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Child health inequality in Sub-Saharan Africa

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ABSTRACT

We investigate child height inequality and inequality of predicted height in the Sub-Saharan Africa (SSA) region by socioeconomic, demographic and geographical factors. We characterize their changes in age-cohorts (from 0-1 up to 4-5 years old) and determine the contribution of each factor to these changes. We extract data from the Demographic and Health Surveys (DHS) for 33 SSA countries covering the period from 2009 to 2016. Our measure of health is the standardized height of children below the age of five, adjusted by the age and gender distribution in each country. We show that height inequality is lower for older children than for their younger peers. However, the share of inequality caused by our set of factors rises along the age distribution in more than 80% of countries. We find that family background (reflected by maternal education and the household wealth), followed by home infrastructures related to water, toilet and cooking facilities, and the region of residence contribute to explaining the differences observed in child health inequality along the age distribution in SSA.

1. Introduction

Health plays an important role in the intergenerational transmission of economic status and also in the development of cognitive abilities (Case et al., 2002, 2005; Oreopoulos et al., 2008; Currie, 2009; Case and Paxson, 2010). Health inequality translates into differences in other

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dimensions such as education, income and welfare, which are reproducible over time (Sen, 2002; World Bank, 2006; Fleurbaey and Schokkaert, 2012). Since health differences begin at birth, correcting it during childhood is crucial to improve ongoing opportunities for economic development and to combat other forms of inequality (Barker, 2003; Currie, 2011; Walker et al., 2011).

In this paper, we investigate health inequalities in children under the age of five and their changes along the age distribution (i.e., by age-cohorts between zero and five years old) in the Sub-Saharan Africa (SSA) region. Despite the high growth rates of the last decade, the region is still the poorest and the second most unequal in the world (Thorbecke, 2013; Beegle et al., 2016; Alvaredo et al., 2018).[1] Moreover, SSA is also at a disadvantage compared to developed countries in terms of life expectancy and under-five mortality rates (WHO, 2018, 2019; Liou et al., 2020; World Bank, 2020).

Our first goal is to provide insights into the following question: is health inequality during the first year of life corrected during the following years in SSA or, on the contrary, are the differences maintained or even accentuated? Understanding health inequality in this age range is of utmost importance because of the strong association between health during childhood and health, human capital and economic status during adulthood (Steckel, 1995; Grantham-McGregor et al., 2007; Victora et al., 2008; Case and Paxson, 2008, 2010; Almond et al., 2018).

We gather information from comparable household surveys carried out under the Demographic and Health Surveys (DHS), covering 33 SSA countries in the 2009-2016 period. Starting from the height-for-age z-score (HAZ), our measure of health is the standardized height of children below five years old (relative to the WHO reference standards) (Pradhan et al., 2003), adjusted by the age-gender distribution of children in each country.[2] Thus, changes in height inequality along the age distribution are not caused by differences in the composition of child gender and/or age structure across country-years.

We restrict the set of inequality indexes to those satisfying Shorrocks's (1982) conditions (see Section 2), which are the most widely used in the literature, such as the Gini index (our baseline measure), the Mean Log Deviation (MLD), the variance, or the variance of the logarithm. Besides, all our estimations consider the sample design of the surveys (Deaton, 1997; O'Donnell et al., 2008) to ensure their representativeness at national, regional and residence (urban, rural) levels.

Our second set of questions is: which types of factor are the most relevant in explaining child height inequality in SSA? Do their contributions to explaining child height inequality change along the age distribution? To answer these questions, we estimate the inequality (for the overall sample of children under five and for each age-group) of the predicted child height based on a set of socioeconomic, demographic and geographical factors. Most of the factors considered have been already used in the literature to analyze the generation of early-life health inequality, namely household wealth, mother's education, mother's height, family size or the region of residence (Strauss and Thomas, 2008; Currie and Vogl, 2013; Almond et al., 2018).

The predicted height is the fitted part of a log-level regression of height on these factors, and its inequality can be interpreted as a between-group inequality, in which each group of children shares the same types of factors (Lambert and Aronson, 1993; Foster and Shneyerov, 2000). The ratio of inequality in predicted height to inequality of total height, referred to as the I-ratio, is also calculated. The higher the I-ratio, the more important is the set of factors in determining total child height inequality. Finally, we use the Shapley decomposition approach (Sastre and Trannoy, 2002; Shorrocks, 2013) to estimate the fraction of inequality explained by each factor or group of factors in each country. Including all the factors simultaneously allows us to identify the partial contribution of each aspect to the generation of child health inequality, for the entire sample and along the age distribution.

In order to obtain a more illustrative view of the decomposition results, we classify our set of factors in the following five groups: family background (mother's education and occupation, and household wealth); mother's demography (her height, body mass index and age); the structure of the family (number of offspring, birth order and single or multiple birth); home infrastructures (type of drinking water, toilet facilities and cooking fuel used at home); and geography (region of residence and whether the household lives in urban or rural areas).[3]

We show that child health inequality is systematically lower in the 4-5 years old cohort than in their younger peers. Although we cannot adequately control for mortality selection in our sample, we find that, in a cross-country comparison, differences in height inequality by cohorts are not correlated with child mortality in the previous age group. We interpret this lack of cross-country correlation as an indication that a mortality selection bias is not behind the reduction in child health inequality across the age distribution in our sample (Moradi and Baten, 2005; Victora et al., 2010).

Indeed, a more detailed analysis of our results reveals that the factors mentioned above are hindering further reduction of child health inequality in the SSA region, given that we observe that their relative importance (its ratio with respect to total inequality) rises along the age distribution in more than 80% of the countries. More specifically, we show that the factors listed as family background, followed by those listed as home infrastructure and geography, are the factors that contribute the most to explaining this result in most of the countries analyzed.

Our results are robust to a set of departures from our baseline analysis, namely: the use of alternative measures of inequality, the use of an alternative functional form for the predicted height, control for outliers in certain key variables, the use of alternative sub-samples or the grouping strategy in the decomposition exercise.

This paper is part of an extensive literature analyzing the determinants of child health inequality in developing countries, and contributes to the understanding of child health inequalities in SSA. A significant number of papers have analyzed this type of inequality and the factors explaining health differences in SSA using a similar approach (Zoch, 2015; Hussien and Ayele, 2016; Sanoussi, 2017; Ebaidalla, 2019; Tsawe and Susuman, 2020, among many others). However, most of them focus on a single country and do not look at health differences by age-cohorts for children under five years old. To the best of our knowledge, this is the first paper that evaluates health inequality in children under five years old along the age distribution and for such a large number of SSA countries. We also track how the importance of socioeconomic and demographic factors changes across the age distribution.

This paper is also related with the health inequality-of-opportunity literature (Trannoy et al., 2009; Fleurbaey and Schokkaert, 2012; Jusot and Tubeuf, 2019). This literature emphasizes that an individual's health depends on variables beyond and within his/her control, named respectively circumstances and effort. As a result, total health inequality

[1] Consumption inequality caused by factors beyond the individual's control, such as parental background or place of birth, represents a high proportion of total inequality in the region (Brunori et al., 2019).

[2] Child height and the HAZ are widely used metrics for modelling long-term child health status in developing countries (Behrman and Deolalikar, 1988; Strauss and Thomas, 1995, 1998; Pradhan et al., 2003), as they capture the cumulative effects of health during childhood (episodes of inadequate nutrition and health care, disease and deprivation), and are associated with health and other outcomes during adulthood (Grantham-McGregor et al., 2007; Victora et al., 2008; Dewey and Begum, 2011; Nsababera, 2020). Moreover, their distributions are strictly comparable between countries (Habicht et al., 1974; de Onis et al., 2006; WHO, 2006).

[3] To create these groups, we have adapted our available information (for all countries) and diverge slightly from other authors in the related literature (Assaad et al., 2012; Krafft, 2015; Aizawa, 2019).

can be seen as a combination of inequality caused by different circumstances (inequality of opportunity) and inequality caused by factors more related to the willingness to exert effort. This distinction is reasonable when dealing with adult health. However, the factors affecting children must be seen as factors beyond their control and their health inequality should be considered entirely as inequality of opportunity (de Barros et al., 2009; Assaad et al., 2012; Jusot and Tubeuf, 2019). Consequently, fighting against sources of child health inequality may be a way of equalizing opportunities during adulthood and fostering posterior economic growth (Marrero and Rodríguez, 2013, 2022).

The rest of the paper is structured as follows. In Section 2, we present the methodology employed to estimate child health inequality, and the decomposition approach. In Section 3, we describe the dataset used and show a descriptive analysis of the main variables in the sample. In Section 4, for each SSA country, we estimate health inequality and the part of health inequality explained by a comprehensive and measurable set of factors. Next, we show how child health inequality evolves along the child age distribution. In Section 5, we show the results of the Shapley decomposition, their evolution along the child age distribution and analyze the factors behind the differences observed in health inequality. Section 6 performs a robustness analysis of the main results. Finally, Section 7 presents the main conclusions.

2. Methodology: child health inequality and determinants

2.1. Child health inequality

Our primary measure of child health is the height-for-age z-score (HAZ), which measures the deviation of a child's height from the median height of a reference population divided by the standard deviation of this population (WHO, 1995, 2006; O'Donnell et al., 2008). For the reference population, the World Health Organization Child Growth Standards ("the WHO standards") are used as representative of the healthy, well-nourished child population for the same sex and age (de Onis et al., 2006).

However, the HAZ precludes the use of common inequality indexes to measure inequality, such as the Gini or the MLD, since these indexes require non-negative values. Using child height is an alternative, but its distribution (and therefore the resulting level of inequality) without any adjustment can be strongly influenced by the gender-age structure of the child population in the country (Pradhan et al., 2003). To resolve this issue, Pradhan et al. (2003) proposes to transform the original HAZ using a fixed age/sex reference group (i.e., girls at 24 months of age), which is provided by the WHO standards. By so doing, the z-score of any child is transformed into the equivalent height for a 24-month-old girl with the same z-score.[4] This equivalent height is referred to as $\widetilde{H}$ in the paper. However, these authors alert to the problem of an arbitrary choice in the reference group to transform the heights, since that choice can influence the resulting level of inequality. Moreover, as we show in our application, this strategy does not remove the age and gender structure entirely from the height distribution of the children.

To overcome this problem, we follow the literature on wage inequality (Katz and Autor, 1999; Kambourov and Manovskii, 2009), and use a regression-based approach to remove the effects caused by age and gender from the distribution of $\widetilde{H}$. For each country, we regress (by OLS) $\widetilde{H}$ (in logs) with the age structure of the child (in months, including linear, quadratic and cubic terms), gender and their cross terms, and include also regional fixed effects to control for the potential differences in the age and gender distribution between regions in the same country.[5]

$$\ln(\widetilde{H}_{ic}) = \alpha_c + \delta_c G_{ic} + \sum_{j=1}^{3} \beta_{jc}(A_{ic})^j + \sum_{j=1}^{3} \gamma_{jc} G_{ic}(A_{ic})^j + \omega_c R_c + \varepsilon_{ic} \quad (1)$$

The sub-index i refers to a child and c to a country; α_c is a constant term (country specific); G_{ic} is a dummy variable (country and gender specific) taking the value 1 when the i-th child is a boy and 0 otherwise; A_{ic} is the age (in months) of the children; R_c represents a set of regional fixed effects, which are country-specific, and ω_c are the associated coefficients.

Using OLS estimates (the "hat" indicates OLS estimates) from (1), we remove the age and gender heterogeneity from the height distribution as follows:

$$H_{ic} = \exp[\ln(\widetilde{H}_{ic}) - \quad \widehat{\delta_c} G_{ic} - \sum_{j=1}^{3} \widehat{\beta_{jc}}(A_{ic})^j - \sum_{j=1}^{3} \widehat{\gamma_{jc}} G_{ic}(A_{ci})^j] \quad (2)$$

This within-group adjusted (by age and gender) variable, H_{ic}, is our measure of child height hereinafter. In the empirical application conducted in Section 4, we corroborate that this adjusted-height variable does not present any age and gender structure, nor the resultant inequality estimations. Thus, our measures of health inequality are based on the distribution of H_{ic}: $I(H_{ic})$, where I is a particular inequality index.

We restrict the set of inequality indexes to those satisfying Shorrocks's (1982) conditions.[6] The family of indices that meet these properties are the most used in the literature, such as the Gini index, the generalized entropy family (like the MLD), the Atkinson index, the variance or the variance of the logarithm. We show results for the Gini index for the reasons explained below, and in Section 6 we also show that our results are robust to the use of the MLD and the variance of the logarithm.

2.2. Factors explaining child health inequality

We measure the part of child health inequality caused by a particular set of factors. Each factor is denoted by C_k, $k = 1, \ldots, K$, and all of them are related to a range of demographic, socioeconomic and geographical aspects of households (see Section 3); K is the total set of factors used. We adopt a strategy based on the measurement of inequality of opportunity. Among the different methods (Roemer and Trannoy, 2015), we use the log-linear regression approach proposed by Ferreira and Gignoux (2011). This approach allows us to take full advantage of a high number of factors simultaneously (14 factors, as described in Section 3), and to estimate the conditional effect that each factor (or group of factors) has in explaining child height inequality.

The approach is based on the estimation of the following reduced-form equation, which relates our measure of child height (adjusted by age and gender) with our full set of factors:

$$\ln(H_{ic}) = \lambda_c + \sum_{k=1}^{K} \theta_{kc}^{'} C_{kic} + v_{ic}, \quad (3)$$

where the residual v_{ic} is the part of $\ln(H_{ic})$ not explained by the set of factors, and it is assumed to be normally distributed.

[4] For example, a male child of 40 months old with a height of 84.4 centimeters has a z-score of − 3.77; thus, the equivalent height for a female child of 24 months old with the same z-score of − 3.77 would be 73.5 centimeters.

[5] Palomino et al., (2019, 2021) follows a similar procedure to adjust income and wealth to the age-gender distribution of the adult population in a set of European countries.

[6] These conditions are the following: number of components; continuity and symmetric treatment of factors; independence of level of disaggregation; consistent decomposition; population symmetry and normalization for equal factor distribution; and two factor symmetry (for details, see Shorrocks, 1982).

Eq. (3) is estimated by OLS considering the sample design of the surveys (a stratified two-stage cluster design) and using sampling weights to ensure their representativeness at the national, regional and residence (urban, rural) level, as described in Section 3. Standard errors are robust to the cluster level and to heteroskedasticity.[7] For each country, we estimate this equation for the overall sample (children below 5 years old) and for each age group (0-1, 1-2, 2-3, 3-4, and 4-5). Next, the resultant fitted height is what we refer as the “smoothed child height” or “explained child height” distribution:

$$\widehat{H}_{ic} = \exp\left[\widehat{\lambda}_c + \sum_{k=1}^{K} \widehat{\theta}_{kc} C_{kic}\right] \tag{4}$$

Hence, the inequality of this 'smoothed distribution', denoted by $I(\widehat{H}_{ic})$, is the inequality in child height caused by differences in our set of factors. In other words, if all children in the sample share the same set of factors or if no factor influences child height, the resulting $I(\widehat{H}_{ic})$ would be zero. It is worth noting that, since our measure of height is already adjusted for age and gender, $I(\widehat{H}_{ic})$ would be generated by factors other than age and gender.[8]

In the inequality-of-opportunity literature mentioned, the inequality of this smoothed distribution is called inequality of opportunity. However, all factors (included or not in (3)) related to the child must be seen as factors beyond his or her control. Hence, child health inequality must be considered entirely as inequality of opportunity (de Barros et al., 2009; Assaad et al., 2012; Jusot and Tubeuf, 2019), and $I(\widehat{H}_{ic})$ must be interpreted as the inequality in the child height explained by our set of factors. By analogy, and to simplify the notation, we refer to this inequality in explained height as “explained inequality”.

$I(\widehat{H}_{ic})$ can also be interpreted as a between-group inequality (Marrero and Rodríguez, 2012), where each group shares the same types of factors.[9] Hence, more informative than the explained inequality is its ratio with respect to total inequality, $I(\widehat{H}_{ic})/I(H_{ic})$, which we call the I-ratio. This ratio is between zero and one, and represents the share of between-group inequality to total height inequality: the higher the I-ratio, the more important is the set of factors in determining total inequality.

As mentioned above, among the different inequality measures, we focus on the most widely used indexes in the inequality-of-opportunity literature, the Gini index and the MLD, and also the variance of the logarithm.[10] We use the Gini index as our baseline measure of inequality, and the MLD and the variance of the logarithm as robustness checks (Section 6). The reason for choosing the Gini index as our baseline measure follows the argument provided by Aaberge et al. (2011), Brunori et al. (2019) and Ramos and Van de Gaer (2020). The MLD and the variance of the log are more sensitive to extreme values than the Gini index. Therefore, since the smoothed distribution, by construction, does not contain extreme values, the resulting I-ratio may be strongly affected by the presence of extreme values and tends to be downward biased for the MLD and the variance of the logarithm. However, this bias is avoided when the Gini index is used, as it is less sensitive to extreme values.

The inequality in the explained height is associated with measurable factors, and some of them are related to policy interventions. Hence, measuring and understanding the evolution of their contributions over the age distribution is relevant to reduce the impact of these factors on early-life health. To this end, we take the OLS estimates from (3) and use the Shapley decomposition to estimate the contribution of each factor to our measure of explained inequality (Sastre and Trannoy, 2002; Chantreuil and Trannoy, 2013; Shorrocks, 2013). For each factor, this approach computes all marginal effects on inequality when all other factors are sequentially removed. Then, the contribution of each factor is the average of all these marginal contributions. This procedure produces an exact additive decomposition of the explained inequality into its factors, treating all of them symmetrically. Thus, the contribution of each factor can be interpreted as the expected marginal impact of each factor on explained inequality. The estimated contributions are then normalized between zero and one, and all of them add up to one.

3. Data

We collect data from the DHS (waves VI and VII) for 33 different SSA countries, referring to years between 2009 and 2016, depending on the country (see Table 1). This set of countries represents about 90% of the total population in SSA in the 2013-2018 period, and a total of almost one billion inhabitants in 2019 (World Bank, 2020).

The DHS are household surveys that provide data for a wide range of monitoring and impact evaluation indicators in the areas of population, health, and nutrition. The questionnaires are homogenous, allowing for comparison between countries. They use a minimum of two questionnaires, one for the household and another for women of reproductive age (15–49 years old) (Croft et al., 2018). In general, the DHS are representative at the national, regional (department, state) and residence (urban, rural) level. To achieve this degree of representativeness in our results, we consider the sample design of the surveys and use sampling weights to ensure unbiased estimates (Deaton, 1997; O'Donnell et al., 2008). We use data extracted from the Children Recode module, which includes information on children under five years old born to the woman interviewed in the household. Thus, each child represents an individual observation and we pool them for each country.

3.1. Preliminary exploration of data

Table 1 shows general information about the set of DHS used: the countries, the year(s) of the survey, the sample size, the number of regions in the country (used to control regional fixed effects in the regressions in Section 4), as well as the number of strata and clusters, i.e.,

[7] Note that each child represents an individual observation. In this situation, the children of the same mother would share covariates and this could affect the estimates. However, since we do not have a panel database and almost 90 % of mothers have one or two children, including mother fixed effects is similar to including children fixed effects, which would eliminate almost all variability between children. Instead, we control for many aspects (see Section 3 for more details) related to the mother and the household (her education, occupation, height and age, and the household wealth), thus in some way we are controlling for children belonging to the same “type” of mother, “type” of household or “type” of village. This last aspect, together with consideration of the sample design of the surveys, reduces the correlation of errors at small levels of aggregation (households, mothers, etc.). In Section 6, we perform several robustness checks using alternative sub-samples to further reduce this potential problem.

[8] Indeed, including age and gender as additional factors in Eq. (3) makes no sense, since those factors will not be significant and will only increase uncertainty in OLS estimates.

[9] For the MLD, we can decompose total inequality into a between-group inequality and a within-group inequality. For the Gini index, instead, this decomposition is into a between-group, a within-group and a residual inequality. But, in both cases, the between-group inequality is the measure of inequality of opportunity in the related literature, and it will be our measure of explained inequality.

[10] When the inequality measure is the variance of the child height (in logs), the resultant R^2 of Eq. (3) would be an estimation of the I-ratio. We come back to this point in Section 5.

Table 1
Summary of DHS surveys: coverage, details and child height.

ISO code	Country	DHS year	Sample size	Number of regions	Number of strata	Number of clusters	Height-for-age z-score (HAZ):mean	Height-for-age z-score (HAZ): standard deviation	Stunted prevalence (%)
AO	Angola	2015–2016	6304	18	36	627	-1.53	1.56	37.5
BF	Burkina Faso	2010	6477	13	26	574	-1.39	1.59	34.3
BJ	Benin	2012	7606	12	135	750	-1.57	2.34	44.0
BU	Burundi	2010	3432	5	33	376	-2.11	1.42	55.3
CD	Democratic Republic of the Congo	2013–2014	7967	11	66	540	-1.66	1.84	44.2
CG	Congo	2011–2012	4253	12	25	384	-1.14	1.49	26.8
CI	Cote d'Ivoire	2011–2012	3146	11	21	352	-1.25	1.55	29.9
CM	Cameroon	2011	4841	12	24	580	-1.25	1.68	31.9
ET	Ethiopia	2011	9443	11	23	650	-1.61	1.76	42.3
GA	Gabon	2012	3281	10	20	336	-0.99	1.53	23.0
GH	Ghana	2014	2659	10	20	427	-0.98	1.29	19.2
GM	Gambia	2013	3061	8	14	281	-1.08	1.54	25.8
GN	Guinea	2012	3042	8	15	300	-1.11	1.80	30.9
KE	Kenya	2014	18302	8	92	1612	-1.18	1.42	27.2
KM	Comoros	2012	2381	3	7	252	-1.06	1.90	27.8
LB	Liberia	2013	3125	5	30	322	-1.28	1.62	31.1
LS	Lesotho	2009	1560	10	20	400	-1.54	1.55	39.6
ML	Mali	2012–2013	4296	6	11	585	-1.43	1.88	37.7
MW	Malawi	2010	4538	3	54	849	-1.77	1.58	46.2
MZ	Mozambique	2011	9216	11	21	611	-1.58	1.60	39.4
NG	Nigeria	2013	24335	6	73	904	-1.34	2.00	36.2
NI	Niger	2012	4759	8	19	480	-1.67	1.67	41.9
NM	Namibia	2013	1527	13	26	554	-1.04	1.44	23.1
RW	Rwanda	2010	4043	5	30	492	-1.75	1.40	43.8
SL	Sierra Leone	2013	4063	4	27	435	-1.34	1.97	37.7
SN	Senegal	2010–2011	3445	14	28	392	-1.21	1.60	28.9
TD	Chad	2014–2015	9740	21	41	626	-1.61	1.94	43.0
TG	Togo	2013–2014	3125	6	11	330	-1.27	1.39	28.2
TZ	Tanzania	2010	6543	26	51	475	-1.64	1.44	40.0
UG	Uganda	2011	2038	10	19	712	-1.39	1.54	32.6
ZA	South Africa	2016	1080	9	26	750	-1.15	1.42	25.9
ZM	Zambia	2013–2014	11182	10	20	722	-1.58	1.61	39.6
ZW	Zimbabwe	2010–2011	4184	10	18	406	-1.35	1.43	31.6

Notes: Construct by the authors using data from the DHS databases (2009–2016). In columns, sample size means the number of children under five used in each country; regions, strata and clusters are the variables to control regional fixed effects and sample design; and the average HAZ and its standard deviation. Stunted prevalence is the percentage of children under five with an average HAZ less than -2.

the information used in the sample design to perform estimations.[11] The table also summarizes information on child height: the average and the standard deviation of the child HAZ, and the prevalence of stunted children. A zero value of the HAZ indicates that a child has a healthy growth pattern, equal to the median height of the reference population, while a positive or negative HAZ means that a child has an accelerated or a delayed growth pattern, respectively. The WHO highlights two critical situations: above +3, which indicates an "endocrine disorder"; and below -2, which is referred to as "stunting" and is a widely used indicator of an unhealthy population in the country (WHO, 2008).

In our sample (Table 1), all countries show negative HAZ and their sample average is -1.39 (left graph in Fig. 1); on average, 34.7% of children are stunted (right graph in Fig. 1). The graphs are very similar, since the cross-country correlation between the percentages of stunted children and the average HAZ is -0.9689. In all countries, low average HAZ are associated with high percentages of stunted children and vice versa. We also observe notable differences between countries in both measures. The highest HAZ and lowest percentages of stunted children are found in the south, the coast and northwest areas, while the worst health areas coincide with interior and tropical zones.

While the overall correlation between the stunted children group and the standard deviation of the HAZ (compare columns 9 and 10 in Table 1) is positive but low (0.3466), the correlation turns strongly positive if we compare countries with similar HAZ averages (e.g., compare Cote d'Ivoire with Cameroon, or Gabon with Ghana). Indeed, its partial correlation (i.e., given the average HAZ) is 0.8869. Hence, given average health levels, the dispersion of the health distribution can play a key role in explaining the percentage of stunted children in a country. Thus, the analysis of inequality in the following sections will provide important insights into combating stunting, although an analysis of this latter topic is beyond the scope of the paper.

3.2. Explanatory factors of child health inequality

The DHS contains information on socioeconomic, demographic and geographical factors that we consider to explain differences in child health within a particular country, year and age. Following the related literature (Assaad et al., 2012; Krafft, 2015; Aizawa, 2019, among others), and to simplify the exposition of the results, we classify these factors in five groups (see Table 2): family background, including mother's education, mother's occupation and a wealth index of the household; mother's demography, such as mother's height, mother's body mass index (BMI) and mother's age; the family structure, including the number of offspring, the birth order of the child and the type of childbirth (i.e., single or multiple birth); home infrastructures, such as the source of drinking water, the type of toilet facilities and the type of cooking fuel; and geography, including the region of residence and the

[11] The DHS sample is usually based on a stratified two-stage cluster design, where first the primary sampling units or clusters (PSUs) are selected, typically enumeration areas from census files, and then a sample of households is selected in each enumeration area.

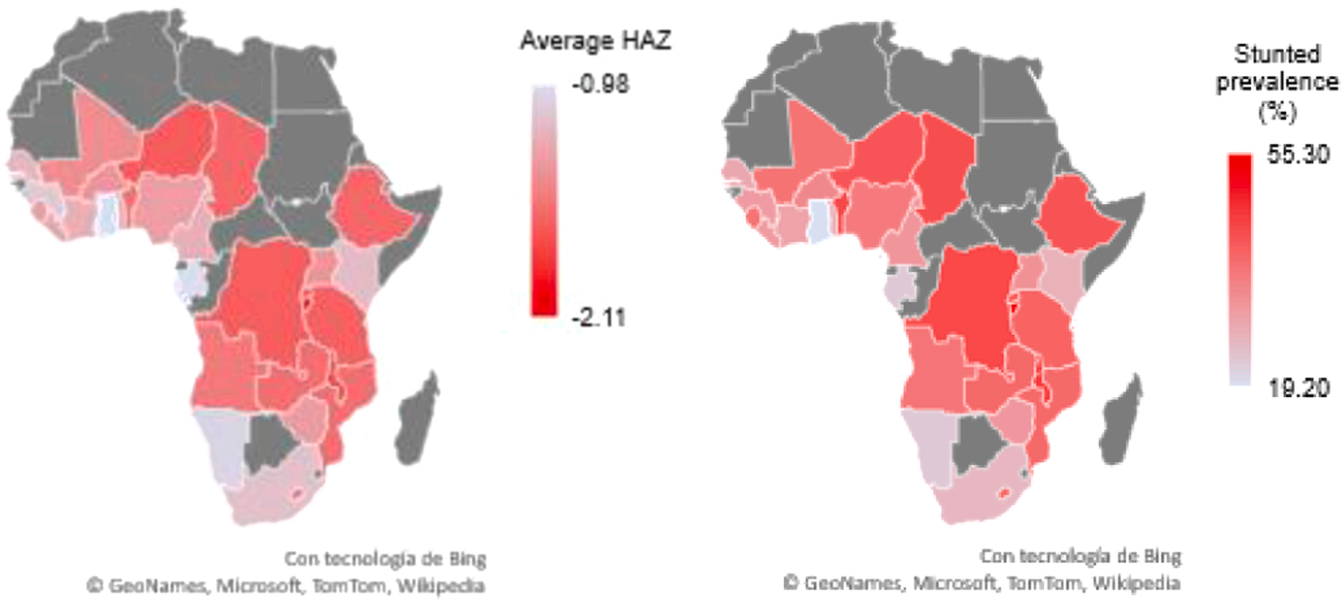

Fig. 1. Height-for-age z-score (HAZ) and stunted prevalence in SSA. Notes: Construct by the authors using data from the DHS databases (2009–2016). In the Map, dark grey means missing data; in the left graph the average HAZ, while in the right graph the percentage of stunted prevalence (%). Stunted prevalence is the percentage of children under five with an average HAZ less than -2.

Table 2
Factor groups and their composition variables.

	Factor groups	Variables
I	Family background	Mother's education, household wealth index, mother's occupation
II	Mother's demography	Mother's height, mother's body mass index, mother's age
III	Family structure	Offspring, birth order, type of childbirth
IV	Home infrastructures	Source of drinking water, type of toilet facility, type of cooking fuel
V	Geography	Region of residence, place of residence

Note: Construct by the authors using data from the DHS databases (2009–2016). See Table A1 in Appendix A for details about the definition and the metric of these factors.

place (urban or rural) of residence.

We choose this set of factors for two main reasons. First, they are available for almost all countries, and so our analysis allows for better comparability.[12] Second, they are widely used in the related literature, meaning that our results are comparable with other studies. While the grouping strategy does not affect the estimation of the inequality of predicted child height in Section 4, it can affect the decomposition exercise performed in Section 5. In Section 6 we analyze the robustness of this latter result to alternative grouping strategies.

There is an extensive literature analyzing the importance of these factors on child health. For instance, numerous studies have examined the association between child health and parental socioeconomic status (as measured by parental income, wealth, education or occupation), reporting that these dimensions are strongly and positively correlated (Case et al., 2002; Currie, 2009; Lindeboom et al., 2009). Maternal nutrition also plays an important role in determining child health. In general, short maternal height and low body mass index (BMI) are associated with lower early HAZ (Subramanian et al., 2009; Black et al., 2013; Victora et al., 2021). There is also empirical evidence of the association between maternal age at childbirth and child outcomes (Fall et al., 2015).

Regarding the influence of family structure, the family size can limit the resources devoted to childcare, as well as the time devoted to them. This aspect may also be correlated with preferences for having children and even with wealth. Combined with family size, the birth order of the child is also a very important factor in relation to the time that parents spend on childcare and resources devoted to their education (see Hatton and Martin, 2009; Jayachandran and Pande, 2017; or Pruckner et al., 2021, among many others). The type of childbirth variable attempts to control for the children being born from a single birth or multiple birth (i.e., two, three or more children born at the same time). In a multiple birth situation, it is expected that the child has a lower height-for-age just because of this status (Behrman and Rosenzweig, 2004; Rosenzweig and Zhang, 2009), and we must control for this situation to avoid bias estimations of other correlated factors.

Inadequate access to sanitation facilities (both inside and outside households), such as piped water, toilets and clean fuel, can harm child's health (Fink et al., 2011; Duflo et al., 2015; Choudhuri and Desai, 2021).[13] Finally, urban-rural differences in child health are well documented: children living in urban areas tend to have, on average, better health than children in rural areas (Smith et al., 2005; Van de Poel et al., 2007; Ameye and De Weerdt, 2020). In general, geographical variables in the model seek to control a set of fixed effects related with, for example, the access to facilities, incidence of infectious diseases, or even local institutional or cultural aspects.

Table 3 shows the descriptive statistics of main factors included in Table 2. On average, the percentage of children with mothers with at least secondary education is 25.8%, although we observe notable differences between countries: South Africa (88.7%), Namibia (68%) and Zimbabwe (64.8%) show high percentages in this variable, while

[12] The only exception is Angola, which does not have data on mother's demography (mother's height, mother's body mass index and mother's age). However, we decided to keep it in our sample of countries.

[13] These factors are related with family background. However, their natures are totally different. While family background is related with the socioeconomic status of the parents, home infrastructures depend on socioeconomic status but also on the general infrastructures in the region. Since all factors are considered simultaneously in Eq. (3), for a given level of household's wealth (or family background status), household infrastructures are also related with sanitation aspects and quality of life, which may have an extra effect on child health.

Table 3
Descriptive statistics of main explanatory factors.

ISO code	Country	Mothers with at least secondary education (%)	Household in the richer and richest wealth index quintile (%)	Mother's height (cm)	Mother's age (years)	Number of offspring	Improved source of drinking water (%)	Toilet facilities (%)	Rural (%)
AO	Angola	27.08	22.24	–	26	3	59.87	63.49	44.73
BF	Burkina Faso	5.28	37.32	161.6	27	3	75.79	31.98	78.66
BJ	Benin	10.20	33.67	159.7	27	3	75.61	35.45	63.22
BU	Burundi	9.49	42.15	155.5	28	3	75.32	97.01	82.65
CD	Democratic Republic of the Congo	33.59	29.76	156.6	27	3	38.78	83.13	70.85
CG	Congo	49.27	16.34	158.1	26	3	53.27	82.69	74.55
CI	Cote d'Ivoire	9.20	29.31	158.7	26	3	76.45	58.76	66.86
CM	Cameroon	33.15	33.44	160.0	26	3	64.26	92.29	60.22
ET	Ethiopia	4.89	34.60	157.3	27	3	52.44	48.37	82.98
GA	Gabon	53.68	17.75	158.0	26	3	80.76	97.21	38.52
GH	Ghana	44.52	27.41	159.1	28	3	83.90	67.97	60.01
GM	Gambia	22.17	28.80	162.3	27	3	88.18	97.10	65.73
GN	Guinea	9.95	35.19	159.5	26	3	73.09	82.39	71.27
KE	Kenya	25.25	28.18	159.9	26	3	62.16	76.14	67.43
KM	Comoros	31.26	32.99	156.5	27	3	90.35	99.39	65.92
LB	Liberia	19.57	16.95	156.6	26	3	64.35	40.29	68.32
LS	Lesotho	36.91	29.43	156.9	25	2	74.32	49.93	83.26
ML	Mali	8.67	39.98	161.3	26	3	66.30	87.99	75.59
MW	Malawi	13.52	32.07	155.9	26	3	78.71	87.29	90.52
MZ	Mozambique	14.38	43.29	155.4	26	3	56.17	62.70	67.67
NG	Nigeria	32.48	34.01	158.3	27	3	60.42	69.47	67.15
NI	Niger	6.01	45.32	160.5	27	4	67.20	32.03	78.10
NM	Namibia	67.96	34.06	161.0	26	2	86.08	43.97	54.61
RW	Rwanda	9.40	36.01	156.6	28	3	72.24	98.76	86.42
SL	Sierra Leone	17.90	36.78	157.7	27	3	56.46	77.70	69.36
SN	Senegal	6.65	22.29	162.8	27	3	68.57	76.48	70.67
TD	Chad	8.32	39.59	161.9	26	4	55.14	28.75	78.67
TG	Togo	19.87	30.73	158.9	28	3	60.47	36.53	71.70
TZ	Tanzania	11.07	35.44	156.3	27	3	48.35	78.68	81.47
UG	Uganda	22.17	36.37	159.1	26	3	72.47	84.88	78.87
ZA	South Africa	88.72	28.23	158.4	26	2	91.37	95.97	46.92
ZM	Zambia	32.90	29.30	157.3	26	3	58.43	83.12	63.04
ZW	Zimbabwe	64.78	36.62	159.9	25	2	74.98	65.81	71.10

Note: Construct by the authors using data from the DHS databases (2009–2016). See Table A1 in Appendix A for details about the definition and the metric of these factors.

Ethiopia (4.9%), Burkina Faso (5.3%) or Niger (6.0%) show much lower percentages. Notice that the education of the mother is not only related with household's wealth, but also with cultural and religious factors.[14] Regarding the wealth index, on average, almost one third of children (32%) belong to households within the richer and richest quintiles of wealth. This variable shows less between-country variability than the education of the mother. Thus, Niger (45.3%), Mozambique (43.6%) and Burundi (42.2%) are the countries with the highest percentages of children belonging to households in the top two wealth quintiles, while Congo (16.3%), Liberia (16.9%) and Gabon (17.7%) are the countries showing the lowest percentages related to this aspect.

The average height of the mother is between 155 and 162 centimeters, depending on the country, and the average age of the mother when they have the child is about 26 years old. On average, mothers have three offspring. With respect to home infrastructures, 68.5% of children live in households with access to an improved source of drinking water, and just two countries show a percentage below 50% (Democratic Republic of the Congo and Tanzania). On average, 70.1% of children live in households with toilet facilities, although in nine countries in the sample less than 50% of children have such facilities in their homes. Finally, except in Angola, Gabon and South Africa, more than 50% of children live in a rural residence.

Regarding remaining factors (not shown in the table), the percentage of mothers working in services-sales occupations and agriculture is about 22% and 35% on average, approximately; the average BMI of the mothers in our sample is between 20.3 (Ethiopia) and 27.9 (South Africa); with respect to the birth order of children, the third is the average position, while around 97% of births are single birth; the percentage of children living in households that use solid cooking fuel is 88% on average.

4. Child health inequality results

We first provide health inequality estimates for children under five years old. Second, we analyze main determinants of child health inequality and estimate the fraction of inequality explained by these factors. Finally, we analyze child health inequality along the age distribution.

4.1. Child health inequality and determinants

We estimate Eq. (1) and recover child health adjusted for age and gender, H_{ic}. For most countries, the estimated OLS coefficients are significant and with the expected sign. First, the coefficient for boys is positive and significant; second, the estimated sequence of parameters β_{jc}, j=1,2,3 in (1) shows a positive correlation between child height and age, and the significance of the squared and even the cubic terms in

[14] For example, these three countries are majority Muslims (61 % in Burkina Faso and 99 % in Niger) or Muslim is one of the main religions (28 % in Ethiopia). Conversely, countries with the Christianity as the majority religion, such as Congo, Gabon, Ghana or South Africa, are characterized by high percentages of mother with at least secondary education and percentages of households in the top two wealth quintiles below the average (ICF, 2016).

some countries indicate that the height-age structure is non-linear; third, the estimated cross-terms indicate that the correlation between age and height is more relevant for boys than for girls, although the latter effect is significant only in a few countries.

Then, we calculate child health inequality as an inequality index applied to this adjusted height series, $I(H_{ic})$. As noted in Section 2, we use the Gini index as our baseline inequality measure. Results for the MLD and the variance of the log are discussed in Section 6. Qualitatively, the results are strongly robust to the use of the Gini index, the MLD or the variance of the log.

Fig. 2 shows child health inequality estimates for children below 5 years old for each country. The left graph shows the results in a map. The Gini index coefficient ranges from 2.5% to 5%, while the MLD goes approximately from 0.1% to 0.4% and the variance of the log ranges from 0.8% to 0.2%. These values are within the range of previous estimations of child health inequality in the literature using similar approaches (Assaad et al., 2012; Krafft, 2015; Hussien and Ayele, 2016). The highest levels of child health inequality are found in the interior, central and northwest areas. These areas, in general, coincide with poorer and tropical zones, with a higher prevalence of infectious diseases; the coast, the south and the south-east generally have lower levels of health inequality.

In the right graph in Fig. 2, countries are sorted from the highest to the lowest inequality estimates. Benin, Nigeria, Sierra Leone, Comoros and Mali are the countries with the highest levels of inequality, while Rwanda, Togo, Zimbabwe, Namibia and Ghana are those showing the lowest levels.

Next, for each country, we estimate Eq. (3) and show results in Table A2 (Appendix A). In general, the coefficients have the expected sign, and we comment next the most significant and robust results for all countries. For the most relevant cases, we connect our results with the literature. Regarding the first group of factors (family background), mother's education is highly significant in most countries, and its partial correlation with children's height is positive. With respect to the omitted category (mothers without any education), having completed secondary or tertiary education is associated with height increases of around 0.7% and 1.9%, respectively. In countries such as Ethiopia, Rwanda and Senegal, this percentage can vary between 2.8% and 4.3%. Notice that these three countries have small percentages of mothers with at least secondary education (Table 3). In these countries, where women have less access to education, having a mother with at least secondary education plays an even more important role in promoting the health of the child.

The wealth index is also positively correlated with child height. Taking the poorest category as the reference group, children in households within the two richest wealth quintiles are on average between 0.7% and 1.3% taller. This variable is particularly relevant in countries such as Burundi, Cameroon, Democratic Republic of the Congo and Kenya. Mother's occupation (the omitted category is "not having a job"), for given levels of education, wealth index of the household and all other factors, tends to be positively correlated with child height, but it is only significant in four countries (Benin, Chad, Cote d'Ivoire and Kenya). The results in this first group are in line with the large body of literature linking parental socioeconomic status (as measured by education, income, wealth or occupation) and child health (Case et al., 2002; Currie, 2009; Lindeboom et al., 2009).

For the second set of factors (mother's demography), mother's height is strongly and positively correlated with children's height in all countries. This correlation reflects the intergenerational transmission of height between mothers and children (Subramanian et al., 2009; Venkataramani, 2010; Bhalotra and Rawlings, 2011). Taking the average estimated coefficient for all countries, our estimation predicts an elasticity of 0.279 (evaluated at the sample mean): differences in maternal height of 10% translate to differences in the (adjusted) height of their children of about 2.8%.[15] Regarding maternal age at delivery, the linear coefficient is positive while the quadratic term is, in general, negative, which indicates the existence of an inverted U-shaped relationship between this variable and child height: being a mother too young or too old are negatively associated with child height (Fall et al., 2015).[16] Similar to Black et al. (2013) and Victora et al. (2021), the relationship between maternal BMI and child height also presents an inverted U-shape: maternal under- or over-weight is negatively associated with the child's height.

Regarding the third group of factors (family structure), taking "single birth" as the reference group, being the first or the second child in a multiple birth is associated (on average) with a height reduction of around 2.8%, and this variable is significant in almost all countries. These results are robust to all countries and in line with the related literature (Behrman and Rosenzweig, 2004; Rosenzweig and Zhang, 2009). However, we do not find robust results for the other two variables in this group: birth order and offspring. For instance, for birth order, we find significant and negative coefficients for almost half of the countries, in line with Hatton and Martin (2009), Zhong (2016), and Jayachandran and Pande (2017), and non-significant correlations for the other half, in line with recent findings (Spears et al., 2022).[17] However, contrary to what might be expected, we find that the partial correlation of offspring is only negative and significant for 2 countries, not significant (negative or positive) for 21 countries, and even positive and significant in the rest of 10 countries. A strong collinearity between birth order and offspring (correlation of 0.90 for the entire sample, and even above 0.90 within each country) could be affecting this unexpected finding.[18] An excess of collinearity means that both variables are capturing almost the same aspect in the model, and the precision of their estimates are low, hence non-significances and changes of signs can be easily observed. An indicative of this collinearity is that the number of negative coefficients for "offspring" increases considerably when "birth order" is not included

[15] The average of all estimated coefficients for this variable is 0.00176: ten more centimeters of the mother is associated with 1.76 % more centimeters of the child (for our adjusted height measure). Using the average height level of the mother for the whole sample (159 cm.), and taking the average estimated coefficient of 0.00176, the elasticity between these variables evaluated at this average height of the mother, is equal to 0.279 (0.00176 $\times$159).

[16] On the one hand, older mothers are at a higher risk for preterm birth and health problems (such as high blood glucose) that negatively affect child's height. On the other hand, children of more mature mothers are advantaged nutritionally and educationally, which favors child's height. In most of the countries in our sample, the former effect seems to predominate over the latter.

[17] In addition, other studies such as Brenøe and Molitor (2017) or Pruckner et al. (2021) have found a positive relationship between child health and birth order.

[18] In our original estimates, birth order and offspring are measured as in the DHS database: as a discrete variable, taking values between 1 and 18 for birth order and between 0 and 12 for family size (the total number of siblings). Among other reasons, such a high positive correlation is because, in our sample, there are many families with several children, and therefore the birth order of a child under 5 years old is mechanically highly correlated with the number of siblings in the family.

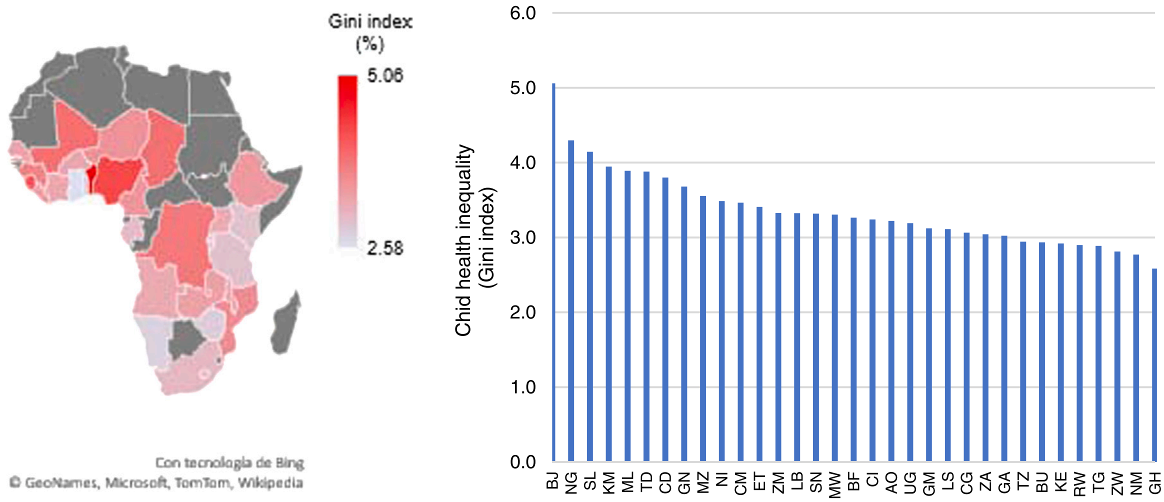

Fig. 2. Child health inequality in SSA (Gini, x100). Notes: Construct by the authors using data from the DHS databases (2009–2016). In the Map, dark grey means missing data. The acronym of each country is as follows: AO: Angola; BF: Burkina Faso; BJ: Benin; BU: Burundi; CD: Democratic Republic of the Congo; CG: Congo; CI: Cote d'Ivoire; CM: Cameroon; ET: Ethiopia; GA: Gabon; GH: Ghana; GM: Gambia; GN: Guinea; KE: Kenya; KM: Comoros; LB: Liberia; LS: Lesotho; ML: Mali; MW: Malawi; MZ: Mozambique; NG: Nigeria; NI: Niger; NM: Namibia; RW: Rwanda; SL: Sierra Leone; SN: Senegal; TD: Chad; TG: Togo; TZ: Tanzania; UG: Uganda; ZA: South Africa; ZM: Zambia; ZW: Zimbabwe. Child health inequality is the estimated inequality in our measure of child height adjusted by age and gender, $I(H_{ic})$.

in the model.[19]

In spite of that, and even when the women interviewed in the DHS are all women of reproductive age (15–45 years), and we are including the age of the mother, we must warn that our results can suffer from an incomplete fertility problem, which could affect our birth order and offspring estimates. Notice also that our estimates measure partial effects. Hence, given the wealth index, mother's education and occupation and all other factors included in the model, having more children may be correlated with a stronger preference for having children, which could explain a positive partial correlation between child height and offspring.[20]

For the fourth set of factors (home infrastructures), the variables included in this category are not individually significant with respect to their omitted category in most of the cases, although the estimated coefficients present the expected signs. For example, the estimated coefficient of "having an improved source of drinking water" (with respect to an "unimproved source of drinking water") is in general positive but only significant in Mali. In general, households with toilet facilities are positively correlated with child height, but its coefficient is positive and significant only in Burkina Faso, Cote d'Ivoire and Niger. Regarding cooking fuel, taking "solid cooking fuel" as the reference group, having non-solid cooking fuel is positive and significant in Congo, Guinea and Sierra Leone, but it is negative and significant in Burundi, Cote d'Ivoire, Gambia, Tanzania and Zambia. The small number of significant coefficients is due partially to the strong correlation between household facilities and the wealth index and other factors already included in the regression. For example, if we omit the wealth index and the regional dummies from the regression, the variables drinking water, toilet facilities and/or cooking fuel become significant (and with the expected sign) in a larger number of countries, such as Cameroon, Congo, Liberia, Mozambique, Niger, Nigeria and Rwanda, which reconcile our estimates with the general results of the existing literature (Fink et al., 2011; Duflo et al., 2015; Choudhuri and Desai, 2021).

Finally, regarding the fifth group of factors (geography), living in an urban area is rarely significant (taking a rural residence as the reference group), and is positively correlated with children's height in Congo, Comoros and South Africa, but negatively in Cameroon and Zambia. This difference in sign by country reflects the diversity of results in the related literature, which reports that urban children are generally in better health than their rural counterparts, but also that child health outcomes are worse in more economically active urban areas, probably as a consequence of poor child feeding practices (Smith et al., 2005; Van de Poel et al., 2007; Ameye and De Weerdt, 2020). Dummy regions are generally quite significant across countries, showing the existence of specific regional (within-country) fixed effects, which are related to geography (i.e., elevation, or being a coastal or inland region), the climate, local governments, conflicts or the risk of diseases such as malaria, which are relevant to explain child height differences within the same country.[21]

Using the estimates from (3), we calculate the smooth distribution of child height, $\widehat{H}_{ic}$. Figs. 3 and 4 show the inequality in child height explained by our set of factors and the resulting I-ratio. Measuring and understanding the explained part of inequality is relevant, since the implementation of policies that affect these observed factors can be

[19] We consider an alternative way to measure "birth order" (Jayachandran and Pande, 2017; Spears et al., 2022) to reduce this collinearity. We construct two dummies: "second", which takes value 1 if the child is the second at birth; and "third" if the child is the third or more at birth. By doing that, the correlation between "offspring" and the new version of "birth order" is significantly reduced. We have re-estimated our models and obtained a larger number of countries (6 countries) with a negative coefficient for offspring and some of them are now more significant. However, even in this case, we still have four countries showing a positive and significant coefficient for "offspring", once controlled by "birth order".

[20] Given the difficulty of dealing with incomplete fertility without a panel database, we consider the following alternative analysis: we look at a subset of parents (and their children) that declare "do not wanted any more children, are sterilized or declared infecund". Qualitatively, in terms of birth order and offspring, our results remain practically the same: birth order is negatively correlated with child height and significant in most of the cases, while the partial correlation between the number of offspring and child height is negative, not significant and even positive and significant, depending on the country analyzed. However, using this restricted sample means that we are reducing the original sample by approximately 75 %, and it is no longer representative of the original sample design.

[21] During the Green Revolution, Wise (2020) suggests that food production became more mono-cultural and that malnutrition amongst both children and parents increased as a result. Since this event affects more in some regions than in others, that could partially explain the importance of "geography" in child height in most countries.

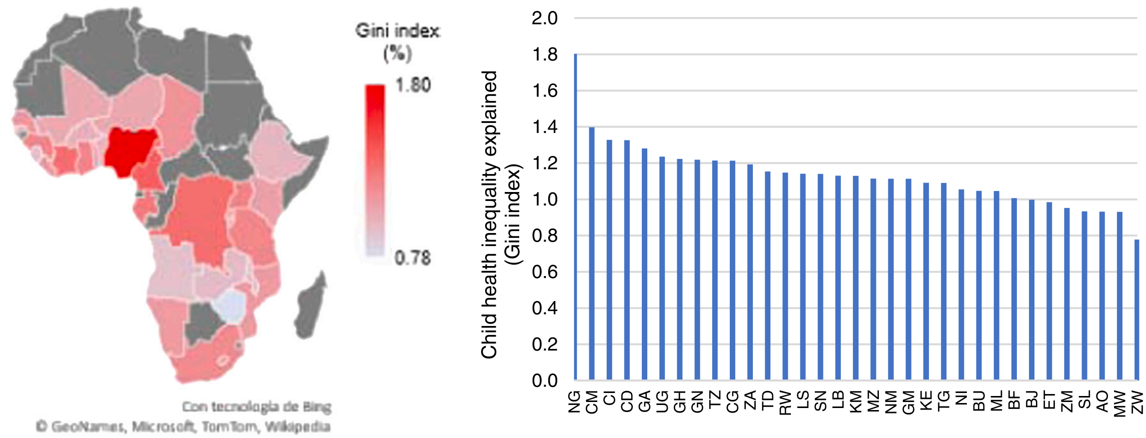

Fig. 3. Inequality of explained child health in SSA (Gini, x100). Notes: Construct by the authors using data from the DHS databases (2009–2016). In the Map, dark grey means missing data. See note in Fig. 2 for the meaning of the acronym for each country. The measure of inequality is the inequality (Gini index) in child height caused by differences in our set of factors, $I(\widehat{H}_{ic})$.

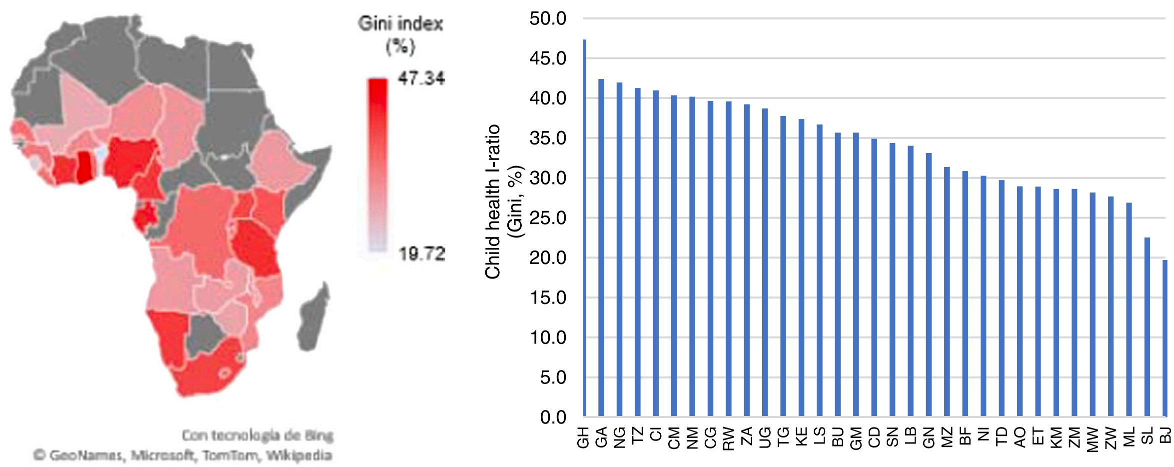

Fig. 4. Child health I-ratio in SSA (%). Notes: Construct by the authors using data from the DHS databases (2009–2016). In the Map, dark grey means missing data. See note in Fig. 2 for the meaning of the acronym for each country. Child health I-ratio is the share of the inequality of explained height over total height inequality, $I(\widehat{H}_{ic})/I(H_{ic})$.

effective in improving inequality in child height. The unexplained part of child height inequality may be associated with other unobserved factors, such as luck, genetics or unexpected shocks, as well as with problems measuring our set of factors.

Indeed, it is worth mentioning that we are measuring a lower bound of the explained inequality and the I-ratio. First, we are not including all potential variables related with each group of factors (i.e., family background, family structure, etc.). Second, in general, these variables are imperfectly measured (e.g., due to measurement error, biased reporting, etc.). Third, the set of variables considered may not be fully capturing the broader factor group (e.g., mother's occupation may be irrelevant in highly patriarchal societies). Therefore, improving in these three aspects would generally increase the explained inequality and the I-ratio. Also, since these aspects can vary between countries, this could affect the comparisons between countries.

Unlike for total inequality, in the explained inequality and the I-ratio, we do not find a clear geographical pattern. For example, we find countries in the south, the interior, and in the west and east coast with similar I-ratios. Regarding the ranking of the I-ratio, Ghana, Gabon, Nigeria, Tanzania and Cote d'Ivoire now show the highest shares of I-ratio (about 41%-47% of the Gini), while Malawi, Zimbabwe, Mali, Sierra Leone and Benin experience the lowest shares (about 20-28% of the Gini).

To end this sub-section, for our set of 33 countries, Table 4 compares the position of the three measures analyzed (total, explained inequality and the I-ratio). The table shows the division of our sample of countries according to its position (using key percentiles) in the ranking of these three measures. It classifies countries as low-inequality (below the 25th percentile, p25), mid-inequality (between the 25th and 75th percentiles) and high-inequality (above the 75th percentile, p75). Additionally, the countries in bold letters show an I-ratio above p75 (high I-ratio) and countries underlined are those with an I-ratio below p25 (low I-ratio); all other countries have an intermediate level of the I-ratio (between p25 and p75).

For example, Zimbabwe is below p25 both in total inequality and in explained inequality, while Democratic Republic of the Congo, Guinea and Nigeria are above p75 in both measures. Benin and Sierra Leone are above the p75 in total inequality but below p25 in explained inequality, and the contrary occurs with Ghana. Other countries, such as Mozambique, Senegal and South Africa, are in intermediate positions in both measures. We find that, in general, countries with the lowest (highest) levels of explained inequality present also the lowest (highest) levels of the I-ratio. We find some exceptions: Namibia, Tanzania and Congo, which show intermediate levels of explained inequality and are above p75 in the I-ratio; or Comoros and Mali, which also belong to the intermediate levels of explained inequality but present low levels of the

Table 4
Low, mid and high child health inequality, inequality of explained health and I-ratio in SSA.

	Low explained inequality (<p25)	*Mid explained inequality (p25-p75)*	*High explained inequality (>p75)*
Low total inequality (<p25)	Zimbabwe	Burundi, Kenya, **Namibia**, Rwanda, Togo, **Tanzania**	**Ghana**
Mid total inequality (p25-p75)	Angola, Burkina Faso, Ethiopia, Malawi, Zambia	**Congo**, Gambia, Lesotho, Liberia, Mozambique, Niger, Senegal, South Africa	**Cameroon, Cote d'Ivoire**, **Gabon**, Uganda
High total inequality (>p75)	Benin, Sierra Leone	Chad, Comoros, Mali	Democratic Republic of the Congo, Guinea, **Nigeria**

Notes: Construct by the authors using data from the DHS databases (2009–2016). In rows, child (total) health inequality; in columns, child health inequality explained by the set of factors. The notation (<p25) and (>p75) means to be below and above the 25th and 75th percentile in the ranking of the corresponding health inequality measure, respectively. Countries in underlined are those below p25 in child health I-ratio (low I-ratio), while countries in bold letter are those above p75 in this measure (high I-ratio). Child health inequality is the estimated inequality in our measure of child height adjusted by age and gender, $I(H_{ic})$. The explained inequality is the inequality (Gini index) in child height caused by differences in our set of factors, $I(\widehat{H}_{ic})$. Child health I-ratio is the share of the inequality of explained height over total height inequality, $I(\widehat{H}_{ic})/I(H_{ic})$.

I-ratio.

4.2. *Child health inequality along the age distribution*

As the DHS are not longitudinal, we cannot follow the health status of the children over time. However, their large sample size allows us to distinguish child health along the age distribution for each country (from 0 to 1 up to 4–5 years old). The evidence provided in this section is based on comparing different inequality measures over the child age distribution for each country. In all cases, we use child height adjusted for age and gender, as in Section 4.1.

For each country and age group, first, we estimate total child height inequality; second, we estimate Eq. (3) and then apply the Gini index to the resulting explained child height distribution. Results of these estimations show, in general, the expected signs, and the most significant factors are similar to the ones found for the overall sample.[22]

We start showing the changes of average height inequality (for total inequality, inequality of explained height and the I-ratio) along the age distribution. Fig. 5 shows these average values for each age group relative to the youngest age group (i.e., normalized to 1 for the 0–1 years old group): the average evolution is decreasing for total inequality, relatively flat for inequality of explained height and increasing for the I-ratio.

A more detailed analysis for these findings is provided in Fig. A1 (Appendix A), which shows child health inequality and the inequality of explained health over the age distribution for each country. As in Fig. 5, we normalize to one, the younger age group (the 0–1 age group), and show the I-ratio for each age group. One finding is common to almost all countries: total child health inequality shows a downward slope along the age distribution (the exception is Chad, where the slope is almost flat).[23] However, the results for explained inequality are mixed; the level is lower in the 4–5 years old group than in the 0–1-year-old group in 18 countries (55% of the sample), but higher in 15 countries (45% of the sample). In contrast, the I-ratio rose between the ages of 0–1 and 4–5 years in 27 countries (80% of the sample), and fell only in six countries.

Figs. 6, 7 and 8 summarize these results in a more compact way. For all countries, they compare each measure of inequality (total, explained and the I-ratio) for the younger age group (0–1 year, on the x-axis) and for the older group (4–5 years, on the y-axis). The downward trend in total child health inequality along the age distribution is well observed in Fig. 6: all countries are below the 45-degree line. Looking at Fig. 7, we can see the mixed results for explained inequality: almost half of the countries are below the 45-degree line, and the other half are above it. Finally, in Fig. 8, most countries are above the 45-degree line for the I-ratio. Therefore, in general, our set of factors is impeding a further reduction of child health inequality along the age distribution.

Our results, as they are generated with samples of children who are alive, could be affected by a mortality selection bias (Moradi and Baten, 2005; Victora et al., 2010). Since inequality is calculated with the set of living children, the exclusion of the dead (in general, unhealthier) children would narrow the health gaps between children and exert a downward pressure on our child health inequality estimates, and also on the impact of our set of factors on child height. Hence, in this case, correcting mortality bias would probably increase inequality, the explained inequality and even the I-ratio, although this latter result is less clear. However, this bias may underlie the reduction in child health inequality along the age distribution, as far as higher mortality rates in children with poor health during their first years of life will reduce subsequent inequality.

There is not an easy way to control for this potential bias in our sample, and a sophisticated analysis is beyond the scope of this paper.[24] Inspired by Moradi and Baten (2005) and Moradi (2010), we perform the following exercise (see Online Appendix I for details), and we conclude that mortality bias does not seem to be a great concern in our sample.

For the cross-country, we compare the proportion of children who died in each age group with the changes in health inequality and explained health inequality in later age groups (Fig. I.1 and I.2 in the Online Appendix I). That is, we compare child mortality in the 0–1 age

[22] The details of the estimation results for each child age and country are available upon request. For instance, we find that mother's education and the wealth index remain the most important variables within the family background group, and mother's job remains rarely significant. Regarding the mother's demography, mother's height is highly significant in almost all countries, while mother's age and mother's BMI are significant for a reduced number of countries and age group. A similar situation is detected for the number of offspring and the birth order in the family structure group; the multiple birth variable is the one with the highest significance. As for the home infrastructures group, they are significant for a reduced number of subsamples. Place of residence remains rarely significant, and something similar occurs with region dummies. Nevertheless, the significance and the magnitude of the coefficients may change with the age group.

[23] There is an extensive literature that analyzes the evolution of the health gradient along the age distribution, since changes in the health gradient are associated with changes in health inequality. The evidence found in this literature is mixed: while in some studies the observed gradient is greater for older children (Case et al., 2002; Fernald et al., 2012; Bommer et al., 2019), other studies find little or no evidence for this association (Currie and Stabile, 2003; Cameron and Williams, 2009; Devkota and Panda, 2016). These studies differ in the period of time, countries or group of countries analyzed, as well as in the health variable used. Note that we followed a different approach (Section 2) more along the lines of Pradhan et al. (2003) or Assaad et al. (2012), among others. Hence, our results could be different for that reason alone, and are consistent with the mixed evidence found.

[24] To properly test for this possibility, we need longitudinal information, that we do not have. Indeed, many papers in the literature warns about the potential existence of mortality selection bias in their sample, but they are not able to overcome this problem properly (see the discussion in Moradi and Baten, 2005, and Moradi, 2010, among others). See Ahn and Shariff (1995) or Lee et al. (1997) for alternative discussions on this issue.

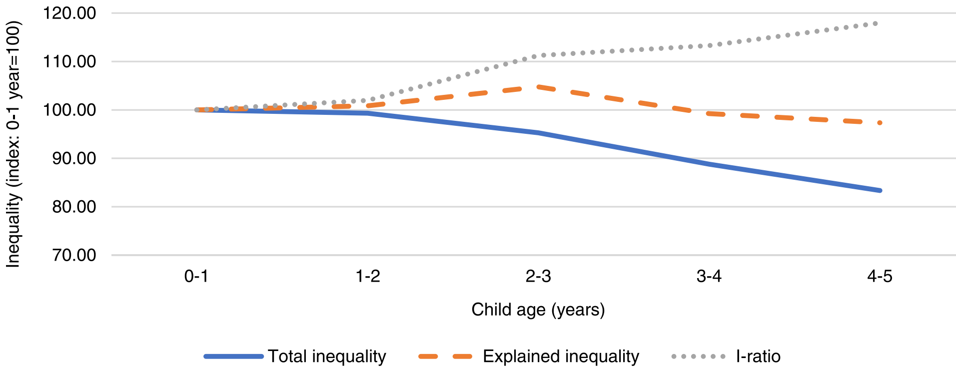

Fig. 5. Child health inequality, inequality of explained child health and I-ratio along the age distribution in SSA countries (Average values, Gini index) (Normalize = 100 at 0–1 years old). Note: Construct by the authors using data from the DHS databases (2009–2016). Child health inequality (total inequality) is the estimated inequality in our measure of child height adjusted by age and gender, $I(H_{ic})$, while child health inequality explained is the inequality in child height caused by differences in our set of factors, $I(\widehat{H}_{ic})$. Child health I-ratio is the share of the inequality of explained height over total height inequality, $I(\widehat{H}_{ic})/I(H_{ic})$. We normalize to 100 the values of the youngest age group (0–1 years old).

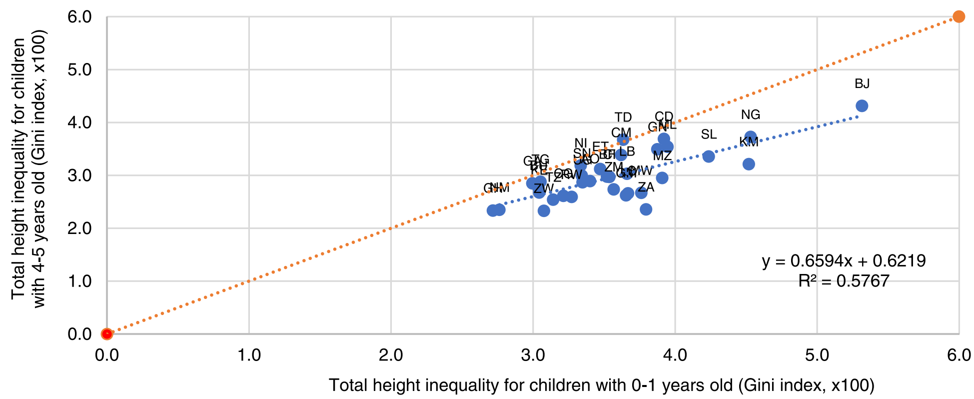

Fig. 6. Correlation between health inequality for children with 0–1 and 4–5 years old in SSA. Note: Construct by the authors using data from the DHS databases (2009–2016). See note in Fig. 2 for the meaning of the acronym for each country. Total height inequality is the estimated inequality in our measure of child height adjusted by age and gender, $I(H_{ic})$.

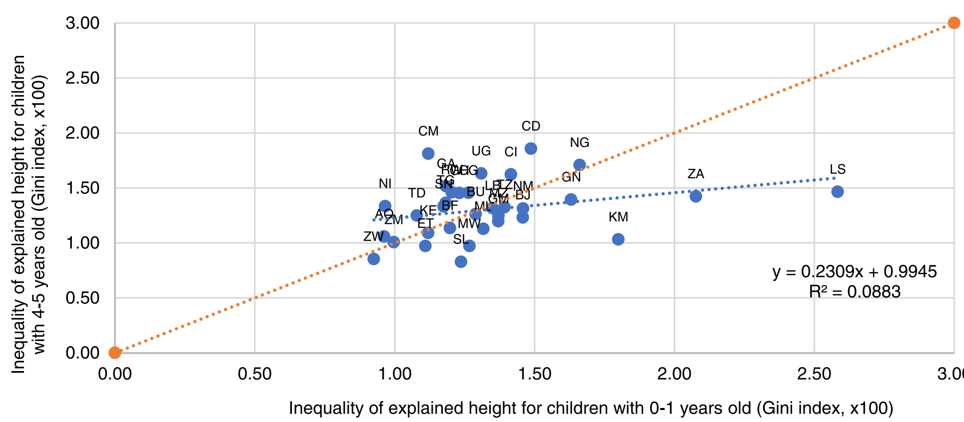

Fig. 7. Correlation between inequality of explained health for children with 0–1 and 4–5 years old in SSA. Note: Construct by the authors using data from the DHS databases (2009–2016). See note in Fig. 2 for the meaning of the acronym for each country. The inequality of explained height is the inequality in child height caused by differences in our set of factors, $I(\widehat{H}_{ic})$.

group with inequality in the 1–2 age group; mortality in the 1–2 age group with inequality in the 2–3 group, etc. We would expect a negative and significant correlation for almost all age groups if the mortality selection bias would be a serious concern. Thus, we interpret the absence of significant correlations in all age groups as an indication that our results are not strongly affected by a mortality selection bias. Instead, the reduction of height inequality along the age distribution must be due to improvements in the way that certain factors affect child health along the age distribution, or to general health improvements due to public health interventions or health technology discoveries across all SSA countries (Sen and Bonita, 2000; Jamison et al., 2013).

It is also worth mentioning the positive correlation of the two variables considered in Figs. 6, 7 and 8, although their intensities are different. According to Fig. 6, there is a strong inertia between height inequality in the younger (0–1 years old) and the older child age-cohort (4–5 years old). Hence, reducing inequality in the early years of life may have important consequences for later health inequality. This inertia is weaker for explained inequality (Fig. 7): the explained health inequality for five-year-old is less dependent on the explained inequality observed for one-year-old. That means that there exists room to intervene and

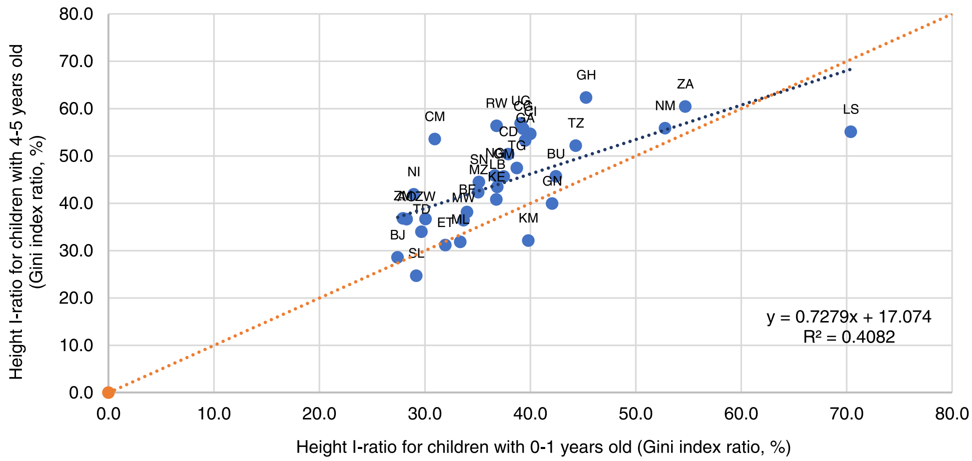

Fig. 8. Correlation between health inequality I-ratio for children with 0–1 and 4–5 years old in SSA. Note: Construct by the authors using data from the DHS databases (2009–2016). See note in Fig. 2 for the meaning of the acronym for each country. Height I-ratio is the share of the inequality (Gini index) of explained height over total height inequality, $I(\widehat{H}_{ic})/I(H_{ic})$.

reduce the health inequality explained by our set of factors during the first five years of life. As expected, the inertia for the I-ratio (Fig. 8) is between the rates observed for total and explained inequality.

To end this section, we classify countries according to common trends (along the child age distribution) in total inequality, explained inequality and the I-ratio. Table 5 summarizes these results. A first group (11 countries) is characterized by a reduction in total inequality, an increase in explained inequality and an implied large increase in the I-ratio along the age distribution (above 30%): Angola, Cameroon, Congo, Democratic Republic of the Congo, Cote d'Ivoire, Gabon, Ghana, Niger, Rwanda, Uganda and Zambia. A second group is composed by 16 countries, where total health inequality falls but explained inequality increases or decreases slightly and, in all cases, the I-ratio rises along the age distribution but less than in group 1. These countries are Benin, Burkina Faso, Burundi, Chad, Gambia, Kenya, Liberia, Malawi, Mozambique, Namibia, Nigeria, Togo, Senegal, South Africa, Tanzania, Togo and Zimbabwe. A third group, characterized by a greater reduction in explained inequality than in total inequality, so the I-ratio decreases, is formed by 4 countries: Ethiopia, Guinea, Mali and Sierra Leone.

Table 5
Trends in child health inequality, inequality of explained health and I-ratio for children with 0–1 and 4–5 years old in SSA.

	Explained inequality. (4–5) < < Explained inequality (0–1)	Explained inequality (4–5) < => Explained inequality (0–1)
I-ratio (4–5) < I-ratio (0–1)	Comoros and Lesotho. *(Large decrease of I-ratio)*	Ethiopia, Guinea, Mali and Sierra Leone. *(Moderate decrease of I-ratio)*
I-ratio (4–5) > I-ratio (0–1)	Benin, Burkina Faso, Burundi, Chad, Gambia, Kenya, Liberia, Malawi, Mozambique, Namibia, Nigeria, Senegal, South Africa, Tanzania, Togo and Zimbabwe *(Moderate increase of I-ratio)*	Angola, Cameroon, Congo, Democratic Republic of the Congo, Cote d'Ivoire, Gabon, Ghana, Niger, Rwanda, Uganda and Zambia *(Large increase of I-ratio)*

Note: Construct by the authors using data from the DHS databases (2009–2016). In rows, the evolution of the child health I-ratio; in columns, the evolution of child health inequality explained by the set of factors. Child health inequality is the estimated inequality in our measure of child height adjusted by age and gender, $I(H_{ic})$. The explained inequality is the inequality (Gini index) in child height caused by differences in our set of factors, $I(\widehat{H}_{ic})$. Child health I-ratio is the share of the inequality of explained height over total height inequality, $I(\widehat{H}_{ic})/I(H_{ic})$.

Finally, a fourth group composed by Comoros and Lesotho, where explained inequality falls much more than total health inequality, and hence it makes the I-ratio drops much more than in group 3 (a reduction greater than 20%).

Moreover, it is noteworthy that, between the eight countries above p75 of explained inequality in Table 4, six of them – Cameroon, Cote d'Ivoire, Democratic Republic of the Congo, Gabon, Ghana, Uganda – show a large increase in the I-ratio between the 0–1 and the 4–5 age groups.

In summary, we have shown that total child health inequality declines along the age distribution in almost all SSA countries. However, the child health I-ratio increases with age in most countries. These results indicate that, in most SSA countries, child health inequality explained by our set of factors increases in importance as children get older. Therefore, reducing inequality in child health inevitably involves levelling these sets of factors in early-life and/or reducing the impact that these factors have on child health through the implementation of compensatory policies.

5. Decomposing child health inequality

What are the most important factors that explain child height inequality in SSA? How does the importance of each set of factors change along the age distribution? We answer these questions in this section.

We use the Shapley approach to decompose the explained child health inequality attributed to each set of factors considered. More specifically, for our application, we follow Israeli (2007) and apply the

Shapley decomposition to the estimated R^2 from Eq. (3).[25] Decomposing the R^2 does not divert us from our goal, since the R^2 also represents an I-ratio (i.e., it is the ratio of the log-variance): the proportion of child height variability explained by our set of factors. Moreover, in our sample, the cross-country correlation between the R^2 and our estimated I-ratio is 0.986 (for the Gini index). The decomposition exercise includes all factors simultaneously. It calculates the partial contribution of each factor (or group of factors) to the generation of inequality in predicted child height. For each country, we perform this decomposition for the whole sample and for each age-cohort.

For children under five years old, Table 6 shows the decomposition for all countries. On average, we find that the "mother's demography" group is the most important. This group, on average, is responsible for 44% of the child health variability explained by all factors. "Family background", with an average relevance of 20.7%, and "geography", with an average share of 20.6%, are the second and third most relevant groups. Finally, "family structure" and "home infrastructures" are the least important groups, representing, on average, around 9% and 6% of the explained child health variability respectively.[26]

As we will show below, the results may change when we look at the set of factors explaining changes in inequality along the age distribution. In Section 6, we perform a robustness test of this decomposition to alternative grouping strategies, and show that the main results do not change. A closer inspection of the results reveals some important inter-country differences in the contribution of these factors. For example, the contribution of "mother's demography" is 78% in Zimbabwe, 42% in Mozambique and 20.6% in Benin. Regarding "family background", the percentage ranges from 8.2% in Zimbabwe to 30.3% in Rwanda, while it represents 15.6% and 24.8% in Liberia and Kenya, respectively. "Geography" is the most important factor in Benin (51.8%), Chad (45%), Comoros (38.8%) and Nigeria (42%), but it has very little influence in Malawi (1.4%). With respect to the "family structure" group, the maximum contribution is 20% in Malawi, while the minimum is 4% in Burundi. Finally, "home infrastructures" shows, in general, a contribution below 10% in 29 countries out of 33 (12.4% is the highest rate, in Cote d'Ivoire).

Next, we look at the Shapley decomposition in the different age groups. In general, for all age groups, the most relevant factors are the same than for the overall sample: first, "mother's demography", followed by "family background" and "geography", and finally "family structure" and "home infrastructures". We focus on the changes in their contributions along the age distribution, so we can connect them with the changes in child health inequality characterized in the previous section. Table 7 and Fig. 9 summarize these changes along the age distribution. Table 7 shows the contributions (the average levels) for each age-cohort and each set of factors. To emphasize the evolution along the age distribution, we normalize the contribution of all factors in the 0–1 age group to 100 in Fig. 9.

On average, the group of factors related to "family background" shows a clear upward trend along the age distribution, with an average share of 19.6% for the 0–1 group and 29.3% for the 4–5 age group (a change of 9.7 points). The "home infrastructures" group, in spite of showing one of the smallest percentages (on average) in Table 6, also presents an upward trend, although less pronounced than for "family background": it represents 5.8% for the 0–1 age group and 7.4% for the 4–5 group (a change of 1.6 points).

In contrast, the contributions of "geography" and "family structure" decrease along the child age distribution. For instance, the contribution of "family structure" falls from 15.5% for the 0–1 age group to 6.1% for the 4–5 group (a fall of 9.4 points), which basically compensates for the increase in "family background". Meanwhile, the contribution of "geography" falls from 24.4% for the 0–1 group to 22.8% for the 4–5 age group (a fall of 1.6 points), which compensates for the increase in the share of "home infrastructures". Finally, "mother's demography", which is the most important (recall Table 6), shows a stable trend: its relevance is almost constant, around 34.5%, along the entire age distribution of the children.

The previous analysis corresponds to an average overview of SSA countries. However, a closer inspection at the data identifies some relevant differences between countries. Figure II.1 (Online Appendix II) displays the set of graphs for this decomposition for each country. For instance, contrary to the average trend, the contribution of "family background" to explaining child health inequality falls in Chad, Namibia and Senegal; also, the importance of "mother's demography" rises in Burkina Faso, Lesotho and Rwanda, and falls in Gabon, Liberia and Uganda; "family structure" shows an upward trend along the age distribution in Burundi, Ethiopia and Gambia.

Do these differences in the changes along the age distribution of the factor's contributions correlate with the analogous changes observed in inequality of explained height? To provide insights into this question, Fig. 10(a-e) shows the cross-country correlation of two variables: the difference in the inequality of explained height between the 4–5 and the 0–1 age groups (y-axis), and the difference in the Shapley value between these age groups for each group of factors (x-axis). We find positive and highly significant cross-country correlations for three groups: "family background", "home infrastructures" and "geography". In contrast, the cross-country correlation is almost null for "family structure", while the correlation is positive but hardly significant for "mother's demography". Though not a causality analysis, this cross-country exercise provides insights to identify groups of factors that require intervention to correct health inequality as children grow. Nevertheless, in no case should the results be interpreted as policy recommendations.

6. Robustness analysis

We perform a set of robustness checks on our main results along five dimensions. First, we consider alternative inequality measures, such as the MLD or the variance of the log. Second, we allow an alternative functional form of Eqs. (1) and (3). Third, we detect and control for outliers in some relevant variables included in (3). Fourth, we consider alternative sub-samples. Fifth, we use different groups of explanatory factors in the decomposition exercise. Some tables and figures of these robustness analyzes are available in Online Appendix III-VII, and others are available upon request.

6.1. Alternative inequality measures

Although we can apply any inequality index to our measure of child height and explained height, we restrict our robustness analysis to some of the indices that satisfy Shorrocks's (1982) conditions, as mentioned in Section 2. This analysis may be relevant because different inequality

[25] The Shapley decomposition is computationally intensive, and its intensity increases exponentially with the number of factors included in the analysis: 2^K (K = number of factors) combinations must be considered. Moreover, this decomposition is even more intensive for the Gini (Wendelspiess Chávez Juárez and Soloaga, 2014). In fact, according to these authors, the computation of the Shapley decomposition is advisable with only a few factors (no more than 20). In our case, not considering the geography group, in which for some countries we have up to 26 regions, we have 23 possible individual factors. In addition, we apply this decomposition to 33 countries, for the overall sample and five age groups (198 times). For all these reasons, we apply the Shapley decomposition to the R^2, which is computationally much less intensive than the Gini and the MLD. Moreover, in our case, the R^2 of the log-linear regression (3) is strongly correlated with the estimated I-ratio for the Gini and for the MLD. Hence, our decomposition can be seen as a decomposition of any of the I-ratios estimated in Section 4.

[26] In general, the contribution of home infrastructures increases in almost all countries, even more than double in some of them (for example, in Cameroon, Congo or Nigeria) when the regional dummies and wealth variables are dropped from the Eq. (3). This result connects with our comment about home infrastructures group estimates in Section 4.1.

Table 6
Distribution of the factors' contribution explaining child health inequality in SSA (%): Shapley decomposition.

ISO code	Country / Factors	Family background	Mother's demography	Family structure	Home infrastructures	Geography
AO	Angola *	48.50	–	11.43	14.84	25.23
BF	Burkina Faso	16.61	46.14	6.92	9.17	21.15
BJ	Benin	19.46	20.61	5.08	3.07	51.79
BU	Burundi	28.92	49.66	4.00	1.04	16.39
CD	Democratic Republic of the Congo	21.80	38.59	6.79	4.05	28.77
CG	Congo	14.71	55.73	7.41	5.42	16.73
CI	Cote d'Ivoire	21.12	48.94	6.85	12.35	10.75
CM	Cameroon	26.85	33.60	5.99	11.30	22.26
ET	Ethiopia	15.65	48.53	16.30	2.02	17.49
GA	Gabon	18.55	53.49	5.66	6.56	15.74
GH	Ghana	16.57	51.79	9.79	6.76	15.09
GM	Gambia	26.51	47.84	6.54	0.95	18.17
GN	Guinea	18.74	40.45	14.99	4.19	21.64
KE	Kenya	24.77	49.11	8.62	6.92	10.57
KM	Comoros	23.78	27.26	4.73	5.38	38.85
LB	Liberia	15.64	60.95	13.92	3.10	6.39
LS	Lesotho	26.48	38.63	9.95	6.83	18.11
ML	Mali	24.17	37.26	8.63	9.69	20.26
MW	Malawi	12.39	63.39	20.07	2.74	1.41
MZ	Mozambique	18.15	42.31	9.11	7.70	22.73
NG	Nigeria	22.71	21.15	5.28	8.90	41.96
NI	Niger	8.90	45.89	15.85	7.68	21.68
NM	Namibia	24.12	42.41	7.59	11.20	14.68
RW	Rwanda	30.34	46.47	6.99	1.15	15.05
SL	Sierra Leone	18.19	45.55	6.35	1.52	28.39
SN	Senegal	22.85	41.63	8.25	9.03	18.24
TD	Chad	16.94	29.96	4.46	3.54	45.10
TG	Togo	25.28	44.02	8.06	9.09	13.56
TZ	Tanzania	13.14	48.00	7.04	10.03	21.80
UG	Uganda	21.21	48.70	8.87	0.26	20.96
ZA	South Africa	18.01	41.26	10.83	7.27	22.63
ZM	Zambia	13.99	58.10	7.45	8.66	11.80
ZW	Zimbabwe	8.19	77.92	7.69	1.58	4.62

Notes: Construct by the authors using data from the DHS databases (2009–2016). In rows, our sample of countries; in columns, the groups of factors explaining child health inequality. Family background: mother's education, wealth index, mother's occupation. Mother's demography: mother's height, mother's body mass index, mother's age. Family structure: offspring, birth order, type of childbirth. Home infrastructures: source of drinking water, type of toilet facilities, type of cooking fuel. Geography: region of residence and place (urban or rural) of residence. Each row adds up 100.

* Angola does not contain information about "mother's demography". Hence, we show their results just for illustrative purposes, as far as their results are not comparable with other countries.

Table 7
Average contribution of each set of factors to inequality of explained height along the age distribution in SSA (%).

	All sample	0–1	1–2	2–3	3–4	4–5
Family background	20.70	19.59	24.08	23.48	27.78	29.32
	(7.40)	(8.91)	(8.76)	(7.46)	(9.40)	(8.91)
Mother's demography	43.80	34.64	36.20 (13.71)	37.74	34.30	34.38
	(13.92)	(13.05)		(15.36)	(13.45)	(10.94)
Family structure	8.71	15.56	10.64	8.35	7.95	6.12
	(3.75)	(8.22)	(5.29)	(4.72)	(5.58)	(3.27)
Home infrastructures	6.18	5.80	6.19	7.87	7.45	7.35
	(3.79)	(3.97)	(4.51)	(5.09)	(4.54)	(4.09)
Geography	20.61	24.40	22.90 (11.44)	22.56	22.53	22.83
	(10.98)	(9.96)		(11.47)	(10.12)	(8.66)

Notes: Construct by the authors using data from the DHS databases (2009–2016). In rows, the groups of factors explaining child health inequality; in columns, the age-cohort group. For each country, we use the Shapley decomposition approach to estimate the contribution of each set of factors. We show the average values for the 33 countries (standard deviations in parenthesis). The factors included in each group are described in Table 2.

measures are more sensitive in some parts of the distribution than in others. For example, the MLD and the variance of the logarithm are more sensitive to changes in the lower tail of the distribution, while the Gini index is less sensitive to these extremes and focuses more on the dispersion around the mean. More specifically, we replicate all results for the MLD and the variance of the logarithm. Results are available in Online Appendix III for the MLD and upon request for the variance of the logarithm. The differences with respect to the Gini index are in the estimated levels and the resulting I-ratio, as expected, but the trends and qualitative results are robust to the inequality measure used.[27]

6.2. *Linear functional form in Eqs. (1) and (3)*

In the income and wealth inequality literature, the most common

[27] For example, the average I-ratio is 34.3 % for the Gini index, 11.9 % for the MLD and 11.73 % for the variance of the logarithm.

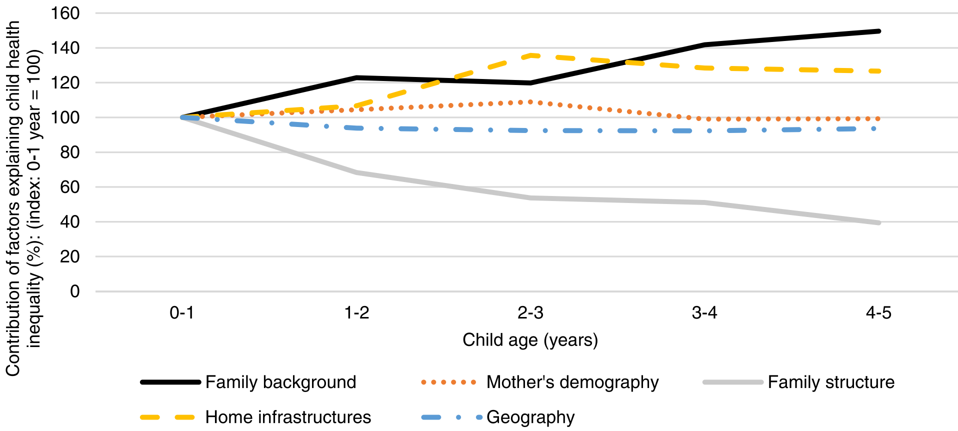

Fig. 9. Average contribution of each set of factors to inequality of explained height along the age distribution in SSA (Index = 100 at 0–1 years old). Note: Construct by the authors using data from the DHS databases (2009–2016). For each country, we use the Shapley decomposition approach to estimate the contribution of each set of factors. See Table 2 for the factors included in each group. We normalize to 100 the values of the youngest age group (0–1-year-old) from the sample mean of the 33 countries.

strategy is to take logs to the left-hand side variable in Eqs. (1) and (3). While the level of income or wealth does not follow a normal distribution, their log-transformations do, and this is the main reason for using this transformation. Another reason for using logs is to improve the interpretation of the estimated coefficients: they are quasi-elasticities or elasticities if the associated explanatory factor is also in logs. However, in our case, the height measure (whether or not adjusted for age and gender) is not log-normally distributed. Hence, it is not clear which specification is the best. To check this situation, we replicate all results but using the level of $\widetilde{H}$ in (1) and the level of H in (3). Table IV.1 in the Online Appendix IV shows the estimated results for $I(H_{ic})$, $I(\widehat{H}_{ic})$ and the I-ratio for the overall sample and the youngest (0–1 years) and oldest (4–5 years) groups of children. We show that the main results in terms of estimated levels and trends in all our inequality measures are very similar to those obtained for the log-specification. The Shapley decomposition results are also unchanged (results are available upon request).

6.3. Presence of outliers

Certain influence variables in our sample show some anomalous observations, which can affect the inequality estimates of the Shapley decomposition. For example, we find that some HAZ observations are extremely anomalous for SSA, for instance below -5 or above +5. Also, among the explanatory variables, maternal height and BMI contain several highly anomalous observations. For example, 0.2% of the mothers are abnormally short (below 130 cm.) and 0.1% are abnormally tall (above 187 cm.); also, 0.5% of the mothers have a BMI above 39 or below 14. These are the three variables presenting more outliers in our sample. In the robustness analysis, we apply a conservative rule and remove (for each country) the observations below -5 and above +5 HAZ, and the smallest 2% observations and the largest 2% of mother's height and mother's BMI. Then, we re-estimate the different inequality measures for the overall sample and along the age distribution, and the Shapley decomposition. The main results are the same for all countries. Tables V.1-V.3 in the Online Appendix V show the results for inequality (results for the Shapley decomposition are available upon request).

6.4. Restricting the sample: dealing with age misreporting and families with multiple children of the same age

One concern with household surveys in developing countries is that reported age in months is often misleading, particularly in the absence of birth certificates and in places where women tend to have many children (Romero Prieto et al., 2021). Whenever this misreporting follows a random walk process, the situation generates less efficient estimations. However, if the misreporting correlates with child height or with the explanatory variables, this may introduce bias in the estimates of inequality, explained inequality and the Shapley decomposition. To address this issue, we conduct two robustness analyses. First, we restrict the sample to children who have birth certificate. Second, we restrict the sample to families with three children or fewer. In both cases, we re-estimate the models for these restricted samples, and compare the results.

Birth certificate information is scarce in many countries, and we just present an illustration for Cote d'Ivoire and Togo (Table VI.1 in Online Appendix VI). For the second restricted sample, we present inequality estimation results for all countries (Table VI.2 in Online Appendix VI).

In general, for these sub-samples, we find that total inequality is smaller, explained inequality is larger, and therefore the I-ratio tends to be higher. Nevertheless, the trends in total inequality by age-cohorts, explained inequality and I-ratio are similar to those in the unrestricted sample. Besides, most factors lose significance except those for mother's education, wealth index and mother's height. The trends over the age distribution of the Shapley decomposition are similar in both sub-samples, but the contribution of "family background" rises, and that of the "family structure" group falls.

We perform a final robustness analysis. We have families with multiple children below 5 years in our sample, and some of them are siblings with the same age in years (i.e., siblings born from multiple births or with the same age in years at the date of the interview). This situation could affect our results because several children share the same mother within the same age range, and we should control for that. We handle this situation by restricting the sample to mothers with only one child in each age range. Table VI.3 (Online Appendix VI) shows main results for this sub-sample: smaller estimates for total inequality, explained inequality and the I-ratio, but the trends along the age distribution each inequality measure are similar to those under the unrestricted sample.

A final caveat is that the use of these restricted samples may introduce a representativeness problem: the new restricted samples are not representative of the population of each country, and therefore the sample design used in our estimates is incorrect. For example, for the case of children who have birth certificate, or families with three children or fewer, the restricted samples are biased towards wealthier families with more educated mothers, that tend to have birth certificates or have fewer offspring in our sample (Bhatia et al., 2017; Jeong et al., 2018).[28] Thus, in general, the results obtained from any sub-sample must be taken with caution and the comparison between the different samples can be misleading.

[28] For instance, while almost all mothers in Togo with higher education or belonging to the richest quintile of the wealth index have birth certificates for their children, only 60 % of mothers with no education or belonging to the poorest quintile have the birth certificate of their children.

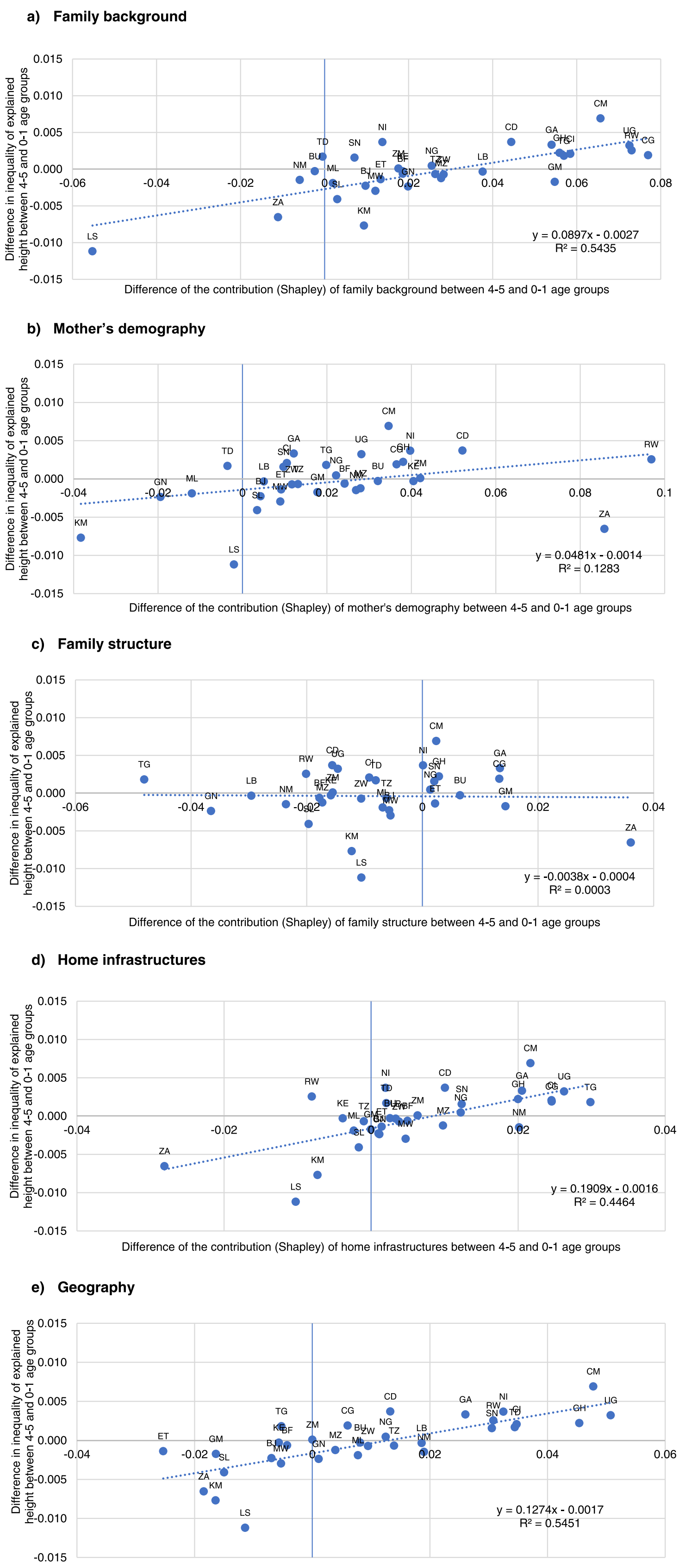

Fig. 10. (a-e). Correlation between changes in the Shapley values of each set of factors and changes in explained child health inequality between 0 and 1 and 4–5 years in SSA. Note: Construct by the authors using data from the DHS databases (2009–2016). In the y-axis we consider the difference between the estimated Gini of the explained height for the 4–5 years old group and the 0–1 years old group. Thus, it captures the changes in the inequality of the child height explained by all factors along the age distribution for each country. The x-axis shows the Shapley difference between these two age groups for each group of factors considered. It captures how the importance of each factor has changed along the age distribution for each country.

6.5. Alternative groups of explanatory factors

Our grouping strategy in Section 5 attempted to capture different socioeconomic aspects (family background, genetic factors, household and/or regional environment), inspired by the classifications used in Assaad et al. (2012), Kraft (2015) and Aizawa (2019). However, although our inequality estimations are not sensitive to this grouping strategy, the Shapley decomposition may be. The Shapley approach is sensitive to the number of factors included and, in our case, to the grouping strategy, since the decomposition approach is not independent of the aggregation level of the factors (Sastre and Trannoy, 2002). We check whether our main results are robust to this grouping strategy.

We proceed as follows. First, as in Assaad et al. (2012) and Kraft (2015), we differentiate between mother's education, the wealth index, and mother's occupation. Thus, we split our baseline "family background" group into its component parts. Second, we come closer to the groups proposed by Aizawa (2019), which merge our "mother's demography" and "family structure" groups and keep separate the factors included in our baseline "family background" group. Finally, we propose a third division that has not been applied in any previous work. We remove two of the most important variables in our baseline analysis: mother's height and mother's BMI. In developing countries, these two variables can be indicators of high-income households. By removing these two variables from the analysis, we obtain a clearer picture of the importance of all other socioeconomic factors in the model. Some results are summarized in the Online Appendix VII.

Regarding the first grouping alternative, the "mother's demography" group continues to be the most important, with shares similar to those of the baseline grouping strategy. Among the three factors included in the "family background" group, the wealth index is the most important (with an average of 11.6% for all countries), followed by mother's education (average of 7.8%) and mother's occupation (average of 4.5%). The sum of the contributions of these three factors is now higher than the contribution obtained for the "family background" group in the baseline specification. The "geography" and the "home infrastructures" groups lose importance, while "family structure" continues to present similar shares. More importantly, the main conclusions regarding the trends along the age distribution remain unchanged: factors related with "family background" increase their importance along the age distribution, especially the wealth index and the education of the mother; an upward trend along the age distribution is also observed for "home infrastructures", while a downward trend is still observed for "geography" and "family structure", and "mother's demography" factors show a flattened trend. For the second grouping strategy, the results are similar to those in the first case. The only difference is, as expected, that the merged group increases its contribution with respect to the previous "mother's demography" group, but the trends along the age distribution remain almost unchanged.

Finally, after removing mother's height and mother's BMI, the expected result is that all the remaining groups of factors increase their contributions. But the gains are not symmetrical: the group with the largest gains is "family background" (15.9 more percentage points), followed by "geography" (12.2 more points), "family structure" (5.6 more percentage points) and finally "home infrastructures" (only 4.2 more points). More importantly, the trends along the age distribution are similar for each group.

7. Conclusions

Since health inequality begins at birth, correcting it during childhood is crucial to improve future opportunities for development and to combat other forms of inequality during adulthood. This paper contributes to the understanding of child health inequalities and their determinants in Sub-Saharan African (SSA) countries, one of the poorest regions in the world (and the second most unequal).

Child height (standardized, and adjusted for age and gender) is the anthropometric measure we use to proxy child health. We collected data from the Demographic and Health Surveys (DHS), covering a total of 33 SSA countries between 2009 and 2016. The set of determinants considered are the following: family background (mother's education, mother's occupation and household wealth); mother's demography (her height, BMI and age); the structure of the family (offspring, birth order and type of birth); home infrastructures (type of drinking water, toilet facilities and cooking fuel used at home); and geographical aspects (region of residence and whether the household lives in urban or rural areas).

First, we analyze whether the initial levels of health inequality (children below 1 year old) are corrected with age (up to 5 years old) or whether, on the contrary, health differences are maintained or even accentuated. Second, we characterize the socioeconomic, demographic and geographical determinants of child height and estimate the inequality of the explained height using these factors. Finally, we use a Shapley decomposition approach to characterize the factors causing the changes in child health inequality along the age distribution.

Our results show that, both for the overall sample and for each age group, mother's education, household wealth, mother's height, type of birth (single or multiple) and the region of residence are the most important factors correlated with child height. For example, compared with mothers without education, those with secondary or tertiary education are, respectively, about 0.7% and 1.9% taller. Or, taking average estimates, maternal height differences of 10% are translated to differences in the (adjusted) height of their children of about 2.8%. Using the entire set of determinants, we explain between 40% and 45% of child heath inequality in countries such as Ghana, Gabon, Nigeria, Tanzania and Cote d'Ivoire, and between 20% and 25% in Benin, Sierra Leone and Mali. These percentages are lower bounds, as far as we are not including all potential variables related with each group of factors and factors are probably imperfectly measured.

Our results can be used to classify countries according to their health inequality levels. For example, Democratic Republic of the Congo, Guinea and Nigeria show high levels of health inequality and also high levels of health inequality explained by the selected set of factors. Only Zimbabwe shows low levels of both inequality measures; Ghana shows low levels of child health inequality but high levels of inequality explained by our group of factors, while Benin and Sierra Leone show high total inequality and low explained health inequality.

We find that child health inequality decreases along the age distribution in all countries, with the exception of Chad. In contrast, the importance of our set of factors (i.e., the ratio between the inequality of explained height and total height inequality, referred to as the I-ratio) increases along the age distribution in 80% of countries. Thus, in general, the set of factors considered seems to be preventing a greater reduction of child health inequality in SSA.

On average and for all age groups, we find that, in general, "mother's demography" factors are the most important for explaining child health inequality in SSA, followed by "family background" and "geography". "Family structure" and "home infrastructures" are the least important sets of factors. However, the contribution of these aspects may change along the age distribution, and these changes are not uniform across countries. For instance, on average, the contributions of "family background" and "home infrastructures" show an upward trend along the age distribution, while the contribution of "geography" and "family structure" decreases; "mother's demography" factors present a flat trend.

Finally, in a cross-country analysis, we find that differences in child health inequality between the 0–1 and 4–5 age groups are positively correlated with the differences in the contributions of "family background", "home infrastructures" and "geography" factors; in contrast, "mother's demography" factors and "family structure" do not significantly correlate with differences in child health inequality.

Among all the factors analysed, education is the one that does most to change a disadvantageous initial health situation. This finding is consistent with the related literature concluding that improving and equalizing mother's education is one of the most important factors for correcting child health inequality during childhood (Smith and Haddad, 2000, 2002; Harttgen, Klasen and Vollmer, 2013; Headey, 2013). Overall, our results are consistent with the idea that reducing child health inequality will inevitably require leveling out the socioeconomic, cultural, and environmental factors that affect early-life (Smith and Haddad, 2000; UNICEF, 2012).

CRediT authorship contribution statement

David Pérez-Mesa: Term, Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Gustavo A. Marrero**: Term, Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Sara Darias-Curvo:** Term, Conceptualization, Validation, Investigation, Resources, Writing – original draft, Visualization, Funding acquisition.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ehb.2022.101176.

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