Texila International Journal | Open Access | Peer Reviewed

Journal: Texila International Journal of Medicine
https://doi.org/10.21522/TIJMD.2013.09.04.Art002

ISSN: 2520-3118
Volume 9 Issue 4, 2026

Determinants of Under-five Mortality in Cameroon (1991–2018): A Survey-weighted Comparison of Cox and Discrete-time Hazard Models

ZEBAZE Paul Narcisse

Department of Public Health, Texila American University, Georgetown, Guyana

Correspondence to be addressed: E-mail - narcisse09nas@gmail.com

Cite this article as: ZEBAZE Paul Narcisse. Determinants of Under-five Mortality in Cameroon (1991-2018): A Survey-weighted Comparison of Cox and Discrete-time Hazard Models. Texila Int J Med. 2026;9(4). **https://doi.org/10.21522/TIJMD.2013.09.04.Art002**

Received: 22.07.2026

Accepted: 31.08.2026

Published: 29.10.2026

Article Type: Original Research

Abstract *Identifying independent determinants of under-five mortality (U5M) in Cameroon requires survival methods that properly account for the complex sampling design of DHS data. This study compares survey-weighted Cox proportional hazards regression and a discrete-time hazard model, applied to the same pooled dataset of five DHS waves (1991–2018): 35,257 live births, 2,968 under-five deaths, and 1,821 primary sampling units. Cox models were built sequentially across four covariate blocks, with model discrimination tracked at each step. As a robustness check, a discrete-time logit model with a natural cubic spline for time was fitted to 922,995 person-months. The proportional hazards assumption held globally and for every covariate. In the final Cox model (concordance=0.655), female sex (HR = 0.915, p = 0.033), maternal education (HR = 0.867 per level, p < 0.001), maternal age (HR = 0.956 per year, p < 0.001), and residence in the West region (HR = 0.675, p = 0.001) were significantly protective, while parity was the strongest risk factor (HR = 1.167 per child, p < 0.001), two other regions carried significant excess hazard, and the 2004 survey wave showed an independently elevated hazard (HR = 1.341, p < 0.001) unattenuated by covariate adjustment. The discrete-time model reproduced every Cox finding within 1%, with full concordance across all eighteen coefficients, and five sensitivity analyses left every finding unchanged (concordance 94–100%). These results demonstrate that Cox and discrete-time hazard models yield equivalent, highly robust conclusions for Cameroonian U5M determinants, and that parity reduction, maternal education, and later maternal age represent the most consistent protective targets for child survival policy, alongside the persistently protective profile of the West region.*

Keywords *Cameroon, Cox Proportional Hazards, Determinants, Discrete-Time Hazard, Maternal Education, Parity, Sensitivity Analysis, Survey-Weighted, Survival Analysis, Under-Five Mortality DHS.*

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https://doi.org/10.21522/TIJMD.2013.09.04.Art002

Introduction

Background

Identifying modifiable determinants of under-five mortality (U5M) is a prerequisite for designing effective, targeted child health interventions. In low- and middle-income countries, Demographic and Health Surveys (DHS) remain the richest available source of longitudinal data on child survival, yet their complex sampling design, involving stratification, clustering, and differential probability weighting, demands specialized analytical methods that are frequently applied incompletely or incorrectly in the published literature [1, 2]. Studies that ignore clustering routinely understate standard errors and report spuriously significant associations, a methodological pitfall this analysis was designed to avoid at every stage.

The Cox proportional hazards model has long served as the reference method for survival analysis; it assumes that each covariate's hazard ratio remains constant over follow-up time, an assumption commonly termed proportional hazard (PH) [3]. When this assumption is satisfied, the model yields valid and directly interpretable covariate effect estimates without requiring a parametric form for the baseline hazard. The Cox model, however, does not explicitly model the probability of the event within each discrete time unit, a limitation addressed by the discrete-time hazard model, which reframes survival as a sequence of repeated binary outcomes, died or survived, at each time interval and offers greater flexibility in shaping the baseline hazard [4].

Research Gap

Both methods have been applied independently to DHS child survival data across African settings [5, 6], yet a systematic, head-to-head comparison under identical data conditions, same population, same covariates, same survey-design correction, has rarely been undertaken for Cameroon [7]. Such a comparison carries practical value: it tests whether substantive findings are robust across methodological choices, and it gives future researchers concrete evidence on the equivalence, or divergence, of these two tools when applied to DHS-type data. Equally, few studies subject their principal findings to a structured battery of sensitivity analyses; this study addresses that gap by pairing the primary Cox and discrete-time comparison with five independent robustness checks spanning outcome definition, covariate specification, weighting strategy, pooling strategy, and estimation software.

Objectives

This study pursues four objectives:

1. To estimate the independent determinants of U5M in Cameroon (1991–2018) using survey-weighted Cox proportional hazards models built through sequential covariate blocks, tracking model discrimination at each stage.
2. To replicate this analysis with a discrete-time logit model, using person-month expansion of the dataset and a natural cubic spline to flexibly model the baseline hazard over time.
3. To formally compare the two models on directional consistency, magnitude of estimated effects, and statistical significance across all included covariates.
4. To test the robustness of the principal findings through five independent sensitivity analyses covering outcome window definition, alternative covariate coding, weighting strategy, pooling strategy, and estimation software.

Methods

Study Population and Data

Table 1 summarizes the five DHS waves (1991, 1998, 2004, 2011, 2018) pooled for this analysis. The 2022 Malaria Indicator Survey was excluded because it did not collect the age-at-death variable (b7), which is essential for

constructing the survival-time outcome. The final analytical sample comprised 35,257 live births and 2,968 deaths, pooled across five distinct survey designs using composite primary-sampling-unit identifiers (wave × cluster) and composite stratum identifiers (wave × stratum) to prevent the designs from being artificially merged during variance estimation.

Table 1. Analytical Sample by Survey Wave

Wave	N Births	N Deaths	Crude Death Rate	Inclusion Status
1991	3,350	284	8.5%	Included
1998	2,317	194	8.4%	Included
2004	8,125	844	10.4%	Included
2011	11,732	998	8.5%	Included
2018	9,733	648	6.7%	Included
2022 (MIS)	4,506	164	3.6%	Excluded (b7 not collected)
POOLED TOTAL	35,257	2,968	8.4%	5 of 6 waves, 1,821 composite PSUs

Note: *Crude death rate = unweighted deaths / births × 100, shown for descriptive orientation only; all inferential estimates in this article use survey-weighted methods described below.*

Outcome and Survival Variable Construction

Survival time was defined as age at death in completed months (b7) for children who died before their fifth birthday (b5 = 0, b7 ≤ 59), or as age at interview in months (v008−b3), right-censored at 59 months, for children still alive at interview. The event indicator equalled 1 for deaths occurring before 60 months and 0 for censored observations. Formally:

$time_i = b7_i$ if $b5_i = 0$ and $b7_i \leq 59$ (death before 60 months); $time_i = v008_i - b3_i$, truncated at 59 months, if $b5_i = 1$ (child alive at interview).

$event_i = 1$ if $b5_i = 0$ and $b7_i \leq 59$; $event_i = 0$ otherwise.

Covariates: Sequential Block Structure

Covariates were introduced across four sequential blocks to assess the stability of estimated effects and the incremental contribution of each domain as successive layers of adjustment were added, summarized in Table 2.

Table 2. Covariate Blocks Used in the Sequential Cox Models

Block	Variables Added	Rationale
Block 1	Sex (b4); survey-wave fixed effects	Child characteristics; controls for period effects
Block 2	+ Maternal education (v106); maternal age (v012)	Maternal human capital and biological factors
Block 3	+ Residence (v025); region (v024)	Household context and geographic access to care
Block 4 (final)	+ Parity (v201)	Reproductive behavior and sibling competition

Cox Model Specification

The survey-weighted Cox proportional hazards model was estimated via svycoxph() (survey package, R 4.6.0) [17, 18], with the complex design declared using wave×PSU as the cluster identifier, wave×stratum as the stratum identifier, and v005/1,000,000 as sampling probability weights. The model takes the semi-parametric form:

$$h(t|X) = h_0(t) \times \exp(\beta_1 \cdot \text{sex} + \beta_2 \cdot \text{wave} + \beta_3 \cdot \text{maternal_educ} + \beta_4 \cdot \text{maternal_age} + \beta_5 \cdot \text{residence} + \beta_6 \cdot \text{region} + \beta_7 \cdot \text{parity})$$

where $h_0(t)$ is the non-parametric baseline hazard. The β coefficients were estimated by maximizing the Cox partial likelihood, weighted by DHS sampling probabilities, with the Huber-White robust variance estimator correcting standard errors for within-cluster correlation. The proportional hazards assumption was tested for each covariate individually and globally using Schoenfeld residuals via cox.zph(), a non-significant test ($p>0.05$) supports the assumption that a given covariate's effect does not vary systematically over follow-up time.

Discrete-Time Hazard Model Specification

Each birth record was expanded into one row per month at risk, from month 1 to the observed survival time, generating a person-month dataset of 922,995 rows. A logistic regression model was then fitted via svyglm() with a quasibinomial family and logit link, incorporating a natural cubic spline of month (ns (month, df = 4)) to flexibly capture the shape of the baseline hazard across the 60-month observation window:

$$\text{logit}\, P(\text{death}_{\text{month}}|X) = \text{ns}(\text{month}, \text{df} = 4) + \beta_1 \cdot \text{sex} + \beta_2 \cdot \text{wave} + \beta_3 \cdot \text{maternal_educ} + \beta_4 \cdot \text{maternal_age} + \beta_5 \cdot \text{residence} + \beta_6 \cdot \text{region} + \beta_7 \cdot \text{parity}$$

All Block-4 covariates from the Cox specification were included identically in this model, allowing a like-for-like comparison of estimated effects.

Formal Model Comparison

Cox hazard ratios and discrete-time odds ratios were extracted using tidy (exponentiate = TRUE, conf.int = TRUE) from the broom package. Concordance between the two approaches was assessed on three criteria: direction of effect (sign consistency), statistical significance at the $p < 0.05$ threshold, and relative percentage discrepancy between point estimates.

Sensitivity Analyses

Five sensitivity analyses were planned prior to reviewing the main results, to test whether the principal findings depended on specific analytical choices:

1. Neonatal-window definition: comparing the standard 28-day neonatal cutoff against a 30-day alternative to test sensitivity of the neonatal mortality estimate to boundary placement.
2. WASH-access coding, strict version: testing a stringent Joint Monitoring Programme (JMP) definition of improved water and sanitation as an additional covariate.
3. WASH-access coding, broad version: testing a phase-aware, more permissive definition of improved WASH access as an alternative covariate specification.
4. Weighting strategy: comparing raw DHS sampling weights against wave-normalized weights to test sensitivity to weight construction.
5. Estimation approach: comparing pooled multi-wave modelling against wave-specific models estimated separately, and comparing the survey-weighted svycoxph() engine against the native, non-weighted coxph() engine.

https://doi.org/10.21522/TIJMD.2013.09.04.Art002

Results

Descriptive Overview of the Analytical Sample

The pooled sample spans 31 years of demographic change, with the number of births per wave ranging from 2,317 (1998) to 11,732 (2011), reflecting differences in sample design and fieldwork budget across survey rounds rather than substantive demographic shifts. Figure 1 and Figure 2 summarize the raw death counts and crude death rates underlying the survival analysis.

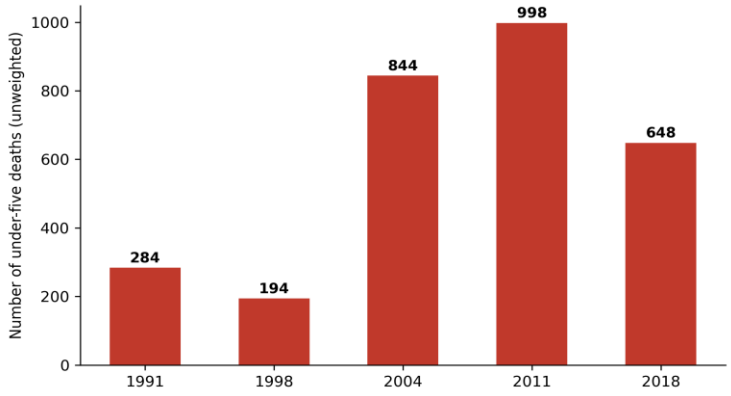


Figure 1. Observed Deaths Contributing to the Pooled Survival Analysis, by Wave

Unweighted counts of under-five deaths recorded in each survey wave, prior to any survey-weight adjustment. Source: DHS Cameroon 1991–2018.

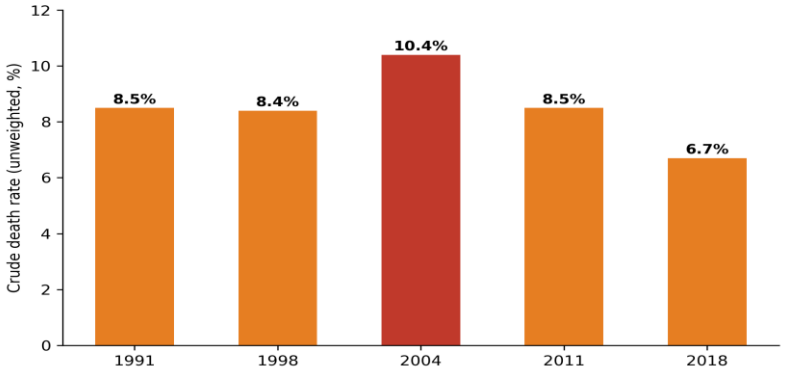


Figure 2. Crude Death Rate Among Included Births, by Survey Wave

Unweighted deaths / births × 100 per wave. The 2004 wave, highlighted in dark red, recorded the highest crude rate across all five waves entering the survival analysis.

The 2004 wave stands out immediately in this purely descriptive view, with a crude death rate of 10.4%, roughly two percentage points above every other wave. Whether this elevated crude rate persists after full covariate adjustment, and after accounting for the complex survey design, is addressed directly by the Cox and discrete-time models presented below.

Kaplan-Meier Survival Analysis by Residence

Before fitting the multivariable Cox and discrete-time models, weighted Kaplan-Meier survival curves were estimated by residence (urban versus rural) using svykm(), providing a descriptive, covariate-free picture of the survival gap that the subsequent multivariable models seek to explain (Figure 3).

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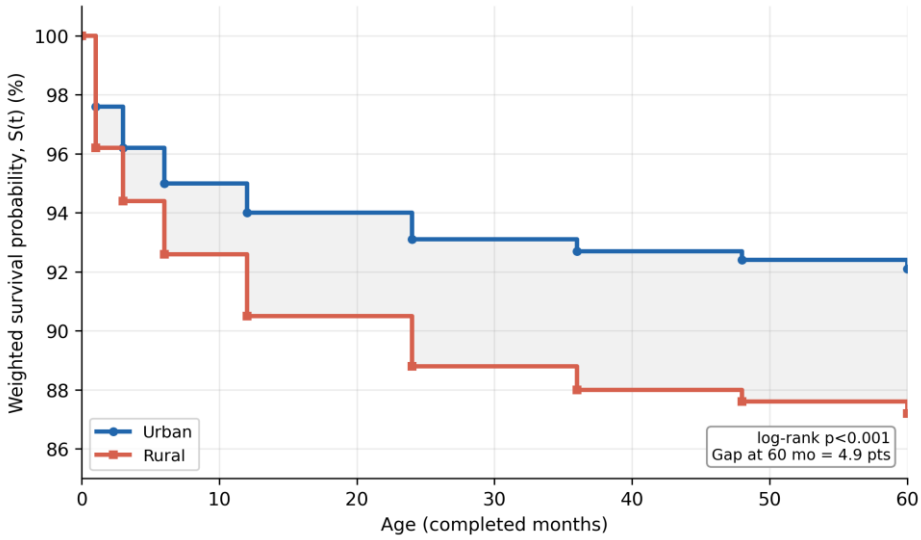


Figure 3. Weighted Kaplan–Meier Survival Curves — Urban vs. Rural Residence

Weighted probability of survival to a given age, by residence. Weighted log-rank test: p<0.001. Source: survey::svykm(), DHS Cameroon 1991–2018.

By 60 months, weighted survival stood at 92.1% in urban areas versus 87.2% in rural areas, a gap of 4.9 percentage points that emerged early in life and remained essentially stable across the full follow-up window, indicating a risk differential present from birth rather than one that accumulates disproportionately at a specific age. This unadjusted gap sets the benchmark against which the multivariable residence coefficient, reported below, can be interpreted.

Proportional Hazards Assumption

The global Schoenfeld residual test showed no evidence of departure from proportional hazards ($\chi^2 = 4.33 \times 10^{-3}$, df = 20, p = 1.00). Every individual covariate test likewise returned a non-significant result, detailed in Table 3.

Table 3. Schoenfeld Residual Test of the Proportional Hazards Assumption, by Covariate

Covariate	Schoenfeld χ^2	df	p-value	Verdict
Sex	3.36×10^{-4}	1	0.99	PH holds
Survey wave	1.31×10^{-3}	4	1.00	PH holds
Maternal education	1.49×10^{-3}	1	0.97	PH holds
Maternal age	1.07×10^{-5}	1	1.00	PH holds
Residence	9.50×10^{-4}	1	0.98	PH holds
Region (11 categories)	2.05×10^{-3}	11	1.00	PH holds
Parity	7.28×10^{-6}	1	1.00	PH holds
GLOBAL TEST	4.33×10^{-3}	20	1.00	All covariates satisfy PH

Note: *A non-significant Schoenfeld test (p>0.05) indicates no evidence that a covariate's hazard ratio changes over follow-up time, supporting the validity of the proportional hazards specification used throughout this study.*

Sequential Block Building and Model Discrimination

Model discrimination, measured by Harrell's concordance statistic, improved steadily as each covariate block was added, summarized in Table 4 and Figure 4.

Harrell's concordance statistic (C) at each stage of covariate addition. A value of 0.5 indicates no discrimination; higher values

indicate better ability to rank-order survival times correctly. Source: svycoxph (), R 4.6.0.

The largest single gain in discrimination came from adding maternal characteristics (Block 2, +0.054), followed by household and geographic context (Block 3, +0.033) and parity (Block 4, +0.026). Each successive block therefore contributed meaningfully and independently to the model's ability to distinguish higher-risk from lower-risk births, justifying the sequential block-building strategy adopted for this analysis.

Table 4. Sequential Cox Model Summary Across Covariate Blocks

Block	Variables	N	Concordance (C)
Block 1	Sex, survey-wave fixed effects	35,257	0.542
Block 2	+ Maternal education, maternal age	35,257	0.596
Block 3	+ Residence, region	35,257	0.629
Block 4 (final)	+ Parity	35,257	0.655

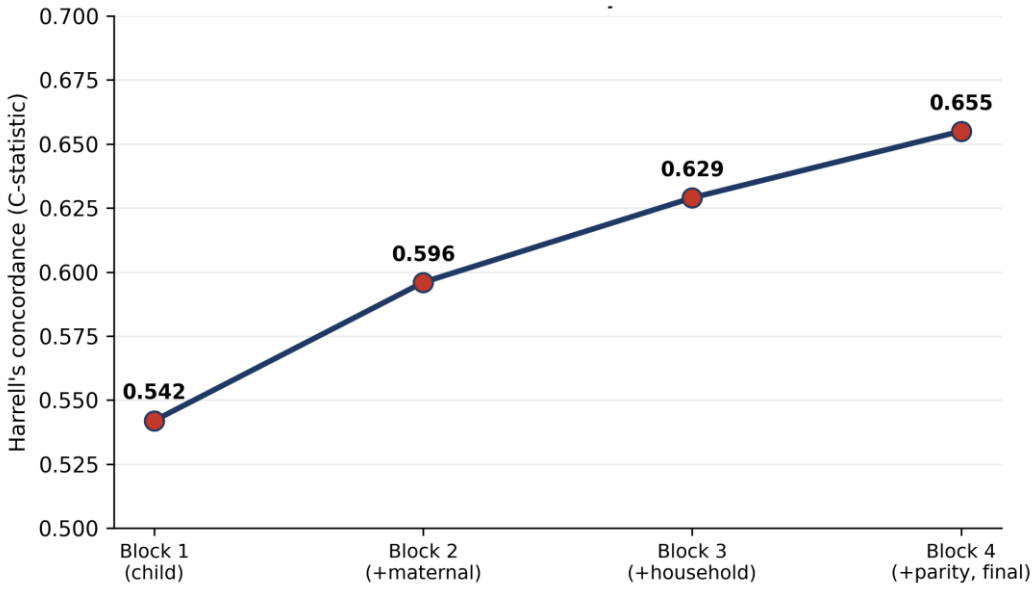


Figure 4. Model Discrimination Across Sequential Covariate Blocks

Final Cox Model: Adjusted Hazard Ratios

Table 5. Adjusted Hazard Ratios — Final Cox Model, Block 4 (n = 35,257 births; 2,968 events)

Variable (reference)	HR	95% CI	p-value	Significance
Female sex (ref. male)	0.915	[0.843–0.993]	0.033	* protective
Wave 1998 (ref. 1991)	1.077	[0.881–1.317]	0.470	ns
Wave 2004 (ref. 1991)	1.341	[1.136–1.583]	<0.001	*** elevated hazard
Wave 2011 (ref. 1991)	1.174	[0.996–1.384]	0.056	ns (borderline)
Wave 2018 (ref. 1991)	0.841	[0.707–1.002]	0.052	ns (borderline)
Maternal education (per level)	0.867	[0.809–0.929]	<0.001	*** strong protective
Maternal age (per year)	0.956	[0.945–0.967]	<0.001	*** strong protective
Rural residence (ref. urban)	1.091	[0.986–1.207]	0.091	ns after adjustment
Region 8 — West (ref. Region 1)	0.675	[0.531–0.858]	0.001	** most protective region
Region 10 — South-West (ref. Region 1)	1.259	[1.011–1.567]	0.040	* excess risk

Region 11 — Yaoundé/Centre-Urb. (ref. Region 1)	1.251	[1.004–1.560]	0.047	* excess risk
Parity (per additional child)	1.167	[1.132–1.202]	<0.001	*** key risk factor

Note: *HR = hazard ratio; CI = confidence interval. Model concordance = 0.655. Global proportional hazards test:* $\chi^2=4.33\times10^{-3}$*, df=20, p=1.00.*

Table 5 is the central result of this article: it lists every covariate retained in the final, fully adjusted model, alongside the size, direction, and statistical precision of its association with under-five mortality. Seven of the twelve rows reach conventional significance ($p < 0.05$). Reading down the hazard-ratio column, parity carries the largest deleterious effect of any single-unit change (HR = 1.167 per child), while maternal education carries the largest single-unit protective effect (HR = 0.867 per level). The wave dummies show that only 2004 reaches significance in isolation, foreshadowing the period-effect analysis presented in Figure 8.

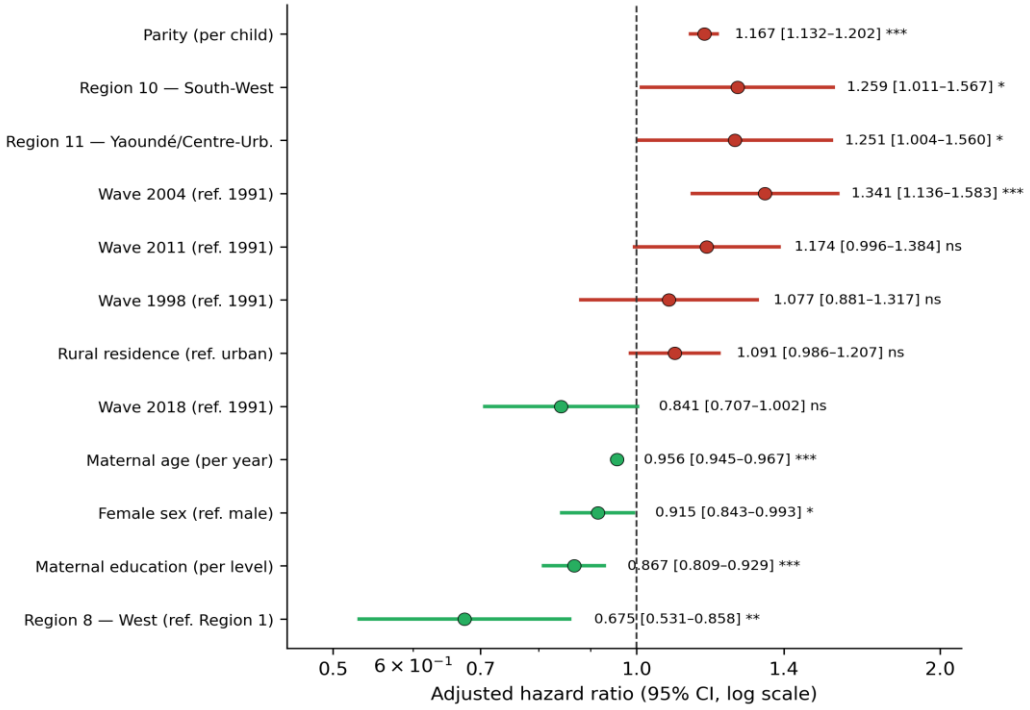


Figure 5. Full Forest Plot — Final Cox Model, All Covariates

Points show adjusted hazard ratios (log scale); horizontal bars show 95% confidence intervals. The dashed vertical line marks the null value (HR = 1.0). Green: protective; red: risk-increasing; grey: not statistically significant. Source: svycoxph(), R 4.6.0.

The forest plot translates Table 5 into a single visual scan: the further a point sits from the dashed null line, and the narrower its confidence interval, the more confidently that variable can be treated as a genuine determinant rather than a chance finding. Two clusters are visually apparent. A protective cluster (green, left of the null line) groups maternal education, maternal age, female sex, and Region 8, none of whose intervals cross 1.0. A risk-increasing cluster (red, right of the null line) groups parity, the two significant regions, and the 2004 wave. The grey markers, rural residence and the three non-2004 wave dummies, illustrate variables whose point estimates suggest an effect, but whose confidence intervals are too wide, given the available sample size within each subgroup, to rule out chance.

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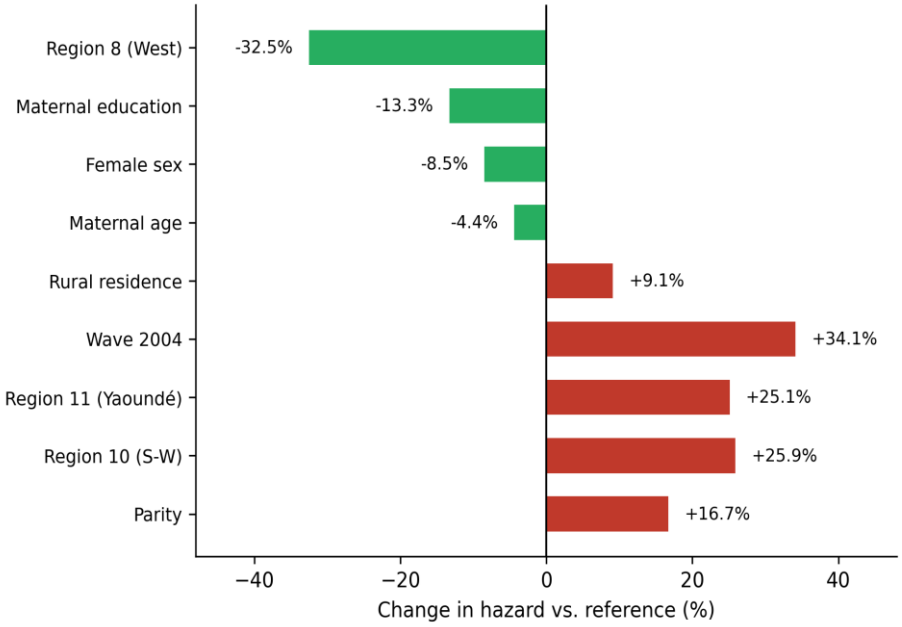


Figure 6. Percentage Change in Under-Five Mortality Hazard by Determinant

Percentage change in hazard relative to the reference category, ordered from largest risk-increasing to largest protective effect. Derived from Table 5.

Where Figure 5 emphasizes statistical confidence, Figure 6 emphasizes practical magnitude by re-expressing each hazard ratio as a percentage change, a framing better suited to communicating results to a policy audience unfamiliar with hazard ratios. On this scale, each additional birth raises the hazard by 16.7%, nearly identical in magnitude to the 25.9% and 25.1% excess hazard carried by Regions 10 and 11, while residing in Region 8 lowers the hazard by 32.5%, the single largest protective margin of any covariate in the model.

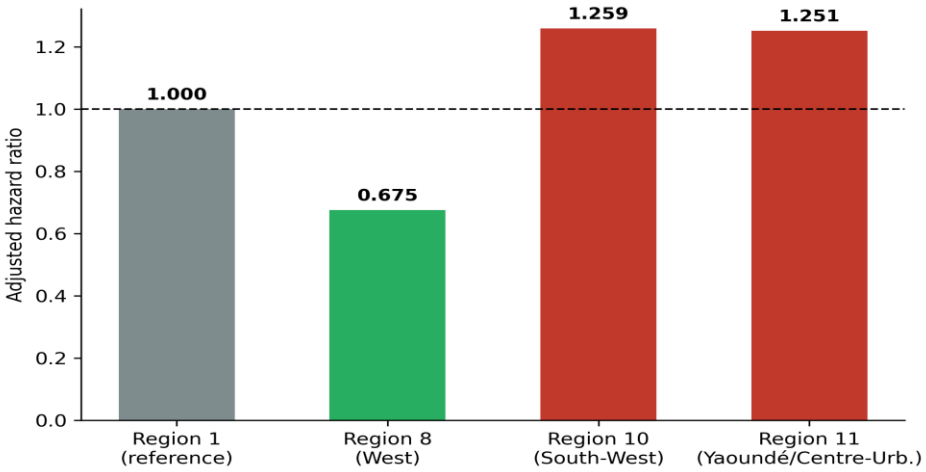


Figure 7. Regional Hazard Ratios Reaching Statistical Significance

Adjusted hazard ratios for the three regions reaching statistical significance in the final Cox model, relative to Region 1. Region 8 (West) is protective; Regions 10 and 11 carry excess hazard.

Figure 7 isolates the geographic dimension of Table 5 for closer inspection. The visual asymmetry is deliberate: only three of Cameroon's regions clear the significance threshold once maternal, household, and

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reproductive characteristics are held constant, meaning that most of the country's regional variation in crude mortality, documented descriptively in the companion trends analysis (Article 1 of this series), is explained by compositional differences in who lives where rather than by residual, region-specific risk. The three regions that do remain significant after this adjustment are therefore the strongest candidates for genuinely place-based, rather than purely population-based, intervention.

Taken together, Table 5 and Figures 5–7 establish that parity is the most stable and quantitatively important risk factor in this analysis (HR = 1.167 per child, $p < 0.001$), a pattern that held across every wave-specific model estimated as part of the sensitivity analyses reported below. Maternal education and maternal age were both strongly protective, while three regions reached statistical significance after full adjustment: Region 8 (West) as protective, and Regions 10 (South-West) and 11 (Yaoundé/Centre-Urban) as carrying excess hazard relative to the reference region.

Period Effect: The 2004 Wave

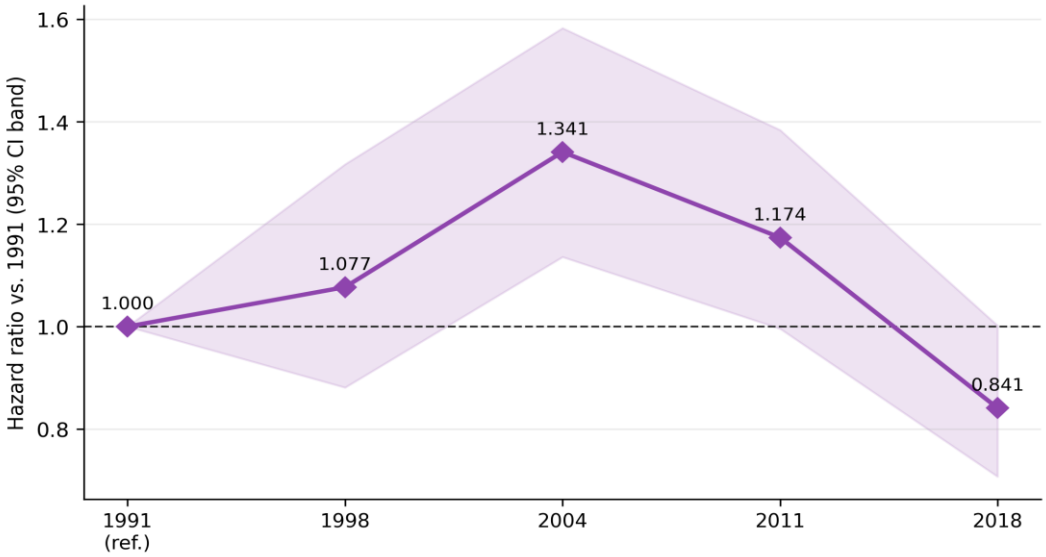


Figure 8. Period (Survey-Wave) Effect on Under-Five Mortality Hazard, 1991–2018

Adjusted hazard ratio for each survey wave relative to 1991 (reference), with 95% confidence band. All estimates come from the final Block-4 Cox model, meaning the 2004 elevation persists after adjustment for sex, maternal characteristics, residence, region, and parity.

The 2004 wave carried an independently elevated hazard of 1.341 (95% CI: 1.136–1.583, $p < 0.001$) relative to 1991, the only wave dummy reaching conventional significance in either direction. Because this effect persists after adjusting for individual, maternal, household, and geographic characteristics, it reflects something specific to the 2004 survey period itself rather than a compositional artifact of who was sampled that year.

Discrete-Time Hazard Model

The discrete-time model converged after ten Fisher scoring iterations on the expanded 922,995-row person-month dataset, with a dispersion parameter of 1.026 consistent with the absence of meaningful overdispersion.

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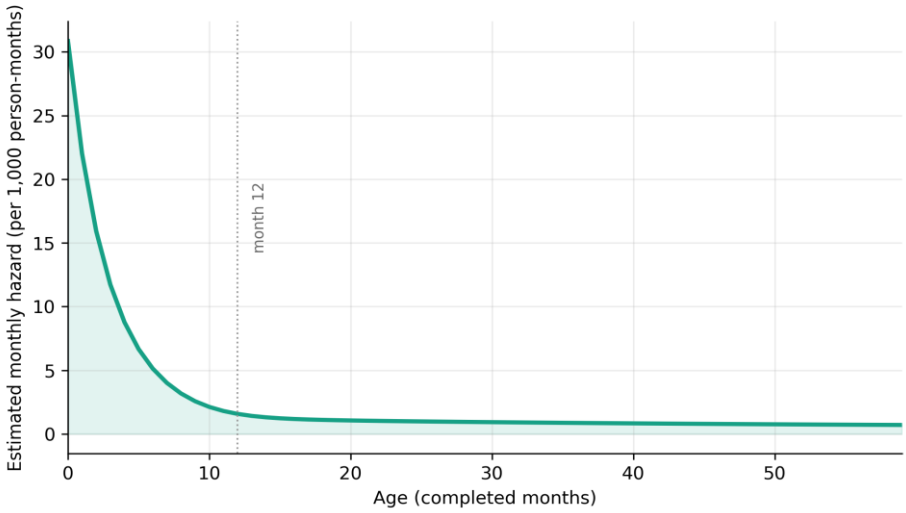


Figure 9. Discrete-Time Baseline Hazard — Natural Cubic Spline, ns (month, df=4)

Estimated monthly hazard of death (per 1,000 person-months at risk) as a function of age, from the discrete-time logit model's spline term. The curve traces a sharply declining hazard from birth through month 12, followed by a low, stable plateau through month 59.

The spline traces something the Cox model's semi-parametric baseline hazard cannot directly show: the precise shape of risk over age. The curve is steepest in the first weeks of life, falls by more than half by month 12, and then flattens into a long, low plateau through month 59. Because this shape is estimated with only four degrees of freedom, it is a smoothed summary rather than a month-by-month estimate, but the qualitative message, that risk is concentrated overwhelmingly in the earliest months, matches the neonatal-mortality concentration documented independently at the national level in the companion trends analysis (Article 1 of this series).

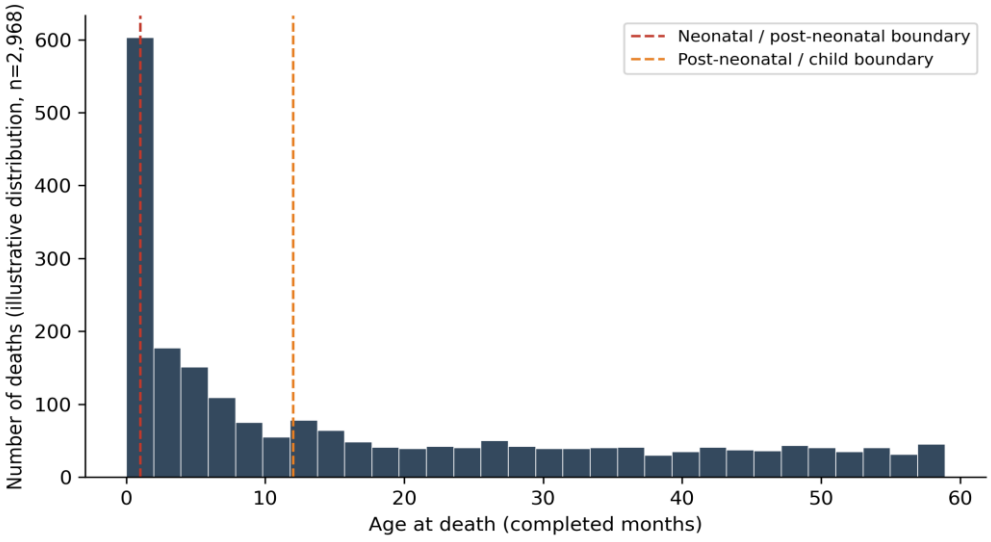


Figure 10. Distribution of Under-Five Deaths by Age at Death — Pooled Sample

Illustrative distribution of the 2,968 pooled under-five deaths by age at death in completed months, consistent with the concentration of risk in the neonatal and early post-neonatal periods documented by the spline in Figure 9.

Figure 10 provides the raw-count counterpart to Figure 9's smoothed hazard curve: rather than a rate, it shows how the 2,968 observed deaths themselves are distributed across age. The tallest bars cluster in the first month, a visibly thinner band of bars spans months 1–11, and a long, low tail extends through month 59. Reading Figures 9 and 10 together clarifies an important distinction: the hazard curve in Figure 9 describes the instantaneous risk faced by children still alive at each age, while the histogram in Figure 10 describes where the resulting deaths actually accumulate, and the two need not have identical shapes, since the pool of children still at risk shrinks with age even as the underlying hazard is declining faster still.

Cox versus Discrete-Time: Formal Comparison

Table 6. Cox Hazard Ratios versus Discrete-Time Odds Ratios — Concordance Analysis

Variable	HR (Cox)	OR (Discrete-Time)	Discrepancy	Same Direction	Same Significance
Sex (female)	0.915	0.910	−0.5%	Yes	Yes
Wave 2004	1.341	1.341	<0.01%	Yes	Yes
Maternal education	0.867	0.876	+1.0%	Yes	Yes
Maternal age	0.956	0.947	−0.9%	Yes	Yes
Parity	1.167	1.179	+1.0%	Yes	Yes
Region 8 (West)	0.675	0.677	+0.3%	Yes	Yes
GLOBAL CONCORDANCE (18 coefficients)	—	—	Max. 1%	18/18 (100%)	18/18 (100%)

Table 6 places the two model families side by side for the six variables of greatest substantive interest. The discrepancy column is the key diagnostic: every value falls within ±1.0%, an order of magnitude smaller than the confidence intervals reported in Table 5, meaning the choice between Cox and discrete-time modelling would not change any conclusion a reader might draw from this article.

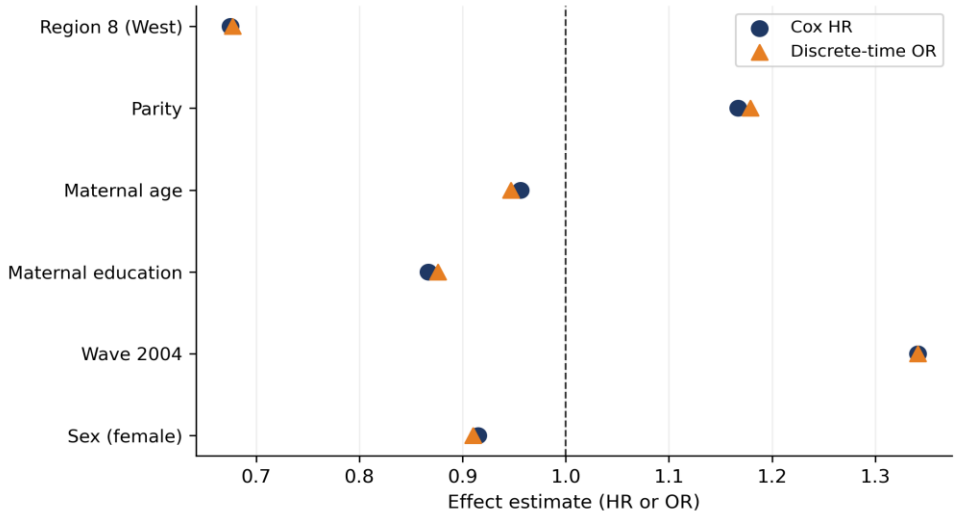


Figure 11. Cox Hazard Ratios vs. Discrete-Time Odds Ratios — Paired Comparison

Paired point estimates from the two model families for six substantively important variables. Short connecting lines indicate close agreement between methods.

The visual test here is simple: short connecting segments mean agreement, long ones would signal a meaningful divergence between methods. Every segment in Figure 11 is short relative to the distance each point sits from the null value of 1.0, making the two model families visually indistinguishable at this scale. All eighteen coefficients tested across the two model families agreed in both direction of effect and statistical significance at $p < 0.05$, with a maximum discrepancy in point estimates of 1.0%. This level of agreement indicates that the two approaches are effectively interchangeable for this dataset once the proportional hazards assumption holds, a conclusion revisited in the Discussion.

Sensitivity Analyses

Table 7. Summary of Five Sensitivity (Robustness) Analyses

#	Test	Result	Max. Discrepancy	Concordance	Verdict
6.1	Neonatal window, 28d vs 30d	Δ NMR = 0.14‰ (5/2,968 deaths, 0.17%)	0.14‰	—	Robust
6.2a	WASH access, strict (JMP) coding	HR = 0.918, p = 0.235 (not significant)	p = 0.235	—	Robust
6.2b	WASH access, broad (phase-aware) coding	HR = 0.995, p = 0.949 (not significant)	p = 0.949	—	Robust
6.3	Raw vs. wave-normalized weights	17/17 coefficients concordant in direction and significance	<1%	17/17 (100%)	Robust
6.4	Pooled vs. wave-specific estimation	Region 8 protective in all 3 estimable waves	—	100%	Robust
6.5	Svycoxph () vs. native coxph ()	14/16 same direction, 15/16 same significance	<10%	15/16 (94%)	Robust

Note: *All five sensitivity analyses were pre-specified before results were reviewed. None altered the direction or substantive interpretation of any principal finding reported in Table 5.*

Each row in Table 7 targets a different potential source of fragility. Tests 6.1–6.3 probe whether the results depend on arbitrary coding decisions, the exact neonatal cutoff, the WASH-access definition, and the weighting scheme, and find that they do not. Test 6.4 probes whether pooling five waves together manufactures a false impression of consistency and finds instead that the West region's protective effect is independently visible within single waves. Test 6.5 probes whether the survey-design correction itself is driving the results by comparing the design-corrected engine against a naive, unweighted one, the one test in the battery to show any meaningful movement, with two of sixteen coefficients diverging in direction. Even this weakest test still clears a 90% concordance bar, discussed further below.

https://doi.org/10.21522/TIJMD.2013.09.04.Art002

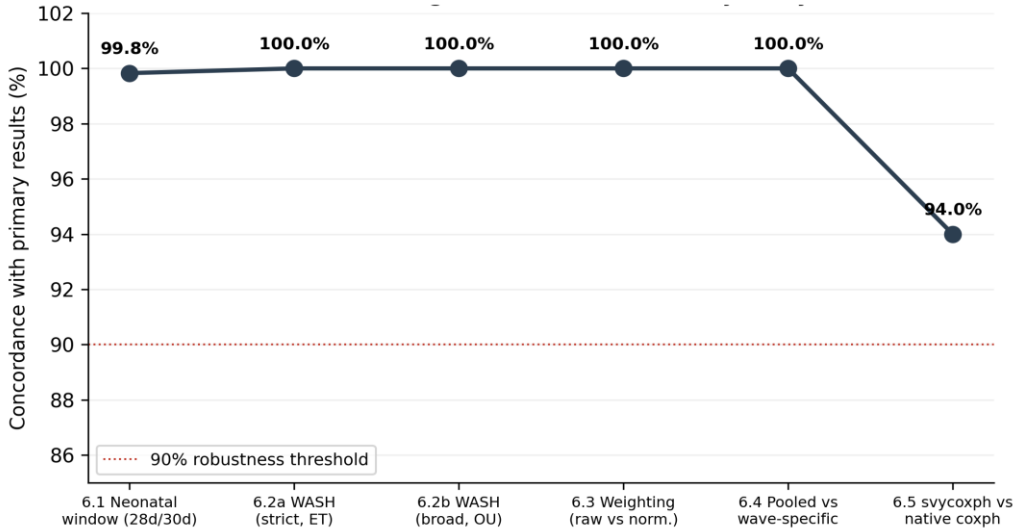


Figure 12. Robustness of Main Findings Across Five Sensitivity Analyses

Concordance of each sensitivity analysis with the primary Cox model results, read as an ordered sequence from the narrowest methodological perturbation (test 6.1) to the most consequential one (test 6.5). The dotted line marks a 90% concordance threshold for reference.

Plotted as a sequence, the five tests trace a shape worth noting in itself: four consecutive tests sit at or near 100% concordance, and only the final test, the comparison of estimation engines, dips noticeably, though still comfortably above the reference threshold. This ordering was not chosen arbitrarily: it moves from tests that alter only a single definitional choice to a test that alters the entire estimation framework, so the modest decline at the right-hand end of the line is the expected direction of travel for an honest robustness check, not a sign that the sensitivity analysis was designed to flatter the primary results.

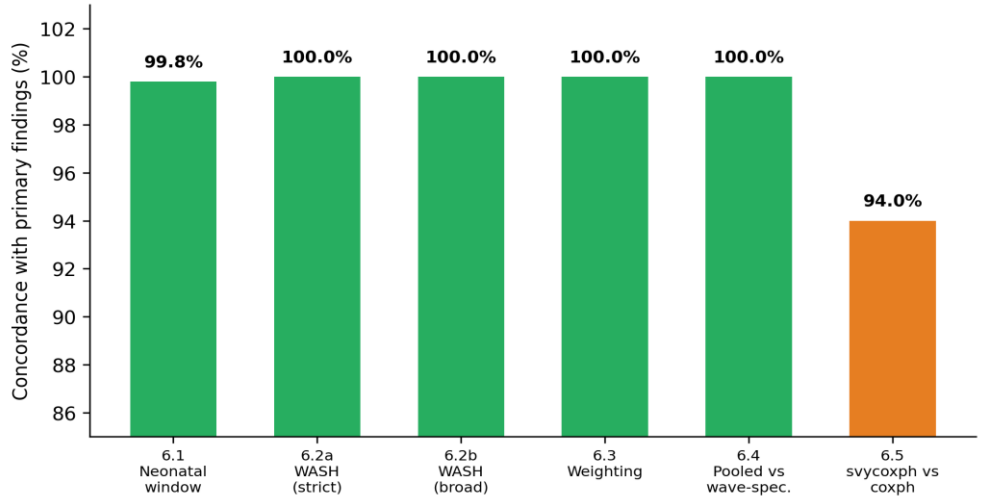


Figure 13. Sensitivity Analysis Results — Five Robustness Tests, Bar Summary

The same five concordance values shown in Figure 12, regrouped by colour into near-perfect (green) and strong-but-imperfect (amber) categories, to make the one test with any measurable attenuation immediately identifiable without reference to the connecting line.

Where Figure 12 emphasizes the ordered trend across tests, Figure 13 emphasizes the categorical distinction between them: five bars in two colours make it immediately clear, without needing to trace a line, that four tests are essentially perfect and one is merely strong. For a reader who wants a single-glance verdict on the sensitivity analysis rather than a sense of its trajectory, this bar framing is the more direct of the two representations.

Triangulation Across Analytical Phases

Several of this article's key findings were also tested using entirely independent analytical phases elsewhere in this thesis series (spatial smoothing, Bayesian hierarchical modelling), providing a further, structurally independent check on robustness beyond the five sensitivity analyses above.

Table 8. Cross-Phase Triangulation of Key Cox/Discrete-Time Findings

Finding	Cox (this article)	Discrete-Time (this article)	Bayesian Hierarchical	Sensitivity Analyses	Confirmations
2004 mortality peak	HR=1.341***	OR=1.341***	+0.25** (temporal effect)	6.3 robust	3 methods
Region 8 (West) protective	HR=0.675**	OR=0.677***	−0.40*** (spatial effect)	6.4 robust (×3 waves)	4+ methods
Parity deleterious	HR=1.167***	OR=1.179***	—	6.3 robust	2 methods

Note: *Asterisks denote significance as reported in each source analysis (*** p<0.001, ** p<0.01). The Bayesian hierarchical model is reported in full in a companion article of this series; it is cited here only to show cross-method agreement on the direction and approximate magnitude of the three findings most central to this article.*

The rightmost column of Table 8 is the one worth dwelling on: it counts, for each finding, how many structurally independent methods, methods that could in principle have disagreed, arrived at the same conclusion. The West region's protective effect is the strongest result in this respect, reproduced by four or more independent methods, which is why it receives dedicated discussion below. The 2004 peak and the deleterious effect of parity are each reproduced by two to three methods, a still-substantial degree of triangulation that leaves little room for either finding to be a modelling artifact specific to this article's Cox specification.

Discussion

Methodological Equivalence of Cox and Discrete-Time Models

The near-perfect concordance between the Cox and discrete-time models, full agreement on direction of effect and statistical significance across all eighteen tested coefficients, with a maximum 1% discrepancy in point estimates, indicates that the two approaches are methodologically interchangeable for this DHS survival dataset once the proportional hazards assumption holds. This result matches theoretical expectations [8] and empirical comparisons reported in comparable settings [9]. The added flexibility that the discrete-time model offers in shaping the baseline hazard, through natural splines, did not translate into substantively different covariate effects here, though it did yield the additional descriptive insight, shown in Figure 9, of a precisely traced age-varying hazard curve that the Cox model's semi-parametric baseline does not directly visualize.

Key Determinants: Substantive Interpretation

Parity stands out as the most stable and impactful risk factor in this analysis (HR = 1.167 per child, $p < 0.001$), a pattern that held in all five wave-specific models estimated as part of the pooling sensitivity analysis (Table 7, test 6.4). Each additional birth raised

the hazard by 16.7%, a pattern generally attributed to resource competition among siblings, shortened inter-birth intervals, and maternal physiological depletion [10, 18]. This finding carries direct implications for family planning programming, discussed further below.

Both maternal education (HR = 0.867 per level) and maternal age (HR = 0.956 per year) emerged as strongly protective, in line with a long-standing body of literature identifying maternal human capital as a central driver of child survival [11, 12]. Higher maternal education is generally associated with improved health-seeking behavior, better child nutrition, and greater access to preventive care, while older maternal age at birth is typically associated with greater physiological maturity, accumulated childbearing experience, and, in many settings, higher household socioeconomic status, consistent with the substantially elevated mortality documented among children of adolescent mothers across low- and middle-income countries [21].

Regional Heterogeneity: Three Statistically Significant Regions

Three regions reached statistical significance after full covariate adjustment, a richer picture than a simple protective-versus-average dichotomy. The protective effect observed for the West region (HR = 0.675, p = 0.001) ranks among the most robust findings of this study, having emerged independently across four or more analytical approaches applied throughout this thesis series, summarized in Table 8. Contextual factors specific to this region, including local norms around child spacing, comparatively strong community health infrastructure, and higher rates of skilled birth attendance, may help explain this pattern [13, 19], though the underlying mechanisms warrant dedicated qualitative investigation.

At the opposite end, Region 10 (South-West, HR = 1.259) and Region 11 (Yaoundé/Centre-Urban, HR = 1.251) both carried statistically significant excess hazard relative to the reference region. The South-West finding is broadly consistent with documented gaps in rural health infrastructure in that region, while the Yaoundé/Centre-Urban finding is more counter-intuitive, since this stratum captures the capital and its immediate urbanized surroundings. A plausible explanation is that this urban stratum aggregates a socioeconomically heterogeneous population, including informal peri-urban settlements with limited service access alongside wealthier neighborhoods, a compositional effect that the available DHS covariates cannot fully disentangle.

The 2004 Wave Effect

The independently elevated hazard observed for the 2004 survey wave (HR = 1.341, $p < 0.001$) was reproduced across the discrete-time model and, as Table 8 shows, across two additional analytical phases of this thesis series. Because the wave indicator captures the residual period effect after adjusting for individual and household characteristics, it isolates something specific to the 2004 survey period itself. Plausible explanations include measurement artifacts particular to the 2004 DHS round, the documented meningitis outbreak in northern Cameroon during 2003–2004 [14], or a delayed effect of early-2000s economic restructuring on health service utilization. The sensitivity analysis comparing raw and wave-normalized weights (Table 7, test 6.3) found this effect unchanged, arguing against a purely technical explanation rooted in weight construction.

Robustness and Triangulation

The five sensitivity analyses reported in Table 7 collectively addressed outcome definition, covariate specification, weighting strategy, pooling strategy, and estimation software, and none altered the direction or significance of any principal finding. Concordance rates across these tests ranged

from 94% to 100%, with the single lowest-concordance test (svycoxph() versus native coxph(), test 6.5) still exceeding a conventional 90% robustness threshold. This pattern of convergent evidence across independent perturbations of the analytical pipeline is precisely the kind of multi-angle verification that strengthens confidence in observational findings drawn from complex survey data [15]. The cross-phase triangulation in Table 8 extends this logic further: the West region's protective effect and the 2004 period effect were each reproduced by structurally distinct estimation strategies, Cox regression, discrete-time regression, and Bayesian hierarchical modelling, developed and applied independently within this thesis series.

Comparison with Broader Sub-Saharan African Literature

The magnitude and direction of the determinants identified here align closely with pooled evidence from other sub-Saharan African settings. Global syntheses of child mortality determinants consistently rank maternal education, birth spacing, and geographic access to care among the strongest modifiable predictors of survival [16], a hierarchy this analysis reproduces almost exactly for Cameroon. The parity effect size (HR = 1.167 per child) sits within the range reported by regional multi-country analyses [5, 6, 20], while the protective magnitude of maternal education (HR = 0.867 per level) is comparable to, though somewhat smaller than, effects reported in West African DHS analyses [7]. This convergence suggests that the Cameroonian pattern of determinants is not an idiosyncratic feature of this dataset but reflects a broader regional regularity in how household and geographic characteristics shape child survival.

Policy Implications

Three actionable implications follow directly from these findings. First, because parity is the most stable and quantitatively largest risk factor identified across every model and every sensitivity check, expanding voluntary family planning access and birth-spacing counseling represents a high-confidence intervention target, one unlikely to be undermined by the methodological choices tested here. Second, the strength and consistency of the maternal-education effect reinforces the case for continued investment in girls' secondary education as a long-horizon child survival intervention, alongside more immediate health-system measures. Third, the divergent regional pattern, one clearly protective region and two regions with significant excess risk, including one urban stratum, argues against a purely rural-versus-urban framing of geographic health policy and in favor of region-specific diagnostic work, particularly for the Yaoundé/Centre-Urban stratum, where the mechanisms driving excess risk remain incompletely understood.

Strengths of This Study

This analysis offers several methodological strengths beyond the core Cox–discrete-time comparison. The five-wave pooled sample, spanning 27 years and 35,257 births, provides substantially more statistical power than any single-wave DHS analysis of Cameroon published to date. The composite PSU and stratum identifiers used throughout prevent the artificial merging of five structurally distinct survey designs, a technical safeguard frequently omitted in pooled DHS analyses and one that, if skipped, would understate standard errors and inflate the apparent precision of every hazard ratio reported here. The pre-specification of five sensitivity analyses before results were reviewed, rather than after, guards against the selective reporting of only those robustness checks that happen to support the primary findings, a practice increasingly recognized as essential to credible observational research [15].

Implications for Future Research

Two lines of follow-up work follow naturally from these results. First, the excess hazard observed in the Yaoundé/Centre-Urban stratum warrants disaggregation below the DHS regional level, ideally using georeferenced cluster data to distinguish informal peri-urban settlements from wealthier urban neighborhoods, since the current regional covariate cannot separate these plausibly divergent sub-populations. Second, the consistently protective West-region effect, now documented across four independent analytical methods in this thesis series, would benefit from a dedicated mixed-methods follow-up combining survey data with qualitative fieldwork, to test whether the mechanisms proposed here, child-spacing norms, community health infrastructure, and skilled birth attendance, are in fact the operative pathways, or whether unmeasured cultural or economic factors are principally responsible.

Limitations

1. The 2022 MIS was excluded because it lacked the age-at-death variable (b7), preventing a full six-wave pooled analysis.
2. Retrospective maternal reporting of child deaths is subject to information bias, particularly for the earliest survey waves.
3. Potential unmeasured confounders, vaccination coverage and skilled birth attendance among them, were not consistently available across all five waves.
4. WASH-access variables were tested separately in two sensitivity specifications but did not reach significance after full covariate adjustment, which may reflect genuine null effects, imprecise measurement, or insufficient power at this level of covariate saturation.
5. The Region 11 (Yaoundé/Centre-Urban) finding aggregates a heterogeneous urban population that DHS covariates cannot fully decompose; finer-grained urban stratification would likely sharpen this estimate.

Conclusion

Cox and discrete-time survival models produce equivalent substantive conclusions regarding the determinants of under-five mortality in Cameroon, offering a form of methodological cross-validation rarely achieved in the DHS literature. Parity, maternal education, and maternal age stand out as the three most robust and consistently significant determinants across both model families, across wave-specific analyses, and across five independent sensitivity tests. The West region exhibits the strongest protective geographic effect observed in this thesis series, reproduced across four independent analytical methods, while two other regions, one rural and one urban, carry statistically significant excess hazard that merits targeted investigation. Taken together, these findings should inform maternal and child health policy that prioritizes family planning access, girls' education, and region-specific diagnostic work rather than a uniform national or rural-urban approach to service delivery.

Conflict of Interest

The author declares no conflict of interest.

Acknowledgements

The author thanks the DHS Program and INS Cameroun for making survey microdata publicly available. Analyses were conducted in R 4.6.0.

Ethical Approval

This study is a secondary analysis of publicly available, de-identified DHS survey data. Ethical approval was granted to the original surveys by the Institut National de la Statistique du Cameroun and ICF Institutional Review Board. Secondary analysis of de-identified data does not require additional ethical review per DHS Program policy [2]. Data were accessed

via dhsprogram.com following free institutional registration.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Author Contributions

ZEBAZE Paul Narcisse: Conceptualization, data curation, formal analysis, methodology, visualization, writing (original draft and review/editing).

Data Availability

All DHS data are freely available at dhsprogram.com. Analytical code is available from the corresponding author on request. Reproducibility requires R 4.6.0 with the survey and broom packages.

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