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Decomposing changes in child health inequality in Sub-Saharan Africa

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Abstract: We analyse recent changes in child health inequality in 15 Sub-Saharan African countries, characterise the observed and unobserved features that contribute to these changes within each country, and examine the cross-country correlation between changes in child health inequality and changes in mean child health. We use a regression-based decomposition approach to estimate the contribution of a set of factors to changes in child health inequality, which is fully comparable to existing decomposition methods for mean child health. Among the observed characteristics, we consider between-regional features related to geographical aspects and within-regional factors including family background, mother's demography, family structure and home infrastructures. Child health inequality decreased over time in most countries, but the proportion of inequality explained by observed characteristics increased. While the unobserved and between-regional features contribute to reducing health inequality, within-regional factors related to mother's demography and family background have pushed inequality in the opposite direction. It is precisely these two sets of characteristics that are behind the positive cross-country correlation between changes in child health inequality and changes in mean child health: while their contributions are detrimental to health inequality, they are beneficial to mean health.

Keywords: Child health inequality, Inequality decomposition, Mean health, Sub-Saharan Africa

JEL-Code: I14, I15, O10, P52

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1. Introduction

Sub-Saharan Africa (SSA) has experienced significant improvements in several dimensions of welfare over the last two decades (World Bank, 2021). Despite population growth, a strong economic growth process has led to an increase in per capita income and a reduction in poverty rates in the region, which has subsequently favoured access to basic goods and services such as health, sanitation, education and nutrition (Arndt et al., 2016). In terms of overall health status, life expectancy has increased, and levels and rates of morbidity and mortality are declining, as well as the prevalence of child malnutrition (WHO, 2018). However, although SSA has made significant progress in health outcomes, the region is starting from a very low base and current levels remain the worst in the world. Moreover, there are notable differences in health status between countries (WHO, 2018; World Bank, 2021), as well as within countries and population sub-groups (such as pro-rich and pro-urban inequalities) (Wehrmeister et al., 2020; Mkupete et al., 2022).

Child health and its inequalities are associated with the future distribution of health, human capital and income, and play an important role in the transmission of economic status (Victora et al., 2008; Case and Paxson, 2010). In addition, health inequalities often translate into inequalities in other dimensions of welfare (Fleurbaey and Schokkaert, 2011), which would ultimately hinder economic growth (Berg et al., 2018; Marrero and Rodríguez, 2013, 2023). Thus, improving average child health and reducing its inequality may have positive long-term consequences for economic opportunities and regional development (Currie, 2011; Almond et al., 2018).

This study is part of a large literature analysing the determinants of child health inequality in the SSA region. Previous studies (among others, Dabalen et al., 2015; Adeyanju et al., 2017; Asuman et al., 2020) have assessed the evolution of child health inequality in SSA and the factors explaining this inequality over time. However, they have not examined the contribution of these factors (positive or negative) to the change in health inequality. We provide new evidence based on trends in child health inequality in SSA and, to the best of our knowledge, this is the first study to decompose the contribution of a set of determinants to changes in child health inequality.

We also contribute to recent studies that have analysed changes in mean child health in SSA (Buisman et al., 2019). From a social welfare perspective, understanding changes in health inequality may be as relevant as understanding changes in mean health (Bleichrodt and Van Doorslaer, 2006; Da Costa et al., 2024). Indeed, given that our methodology for decomposing health inequality is perfectly comparable to the Buisman et al. (2019) approach for decomposing mean health, we also examine the existence of cross-country correlations between changes in child health inequality and changes in mean child health, looking for similarities in the factors contributing to these changes.

Specifically, using information from the Demographic and Health Surveys (DHS), we analyse changes in child health inequality in 15 SSA countries over two consecutive periods, 2008-2013 and 2013-2018. In addition, we apply a regression-based decomposition approach (Fields, 2003; Brewer and Wren-Lewis, 2016) to estimate the contribution of a set of factors to the change in child health inequality in a country. This decomposition method provides an exact additive decomposition of child health inequality and its changes into the contributions of all features. We distinguish between observed and unobserved factors, the former distinguishing among between-regional aspects more related to geography and within-regional factors related to family background, maternal demography, family structure and home infrastructure.

Starting from the height-for-age z-score (HAZ), our measure of child health is the standardised height of children under five, adjusted for the age and gender distribution of children in each country (Pérez-Mesa et al., 2022). Child health inequality is then provided by a specific inequality index applied to this adjusted height series. We restrict the set of inequality indices to those that satisfy the conditions of Shorrocks (1982), such as the Gini index, the MLD and the log-variance. Our results are robust to the inequality index used.

We find that child height inequality has decreased over time in most countries, even though the inequality explained by the set of observed characteristics has increased in this period. Thus, while unobserved factors have largely contributed to reducing health inequality in most countries, observed characteristics have moved in the opposite direction. A complementary result is that we observe a high and positive correlation between the contribution of unobserved factors and changes in total child health inequality, whereas this correlation is negative and significant for observed characteristics. A closer examination of the latter finding reveals that the observed aspects behind this negative correlation are the within-regional factors, and in particular factors related to mother’s demography and family background. On the other hand, family structure and home infrastructures show non-significant correlations with changes in inequality.

Finally, we find a positive but weak correlation between changes in child health inequality and changes in mean child health. In addition, mean height and health inequality improved in most countries over the period. However, there are three countries (Ethiopia, Cameroon and Rwanda) where both dimensions of welfare evolved in the opposite direction (i.e., both mean and inequality increased), while only one country (Guinea) shows a negative evolution in both dimensions. Further analysis of the data shows that mother's demography and family background features are generally detrimental for child health inequality, whereas they are beneficial for the evolution of mean child health.

The remainder of the paper is structured as follows. In Section 2, we present the methodology used to estimate child health inequality and the decomposition approach. In Section 3, we describe the data set and present a descriptive analysis of the main variables in the study. In Section 4, we estimate child health inequality and the proportion of health inequality explained by a set of observed factors for each SSA country and time period. We then show the contribution of each set of features to the change in child health inequality. Finally, we analyse the cross-country correlation between changes in child health inequality and changes in mean child health. Section 5 discusses the results and presents the main conclusions.

2. Methodology

2.1. Measuring child health and its inequality

Child height has been widely used to model the long-term health status of children in developing countries because it captures the cumulative effects of health during childhood (Pradhan et al., 2003; Currie and Vogl, 2013). It is also associated with health outcomes in later life, economic status and human capital (Grantham-McGregor et al., 2007; Victora et al., 2008). Furthermore, child height distributions are strictly comparable across countries (de Onis et al., 2006).

Our measure of child health departs from the height-for-age z-score (HAZ). Since the HAZ cannot be used directly to calculate health inequality using standard inequality indices (such as the Gini index or MLD), we follow Pérez-Mesa et al. (2022). First, we transform each child's HAZ into its equivalent height for a 24-month-old girl with the same z-score (Pradhan et al., 2003), thus obtaining a set of comparable heights (in centimetres) for all children in the sample, $\widetilde{H}$. Second, we use a non-linear parametric regression to remove the influence of sex and age structure from the child height distribution and construct a mean-invariant age and sex-adjusted height series, denoted by H.[1] Finally, we compute our measure of child health inequality as $I(H)$, where $I(\cdot)$ is a particular inequality index that satisfies the conditions of Shorrocks (1982). Specifically, we consider the Gini index, the MLD and the logarithmic variance. We also use H to measure mean child health (for each country-wave), whose changes are compared with those of health inequality in section 4.3.

2.2. Child health determinants and explained inequality

We distinguish between the part of the adjusted child height explained by observed and unobserved features. To this end, we follow the methodology proposed by Ferreira and Gignoux (2011) in the literature on inequality of opportunity and, for each country-wave c, we estimate the following reduced-form regression:

$$\ln(H_{ic}) = \lambda_c + \pi_c R_{ic} + \tau_c U_{ic} + \sum_{k=1}^{K} \theta_{kc} C_{kic} + v_{ic}, \quad (1)$$

where R_{ic}, U_{ic} and C_{kic} represent a set of observed factors, while λ_c and v_{ic} capture the unobserved ones (time-fixed and time-variant child features). Among the observed aspects, we distinguish between geographical factors, including a set of regional fixed effects (R) and whether the child lives in a rural or urban area (U), and a set of features related to the child and his/her household (C_k) (see Section 3 for details). Thus, π_c and τ_c capture between-regional differences, while the set of coefficients θ_{kc} characterizes within-regional gradients. Notice that the nature of between- and within-regional factors are totally different. For instance, between-regional aspects are associated with different public health policies at the regional level, while within-regional features are related to child and/or household characteristics within the region. The latter information is useful for identifying disadvantaged groups and targeting specific policies for these groups within the region.

We estimate equation (1) by OLS for each country wave (two waves for each country), taking into account the sample design of the surveys and using sampling weights. For each country, we select the same set of regions and other observed factors for both waves to make the results comparable across waves. Standard errors are robust to cluster level and heteroskedasticity in the error terms. Finally, we obtain the 'smoothed child height' (or 'explained child height') distribution, denoted by $\widehat{H}$:

$$\widehat{H}_{ic} = \exp\left[\hat{\lambda}_c + \hat{\pi}_c R_{ic} + \hat{\tau}_c U_{ic} + \sum_{k=1}^{K} \hat{\theta}_{kc} C_{kic}\right]. \quad (2)$$

The 'smoothed distribution' is the proportion of the adjusted child height that is explained by our set of observed characteristics. Since taking the exponential of a prediction from a model estimated on the log scale can introduce a retransformation bias in the presence of heteroscedasticity, we use Duan's smearing estimator to multiply it by our smoothed distribution to obtain a measure of explained child height corrected for this bias (Duan, 1983; Manning and Mullahy, 2001).[2]

Finally, using the version of $\widehat{H}$ adapted by the Duan's smearing factor, we apply an inequality index $I(\cdot)$ to the 'smoothed distribution' to obtain the part of child height inequality associated with differences in our group of observed factors, $I(\widehat{H})$, which we call explained inequality.

We also compute the share of total child health inequality explained by this set of factors, $I(\widehat{H}_{ic})/I(H_{ic})$, that we refer as the I-ratio.[3]

2.3. A regression-based decomposition of inequality

We use a multivariate regression-based decomposition approach to quantify the contribution of each factor (observed and unobserved) to changes in child height inequality over time (Fields, 2003; Brewer and Wren-Lewis, 2016). This approach is useful for several reasons. First, it is perfectly compatible with our results in (1), as it uses their estimates. Second, it allows to deal with a large set of correlated observed features, as in our case. Third, it provides an exact additive decomposition of health inequality into observed and unobserved factors (or explained and unexplained), but also into all the observed features included in (1). Finally, this method is comparable to the decomposition proposed by Buisman et al. (2019) for changes in average child health (see Section 4.3).

To simplify notation, all observed features in (1) are grouped into Z ($\mathrm{Z} = \{R, U, C_k\}$). Unobserved time-variant factors are captured by the error term v. Total child health inequality $I(H)$ and explained inequality $I(\widehat{H})$ are denoted by I and $\hat{I}$, respectively. For each country, we refer to the first wave as t_0 and the second wave as t_1. Thus, for a particular period t, total inequality (i.e., using the Gini index) is denoted by I_t and explained inequality as $\hat{I}_t$.

Following Fields (2003), the *relative factor inequality weight* of any factor *x* for total inequality (i.e. the share of inequality attributed to this factor *x*) is given by:

$$S_x = \frac{\mathrm{cov}[\hat{\beta}_x \mathrm{X}, \ln H]}{\hat{\sigma}^2_{\ln H}} = \hat{\beta}_x \frac{\hat{\sigma}_{\mathrm{X}}}{\hat{\sigma}_{\ln H}} \mathrm{cor}[\mathrm{X}, \ln H], \tag{3}$$

where $\hat{\beta}_x$ are the estimated OLS coefficients from (1), taking into account that $\hat{\beta}_x = 1$ for the residual (i.e., when $x = v$), and $\hat{\sigma}^2_{\ln H}$ is the variance of the dependent variable in (1). Adding up all the shares of the features included in Z, we obtain the relative factor inequality weight for the observed (explained) part of child health inequality, while S_v provides the share for the unobserved (unexplained) part.[4] Hence, the contribution of a particular observed feature $z \in Z$ to total height inequality in period t is given by $S_{z,t} I_t$, and the contribution of the unobserved part is $S_{v,t} I_t$.

Then, for each country, we calculate the (annualised) contribution of each observed and unobserved features to the change in total health inequality between two time periods as follows:

$$\Delta_z I_{(t_1 - t_0)} = \frac{S_{z,t_1} I_{t_1} - S_{z,t_0} I_{t_0}}{t_1 - t_0}, \tag{4}$$

$$\Delta_v I_{(t_1-t_0)} = \frac{S_{v,t_1} I_{t_1} - S_{v,t_0} I_{t_0}}{t_1 - t_0}. \quad (5)$$

We can aggregate (4) for all observed factors in Z or by subgroups. For the case of the explained inequality, we just need to replace H by $\widehat{H}$ in (3) to obtain the resulting set of relative factor inequality weights, denoted by $\hat{S}_z$. Thus, analogous to (4), the contribution of a particular observed factor to the change in explained inequality is determined by:

$$\Delta_z \hat{I}_{(t_1-t_0)} = \frac{\hat{S}_{z,t_1} \hat{I}_{t_1} - \hat{S}_{z,t_0} \hat{I}_{t_0}}{t_1 - t_0}. \quad (6)$$

From (6), we can distinguish into within-regional features (the C_k factors included in Z) and between-regional aspects (R and U in Z). Furthermore, we can substitute the explained inequality $\hat{I}$ by the I-ratio $\hat{I}/I$ to obtain the analogous decomposition.

3. Data description: child health and determinants

We collect information from the DHS on 15 SSA countries to identify the factors underlying changes in child health inequality. These countries have comparable information from the last two consecutive and completed DHS waves, DHS VI and DHS VII, covering the periods 2008-2013 and 2013-2018, respectively. Each child under 5 years of age represents an individual observation, which we pool for each country-wave. Table 1 summarises the survey information used on countries, years and sample size. It also presents information on child height: the mean and standard deviation of our adjusted height measure and, for illustrative purposes, the average HAZ. [5]

On average, children's health improved over time: our mean adjusted height series increased from 80.94 cm in the first wave to 81.29 cm in the second, and the mean HAZ decreased from -1.48 to -1.37. In fact, only two countries (Benin and Nigeria) did not improve their average health. Moreover, all countries show a negative HAZ in both periods; Burundi, Malawi and Rwanda are the countries with the lowest health levels in both waves, while Cameroon and Guinea are the countries with the highest adjusted height levels. In addition, the standard deviation of adjusted height decreased in 10 out of 15 countries.

The DHS also contains disaggregated information on a set of socioeconomic, demographic and geographic factors that have been widely used to explain differences in child health (Strauss and Thomas, 2008; Almond et al., 2018). Following Pérez-Mesa et al. (2022) and Assaad et al. (2012), among others, we group factors with similar characteristics into five categories (Table A1, Supplementary Material A): family background, including mother's education, household wealth, and mother's occupation; mother's demography, such as mother's height, mother's body mass index (BMI), and mother's age; family structure, including number of offspring, birth order of children, and type of birth (single or multiple); household infrastructures, such as source of drinking water, type of toilet facilities, and type of cooking fuel; and geography, including region and place of residence (urban or rural).[6] The geography group coincides with R and U in (1) (between-regional characteristics), while the other factors are associated with C_k (within-regional features). Tables A2, A3 and A4 in Supplementary Material A shows the details of factors included in C_k and their descriptive statistics for each country-wave.

Table 1. DHS surveys: coverage and child health

		DHS year		Sample size		Adjusted height (cm)		Standard deviation adjusted height		HAZ	
ISO code	Country	DHS VI	DHS VII	DHS VI	DHS VII	DHS VI	DHS VII	DHS VI	DHS VII	DHS VI	DHS VII
BJ	Benin	2011-2012	2017-2018	7009	11418	81.43	81.16	6.43	3.92	-1.33	-1.41
BU	Burundi	2010	2016-2017	3377	5955	78.78	78.82	4.01	3.73	-2.15	-2.14
CM	Cameroon	2011	2018	4773	4194	81.75	82.25	4.83	5.18	-1.23	-1.07
ET	Ethiopia	2011	2016	9217	8621	80.51	81.22	4.67	4.98	-1.61	-1.39
GN	Guinea	2012	2018	2996	3333	82.31	82.31	5.19	5.53	-1.06	-1.05
LS	Lesotho	2009	2014	1541	1231	80.90	81.16	4.39	4.00	-1.49	-1.41
ML	Mali	2012-2013	2018	4173	6650	81.25	82.22	5.28	4.66	-1.38	-1.08
MW	Malawi	2010	2015-2016	4462	5071	80.14	80.80	4.55	4.10	-1.73	-1.52
NG	Nigeria	2013	2018	23445	10977	81.69	81.00	5.71	4.72	-1.25	-1.46
RW	Rwanda	2010	2014-2015	3998	3494	80.12	80.75	4.01	4.12	-1.74	-1.54
SL	Sierra Leone	2013	2019	3940	4047	81.48	81.72	5.64	4.48	-1.31	-1.24
TZ	Tanzania	2010	2015-2016	6472	8570	80.37	81.09	4.14	4.14	-1.66	-1.43
UG	Uganda	2011	2016	2011	4286	81.25	81.93	4.49	4.30	-1.39	-1.17
ZM	Zambia	2013-2014	2018	11005	8483	80.71	81.06	4.66	4.29	-1.55	-1.44
ZW	Zimbabwe	2010-2011	2015	4161	4736	81.40	81.84	4.06	4.10	-1.34	-1.20

Note: Constructed by the authors using data from the DHS. Sample design and sampling weights are used to estimate these statistics.

4. Results: child health inequality and decomposition

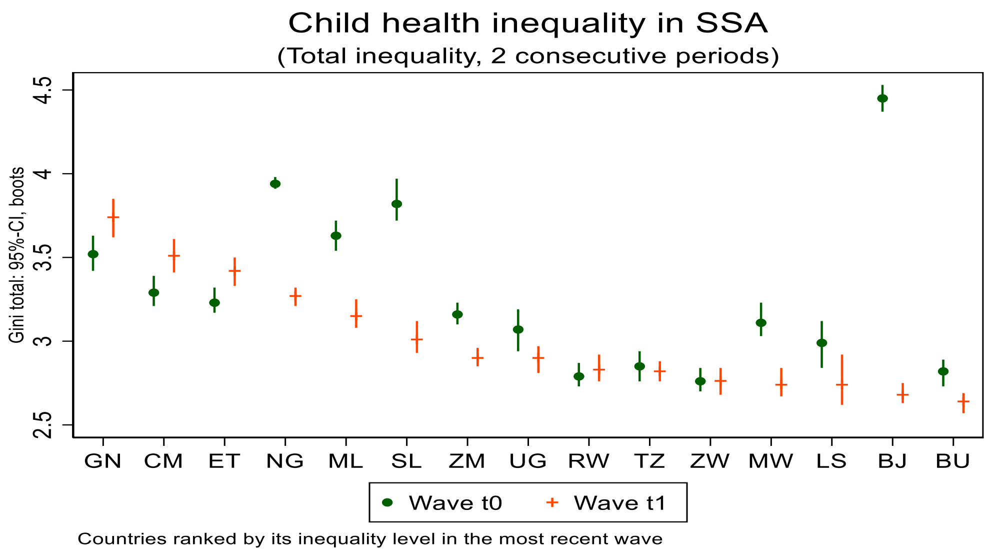
This section presents the following results for each country: first, we provide estimates of child health inequality and its changes between two consecutive periods; second, we examine the main (observed) characteristics affecting child health inequality; third, we analyse the impact of each group of features (observed and unobserved) on changes in child health inequality; finally, we compare the contributions to changes in child health inequality with those to changes in mean child health.[7]

4.1. Child height inequality

We consider alternative inequality measures to estimate child health inequality, such as the Gini index, MLD and log-variance. The results are robust to the inequality measure used, and therefore we focus on the Gini index.[8] For each country and both waves, we compare the point estimates and their confidence intervals of total inequality (Figure 1), explained inequality and the I-ratio (Figure 2). Confidence intervals are calculated by bootstrapping (200 simulations) and using their bias-corrected version (Efron, 1987; Cameron et al., 2008). In each figure, countries are ordered from the highest to the lowest level of inequality in the second wave. Table A1 in the Appendix shows point estimates for all these alternative inequality measures (an asterisk indicates that changes are significant at 5%).

On average, child health inequality decreased between the two waves, as its maximum and minimum levels.[9] The point estimates decreased in most countries (10 out of 15), increased in four countries and remained virtually unchanged in one (Zimbabwe). Comparing the confidence intervals, 7 out of the 10 decreases are highly significant (Nigeria, Mali, Sierra Leone, Zambia, Malawi, Benin and Burundi), while the confidence intervals for the other three countries overlap at some point (Uganda, Tanzania and Lesotho).[10] In contrast, only three increases are significant (Guinea, Cameroon, Ethiopia). Moreover, while some of the decreases are large, the increases are much smaller.

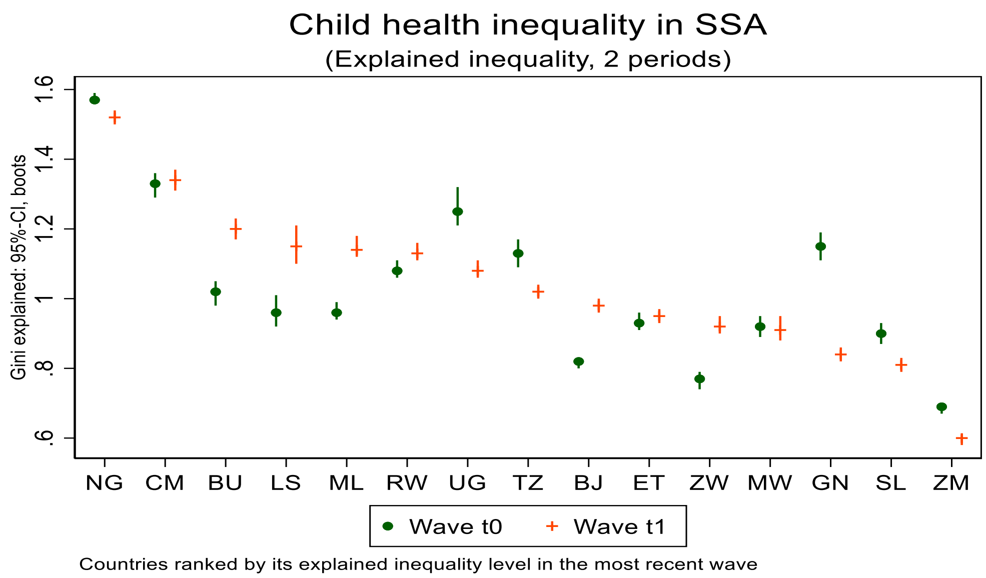
Figure 1. Evolution of total child health inequality in Sub-Saharan Africa (Gini index, %)

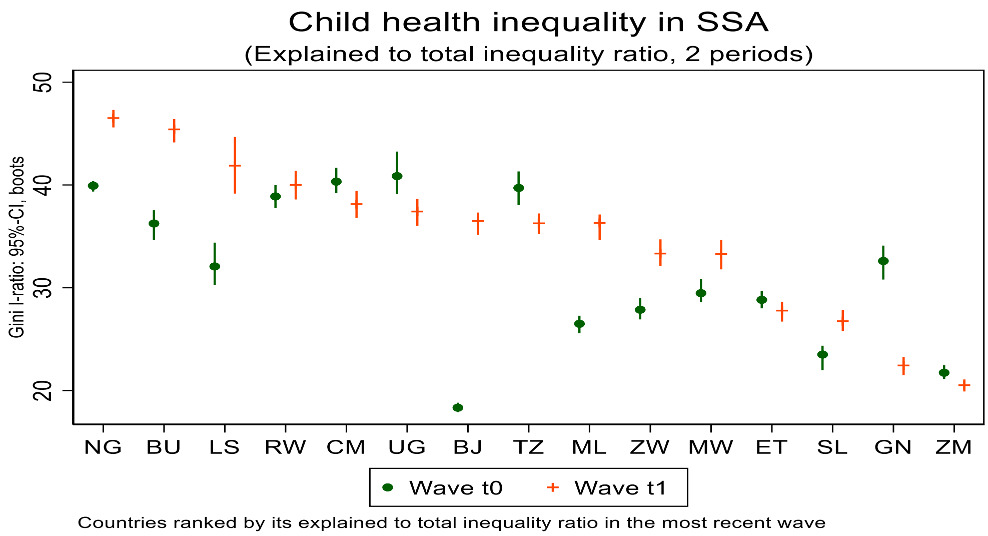


Note: Constructed by the authors using data from the DHS. Countries are ordered from highest to lowest total child health inequality in t_1. 95% confidence intervals (bias-corrected) are constructed using bootstrapping. See Table 1 for acronyms.

Figure 2 shows similar information than Figure 1 but for the explained inequality and the I-ratio. First, we estimate equation (1) by weighted OLS for each country-wave. Then, we compute explained inequality, $I(\hat{H})$, and the I-ratio, $I(\hat{H})/I(H)$).[11] Table B1 (Supplementary Material B) shows the estimated coefficients of the determinants of child health for each country-wave. In general, these estimates have the expected sign and are in line with the evidence shown in the literature, as in Pérez-Mesa et al. (2022).[12]

Figure 2. Evolution of explained child health and child health I-ratio in Sub-Saharan Africa (Gini index, %)





Note: Constructed by the authors using data from the DHS. Countries are ordered from highest to lowest level of inequality in t_1. 95% confidence intervals (bias-corrected) are constructed using bootstrapping.

Explained inequality increased in 8 out of 15 countries and decreased in the other seven countries. These changes are significant in most countries (12 out of 15); however, in contrast to total inequality, increases are now more significant (in terms of magnitude) than decreases. Looking at the I-ratio, the result is even clearer: on average for all countries, the I-ratio increased from 31.8% to 34.8%; moreover, the I-ratio increased in 9 out of 15 countries and this increase is significant in eight of them (Nigeria, Burundi, Lesotho, Benin, Mali, Zimbabwe, Malawi and Sierra Leone), while the decreases are much smaller and significant in 4 out of 6 countries (Uganda, Tanzania, Guinea and Zambia). In Rwanda, Cameroon and Ethiopia, the confidence intervals of the two waves overlap.

We can therefore conclude that while total inequality in child height is decreasing in most countries, the part of the inequality explained by our set of observed characteristics is generally becoming more relevant. In other words, the decline in inequality in our sample must be explained by unobserved characteristics (i.e., probably related to the implementation of public health policies at the national level), while our observed factors contribute in the opposite direction and explain a larger part of the existing child health inequality in the region. This finding may be relevant to better identify the drivers of changes in health inequality and to design specific policies within the country. We develop this result further in the concluding section.

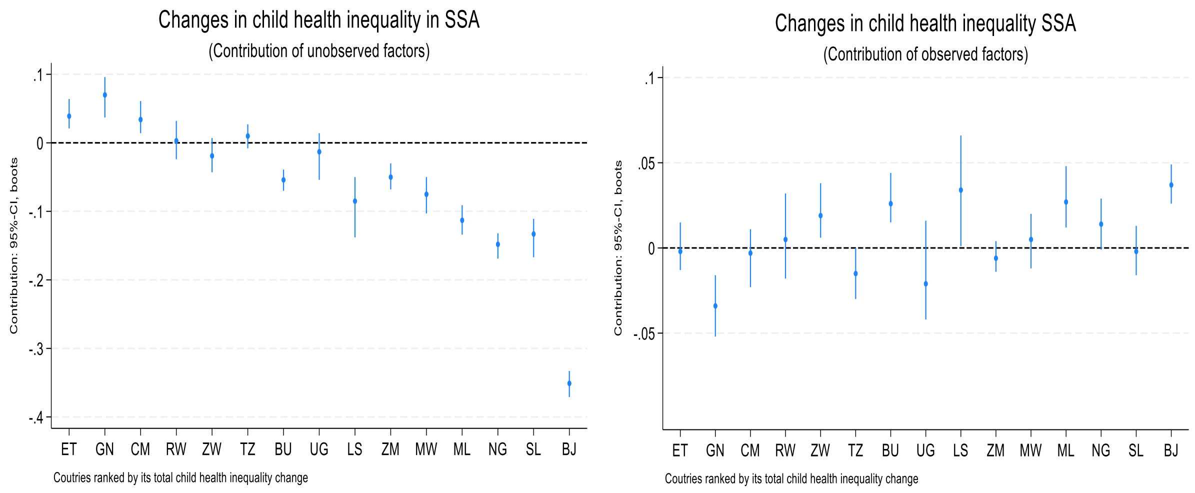
4.2. Decomposing changes in child height inequality

How do the different sets of factors contribute to explaining changes in child health inequality in SSA? We distinguish between unobserved (residual or unexplained) and observed (explained) factors. For the observed aspects, we distinguish between within-regional characteristics (family background, mother's demography, family structure and home infrastructures) and between-regional factors (geography).

For each country-wave, Tables C1 and C2 (Supplementary Material C) show the relative factor inequality weights (equation (3)) of the observed and unobserved characteristics, and those of their factor groups (within-regional and between-regional factors).[13] We then estimate the (annualised) contributions of each group of factors to changes over time in total child health inequality and explained inequality (equations (4)-(6)).

Figure 3 shows the contributions of observed and unobserved features to changes in total child health inequality. As in the previous figures, we present point estimates and their 95% confidence intervals. Countries are ranked from highest to lowest change in total inequality (annualised p.p.). On average, unobserved factors contribute to reducing inequality in most countries (10 out of 15), while observed characteristics have a positive contribution in 8 out of 15 countries. These results are consistent with the trends described in Figures 1 and 2. Looking at the confidence intervals, the negative contributions of the unobserved part are significant in 8 out of 10 countries (i.e., the confidence interval does not contain the value zero), while the positive contributions are significant in three countries. In contrast, only six contributions to the change in the observed factors are significant and the majority (five) are positive. In general, the size of the contributions is much larger for the unobserved factors than for the observed ones.

Figure 3. Contribution of unobserved and observed features to changes in total child health inequality in Sub-Saharan Africa (Gini index, annualised p.p.)

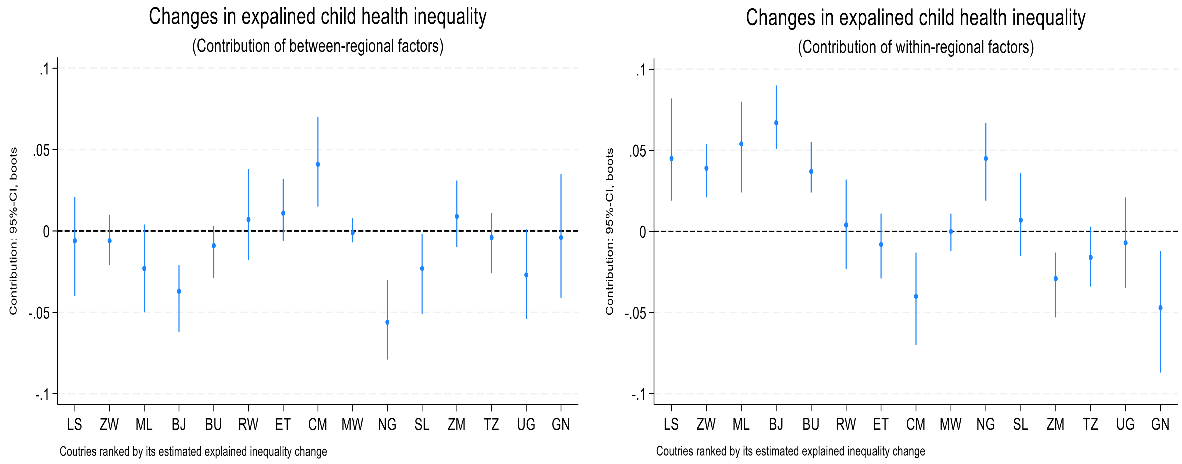


Note: Constructed by the authors using data from the DHS. Countries are ordered from highest to lowest change in total child health inequality. Positive (negative) contribution means that it contributes to increasing (reducing) total inequality. 95% confidence intervals (bias-corrected) are constructed using bootstrapping.

We complement this evidence by comparing these contributions with changes in child health inequality (Figure A1 in the Appendix): a high and positive correlation is shown for unobserved factors (left graph) and a negative and significant correlation for observed aspects (right graph). A priori, the negative correlation is not an expected result. Indeed, we would expect both components to be positively correlated with the change in inequality. As noted above, while the unobserved aspects are driving the reduction in total child health inequality in the region, the set of observed factors is preventing a further reduction in inequality and becoming more important in explaining health inequality in SSA.

We now focus on the contributions to changes in explained inequality. Figure 4 presents point estimates and 95% confidence intervals of the contributions of between- and within-regional factors to changes in explained child health inequality. On average, between-regional aspects (geographical characteristics) contribute negatively (i.e., reduced explained inequality), and this is the case in 10 out of 15 countries. However, this negative contribution is only significant in three countries (Benin, Nigeria and Sierra Leone) and significant but positive in Cameroon. Furthermore, looking at within-regional features, they contribute to increasing explained inequality in 8 out of 15 countries and are significant in six of them (Lesotho, Zimbabwe, Mali, Benin, Burundi and Nigeria); in contrast, their contribution is negative in six countries but significant only in Cameroon, Zambia and Guinea.

Figure 4. Contribution of between- and within-regional features to changes in explained child health inequality in Sub-Saharan Africa (Gini index, annualised p.p.)



Note: Constructed by the authors using data from the DHS. Countries are ordered from highest to lowest change in explained child health inequality. Positive (negative) contribution means that it contributes to increasing (reducing) explained inequality. 95% confidence intervals (bias-corrected) are constructed using bootstrapping.

In addition, Figure A2 (Appendix) shows that the correlation between changes in total health inequality and the contribution of between-regional factors is positive (and almost insignificant) (left graph), while it is negative (and highly significant) for within-regional characteristics (right graph). Thus, it seems that within-regional factors are behind the negative correlation between observed factors and changes in inequality (Figure A1, Appendix).

To conclude this section, we examine which groups of observed factors are driving the within-regional contributions. Figure A3 (Appendix) summarises these results. Looking at each group of factors, they have in general a positive contribution, but most of the contributions are not significant. Specifically, we find that mother's demography contributes to increasing explained inequality in the majority of countries (10 out of 15), while family background follows almost the same pattern as explained inequality. These two groups of factors have the largest positive contributions to the change in explained inequality, although the mother's demography is more relevant than family background. Finally, family structure and home infrastructure are the components that contribute least to the change in explained inequality in child health. These two groups of factors show a positive and negative correlation with changes in explained inequality, respectively, but both are generally non-significant.[14]

4.3. Comparing changes in child health inequality and mean child health

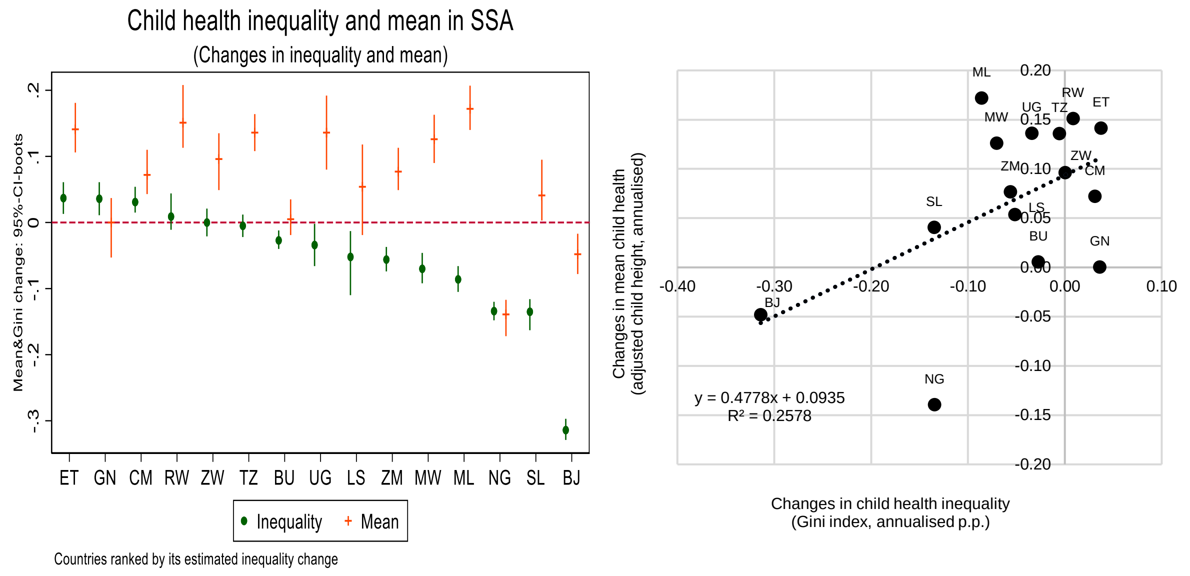
From a social welfare perspective, changes in inequality can be as relevant as changes in the mean of an outcome (Bleichrodt and Van Doorslaer, 2006; Da Costa et al., 2024). Thus, a previous study by Buisman et al. (2019) decomposed changes in mean child health into observed and unobserved factors for SSA, which is perfectly comparable to our methodology for child health inequality. We now compare the decomposition of the two measures and analyse which factors contribute to their changes, as well as the relationship between them.

Figure 5 shows the point estimates of changes in both measures with their 95% confidence intervals (left graph) and the cross-country correlation between changes in average child health and changes in child health inequality (right graph). There is a positive and significant (though weak) cross-country correlation between both changes in our set of 15 SSA countries. While child health inequality has declined in most countries (in line with Figure 1), mean child health has increased in most countries (and 10 out of the 12 significant changes are positive). More importantly, most countries improved on at least one of the two measures, with the exception of Guinea.

Furthermore, comparing the results of the two decompositions can provide insights into this correlation. Figure E1 (Supplementary Material E) contrasts the contribution of each set of factors to the change in mean health with that obtained for the change in child health inequality. First, there is a positive correlation for the contributions of unobserved characteristics in both dimensions (top left graph), although the correlation is also positive (and more significant) when comparing the contributions of observed characteristics (top right graph).

A closer look at the observed factors (second row of graphs) reveals a more conclusive result: within-regional features are behind this positive correlation. Specifically, when we focus on the four groups of within-regional aspects (last four graphs), we find that mother's demography and family background seem to drive this positive correlation between changes in mean and changes in inequality; thus, while their contributions are detrimental to health inequality, they are beneficial to mean health. Moreover, the correlation is almost zero for the family structure and home infrastructure groups; however, we observe in both cases that these factors have contributed to reducing inequality and increasing the mean in some countries, while we find the opposite in other ones.

Figure 5. Evolution of child health inequality (Gini index, annualised p.p.) and mean child health (adjusted child height, annualised) in Sub-Saharan Africa



Note: Constructed by the authors using data from the DHS. Countries are ordered from highest to lowest change in total child health inequality. Child health inequality is the estimated inequality in our measure of child height adjusted by age and gender, $I(H_{ic})$. Mean child health is the child height adjusted by age and gender (H_{ic}). 95% confidence intervals (bias-corrected) are constructed using bootstrapping.

5. Conclusions

We collect data from the DHS to analyse the evolution of child health inequality in 15 SSA over two time periods, 2008-2013 and 2013-2018. We use a regression-based decomposition approach to quantify the contribution of a set of factors to changes in child height inequality, distinguishing between observed features (related to family background, mother's demography, family structure, home infrastructures and geography) and unobserved factors. In addition, we compare these results with those on the contribution to changes in mean health and analyse the relationship between the two decompositions, as both measures are relevant from a welfare perspective. As health inequalities begin at birth and often translate into inequalities in other dimensions of welfare (income, wealth, education), correcting them early in life could have positive long-term consequences for later economic opportunities and regional development.

Using the adjusted child height as measure of health, we find that total child health inequality declined in most countries between the two periods considered, while the part of the inequality explained by our set of observed characteristics becomes more relevant. Thus, we show that unobserved characteristics contribute to reducing health inequality in most countries, while observed aspects contribute to increasing it. Among the observed features, within-regional factors are behind this positive contribution, and more specifically those related to mother's demography and family background.

We also find evidence of a positive but weak correlation between changes in child health inequality and changes in mean child health. This positive relationship is driven by unobserved factors and, among the observed characteristics, by mother's demography and family background. Thus, when these factors contribute more to improving one dimension (i.e., mean health), they are less beneficial (or detrimental) to the other dimension (i.e., health inequality).

Finally, we show that almost all SSA countries (14 out of 15) have improved in at least one dimension (mean or inequality) over this period; only Guinea shows an increase in inequality while mean health has remained stable. Six countries were the winners, improving their mean child health and reducing inequality in child health: Uganda, Lesotho, Sierra Leone and especially Zambia, Malawi and Mali.

We are analysing a period of between 4 and 7 years at most, and we find significant reductions in child health inequality. Therefore, it seems possible to reduce child health inequalities in a short period of time. However, we have seen at the same time that usual determinants of health inequality (such as family background, home facilities, family structure, etc.) have not been the driving forces behind this reduction; on the contrary, they have become (slightly) more important in determining child health inequality in many countries. The reason may be that these factors have a strong inertia and are very difficult to change, generating much intergenerational transmission and immobility. Improving social mobility stemming from these factors would probably help to reverse this result, and these factors could also contribute to reducing health inequalities.

What might be these unobserved factors that explain the reduction in child health inequality over this short period? Given that we control for regional fixed effects, the reason must lie in factors that have improved the distribution of child health at the country level. This may be explained by the implementation of national public health policies that, by disproportionately benefiting those with poorer health, can improve the average child health and reduce its inequality within the country. Recent studies (Osgood-Zimmerman et al., 2018 or Bethencourt et al., 2023, among others) point to the remarkable improvement in the implementation and effectiveness of interventions in SSA after 2000 focused on reducing childhood illness (such as malaria control, vaccination coverage, etc.), and highlight the significant effect of these policies along with general sociodemographic progress on the improvements in child health.

Our results suggest that, in order to further reduce inequalities in child health, it is necessary to maintain these public health policies (these improvements in our unobserved factors), since these improvements can have important positive effects even in a short period of time. However, to accelerate and sustain them, it is also important to reduce the social immobility and its transmission in health caused by the factors we have called observed in our study. For example, reducing the effect of family background and place of residence on health literacy or the transmission of healthy habits from mother to child would reduce future inequalities in child health.

Overall, as our results are descriptive and based on regression and correlation analyses, they should be taken as potential lines of future research rather than policy recommendations. In addition, more country-specific studies are needed to identify the factors underlying changes in child health inequality, in order to tackle inequality within a given country and avoid creating trade-offs between child health inequality and average levels of child health.

Endnotes

[1] The adjustment for sex and age may alter the mean of the Pradhan's height series. We have rescaled our adjusted height series to maintain the same mean as the unadjusted one. Thus, now the trend of our adjusted height variable is consistent with the trend of HAZ and Pradhan's height. Height inequality is not affected by this rescaling.

[2] When the dependent variable is transformed by taking the natural logarithm, its expected value variable conditional on the explanatory variables depends on the exponentiated fitted term but also on the expected value of the exponentiated error term. We must correct it by multiplying by the Duan's smearing factor, which is the average of the exponentiated estimated error terms, $D_{smear} = \frac{1}{N}\sum_{i=1}^{N} e^{\widehat{v_i}}$ (Manning and Mullahy, 2001).

[3] Our estimations must be seen as a lower bound of the explained inequality and the I-ratio since we do not observe all relevant factors affecting health inequality.

[4] These relative factor inequality weights are generally positive (i.e., they contribute to increasing height inequality), and they all add up to 1. The relative factor inequality weights are invariant for a broad family of inequality measures that satisfy Shorrocks' conditions (Shorrocks, 1982). Therefore, we do not need to add any particular inequality index to perform the decomposition.

[5] We consider the sample design (clustering and stratification) of the surveys and use sampling weights to ensure that our results do not show biased estimates, and to achieve its representativeness at the national, regional (departments, states) and residence level (urban, rural) (O'Donnell et al., 2008; Croft et al., 2018).

[6] Numerous studies evidence the relationship between child health and these groups of observed factors: family background (Case et al., 2002; Currie, 2009); mother's demography (Subramanian et al., 2009; Victora et al., 2021); family structure (Rosenzweig and Zhang, 2009; Hatton and Martin, 2010); home infrastructures (Fink et al., 2011; Choudhuri and Desai, 2021); and geography (Smith et al., 2005; Paciorek et al., 2013).

[7] Although we are aware that measurement errors may influence our results, the adjustments commented in Section 2 and taking into account the sample design and sampling weights in all country-waves should reduce this concern.

[8] Since the results presented in Sections 4.1 and 4.2 are robust to the inequality measure considered (Gini index, MLD and log-variance), we only show the results for the Gini index. Results for MLD and log-variance are available upon request.

[9] Inequality levels are in the range of previous estimates of child health inequality reported in the literature using similar approaches, indices and measures (Assaad et al., 2012; Krafft, 2022; Pérez-Mesa et al., 2022).

[10] Benin presents the most notable reduction, as it moved from the most unequal country in the first wave to the second least unequal in the second wave. Although a detailed analysis of this reduction is beyond the scope of the paper, it could be a reflection of high within-cluster heterogeneity and/or poor quality of anthropometric data due to measurement errors (Assaf et al., 2015; Perumal et al., 2020). The inclusion or deletion of this country does not influence the main conclusions of the paper.

[11] Since the set of factors considered in our regressions are beyond the children's control, they are considered exogenous. Thus, we are not concerned by endogeneity of regressors, but focus only on the associations between child health and its explanatory factors.

[12] We find a positive and highly significant relationship between family socio-economic status and child health, as well as with mother's height. Furthermore, mother's age and mother's BMI have a significant but non-linear effect on child health, while the relationship with family structure variables is generally negative. Finally, regional fixed effects present a significant relationship with child health, but home facilities are usually insignificant once all other factors are taken into account. See Supplementary Material B for detailed comments on these results.

[13] We show the results using the Gini index, as with the inequality estimates, but all results in this section are similar for the MLD and log-variance. Results are available upon request.

[14] Considering all factors individually, on average, between-regional features (region and place of residence) and source of drinking water are the most negative contributors to the change in explained health inequality, while mother's BMI, household wealth, type of cooking fuel and mother's education are the factors that most increase it (results available upon request).

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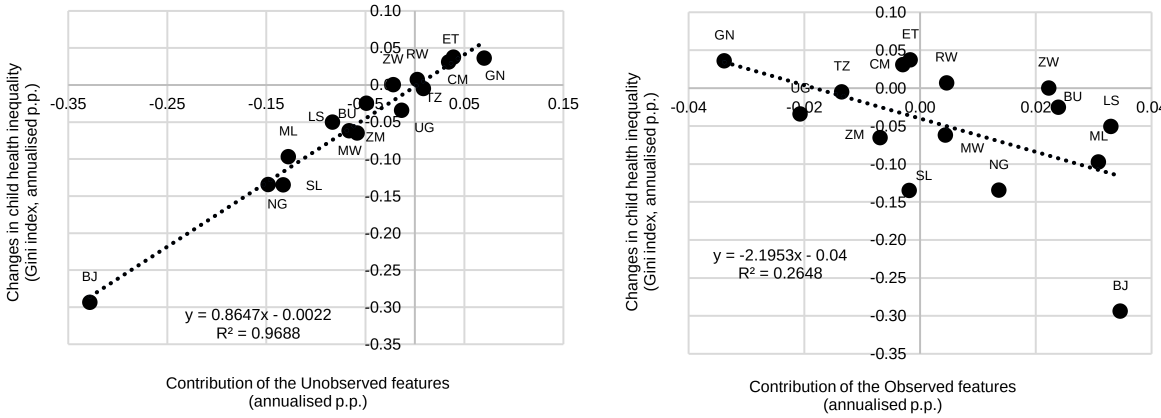
Appendix

Table A1. Child health inequality estimates in Sub-Saharan Africa: total inequality, explained inequality and I-ratio (Gini index, %)

		Total child health inequality (%)			Explained child health inequality (%)			Child health I-ratio (%)		
ISO code	Country	DHS VI	DHS VII	Change (annualised p.p.)	DHS VI	DHS VII	Change (annualised p.p.)	DHS VI	DHS VII	Change (annualised p.p.)
BJ	Benin	4.45	2.68	-0.31*	0.82	0.98	0.029*	18.34	36.50	3.24*
BU	Burundi	2.82	2.64	-0.03*	1.02	1.20	0.028*	36.26	45.41	1.44*
CM	Cameroon	3.29	3.51	0.03*	1.33	1.34	0.002	40.33	38.14	-0.31
ET	Ethiopia	3.23	3.42	0.04*	0.93	0.95	0.004	28.83	27.78	-0.21
GN	Guinea	3.52	3.74	0.04*	1.15	0.84	-0.052*	32.61	22.44	-1.70*
LS	Lesotho	2.99	2.74	-0.05	0.96	1.15	0.039*	32.08	41.88	2.01*
ML	Mali	3.63	3.15	-0.09*	0.96	1.14	0.032*	26.50	36.31	1.74*
MW	Malawi	3.11	2.74	-0.07*	0.92	0.91	-0.001	29.48	33.28	0.72*
NG	Nigeria	3.94	3.27	-0.13*	1.57	1.52	-0.011*	39.93	46.51	1.32*
RW	Rwanda	2.79	2.83	0.01	1.08	1.13	0.011*	38.89	40.01	0.27
SL	Sierra Leone	3.82	3.01	-0.13*	0.90	0.81	-0.016*	23.51	26.75	0.54*
TZ	Tanzania	2.85	2.82	-0.01	1.13	1.02	-0.020*	39.72	36.27	-0.64*
UG	Uganda	3.07	2.90	-0.03	1.25	1.08	-0.034*	40.87	37.42	-0.69*
ZM	Zambia	3.16	2.90	-0.06*	0.69	0.60	-0.020*	21.74	20.52	-0.26*
ZW	Zimbabwe	2.76	2.76	0.00	0.77	0.92	0.033*	27.87	33.33	1.19*
Mean		3.29	3.01	-0.05	1.03	1.04	0.002	31.80	34.84	0.58

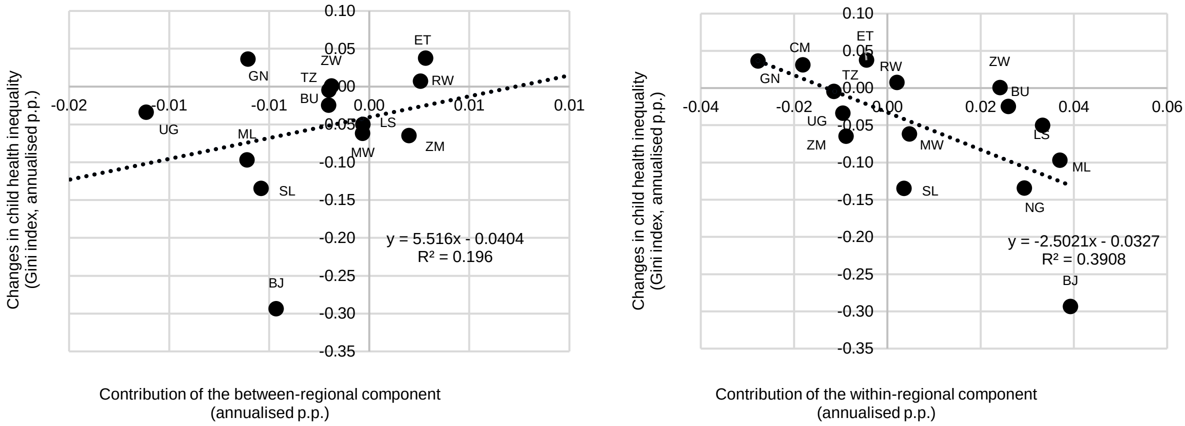
Note: Constructed by the authors using data from the DHS. Total child health inequality is the estimated inequality in our measure of child height adjusted by age and gender, $I(H_{ic})$; explained child health inequality is the inequality in child height caused by differences in our set of factors, $I(\widehat{H}_{ic})$; and child health I-ratio is the share of the explained inequality over total health inequality, $I(\widehat{H}_{ic})/I(H_{ic})$. Mean refers to the average value for all countries in each wave, and changes are in annualised percentage points. The asterisk indicates changes are significant at 5%.

Figure A1. Correlation between changes in child health inequality and contribution of the unobserved (left graph) and observed (right graph) parts in Sub-Saharan Africa (Gini index, annualized p.p.)



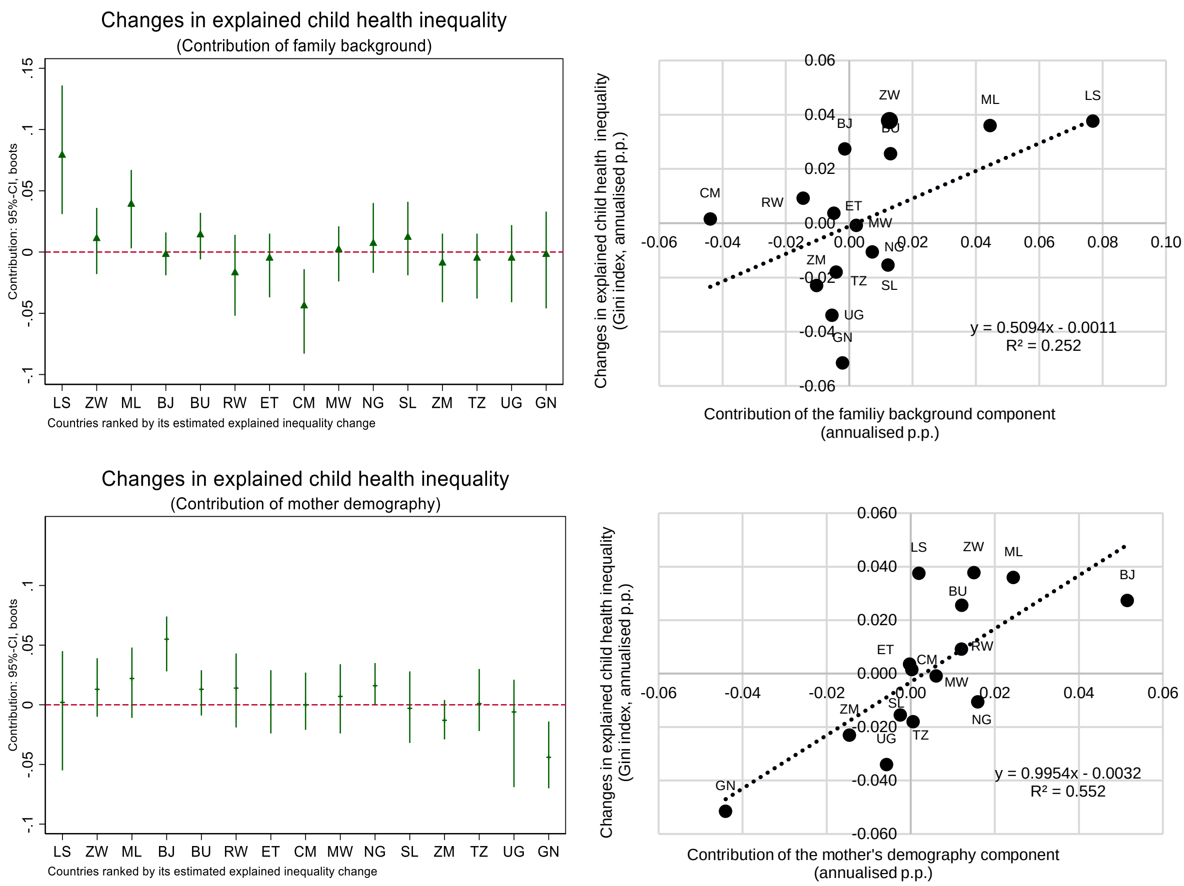
Note: Constructed by the authors using data from the DHS.

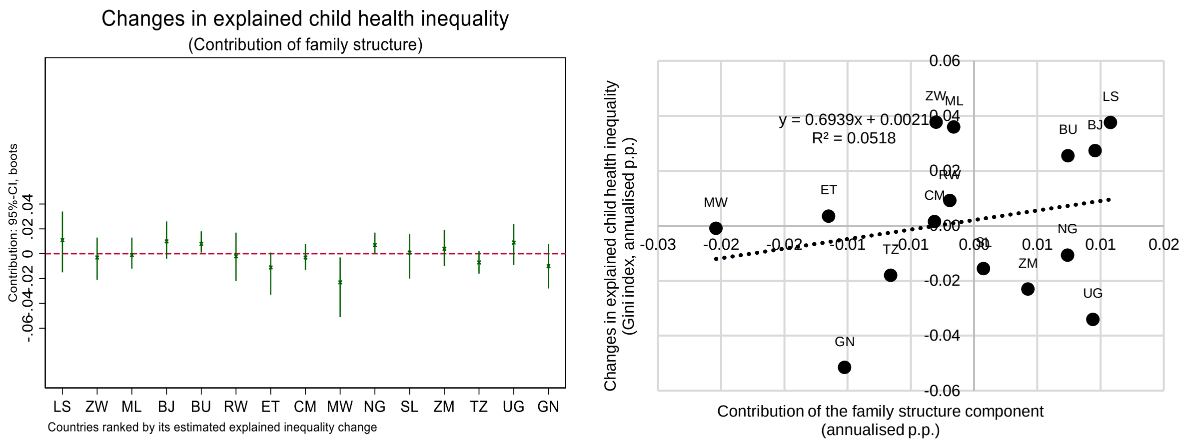
Figure A2. Correlation between changes in child health inequality and contribution of the between- (left) and within-geographical (right) features in Sub-Saharan Africa

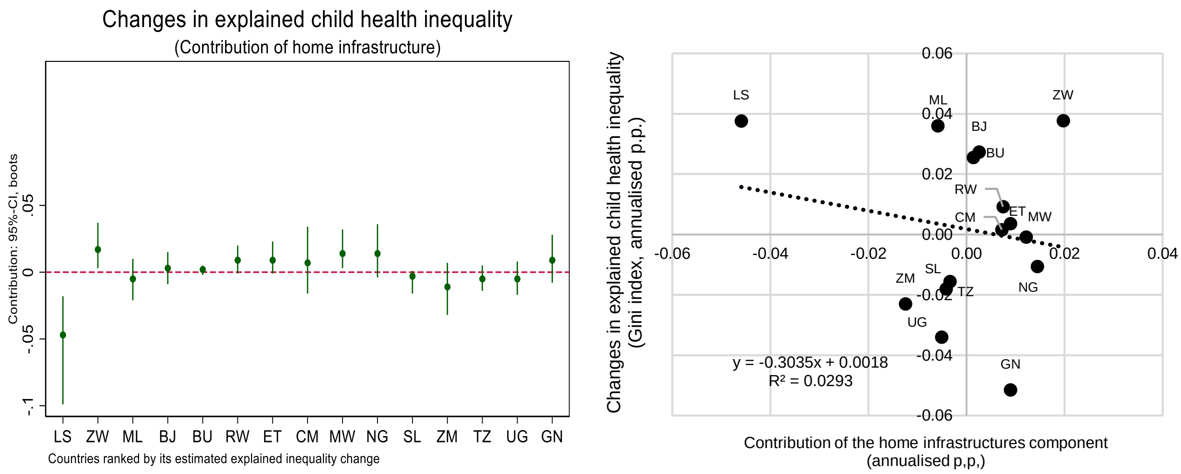


Note: Constructed by the authors using data from the DHS.

Figure A3. Contribution of features to change in explained child health inequality (left) and correlation with explained child health inequality (right) in Sub-Saharan Africa







Note: Constructed by the authors using data from the DHS. Countries are ordered from highest to lowest change in explained child health inequality. Positive (negative) contribution means that it contributes to increasing (reducing) explained inequality. 95% confidence intervals (bias-corrected) are constructed using bootstrapping.