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## ABSTRACT

### Developments in Undernutrition in Indian Children Under Five: A Decompositional Analysis

This study uses two waves (2004–2005 and 2011–2012) of the nationally representative Indian Human Development Survey to conduct a systematic decompositional analysis of the demographic and socio-economic factors contributing to undernutrition among children under five in India. The analytic method combines three types of decomposition: Blinder- Oaxaca, non-linear, and unconditional quantile. Child undernutrition is measured by z-scores for height-for-age (*HAZ*), weight-for-height (*WHZ*), weight-for-age (*WAZ*), and for the Composite Index of Anthropometric Failure (*CIAF*). Although our results show modest improvements on some measures, undernutrition among India's young children remains widespread. The improvements we do identify are partly attributable to changes in household wealth and maternal characteristics like body mass index and education.

JEL Classification: I15, I31, C21

Keywords: child undernutrition, India, decomposition

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# **Developments in Undernutrition in Indian Children Under Five: A Decompositional Analysis**

## **1. Introduction**

The United Nations (UN) regards improved child health as a key indicator of progress towards number three of its Sustainable Development Goals: a universal guarantee of a healthy life and well-being at all ages. Since an estimated one-third of deaths among children under five are attributable to undernutrition, child nutritional levels are an important means of gauging the condition of a country's children. Undernutrition not only puts children at a greater risk of disease vulnerability, it also adversely affects their physical, cognitive, and mental development (Barker, 1995). It can thus be expected to adversely impact productivity in later life (Strauss & Thomas, 1995). In fact, eliminating childhood undernutrition should cut child mortality by over 50% and reduce the burden of diseases by about 20% (Murray & Lopez, 1997; Pelletier, 1994; Tomkins & Watson, 1989).

Globally, India performs poorly across most standard child nutritional measures, and accounts for more than 40% of global stunting (Haddad et al., 2015). Moreover, data from the India's nationally representative National Family Health Survey (NFHS), conducted in 1992, 1998–99, and 2005–06, paint a bleak picture of child nutrition in the country. In 2005–06, an estimated 38.4% of children under three were stunted and 46% were underweight. Although both these indicators have improved slightly since 1998–99, wasting, defined as an abnormally low weight for the child's height, still affects 19% of children under three with a slight deterioration from 1998–99 (UNDP, 2007). In fact, a recent NFHS-based analysis of trends in infant undernutrition in India between 1992 and 2005 reveals a 49%, 44%, and 40% overall prevalence of underweight in 1992, 1998, and 2005, respectively (Subramanyam, Kawachi, Berkman, & Subramanian, 2010) with a corresponding 52%, 51%, and 45% prevalence of stunting. Hence, although child nutrition indicators suggest small improvements, unacceptably large numbers of Indian children are still nutritionally compromised.

The aim of this paper, therefore, is to use the 2004–05 and 2011–12 data from the Indian Human Development Survey (IHDS) to conduct a comprehensive decompositional analysis of the demographic and socio-economic factors contributing to changes in childhood undernutrition outcomes in India. Our undernutrition measure is  $z$ -scores for weight-for-height (*WHZ*), height-for-age (*HAZ*), weight-for-age (*WAZ*), and the Composite Index of Anthropometric Failure (*CIAF*). In particular, we seek to identify the demographic and socio-economic factors that influence changes in the nutritional status of children aged 0–5 years during the 2004–2012 period. We employ both linear Blinder-Oaxaca (BO) and non-linear decomposition (Fairlie, 1999), as well as the unconditional quantile technique developed by Firpo, Fortin, and Lemieux (2009) to evaluate the impact of distributional changes in observed characteristics on the unconditional marginal distribution of the three undernutrition measures ( $z$ -scores). Our analysis provides the most up-to-date profile of the nutritional status of India’s children.

In general, we show that stunting, underweight, and anthropometric failure improved slightly over the 2004/2005–2011/2012 period but wasting became slightly worse. Nevertheless, *severe* wasting, stunting, and underweight all improved a little. In all three decompositional analyses (Blinder-Oaxaca, non-linear, unconditional quantile), these small changes in undernutrition measures are partly explainable by household economic conditions (household wealth), although maternal characteristics like mother’s body mass index (BMI) and education also make a noticeable contribution.

The remainder of the study is structured as follows: Section 2 reviews the relevant literature on child undernutrition in India, section 3 describes the data and methods, and section 4 reports the results. Section 5 concludes the paper.

## **2. Prior studies**

### 2.1 Socio-economic factors of child undernutrition in India

A large body of research using nationally representative secondary data sets to investigate the socio-economic factors associated with poor child nutrition in India suggests that inequalities appear to be increasing for vulnerable groups such as girls and individuals in lower socio-economic groups (Brennan, McDonald, & Shlomowitz, 2004; Gragnolati, Shekar, Das Gupta, Bredenkamp, & Lee, 2005; Lokshin, Das Gupta, Gragnolati, & Ivaschenko, 2005; Tarozzi &

Mahajan, 2007). However, whereas Tarozzi and Mahajan (2007) find an increase in gender inequities in child nutrition over the 1990s, with the nutrition of boys in India improving substantially more than that of girls; Pathak and Singh (2011) show that over the 1992–2006 period, the burden of undernutrition was disproportionately concentrated among poor children. Pathak and Singh (2011) further demonstrate that child differences in nutritional outcomes have widened between rich and poor households, and that child nutritional outcomes are relatively better in areas where households have been able to access Integrated Child Development Services (ICDS). One objective of this Government of India funded program is to improve the nutritional and health status of children in the 0–6 age group, while also reducing mortality, sickness, undernutrition, and school dropout rates. Pathak and Singh’s findings are consistent with Subramanyam et al.’s (2010) conclusion that over these 14 observation years, social disparities in undernutrition either widened or stayed the same.

Other recent studies focus either on undernutrition among Indian children or on India’s declining nutritional intake (Gragmolati et al., 2005; Lokshin et al., 2005; Pathak & Singh, 2011; Tarozzi & Mahajan, 2007), which reflects a strong reduction in per capita calorie consumption despite robust economic growth over the 1990s (Deaton & Dréze, 2009; Ray, 2007; Ray & Lancaster, 2005). The trends observed in these studies suggest a *possible* nexus between the poor nutritional outcomes of young children and household calorie consumption. Another strand of literature, however, concentrates on the role of poor health infrastructure. For example, Paul et al. (2011) attribute the poor nutritional outcomes among Indian children to weak health systems and a policy focus on children aged 3–6 years at the expense of those aged 0–2 years, even though much of the growth occurs over this latter age.

More recent studies by Spears (2012) and Hammer and Spears (2013) explain poor child nutrition among Indian children in terms of sanitation, arguing that environmental threats from open defecation and exposure to faecal germs reduce nutrient absorption, while exposure to early life disease leads to undernutrition, stunting, and diarrhoea. Using data from the NFHS, Spears (2013) shows that open defecation remains exceptionally widespread in India and sanitation has not improved substantially despite rapid economic growth. However, although these studies provide useful benchmarks for assessing child nutritional outcomes and the socio-economic factors that influence them, they are based on National Family and Health Survey (NFHS) and National Sample Survey (NSS) data sets that are over a decade old.

## *2.2 Applying decomposition: explaining the socio-economic factors underlying child undernutrition in India*

Several empirical studies employ various decompositional approaches to analyse the gap in child undernutrition/health between certain groups (such as poor/non-poor, Muslims/Hindu, rural/urban). For example, Kumar and Singh (2013) apply BO decomposition to 2005–2006 NFHS data to measure the gap in under-five child undernutrition between poor and non-poor households in urban India. They identify the main contributing factors as underutilization of health care services, poor body mass index (BMI) in mothers, and low levels of parental education among impoverished urbanists. In earlier work, Bhalotra, Valente, and van Soest (2010) apply non-linear decomposition (Fairlie, 2006) to three waves of the NFHS (1992/1993, 1998/1999, and 2005/2006) to measure the Hindu-Muslim gap in under-five child undernutrition as measured by stunting and wasting. They show that the 29% difference in stunting is mainly attributable to maternal education, maternal age at parturition, and child's birth year, while the 20% gap in wasting is primarily explainable by maternal education and state of residence. In a regression-based decomposition of the same data sets to assess (concentration index-based) inequalities in under-five child mortality and undernutrition outcomes, Chalasani (2012) identifies wealth and mother's education as the two largest contributors to severe stunting and severe underweight inequality over the 1992/1993–2005/2006 period. These results are supported by Kumar and Kumari (2014), who use BO decomposition to show that household economic status (wealth score) and parental education are the most significant contributors to the rural-urban gap in childhood undernutrition in India (measured as  $z$ -scores of weight-for-age). Similarly, Mazumdar (2010) identifies household wealth and mother's education as the two largest contributors to inequality in child undernutrition, and emphasizes the importance of poverty in explaining the child undernutrition inequalities revealed by the 2005/2006 NFHS. On the other hand, Van de Poel and Speybroeck (2009), in their earlier BO decomposition of 1998/1999 IDHS data, attribute the observed child undernutrition gap between scheduled castes and scheduled tribes primarily to lower wealth, education level, and use of health care services. In a more recent analysis of 2005/2006 NFHS data, Cavatorta, Shankar, and Flores-Martinez (2015) apply Machado and Mata's (2005) conditional quantile decomposition approach (among

other methods) to show that the surprisingly modest height-for-age disparities across six Indian states<sup>1</sup> can be explained by covariate differences in endowment effects.

In sum, past analyses of undernutrition changes in Indian children under five point to household economic status (particularly wealth) and maternal education as the two most important contributors. With few exceptions, however, this research uses BO decomposition, which can provide misleading estimates when the outcome variable is binary and explanatory variables differ substantially across groups (Fairlie, 2016). To our knowledge, only two studies analyse child undernutrition using non-linear decomposition: Bhalotra et al. (2010), who use the Fairlie (1999) method to identify Hindu-Muslim disparities in under-five child mortality and undernutrition, and Cavatorta et al. (2015), who employ Machado and Mata's (2005) conditional quantile decomposition technique to explore the relative contributions of covariates and coefficients over the entire height-for-age distribution. However, we can find no previous studies using the Fairlie (1999) non-linear decomposition to examine anthropometric failure differences between groups or over time, and the Machado and Mata (2005) method is not extendable to a detailed decomposition for each determinant (Edoka, 2012). We remedy both these problems in our present analysis of newly released IHDS data for 2004–05 and 2011–12. First, by taking into account binary measures of childhood undernutrition (wasting, stunting, underweight, and anthropometric failure), we are able to apply Fairlie's (1999) non-linear decompositional approach to new variables (in particular, *CIAF*). Likewise, by using re-centred influence function regression (RIFR) in our unconditional quantile regression decomposition of the disaggregated contributions of individual determinants at different quantiles, we remedy the limitations of the conditional quantile regression used by Machado and Mata (2005).

### **3. Data and methods**

#### **3.1 Data**

The data for this analysis are taken from the India Human Development Survey (IHDS), a collaborative research program between researchers from the National Council of Applied Economic Research, New Delhi, and the University of Maryland. Designed primarily to document changes in Indian households' daily lives during an era of rapid transformation,

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<sup>1</sup> The selected states are Tamil Nadu, Bihar, Uttar Pradesh, Madhya Pradesh, Odisha and Gujarat.

this nationally representative multi-topic survey was administered to households in 1,503 villages and 971 urban neighbourhoods across India. The first phase, IHDS-I (2004–2005), comprised two one-hour interviews with each household on such topics as health status, education, employment, economic status, marriage, fertility, gender relations, and social capital. The second phase, IHDS-II (2011–2012), consisted mostly of re-interviews with the same households.

Our analytic sample is restricted to children under five for whom detailed information is available on household socio-economic, demographic, and labour market characteristics. Because data on certain outcome variables of interest are limited, our final pooled sample contains 8,481 observations for wasting, 8,418 observations for stunting, 9,962 observations for underweight, and 7,424 observations for the CIAF.

## 3.2 Study variables

### 3.2.1 *Dependent variables*

In line with the World Health Organization’s new reference standards (WHO Multicentre Growth Reference Study Group, 2006), we first measure the children’s nutritional outcomes conventionally using  $z$ -scores of height-for-age (*HAZ*), weight-for-height (*WHZ*), and weight-for-age (*WAZ*). As demonstrated in a seminal article by Waterlow et al. (1977), the height-for-age and the weight-for-height  $z$ -scores, each expressed in standard deviations from the reference population mean,<sup>2</sup> are good indicators of nutritional status. Whereas *HAZ* measures long-term nutrition by showing the cumulative effects of growth deficiency (often associated with chronic insufficient food intake, frequent infections, sustained incorrect feeding practices, and/or low socio-economic family status), *WHZ* reflects child growth and is typically seen as a measure of short- rather than long-term health status (Maitra, Rammohan, Ray, & Robitaille, 2013). The *WAZ*  $z$ -score, on the other hand, is able to reflect both acute and chronic undernutrition, making it a better single indicator of childhood undernutrition (Deaton & Dréze, 2009).

Based on these  $z$ -scores, we calculate three measures of undernutrition: wasting, stunting, and underweight. Children with values below -2 (below -3) of the reference population are considered undernourished (severely undernourished) (WHO Multicentre Growth Reference

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<sup>2</sup> The reference population includes approximately 8,500 children from widely different ethnic backgrounds and cultural settings (Brazil, Ghana, India, Norway, Oman, and the U.S.).

Study Group, 2006). It should be noted, however, that to facilitate interpretation in the BO decomposition model, we decompose only the negative  $z$ -scores of *WHZ*, *WAZ*, and *HAZ* (cf. Kumar & Singh, 2013; Uthman, 2009; Van de Poel & Speybroeck, 2009). Because these three conventional undernutrition measures reflect different aspects of anthropometric failure, however, they cannot individually determine the overall prevalence of child undernutrition in a population (Nandy, Irving, Gordon, Subramanian, & Smith, 2005; Nandy & Svedberg, 2012; Svedberg, 2000). They thus tend to underestimate the true extent of undernutrition, primarily due to the overlapping of children into multiple categories of anthropometric failure (Nandy et al., 2005; Nandy & Svedberg, 2012; Sen & Mondal, 2012). For instance, underweight cannot identify children who are suffering from underweight combined with stunting and/or wasting (Nandy & Svedberg, 2012; Sen & Mondal, 2012).

We remedy this weakness by using the composite index of anthropometric failure (CIAF), first proposed by Svedberg (2000) as an aggregated single anthropometric proxy for the overall estimation of malnourished children. In our analysis, we combine Nandy et al.'s (2005) Group Y, underweight only, with six of Svedberg's groups (2000): Group A, no failure; Group B, wasting only; Group C, wasting and underweight; Group D, wasting, stunting, and underweight; Group E, stunting and underweight; and Group F, stunting only (see Table A1 for a detailed classification). *CIAF* is thus a dummy variable for which 0 indicates no failure and 1 signals one or more anthropometric failures.

### 3.2.2 Explanatory variables

Our explanatory variables encompass four types of characteristics: maternal, economic, hygienic, and other.

*Maternal characteristics.* This category includes two variables shown to be critical to child nutritional outcomes: mother's educational attainment and maternal BMI. The first is measured on a 4-point scale from 1 = no education, 2 = primary school, 3 = secondary school, to 4 = tertiary and above; the second is reported weight (kg) divided by height squared (m). The link between maternal body weight and child nutrition is well established in the literature: a child's growth and development is likely to be influenced by maternal nutrition history as reflected by BMI. Typically, a BMI under 18 is considered underweight and possibly malnourished, 20–25 is considered healthy, 26–30 is overweight, and over 30 is obese.

*Economic characteristics.* We measure a household's economic status using the household wealth index included in the data set, which is divided into five population quintiles from the poorest to the wealthiest 20 percent of households (see Filmer & Pritchett, 2001). This index is calculated based on 33 dichotomous items measuring household ownership of assets and housing quality. These wealth quintiles are summed using principal component analysis, which provides a reasonably reliable measure of household economic status, one less likely to be affected by the transitory nature of labour income. Relative to income and consumption, therefore, the household assets measure is the least volatile and thus arguably a better long-run measure for household economic status.

*Hygienic characteristics.* The adverse effects on child growth of poor hygiene are confirmed by Prüss-Üstün, Bos, Gore, and Bartram (2008), who show that an estimated half of all cases of undernutrition in children under five are caused by unsafe water, inadequate sanitation, or insufficient hygiene. We therefore include among our explanatory variables three dummies that capture the level of sanitation and hygiene practised in the household: drinking water source, flushing toilet, and hand-washing behaviour. The drinking water source dummy equals 1 if the household's drinking water is piped or supplied by tube well or hand pump; 0 otherwise. The flushing toilet dummy equals 1 if the household has access to a flushing toilet; 0 otherwise. The hand-washing dummy equals 1 if the mother washes her hands after defecating; 0 otherwise.

*Other (control) characteristics.* Our specifications also include two child characteristics: age and gender. The child age dummy is divided into three categories ( $0 \leq \text{age} \leq 1$  year,  $1 < \text{age} \leq 3$  years, and  $3 \text{ years} \leq \text{age} < 5$  years) so as to capture any possible non-linearities, which could be important given the long-run implications of undernutrition at an early age (see Grantham-McGregor, 1995; Maitra et al., 2013). The gender dummy equals 1 if the child is male; 0 otherwise. We also control for the father's education measured in the same way as the mother's. Because religion and caste both appear related to child undernutrition (see, e.g., Bhalotra et al., 2010), we also include dummies for these, each again divided into three categories: 1 = Hindu, 2 = Muslim, 3 = other; and 1 = other castes, 2 = other backward castes, 3 = scheduled castes or tribes. To control for possible regional differences, we include a rural dummy (1 = rural, 0 = urban) and also a set of state dummies (cf. Maitra et al., 2013) to capture any state-level policies that influence child undernutrition.

### 3.3 Estimation procedure

#### 3.3.1 Blinder-Oaxaca (BO) decomposition

We use BO decomposition to explain differences in the nutritional measures *WHZ*, *HAZ*, and *WAZ* as a function of selected explanatory factors. For a linear regression, the mean-based BO decomposition of child undernutrition over time is based on the assumption that the relation between child undernutrition and a set of socio-economic and demographic characteristics is linear and additive. One advantage of BO decomposition over regression analyses is that it quantifies the contribution of specific factors accounting for the average gap in an outcome (Blinder, 1973; Oaxaca, 1973). More specifically, it not only quantifies the distribution differences of factors that explain the average gap, it identifies the differences in these factors' effects (Jann, 2008; Kumar & Singh, 2013). In our case, the total difference in mean  $z$ -scores of our three measures of child undernutrition can be decomposed as follows:

$$\bar{Y}^{2011/12} - \bar{Y}^{2004/05} = (\bar{X}^{2011/12} - \bar{X}^{2004/05})\hat{\beta}^{2011/12} + \bar{X}^{2004/05}(\hat{\beta}^{2011/12} - \hat{\beta}^{2004/05}) \quad (1)$$

where  $\bar{X}^i$  is a vector of the averaged values of the independent variables and  $\hat{\beta}^i$  is a vector of the coefficient estimates for wave  $i$  (here,  $i = 2004/2005, 2011/2012$ ).

#### 3.3.2 Re-centred influence function regression (RIFR) decomposition

Because covariate versus coefficient contributions may differ between the median and upper tail of the childhood undernutrition distribution and its lower tail (where severe undernutrition is more likely to be prevalent), we use RIFR decomposition (Firpo et al., 2009) to investigate the contributions of demographic and socio-economic characteristics at different quantiles of the unconditional marginal distribution. As highlighted by Srinivasan, Zanello, and Shankar (2013), such distribution-wide exploration could be valuable, especially when it targets the most vulnerable in a policy setting. The RIFR method involves a two-step procedure. In the first step, we calculate an influence function (IF) at each quantile  $\tau$  of the distribution of the outcome variable ( $z$ -score of child undernutrition), which is obtained as follows:

$$RIF(zscore; q_\tau) = q_\tau + (\tau - 1[zscore \leq q_\tau])/f_{zscore}(q_\tau) \quad (2)$$

where  $q_\tau$  represents the unconditional  $\tau$ th quantile of the  $z$ -score,  $f_{zscore}(q_\tau)$  is the unconditional density of the  $z$ -score at the  $\tau$ th quantile, and  $1[zscore \leq q_\tau]$  is an indicator

function for whether the outcome variable is small or equal to the  $\tau$ th quantile. For each quantile, the coefficient on  $X$  for waves 2004/2005 and 2011/2012 are then estimated by regressing the RIF on  $X$ :

$$q_{wave,\tau} = E_X \left[ E \left[ \widehat{RIF}(zscore; q_{wave,\tau}) | X_{wave} \right] \right] = E[X_{wave}] \hat{\theta}_{wave,\tau} \quad (3)$$

where  $q_{wave,\tau}$  is the unconditional  $\tau$ th quantile of the  $z$ -score for wave 2004/05 and 2011/12, respectively.  $\hat{\theta}_{wave,\tau}$  is the coefficient of the unconditional quantile regression, which captures the marginal effect of a change in the distribution of  $X$  on the unconditional quantile of the  $z$ -score.

In the second step, we employ the BO decomposition strategy at different quantiles (25%, 50%, and 75%) calculated by the RIFR:

$$\hat{\Delta}_{zscore}^{\tau} = \left[ \widehat{RIF}(zscore_{2011/12}; q_{2011/12,\tau}) \right] - \left[ \widehat{RIF}(zscore_{2004/05}; q_{2004/05,\tau}) \right] \quad (4)$$

$$\hat{\Delta}_{zscore}^{\tau} = (\bar{X}_{2011/12} - \bar{X}_{2004/05}) \hat{\theta}_{2011/12,\tau} + \bar{X}_{2004/05} (\hat{\theta}_{2011/12,\tau} - \hat{\theta}_{2004/05,\tau}) \quad (5)$$

Both the explained and unexplained parts are then decomposed into the contributions of each covariate at the  $\tau$ th quantile in equation (5), which is in effect analogous to the BO decomposition in equation (1).

### 3.3.3 Fairlie's (1999) non-linear decomposition

As stressed by Fairlie (2016), applying standard BO decomposition to a linear probability model provides misleading estimates when dependent variables are binary, particularly if the group differences for an influential independent variable are relatively large. In this case, it is preferable to apply a relatively straightforward simulation technique for non-linear decomposition. Accordingly, in estimating the contributions of socio-economic and demographic factors to identified differences in our key undernutrition indicators – (severe) wasting, stunting, underweight, and the combined CIAF indicator – we follow Fairlie (1999) by employing a non-linear decomposition approach when the dependent variable is binary. Here, wasting, stunting, underweight, and overall anthropometric failure are the dependent variables, so the decomposition for the non-linear equation,  $Y = F(X\hat{\beta})$ , can be expressed as

$$\begin{aligned}
& \bar{y}^{2011/12} - \bar{y}^{2004/05} \\
&= \left( \sum_{i=1}^{N^{2011/12}} \frac{F(X_i^{2011/12} \hat{\beta}^{2004/05})}{N^{2011/12}} - \sum_{i=1}^{N^{2004/05}} \frac{F(X_i^{2004/05} \hat{\beta}^{2004/05})}{N^{2004/05}} \right) \\
&+ \left( \sum_{i=1}^{N^{2011/12}} \frac{F(X_i^{2011/12} \hat{\beta}^{2011/12})}{N^{2011/12}} - \sum_{i=1}^{N^{2011/12}} \frac{F(X_i^{2011/12} \hat{\beta}^{2004/05})}{N^{2011/12}} \right) \quad (6)
\end{aligned}$$

where  $N^j$  denotes the sample size of each wave ( $j = 2004/2005, 2011/2012$ ). Two aspects are worth noting: First, the BO decomposition in equation (1) is a special case of equation (6) where  $F(X_i\beta) = X_i\beta$ . Second, in equations (1) and (6), the first (explained) term on the right indicates the contribution resulting from a difference in the distribution of the determinant of  $X$ , and the second (unexplained) term refers to the part attributable to a difference in the effect of the determinants. Equally noteworthy, the second term captures all the potential effects of differences in unobservables (Fairlie, 2016). Here, in keeping with the majority of previous research using decomposition, we focus on the explained terms and their disaggregated contribution for individual covariates, which result primarily from the difficulty of interpreting the unexplained part.<sup>3</sup> The contribution of a variable is given by the average change in function if that variable is changed while all other variables remain the same. It should further be noted that for severe childhood undernutrition in terms of *WHZ*, *HAZ*, and *WAZ*, we use the same specification as in equation (6).

One potential concern related to Fairlie's (1999) sequential decomposition is path dependence, the possibility that changing the order of variables in the decomposition may produce different results (Fairlie, 2016; Schwiebert, 2015). We therefore test the decomposition estimates' sensitivity to variable re-ordering by randomizing their order in the decomposition (Fairlie, 2016; Schwiebert, 2015). As Fairlie (2016) also emphasizes, however, the decomposition procedure approximates the average decomposition over all possible orderings while preserving the summing up of properties by using a large number of replications. We therefore use 1,000 replications, the minimum number recommended for most applications (see, e.g., Fairlie, 2016). As a robustness check, we also perform an analysis using 5,000 replications.

When reporting the two-fold (explained vs. unexplained) decomposition results for these three decompositional methods, we categorize the disaggregated contributions of the

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<sup>3</sup> For a more detailed discussion of the unexplained part, see Jones (1983).

determinants in the explained part into four main dimensions: maternal characteristics (mother's BMI and its squared term; mother's primary, secondary, tertiary school and above), household economic status (household wealth: poorest, poor, middle, rich, and richest); hygiene (the sum of water source, flushing toilet, and hand washing); and other (child age dummy for  $1 < \text{age} \leq 3$  and  $3 \leq \text{age} < 5$ ; child gender dummy; father's primary, secondary, tertiary school and above; caste: other backwards, schedules castes and tribes; religion: Muslim and other; and finally, 32 state dummies and a rural dummy).

## 4. Results

### 4.1 Descriptive statistics

As Table 1 shows, stunting, underweight, and anthropometric failure improved modestly over the 2004/2005 to 2011/2012 period (a 44.0% to 35.5% decline in stunting, 33.1% to 27.2% in underweight, and 58.4% to 49.4% in CIAF). Wasting, however, slightly worsened over the same period, increasing from 16% to 16.9%. As regards *severe* undernutrition, all three individual indicators – wasting, stunting, and underweight – improved slightly during the same period; however, at different magnitudes: from 6.3% to 5.7% for severe wasting, from 25.4% to 17.5% for severe stunting, and 13.5% to 10.2% for severe underweight. Nonetheless, the CIAF indicates a much higher prevalence of undernutrition among children under five than do the individual measures, a finding well in line with previous observations (Nandy et al., 2005; Nandy & Svedberg, 2012; Sen & Mondal, 2012), and one that underscores the serious state of undernutrition among India's children.

Table 1 Descriptive statistics

Variables	2004-2005	2011-2012	Mean difference
<b>Nutritional outcomes</b>			
Weight-for-height z-score (WHZ)	-0.473	-0.628	0.155***
Height-for-age z-score (HAZ)	-1.437	-1.152	-0.285***
Weight-for-age z-score (WAZ)	-1.092	-0.945	-0.147***
<b>Undernutrition measures</b>			
Wasting (WHZ<-2)	0.160	0.169	-0.010
Stunting (HAZ<-2)	0.440	0.355	0.085***
Underweight (WAZ<-2)	0.331	0.272	0.059***
Severe wasting (WHZ<-3)	0.063	0.0570	0.005
Severe stunting (HAZ<-3)	0.254	0.175	0.079***
Severe underweight (WAZ<-3)	0.135	0.102	0.033***
Anthropometric failure (CIAF)	0.584	0.494	0.090***

Maternal characteristics			
Mother's education: no education	0.573	0.489	0.084***
Mother's education: primary	0.087	0.101	-0.014**
Mother's education: secondary	0.293	0.368	-0.076***
Mother's education: tertiary and above	0.048	0.042	0.006
Mother's BMI (kg/m <sup>2</sup> )	20.510	20.74	-0.230***
Economic status			
Household wealth: poorest	0.344	0.199	0.145***
Household wealth: poor	0.240	0.248	-0.007
Household wealth: middle	0.200	0.183	0.018**
Household wealth: rich	0.124	0.184	-0.060***
Household wealth: richest	0.091	0.187	-0.095***
Hygiene			
Water source	0.837	0.848	-0.011
Flushing toilet	0.177	0.259	-0.082***
Hand washing	0.992	0.993	-0.001
Other controls			
Child's age (in years): 0 ≤ age ≤ 1	0.307	0.309	-0.002
Child's age (in years): 1 < age ≤ 3	0.213	0.205	0.008
Child's age (in years): 3 < age < 5	0.480	0.486	-0.006
Child' gender (1 = male, 0 = female)	0.513	0.524	-0.011
Father's education: no education	0.378	0.312	0.066***
Father's education: primary	0.101	0.127	-0.026***
Father's education: secondary	0.445	0.487	-0.042***
Father's education: tertiary and above	0.076	0.074	0.002
Caste: other	0.242	0.208	0.034***
Caste: other backward	0.408	0.399	0.009
Caste: scheduled caste/tribe	0.350	0.393	-0.043***
Religion: Hindu	0.766	0.763	0.003
Religion: Muslim	0.168	0.196	-0.027***
Religion: other	0.065	0.041	0.024***
Rural	0.650	0.729	-0.080***

Note: Mean values are reported for key variables in the IHDS 2004/2005 and 2011/2012. The significance of the mean difference is based on independent *t*-tests. \*  $p \leq 0.05$ , \*\*  $p \leq 0.01$ , \*\*\*  $p \leq 0.001$ .

Figure 1 reports the kernel densities of the *z*-scores stratified by year. Using a Kolmogorov-Smirnov test for the equality of distributions, we consistently reject the null hypothesis that the distributions are the same over the two survey waves. However, two points are worth emphasizing: First, the mass of the distribution for *HAZ* and *WAZ* in 2011/2012 lies to the right of the 2004/2005 wave, suggesting improvements in these two measures of child undernutrition. Second, a relatively small part of the *WHZ* distribution in 2011/2012 lies to the left of the 2004/2005 distribution, indicating a slight deterioration in the weight-to-height measure. This observation is consistent with Maitra et al.'s (2013) finding for the 1998/1999 – 2005/2006 period based on NFHS data.

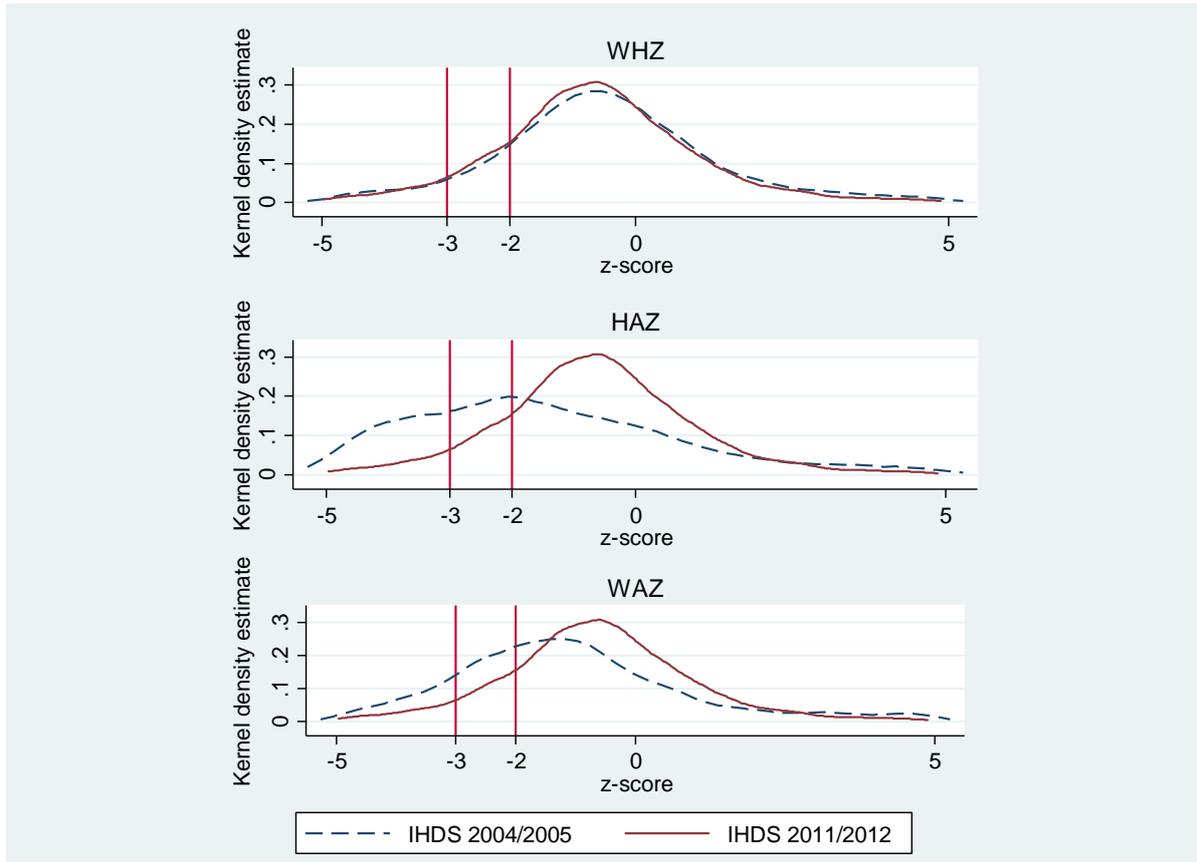


Figure 1 Kernel density estimates for *WHZ*, *HAZ*, and *WAZ* by year

Note: Kolmogorov–Smirnov test *p*-value: *WHZ*: combined K–S 0.048; *p*-value = 0.000; *HAZ*: combined K–S 0.098; *p*-value = 0.000; *WAZ*: combined K–S 0.062; *p*-value = 0.000

## 4.2 Explaining the differences in nutritional outcomes

### 4.2.1 *Blinder-Oaxaca decomposition estimates*

The results of the conventional BO decomposition for the *WHZ*, *HAZ*, and *WAZ* *z*-scores are reported in Table 2, with a (previously explained) focus on the explained part. This table reveals no significant explained differences in *WHZ* between 2004–2005 and 2011–2012. For *HAZ* and *WAZ*, however, which do document an improvement in undernutrition, the contributions of the explained part differ, with about 14–26% of the difference explainable by varying covariate endowments. As regards the separate contributions to the explained part made by differences in the individual distribution of each dimension, household economic status (measured by household wealth) is the most important contributor to explaining improvement in the average values of *HAZ* (115%) and *WAZ* (84%). The maternal characteristics such as mother’s BMI and mother’s education are also relatively important

contributors (*HAZ*: 16%; *WAZ*: 24%). These results are well in line with the NFHS-based findings of Chalasani (2012), Van de Poel and Speybroeck (2009), and Mazumdar (2010), who also identify household wealth and maternal education as the two largest contributory factors to childhood undernutrition. The importance of household wealth in reducing poor nutrition outcomes is also in keeping with the descriptive statistics reported in Table 1, which indicate that between the 2004–2005 and 2011–2012 periods, the proportion of children under five declined in the poorest wealth quintile but increased in the two richest wealth quintiles.

Table 2 Blinder-Oaxaca (BO) decomposition of socio-economic differences in undernutrition among Indian children under five: IHDS 2004/2005–2011/2012

	<i>WHZ</i>	Contribution	<i>HAZ</i>	Contribution	<i>WAZ</i>	Contribution
Overall		%		%		%
2004-2005	-1.4179*** (0.019)		-2.3455*** (0.022)		-1.8944*** (0.017)	
2011-2012	-1.3970*** (0.020)		-2.0669*** (0.024)		-1.7054*** (0.019)	
Total difference	0.0209 (0.028)		0.2786*** (0.032)		0.1889*** (0.026)	
Explained			0.0393** (0.016)	14	0.0494*** (0.012)	26
Unexplained			0.2393*** (0.034)	86	0.1395*** (0.027)	74
<b>Explained part</b>						
Maternal characteristics			0.0073* (0.004)	19	0.0118*** (0.004)	24
Economic status			0.0453*** (0.012)	115	0.0415*** (0.009)	84
Hygiene			0.0012 (0.004)	3	-0.0014 (0.003)	-3
Other			-0.0144 (0.010)	-37	-0.0024 (0.007)	-5
<i>N</i>	5,669		6,414		7,686	

*Note:* The dependent variables are *z*-scores of weight-for-height, height-for-age, and weight-for-age. Maternal characteristics are mothers' BMI and its squared term; and the mother's education categories of primary, secondary, and tertiary and above. Household wealth is captured by the five wealth quintiles (with poorest as the reference category). Hygiene is access to piped/tube water for drinking, a flushing toilet, and mother's hand-washing behaviour. Other variables in the group are child age; gender; father's educational categories of primary, secondary, and tertiary and above; caste groups of other backward and scheduled/tribes; religion groups of Muslim and others; state dummies for all states excluding Uttar Pradesh, and a rural dummy. Standard errors are in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

#### 4.2.2 RIFR decomposition estimates

In a next step, we investigate the explanatory power of demographic and socio-economic characteristics at different quantiles of the unconditional marginal distribution of the undernutrition distribution (see Table 3). Three major findings are worth highlighting: First, household wealth (a proxy for the household economic status) once again consistently makes the largest contribution to the overall explained part for both *WAZ* and *HAZ* (panels B and C, respectively). However, such is not the case for any of the three quantiles for the *WHZ* indicator (panel A), where the difference cannot be explained with the socio-economic

variables used in the analysis. In fact, based on maternal characteristics, the *WHZ* gap should be consistently smaller. In the case of *HAZ* (panel B), in the lower parts of the distribution, about 10-11% of the gap can be explained with our variables, whereas in the upper part (75% quantile), the difference cannot be explained. In fact, in the 75% quantile, based on the considered determinants, the gap should be larger than it actually is. The fact that differences at the upper end of the distribution cannot be readily explained with the traditional determinants of undernutrition is not all that surprising. In the 25% quantile (i.e. those children particularly affected by undernutrition), the explained part of 10% can, to a large extent, be explained by household wealth. Turning to *WAZ* (panel C), we note that in the bottom part of the distribution, about 20-36% of the gap can be explained by our variables. Household wealth, once again, plays a main role, accounting for much of the explained part of the gap.

Table 3: RIFR decomposition of socio-economic differences in *WHZ*, *HAZ*, and *WAZ* among Indian children under five: IHDS 2004/2005–2011/2012

Panel A						
	<i>WHZ</i>					
	25%	Contribution	50%	Contribution	75%	Contribution
Overall		%		%		%
2004-2005	-1.4884*** (0.027)		-0.5513*** (0.026)		0.4443*** (0.031)	
2011-2012	-1.5492*** (0.036)		-0.6641*** (0.026)		0.2546*** (0.036)	
Total difference	-0.0608 (0.042)		-0.1128*** (0.036)		-0.1897*** (0.050)	
Explained			0.0242 (0.017)	-21	0.0320 (0.020)	-17
Unexplained			-0.1370*** (0.039)	121	-0.2217*** (0.054)	117
Explained part						
Maternal characteristics			0.0149** (0.006)	-62	0.0204*** (0.007)	-64
Economic status			0.0063 (0.012)	-26	0.0120 (0.015)	-38
Hygiene			0.0016 (0.005)	-7	-0.0029 (0.006)	9
Other			0.0015 (0.012)	-5	0.0026 (0.012)	-7
<i>N</i>	8,481		8,481		8,481	
Panel B						
	<i>HAZ</i>					
	25%	Contribution	50%	Contribution	75%	Contribution
Overall		%		%		%
2004-2005	-2.9910*** (0.041)		-1.7046*** (0.034)		-0.1274** (0.056)	
2011-2012	-2.4898*** (0.041)		-1.3866*** (0.043)		0.0371 (0.049)	
Total difference	0.5012*** (0.056)		0.3180*** (0.055)		0.1645** (0.076)	
Explained	0.0506* (0.027)	10	0.0359 (0.030)	11	-0.0667 (0.040)	-41
Unexplained	0.4506*** (0.062)	90	0.2821*** (0.056)	89	0.2312*** (0.073)	141
Explained part						
Maternal characteristics	0.0092 (0.007)	18	0.0101 (0.008)	28	-0.0015 (0.010)	2

Economic status	0.0698*** (0.019)	138	0.0579*** (0.017)	161	0.0221 (0.024)	-33
Hygiene	0.0051 (0.007)	10	0.0037 (0.007)	10	-0.0012 (0.010)	2
Other	-0.0335* (0.017)	-66	-0.0358* (0.020)	-99	-0.0861*** (0.029)	129
<i>N</i>	8,418		8,418		8,418	
Panel C			WAZ			
	25%	Contribution	50%	Contribution	75%	Contribution
Overall		%		%		%
2004-2005	-2.3631*** (0.029)		-1.3058*** (0.033)		-0.1695*** (0.039)	
2011-2012	-2.0723*** (0.031)		-1.1190*** (0.030)		-0.1120*** (0.039)	
Total difference	0.2909*** (0.040)		0.1869*** (0.045)		0.0575 (0.050)	
Explained	0.0581*** (0.021)	20	0.0666*** (0.023)	36		
Unexplained	0.2328*** (0.046)	80	0.1203*** (0.043)	64		
Explained part						
Mother characteristics	0.0203*** (0.006)	35	0.0160** (0.007)	24		
Economic status	0.0470*** (0.014)	81	0.0721*** (0.013)	108		
Hygiene	-0.0003 (0.005)	-1	-0.0026 (0.006)	-4		
Other	-0.0089 (0.013)	-15	-0.0189 (0.015)	-28		
<i>N</i>	9,962		9,962		9,962	

Note: The groups are the same as in Table 2. The dependent variables are the *z*-scores of weight-for-height (*WHZ*), height-for-age (*HAZ*), and weight-for-age (*WAZ*). Standard errors are in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

### 4.3 Explaining the differences in undernutrition between 2004–2005 and 2011–2012

#### 4.3.1 Undernutrition in children under five at a $<-2$ standard deviation cut-off

A useful way to measure the extent of the undernutrition is to classify the *z*-scores into the three levels suggested by Kassouf and Senauer (1996): (i) severe: *z*-score  $<-3$ , (ii) moderate: *z*-score in the  $-3$  to  $-2$  interval, and (iii) normal and mild (combined into one category): *z*-score larger than  $-2$ . Given that all three undernutrition indicators (wasting, stunting, underweight) and the CIAF are binary measures, we estimate the non-linear decomposition regressions proposed by Fairlie (1999). Because our aim is to identify the factors that influence both general and severe undernutrition in children under five, in Tables 4 and 5, we report the results for cut-offs of  $-2$  standard deviations (general undernutrition) and  $-3$  standard deviations (severe undernutrition), respectively.

As Table 4 shows, the contributions of the explained part vary substantially for the different measures of child undernutrition: 6% for stunting, 22% for mild underweight, and 21% for the CIAF, with no significant explained differences for wasting. For the individual contribution of each dimension in the explained part, household economic status (household

wealth) uniformly explains the largest proportion of improvements in stunting, underweight, and anthropometric failure, with contributions of 161%, 89%, and 66%, respectively. Likewise, maternal characteristics (including maternal BMI and education) explain 69% of stunting, 48% of underweight, 23% of anthropometric failure.<sup>4</sup>

Table 4: Non-linear decomposition of socio-economic differences in undernutrition among Indian children under five: IHDS 2004/2005-2011/2012 (based on probit estimates)

	Wasting	Contribution	Stunting	Contribution	Underweight	Contribution	CIAF	Contribution
		%		%		%		%
2004-2005	0.1595		0.4398		0.3314		0.5842	
2011-2012	0.1691		0.3546		0.2724		0.4943	
Total difference	0.0096		-0.0852		-0.0590		-0.0899	
Explained			-0.0049	6	-0.0132	22	-0.0185	21
Unexplained			-0.0803	94	-0.0458	78	-0.0714	79
<b>Explained part</b>								
Maternal characteristics			-0.0034*** (0.001)	69	-0.0063*** (0.001)	48	-0.0042*** (0.001)	23
Economic status			-0.0079** (0.004)	161	-0.0117*** (0.003)	89	-0.0122*** (0.004)	66
Hygiene			-0.0027 (0.002)	55	-0.0007 (0.001)	5	-0.0021 (0.002)	11
Other			0.0092*** (0.003)	-187	0.0054*** (0.002)	-42	-0.0000 (0.003)	0
Number of replications	1,000		1,000		1,000		1,000	

Note: The groups are the same as in Table 2. The dependent variable is a dummy for whether the respondent is suffering or has suffered from wasting, stunting, underweight, and/or anthropometric failure. Standard errors are in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

#### 4.3.2 Severe undernutrition in children under five with a $<-3$ standard deviation cut-off

Following Chalasani (2012), we also examine severe forms of stunting and underweight (Table 5), showing that once again, household economic status (household wealth) is the most important contributor to improvement in severe childhood undernutrition at 65% and 69% for stunting and underweight, respectively. Maternal characteristics also remain relatively important, particularly for severe underweight, with a contribution of 39%.

Table 5: Non-linear decomposition of socio-economic differences in severe undernutrition among Indian children under five: IHDS 2004/2005– 2011/2012 (based on probit estimates)

	Severe wasting	Contribution	Severe stunting	Contribution	Severe underweight	Contribution
		%		%		%
2004-2005	0.0625		0.2539		0.1348	
2011-2012	0.0573		0.1751		0.1022	
Total difference	-0.0052		-0.0788		-0.0326	

<sup>4</sup> To check the possible biases from path dependence, and also to measure the case of severe undernutrition in under-five Indian children, we also randomize the variable order and re-run the estimates with 1,000 and 5,000 replications. The results, available from the authors upon request, are qualitatively similar.

Explained		-0.0082	10	-0.0103	32
Unexplained		-0.0706	90	-0.0223	68
<hr/>					
Explained part					
Maternal characteristics		-0.0018** (0.001)	22	-0.0040*** (0.001)	39
Economic status		-0.0135*** (0.003)	165	-0.0071*** (0.002)	69
Hygiene		0.0005 (0.002)	-6	-0.0009 (0.001)	9
Other		0.0066*** (0.002)	-81	0.0017 (0.001)	-17
<hr/>					
Number of replications	1,000	1,000		1,000	

*Note:* The groups are the same as in Table 2. The dependent variable is a dummy for the respondent is suffering or has suffered from wasting, stunting, underweight, and/or anthropometric failure. Standard errors are in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Taken together, the results for the BO, non-linear, and IRFR decompositions suggest that household economic status (proxied by household wealth) consistently makes the largest contribution to the explained part of the observations, irrespective of whether the measure used is the *WHZ*, *HAZ*, or *WAZ*. The same holds for *CIAF* in the non-linear decomposition. Maternal characteristics are also important, however, especially for severe underweight, all three percentiles of the *WHZ*, and the 25% and 50% quantiles of *WAZ*. These outcomes conform closely to earlier decomposition results for India based on NFHS data (Chalasan, 2012; Mazumdar, 2010; Van de Poel & Speybroeck, 2009), suggesting that the underlying drivers of child undernutrition in India have remained the same.

## 5. Conclusions

The poor nutritional outcomes for children in India, coupled with the high economic growth rates in recent decades, have been the subject of much research. Not only is India the largest contributor to the critical public health problem of wasting in South Asia (UNICEF, 2013), but it has the worst record for stunting in children under five. Nevertheless, the studies that yielded these observations are based on data that are over a decade old, so although their identification of the most adversely affected socio-economic groups is useful, the international community still has limited understanding of the critical factors contributing to undernutrition in Indian children.

To help remedy this problem, we analyse recently released data from phases I (2004/2005) and II (2011/2012) of the nationally representative Indian Human Development Studies to provide a more up-to-date and comprehensive profile of the key demographic and socio-

economic determinants of undernutrition in Indian children under five. In a first analytic step, we use *z*-scores for weight-for-height (*WHZ*), height-for-age (*HAZ*), weight-for-age (*WAZ*), and overall anthropometric failure (*CIAF*) to sketch undernutrition trends in this population from 2005 to 2012, which allows us to identify any changes in nutritional outcomes. Next, using conventional BO decomposition, we assess the disaggregated contributions of demographic and socio-economic determinants to the changes in various indicators of child undernutrition over the period under study. In this way, we are able to identify the characteristics that are most effective in explaining child nutrition so that they can be better targeted by policy intervention. We then introduce an unconditional quantile decomposition technique – the re-centred influential function regression (RIFR) – to identify the contributions of demographic and socio-economic characteristics at different quantiles of the unconditional marginal distribution of the childhood undernutrition distribution. Because our wasting, stunting, underweight, and anthropometric failure measures are all binary, we are able to overcome any possible biases from the conventional BO decomposition by applying the non-linear decomposition technique proposed by Fairlie (1999).

Our analysis yields the following major findings: First, even though more children were represented in the higher wealth quintiles in IHDS-II (2011–2012), wasting had worsened slightly since IHDS-I (2004–2005). Given that wasting results from a child being unable to take in adequate calories because of repeated infections and/or diarrhoea, a wasted child is at high risk of death. Nevertheless, a modest improvement is observable in stunting, underweight, and overall anthropometric failure, as well as in severe undernutrition. On the other hand, the *CIAF* scores reveal a much higher prevalence of child undernutrition, suggesting that conventional undernutrition indicators like wasting, stunting, and underweight may underestimate its actual extent. This finding is consistent with those of previous studies using older data sets (Nandy et al., 2005; Nandy & Svedberg, 2012; Savanur & Ghugre, 2015; Sen & Mondal, 2012), underscoring the *CIAF*'s validity for evaluating overall undernutrition and identifying children with multiple anthropometric failures.

In addition, even though our analysis points to uneven progress in improving *WHZ*, *WAZ*, and *HAZ*, all three decomposition techniques (BO, non-linear, and RIFR) indicate that household economic status consistently makes the largest contribution to the explained part of all three nutritional measures. It is also the largest contributor to the explained part of *CIAF* in the non-linear decomposition. Nevertheless, maternal characteristics also play a relatively

important role, especially for severe underweight, all three percentiles of the *WHZ* and 25% and 50% quantiles of *WAZ*. The robustness of these findings has important implications for the development of appropriate policies to address the critical factors that may be contributing to the slow progress in improving nutrition among India's children.

As highlighted by the recently released 2013 *Lancet* Maternal and Child Nutrition Series (MCNS) (Lancet, 2013), the new sustainable development agenda should prioritize all forms of undernutrition, with a special emphasis on nutrition-specific interventions and programs (e.g. addressing the immediate determinants of child undernutrition), nutrition sensitive programmes and approaches (e.g. addressing the underlying determinants of child undernutrition), and building an enabling environment (e.g. addressing the basic determinants of child undernutrition). Our research has highlighted the main determinants of undernutrition among Indian children. Appropriate policies focusing on these determinants (household wealth, maternal BMI and education) need to be fostered. It is worth noting that these lacklustre trends in child nutrition in India have occurred despite a funding increase from US\$35 million in 1990 to US\$170 million in 2000 for the ICDS program, and a 2005 Indian government decision to give high priority to its expansion. Moreover, although the ICDS is the most well-known of India's national dedicated maternal and child health nutrition and education programs, there are at least two other national and 10 regional nutrition and education programs, including the National Midday Meal Scheme, the National Rural Health Mission, the Comprehensive Rural Health Project, the Integrated Nutrition and Health Program, and the Public Distribution System. Unfortunately, these programs appear to compete rather than collaborate with one another in the achievement of optimal maternal and child health outcomes (Mann, Eble, Frost, Premkumar, & Boone, 2010; Tarozzi, 2002).

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## Appendix:

Table A1 Anthropometric failure groups among children under five

Group	Description	Wasting	Stunting	Underweight
A	No failure: Children whose height and weight are above the age-specific norm and do not suffer from any anthropometric failure	No	No	No
B	Wasting only: Children with acceptable weight and height for their age but who have subnormal weight-for-height	Yes	No	No
C	Wasting and underweight: Children with above norm heights but whose weight-for-age and weight-for-height are too low.	Yes	No	Yes
D	Wasting, stunting, and underweight: Children who suffer from anthropometric failure on all three measures	Yes	Yes	Yes
E	Stunting and underweight: Children with low weight-for-age and low height-for-age, but who have acceptable weight for their height	No	Yes	Yes
F	Stunting only: Children with low height-for-age but who have acceptable weight, both for their age and for their short height.	No	Yes	No
Y	Underweight only: Children who are only underweight.	No	No	Yes

*Source:* Based on Nandy and Svedberg (2012).

*Note:* The theoretical combination of wasting and stunting is not physically possible because a child cannot simultaneously experience wasting and stunting and not be underweight.