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Drivers of changes in child nutritional conditions: A panel data-based study on Indonesian households, 1997–2014

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Abstract

Using panel data from Indonesia, this paper analyzes short and long-term drivers of nutritional conditions among children aged 0–15 years. I estimate a Mundlak model in order to better account for the relatively larger "between" variation that is found in the data, and to control for endogeneity biases that may arise due to the correlation of unobserved heterogeneity and observed explanatory variables. As results suggest, children with older, more experienced mothers, and those breastfed, exhibit improved height outcomes, aligning with existing research on breastfeeding's positive health effects. While prior research emphasized the importance of maternal education, this study reveals that, once accounting for father's education, the long-term effect of the mother's education loses statistical significance. Finally, the findings of this study suggest that household wealth and access to adequate sanitation facilities strongly affect short -and long-run improvements in children anthropometric outcomes.

KEYWORDS

child nutrition, Indonesia, Mundlak, panel data, short and long run effects

JEL CLASSIFICATION

J13, O12, O53

1 | INTRODUCTION

It is well documented that malnutrition is damaging to child development, with negative repercussions on a number of human development dimensions at current and later stages of a child's life (Alderman et al., 2001; Glewwe et al., 2001; Grossman, 2006).

Inspired by the pioneering article by Caldwell (1979), previous empirical research has extensively argued that one of the most important factors that can contribute to improving a child's health or nutritional status is maternal education. Better educated mothers are indeed supposed to be more capable of earning money and might also be better at processing information and acquiring skills to take care of the children (Cleland and van Ginneken, 1988; Defo, 1997). Alternatively, income alone may play an independent role in enhancing child's health as having more resources available to a household should translate into higher expenditures on food and health. Moreover, lack of access to material resources and meager living conditions may actually represent the most important obstacle to being adequately nourished and healthy (see, inter alia, Esrey et al., 1991; Rutstein, 2000; Wang, 2003).

Nonetheless, the mechanisms lying behind the relationship that links child health, mother's education, and household wealth still remains an important field of research as up until present day; there seems to be no clear consensus on the transmission channels that lead to long-lasting improvements in children health conditions. This is especially true for the Indonesian context. Over the past three decades, this country has made remarkable progress in terms of both economic growth and poverty reduction. Moreover, the Indonesian education system has benefited from massive supply-side interventions, such as the INPRES program, that have led a to large increase in the education of both men and women, leading to higher incomes, older age at marriage, and lower premature births (Breierova & Duflo, 2004). Significant progress has also been made in reducing child mortality rates. In the early 2000s, the ratio was approximately 52 per thousand live births, which has since dropped to around 22 per thousand live births in 2021. However, despite these advancements, there has not been significant improvement regarding children's nutritional conditions as Indonesia continues to face alarming rates of stunting. According to estimates provided by UNICEF-WHO, although the prevalence of stunting among children under five has shown a modest improvement of about 9.4% over the past two decades, as of 2022, approximately one-third (31%) of children under five are still affected by stunted growth.

This paper presents an empirical analysis that aims to document and explain changes observed in the nutritional status of children aged 0–15 between 1997 and 2014. The analysis utilizes a comprehensive panel of survey data, which represents over 80% of the Indonesian population. The dataset consists of individual, family, and community-level information for a sample size of 4870 children who were followed for at least 3 years up to 10 years.

In order to better account for the relatively larger "between" variation that is found in the data, and to address most relevant concerns on endogeneity bias streaming from household-level unobserved heterogeneity, I employ the Mundlak's (1978) approach, also called pseudo fixed effects estimator.

This approach has gained popularity in both health and non-health research contexts, particularly in situations involving short panels with limited time variation of explanatory variables within observation units. Traditional fixed effects estimators are not ideal for these cases as they tend to generate biased estimates toward zero and do not capture the impact of time-invariant factors.

Specifically, the Mundlak model employs a random-effect estimator and incorporates each explanatory variable twice: once in its original form and once as its average value over time. This approach relaxes the unrealistic assumption of zero correlation between observed and unobserved variables in the random effects model. It considers this potential correlation by assuming that any correlation between the time-constant variation in explanatory variables and the error term must be captured by their respective time-averaged values for each individual (or household).

The contribution of this paper to the broader literature on the determinants of child health is threefold. First, it relies on longitudinal data to document and explain changes over time and across households in nutrition conditions of children observed over a long time span. The vast majority of published studies on this issue has solely relied on cross-sectional data - which although being useful in providing information on the total effect of parental and household level variables-arguably does not inform us on the role that these variables have on the evolution of child nutritional conditions over time. The use of panel data, on the other hand, offers a great advantage over cross-sectional datasets, since it allows to analyze the intertemporal connections between the variables of interest and to answer, therefore, the question of what drives the improvements in child health over time.

Moreover, the use of panel data, which is rare especially in developing countries contexts, has distinct advantages over cross-sectional data, as by exploiting information on both the intertemporal dynamics and the individuality of the entities, it allows to control more effectively for unobserved heterogeneity (Hsiao, 2010).

Second, as I argue, the determinants of child health operate in a dynamic framework involving substantial time lags, an idea that has not always being captured in the literature. The impact on child height of parents' education or household wealth, for instance, may take a long time to manifest itself. Yet, it is not a priori clear, whether other variables such as mother's health conditions or access to improved sanitation facilities and to safe water can be temporary or persistent. To address this, I employ the permanent-transitory decomposition of the impact of key determinants of child nutrition. This interpretation of the within and between estimates in the Mundlak model has been utilized in various studies using panel data to examine aid (Martínez-Zarzoso et al., 2014), trade (Egger & Url, 2006), subjective well-being (van Praag et al., 2003) and mortality (Bender et al., 2013; Bender & Theodossiou, 2015).

In relation to my research, the between-coefficients estimated through the Mundlak model capture overall trends and persistent disparities between households, while the within-estimates reveal individual responses to temporal changes in independent variables. The distinction used in interpreting these coefficients represents a significant contribution compared to previous literature on child health as it allows us to identify both transitory and long-lasting drivers of child nutrition outcomes.

Finally, this analysis expands our current understanding of the interplay between child nutrition and key policy amenable factors, such as access to sanitation and safe water, in the Indonesian context—a country still grappling with relatively high rates of child stunting.

In 2011, Indonesia became part of the global Scaling Up Nutrition (SUN) Movement, aiming to mobilize efforts across various sectors to reduce stunting and other forms of undernutrition. In 2018, the government launched Indonesia's National Strategy to Accelerate Stunting Prevention, also known as StratNas stunting. Both initiatives acknowledge and stress the necessity of a multisectoral approach. However, there is a lack of information on the determinants of stunting in Indonesia to guide the development of multi-sector programs, and the implementation of a comprehensive multisectoral response is yet to be realized.

Most of previous studies focusing on this country context has shown- in a cross-sectional data framework-significant correlations between water, sanitation, and hygiene (WASH) and child stunting or the risk of diarrhea (e.g., Komarulzaman et al., 2017; Torlesse et al., 2016). Only a couple of studies published more recently, has relied on longitudinal data (Cameron et al., 2021) or on experimental evidence (Cameron et al., 2019) to provide more robust findings. This research has shown that water and sanitation exposures early in life significantly affect cognitive achievement in later childhood and adolescence (Cameron et al., 2021). Yet, Cameron et al., 2019 find that a sanitation promotion intervention in rural Indonesia had no impact on anthropometric outcomes on children aged 0–5 years.

The remainder of this paper proceeds as follows: the next section provides the literature background on the determinants of child nutritional status, from both theoretical and empirical perspectives. Section 3 lays out the empirical model used. Section 4 describes the data and outlines the main trends in child nutritional status and its determinants and Section 5 presents the empirical findings. Section 6 concludes.

2 | THE STATE OF THE ART OF THE RELEVANT LITERATURE

Throughout the course of the last 30 years, a variety of articles in the fields of development economics, development studies, and health economics have tried to understand from different perspectives what the determinants of child malnutrition in low-income countries are.

The main theoretical frameworks of reference are the one set out in Schultz (1984), Behrman and Deolalikar (1988), and Thomas and Strauss (1992). In these models, a child health production function is typically set as one set of constraints in a process of parental utility maximization where child health is one of the arguments of the parent's preferences function.[1] According to these models, household's wealth or income mainly contributes to enhancing child health outcomes via raising expenditures on food and health goods. Parental education, on the other hand, exerts an indirect positive role on child health through its effect on household income as well as through better skills and knowledge on child caring practices that directly translate into better child health outcomes. It is of crucial importance to note that household and individual characteristics not only interact with each other but also with external factors, such as those linked to social norms, and traditions, which can directly influence parental decisions regarding, for example, nutrition choices and health practices for their offspring. On the other hand, the effect of some crucial community-level variables such as the availability of vaccines and the presence of a health facility can interact positively or negatively with household and individual-level characteristics such as the willingness to use and the ability to pay for health services.[2]

While estimation techniques of these child health models are discussed in detail in Thomas et al. (1990), Barrera (1990) and several others, in what follows I will identify key similarities and differences in the approaches followed in the empirical literature of reference.

Usually, the dependent variable of interest is the child standardized height (measured by the height for age z-scores). This variable has been sometimes used as a proxy of child health. According to the World Health Organization, indeed, the height for age measures the nutritional status of the child to the extent that it defines whether child growth reflects a "process of failure to reach linear growth potential as a result of suboptimal health and/or nutritional conditions" (De Onis et al., 1997 p.46).

Depending on the nature and on the availability of data, the methodologies to unravel the empirical dynamics underlying the health production function have been varying quite extensively.

In several studies, scholars estimate *conditional health demand functions*, that is, a regression model that, by definition, includes variables on income or expenditure and on price levels but not on the health inputs though which the effect of the socio-economic variables is transmitted. The recent empirical literature on child health in Indonesia has largely relied on this approach.[3] Alternatively, a smaller branch of the literature has relied on the estimation of *static health production functions* (e.g., Barrera, 1990) where health inputs are included. There is, moreover, a third strand of the empirical literature that has attempted to include both socio-economic and proximate determinants in the estimation strategy. This "pathways" approach appears to be more complete since it provides an empirical assessment of all the direct and indirect linkages between child health and its drivers. Here again, the estimation strategies have been quite diverse, running from cross-countries analyses based on Demographic and Health Survey data (Harttgen et al., 2013; Sommerfelt & Stewart, 1994) to graphical chain models (i.e., Caputo et al., 2003; Foraita et al., 2008) where the focus has been explicitly given to the dependence chain of the immediate, intermediate and underlying factors affecting undernutrition.

Several case studies have used instrumental variables (IV) estimation strategies and quasi-experimental designs to link parental education and child nutritional outcomes (Ali & Elsayed, 2018; Chou et al., 2010; Djemai et al., 2023; Glewwe, 1999; Güneş, 2015). The rationale behind the use of IV lies in the endogeneity of the relationship between child health and parental education. It is, indeed, reasonable to assume that unobservable factors such as parental preferences, values, and characteristics can influence both the level of education they choose to pursue and their children's health (Chou et al., 2010). Namely, certain unobservable parental traits, such as greater motivation or ability, are key drivers of their educational choices and the investments they make toward ensuring the well-being of their children. Parental time preferences play also a significant role: as argued in Fuchs (1982), individuals who have a higher orientation toward the future tend to stay in school longer, invest more in their own health, and prioritize their children's well-being. If these assumptions hold true, then the coefficient on variables such as mother's or father's education in the health equation, rather than representing the causal effect of these variables, might indicate the correlation between these unobserved parental characteristics and both their educational attainment and child health.

While the IV approach addresses this source of endogeneity, finding truly exogenous sources of variation in parental schooling is challenging. Therefore, in the absence of a reliable and valid instrument for parental education, a few studies (e.g., Aslam & Kingdon, 2012; Burchi, 2010) have included all relevant variables such as parental labor force participation, household income, parental health knowledge, exposure to media, and autonomy within the household, which can serve as proxies for the parent's unobserved traits and pathways through which their schooling may influence child health outcomes.

Whether all these studies have undoubtedly contributed to a better understanding of the determinants of child nutritional conditions in developing countries, they face two major challenges, namely in accounting for heterogeneity and potential endogeneity.

First, the vast majority of published studies in this field have solely relied on cross-sectional data and thus has not been able to follow over time the child's growth process and to examine the time-varying effects of the explanatory variables. In other words, whether much is known about the total effect of key variables on the stock of child nutritional status at a particular point in time, relatively less attention has been put so far on the dynamics and improvements in the variable of interest. Second, in practice data availability constraints and measurement problems do not allow for a complete inclusion of all the possible determinants of child health (Lay & Robilliard, 2009). Even in cases where most of the proximate determinants are controlled for, the validity of the results may be questioned (Aslam & Kingdon, 2012). This is basically because of endogeneity issues which only a relatively small numbers of studies attempted to solve with the inclusion of household or community fixed effects (e.g., Desai & Alva, 1998; Strauss, 1990) or with instrumental variables approaches (e.g., Aslam & Kingdon, 2012; Burchi, 2010; Glewwe, 1999; Güneş, 2015; Sahn & Alderman, 1997; Thomas et al., 1991).

Lastly, in many studies, the variables associated with the local health environment or any other kind of community level variables have not always been included.[4]

Panel data, especially in developing countries contexts, are rare and offers a valuable opportunity to track groups of children as they grow. As argued in Hsiao (2010), it has distinct advantages over cross-sectional data, including increased degrees of freedom and less collinearity among explanatory variables. As a result, it allows for more accurate parameter estimates. Additionally, by utilizing information on both the intertemporal dynamics and the individuality of the entities, panel data allows to control for unobserved heterogeneity more effectively than with cross-sectional data (Hsiao, 2010).

This paper adds to the existing research on the drivers of child nutrition by exploiting the advantages of longitudinal data and employing a consistent econometric approach that accounts for unobserved heterogeneity. In doing so, it aims to understand how children's nutritional conditions improve over time and why there is variation across different households in this regard.

3 | EMPIRICAL MODEL

3.1 | Estimation issues

In order to analyze the drivers of changes in child nutritional status it should be considered that there might be an issue of correlation between the unobserved variables and the observed ones. More specifically, household-level variables such as parental education and income might be correlated with household level factors which are unobserved in the data. As argued above, parents' education and their investments in their children's wellbeing are both influenced by unobserved factors such as their time preferences, abilities, and motivation. Additionally, there could be a correlation between a parent's level of education and unobservable attributes of their partner through the dynamics of the marriage market; more educated women may be more likely to marry individuals who prioritize the well-being of their children (Breierova & Duflo, 2004).

With panel data, this unobserved heterogeneity can be dealt with in a number of ways. A possible solution would be to use household- level fixed effects, which, by controlling for unobserved heterogeneity within the household, would sweep out the bias. Unfortunately, there are two important limits entailed in the household- level fixed effects (FE) specification. First, if there is little or no change over time in the dependent and explanatory variables within households, household-level variables that do not differ by child and are time-invariant will be dropped. More generally, in cases where there are short panels with limited within-group variation in the explanatory variable, the fixed effects estimator may result in biased estimates that tend toward zero and further amplify measurement error (Mundlak, 1978).

Second, the household FE estimator essentially assesses how changes in the explanatory variable, *within* each household, are associated with changes in the dependent variable, *within* each household. Hence, fixed effects are equivalent to considering only deviations from individual means and thus ignore the cross-sectional variations of the means themselves (Nerlove, 2005). Neglecting the variation that occurs *between* households, however, may not be a desirable option from both an econometric and economic perspective. The econometric reason is that this procedure can yield standard errors that are considerably higher than those produced by methods that look at both the within and the between variation. From an economic perspective, instead, it is important to capture the variation occurring *between* households, as it is exactly in there that the very bulk of heterogeneity might take place. This is, indeed, what can be found in the data used in this analysis (see Table A1 in the Appendix).

While the variation over time *within* households in some of the explanatory variables (e.g., income) is more likely to have a transitory effect on the nutritional status of child, the variation between households is mainly related to household specific factors that vary very little over time (including the effect of norms, preferences, and culture) and therefore can better explain differences in the dependent variable both cross-sectionally and over a longer time horizon.

3.2 | Estimation strategy

In this paper, I set up the following empirical model of the drivers of achievements in child nutritional status (H_{it}):

$$H_{it} = \alpha + \beta_1 E_{it} + \beta_2 SE_{it} + \beta_3 HI_{it} + \gamma_1 C_{it} + \gamma_2 I_i + \gamma_3 Z_i + \pi_1 \overline{E}_{i.} + \pi_2 \overline{SE}_{i.} + \pi_3 \overline{HI}_{i.} + \lambda_t + v_{it} \tag{1}$$

where for each i child observed in year t, E_{it} represents local health environment characteristics (i.e., the presence of health facilities at the community level); SE_{it} is a vector of household-level time- varying socio-economic variables, (such as household wealth, household size, mother's and father's education and place of residence) and HI_{it} represents the vector of time-varying inputs which are common across children of the same household (i.e., mother's health status, household sanitation, and water conditions and parental ownership of health insurance). Time invariant and child specific health inputs, such as being breastfed, mother's age at birth, and birth order are instead included in the vector I_i. Z_i includes other child specific and time invariant characteristics (i.e., sex, genetic endowment) and C_{it} is a vector of the only time varying and child specific characteristics: age and the squared of age. λ_t are the survey-year dummies and v_{it} is a random error term.

As it can be observed from Equation (1), each variable of the community and household level time-variant vectors E_{it}, SE_{it}, and HI_{it} are included twice, once in its original form and once averaged over time (indicated by subscript ".").

The generalized least squares (GLS) estimation of this model, also known as Mundlak model (Mundlak, 1978) produces within effects (β) and additional between (between-within) effects (π).

Since the vectors SE_{it} and HI_{it} contain variables which are time-varying but common to all the children living in the same household, the coefficients β_2 and β_3 will estimate the individual (or within-households) effects while π_2 and π_3 give the additional average (or between-households) effects.[5]

By using the Mundlak model, I am opting, therefore, for a "compromise" between the fixed and the random effect models.

Essentially, the Mundlak model relaxes the assumption of no correlation between the observed and unobserved variables by exploiting the knowledge that the only portion of the time constant variation in the explanatory variables that can be correlated with the error term must be correlated with only the time average values of these explanatory variables for each individual (or household).

Let μ_i being unobserved time-invariant characteristics, such as parental preferences and behavior, which would be captured in the error term of a simple OLS specification of (1) including the time varying explanatory variables only in its original form.

Assuming that these unobserved effects are a function of parental socio-economic status, the following additional auxiliary regression, based on Mundlak (1978) and Baltagi (2008, 2023), can be considered:

$$\mu_i = \overline{\Omega'}_i \pi_\mu + \epsilon_i \tag{2}$$

where $\overline{\Omega'}_i = (\overline{SE}_{i.}, \overline{HI}_{i.}, \overline{E}_{i.})$ is a $1 \times \mathrm{K}$ vector of observations on our time-varying explanatory variables averaged over time and where $\epsilon_i \sim IIN\left(0, \sigma_\epsilon^2\right)$.

The underlying assumption in Equation (2) is that the individual effects μ_i are a linear function of the averages of all the explanatory variables across time. As argued in Mundlak (1978) and Baltagi (2023), as long as $\pi_\mu = 0$, these individual effects are not correlated with the explanatory variables.

A joint test on the significance of the estimates of the time averages $\overline{\Omega'}_i$ essentially test for $\pi_\mu = 0$ and reveal whether random effects estimates would be biased (Mundlak, 1978; Wooldridge, 2019; Baltagi, 2023). In all the estimations carried on in this paper, the joint tests for the time averages are statistically significant, hence rejecting the null that that the random effects are not correlated with the regressors and confirming that this bias is properly addressed through the Mundlak approach.[6]

The reliability of causal interpretations with the Mundlak model relies on the assumptions that the unobserved heterogeneity is captured by the averages over time in all the observed household characteristics and that it is correlated with the observables, but is time invariant.

As shown in Equation (2), unobserved heterogeneity is indeed assumed to vary linearly with the group means. That is, the correlation between unobserved household level factors (i.e., culture, beliefs, and preferences) and the observed variables such as parental socio-economic status and child height, is linear and constant over time.

This assumption in the context of this analysis is reasonable. Using one of the examples mentioned earlier, it implies that the effect of parental time preferences on their own educational and wealth achievements and on their investments in child well-being is the same within the household throughout the period. Moreover, the values of the variables included in the vectors $\overline{SE}_{i.}$, $\overline{HI}_{i.}$, which are averaged over a time span of 3–10 years in this study, likely serve as a proxy for the "permanent" or lifetime component of household socio economic status and, as such, they reflect the effect of intangible or unobserved factors.

Lastly, it can be noted that the Mundlak specification in Equation (1) reveals some dynamics of the relationship between child health and household-level variables without having to specify a lag structure. As shown by Egger and Pfaffermayr (2005), using Monte Carlo simulations on the properties of the Mundlak (1978) model, a static panel model specification such as that represented in Equation (1), can be viewed as a representation of a model with lagged exogenous variables where the unspecified lag dynamics are fully compensated by the inclusion of the group means.

Hence, the within and the additional between estimates produce reasonable approximations of the short (transitory) and long run (permanent) effects (Egger & Pfaffermayr, 2005; Egger & Url, 2006; Bender & Theodossiou, 2015). Intuitively, this can be explained by recalling that the between structural parameters are based on the cross-sectional component of the panel while the within parameters rely on the time-series component (Baltagi, 2008). Therefore, the formers will capture overall trends and persisting differences between households while the latter will identify individual responses to temporal changes in the independent variables.[7] The use of this distinction in the interpretation of the coefficients is an important novel contribution to previous literature on child undernutrition, as it allows us to identify the role of both temporary and long-lasting household level factors in driving child health achievements.

4 | DATA AND DESCRIPTIVE STATISTICS

The data used in this analysis are from the Indonesia Family Life Survey (IFLS), a panel of individuals, households, communities, and facilities that were traced in 1997 (IFLS2), 2000 (IFLS3), 2007 (IFLS4), and 2014 (IFLS5). The IFLS is not nationally representative: it covers 13 (out of 27) provinces, which are home to 83% of Indonesia's population, and it prioritizes rural areas.

This survey suits my research questions well as it contains a wealth of information collected at the household and community level, including indicators of socio-economic well-being (wealth, assets, housing conditions, education), in addition to information on fertility, anthropometric characteristics, health status, as well as on the presence of and access to health services. Moreover, the 17-year time period on which this study is based spans several different events such as the dramatic economic and political upheavals in the late 1990s at the time of the Asian Crisis, and some natural disasters (e.g., the Indonesian forest fires in late 1997 or the 2004 Indian Ocean tsunami) which unexpectedly affected the Indonesian population.

To focus on the nutritional status of children, I limited my analysis to households with children aged 15 or younger in their most recent wave. Additionally, I include only children with height-for-age z-scores within the plausible range of −6 to 3, as recommended by WHO (1995). By constructing child-level panel data from the four surveys, I am able to retain 43.11% of eligible children from the original sample after screening out observations with missing data and those recorded in multiple households or inconsistent information across books.[8] Hence, my panel is restricted to 4,870 children (10,440 observations): 33.43% of them were followed in 1997 and 2000; 13.68% in 1997, 2000, and 2007, 16.57% in 2000 and 2007; 6.68% in 2000, 2007, and 2014 and 29.65% in 2007 and 2014.[9]

To address the issue of high attrition rate, a test was conducted to compare the sample of children analyzed in this study with the group of observations that were not included in the analysis. This comparison aimed to understand any differences between these two groups and account for any potential biases caused by missing information for child anthropometric measures. The results of this test depicted in Figure A1 of the Appendix suggest that children who were not included in this study tend to be older and come from larger households compared to those who were included. This finding can be attributed to a higher proportion of excluded observations with missing anthropometric data, which tend to have these same characteristics. Conversely, the sample of children retained for analysis, similar to those with missing anthropometric information, is more likely than the non-retained sample to reside in rural areas and communities with fewer health posts available.

The original data from several different IFLS files has been organized so that the level of observation in the panel is the individual child to which I link information regarding several household, community and individual characteristics. Based on height and age data, the dependent variable is the child's height-for-age z-score which was constructed by using the international standards provided in the World Health Organization Multicenter Growth Reference Study (WHO-MGRS).[10] As also noted by Gillespie and Haddad (2001), child z-scores represent a fine anthropometric measure to capture a child's nutritional status as it reflects pre and post-natal growth[11] with its deficit (i.e., stunting[12]) showing the long-term, cumulative effects of inadequacies in nutrition and/or health. Table A3 in the Appendix describes the main variables that will be used in the regression analysis.

Table 1 provides descriptive statistics for the anthropometric individual characteristics together with some information on the share of children (separately for boys and girls) who are stunting and extremely stunting (i.e., where the z-score is below the −3 standard deviation of the height-for-age norm).

The average height-for-age z-scores indicate that there is a high prevalence of undernutrition, with scores close to the stunting threshold. This finding confirms previous studies, which have revealed similar findings for the South-East Asian region, highlighting the unusually high rates of undernutrition in this area.[13]

However, note also that the z-scores have improved substantially between 1997 and 2014,[14] for both boys and girls.

TABLE 1 Child characteristics. Descriptive statistics.

	Mean	1997	2000	2007	2014
Age (in years)	7.71 (4.46)	6.31 (3.82)	7.00 (4.67)	7.59 (4.54)	11.06 (2.72)
Health status characteristics					
Height for age z-score	−1.61 (1.50)	−1.79 (1.36)	−1.67 (1.46)	−1.57 (1.81)	−1.33 (1.06)
Boys	−1.62 (1.47)	−1.78 (1.42)	−1.71 (1.27)	−1.60 (1.82)	−1.31 (1.10)
Girls	−1.60 (1.54)	−1.81 (1.32)	−1.64 (1.64)	−1.53 (1.79)	−1.35 (1.02)
Stunting (%)	36.27	43.41	39.15	34.03	25.66
% of boys	37.09	44.64	40.88	34.96	24.65
% of girls	35.39	42.16	37.33	32.99	26.78
Extreme Stunting (%)	10.84	14.82	11.86	9.98	5.13
% of boys	11.52	14.94	12.64	11.20	5.81
% of girls	10.11	14.70	11.04	8.62	4.76
Breastfed (%)	79.73	77.85	77.46	81.78	83.71
Observations	10,440	2294	3262	3115	1769

Note: Total sample size is 4870 children (10,440 observations): 33.43% of them were followed in 1997 and 2000; 13.68% in 1997, 2000 and 2007, 16.57% in 2000 and 2007; 6.68% in 2000, 2007 and 2014 and 29.65% in 2007 and 2014. Standard deviations in parentheses.
Source: Own elaboration on IFLS data.

In addition, the percentages of children who suffer from stunting seem to be quite high, especially for boys. These results are consistent with those presented in De Silva & Sumarto, 2018; Mani, 2014; Kevane & Levine, 2003; Ralston, 1997; Frankenberg et al., 1996; Deolalikar, 1990; Basuni, 1989 and may hint at the presence of a gender-bias (disadvantaging boys) in anthropometric failures which characterize several regions of this country. The main reason for this gap, however, does not lay in the inequality in treatment of boys and girls, but rather can be attributed to different activity patterns, which increase male children's exposure to disease (Kevane & Levine, 2003).

Among the proximate determinants of child nutritional conditions, breastfeeding is one child specific variable that will be included in the regression analysis as one hypothesized pathway relating mothers' socio-economic status and child health. The variable used for breastfeeding in this analysis is a dummy that takes the value 1 if the mother of the i*th*-indexed child reported ever having breastfed her child and no food/beverages or water was introduced before the first month of life.[15]

As also extensively confirmed by numerous medical studies, breastfeeding is an important input to child development since the breast milk contains several nutrients that make the child more resistant to diseases. While there may be a number of other channels through which maternal education exerts its effect on child health (i.e., exposure to mass-media, general health knowledge), this variable could be regarded as a concrete pathway through which maternal education is transformed into knowledge and practice of child health seeking behavior.

Moreover, contrary to variables such as general health knowledge (which are potentially endogenous, as parents of an unhealthy child can improve their health knowledge "through experience") breastfeeding is unlikely to be endogenous with respect to child health since mothers usually start breastfeeding shortly after they give birth, thus too early to realize about their child's health conditions and change their behavior.

Figure A3 in the Appendix shows estimates from a linear probability model where, in each wave of the IFLS survey, the "breastfed" dummy variable was regressed against mothers' education and some controls such as sex of the child, residence, household wealth, the number of health posts and midwives in the village, birth order and mother age at birth. Results, which clearly indicate that more educated mothers are significantly more likely to practice breastfeeding, give us the first piece of evidence for the existence of this transmission channel.[16]

The upper part of Table 2 reports descriptive statistics related to mothers' current health and age at birth. There are two potential mechanisms through which maternal age at birth can have an impact on children development outcomes. The first mechanism, known as the direct or biological effect, suggests that it is advantageous to be born to younger mothers due to the increase in medical risk factors associated with older maternal age. Yet, pregnancies carried at relatively younger ages have a higher risk of poor birth outcomes; including low birth weight and prematurity (see Conde-Agudelo et al., 2005; Fraser et al., 1995; Gilbert et al., 2004). On the other hand, the second mechanism, referred to as the indirect or resource effect, proposes that it is beneficial for children to have older mothers because they tend to be wealthier, possess more life experience, and live within stable family relationships (Fredriksson et al., 2022).

As reported in Table 2, the average age at birth of mothers is not dramatically low, but it should also be noted that about 10% of children in this sample are born from mothers who gave birth at ages that are considered riskier for child health (i.e., below 21 years).

Furthermore, Table 2 shows that the prevalence of undernourished mothers is comparatively low, despite the high prevalence of anthropometric shortfall for their children. It can be also observed that, among mothers and fathers, some degree of improvement in educational

TABLE 2 Maternal, households, and community characteristics. Descriptive statistics.

	Mean	1997	2000	2007	2014
Mother's characteristics					
Body mass index ≤18.5 (%)	7.58	8.24	8.46	7.96	4.46
Mother's age at birth	28.00 (6.28)	27.39 (6.18)	27.66 (6.20)	28.49 (6.29)	28.56 (6.44)
No education (0 years of schooling)	4.61%	5.76%	4.29%	4.46%	3.73%
Incomplete primary education	25.32%	31.29%	27.80%	21.83%	16.39%
Primary education (6 years of schooling)	30.67%	33.11%	32.58%	28.67%	26.08%
Incomplete Junior High School	4.56%	3.81%	4.09%	5.38%	5.29%
Junior High School (9 years of schooling)	14.57%	12.46%	13.72%	15.76%	12.73%
Incomplete Senior High School	1.74%	1.73%	1.93%	1.23%	2.31%
Senior High School (12 years of schooling)	14.90%	11.84%	13.00%	16.72%	20.86%
University	3.63%	-	2.59%	5.96%	7.60%
Father's characteristics					
No education (0 years of schooling)	3.24%	3.43%	3.50%	3.05%	2.66%
Incomplete primary education	24.27%	27.97%	24.22%	22.86%	20.69%
Primary Education (6 years of schooling)	26.08%	28.95%	27.54%	24.13%	21.37%
Incomplete Junior High School	4.64%	4.86%	4.31%	4.84%	4.64%
Junior High School (9 years of schooling)	12.96%	12.90%	13.49%	12.04%	13.56%
Incomplete Senior High School	2.64%	2.21%	2.40%	2.84%	3.61%
Senior High School (12 years of schooling)	20.66%	19.68%	19.49%	21.51%	23.52%
University	5.51%	-	5.05%	8.73%	9.96%
Household characteristics					
Household size	5.32 (1.74)	5.59 (1.77)	5.50 (1.79)	5.14 (1.73)	4.93 (1.50)
Safe water (%)	15.62	17.04	17.53	13.51	13.96
Own toilet (%)	68.73	60.03	66.12	71.20	80.49
At least one parent having health insurance (%)	22.56	10.59	10.16	26.84	53.88
Rural (%)	49.14	52.05	52.27	43.66	49.23
Wealth Index	0.15 (1.37)	0.25 (1.34)	0.17 (1.36)	0.07 (1.41)	0.11 (1.31)
Community characteristics					
Number of health posts	8.59 (6.47)	7.85 (5.64)	8.76 (7.58)	8.36 (5.29)	9.66 (7.01)

Note: Total Sample Size is 4,870 children (10,440 observations): 33.43% of them were followed in 1997 and 2000; 13.68% in 1997, 2000, and 2007, 16.57% in 2000 and 2007; 6.68% in 2000, 2007, and 2014 and 29.65% in 2007 and 2014. Standard deviations in parentheses.
Source: Own elaboration on IFLS data.

achievement over time is recorded in the higher levels of schooling (i.e., senior high school and university). It should be noted that the intertemporal variation of these figures can be partially attributed to the unbalanced nature of our panel. Still, even if we look at the figures for each sub-sample (see Table A4 in the Appendix) we see a similar picture suggesting a slight improvement (i.e., around 0.4−0.5 years of schooling among women and around 0.5−0.8 among men over a period of 3−10 years) in educational achievement for these parents.

Although measurement error cannot be ruled out as a driver of this improvement, it is plausible that the increase is also influenced by younger generations of mothers and fathers pursuing higher education. This includes university degrees or lower-level qualifications obtained through adult education schools, which are documented in IFLS.

At the household level, it can be observed that ownership of sanitation facilities has increased over time while the use of safe water[17] for drinking and cooking remains at low levels, hence around 85% of these household were indeed lacking access to improved water sources.

Two variables were used in this paper to proxy for the availability of and access to health infrastructure: the number of health posts and midwives in the community and a binary variable indicating ownership by at least one parent of health insurance. During the regime of President Suharto, only civil servants, soldiers, and formal sector workers, such as State-Owned Enterprise workers, were covered by health insurance ("Askes" and "Jamsotek"). In 1994 and in 2004 two additional mandatory public health insurance scheme were introduced: the national health insurance program ("Kartu Indonesia Sehat") and the "Asuransi Kesehatan Keluarga Miskin", which was later on replaced by the Jaminan Kesehatan Masyarakat/JAMKESMAS (Social Health Insurance) scheme. These programs provided health services, including outpatient and inpatient care, contraception, prenatal care, and delivery, targeting especially poor people. However, since the first two schemes were under an "open scheme" (i.e., eligibility was self-assessed by the applicant), there have been considerable leakages to the non-poor (Sparrow, 2008). Yet, especially in rural areas, the utilization of this insurance was largely subjected to the availability of health posts (Plummer & Boyle, 2016).

From the figures reported in Table 2, we see that the percentage of households with at least one parent having health insurance went up from around 10% in 1997–2000 to 27% and 54% in 2007 and 2014.

The average number of health posts and village midwives per survey-year has increased by approximately 23%. However, there is significant variation across households in terms of access to the healthcare infrastructure, as indicated by the relatively high standard deviation. Figure A5 shows that while the distribution of health posts in rural and urban areas overlapped in 1997 and 2000, it became more dispersed in rural areas by 2007 and centered around a lower mean compared to urban areas in 2014.

Similarly, Table A5 reveals no notable differences in the mean value of the "health insurance" variable during the first three survey-years but indicates a significantly lower percentage of rural households with health insurance compared to their urban counterparts in 2014.

Lastly, addressing a potential source of endogeneity-related concerns on the use of per capita consumption expenditure as a measure of income, I have constructed, following Filmer and Pritchett (2001), an indicator of household wealth using factor analysis including information on household ownership of durable goods and household dwelling conditions. As the signs of the factor loadings suggest, higher values of the index correspond to higher values of household wealth (see Table A6 reported in the Appendix).

5 | FINDINGS

Before delving into the findings of the full-specified model for child nutrition, an initial analysis is conducted to evaluate the "gross-effect" of parental education on child nutritional status. This assessment involves estimating simplified models that regress height-for-age z-score (a measure of child nutritional status) on basic household and child characteristics, as well as each individual parental schooling variable. The results are presented in Table 3.

The first three columns show the coefficients obtained by Ordinary Least Squares (OLS) regressions. In the fourth to sixth columns the "within" and "between" coefficients estimated in the Mundlak regressions are reported. In order to account for the non-linear relationship between age and height for age, all the regressions include age (in months) and the quadratic form of child age in addition to its linear form.[18] Furthermore, I control for gender, the child genetic endowment (as proxied by parent's height), location of residence (rural/urban), and for community health infrastructure. The latter two variables are included twice (once in its original form and once averaged over time) in the Mundlak specifications as they vary over time.[19] Standard errors are clustered at the household level in order to correct for serial and contemporaneous correlation (Bertrand et al., 2004).

The high statistical significance of the OLS coefficients clearly suggests that there are strong correlations between improvements in children's nutritional status and parent's education. Yet, any inference regarding causality cannot be derived from these "naïve" estimates. The size difference between the OLS and the Mundlak coefficients shows the amount of the omitted variable bias. This bias tends upward due to the correlation between socio-economic variables and time invariant variables that are not included in this set of regressions or that are not observable. Once controlling for endogeneity with the Mundlak model, it can be observed that mother's and father's schooling together do not significantly explain within household improvements in child health.

While the data structure partially contributes to this finding (specifically, as argued above, there is a limited within-variation in parental education over time), we see from the between-estimates that there seems to be a long run effect of mother's and father's education, which is in line with the idea of the indirect effect of parents' schooling on child health.[20] Yet, when both father's and mother's education are included in the estimation (Col.6), we observe that only father's education exerts a significant long-run effect on child health. This finding, compared to the OLS estimates reported in Col.3, points to the presence of an unobserved omitted variable bias in the latter. Specifically, it indicates a correlation between the wife's education and unobserved characteristics of her husband, which can be attributed to the functioning of the marriage market. In other words, women with higher levels of education are more likely to marry men who prioritize their children's well-being.

Table 4 reports the estimates for the full-specified Mundlak model.[21]

Departing from the "gross-effect" specification of Col.6 in Table 4, I add sequentially several health inputs.

As it can be observed from Col.1, keeping constant the child genetic endowement, gender, and age, I do not find significant evidence of unequal distribution of resources among siblings. First born children do not show better nutrition outcomes than later born children. Yet, the statistical significance of the negative between coefficients of "household size" points to the presence of a quantity- quality trade-off.

From columns 2 and 3 it can be observed that two lagged health inputs (breastfeeding and maternal age at birth) significantly affect achievements in children nutritional conditions.

TABLE 3 The "gross-effect" of parental education on child nutrition.

	(1)	(2)	(3)	(4)	(5)	(6)
Male	−0.047 (0.034)	−0.049 (0.034)	−0.048 (0.034)	−0.046 (0.033)	−0.048 (0.033)	−0.048 (0.033)
Mother height	0.026*** (0.004)	0.027*** (0.004)	0.026*** (0.004)	0.022*** (0.002)	0.023*** (0.002)	0.022*** (0.002)
Father height	0.014*** (0.003)	0.013*** (0.003)	0.013*** (0.003)	0.011*** (0.002)	0.011*** (0.002)	0.011*** (0.002)
Age	−0.008*** (0.001)	−0.008*** (0.001)	−0.008*** (0.001)	−0.008*** (0.001)	−0.008*** (0.001)	−0.008*** (0.001)
Age squared	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Short run effects (*within estimates*)						
Rural	−0.096*** (0.032)	−0.096*** (0.032)	−0.096*** (0.032)	0.001 (0.033)	0.000 (0.033)	0.001 (0.033)
Health posts	0.007** (0.003)	0.007** (0.003)	0.007** (0.003)	0.005*** (0.002)	0.005*** (0.002)	0.005*** (0.002)
Mother education	0.032*** (0.005)		0.021*** (0.007)	0.006 (0.015)		0.013 (0.016)
Father education		0.028*** (0.005)	0.014** (0.007)		−0.014 (0.013)	−0.018 (0.014)
Long run effects (*between estimates*)						
Rural				−0.193*** (0.058)	−0.191*** (0.058)	−0.192*** (0.058)
Health posts				0.003 (0.003)	0.003 (0.003)	0.003 (0.003)
Mother education				0.028* (0.016)		0.008 (0.018)
Father education					0.046*** (0.014)	0.035** (0.016)
Constant	−7.491*** (0.681)	−7.462*** (0.682)	−7.469*** (0.679)	−6.512*** (0.367)	−6.488*** (0.367)	−6.503*** (0.367)
R^2	0.063	0.062	0.063	0.064	0.064	0.065
Joint test of Mundlak variables						
Chi^2				15.92	23.26	19.44
p-value				0.001	0.000	0.001
Observations	10,440	10,440	10,440	10,440	10,440	10,440
Number of ids	4870	4870	4870	4870	4870	4870

Note: Reported in parentheses are the robust standard errors, allowing for intra household correlation. Year fixed effects included (coefficients not shown). The reported R^2 is the adjusted *R*-squared for the OLS regressions and the overall *R*-squared for the Mundlak regressions.

***$p < .01$; **$p < .05$; *$p < .1$.

Source: Own elaboration on IFLS data.

TABLE 4 Drivers of child nutrition. Mundlak estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Male	−0.048 (0.033)	−0.069* (0.037)	−0.050 (0.033)	−0.044 (0.033)	−0.049 (0.034)	−0.046 (0.033)	−0.043 (0.033)	−0.039 (0.033)
Mother Height	0.021*** (0.002)	0.022*** (0.003)	0.022*** (0.002)	0.022*** (0.002)	0.022*** (0.002)	0.021*** (0.002)	0.021*** (0.002)	0.021*** (0.002)
Father Height	0.012*** (0.002)	0.012*** (0.002)	0.011*** (0.002)	0.011*** (0.002)	0.012*** (0.002)	0.011*** (0.002)	0.010*** (0.002)	0.010*** (0.002)
Age	−0.007*** (0.001)	−0.008*** (0.001)	−0.007*** (0.001)	−0.007*** (0.001)	−0.007*** (0.001)	−0.007*** (0.001)	−0.008*** (0.001)	−0.015*** (0.001)
Age squared	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Birth order	−0.020 (0.015)							
Breastfeeding		0.046* (0.025)						
Mother age at birth			0.006*** (0.003)					
Child at school								0.404*** (0.050)
Short run effects (*within estimates*)								
Mother has low BMI				−0.074 (0.083)				
Health insurance					−0.045 (0.051)			
Safe water						−0.070 (0.068)	−0.073 (0.068)	
Sanitation						0.094* (0.050)	0.085* (0.050)	
Wealth index							0.034* (0.018)	0.032* (0.018)
Rural	0.001 (0.033)	−0.011 (0.037)	0.002 (0.033)	0.001 (0.033)	−0.003 (0.033)	0.000 (0.033)	−0.001 (0.033)	−0.001 (0.033)
Health posts	0.005** (0.002)	0.005** (0.002)	0.005** (0.002)	0.005** (0.002)	0.005** (0.002)	0.005*** (0.002)	0.005*** (0.002)	0.005*** (0.002)
Mother	0.014	0.018	0.014	0.014	0.014	0.014	0.014	0.015
Education	(0.016)	(0.018)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Father	−0.018	−0.019	−0.018	−0.018	−0.018	−0.017	−0.017	−0.019
Education	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
HH size	0.004 (0.016)	0.008 (0.019)	−0.000 (0.016)	−0.001 (0.016)	−0.003 (0.016)	−0.002 (0.016)	−0.004 (0.016)	−0.004 (0.016)
Long run effects (*between estimates*)								
Mother has low BMI				−0.233** (0.112)				
Health insurance					0.074 (0.073)			
Safe water						0.260*** (0.086)	0.223*** (0.086)	
Sanitation						0.184*** (0.067)	0.077 (0.069)	

TABLE 4 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wealth Index							0.093*** (0.025)	0.111*** (0.024)
Rural	−0.194*** (0.058)	−0.172*** (0.065)	−0.196*** (0.058)	−0.197*** (0.058)	−0.182*** (0.059)	−0.195*** (0.058)	−0.179*** (0.058)	−0.180*** (0.058)
Health Posts	0.003 (0.003)	0.002 (0.003)	0.003 (0.003)	0.003 (0.003)	0.003 (0.003)	0.001 (0.003)	−0.000 (0.003)	0.001 (0.003)
Mother education	0.003 (0.018)	−0.004 (0.020)	0.008 (0.018)	0.006 (0.018)	0.005 (0.018)	0.003 (0.018)	−0.002 (0.018)	−0.004 (0.018)
Father education	0.037** (0.016)	0.039** (0.017)	0.036** (0.016)	0.035** (0.016)	0.036** (0.016)	0.026* (0.016)	0.018 (0.016)	0.022 (0.016)
HH size	−0.032* (0.019)	−0.058** (0.023)	−0.041** (0.019)	−0.037** (0.019)	−0.033* (0.019)	−0.039** (0.019)	−0.037** (0.019)	−0.035** (0.019)
Constant	−6.281*** (0.372)	−6.394*** (0.421)	−6.433*** (0.378)	−6.278*** (0.372)	−6.298*** (0.375)	−6.268*** (0.371)	−5.845*** (0.374)	−5.557*** (0.373)
R^2 overall	0.067	0.066	0.067	0.069	0.067	0.073	0.080	0.084
Joint test of Mundlak variables								
Chi^2	19.37	24.28	23.54	27.27	22.14	37.01	40.89	32.76
p-value	0.002	0.000	0.000	0.000	0.001	0.000	0.000	0.000
Observations	10,440	8707	10,440	10,440	10, 440	10,440	10,440	10,440
Number of ids	4870	4031	4870	4870	4, 870	4870	4870	4870

Note: Reported in parentheses are the robust standard errors, allowing for intra household correlation. Year fixed effects included (coefficients not shown).
***$p < .01$; **$p < .05$; *$p < .1$.
Source: Own elaboration on IFLS data.

Children of mothers who practiced breastfeeding and children born form older mothers show respectively an improvement of about 5% and 1% respectively.

This effect is significantly different from zero although its magnitude is quite small. If we take as a reference the growth rate of an adequately nourished 3 (5) years old female child from the MRGS sample, a 1%–5% increase is translated into a larger growth rate of 0.04–0.22 (0.05–0.24) cm.[22]

Specifications 4 and 5 include two additional mediating factors. The first one is a binary variable pointing to mother's low BMI as a proxy for mother's current health status. While my results point to a not significant temporary effect of this variable on child health, there are significant long-run complementarities. Specifically, the z-scores of children from mothers with a chronic energy deficiency (i.e., having their Body Mass Index below 18.5) are about 0.2 standard deviations worse-off than other children.

In Col. 5 I add a dummy on the ownership of health insurance by at least one parent as a proxy for health care access and utilization. The effect of the ownership of health insurance, however, is not significantly different from zero, pointing to the limits of the Indonesian health insurance programmes in effect at that time and, in particular to, what the literature has defined as the problem of "discrepancy between health card ownership and utilization" (Sparrow, 2008 p.198).

Household-level time varying inputs such as the use of safe water and improved sanitation facilities are considered in Col.6.

An improvement in household's hygienic conditions (i.e., using own toilet instead of public latrines or other outdoor devices) is significantly associated with an increase of around 0.09 standard deviations in child height-for-age z-scores (equivalent to approximately 0.4 cm for girls aged 3–5 years). However, considering that there is a time gap of 3–7 years between each survey-years, the individual-level impact of this effect is relatively small.

Access to safe water, on the other hand, does not significantly explain temporary variations in children nutritional status. Yet, as implied by the statistical significance of the between- estimates, the provision of basic sanitation infrastructure and the use of safe water sources significantly explain longer-run achievements in child nutrition.

The estimation reported in Col.7, complete the picture by adding household wealth. As implied in our findings, both the within and between estimated coefficients are statistically significant. Yet, considering the magnitude of the coefficient, the role of a temporary shock in household wealth on child nutrition is relatively less important than the one played by good childcare practices (such as breastfeeding) and by the adoption of basic sanitation infrastructure.

Last, in the specification reported in Col.8, I include a dummy on child enrolment at school (conditional on being of school age). This aims to capture school inputs, such as the time spent at school and the meal consumed at school, which can positively affect child health. Children who are at school, conditional on their age, gender, genetic endowments, and socio-economic background, show an improvement of around 0.40 standard deviations compared to school age children that are not at school. However, the robustness of this finding has to be taken carefully because of the endogeneity of the child enrolment variable.

Throughout all the estimations, some additional interesting insights emerge.

First, it can be observed that a positive and robust temporary effect is exerted by the supply-side variables at community level—such as the number of health posts and midwives.

Second, consistent with previous studies on Indonesia (Kevane & Levine, 2003; Levine & Ames, 2003; Mani, 2014), I do not find any evidence of a gender bias in child health; whereas as implied by the significant between estimates of the “rural” variable” a significant long-run gap in child nutritional status can be observed between rural and urban areas. Precisely, children living in rural areas grow around 0.8–0.9 cm less than other children do.

Last, it is also worth noting that measures of parental height, which are included in all the specifications to capture the role of both parents' genetic endowments on child nutritional status (see Thomas & Frankenberg, 2002), always display a statistically significant coefficient and the magnitude of the effect is relatively larger for mother's height. These results are consistent with earlier findings in the literature (e.g., Mani, 2014; Ghuman et al., 2005; Thomas et al., 1991).

6 | CONCLUDING REMARKS

The purpose of this analysis was to investigate the role of individual, household and community characteristics in driving achievements in the nutritional conditions of Indonesian children, as measured by their height-for-age z scores. This study therefore extends the state-of-the-art of the related literature by identifying distinct temporary and long run effects of proximate and socio-economic drivers of child health. In order to do so, I rely on longitudinal survey data and apply a methodology (i.e., the Mundlak approach of household-average fixed effects) which accounts for unobserved heterogeneity and addresses the limits of standard fixed effects in data context, such as the present one, of limited within variation in the explanatory variables. The underlying idea in the empirical strategy performed in this paper is that unobserved household level factors like culture, beliefs, and preferences are captured by the averages over time in all the observed household socio-economic characteristics. The assumption is that these average values can proxy for the “permanent” or lifetime component of the household socio- economic status and, as such, they would also reflect the effect of those intangible or unobserved factors. One has to be careful, however, to note that these assumptions entail two caveats. First, there might be unobserved home-invariant factors (such as peer-networks effects) that are not captured by the average values of the variables used in my analysis. Secondly, we assume that all the unobserved child- specific endowment is accounted for by the parental height proxies for child genetic potential and by the other observed covariates.

There are, nevertheless, some interesting findings that emerge from this study.

First, controlling for unobserved heterogeneity within the household, I find that children from older and from more experienced mothers and breastfed children have better improvements in child height.

This latter finding aligns with prior academic research in the fields of pediatrics and child development, which has consistently demonstrated the positive influence of breastfeeding on several health outcomes such as mortality (Sankar et al., 2015); diarrhea morbidity and hospitalizations; and respiratory infections (Horta & Victora, 2013).

Despite numerous observational studies investigating the correlation between breastfeeding and anthropometric measures, recent systematic reviews indicate a lack of causal studies on these outcomes. According to Giugliani et al., 2015 and Victora et al., 2016, these limited causal studies fail to provide significant evidence supporting an impact of breastfeeding on children's measurements at 6 months old or up to 2 years old. It should be noted that these studies primarily involve randomized controlled trials or quasi-experimental studies that compare children who have received breastfeeding promotion interventions with control groups. Further research is needed to explore the direct causation between breastfeeding practices and long-term child anthropometric outcomes, independently of any specific breastfeeding campaigns.

Secondly, the Mundlak estimations show that once controlling for father's education, the between or long run coefficient on mother's education is no longer statistically significant.

While a substantial body of evidence generally supports the notion that a mother's education has a stronger impact on child health compared to that of fathers, some caveats are needed in the interpretation of this evidence. First, some of these studies did not account for unobserved heterogeneity. As pointed by Fafchamps and Shilpi (2014) "part of the association between female education and household outcomes is driven by marriage market matching with more educated men" (p. 110). Moreover, there are fewer studies examining both the role of maternal and paternal education, which provide divergent findings.

For instance, while some studies found similar effects for father's and mother's education on child mortality or on child health (Breierova & Duflo, 2004; Chou et al., 2010; Lindeboom et al., 2009), empirical evidence from Bangladesh and Zimbabwe (Djemai et al., 2023; Semba et al., 2008) suggests that, in these contexts, father's education consistently emerges as a more reliable predictor of childhood health than maternal education. The relatively limited focus on the influence of father's education on health outcomes is primarily due to the fact that fathers typically have a less visible role in caregiving for children. However, as noted by Chen and Li (2009), father's education may have a stronger relationship with child outcomes because fathers are often more educated than mothers in developing countries. In the context of this study, it is noteworthy that the average father in our sample has 1.5 more years of education than the average mother. Thus, if the highest level of education within a household is a determining factor, father's education may indeed be a crucial factor in child health.

Another rationale for the significance of father's education lies in the lower social status and empowerment of mothers, potentially limiting their influence on decisions related to child health. This leads to fathers playing a more active role in certain types of health-related decisions, such as spending choices. Notably, once we control for household wealth, the coefficient for father's education in this study declines and loses its statistical significance.

Lastly, the findings from this study contribute to an expanding body of knowledge that illustrates a relationship between WASH and child growth. They show that the bulk of the variation of child nutrition between households is driven by differences in place of residence (urban/rural) as well as in use of safe water and access to improved sanitation. Interestingly, even holding household wealth constant, we observe that children living in households that got access to improved sanitation (having a toilet in the household) show significant increases in their stature.

These findings are of great concern to Indonesia, where in the most recent years over 50% of the population lacks access to improved water supplies and nearly 25 million people still practice open defecation, ranking it among the top three countries globally (UNICEF, 2019). Despite progress in reducing open defecation rates and increasing access to improved drinking water over the past decade, efforts must be focused on reducing disparities in WASH services between regions, urban/rural areas, and different wealth quintiles, as recently highlighted by the Government of Indonesia.[23]

While the findings of this study support the existence of a positive relationships between access to improved sanitation and child height, limited experimental evidence show contrasting results on the effect of sanitation interventions on child health outcomes. As shown in a recent systematic reviews of RCT interventions, among eight Community-Led Total Sanitation (CLTS) trials which considered the effects of on child height, only two (Dickinson et al., 2015; Pickering et al., 2015) show a positive and significant effect (Kanda et al., 2021). Interestingly, Cameron et al., 2019 show that while in Indonesia a CLTS trial conducted in rural areas had no impact on anthropometric outcomes on children aged 0–5 years, the program was much less effective among poorer households. More experimental evidence in the form of rigorous sanitation intervention trials across different settings are therefore needed to determine what truly works and under which circumstances.

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CONFLICT OF INTEREST STATEMENT
The author declares no conflicts of interest.

DATA AVAILABILITY STATEMENT
The data that support the findings of this study are available from the corresponding author upon request.

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ENDNOTES
[1] For a detailed exposition of these models the reader can refer to Behrman and Deolalikar (1988) and Thomas and Strauss (1992). Alternatively, section II in Mani (2014) provides a synthetic but sharp and clear exposition.

[2] Similarly, the quality of schools and of the services that schools offer (e.g., meal provision) is an important mechanism. The quality of schools might moreover be correlated with mother education and with their preference for child quality.

[3] Mani (2014), following children aged 0–5 in 1993 through 2000, uses prices as instrumental variables to unravel the effect of household income and parent education on child height standardized by using the US population as reference. De Silvia and Sumarto, (2018) rely on quintile regression methodology on two separate cross-sectional datasets(for the years 2000 and 2007 to estimate the association of socio-economic factors to the probability of stunting.

[4] This may be one of the main reasons why-as noted by Frost et al. (2005)–the arguments which have propped up the thesis that reproductive factors are the transmission channels linking socio-economic variables and child morbidity or mortality have found mixed empirical support.

[5] Since the *Eit* vector includes variables observed at the community level, the coefficient $\beta 1$ and $\pi 1$ provide estimates of the within-community and of the between-community effects.

[6] As argued in Baltagi (2023): “Rejecting the null does not mean that the fixed effects estimator is efficient. However, empirical researchers settle on reporting it as their preferred estimator when the null is rejected. This is not at odds with the Mundlak (1978) idea that once the correlation of the random effects with all the regressors through their time mean is accounted for, the random effects estimator of β becomes the fixed effects estimator.” (Baltagi, 2023: 241).

[7] It should be noted that, as recommended by Egger and Pfaffermayr (2005), long and, especially short run effects tend to be underestimated if the induced autocorrelation of the error term is high. A test for this autocorrelation, however, as shown in Wooldridge (2010) is not needed when $T \leq 3$. With $T = 2$ the autocorrelation test would neither be available nor necessary. With $T = 3$ the test would result in a cross-section regression because the $t = 1$ and $t = 2$ time periods are lost (Wooldridge, 2010, p. 283). Moreover, Egger and Pfaffermayr (2005) show that the asymptotic bias of the within and between estimators as proxies for the short and long term effects depend positively upon the number of years in the panel and negatively upon the importance of the cross-sectional variation in the explanatory variables (as cited in Baltagi, 2008). Lastly, for statistic panel data with large N and small T (as the one that it is used in this paper), Pirotte (1999) shows that the probability limit of the between estimator converges to long run effects.

[8] More precisely, 30.35% of the observations from the original sample of eligible children were dropped because of missing or implausible information in the anthropometric measures (height, weight) which were necessary for the construction of the main outcome variable (height-for-age z-scores) and for three explanatory variables used in this analysis (mother's and father's height; mother's BMI). These observation represent around 53.3% of the attrition rate. The remaining component of the attrition rate is represented by observations with missing information, at least in one wave, on mother's and father's years of schooling and household wealth or by observations recorded in multiple households.

[9] Note that the panel is naturally unbalanced as I follow children aged 15 or younger in the most recent wave where they are observed and provided that that the time gap between waves is of 3 years for IFLS 2 (1997) and IFLS 3 (2000) but of 7 years between IFLS 3, IFLS 4 (2007) and IFLS 5 (2014). Hence, for instance, a child aged 10 years old in 2014 can only be observed in two waves (2007 and 2014). However, given the unbalanced structure of the panel, a test was conducted in order to check the presence of systematic differences between the group of children followed in three waves and those followed in just two waves. The results, shown in Table A2 in the Appendix, indicate that whether it is more likely to observe in all the three waves children with initial lower age, there are no remaining significant differences in basic demographic and socio-economic characteristics.

[10] These standards are considered to be universally applicable as they are based on a sample of children from a diverse set of countries which has a considerable built-in ethnic or genetic variability as well as cultural variation in how children are nurtured. Furthermore, by being standards (and not references) they clearly define how children should grow and identify deviations from the pattern as abnormal growth (WHO, 2006).

[11] According to the WHO, indeed, the height for age z-score is a measure of the nutritional status of the child to the extent that it defines whether child growth reflects a "process of failure to reach linear growth potential as a result of suboptimal health and/or nutritional conditions" (De Onis et al., 1997 p.46).

[12] According to the National Center for Health Statistics/World Health Organization International Growth Reference, children whose z-score is two standard deviations below the median height-for age curve are classified as stunted (Dibley et al., 1987).

[13] See, inter alia, Klasen, 2008; Harttgen & Misselhorn, 2006; Smith et al., 2003; Gillespie and Haddad, 2001. Note, also, that stunting rates in the IFLS are consistent with the estimates based on nationally representative data, such as the Riskesdas survey. For instance, Shrimpton and Rokx (2013), based on Riskesdas survey data, report that in 2010 the stunting rates for children aged 0–15 were around 35%. Among children aged 0–5, the Unicef modeled estimates of stunting reveal that stunting rates decreased from around 40.4% in 2000 to 37.5% in 2007 and to 33.6% in 2014.

[14] The kernel density functions of height-for-age z-scores in each survey-year are presented in Figure A2 and in Figure A6. There is a substantial shift to the right in the distribution indicating an increase in the height of children over this period.

[15] Due to insufficient information and missing data in relevant variables, I was unable to create more precise indicators of optimal breastfeeding. However, according to the World Health Organization, ideal breastfeeding practices include initiating breastfeeding within 1 h after birth, exclusively feeding the infant (without water, formula, milk, or food) for the first 6 months and continuing until 24 months (Kramer & Kakuma, 2012; Labbok and Krasovec, 1990; WHO, 2008).

[16] Of course, showing that breastfeeding is a transmission channel for mothers' education does not necessarily imply that it cannot be a pathway also for other maternal characteristics (i.e., health, employment and wealth status). Whether in the main regression analysis I will control for some of these factors, here the main concern is on the relationship between maternal education and child health-seeking behaviour.

[17] Safe water is defined as bottled water or as pipe, underground (pump or well), spring and rain water and all of them are boiled first.

[18] As it can be already inferred from Figure A4 (reported in the Appendix) there might be some specific age effects, which can drive part of the results. As our regressions results moreover show, a non-linear relationship is found. This is consistent with the much of the literature on health outcomes (see, Mani, 2014; Sahn & Alderman, 1997; Strauss et al., 2004) where the relationship between height for age and age follows a U-shaped pattern, where z-scores decline in the very first years of life and then improve or remain unchanged (usually after the second years of life).

[19] Rural location changes over time because of households moving to different location or because of changes over time in the rural/urban classification of the location.

[20] If parental education is a proxy for the efficiency with which health inputs are transformed by parents into their children health output (Barrera (1990); Strauss & Thomas, 1998; Fedorov & Sahn, 2005; Mani, 2014), it can be argued indeed, that the bulk of the effect of this variable can only be long-term. This is because parental education does not directly impact improvements in child nutrition but rather influences them indirectly through its effects on intermediary factors.

[21] The corresponding OLS estimates are reported in Table A7 in the Appendix. The comparison of the OLS and Mundlak coefficients suggests the extent to which estimates change once controlling for endogeneity and it can be observed, indeed, that there is an upward bias in the OLS model that is due to unobservable household factors that are correlated with parental schooling and with household wealth.

[22] As previously discussed, the positive effect of the variable "mother's age at birth" captures the indirect or resource effect of mother's wealth and life experience. Yet, it does not inform us on the effect streaming through child rearing experience. For this reason, I re-estimated the specification of Col.3 by using the difference of mother's current age and her age at her first child's birth. The estimated coefficient of 0.005 (significant at the 10% level) indicates that mothers with 1 more year experience in child rearing show an improvement of around 1% in their height for age.

[23] https://www.sanitationandwaterforall.org/sites/default/files/2022-07/2022%20Country%20Overview_Indonesia.pdf

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APPENDIX A

TABLE A1 Between-households and within-household variation in time-varying variables.

		Standard deviation		
	Mean value	**Overall**	**Between households**	**Within households**
ZHFA	−1.61	1.51	1.23	0.88
Rural	0.49	0.50	0.35	0.36
Mother education	6.99	3.77	3.70	0.79
Father education	7.46	3.91	3.82	0.90
HH size	5.32	1.74	1.57	0.76
Water	0.16	0.36	0.32	0.17
Sanitation	0.69	0.46	0.40	0.24
Wealth Index	0.15	1.36	1.20	0.66
Insurance	0.23	0.42	0.34	0.25

Source: Own elaboration on IFLS data.

TABLE A2 Test for systematic differences in sample composition.

	Mean value for children followed over three waves	**Mean value for children followed over two waves**	**Mean difference**	**Correlation with dependent variable**
ZHFA	−1.57	−1.67	−0.093 (0.069)	0.002 (0.003)
Male	0.54	0.51	−0.027 (0.020)	0.009 (0.009)
Age	1.95	5.03	3.082 (0.139)***	−0.047*** (0.001)
Rural	0.54	0.49	−0.046 (0.020)	0.004 (0.009)
HH size	5.37	5.33	−0.044 (0.074)	−0.004* (0.002)
Mother education	6.68	7.02	0.347 (0.152)	−0.000 (0.002)
Father education	7.12	7.48	0.358 (0.157)	−0.001 (0.002)
Wealth index	0.08	0.09	0.012 (0.056)	−0.002 (0.003)
Observations	4170	700		4870
R-squared				0.257

Note: The second and third columns report the mean values in each group of the initial values of the variables listed in the first column. The fourth column reports the mean difference and its standard errors for the test of the equality of means of the two groups. The fifth column report the coefficients and standards errors of a regression with the dependent variable being a binary variable equal to 1 if the child was observed over three waves. Estimation method: linear probability model. Standard errors in parentheses.

***$p < .01$; *$p < .1$.

TABLE A3 Description of variables used.

Variable	Description	Vector of reference in Equation 1	Mean (standard deviation)
ZHFA	Height-for-age z-scores	H_{it}	−1.61 (1.50)
Mother education	Mother's completed years of schooling	*SEit*	6.99 (3.77)
Father education	Father's completed years of schooling		7.45 (3.91)
Wealth index	Household wealth index		0.15 (1.37)
Rural	Dummy equals 1 if place of residence is in rural areas, 0 otherwise		0.49 (0.49)
Male	Dummy equals 1 if male, 0 otherwise	*Zi*	0.52 (0.50)
Father height	Father height (in centimeters)		159.04 (8.69)
Mother height	Mother height (in centimeters)		151.87 (7.49)
Age	Child age in months	*Cit*	92.55 (53.57)
Age squared	Child age in months squared		11436.69 (9993.73)
Child at school	Dummy equals 1 if the child is in school age and currently attend school, 0 otherwise		0.66 (0.47)
Breastfed	Dummy equals 1 if the child was ever breastfed and no other food was introduced before the first month of life, 0 otherwise	*I*(*C*)*i*	0.80 (0.40)
Mother Age at birth	Mother's age when she gave birth		28.00 (6.28)
Birth order	Child's birth order		2.23 (1.37)
Mother has low BMI	Dummy equals 1 if the mother's BMI is equal or below the 18.5 threshold, 0 otherwise	*HIit*	0.08 (0.26)
HH size	Number of members living in the same household		5.32 (1.74)
Safe water	Dummy equals 1 if household has access to safe water for drinking or cooking, 0 otherwise		0.16 (0.36)
Sanitation	Dummy equals 1 if household has a toilet, 0 otherwise		0.69 (0.46)
Insurance	Dummy equals 1 if the child's mother or father have health insurance, 0 otherwise		0.23 (0.42)
Health posts	Number of health posts and midwives in the community	E_{it}	8.59 (6.47)

Source: Own elaboration on IFLS data.

TABLE A4 Average absolute change in household-level variables between waves.

	Change between 1997 and 2000	Change between 1997 and 2007	Change between 2000 and 2007	Change between 2000 and 2014	Change between 2007 and 2014
Household size	−0.04 (1.28)	−0.17 (1.69)	−0.07 (1.68)	−0.25 (1.98)	0.04 (1.42)
Mothers' years of schooling	0.53 (1.18)	0.59 (1.12)	0.51 (1.12)	0.58 (1.53)	0.42 (1.10)
Fathers' years of schooling	0.71 (1.45)	0.80 (1.47)	0.58 (1.14)	0.60 (1.32)	0.49 (1.17)
Wealth Index	−0.031 (1.22)	0.122 (1.38)	0.228 (1.25)	0.256 (1.45)	0.164 (1.27)
Percentage of households using safe water for drinking and cooking	−0.96	1.02	−1.97	−2.17	1.48
Percentage of households having own toilet	7.1	18.56	13.43	19.56	13.14
Percentage of households living in rural areas	−3.16	−10.81	−11.42	−8.38	8.01
Percentage of households with at least one parent having health insurance	−1.09	17.28	19.82	46.01	27.5
Observations followed in	Waves 1 and 2	Waves 1, 2 and 3	Waves 2 and 3	Waves 2, 3 and 4	Waves 3 and 4
Number of observations	3256	1834	1614	848	2888

Note: Total Sample Size is 4870 children (10,440 observations): 33.43% of them were followed in 1997 and 2000; 13.68% in 1997, 2000 and 2007, 16.57% in 2000 and 2007; 6.68% in 2000, 2007 and 2014 and 29.65% in 2007 and 2014. Standard Deviations in parentheses.
Source: Own elaboration on IFLS data.

TABLE A5 Differences in ownership of health insurance, use of safe water and ownership of own sanitation facilities between urban and rural areas.

	Mean value in rural areas	Mean value in urban areas	Mean difference
Health insurance			
1997	0.117	0.093	−0.024 (0. 013)
2000	0.097	0.107	0.010 (0.011)
2007	0.266	0.270	0.004 (0.016)
2014	0.488	0.588	0.101*** (0.024)
Safe water			
1997	0.180	0.160	−0.020 (0.016)
2000	0.187	0.162	−0.025 (0.013)
2007	0.132	0.138	0.006 (0.012)
2014	0.107	0.171	0.065 (0.016)***
Sanitation			
1997	0.596	0.604	0.008 (0.020)
2000	0.675	0.646	−0.029 (0.017)
2007	0.722	0.704	−0.02 (0.016)
2014	0.750	0.859	0.11 (0.19)***

Note: This table reports the mean values of the binary variable "health insurance," "safe water," and "sanitation" in rural and urban areas. The third column reports the mean difference and its standard errors for the test of the equality of means of the two groups.
Source: Own elaboration on IFLS data.

TABLE A6 Factor loadings and eigenvalue for the wealth index.

	1997	2000	2007	2014
Water source is inside the house	0.401	0.379	0.334	0.287
Household owns a refrigerator	0.328	0.355	0.412	0.428
House in is not surrounded by trash, human and animal wastes, puddles	0.271	0.251	0.204	0.104
House has a separate cooking room	0.148	0.133	0.092	0.091
House is owned by the household	0.177	0.209	0.164	0.204
Household owns farmland	0.061	0.144	0.166	0.194
Household owns vehicles	0.352	0.347	0.376	0.393
Household owns appliances	0.411	0.390	0.358	0.312
Household owns savings, certificates, deposits and stocks	0.390	0.391	0.385	0.391
Household owns receivables	0.190	0.205	0.241	0.230
Household owns jewelry	0.342	0.335	0.348	0.398
Household owns other assets	−0.020	0.048	0.117	0.130
Eigenvalue	2.210	2.225	2.251	2.020

Source: Own elaboration on IFLS data.

TABLE A7 The drivers of child nutrition. OLS estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Male	−0.048 (0.033)	−0.069* (0.037)	−0.050 (0.033)	−0.045 (0.033)	−0.048 (0.033)	−0.046 (0.033)	−0.044 (0.033)	−0.040 (0.033)
Mother height	0.026*** (0.003)	0.026*** (0.004)	0.026*** (0.003)	0.026*** (0.003)	0.026*** (0.003)	0.025*** (0.003)	0.025*** (0.003)	0.025*** (0.003)
Father height	0.014*** (0.002)	0.014*** (0.002)	0.013*** (0.002)	0.013*** (0.002)	0.014*** (0.002)	0.013*** (0.002)	0.012*** (0.002)	0.012*** (0.002)
Age	−0.008*** (0.001)	−0.008*** (0.001)	−0.008*** (0.001)	−0.008*** (0.001)	−0.008*** (0.001)	−0.008*** (0.001)	−0.008*** (0.001)	−0.016*** (0.002)
Age squared	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Rural	−0.098*** (0.029)	−0.101*** (0.032)	−0.098*** (0.029)	−0.099*** (0.029)	−0.097*** (0.029)	−0.098*** (0.029)	−0.093*** (0.029)	−0.095*** (0.029)
Health posts	0.007** (0.003)	0.006** (0.003)	0.007** (0.003)	0.007** (0.003)	0.006** (0.003)	0.006** (0.003)	0.005* (0.003)	0.005** (0.003)
Mother education	0.018*** (0.006)	0.016** (0.006)	0.021*** (0.006)	0.020*** (0.006)	0.020*** (0.006)	0.018*** (0.006)	0.014** (0.006)	0.013** (0.006)
Father education	0.015*** (0.006)	0.016*** (0.006)	0.014** (0.006)	0.014** (0.006)	0.015** (0.006)	0.008 (0.006)	0.001 (0.006)	0.003 (0.006)
HH size	−0.021** (0.010)	−0.038*** (0.011)	−0.032*** (0.009)	−0.030*** (0.009)	−0.029*** (0.009)	−0.032*** (0.009)	−0.034*** (0.009)	−0.032*** (0.009)
Birth order	−0.021 (0.014)							
Breastfeeding		0.050* (0.026)						
Mother age at birth			0.006** (0.003)					
Mother has low BMI				−0.249*** (0.059)				
Health Insurance					−0.001 (0.040)			
Safe water						0.126*** (0.040)	0.098** (0.040)	
Sanitation						0.229*** (0.035)	0.154*** (0.036)	
Wealth index							0.102*** (0.012)	0.111*** (0.012)
Child at school								0.454*** (0.051)
Constant	−7.270*** (0.565)	−7.393*** (0.612)	−7.426*** (0.571)	−7.275*** (0.564)	−7.300*** (0.569)	−7.239*** (0.563)	−6.853*** (0.563)	−6.666*** (0.559)
Observations	10,440	8707	10,440	10,440	10,385	10,440	10,440	10,440
Adjusted R^2	0.064	0.063	0.065	0.066	0.064	0.069	0.076	0.080

Note: Reported in parentheses are the robust standard errors, allowing for intra household correlation. Year fixed effects included (coefficients not shown).
***$p < .01$; **$p < .05$; *$p < .1$.
Source: Own elaboration on IFLS data.

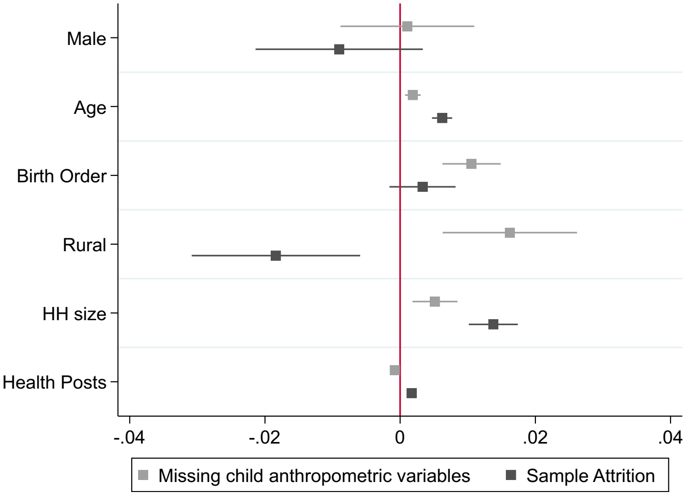

FIGURE A1 Drivers of sample attrition. This graph shows the coefficients and confidence intervals of the variables reported in the y-axis estimated in two models. The first model has as dependent variable a dummy equals to 1 if the observation has missing child height variable, 0 otherwise. The observations with missing child anthropometric data account for around 20.84% of the whole sample and for around 36.63% of the attrition rate. The second model has as dependent variable a dummy equals to 1 if the observation is not retained in the sample used for the main analysis of this paper, 0 otherwise. Estimation method: linear probability model with robust standard errors and wave fixed effects. Number of observations: 24,217. *Source*: Own elaboration on IFLS data. [Colour figure can be viewed at wileyonlinelibrary.com]

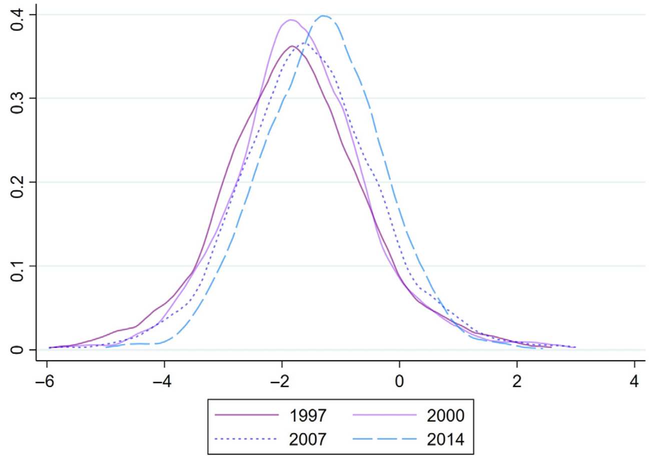

FIGURE A2 Kernel distributions of height-for-age z-scores. *Source*: Own elaboration on IFLS data. [Colour figure can be viewed at wileyonlinelibrary.com]

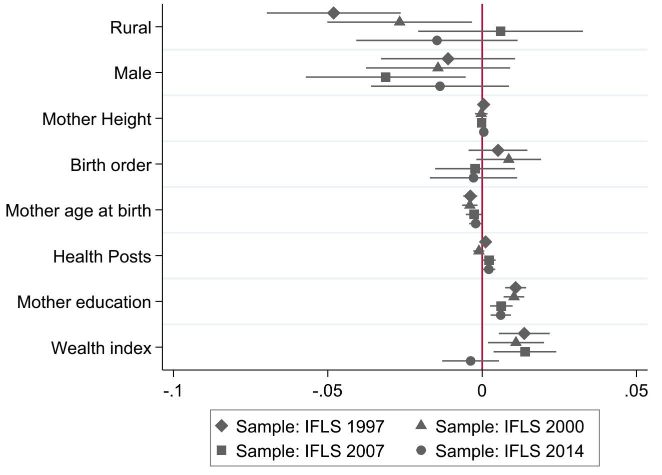

FIGURE A3 Factors associated with the probability of breastfeeding. Dependent Variable = Dummy equals 1 if the child was breastfed, 0 otherwise. Estimation method: linear probability model with robust standard errors. Source: own elaboration on IFLS data. [Colour figure can be viewed at wileyonlinelibrary.com]

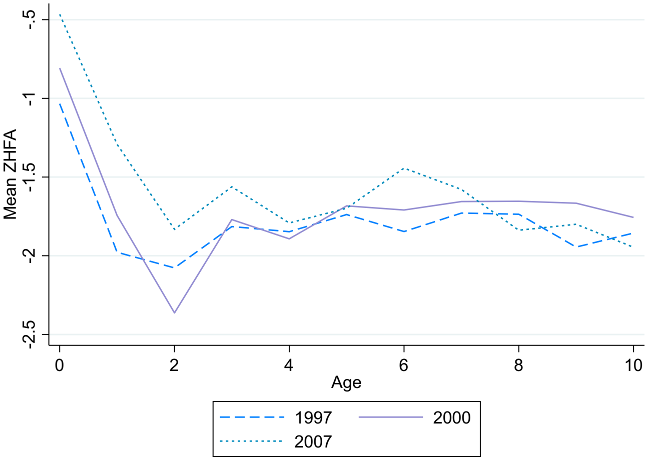

FIGURE A4 Mean height-for-Age z-score by age (in years). *Source*: Own elaboration on IFLS data. [Colour figure can be viewed at wileyonlinelibrary.com]

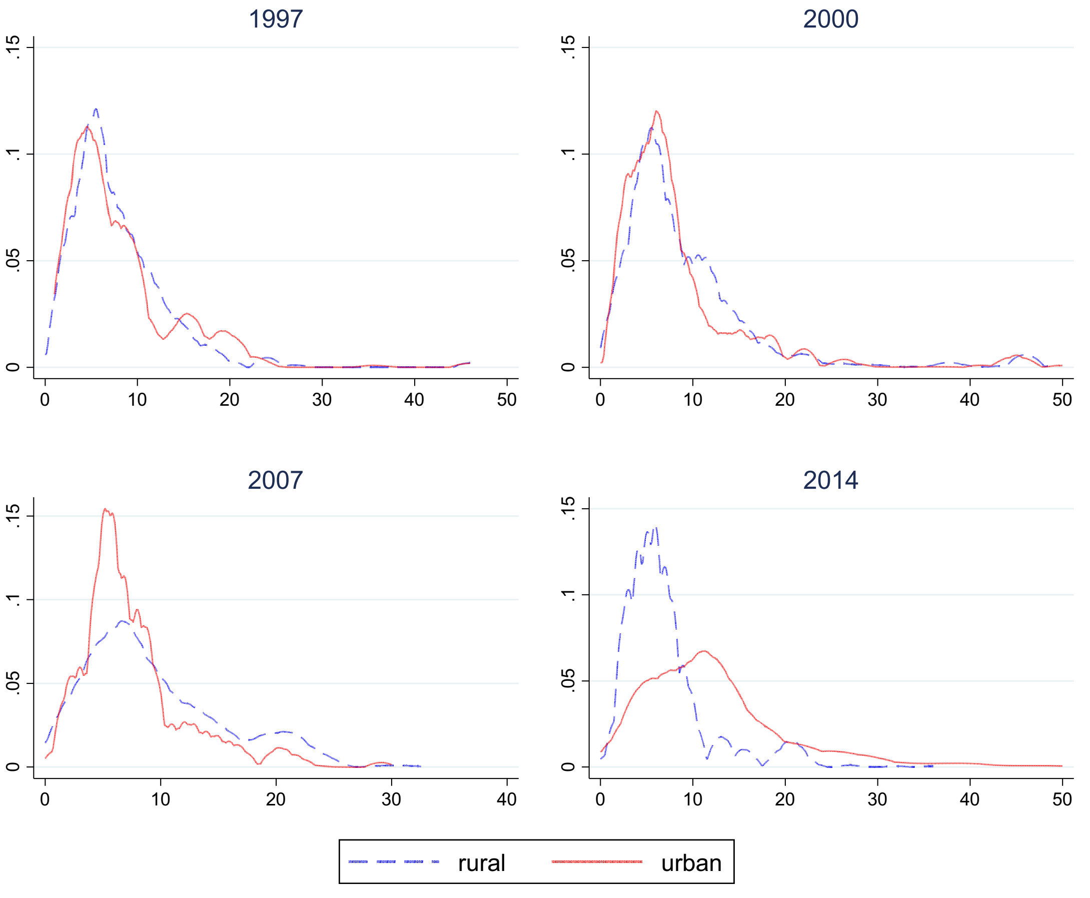

FIGURE A5 Distribution of health posts by survey-year and location. *Source*: Own elaboration on IFLS data. [Colour figure can be viewed at wileyonlinelibrary.com]

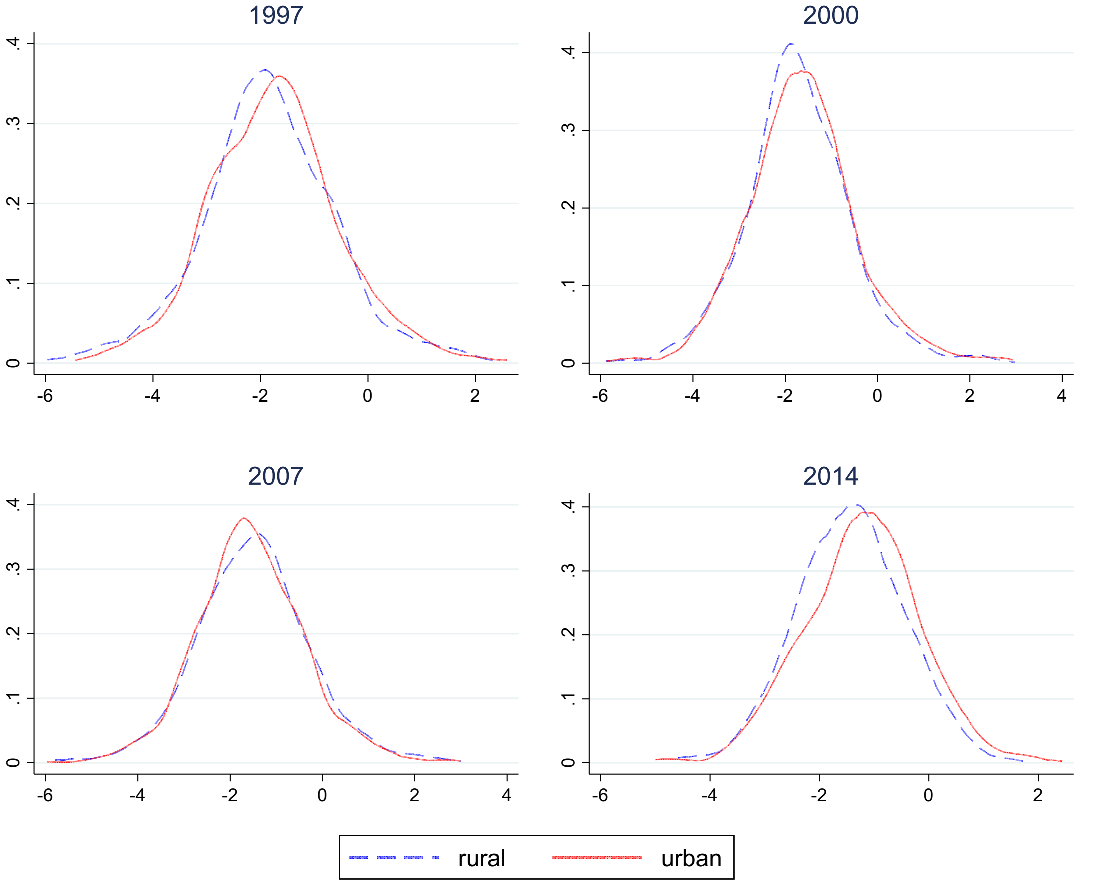

FIGURE A6 Distribution of height-for-age z-scores by survey-year and location. *Source*: Own elaboration on IFLS data. [Colour figure can be viewed at wileyonlinelibrary.com]