%	1.2%	0	0.00	0.00	0.00	6.00	44.1%	0.03 yrs	1.31	2023
BEN	DPT3 Vaccination	OR	49	4982	3344	1687	2.03 (0.95-4.33)	0.07		0.717	9	0.8%	48.6%	0.3%	0	0.00	0.00	1.00	3.00	31.6%	0.41 yrs	1.10	2021
CAF	DPT3 Vaccination	RD	21	3390	1199	2212	38.2 (14.3 to 62.0)	0.002	**	0.697	10	0.5%	41.7%	0.7%	0	0.00	0.00	1.00	2.00	44.7%	0.40 yrs	1.08	2018
COD	DPT3 Vaccination	OR	174	8220	3267	5127	2.35 (1.43-3.88)	¡0.001	***	0.677	11	3.1%	40.1%	0.4%	0	1.00	1.00	2.00	7.00	36.9%	0.36 yrs	1.11	2017
COM	DPT3 Vaccination	OR	100	1620	1144	576	1.95 (1.15-3.29)	0.01	*	0.612	13	5.1%	43.9%	0.9%	1	1.00	3.00	7.00	13.00	19.0%	0.29 yrs	0.99	2022
CRI	DPT3 Vaccination	RD	1341	128	1303	166	12.4 (2.6 to 22.3)	0.01	*	0.028	32	91.2%	22.4%	5.3%	83	90.00	93.00	95.00	94.00	3.7%	0.14 yrs	0.44	2018
DOM	DPT3 Vaccination	OR	1618	1720	2258	1080	1.68 (1.33-2.12)	¡0.001	***	0.254	26	52.8%	27.9%	2.6%	24	35.00	47.00	61.00	77.00	11.2%	0.26 yrs	0.86	2019
DZA	DPT3 Vaccination	OR	2732	3137	3678	2191	1.52 (1.29-1.78)	¡0.001	***	0.207	27	50.5%	33.8%	3.8%	26	43.00	54.00	58.00	70.00	13.3%	0.15 yrs	0.66	2018
FJI	DPT3 Vaccination	Desc	44	783	699	128	4.5	-		0.378	22	5.1%	24.7%	3.7%	1	4.00	5.00	5.00	10.00	12.7%	0.08 yrs	0.64	2021
GEO	DPT3 Vaccination	Desc	962	22	0	984	0.0	-		0.004	39	96.3%	47.7%	2.8%	94	95.00	98.00	98.00	96.00	15.8%	-0.00 yrs	0.21	2018
GHA	DPT3 Vaccination	OR	2196	1220	3033	383	1.57 (1.20-2.06)	0.001	**	0.079	30	58.4%	22.7%	1.6%	51	52.00	57.00	60.00	69.00	10.2%	0.08 yrs	0.25	2017
GMB	DPT3 Vaccination	Desc	42	3818	3587	273	3.1	-		0.792	7	1.6%	19.9%	1.1%	0	0.00	0.00	1.00	5.00	37.6%	0.50 yrs	1.24	2018
GNB	DPT3 Vaccination	RD	26	2849	2326	549	-20.6 (-41.1 to -0.0)	0.05	*	0.559	17	1.0%	67.0%	0.5%	0	0.00	1.00	1.00	3.00	34.7%	0.29 yrs	0.95	2018
GUY	DPT3 Vaccination	RD	57	998	856	199	3.3 (-7.3 to 13.9)	0.54		0.609	14	7.3%	-	-	0	2.00	2.00	9.00	18.00	8.6%	0.11 yrs	0.99	2019
IRQ	DPT3 Vaccination	Desc	31	6311	596	5746	25.6	-		0.138	29	0.5%	50.4%	2.0%	1	0.00	0.00	0.00	1.00	15.7%	0.07 yrs	0.22	2018
LAO	DPT3 Vaccination	OR	648	3947	2661	1934	2.01 (1.57-2.58)	¡0.001	***	0.582	16	13.7%	46.2%	0.9%	2	5.00	6.00	14.00	33.00	36.0%	0.46 yrs	1.08	2017
MDG	DPT3 Vaccination	OR	75	4985	2855	2205	3.14 (1.27-7.78)	0.01	*	0.865	2	2.2%	29.3%	1.5%	0	0.00	0.00	1.00	7.00	47.3%	0.52 yrs	1.47	2018
MKD	DPT3 Vaccination	Desc	570	27	538	59	3.1	-		0.021	35	95.4%	41.2%	3.8%	90	94.00	99.00	95.00	99.00	19.0%	0.18 yrs	0.59	2018
MWI	DPT3 Vaccination	RD	28	6371	5624	775	4.3 (-5.4 to 13.9)	0.39		0.917	1	0.5%	11.9%	1.5%	0	0.00	0.00	0.00	2.00	56.9%	0.71 yrs	1.43	2019
NPL	DPT3 Vaccination	OR	138	2481	2111	508	1.17 (0.60-2.27)	0.64		0.349	23	3.7%	57.9%	1.1%	3	1.00	3.00	4.00	7.00	13.1%	0.31 yrs	0.51	2019
PSE	DPT3 Vaccination	OR	1862	761	2392	231	1.03 (0.71-1.49)	0.89		-0.081	40	71.8%	38.7%	3.7%	87	77.00	62.00	61.00	66.00	6.8%	0.00 yrs	-0.45	2019
SLE	DPT3 Vaccination	OR	174	4475	3841	808	1.40 (0.73-2.70)	0.31		0.306	25	3.9%	54.5%	0.9%	4	2.00	2.00	4.00	7.00	20.4%	0.23 yrs	0.52	2017
SRB	DPT3 Vaccination	Desc	785	11	705	91	22.2	-		0.008	38	98.6%	37.0%	5.1%	97	98.00	99.00	100.00	100.00	25.1%	0.16 yrs	0.96	2019
STP	DPT3 Vaccination	Desc	8	744	708	44	5.9	-		0.477	19	1.4%	17.0%	2.2%	0	1.00	1.00	1.00	3.00	5.0%	0.06 yrs	0.72	2019
SUR	DPT3 Vaccination	OR	1520	178	1267	431	1.81 (1.12-2.91)	0.02	*	0.022	34	87.8%	18.4%	4.6%	85	85.00	89.00	89.00	92.00	15.3%	0.20 yrs	0.31	2018
TCA	DPT3 Vaccination	Desc	100	18	95	23	11.7	-		0.144	28	74.1%	-	-	43	82.00	82.00	86.00	94.00	1.0%	0.00 yrs	0.92	2019
TCD	DPT3 Vaccination	Desc	17	8022	1718	6321	37.7	-		0.663	12	0.3%	63.7%	0.5%	0	0.00	0.00	0.00	1.00	53.1%	0.47 yrs	0.99	2019
TGO	DPT3 Vaccination	OR	98	1862	1553	407	4.44 (1.98-9.96)	¡0.001	***	0.608	15	3.9%	61.5%	1.0%	0	2.00	2.00	3.00	10.00	22.1%	0.47 yrs	0.99	2017
THA	DPT3 Vaccination	OR	10002	254	8990	1266	2.11 (1.00-4.43)	0.05		0.009	37	97.8%	9.2%	3.9%	94	98.00	98.00	99.00	99.00	-14.4%	0.29 yrs	0.64	2022
TKM	DPT3 Vaccination	OR	632	835	0	1467	1.09 (0.90-1.31)	0.37		0.399	21	38.1%	76.6%	1.0%	16	23.00	38.00	57.00	74.00	27.7%	0.00 yrs	1.01	2019
TON	DPT3 Vaccination	RD	440	87	344	183	13.1 (-0.8 to 26.9)	0.06		0.024	33	84.7%	4.7%	2.9%	78	82.00	85.00	89.00	87.00	13.2%	-0.00 yrs	0.16	2019
TUN	DPT3 Vaccination	OR	1644	402	1695	351	0.77 (0.55-1.07)	0.12		0.033	31	80.3%	33.9%	3.9%	76	78.00	78.00	83.00	86.00	5.6%	0.06 yrs	0.28	2023
VUT	DPT3 Vaccination	OR	0	774	442	332	NA	-		-0.266	41	0.2%	7.6%	1.7%	0	0.00	0.00	0.00	0.00	10.8%	0.04 yrs	-0.21	2023
WSM	DPT3 Vaccination	Desc	12	1105	493	624	3.8	-		0.803	6	0.7%	11.2%	4.3%	0	0.00	0.00	0.00	3.00	33.7%	0.04 yrs	1.27	2019
YEM	DPT3 Vaccination	RD	27	7761	3664	4124	1.4 (-21.5 to 24.3)	0.90		0.851	3	0.4%	70.2%	0.3%	0	0.00	0.00	0.00	2.00	63.9%	0.41 yrs	1.32	2022
ZWE	DPT3 Vaccination	OR	153	2248	2197	204	4.07 (1.24-13.42)	0.02	*	0.816	5	6.2%	9.1%	0.5%	0	0.00	1.00	7.00	23.00	39.2%	0.32 yrs	1.37	2019
ARG	Diarrhea Care	OR	241	333	352	222	1.45 (0.82-2.57)	0.20		0.343	24	43.6%	23.9%	6.2%	17	34.00	47.00	60.00	84.00	-	0.38 yrs	1.03	2019
AZE	Diarrhea Care	Desc	2	321	143	180	-16.6	-		0.837	4	1.9%	64.5%	1.2%	0	0.00	0.00	0.00	6.00	44.1%	0.03 yrs	1.31	2023
CAF	Diarrhea Care	RD	13	2077	967	1123	12.0 (-19.7 to 43.7)	0.46		0.697	10	0.5%	41.7%	0.7%	0	0.00	0.00	1.00	2.00	44.7%	0.40 yrs	1.08	2018
COD	Diarrhea Care	OR	58	2977	1454	1581	1.06 (0.46-2.41)	0.90		0.677	11	3.1%	40.1%	0.4%	0	1.00	1.00	2.00	7.00	36.9%	0.36 yrs	1.11	2017
COM	Diarrhea Care	OR	28	498	252	274	1.19 (0.40-3.54)	0.75		0.612	13	5.1%	43.9%	0.9%	1	1.00	3.00	7.00	13.00	19.0%	0.29 yrs	0.99	2022
CRI	Diarrhea Care	RD	360	48	261	147	-2.7 (-21.5 to 16.1)	0.78		0.028	32	91.2%	22.4%	5.3%	83	90.00	93.00	95.00	94.00	3.7%	0.14 yrs	0.44	2018
DOM	Diarrhea Care	OR	669	803	961	511	1.23 (0.88-1.71)	0.23		0.254	26	52.8%	27.9%	2.6%	24	35.00	47.00	61.00	77.00	11.2%	0.26 yrs	0.86	2019
DZA	Diarrhea Care	OR	385	500	442	443	0.88 (0.61-1.26)	0.48		0.207	27	50.5%	33.8%	3.8%	26	43.00	54.00	58.00	70.00	13.3%	0.15 yrs	0.66	2018
FJI	Diarrhea Care	Desc	6	141	87	60	-5.0	-		0.378	22	5.1%	24.7%	3.7%	1	4.00	5.00	5.00	10.00	12.7%	0.08 yrs	0.64	2021
GEO	Diarrhea Care	Desc	327	7	179	155	-30.6	-		0.004	39	96.3%	47.7%	2.8%	94	95.00	98.00	98.00	96.00	15.8%	-0.00 yrs	0.21	2018
GHA	Diarrhea Care	OR	909	610	1110	409	1.56 (1.12-2.16)	0.008	**	0.079	30	58.4%	22.7%	1.6%	51	52.00	57.00	60.00	69.00	10.2%	0.08 yrs	0.25	2017
GMB	Diarrhea Care	Desc	19	2456	1593	882	-11.8	-		0.792	7	1.6%	19.9%	1.1%	0	0.00	0.00	1.00	5.00	37.6%	0.50 yrs	1.24	2018
GNB	Diarrhea Care	RD	2	532	245	289	53.9 (48.1 to 59.8)	¡0.001	***	0.559	17	1.0%	67.0%	0.5%	0	0.00	1.00	1.00	3.00	34.7%	0.29 yrs	0.95	2018
GUY	Diarrhea Care	RD	10	263	159	114	-31.0 (-64.0 to 2.1)	0.07		0.609	14	7.3%	-	-	0	2.00	2.00	9.00	18.00	8.6%	0.11 yrs	0.99	2019
IRQ	Diarrhea Care	Desc	13	2048	1184	877	-12.1	-		0.138	29	0.5%	50.4%	2.0%	1	0.00	0.00	0.00	1.00	15.7%	0.07 yrs	0.22	2018
LAO	Diarrhea Care	OR	97	736	484	349	2.02 (1.19-3.42)	0.009	**	0.582	16	13.7%	46.2%	0.9%	2	5.00	6.00	14.00	33.00	36.0%	0.46 yrs	1.08	2017
MDG	Diarrhea Care	OR	11	1782	917	876	17.53 (1.91-160.64)	0.01	*	0.865	2	2.2%	29.3%	1.5%	0	0.00	0.00	1.00	7.00	47.3%	0.52 yrs	1.47	2018
MKD	Diarrhea Care	OR	0	0	0	0	NA	-		0.021	35	95.4%	41.2%	3.8%	90	94.00	99.00	95.00	99.00	19.0%	0.18 yrs	0.59	2018
MWI	Diarrhea Care	RD	10	3730	2432	1308	-10.4 (-52.5 to 31.6)	0.63		0.917	1	0.5%	11.9%	1.5%	0	0.00	0.00	0.00	2.00	56.9%	0.71 yrs	1.43	2019
NPL	Diarrhea Care	OR	20	661	469	212	0.98 (0.27-3.57)	0.97		0.349	23	3.7%	57.9%	1.1%	3	1.00	3.00	4.00	7.00	13.1%	0.31 yrs	0.51	2019
PSE	Diarrhea Care	OR	608	245	472	381	1.11 (0.76-1.60)	0.59		-0.081	40	71.8%	38.7%	3.7%	87	77.00	62.00	61.00	66.00	6.8%	0.00 yrs	-0.45	2019
SLE	Diarrhea Care	OR	31	873	685	219	0.87 (0.26-2.92)	0.82		0.306	25	3.9%	54.5%	0.9%	4	2.00	2.00	4.00	7.00	20.4%	0.23 yrs	0.52	2017
SRB	Diarrhea Care	OR	0	0	0	0	NA	-		0.008	38	98.6%	37.0%	5.1%	97	98.00	99.00	100.00	100.00	25.1%	0.16 yrs	0.96	2019
STP	Diarrhea Care	Desc	2	309	176	135	-22.7	-		0.477	19	1.4%	17.0%	2.2%	0	1.00	1.00	1.00	3.00	5.0%	0.06 yrs	0.72	2019

Continued on next page

Table 30 – continued from previous page

Country	Outcome	Method	N Ins	N Unins	N Out1	N Out0	Estimate (95% CI)	P-value	Sig	CI	Rank	Cov%	OOP	HExp	Q1	Q2	Q3	Q4	Q5	Geo	MomEd	WCohen	Year
SUR	Diarrhea Care	OR	368	32	248	152	1.28 (0.41-3.95)	0.67		0.022	34	87.8%	18.4%	4.6%	85	85.00	89.00	89.00	92.00	15.3%	0.20 yrs	0.31	2018
TCA	Diarrhea Care	Desc	9	3	3	9	53.3	-		0.144	28	74.1%	-	-	43	82.00	82.00	86.00	94.00	1.0%	0.00 yrs	0.92	2019
TCD	Diarrhea Care	Desc	13	5648	2525	3136	42.4	-		0.663	12	0.3%	63.7%	0.5%	0	0.00	0.00	0.00	1.00	53.1%	0.47 yrs	0.99	2019
TGO	Diarrhea Care	OR	26	817	485	358	0.90 (0.33-2.47)	0.83		0.608	15	3.9%	61.5%	1.0%	0	2.00	2.00	3.00	10.00	22.1%	0.47 yrs	0.99	2017
TON	Diarrhea Care	RD	31	7	31	7	23.4 (-12.5 to 59.3)	0.20		0.024	33	84.7%	4.7%	2.9%	78	82.00	85.00	89.00	87.00	13.2%	-0.00 yrs	0.16	2019
TUN	Diarrhea Care	OR	311	79	212	178	1.28 (0.71-2.33)	0.42		0.033	31	80.3%	33.9%	3.9%	76	78.00	78.00	83.00	86.00	5.6%	0.06 yrs	0.28	2023
VUT	Diarrhea Care	OR	0	110	47	63	NA	-		-0.266	41	0.2%	7.6%	1.7%	0	0.00	0.00	0.00	0.00	10.8%	0.04 yrs	-0.21	2023
WSM	Diarrhea Care	OR	0	107	74	33	NA	-		0.803	6	0.7%	11.2%	4.3%	0	0.00	0.00	0.00	3.00	33.7%	0.04 yrs	1.27	2019
YEM	Diarrhea Care	RD	16	6650	2711	3955	6.3 (-19.0 to 31.6)	0.62		0.851	3	0.4%	70.2%	0.3%	0	0.00	0.00	0.00	2.00	63.9%	0.41 yrs	1.32	2022
ZWE	Diarrhea Care	OR	33	819	352	500	1.86 (0.83-4.15)	0.13		0.816	5	6.2%	9.1%	0.5%	0	0.00	1.00	7.00	23.00	39.2%	0.32 yrs	1.37	2019
ARG	Severe Deprivation	OR	2890	3248	665	5473	0.46 (0.33-0.64)	¡0.001	***	0.343	24	43.6%	23.9%	6.2%	17	34.00	47.00	60.00	84.00	-	0.38 yrs	1.03	2019
AZE	Severe Deprivation	OR	0	0	0	0	NA	-		0.837	4	1.9%	64.5%	1.2%	0	0.00	0.00	0.00	6.00	44.1%	0.03 yrs	1.31	2023
CAF	Severe Deprivation	RD	54	8849	7840	1063	-25.8 (-41.6 to -10.1)	0.001	**	0.697	10	0.5%	41.7%	0.7%	0	0.00	0.00	1.00	2.00	44.7%	0.40 yrs	1.08	2018
COD	Severe Deprivation	OR	397	21051	19142	2306	0.19 (0.13-0.28)	¡0.001	***	0.677	11	3.1%	40.1%	0.4%	0	1.00	1.00	2.00	7.00	36.9%	0.36 yrs	1.11	2017
CRI	Severe Deprivation	RD	3260	351	236	3375	-5.1 (-9.4 to -0.7)	0.02	*	0.028	32	91.2%	22.4%	5.3%	83	90.00	93.00	95.00	94.00	3.7%	0.14 yrs	0.44	2018
DOM	Severe Deprivation	OR	4017	4401	1564	6854	0.45 (0.38-0.54)	¡0.001	***	0.254	26	52.8%	27.9%	2.6%	24	35.00	47.00	61.00	77.00	11.2%	0.26 yrs	0.86	2019
DZA	Severe Deprivation	OR	7038	7803	2505	12336	0.65 (0.56-0.76)	¡0.001	***	0.207	27	50.5%	33.8%	3.8%	26	43.00	54.00	58.00	70.00	13.3%	0.15 yrs	0.66	2018
FJI	Severe Deprivation	OR	0	0	0	0	NA	-		0.378	22	5.1%	24.7%	3.7%	1	4.00	5.00	5.00	10.00	12.7%	0.08 yrs	0.64	2021
GEO	Severe Deprivation	Desc	2451	89	347	2193	1.8	-		0.004	39	96.3%	47.7%	2.8%	94	95.00	98.00	98.00	96.00	15.8%	-0.00 yrs	0.21	2018
GHA	Severe Deprivation	OR	5405	3475	5628	3252	0.55 (0.46-0.66)	¡0.001	***	0.079	30	58.4%	22.7%	1.6%	51	52.00	57.00	60.00	69.00	10.2%	0.08 yrs	0.25	2017
GMB	Severe Deprivation	Desc	96	9800	5813	4083	-29.2	-		0.792	7	1.6%	19.9%	1.1%	0	0.00	0.00	1.00	5.00	37.6%	0.50 yrs	1.24	2018
GNB	Severe Deprivation	RD	54	7412	6743	723	-31.5 (-50.5 to -12.4)	0.001	**	0.559	17	1.0%	67.0%	0.5%	0	0.00	1.00	1.00	3.00	34.7%	0.29 yrs	0.95	2018
GUY	Severe Deprivation	RD	162	2622	790	1994	-12.9 (-18.3 to -7.5)	¡0.001	***	0.609	14	7.3%	-	-	0	2.00	2.00	9.00	18.00	8.6%	0.11 yrs	0.99	2019
IRQ	Severe Deprivation	Desc	92	16523	4191	12424	-1.0	-		0.138	29	0.5%	50.4%	2.0%	1	0.00	0.00	0.00	1.00	15.7%	0.07 yrs	0.22	2018
LAO	Severe Deprivation	OR	1604	10107	6928	4783	0.24 (0.21-0.29)	¡0.001	***	0.582	16	13.7%	46.2%	0.9%	2	5.00	6.00	14.00	33.00	36.0%	0.46 yrs	1.08	2017
MDG	Severe Deprivation	OR	179	12666	11427	1418	0.11 (0.07-0.18)	¡0.001	***	0.865	2	2.2%	29.3%	1.5%	0	0.00	0.00	1.00	7.00	47.3%	0.52 yrs	1.47	2018
MKD	Severe Deprivation	Desc	1430	75	104	1401	-0.3	-		0.021	35	95.4%	41.2%	3.8%	90	94.00	99.00	95.00	99.00	19.0%	0.18 yrs	0.59	2018
MWI	Severe Deprivation	RD	72	15374	6828	8618	-23.5 (-39.7 to -7.2)	0.005	**	0.917	1	0.5%	11.9%	1.5%	0	0.00	0.00	0.00	2.00	56.9%	0.71 yrs	1.43	2019
NPL	Severe Deprivation	OR	294	6361	1761	4894	0.30 (0.19-0.48)	¡0.001	***	0.349	23	3.7%	57.9%	1.1%	3	1.00	3.00	4.00	7.00	13.1%	0.31 yrs	0.51	2019
SLE	Severe Deprivation	OR	425	11295	8903	2817	0.59 (0.41-0.83)	0.003	**	0.306	25	3.9%	54.5%	0.9%	4	2.00	2.00	4.00	7.00	20.4%	0.23 yrs	0.52	2017
SRB	Severe Deprivation	OR	0	0	0	0	NA	-		0.008	38	98.6%	37.0%	5.1%	97	98.00	99.00	100.00	100.00	25.1%	0.16 yrs	0.96	2019
STP	Severe Deprivation	Desc	24	1811	1114	721	-34.3	-		0.477	19	1.4%	17.0%	2.2%	0	1.00	1.00	1.00	3.00	5.0%	0.06 yrs	0.72	2019
SUR	Severe Deprivation	OR	3737	495	913	3319	0.59 (0.44-0.80)	¡0.001	***	0.022	34	87.8%	18.4%	4.6%	85	85.00	89.00	89.00	92.00	15.3%	0.20 yrs	0.31	2018
TCA	Severe Deprivation	OR	0	0	0	0	NA	-		0.144	28	74.1%	-	-	43	82.00	82.00	86.00	94.00	1.0%	0.00 yrs	0.92	2019
TCD	Severe Deprivation	Desc	51	21730	19968	1813	-46.0	-		0.663	12	0.3%	63.7%	0.5%	0	0.00	0.00	0.00	1.00	53.1%	0.47 yrs	0.99	2019
TGO	Severe Deprivation	OR	218	4721	3549	1390	0.23 (0.15-0.35)	¡0.001	***	0.608	15	3.9%	61.5%	1.0%	0	2.00	2.00	3.00	10.00	22.1%	0.47 yrs	0.99	2017
THA	Severe Deprivation	OR	13390	298	1664	12024	1.42 (0.80-2.52)	0.23		0.009	37	97.8%	9.2%	3.9%	94	98.00	98.00	99.00	99.00	-14.4%	0.29 yrs	0.64	2022
TKM	Severe Deprivation	OR	1583	2099	164	3518	0.64 (0.41-1.00)	0.05	*	0.399	21	38.1%	76.6%	1.0%	16	23.00	38.00	57.00	74.00	27.7%	0.00 yrs	1.01	2019
TON	Severe Deprivation	RD	1099	248	200	1147	-6.0 (-14.9 to 2.8)	0.18		0.024	33	84.7%	4.7%	2.9%	78	82.00	85.00	89.00	87.00	13.2%	-0.00 yrs	0.16	2019
TUN	Severe Deprivation	OR	2829	576	463	2942	0.77 (0.57-1.05)	0.10		0.033	31	80.3%	33.9%	3.9%	76	78.00	78.00	83.00	86.00	5.6%	0.06 yrs	0.28	2023
VUT	Severe Deprivation	OR	0	0	0	0	NA	-		-0.266	41	0.2%	7.6%	1.7%	0	0.00	0.00	0.00	0.00	10.8%	0.04 yrs	-0.21	2023
WSM	Severe Deprivation	Desc	28	2655	1050	1633	-24.6	-		0.803	6	0.7%	11.2%	4.3%	0	0.00	0.00	0.00	3.00	33.7%	0.04 yrs	1.27	2019
YEM	Severe Deprivation	RD	0	0	0	0	0.0 (0.0 to 0.0)	-		0.851	3	0.4%	70.2%	0.3%	0	0.00	0.00	0.00	2.00	63.9%	0.41 yrs	1.32	2022
ZWE	Severe Deprivation	OR	361	5744	3106	2999	0.04 (0.02-0.07)	¡0.001	***	0.816	5	6.2%	9.1%	0.5%	0	0.00	1.00	7.00	23.00	39.2%	0.32 yrs	1.37	2019
ARG	Stunting	OR	2830	3192	666	5356	0.75 (0.56-1.00)	0.05		0.343	24	43.6%	23.9%	6.2%	17	34.00	47.00	60.00	84.00	-	0.38 yrs	1.03	2019
AZE	Stunting	Desc	12	2543	165	2390	-0.8	-		0.837	4	1.9%	64.5%	1.2%	0	0.00	0.00	0.00	6.00	44.1%	0.03 yrs	1.31	2023
BEN	Stunting	OR	117	12792	4669	8240	0.43 (0.25-0.73)	0.002	**	0.717	9	0.8%	48.6%	0.3%	0	0.00	0.00	1.00	3.00	31.6%	0.41 yrs	1.10	2021
CAF	Stunting	RD	53	8604	3280	5377	-13.7 (-28.4 to 1.0)	0.07		0.697	10	0.5%	41.7%	0.7%	0	0.00	0.00	1.00	2.00	44.7%	0.40 yrs	1.08	2018
COD	Stunting	OR	391	20582	9208	11765	0.38 (0.23-0.61)	¡0.001	***	0.677	11	3.1%	40.1%	0.4%	0	1.00	1.00	2.00	7.00	36.9%	0.36 yrs	1.11	2017
COM	Stunting	OR	254	4107	744	3617	0.82 (0.56-1.21)	0.32		0.612	13	5.1%	43.9%	0.9%	1	1.00	3.00	7.00	13.00	19.0%	0.29 yrs	0.99	2022
CRI	Stunting	RD	3176	339	244	3271	-2.3 (-11.8 to 7.3)	0.64		0.028	32	91.2%	22.4%	5.3%	83	90.00	93.00	95.00	94.00	3.7%	0.14 yrs	0.44	2018
DOM	Stunting	OR	4000	4367	596	7771	0.67 (0.51-0.87)	0.003	**	0.254	26	52.8%	27.9%	2.6%	24	35.00	47.00	61.00	77.00	11.2%	0.26 yrs	0.86	2019
DZA	Stunting	OR	6947	7666	1420	13193	0.74 (0.64-0.87)	¡0.001	***	0.207	27	50.5%	33.8%	3.8%	26	43.00	54.00	58.00	70.00	13.3%	0.15 yrs	0.66	2018
FJI	Stunting	Desc	108	1950	151	1907	-2.8	-		0.378	22	5.1%	24.7%	3.7%	1	4.00	5.00	5.00	10.00	12.7%	0.08 yrs	0.64	2021
GEO	Stunting	Desc	2446	89	117	2418	-0.9	-		0.004	39	96.3%	47.7%	2.8%	94	95.00	98.00	98.00	96.00	15.8%	-0.00 yrs	0.21	2018
GHA	Stunting	OR	5350	3394	1518	7226	0.83 (0.69-0.99)	0.04	*	0.079	30	58.4%	22.7%	1.6%	51	52.00	57.00	60.00	69.00	10.2%	0.08 yrs	0.25	2017
GMB	Stunting	Desc	96	9774	2015	7855	-9.8	-		0.792	7	1.6%	19.9%	1.1%	0	0.00	0.00	1.00	5.00	37.6%	0.50 yrs	1.24	2018
GNB	Stunting	RD	54	7315	1979	5390	-9.1 (-18.7 to 0.5)	0.06		0.559	17	1.0%	67.0%	0.5%	0	0.00	1.00	1.00	3.00	34.7%	0.29 yrs	0.95	2018
GUY	Stunting	RD	162	2561	311	2412	-1.2 (-6.0 to 3.7)	0.63		0.609	14	7.3%	-	-	0	2.00	2.00	9.00	18.00	8.6%	0.11 yrs	0.99	2019
IRQ	Stunting	Desc	90	16402	1616	14876	-6.2	-		0.138	29	0.5%	50.4%	2.0%	1	0.00	0.00	0.00	1.00	15.7%	0.07 yrs	0.22	2018
LAO	Stunting	OR	1587	9918	4098	7407	0.46 (0.39-0.54)	¡0.001	***	0.582	16	13.7%	46.2%	0.9%	2	5.00	6.00	14.00	33.00	36.0%	0.46 yrs	1.08	2017
MDG	Stunting	OR	179	12636	4972	7843	0.80 (0.56-1.15)	0.22		0.865	2	2.2%	29.3%	1.5%	0	0.00	0.00	1.00	7.00	47.3%	0.52 yrs	1.47	2018

Continued on next page

Table 30 – continued from previous page

Country	Outcome	Method	N Ins	N Unins	N Out1	N Out0	Estimate (95% CI)	P-value	Sig	CI	Rank	Cov%	OOP	HExp	Q1	Q2	Q3	Q4	Q5	Geo	MomEd	WCohen	Year
MKD	Stunting	Desc	1424	75	51	1448	1.2	-		0.021	35	95.4%	41.2%	3.8%	90	94.00	99.00	95.00	99.00	19.0%	0.18 yrs	0.59	2018
MWI	Stunting	RD	71	15197	4959	10309	-3.0 (-18.9 to 13.0)	0.71		0.917	1	0.5%	11.9%	1.5%	0	0.00	0.00	0.00	2.00	56.9%	0.71 yrs	1.43	2019
NPL	Stunting	OR	290	6194	2099	4385	0.51 (0.37-0.72)	¡0.001	***	0.349	23	3.7%	57.9%	1.1%	3	1.00	3.00	4.00	7.00	13.1%	0.31 yrs	0.51	2019
PSE	Stunting	OR	4467	1811	498	5780	1.01 (0.79-1.29)	0.96		-0.081	40	71.8%	38.7%	3.7%	87	77.00	62.00	61.00	66.00	6.8%	0.00 yrs	-0.45	2019
SLE	Stunting	OR	416	11015	3136	8295	1.09 (0.82-1.45)	0.55		0.306	25	3.9%	54.5%	0.9%	4	2.00	2.00	4.00	7.00	20.4%	0.23 yrs	0.52	2017
SRB	Stunting	Desc	1809	24	54	1779	3.5	-		0.008	38	98.6%	37.0%	5.1%	97	98.00	99.00	100.00	100.00	25.1%	0.16 yrs	0.96	2019
STP	Stunting	Desc	24	1792	236	1580	-9.6	-		0.477	19	1.4%	17.0%	2.2%	0	1.00	1.00	1.00	3.00	5.0%	0.06 yrs	0.72	2019
SUR	Stunting	OR	3706	490	237	3959	0.73 (0.43-1.23)	0.23		0.022	34	87.8%	18.4%	4.6%	85	85.00	89.00	89.00	92.00	15.3%	0.20 yrs	0.31	2018
TCA	Stunting	Desc	248	52	6	294	-11.4	-		0.144	28	74.1%	-	-	43	82.00	82.00	86.00	94.00	1.0%	0.00 yrs	0.92	2019
TCD	Stunting	Desc	50	21472	8208	13314	-19.9	-		0.663	12	0.3%	63.7%	0.5%	0	0.00	0.00	0.00	1.00	53.1%	0.47 yrs	0.99	2019
TGO	Stunting	OR	218	4711	1197	3732	0.57 (0.33-0.99)	0.05	*	0.608	15	3.9%	61.5%	1.0%	0	2.00	2.00	3.00	10.00	22.1%	0.47 yrs	0.99	2017
THA	Stunting	OR	23133	568	3206	20495	1.31 (0.74-2.32)	0.36		0.009	37	97.8%	9.2%	3.9%	94	98.00	98.00	99.00	99.00	-14.4%	0.29 yrs	0.64	2022
TKM	Stunting	OR	1581	2095	236	3440	0.60 (0.44-0.83)	0.002	**	0.399	21	38.1%	76.6%	1.0%	16	23.00	38.00	57.00	74.00	27.7%	0.00 yrs	1.01	2019
TON	Stunting	RD	1086	243	39	1290	-2.1 (-5.2 to 0.9)	0.17		0.024	33	84.7%	4.7%	2.9%	78	82.00	85.00	89.00	87.00	13.2%	-0.00 yrs	0.16	2019
TUN	Stunting	OR	2778	567	285	3060	0.97 (0.69-1.35)	0.85		0.033	31	80.3%	33.9%	3.9%	76	78.00	78.00	83.00	86.00	5.6%	0.06 yrs	0.28	2023
VUT	Stunting	Desc	2	1842	526	1318	-28.4	-		-0.266	41	0.2%	7.6%	1.7%	0	0.00	0.00	0.00	0.00	10.8%	0.04 yrs	-0.21	2023
WSM	Stunting	Desc	27	2558	187	2398	-0.3	-		0.803	6	0.7%	11.2%	4.3%	0	0.00	0.00	0.00	3.00	33.7%	0.04 yrs	1.27	2019
YEM	Stunting	RD	56	18819	8729	10146	-4.5 (-20.7 to 11.7)	0.58		0.851	3	0.4%	70.2%	0.3%	0	0.00	0.00	0.00	2.00	63.9%	0.41 yrs	1.32	2022
ZWE	Stunting	OR	360	5728	1379	4709	0.51 (0.35-0.75)	¡0.001	***	0.816	5	6.2%	9.1%	0.5%	0	0.00	1.00	7.00	23.00	39.2%	0.32 yrs	1.37	2019