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Explaining Cross-State Disparities in Child Nutrition in Rural India

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Summary. — What drives the large disparities in height-for-age distributions among Indian states - variation in observed nutrition-related endowments, such as wealth or maternal education, or differential strengths of relationships across states between endowments and height-for-age? We explore this question by comparing a set of states with poor nutrition outcomes with the benchmark of Tamil Nadu, a good performer. Applying counterfactual decomposition methods to National Family Health Survey data, we find that surprisingly modest proportions of HAZ differences are attributable to endowment differences. We discuss our results in light of the superior track record of food and nutrition policies in Tamil Nadu.

Key words — nutrition, India, height-for-age, food policy, nutrition policy

1. INTRODUCTION

Understanding the reasons for persistently poor child nutrition, particularly height for age (HAZ), outcomes in India in the face of relatively strong economic performance has emerged as an important research area in recent years. India has the largest number of stunted children in the world, with a child stunting prevalence that is worse than Sub-Saharan Africa's, despite India's economic advantages (Spears, 2013). Evidence is accumulating that there could be severe lifelong economic, health, and cognitive repercussions arising from these early childhood height deficits (Spears, 2012).

A marked feature of child nutrition outcomes in India and their evolution is their substantial heterogeneity across states. The National Family Health Survey 2005 data (NFHS-3) show that stunting prevalence among under-fives ranges from 24% in Kerala to 57% in Uttar Pradesh. Also, the evolution of stunting prevalence over time and its associations with aspects such as economic growth and agricultural growth is characterized by significant heterogeneity across states. Headey, Chiu, and Kadiyala (2012) present data over 1992–2005 to show that economic progress, including agricultural growth, is strongly correlated with nutritional outcomes in some states but very weakly in others. Menon, Deolalikar, and Bhaskar (2008) compute an Indian State Hunger Index (comprising calorie inadequacy, child underweight and child mortality) using the same methodology as the Global Hunger Index and find that there is substantial variability among states and that much of this variability is contributed by the anthropometry component of the index. Moreover, they find the association between values of the index and state per-capita income and economic growth to be weak.

What explains the observed heterogeneity in nutrition outcomes across states in India? Some of it will be due to differential endowments across states of the variables commonly used in explaining nutrition outcomes using individual and household-level data - household income, assets, education, sanitation, etc. This is, for example, reflected in the correspondence between state Human Development Index values (covering indices of income, life-expectancy and education) and child nutrition outcomes - some of the best performers are the same across these dimensions (e.g., Tamil Nadu, Kerala, Goa), and so are some of the worst performers (e.g., Bihar, Madhya Pradesh). However, the findings of Headey et al. and Menon et al. (2008) noted above suggest that the *strengths of relationships* between observed determinants and nutrition outcomes might also be different across states.

Although other unobservable factors could also be reflected in the strength of relationship between a typical observed covariate such as household income or maternal education and a child nutrition outcome, variations in nutrition-related policies, programs and institutions across states could be important. Tying such elements back to politics, Harriss and Kohli (2009) emphasize that crucial differences in whether a particular state's political landscape allows the poor and marginalized to have political voice, and in the quality of institutions, have an important bearing upon nutrition outcomes that can be achieved with given endowments of wealth and other observables.

In a regression context, the differences in nutrition outcomes across states explained by differences in observed covariates can be termed *covariate effects*. Differences explained by differing strengths of relationships between covariates and outcomes, in other words the "returns" to specific endowments, can be termed *coefficient effects*. Understanding the drivers of differences in nutrition outcomes between better and worse performing Indian states, and the relative roles of covariate and coefficient effects is important because, (i) given the size and diversity of India, a one-size-fits-all national picture is unlikely to be sufficiently informative for nutrition-related programing and policymaking, (ii) not only are there large gaps between states at the two ends of the spectrums of most social and economic development indicators, but many of these gaps are also widening (Purfield, 2006). Furthermore, three of the states of the bottom of the nutrition league, Bihar,

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Madhya Pradesh, and Uttar Pradesh are also where the bulk of the projected population increase in the next decades will come from (Visaria & Visaria, 2003), (iii) A comprehension of the relative roles of covariate and coefficient effects can provide an understanding of the extent to which nutrition convergence can be attained by improving basic endowments that impinge on nutrition, and the extent to which more directly nutrition-related programing and the general quality of institutions and policy-making, as reflected in coefficient effects, are important.

A vibrant literature, reviewed below, has emerged that empirically explores the determinants of child anthropometric outcomes in India. This literature has significantly advanced appreciation of the correlates of improved child nutrition for the nation as a whole. However, less attention has been paid to unpacking heterogeneity in outcomes across specific states. This paper aims to fill this gap in the literature by an empirical case-study approach that compares a set of states displaying relatively poor child nutrition outcomes - Bihar, Madhya Pradesh, Uttar Pradesh, Odisha, and Gujarat, [1] with a benchmark state displaying relatively good outcomes: Tamil Nadu. Given the higher prevalence of malnutrition in rural than in urban areas, the heterogeneity in the characterization of rural *versus* urban nutrition (Smith, Ruel, & Ndiaye, 2005; Srinivasan, Zanello, & Shankar, 2013), and in consonance with the recent literature (Spears, 2013; Headey et al., 2012), we focus on rural areas. We use the last available nationally representative National Family Health Survey (NFHS-3) data and counterfactual decomposition methods to assess covariate and coefficient effects to explain HAZ differentials between benchmark and comparison states. This is done first for mean HAZ differentials using Oaxaca–Blinder decompositions, and then for the entire HAZ distribution using decompositions based on quantile regressions. The latter are termed "Quantile Regression-based Counterfactual Decomposition" (QR-CD) methods, and allow the covariate and coefficient effects to differ along the entire distribution of nutrition outcomes. For example, are covariate *versus* coefficient contributions to cross-state comparisons different at the lower tail of the HAZ distribution (where severe stunting is likely to be prevalent) compared to the middle and upper parts of the HAZ distribution? In a policy atmosphere where targeting of the most vulnerable is important, such distribution-wide insights can be valuable (Srinivasan et al., 2013).

The paper proceeds as follows: Section 2 places this study within the context of previous literature. Sections 3 and 4 present the data and decomposition methods respectively. Section 5 discusses the decomposition results and Section 6 concludes with a discussion of our findings.

2. PREVIOUS LITERATURE

Two literatures of central interest to this study are briefly reviewed in this section: one on the empirical modeling of child anthropometry in India and the other on cross-state political and institutional differences impacting development outcomes.

Among several puzzles surrounding trends in growth, poverty, and nutrition in India, Deaton and Drèze (2009) highlight the very slow improvements in child anthropometric outcomes despite vigorous growth in income. This stagnation, and international comparisons that paint a worrying picture of child nutrition in India, have been debated extensively (see Panagariya, 2013, and the ensuing discussion in the *Economic and Political Weekly*).

A number of studies have carried out regression modeling to explain variation in child anthropometry in India. The UNICEF conceptual framework on child nutrition outcomes (UNICEF, 1990) has underpinned the specification of these studies. The models have typically included a variety of controls capturing observable and quantifiable basic and underlying causes of nutrition, but have often trained special focus on particular aspects of interest. [2] Spears (2013) highlights the importance of the relationship between sanitation and child height in India as well as in other countries and regions. Given the centrality of food intakes to nutrition outcomes, the increasing recognition of the multiple pathways through which agriculture could influence nutrition, and the importance of the agricultural sector to rural Indian livelihoods, a strand of the literature has focused on the links between agriculture and nutrition in India. Bhagowalia, Headey, and Kadiyala (2012), using the cross-sectional India Human Development Survey data, and Headey et al. (2012), using NFHS data, examine the connections between agricultural production conditions, diet diversity, and anthropometric outcomes, finding that while some agricultural variables such as livestock ownership and irrigation have associations with nutrition outcomes, many relationships along the agriculture–nutrition pathways in India are relatively weak and less than clear-cut.

The influence of the relative bargaining power of women in the household as measured by mother's schooling relative to father's on child nutrition outcomes has been examined by Imai, Annim, Gaiha, and Kulkarni (2014), who find a statistically significant positive influence. Other foci in this literature have included the impact of specific programs such as the Integrated Child Development Services (ICDS) on HAZ (Jain, 2015; Kandpal, 2011). Much of the literature has focused on modeling mean anthropometric outcomes. However, a small set of studies (Borooah, 2005; Imai et al., 2014; Kandpal & McNamara, 2009) has modeled the entire distribution of an outcome such as HAZ by using quantile regression methods. They all have found evidence of heterogeneous effects of key covariates on different parts of the outcome distribution, highlighting the value of allowing for such flexibility.

The above-reviewed literature has highlighted some of the key sets of routine observables that help explain variation in outcomes considering India as a whole. Cross-state heterogeneity has been recognized in the literature, for example in the form of controlling for state-specific intercepts (fixed effects). Less attention has been paid, however, to *explicit* consideration of cross-state differences, particularly the differential strengths of association between observables and outcomes across states.

Nonetheless, a separate literature has documented strong cross-state disparities in several dimensions that can impinge on the strength of association between endowments and nutritional outcome (in other words, the returns to endowments). These aspects, such as strength of community and civic society, *quality* and *reach* of public services, institutional quality, and the policy, governance, and political economy aspects they are related to, have been shown to influence development outcomes, although they are not usually measured in datasets like the NFHS. Mayer (2001) constructs an index of state institutional performance, including quality dimensions of medical and educational service provision and access to the public distribution system, and finds strong differences, with Hindi belt states, including Uttar Pradesh, Bihar, Madhya Pradesh, and Odisha at the bottom, and Kerala and Tamil Nadu at the top. Furthermore, he shows that the institutional performance index correlates well with the Human Development and the Gender Development Indices. Besley, Burgess, and Esteve-Volart (2007) and Besley and Burgess (2002) study the links between poverty, growth, and policy in India over time. Besley and Burgess allow the poverty elasticity of income growth to differ across states to reveal striking heterogeneity in elasticities, ranging from −0.3 for Bihar to −1.23 for Kerala. Thus, equivalent income growth rates can result in very different poverty impacts in states at two ends of this spectrum. Relating these elasticity differences to voice and accountability, they find that states with higher newspaper circulation and political competition spend more on calamity relief in times of floods, and provide more public food distribution when food production drops.

Harriss and Kohli (2009) consider the influence of cross-state political and institutional factors on child underweight. They differentiate states on the basis of the extent to which their politics allows for representation of poor and low-caste segments, as well as their position on a scale with "clientelist" politics of accommodation on the one end, and "programmatic" politics on the other. Categories of states are identified, with Madhya Pradesh and Odisha on one end, and Kerala, Tamil Nadu, and West Bengal on the other (more progressive) end, and this political spectrum is argued to have an important bearing on underweight outcomes.

In sum, this literature suggests that there are many reasons to believe that convergence in nutritional outcomes across Indian states is not only about equalizing the commonly observed nutrition correlates. Even if children in states at the two ends of the spectrum were endowed with equal maternal education and hospital access, the quality of those services may differ substantially. Access to the public distribution system may differ due to state policy, and this may over time be reflected in different nutritional outcomes even where other observed correlates were similar. These and other aspects are capable of causing the strengths of relationships between observed correlates and nutrition outcomes to be different in contrasting states. Thus our primary hypothesis is that "coefficient effects" are important when comparing anthropometric outcomes across Indian states. We are also interested in asking whether coefficient effects become more or less important as we proceed along the HAZ distribution, are they more important for the more nutritionally vulnerable?

3. DATA

We use decomposition methods to make cross-state comparisons based on cross-sectional (long-run) relationships between a broad set of covariates and HAZ. NFHS-3 data, representative at national and state levels, are used. Investigating cross-state heterogeneity in India using pairwise methods of comparison, such as the decomposition methods we use, can pose conceptual and practical difficulties due to the large number of possible comparisons. We take a case-study approach, comparing a limited set of states with relatively poor HAZ outcomes against the common benchmark of a state with relatively good HAZ outcomes.

The set of chosen poor performers consists of Bihar, Uttar Pradesh, Madhya Pradesh, Odisha and Gujarat. Under-five stunting prevalence in these states ranges from 45% (Odisha) to 57% (Uttar Pradesh). These five states alone account for about half of India's total number of stunted under-fives. These states, apart from Gujarat, are consistently at the bottom of pile in the indices and metrics used in the literature reviewed above on cross-state institutional and political differences. Gujarat, on the other hand, is of interest since it is viewed as an oddity presenting poor nutritional performance while having a strong showing in terms of other socioeconomic indicators.

The benchmark state for comparison is Tamil Nadu, which is a relatively good performer with a stunting prevalence of 31%. There are other good performers that could be used as a basis for comparison, such as Kerala and Goa. However, Tamil Nadu's population is more comparable with that of the large poor performers like Bihar, UP and Madhya Pradesh. In contrast, in smaller sized states like Kerala and Goa, governance challenges, among other aspects, may be different. Furthermore, Tamil Nadu is frequently singled out as a good example in the literature on state-level heterogeneities in policies, politics and institutions influencing development outcomes, reviewed above. For example, Harriss and Kohli (2009) note that Tamil Nadu's political makeup has long been characterized by mobilization of disadvantaged classes, leading to pioneering programmatic policies such as the Nutritious Noon Meal Scheme and the Tamil Nadu Integrated Nutrition Project (TINP). [3]

HAZ for under-fives is the outcome variable in all our regressions. Accurate decomposition of HAZ differences into covariate and coefficient effects requires well-specified regressions that include key relevant covariates. Correspondingly, we started with a wide set of covariates informed by the UNICEF conceptual framework for child malnutrition and previous literature. Subsequently, we refined our covariate set based upon model fit. The final covariates used to model HAZ outcomes are classified in our analysis as child characteristics, maternal education and marriage age, mother's nutrition, sanitation and environment, demographics, non-agricultural assets, and agricultural assets. [4] The specific variables are as follows:

(a) *Child characteristics*

Variables include gender, age, and age squared. Likewise, child order is included since it has been found to matter in explaining variations of child height in India (Borooah, 2005). Child weight at birth (along with an indicator for missing information on this variable) is also included given the evidence that nutrition in the womb and following birth is important for later nutritional outcomes (Binkin, Yip, Fleshood, & Trowbridge, 1988).

(b) *Maternal education and marriage age*

Maternal education is measured by years of schooling. Age at marriage is included as an element of maternal empowerment. Other proxies or indicators of empowerment, such as having a final say in consumption and purchasing decisions, were tried but did not improve model fit.

(c) *Mother's nutrition*

To account for *in utero* nutritional influences on subsequent nutrition, we use mother's nutritional status (measured by height-for-age) as well as an indicator for whether the mother is anemic, following previous work by Osmani and Sen (2003).

(d) *Mother's employment*

The NFHS dataset contains basic information on sectors in which mothers are employed. We categorize this information into a set of dummy variables indicating the nature of work of the mother: agricultural, manual, or not working, as opposed to professional, technical or managerial, clerical, sales, or services, which were left as the default category. The objective was to capture the influence of maternal employment on care practices and thereby child nutrition.

(e) *Assets*

The NFHS, as with all Demographic and Health Survey (DHS) surveys, does not collect income or consumption information. In accordance with previous studies, information on household assets is thus used to proxy permanent income. These comprise ownership of a set of durable household assets and an indicator of electrification. [5]

(f) *Demographics*

Household size and number of children under six are included to account for intrahousehold resource availability and allocation issues that have a bearing on nutrition.

(g) *Sanitation and Environment*

Following Spears (2013), we include two measures of open defecation: an indicator variable at the household level if the household does not have a toilet facility and defecate in the open field; and a measure of open defecation at the PSU level (i.e., the village), measured as a fraction of the population reporting open defecation without using a toilet or latrine. As the propensity of a child to be in good health may be impacted by the quality of the environment at home, we include an indicator for whether the household uses clean cooking fuel. Additional variables, such as dirty floors and access to piped water were tried but discarded as they did not improve model fit.

(h) *Agricultural assets*

As discussed before, separate focus is trained on variables relating to agricultural involvement, given the prevailing interest in agriculture–nutrition relationships. A set of agricultural assets is included that comprises agricultural land ownership, the proportion of irrigated land, and the availability of livestock in the forms of cows/bulls/buffaloes, goats, and chickens. Given that the quantity and quality of food intake is central to agriculture–nutrition relationships, it would have been ideal to incorporate dietary measures into this analysis. However, we do not use this information since it is collected only for the youngest child in the household that is between six months and two years old, and as such is inadequate for the quantile regression-based analysis that requires large samples.

4. METHODS

The counterfactual decomposition methods we use partition the observed difference between HAZ outcomes in a pair of states being compared, say Tamil Nadu (TN) and Madhya Pradesh (MP), into covariate (differing endowments of observed determinants of HAZ) and coefficient (differing strengths of relationships between observed determinants and HAZ) effects. The first of the decompositions employed is the Oaxaca–Blinder (OB) decomposition of the differences in *mean* HAZ across states. Continuing with the TN and MP example, the underlying regression models in the two states are represented by:

$$\begin{aligned} \mathrm{HAZ}_{\mathrm{i,TN}} &= \mathbf{X}_{\mathrm{i,TN}}\boldsymbol{\beta}_{\mathrm{TN}} + \mathrm{e}_{\mathrm{i,TN}} \\ \mathrm{HAZ}_{\mathrm{i,MP}} &= \mathbf{X}_{\mathbf{i},\mathrm{MP}}\boldsymbol{\beta}_{\mathrm{MP}} + \mathrm{e}_{\mathrm{i}}, \mathrm{MP} \end{aligned} \tag{1}$$

Here, the dependent variable, HAZ, is regressed on a vector of covariates, given by $\mathbf{X}$. Individuals are indexed by i, $\boldsymbol{\beta}$ is the vector of regression coefficients, and $\mathrm{e}_{\mathrm{i,state}}$ represent random errors with the standard properties. The (mean) regressions for each state in (1) yield coefficients denoted by $\widehat{\boldsymbol{\beta}}_{\mathrm{TN}}$ and $\widehat{\boldsymbol{\beta}}_{\mathrm{MP}}$. This allows, with some slight algebraic shuffling, the difference in mean heights between the two state samples to be written as

$$\overline{\mathrm{HAZ}_{\mathrm{i,TN}}} - \overline{\mathrm{HAZ}_{\mathrm{i,MP}}} = \overline{\mathbf{X}}_{\mathbf{i,TN}}\{\widehat{\boldsymbol{\beta}}_{\mathbf{TN}} - \widehat{\boldsymbol{\beta}}_{\mathbf{MP}}\} + \{\overline{\mathbf{X}}_{\mathbf{i,TN}} - \overline{\mathbf{X}}_{\mathbf{i\,,MP}}\}\widehat{\boldsymbol{\beta}}_{\mathbf{MP}} \tag{2}$$

Eqn. (2) says that the difference in mean HAZ outcomes between TN and MP, $\overline{\mathrm{HAZ}_{\mathrm{i,TN}}} - \overline{\mathrm{HAZ}_{\mathrm{i,MP}}}$, can be decomposed into two parts. The first part, $\overline{\mathbf{X}}_{\mathbf{i,TN}}\{\widehat{\boldsymbol{\beta}}_{\mathrm{TN}} - \widehat{\boldsymbol{\beta}}_{\mathbf{MP}}\}$, is the part of the HAZ mean differential arising from differences in coefficients between TN and MP (the "coefficient effect"). The second part, $\{\overline{\mathbf{X}}_{\mathbf{i,TN}} - \overline{\mathbf{X}}_{\mathbf{i,MP}}\}\widehat{\boldsymbol{\beta}}_{\mathrm{MP}}$ is the HAZ differential arising from different endowments of nutrition covariates in TN and MP (the "covariate effect"). A positive (negative) covariate effect in this context would pinpoint the HAZ difference arising from Tamil Nadu's favorable (unfavorable) endowment of that covariate relative to Madhya Pradesh. Likewise a positive (negative) coefficient effect would identify the HAZ difference caused by a stronger (weaker) association in TN relative to MP between the covariate and HAZ.

The decomposition could also be written in a different way,

$$\overline{\mathrm{HAZ}_{\mathrm{i,TN}}} - \overline{\mathrm{HAZ}_{\mathrm{i,MP}}} = \overline{\mathbf{X}}_{\mathbf{i,MP}}\{\widehat{\boldsymbol{\beta}}_{\mathbf{TN}} - \widehat{\boldsymbol{\beta}}_{\mathbf{MP}}\} + \{\overline{\mathbf{X}}_{\mathbf{i,TN}} - \overline{\mathbf{X}}_{\mathbf{i,MP}}\}\widehat{\boldsymbol{\beta}}_{\mathbf{TN}} \tag{3}$$

These decompositions are equally valid, but can in practice result in slightly different estimates of covariate and coefficient effects. Oaxaca (1973) refers to this issue as the "index number problem". To mitigate this problem, Jann (2008) and Elder, Goddeeris, and Haider (2010) recommend using a pooled model over both groups including a group-specific indicator as an additional control variable. We follow their recommendation and include a state-indicator in the linear model to prevent excessive attribution of the HAZ differential to the explained component. We also check these results against an alternative method suggested by Reimers (1983) to use an average coefficient given by $\boldsymbol{\beta}^* \equiv 0.5\widehat{\boldsymbol{\beta}}_{\mathrm{TN}} + 0.5\widehat{\boldsymbol{\beta}}_{\mathrm{MP}}$.

A significant assumption made here is that $\mathrm{E}(\mathrm{e}_{\mathrm{i,state}}|\mathbf{X}_{\mathbf{i}}) = 0$, i.e., the error term is conditionally independent of $\mathbf{X}$. This "zero conditional mean" assumption rules out correlation between unobserved heterogeneity and any of the covariates. Thus, if there are unobservables (like "nutrition consciousness") that are related to both, a covariate (such as maternal nutrition), and child HAZ outcome, then the zero conditional mean assumption fails and the regression yields inconsistent estimates of the covariate's structural parameter. The detailed OB decompositions rely on this assumption.

The OB decomposition described above only decomposes mean HAZ differences between states. We are additionally interested in gaining perspective on covariate and coefficient effects in gaps between entire HAZ distributions. Figure 1 shows the empirical HAZ distributions for Tamil Nadu (long-dashed lines) and each comparator state in turn (solid lines). In each case, the Tamil Nadu distribution lies everywhere to the right of the distribution of the state it is being compared with, indicating the generally more favorable distribution of HAZ in Tamil Nadu. However, the gap between distributions tends to be higher at lower percentiles compared to the middle, indicating that the HAZ distribution is relatively more unfavorable in the other states compared to Tamil Nadu particularly at the lower tail. Percentile values of HAZ presented in Appendix Table 4 confirm this. The gap between TN and other states (except Odisha) at the 10th percentile is

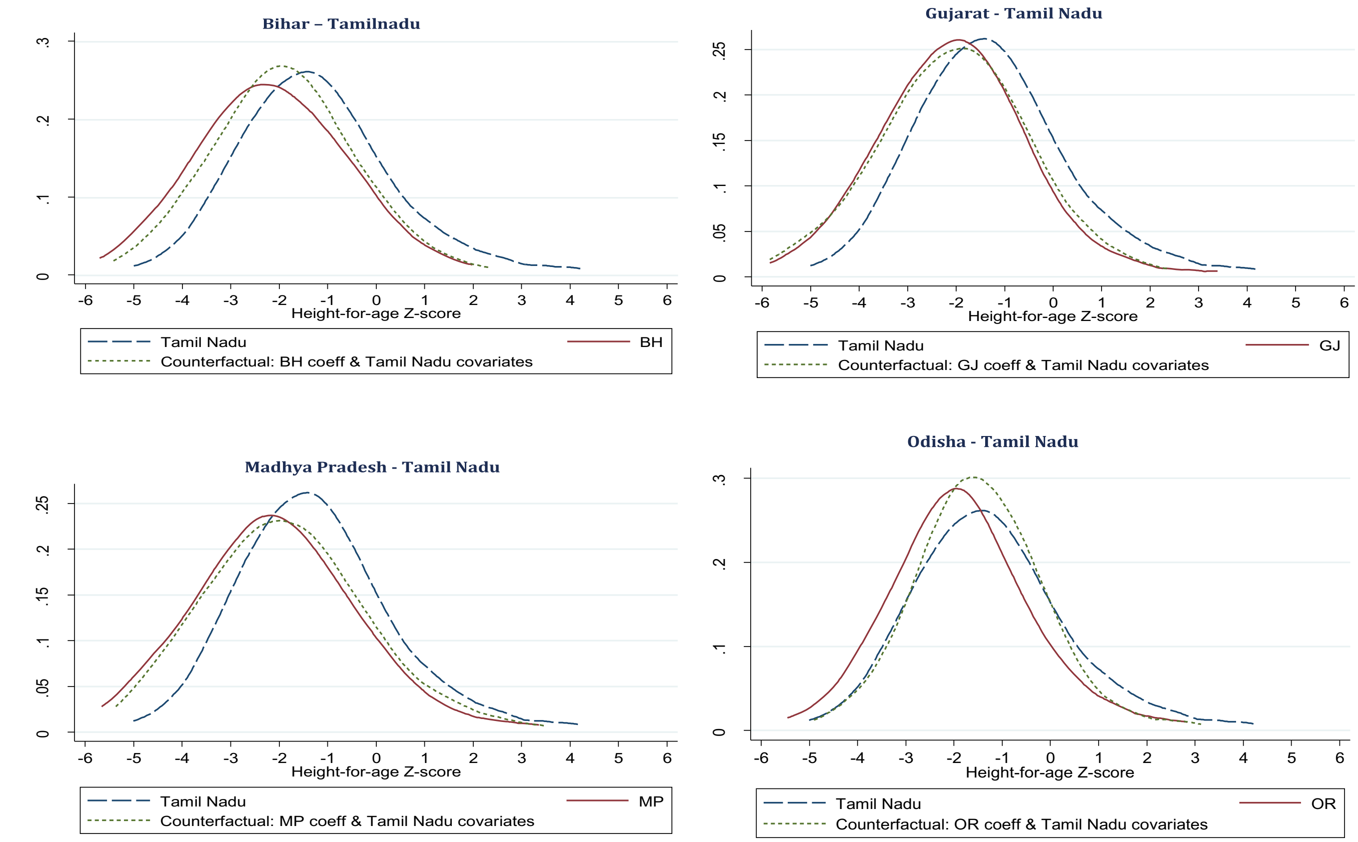

Figure 1. *Simulated marginal and counterfactual densities.*

very substantial - between 1 and 1.5 standard deviations. This narrows somewhat towards the median, but still remains quite large. It is this observed pattern of differences between, for instance, Madhya Pradesh's and Tamil Nadu's HAZ distributions that we seek to explain using quantile regression decomposition methods.

The Machado and Mata (2005) counterfactual decomposition that we use provides relative contributions of covariates and coefficients along the entire HAZ distribution, rather than just mean HAZ. It does so by using quantile regressions to characterize the distribution of HAZ conditional on covariates, and combining estimated quantile regression coefficients in one state with randomly drawn values of covariates from another state to estimate counterfactual distributions. We provide an intuitive discussion below.

Denote the marginal density function of HAZ by F(HAZ), and the distribution of HAZ covariates **X** by G(**X**). Given an observed sample $\{\mathrm{HAZ}, \mathbf{X}\}_{i=1}^{N}$, we can write

$$F(\mathrm{HAZ}) = \int F(\mathrm{HAZ}|\mathbf{X})\,dG(\mathbf{X})$$

Assuming the conditional quantiles of HAZ given $\mathbf{X} = \mathbf{x}$ are linear in **x**, the conditional distribution of HAZ, F(HAZ|**X**), is completely described by the set of quantile regression coefficients $[\boldsymbol{\beta}(\theta),\ 0 < \theta < 1]$. These quantile regression coefficients can be estimated by

$$\widehat{\beta}(\theta) = \underset{\beta}{\operatorname{argmin}} \frac{1}{N} \sum_{i:HAZ_i \geqslant x'\beta}^{N} \theta|\mathrm{HAZ}_i - \mathbf{x}_i'\beta_\theta| + \sum_{i:HAZ_i < x'\beta}^{N} (1-\theta)|\mathrm{HAZ}_i - \mathbf{x}_i'\beta_\theta|$$

$\widehat{\boldsymbol{\beta}}(\theta)$ is estimated separately for each quantile, θ. One can then simulate a draw from the marginal distribution F(HAZ) implied by the conditional quantile model by (i) randomly drawing θ from [0,1] and estimating the corresponding $\widehat{\boldsymbol{\beta}}(\theta)$ (ii) drawing a random value of **X** from the empirical distribution, and (iii) multiplying the estimated coefficients with the draw from **X** to compute a simulated draw from F(HAZ). Repeating this several times simulates F(HAZ) as X is "integrated out". Of course, the observed sample of HAZ already provides a "simulation" of F(HAZ). However the empirical density would not necessarily be consistent with the conditional quantile distribution and would not allow us to undertake counterfactual analysis (Machado & Mata, 2005). For example, suppose we wish to simulate the counterfactual density of height-for-age in Madhya Pradesh, $\mathrm{HAZ}_{\mathrm{TN,MP}}$, under the counterfactual scenario where the HAZ covariates are distributed as in Tamil Nadu, but the coefficients are those of Madhya Pradesh. The counterfactual density is given by

$$F(\mathrm{HAZ}_{\mathrm{TN,MP}}) = \int F_{\mathrm{MP}}(\mathrm{HAZ}|\mathbf{X})\,dG_{\mathrm{TN}}(\mathbf{X})$$

To simulate a draw from this counterfactual marginal density: (i) draw a random θ from [0,1] and estimate the corresponding quantile regression coefficients $\widehat{\boldsymbol{\beta}}_{\mathrm{MP}}(\theta)$ (ii) Take a random draw for **X** from the TN sample, (iii) Multiply the two to simulate a value from the distribution of $\mathrm{HAZ}_{\mathrm{TN,MP}}$. Repeating this several times simulates $F(\mathrm{HAZ}_{\mathrm{TN,MP}})$.

With these simulated counterfactual densities in hand, we can identify, at every quantile, which portion of the original HAZ difference between the state-specific marginal densities, i.e., $F(\mathrm{HAZ}_{\mathrm{MP,MP}}) - F(\mathrm{HAZ}_{\mathrm{TN,TN}})$, is due to differences in HAZ covariate distributions in TN and MP, and which portion is due to differences in the strengths of relationships with HAZ (coefficients) of those covariate sets.

Formally, similarly to the case of the mean decomposition [6]:

$$\begin{aligned}
&q(\mathbf{X}_{MP}, \widehat{\boldsymbol{\beta}}_{MP}(\theta), \theta) - q(\mathbf{X}_{TN}, \widehat{\boldsymbol{\beta}}_{TN}(\theta), \theta) \\
&= [q(\mathbf{X}_{MP}, \widehat{\boldsymbol{\beta}}_{MP}(\theta), \theta) - q(\mathbf{X}_{TN}, \widehat{\boldsymbol{\beta}}_{MP}(\theta), \theta)] \\
&\quad + [q(\mathbf{X}_{TN}, \widehat{\boldsymbol{\beta}}_{MP}(\theta), \theta) - q(\mathbf{X}_{TN}, \widehat{\boldsymbol{\beta}}_{TN}(\theta), \theta)] + \mathit{error} \qquad (4)
\end{aligned}$$

In (4), q(.) represents a quantile function. The first square-bracketed expression on the right hand side of (4) above is the covariate effect and the second is the coefficient effect.

At this stage, it is important to point out a key assumption underlying the QR-CD approach outlined above. In common with other such decomposition methods in this literature, *ignorability*, (or *unconfoundedness*) is assumed. The ignorability assumption states that unobservables are independent of the treatment, conditional on observed covariates. We can again use HAZ distributions in TN *versus* MP to help motivate the meaning and implication of this important assumption. For example, "nutrition consciousness" may be one important unobservable at the household level in our data. Ignorability would imply that once covariates in our specification, such as mother's education, are controlled for, the distribution of nutrition consciousness is not systematically related to the state under consideration. In other words, selection biases can exist as long as they are the same in the two states after controlling for covariates. This assumption enables the identification of the covariate effect and ensures that association of covariates with HAZ across the states is not confounded by the impact of varying distributions of nutrition consciousness. Fortin, Lemieux, and Firpo (2011) discuss some important ways in which ignorability may be violated. Some sources of violation such as self-selection into treatment (states) are probably less important in this cross-state comparison setting. However, covariates such as maternal education and unobservables such as nutrition consciousness may be functions of the state under consideration, causing nutrition consciousness to vary systematically by state even after controlling for maternal education and other covariates. Ignorability is used as an assumption across the decomposition literature. We maintain ignorability as an assumption, but acknowledge that it is a strong one.

In this study, quantile regression coefficients are estimated at a random sample of 2000 quantile points to form the conditional density of HAZ scores. This gives approximately 20 predicted values per quantile. They are then combined with a random set of covariates from a different state to form the counterfactual density. Model selection aimed to reduce the difference between the estimated HAZ marginal density and the HAZ empirical density in Tamil Nadu, and hence to limit the contribution of the error term in the decomposition. Variables that reduced the fit of the benchmark model were therefore excluded. For the Machado–Mata distribution-wide decomposition, we only identify aggregate covariate *versus* coefficient contributions, and not the contributions attached to individual variables.

It must also be noted that we do not aim to identify causal effects in this research. We are interested in the range of HAZ covariates, unlike the case of studies investigating the causal impact of a single focal variable that employ instrumental variables or other causal identification procedures. Our objective is to decompose cross-state HAZ differentials into covariate and coefficient effects. Thus, although our estimates are consistent with a causal model, we take care to interpret some of the regression coefficients estimated here as only associations. This is consistent with the vast majority of decomposition studies in the wage discrimination, nutrition, and other literatures.

5. RESULTS

Since we compare five different states with the benchmark of Tamil Nadu, each step in our analysis generates a large amount of information. To prevent this from becoming overwhelming, we present only selected information in the main body of the paper. Further details are presented in the Appendix.

Table 1 presents sample means for variables in the regressions by state, and also indicates statistically significant differences between group means in each comparison state and Tamil Nadu. It shows that mean HAZ is much higher in the TN sample than in each of the comparison states and that differences in HAZ group means between each state and TN are highly statistically significant. HAZ of the average 0–5 year old in TN is 1.2 standard deviations below the median of the reference population. Mean HAZ of all comparison states except Odisha are below the stunting threshold of −2.

Table 1 also shows that there are substantial differences between TN and comparison states in terms of many key covariates. Prominent among these is mother's education, given the evidence on the importance of this aspect to child nutrition in South Asia (Srinivasan et al. 2013). Average schooling of TN mothers is about six years, in comparison to 2–4 years of education on average in the other states. Household sizes are significantly smaller in TN than in the other states, and mothers are less likely to be anemic. With the exception of Gujarat, TN households on average also have better endowments of assets (interpreted here as measures of permanent income) such as electrification, televisions and motorcycles, and a greater availability of clean cooking fuel. On the other hand, open defecation rates are not substantially different across states apart from a couple of exceptions, suggesting that this covariate is unlikely to have the same pre-eminent role in explaining cross-state HAZ differentials that it does in the cross-country comparison of Spears (2013). When it comes to agricultural assets, TN actually has generally worse endowments than the comparators. Only 33% of rural households in the TN sample report owning land, which is substantially lower than land ownership in the other states. The high degree of landlessness in Tamil Nadu relative to most Indian states, especially those that have instituted land reform, is well recognized (Rawal, 2008). Ruminant livestock ownership is likewise lower in TN. In summary, group means indicate TN has a significantly more favorable endowment of key nutrition covariates, albeit a worse endowment of agricultural assets. [7]

Appendix Table 5 displays results from the separate OLS regressions for each state that are precursors to the Oaxaca–Blinder mean decompositions. Although several variables show mixed patterns of statistical significance across the states, the direction of association of most covariates with HAZ is broadly as expected. Child birth weight and age, and education and nutritional status of the mother display particularly consistent and statistically significant associations with HAZ across states. The child's weight at birth is seen to have a strong positive correlation with current HAZ. However, increasing age is found to impact HAZ negatively, indicating the growth faltering that occurs as infant's age. The coefficient on the quadratic age term indicates that

Table 1. *Sample means*

	TN	Bihar	MP	Gujarat	Odisha	UP
Child HAZ	−1.20	−2.19***	−2.06***	−2.14***	−1.81***	−2.24***
Child characteristics						
Age	30.76	29.51	30.57	29.44	29.62	29.22**
Age2	1233.3	1170.26	1237.11	1167.34	1177.63	1140.8**
Birth order	1.26	1.36***	1.38***	1.36***	1.28	1.38***
Female	0.48	0.46	0.50*	0.47	0.50	0.48
Weight at birth	2.82	2.65***	2.74	2.87	2.84	2.81
Education & marriage age						
Mother's schooling (yrs)	6.17	1.99***	2.41***	3.82***	3.54***	2.45***
Age at 1st marriage	18.75	15.85***	16.21***	17.25***	17.59***	16.33***
Mother's nutrition						
Mother's HAZ	−1.96	−2.30**	−1.91	−1.90	−2.19***	−2.22***
Mother anemic	0.15	0.19**	0.19*	0.21***	0.19*	0.18
Assets						
Has electricity	0.88	0.17***	0.65***	0.82**	0.40***	0.31***
Has television	0.45	0.13***	0.23***	0.34***	0.24***	0.27***
Has refrigerator	0.03	0.03	0.04	0.11***	0.04	0.02
Has motorcycle/scooter	0.18	0.06***	0.11***	0.19	0.09***	0.12***
Has car	0.01	0.01	0.00	0.01	0.00	0.01
Sanitation and environment						
Clean fuel (household)	0.14	0.02***	0.03***	0.14	0.02***	0.03***
Open defecation (household)	0.83	0.84	0.91***	0.75***	0.88***	0.83
Open defecation (village)	0.83	0.83	0.90***	0.72***	0.88***	0.83
Agricultural assets						
Owns agricultural land (household)	0.33	0.55***	0.65***	0.58***	0.67***	0.72***
Proportion irrigated land	20.63	48.95***	27.23***	35.57***	16.79***	68.63***
Has cows/bulls/buffalo	0.22	0.52***	0.66***	0.52***	0.57***	0.69***
Has goats	0.10	0.37***	0.20***	0.17***	0.19***	0.28***
Has chickens	0.18	0.15	0.11***	0.10***	0.29***	0.07***
Mother's employment						
Mother not working	0.59	0.63**	0.37***	0.45***	0.65***	0.66***
Mother manual laborer	0.09	0.02***	0.17***	0.08	0.05***	0.04***
Mother in agriculture	0.27	0.32**	0.44***	0.43***	0.26	0.29
Demographics						
Kids less than age six (proportion)	0.28	0.25***	0.26***	0.26***	0.25***	0.25***
Household size	4.73	6.99***	6.61***	6.47***	5.74***	7.43***

Results of tests of differences between each comparison state and TN are indicated in asterisks. For continuous variables, these are based on *t*-tests of group mean differences, and for dummy variables, these are based on tests of differences in proportions across groups. *, ** and *** represent $p < 10\%$, 5% and 1%, respectively.

faltering levels off for older children. In several states, mother's schooling is found to be positively and significantly associated with HAZ. Likewise, mother's nutrition is an important correlate of child HAZ in these data - the coefficients on mother's current HAZ are large, positive and statistically significant in each of the states, while currently anemic mothers are strongly associated with lower HAZ in children in three of the six states.

Other variables display less strong and consistent associations with HAZ.[8] Open defecation has a negative association with HAZ as expected, but the effect is statistically significant only in TN and Gujarat. Likewise, the fraction of the village reporting open defecation has a generally negative relationship with HAZ, but the variable is statistically insignificant in most states. Of the non-agricultural assets, home electrification shows the most consistent correlation with HAZ - households with electricity in UP, Gujarat and Odisha are associated with a higher HAZ of between 0.2 and 0.3 than households without electricity, after controlling for other correlates. Very little association is found between employment categories of the mother and height for age of children in any of the states under study. Among the agricultural assets, agricultural land ownership is the one category presenting relatively large and largely consistent relationships with HAZ across states. The relationship is statistically significant in Bihar and UP; in five of the six states, children in land-owning households are associated with higher HAZ of approximately 0.2 compared to landless households. In the absence of clear causal identification and further information about the use of the owned land, it is difficult to speculate about the pathway defining this association, however.

The parameters presented in Table 5 suggest substantial heterogeneity in coefficients across states. In Table 6 we report the results from testing the hypotheses that vectors of regression coefficients are the same in TN and each of the comparison states. In each case, the null hypothesis of equal coefficients is resoundingly rejected, suggesting that the Oaxaca–Blinder approach, involving separate regressions for different states, is valid.

Table 2 below summarizes results from the Oaxaca–Blinder decompositions. Given that we have several pairwise comparisons and a multitude of states, the table presents results at the level of the aggregate covariate categories

Table 2. *Oaxaca–Blinder decomposition of mean HAZ gap between Tamil Nadu and Other States*

	Covariate effect			Coefficient effect		
	Estimate	Std. Error	Share (%)	Estimate	Std. Error	Share (%)
A. Oaxaca–Blinder decomposition of 0.986 HAZ gap between Tamil Nadu and Bihar						
Aggregate effect	0.032	0.127	3	0.953***	0.146	97
Sanitation & environment	0.0001	0.018	0	−0.74*	0.416	−75
Child characteristics	−0.077	0.095	−8	0.60	0.652	61
Maternal nutrition	0.099***	0.018	10	0.20	0.163	20
Education & marriage age	0.056*	0.056	6	−0.35	0.473	−36
Mother's employment	0.011	0.014	1	0.34	0.355	35
Assets (non agricultural)	0.010	0.072	1	−0.22	0.169	−23
Agricultural assets	−0.048	0.032	−5	0.05	0.083	5
Demographics	−0.017	0.030	−2	−0.11	0.321	−11
Constant				1.19	1.056	120
B. Oaxaca–Blinder decomposition of 0.853 HAZ gap between Tamil Nadu and Madhya Pradesh						
Aggregate effect	0.091	0.096	11	0.762***	0.000	89
Sanitation & environment	0.032	0.022	4	−0.954**	0.022	−112
Child characteristics	0.030	0.073	3	0.025	0.965	3
Maternal nutrition	−0.005	0.014	−1	0.299**	0.057	35
Education & marriage age	0.051	0.044	6	−0.06	0.902	−7
Mother's employment	−0.007	0.019	−1	−0.472	0.159	−55
Assets (non agricultural)	0.012	0.026	1	−0.271	0.192	−32
Agricultural assets	−0.045	0.044	−5	0.082	0.364	10
Demographics	0.023	0.031	3	0.158	0.643	19
Constant				1.95**	0.050	229
C. Oaxaca–Blinder decomposition of 1.041 HAZ gap between Tamil Nadu and Uttar Pradesh						
Aggregate effect	0.156	0.102	15	0.884***	0.123	85
Sanitation & environment	0.008	0.012	1	−0.885***	0.322	−85
Child characteristics	−0.050	0.084	−5	1.27**	0.521	122
Maternal nutrition	0.079***	0.014	8	0.206	0.143	20
Education & marriage age	0.0837***	0.031	8	−0.038	0.444	−4
Mother's employment	−0.006	0.009	−1	0.158	0.303	15
Assets (non agricultural)	0.127***	0.034	12	−0.404***	0.197	−39
Agricultural assets	−0.096***	0.036	−9	−0.011	0.078	−1
Demographics	0.011	0.022	1	0.068	0.302	7
Constant				0.519	0.892	50
D. Oaxaca–Blinder decomposition of 0.941 HAZ gap between Tamil Nadu and Gujarat						
Aggregate effect	−0.058	0.081	−6	0.999***	0.111	106
Sanitation & environment	−0.066***	0.023	−7	−0.494	0.340	−53
Child characteristics	−0.012	0.047	−1	0.312	0.505	33
Maternal nutrition	−0.011	0.015	−1	0.222	0.164	24
Education & marriage age	−0.006	0.032	−1	−0.677	0.511	−72
Mother's employment	0.008	0.016	1	0.022	0.302	2
Assets (non agricultural)	−0.024	0.019	−3	−0.474**	0.237	−50
Agricultural assets	0.0002	0.035	0	0.041	0.097	4
Demographics	0.054*	0.029	6	0.243	0.339	26
Constant				1.80*	0.949	192
E. Oaxaca–Blinder decomposition of 0.603 HAZ gap between Tamil Nadu and Odisha						
Aggregate effect	0.226***	0.076	38	0.376***	0.105	62
Sanitation & environment	0.040*	0.021	7	−0.156	0.410	−26
Child characteristics	0.027	0.046	5	0.204	0.496	34
Maternal nutrition	0.068***	0.016	11	0.226	0.166	38
Education & marriage age	0.051*	0.027	9	−0.834*	0.464	−138
Mother's employment	−0.002	0.007	0	−0.097	0.321	−16
Assets (non agricultural)	0.078*	0.045	13	−0.327*	0.192	−54
Agricultural assets	−0.021	0.033	−4	0.076	0.093	13
Demographics	−0.018	0.021	−3	−0.162	0.342	−27
Constant				1.447	0.940	240

* $p < 10\%$.
** $p < 5\%$.
*** $p < 1\%$.

described in the previous section. Detailed results for individual variables are shown in Appendix Tables 7–11.

A surprising revelation in Table 2 is that, in aggregate, coefficient effects are very dominant, and covariate differences explain relatively little of the mean gap between Tamil Nadu and each of the states it is being compared to, with the exception of Odisha. Aggregate covariate effects account for only between 3% and 15% of the gap with Tamil Nadu in the cases of Bihar, MP, and UP. In Bihar, for example, these results imply that Tamil Nadu's relatively advantageous endowments of mother's education and empowerment, household economic status, etc. only account for 3% of the HAZ gap between the two states, holding nutrition impacts of these covariates constant across the states. The covariate effect in the Gujarat–Tamil Nadu comparison is actually negative, indicating that Gujarat has a more favorable endowment of nutrition covariates overall than Tamil Nadu, and that the HAZ mean gap between these states is wholly due to coefficient effects. Only the comparison with Odisha presents a sizeable covariate effect at 38%.[9]

However, the small aggregate covariate effects do not imply that individual categories of covariates have insubstantial effects. As seen in Table 3, TN's superior endowments of maternal nutrition, education, and empowerment together help explain between 16% and 20% of the HAZ gap with Bihar, MP, UP, and Odisha. Detailed results presented in Appendix Tables 7–11 show that the maternal nutrition covariate effect is largely determined by gaps in mother's HAZ (rather than anemic status). In the case of education & marriage age, both aspects (mother's schooling as well as age at first marriage) are important. The maternal nutrition, education and marriage age covariates effects are, however, counteracted by TN's inferior endowments of agricultural assets in the determination of the overall coefficient effect. UP's superior distribution of agricultural assets, for example, serves to shrink the gap with TN by about 9%. As seen in Appendix Tables 7–11, relatively low agricultural land ownership in TN is the main contributor to this.

The substantial aggregate coefficient effects comprise a mix of offsetting positive and negative coefficient effects for individual sets of variables. For example, the strength of the association between maternal and child nutrition is higher in TN compared to the other states, and this differential strength contributes 0.2–0.3 HAZ differential to the child HAZ comparisons. However, TN also has a weaker relationship between improved sanitation and environment and child HAZ outcomes than other states, and this serves to narrow the HAZ gap between TN and the others. The effect of the intercept term is positive, large and dominant, indicating that unobservable differences, neither captured in levels of typically modeled nutrition determinants nor in the magnitudes of their nutrition impact, are particularly important in cross-state nutritional heterogeneity.[10]

Appendix Tables 12–17 reports results from the quantile regressions estimated in each of the states. A comparison of the QR results with the mean regression results discussed previously underlines the importance of allowing for differential effects across the HAZ distribution. We highlight a few examples. The mean regression indicated mother's education to have

Table 3. *Quantile Regression-based decomposition: Tamil Nadu versus other states*

	Empirical gap	Simulated gap	Coefficient effect		Covariate effect		Residual	
			HAZ	as%	HAZ	as%	HAZ	as%
Bihar								
10	1.035	0.986	0.646	**62.4**	0.340	**32.8**	0.049	**4.7**
25	0.940	0.862	0.568	**60.4**	0.294	**31.2**	0.078	**8.3**
50	0.940	0.863	0.560	**59.6**	0.303	**32.2**	0.077	**8.1**
75	0.900	0.702	0.574	**63.8**	0.128	**14.2**	0.198	**21.9**
90	0.960	0.929	0.801	**83.4**	0.128	**13.3**	0.031	**3.2**
Madhya Pradesh								
10	1.140	1.074	0.878	**77.0**	0.195	**17.1**	0.066	**5.8**
25	0.870	0.815	0.687	**79.0**	0.127	**14.6**	0.055	**6.3**
50	0.755	0.739	0.572	**75.6**	0.168	**22.2**	0.016	**2.0**
75	0.735	0.635	0.411	**55.8**	0.224	**30.5**	0.100	**13.6**
90	0.720	0.671	0.484	**67.2**	0.186	**25.8**	0.049	**6.8**
Gujarat								
10	0.995	0.963	1.086	**109.1**	−0.123	**−12.3**	0.032	**3.1**
25	0.840	0.719	0.711	**84.6**	0.009	**1.0**	0.121	**14.3**
50	0.875	0.693	0.653	**74.5**	0.040	**4.6**	0.182	**20.8**
75	0.805	0.700	0.610	**75.7**	0.090	**11.1**	0.105	**13.0**
90	1.095	0.989	0.951	**86.8**	0.037	**3.4**	0.106	**9.7**
Odisha								
10	0.470	0.500	−0.049	**−10.5**	0.550	**116.9**	−0.030	**−6.4**
25	0.530	0.461	−0.047	**−8.8**	0.508	**95.8**	0.069	**13.0**
50	0.570	0.578	0.129	**22.5**	0.449	**78.7**	−0.008	**−1.3**
75	0.665	0.622	0.223	**33.4**	0.399	**59.9**	0.043	**6.5**
90	0.705	0.785	0.607	**86.1**	0.177	**25.1**	−0.080	**−11.3**
Uttar Pradesh								
10	1.230	1.276	1.070	**86.9**	0.206	**16.7**	−0.046	**−3.7**
25	1.090	1.054	0.784	**71.9**	0.270	**24.7**	0.036	**3.2**
50	1.010	1.001	0.741	**73.3**	0.260	**25.7**	0.009	**0.9**
75	0.920	0.879	0.624	**67.8**	0.254	**27.6**	0.041	**4.4**
90	0.955	0.966	0.844	**88.4**	0.122	**12.7**	−0.011	**−1.1**

a positive and statistically significant association with child HAZ in Bihar, MP, UP and Odisha. The QR results show that in each of these states, the effect is actually particularly large in the bottom half of the conditional HAZ distribution, and that the association wears off towards the upper tail. Thus for example, the mean regression shows that every additional year of mother's education in Odisha is associated with a 0.05 improvement in mean child HAZ, while the QR results show that the improvement at the 10th conditional percentile of HAZ is 0.09, tapering away towards a 0.05 effect at the median and becoming statistically insignificant at the upper tail. This is masked in the OLS effect size. Similarly, in Gujarat, the mean regression suggests a strong relationship between open defecation and HAZ, with open defecation being associated with a 0.3 reduction in HAZ compared to using toilets, *ceteris paribus.* The QR regression shows that this effect is three times stronger at the 10th conditional percentile, indicating an almost 1 standard deviation difference associated with open defecation compared to toilet use in Gujarat. In the mean regression results, household agricultural land ownership was seen to have a statistically insignificant relationship with HAZ in Tamil Nadu. In contrast, the QR results show a very strong and statistically significant association between agricultural land ownership and HAZ outcomes at the bottom tail of the HAZ distribution in TN. At the 10th and 25th conditional percentiles, agricultural land ownership in Tamil Nadu is associated with an approximately 0.6-improvement in HAZ. However, this association wears off at the center and the upper half of the conditional distribution.

Table 3 summarizes the results from applying the Machado–Mata quantile regression-based decomposition as described previously. The first column shows the state and HAZ quantile at which the decomposition is being undertaken. Column 2 displays the actual (empirical) HAZ gap between TN and a particular state at a particular quantile. In all states except Odisha, the gap compared to TN is highest at the 10th percentile, indicating that these states come off particularly poorly in comparison to TN in terms of extreme malnutrition. As described previously, the decomposition methodology uses the quantile regression estimates to simulate actual and counterfactual distributions, on the basis of which the decomposition is carried out. Column 3 shows the simulated HAZ gap, which can be compared to the empirical gap in column 2 to assess model fit, which is crucial to the accuracy of the decomposition results. The difference between the empirical and simulated gaps is reported in the last two columns (in z-score and % share of gap), and shows the residual to be relatively small (apart from a few exceptions) and in the range found in other decomposition exercises in the literature (e.g., O'Donnell et al., 2009). Thus the chosen set of variables model the HAZ distributions accurately, and provide a reasonable basis for decomposition.

The middle columns in Table 3 show the aggregate covariate and coefficient contributions at selected quantiles. Figure 1 provides a graphical depiction of covariate and coefficient contributions along the entire HAZ distribution. It shows the simulated marginal density (long-dashed and solid lines) and the simulated counterfactual density of HAZ (short-dashed lines) by state. The counterfactual distributions represent the HAZ distributions of each state under the counterfactual that all covariates were distributed as in Tamil Nadu, but their associations with height-for-age (coefficients) remained those pertaining to the state under consideration.

The first broad feature that is evident from the decomposition results presented in Table 3 and Figure 1 is that the covariate effect contributions are typically larger than was found with the mean decomposition discussed previously. For example, in Bihar, the aggregate covariate contribution in the mean decomposition was only 3%, while the Machado–Mata decomposition estimates covariate contribution in excess of 30% in the bottom half of the HAZ distribution, diminishing to about 15% in the upper half. In Odisha, the mean decomposition finds the covariate contribution to be 38%, while the distribution-wide decomposition suggests that covariates explain almost all the HAZ gap with Tamil Nadu in the lower half of the distribution. The second broad feature apparent is that even though the quantile regression-based decomposition indicates a larger contribution for covariates, coefficient effects still generally dominate covariate effects (with the exception of the Odisha-TN comparison).[11] Coefficient effects explain about 60–80% of the gap compared to TN in the Bihar case, about 55–80% of the gap in the MP case, 75–110% of the gap in the Gujarat case, and approximately 67–88% in the UP case.[12]

As for variation of relative covariate and coefficient contributions across the distributions, the five comparison cases do not present a homogeneous picture. In the case of the Bihar–TN comparison, covariate contributions are relatively strong at the bottom of the distribution, indicating that a movement toward equalizing covariate endowments would narrow the HAZ gap by about a third. This effect wears off at the top half of the distribution. Also, in Odisha, almost the entirety of the HAZ gap with TN in the lower tail of the distribution is explained by differential endowments of nutrition determinants. In Madhya Pradesh, the pattern is in reverse, and the covariate contribution strengthens toward the top half of the distribution. Gujarat remains an oddity, presenting a substantial HAZ gap compared to TN despite being possessed of superior endowments of nutrition covariates in many respects—the covariate effect in the Gujarat–TN comparison remains small throughout the distribution.

6. DISCUSSION AND CONCLUSION

This paper has attempted to improve understanding of the drivers of the significant cross-state heterogeneity observed in the height of Indian children. Several Indian states have populations the size of large countries—e.g., Uttar Pradesh alone has a population size comparable to Brazil's. The substantial variation in culture, attitudes, and diets across Indian regions and states is well recognized. As reviewed in this article, there is also considerable cross-state variation in institutions, social capital levels, and political makeup. Sectors key to nutrition, such as agriculture and health, are state-level policymaking concerns in India. All these factors suggest that there may be value in empirical research that trains focus on these cross-state heterogeneities and considers their implications for nutrition.

The literature modeling child nutrition outcomes in India has expanded significantly in recent years and has enabled better understanding of the important drivers of these outcomes. However, much of this literature either (i) focuses on modeling individual outcomes across the country, typically treating cross-state heterogeneities as "intercept-shifters" - state-fixed effects that need to be controlled for, or (ii) conducts analysis using state-level averages of nutrition determinants and outcomes. In contrast, we have focused explicitly on cross-state comparisons while maintaining the variation inherent in individual-level data. While child nutrition in India as a whole has become a major item on the development research agenda, special focus arguably needs to be trained on a set of large poorly performing states that account for a substantial proportion of the nutritional underperformance of the nation as a whole. Tamil Nadu on the other hand, is a large-sized relative good performer whose stunting prevalence is comparable to those of middle-income countries such as the Philippines, Syria, or Egypt. Is Tamil Nadu's superior nutritional performance down to better provisioning of fundamental endowments such as wealth and women's education, or is there more to it?

Our results using mean regression-based decompositions and distribution-wide decompositions based on quantile regressions (which are less restrictive and thus preferred) indicate that relatively modest proportions of the observed differences have to do with varying covariate endowments. Cross-state disparities in HAZ are explained in large proportion by differential associations between covariate endowments and nutrition, as captured in "coefficient effects". As noted previously, our empirical strategy involved starting with a wide set of covariates drawn from the literature, with the final set decided based on model fit. [13] Thus, the chances of our results being an artifact of inadequate covariate coverage are low, at least given the constraints imposed by the types of information available in NFHS and similar DHS datasets. Clearly, Tamil Nadu's performance appears special relative to the comparators.

While "coefficient effects" in such comparisons lump several potential effects together and are not informative about specific factors or actions, it is likely in this setting that nutrition-relevant policies and programs play an important role. For example, O'Donnell, Nicolás, and Van Doorslaer (2009) in their decomposition study of the dramatic improvement in Vietnam's HAZ distribution in the 1990s find covariate and coefficient effects to be equally important, and emphasize the consistency of the strong coefficient effects with health, food, and nutrition policies introduced in the period. Elements of these programs can influence both the slope coefficients (e.g., growth monitoring can arrest growth faltering reflected in the strength of the relationship between child age and HAZ), as well as the intercept, improving height independently of specific variables.

Tamil Nadu's record of superior policymaking in this arena is likely to be important in our cross-state comparison, although we can only speculate about this. From the early 80s until the late 90s, the Tamil Nadu Integrated Nutrition Program (TINP) delivered a set of interventions centered on nutrition education, growth monitoring, primary health care, and food supplementation on a state-wide scale. The TINP has been widely praised and was able to reach under-3s much more effectively than the ICDS program that was rolled out in the rest of the country in this period (Heaver, 2002). Although the TINP merged with the ICDS in the late 1990s, some of its unique features continued in the same form in Tamil Nadu. For example, Tamil Nadu retained its existing model of "two-workers" per ICDS center model of program delivery, wherein one staff member focused on service provision for under-3s, while the other focused on older children. In contrast, other states operated a "one-worker" model wherein a single worker in every ICDS center had responsibility for the entire age-range. These features, and the experience gained under the TINP model could well have had a bearing on nutrition outcomes during the NFHS-3 data collection in 2005.

The public distribution system (PDS) is another policy case in point. In 1997, the PDS system that was characterized by universal coverage around the country until then was converted into a targeted system based on a poverty measure in order to reduce the food subsidy burden. Tamil Nadu was the exception that continued with universal coverage. Swaminathan (2008) shows that targeted PDS has led to high rates of exclusion among the needy. In 2005, more than 70% of officially poor households in Bihar and Uttar Pradesh were excluded from the PDS, while in contrast in Tamil Nadu only a very small percentage did not have access. Agricultural laborers are possibly the group most in need of food subsidies, but nationwide more than 50% did not have access to the PDS, while in Tamil Nadu the percentage was negligible. Swaminathan (2008) also notes Tamil Nadu's pioneering role in the Noon Meal Scheme and its good record relative to other states in implementation, and sums up by noting "*It is not our intention to attribute the entire improvement in nutritional status of children in Tamil Nadu to the State's food and nutrition policies but they must clearly be given their due in any explanation*". This chimes with our interpretation of our large coefficient effects estimates, and suggests that policy reforms in other states that learn from Tamil Nadu's documented past successes have the potential to produce significant improvements in anthropometric outcomes. In this regard, the proposed expansion of the PDS to cover a larger pool of beneficiaries nationwide under the Food Security Bill of 2013 appears promising, although major issues about leakages and wastages still remain. [14] ICDS programs in many states may also have important lessons to learn from the TINP experience. For example, the failure of ICDS to effectively reach under-3s due to the nature of services offered and the focus on center-based activities has been recognized before (Gragnolati, Bredenkamp, Gupta, Lee, & Shekar, 2006), and contrasted with the success of TINP in reaching this critically important group (Heaver, 2002). Contrast has also been drawn between the problem with leakage of take-home food supplements in the ICDS programs of states such as Madhya Pradesh due to household sharing, and the TINP's effective approach of requiring food supplements to be consumed on premises (Gragnolati et al., 2006). Ultimately, many cross-state variations in nutrition sensitivity of policies might be traceable to the political makeup of each state as described by Harriss and Kohli (2009) and reviewed previously. These governance issues deserve further study.

Of the states being compared to Tamil Nadu in this research, Odisha appears something of an exception in that its coefficient effects in the comparison with Tamil Nadu are substantially smaller than in the case of the other states. This finding is consistent with the fact that Odisha, like Tamil Nadu, is recognized as a "positive deviant" in nutrition-related policymaking. [15] Mohmand (2012) describes the improved horizontal coordination across sectors in delivering nutrition, as well as more enlightened and efficient management within relevant sectors implemented in Odisha since the early 2000s. This includes orienting the state's ICDS program to better focus on under-3s, setting up coordination mechanisms across key ministries at the district, block, and sector levels, and appointing personnel with practical nutrition backgrounds to key positions.

In terms of analytical issues, a basic takeaway point from this work is that, given the large scope for heterogeneity across states in India, it is important to allow parameters to vary accordingly. The decomposition methods we use are based on regressions that allow intercepts *as well as* slopes to vary across states - effectively estimating separate models for each state - which we suggest is important in capturing the heterogeneities described above accurately. Additionally, the second of the two decomposition methods we employ allows the impact of each covariate to vary across the distribution of HAZ, an intuitively appealing approach to modeling HAZ outcomes. [16] The weaknesses of this study are also acknowledged - we do not identify causal effects, our model specifications are limited by the nature of the DFHS data, groupwise decomposition methods impose the requirement of identical sets of covariates across groups, and interpretations of coefficient effects are speculative. Nevertheless, this research helps highlight important state-specific dimensions to nutritional improvement in India.

Some additional policy and intervention-relevant insights arise specifically from allowing parameters to vary across states and the HAZ distribution. One such insight is the strong relationship between agricultural land ownership and HAZ in Bihar, MP, and Tamil Nadu specifically. Agricultural land ownership by the household (relative to landlessness) is associated with a substantial improvement in HAZ, particularly in the bottom half of the conditional HAZ distribution containing relatively nutritionally vulnerable children. The limited nature of the NFHS data in terms of livelihoods, diets, and agriculture dimensions do not allow this basic association to be unpacked further, nor can causation be inferred. However, at least, the estimated relationship between agricultural land ownership and HAZ could be argued to present a hypothesis to be pursued further by future research examining causal impact. Other specific areas for priority policy focus in each of the five comparison states are presented in Appendix Table 18, along with contextual information on the current policy landscape. These include a suggested focus on sanitation in Gujarat, where our results suggest a particularly strong relationship between open defecation and HAZ in the lower half of the distribution, the importance of growth monitoring in UP, and programs and policies relating to maternal nutrition and education in Bihar, UP, and MP.

Nutrition has had a relatively low-key presence in the Millennium Development Goals (MDG) framework, with an imperfect underweight measure forming one of nine indicators for MDG1. However, it has gained substantial prominence in the last few years, marked by the inclusion of "Food security and good nutrition" as one of the twelve goals proposed for the post-2015 Development Agenda by the UN High Level Panel (Smith and Haddad, 2015). Stunting is emerging as the metric of choice for nutrition for the post-2015 world, enabling individual-level measurement of chronic deprivation and capturing intergenerational welfare tradeoffs (Haddad 2013). The states studied here account for a sixth of the world's stunted under-5s, and thus this research has relevance for the post-2015 development framework. Gillespie et al. (2013), in the Lancet Series on Maternal and Child Nutrition argue that, in addition to scaling up proven nutrition-specific interventions and increasing the nutrition-sensitivity of interventions in other sectors, focusing on policy processes and outcomes and their political underpinnings will be critical for nutrition in the post-2015 era. Our findings are in agreement with this view.

NOTES

1. We undertake comparison of multiple states against a common benchmark in an attempt to discern general patterns to the extent possible in this framework.

2. We do not offer a comprehensive review of the literature here. Rather, the purpose is to highlight some key themes that have been examined, with a focus on recent literature.

3. Another reason for our choice has an empirical basis. The reliability of the Quantile Regression (QR)-based decomposition method, described below, used to compute covariate and coefficient effects along the entire HAZ distribution is crucially dependent on an empirical fit that minimizes the gap between the observed (empirical) HAZ distribution and the simulated distribution. In practice, Tamil Nadu displayed a better fit than alternatives like Kerala. Sample size issues also came into consideration. QR-based decomposition methods demand large sample sizes for sufficient reliability, and the Kerala rural sample of under-fives was significantly smaller than in the case of Tamil Nadu.

4. Of course, this broad set of variables could be grouped in several alternative ways. The classification we use facilitates connection with previous themes explored in the literature reviewed, such as sanitation, agriculture and maternal education and empowerment.

5. Assets are included individually rather than as a wealth index since individual assets were found to have independent explanatory power in our regressions.

6. Note that the right hand side of (4) refers to the gap arising from *simulated* HAZ distributions for MP and TN. Since the simulated distributions will not match the observed or empirical distributions exactly, the inter-state gap based on empirical distributions will include a residual error term as indicated in (4).

7. Since there is no objective way of categorizing rural households as agricultural or non-agricultural in the NFHS data, households that lack productive assets like land and livestock cannot be assumed to be capital-poor farming households—they may simply be households that are diversified away from agriculture. That said, relatively low levels of ownership of land and livestock are well-known features of TN's agrarian economy.

8. Multicollinearity impacts the precision with which some coefficients in the model are estimated. Versions of the model run omitting key variables contributing to collinearity (e.g., squared age term) improved some standard errors to an extent, but not sufficiently to warrant a change in model specification or insights drawn from it.

9. The alternative Reimers (1983) method of computing the Oaxaca–Blinder decomposition was also implemented. It estimated even smaller covariate contributions than the pooled method reported here, but the results were otherwise consistent.

10. Large contributions to nutrition outcome heterogeneity across groups arising from unobservable factors captured in the intercept term have also been noted in the decomposition studies of Van de Poel and Speybroeck (2009), Van de Poel, O'Donnell, and Van Doorslaer (2009) and O'Donnell and Wagstaff (2008). Van de Poel, O'Donnell, and Van Doorslaer (2009) choose to include intercept effects within covariate, rather than coefficient contributions, in spite of intercepts being parameters to be estimated, arguing that "we prefer to place them with the covariate contribution because they essentially reflect differences in the distributions of determinants, albeit unobservable ones".

11. To check if results are robust to the choice of benchmark, we repeated the Machado–Mata decomposition for the distributions of UP, MP, Gujarat, and Bihar, with Odisha as a benchmark instead of Tamil Nadu. Odisha has a favorable HAZ distribution relative to the four comparators in the exercise, and as discussed later, a well-regarded nutrition policy framework. It arguably shares similarities with the comparators from cultural and dietary standpoints as well. Results show that the broad pattern of results, indicating the dominance of coefficient effects, remains the same. Full details of this exercise are available in the online Appendix (https://sites.google.com/site/elisacavatortawebsite/home/research).

12. Coefficient effects have become more important over time. We also carried out an Oaxaca decomposition on the NFHS-2 from 1998 to 1999, which shows that, coefficient effects were important even in 1998–99 (with the exception of Odisha), although relatively less than in 2005. This suggests that differences in HAZ distributions are increasingly dominated by the role of cross-state differences in the returns to endowments, which are becoming more pronounced relative to cross-state differences in covariates. Full results are available in the online Appendix (https://sites.google.com/site/elisacavatortawebsite/home/research).

13. The model specification presented here is the one that provides the best fit of HAZ scores in the benchmark state (i.e., minimizes the difference between the empirical HAZ distribution of the benchmark state and the simulated HAZ distribution from the quantile regression model).

14. In this respect too, Tamil Nadu has a better record that most states.

15. Odisha's stunting prevalence, although still relatively high, has fallen substantially over time.

16. Focusing on under-fives enables adequate sample sizes at the state level for our analysis. However, since the first 1,000 days in the life of child are particularly important determinants of HAZ-scores, we also performed a Machado–Mata decomposition on a restricted sample of children aged less than 24 months. With the exception of Bihar, the results show a similar pattern: states that show a predominant covariate (coefficients) effect in the full sample also show a predominant covariate (coefficients) effects in the restricted sample; the covariate effect tends to decrease along the HAZ distribution. Results are available in the online Appendix (https://sites.google.com/site/elisacavatortawebsite/home/research).

REFERENCES

Besley, T., & Burgess, R. (2002). The political economy of government responsiveness: Theory and evidence from India. *The Quarterly Journal of Economics, 117*(4), 1415–1451.

Besley, T., Burgess, R., & Esteve-Volart, B. (2007). *The policy origins of poverty and growth in India: Delivering on the Promise of Pro-Poor Growth*. Palgrave McMillan.

Bhagowalia, P., Headey, D., & Kadiyala, S. (2012). Agriculture, income, and nutrition linkages in India: Insights from a nationally representative survey. *IFPRI working paper 1195*.

Binkin, N. J., Yip, R., Fleshood, L., & Trowbridge, F. L. (1988). Birth weight and childhood growth. *Pediatrics, 82*(6), 828–834.

Borooah, V. K. (2005). The height-for-age of Indian children. *Economics & Human Biology, 3*(1), 45–65.

Bose, V., Batra-Dua, S., Menon, S., Mathur, S., Sharma, G., & Chauhan, K. (2014). *A landscape analysis of nutrition initiatives in Madhya Pradesh: Policies, actors and networks*. Delhi, India: IFPRI.

Deaton, A., & Drèze, J. (2009). Food and nutrition in India: Facts and interpretations. *Economic and Political Weekly*, 42–65.

Elder, T. E., Goddeeris, J. H., & Haider, S. J. (2010). Unexplained gaps and Oaxaca–Blinder decompositions. *Labour Economics, 17*(1), 284–290.

Fortin, N., Lemieux, T., & Firpo, S. (2011). Decomposition methods in economics. *Handbook of Labor Economics, 4*, 1–102.

Gillespie, S., Haddad, L., Mannar, V., Menon, P., & Nisbett, N.Maternal and Child Nutrition Study Group. (2013). The politics of reducing malnutrition: building commitment and accelerating progress. *The Lancet, 382*(9891), 552–569.

Gragnolati, M., Bredenkamp, C., Gupta, M. D., Lee, Y. K., & Shekar, M. (2006). ICDS and persistent undernutrition: Strategies to enhance the impact. *Economic and Political Weekly*, 1193–1201.

Haddad, L. (2013). How should nutrition be positioned in the post-2015 agenda?. *Food Policy, 43*, 341–352.

Harriss, J., & Kohli, N. (2009). Notes on the differing 'states' of child undernutrition in rural India. *IDS Bulletin, 40*(4), 9–15.

Headey, D., Chiu, A., & Kadiyala, S. (2012). Agriculture's role in the Indian enigma: help or hindrance to the crisis of undernutrition?. *Food Security, 4*(1), 87–102.

Heaver, R. (2002). India's Tamil Nadu nutrition program: Lessons and issues in management and capacity development. Report to the World Bank.

Imai, K. S., Annim, S. K., Kulkarni, V. S., & Gaiha, R. (2014). Women's empowerment and prevalence of stunted and underweight children in Rural India. *World Development, 62*, 88–105.

Jain, M. (2015). India's struggle against malnutrition—Is the ICDS program the answer?. *World Development, 67*, 72–89.

Jann, B. (2008). A Stata implementation of the Blinder–Oaxaca decomposition. *Stata Journal, 8*(4), 453–479.

Kandpal, E. (2011). Beyond average treatment effects: Distribution of child nutrition outcomes and program placement in India's ICDS. *World Development, 39*(8), 1410–1421.

Kandpal, E., & McNamara, P. E. (2009). Determinants of nutritional outcomes of children in India: A quantile regression approach. In *2009 Annual Meeting, July 26–28, 2009, Milwaukee, Wisconsin (No. 49415)*. Agricultural and Applied Economics Association.

Machado, J. A., & Mata, J. (2005). Counterfactual decomposition of changes in wage distributions using quantile regression. *Journal of Applied Econometrics, 20*(4), 445–465.

Mayer, P. (2001). Human development and civic community in India: Making democracy perform. *Economic and Political Weekly*, 684–692.

Menon, P., Kohli, N., Pradhan, M., Pradhan, N., Cyriac, S., & Priyadarshi, M. (2014). In *The challenge of child undernutrition in Uttar Pradesh: Findings from a Situation Assessment. POSHAN Report No 3*. New Delhi: International Food Policy Research Institute.

Menon, P., Deolalikar, A., & Bhaskar, A. (2008). *Comparisons of hunger across states: India state hunger index*. International Food Policy Research Institute.

Mohmand, S. K. (2012). *Policies without politics: Analysing nutrition governance in India*. Institute of Development Studies.

Noznesky, E. A., Ramakrishnan, U., & Martorell, R. (2012). A situation analysis of public health interventions, barriers, and opportunities for improving maternal nutrition in Bihar, India. *Food & Nutrition Bulletin, 33*(Suppl. 1), 93–103.

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International Economic Review, 14*(3), 693–709.

O'Donnell, O. A., & Wagstaff, A. (2008). *Analyzing health equity using household survey data: A guide to techniques and their implementation*. World Bank Publications.

O'Donnell, O., Nicolás, Á. L., & Van Doorslaer, E. (2009). Growing richer and taller: Explaining change in the distribution of child nutritional status during Vietnam's economic boom. *Journal of Development Economics, 88*(1), 45–58.

Osmani, S., & Sen, A. (2003). The hidden penalties of gender inequality: Fetal origins of ill-health. *Economics & Human Biology, 1*(1), 105–121.

Panagariya, A. (2013). Does India really suffer from worse child malnutrition than Sub-Saharan Africa?. *Economic & Political Weekly, 48*(18), 98–111.

Purfield, C. (2006). *Mind the gap-is economic growth in India leaving some states behind?*. International Monetary Fund.

Rawal, V. (2008). Ownership holdings of land in rural India: Putting the record straight. *Economic and Political Weekly*, 43–47.

Reimers, C. W. (1983). Labor market discrimination against Hispanic and black men. *The Review of Economics and Statistics*, 570–579.

Smith, L. C., & Haddad, L. (2005). Reducing child undernutrition: past drivers and priorities for the post-MDG Era. *World Development, 68*, 180–204.

Smith, L. C., Ruel, M. T., & Ndiaye, A. (2005). Why is child malnutrition lower in urban than in rural areas? Evidence from 36 developing countries. *World Development, 33*(8), 1285–1305.

Spears, D. (2012). Height and cognitive achievement among Indian children. *Economics & Human Biology, 10*(2), 210–219.

Spears, D. (2013). How much international variation in child height can sanitation explain? *Policy research working paper no. 6351*. World Bank.

Srinivasan, C. S., Zanello, G., & Shankar, B. (2013). Rural-urban disparities in child nutrition in Bangladesh and Nepal. *BMC Public Health, 13*(1), 581.

Swaminathan, M. (2008). Programmes to protect the hungry: Lessons from India. *DESA working paper no. 70*. United Nations.

UNICEF (United Nations Children's Fund) (1990). *Strategy for improved nutrition of children and women in developing countries*. UNICEF: A UNICEF policy review.

Van de Poel, E., O'Donnell, O., & Van Doorslaer, E. (2009). What explains the rural-urban gap in infant mortality: Household or community characteristics?. *Demography, 46*(4), 827–850.

Van de Poel, E., & Speybroeck, N. (2009). Decomposing malnutrition inequalities between Scheduled Castes and Tribes and the remaining Indian population. *Ethnicity & Health, 14*(3), 271–287.

Visaria, L., & Visaria, P. (2003). Long-term population projections for major states, 1991–2101. *Economic and Political Weekly*, 4763–4775.

APPENDIX

Table 4. *Percentile values of HAZ*

Percentile	TN HAZ	UP HAZ	Bihar HAZ	Odisha HAZ	MP HAZ	Gujarat HAZ
10	−3.16 (−3.31, −2.96)	−4.34 (−4.44, −4.24)	−4.21 (−4.36, −4.03)	−3.64 (−3.78, −3.48)	−4.33 (−4.46, −4.16)	−4.11 (−4.32, −3.88)
25	−2.27 (−2.43,−2.15)	−3.37 (−3.44, −3.32)	−3.25 (−3.33, −3.12)	−2.82 (−2.91, −2.73)	−3.15 (−3.29, −3.01)	−3.12 (−3.28, −3.02)
50	−1.32 (−1.51, −1.22)	−2.32 (−2.38, −2.25)	−2.26 (−2.36, −2.15)	−1.87 (−1.98, −1.78)	−2.07 (−2.15, −1.95)	−2.19 (−2.27, −2.05)
75	−0.23 (−0.52, −0.03)	−1.24 (−1.3, −1.16)	−1.22 (−1.33, −1.05)	−0.90 (−1.00, −0.79)	−1.09 (−1.2, −0.93)	−1.17 (−1.29, −1.05)
90	0.8 (0.60, 1.15)	−0.18 (−0.28, −0.03)	−0.131 (−0.28, 0.01)	0.107 (−0.02, 0.28)	0.08 (−0.06, 0.31)	−0.33 (−0.43, −0.11)

95% confidence intervals in parentheses.

Table 5. *HAZ mean regression coefficients*

Variables	TN	Bihar	MP	UP	Gujarat	Odisha
Child characteristics						
Age	−0.0655***	−0.115***	−0.105***	−0.127***	−0.0785***	−0.0642***
	(0.0161)	*(0.00934)*	*(0.0105)*	*(0.00616)*	*(0.0120)*	*(0.0104)*
Age^2	0.00086***	0.0014***	0.0013***	0.0016***	0.0011***	0.0008***
	(0.00025)	*(0.00015)*	*(0.00016)*	*(0.00010)*	*(0.00019)*	*(0.00016)*
Birth order	0.0169	0.126	0.196**	0.137***	0.0215	0.0748
	(0.145)	*(0.0826)*	*(0.0875)*	*(0.0524)*	*(0.105)*	*(0.0987)*
Female	0.232*	−0.131*	0.0713	−0.0494	0.142	−0.182**
	(0.126)	*(0.0758)*	*(0.0834)*	*(0.0508)*	*(0.0991)*	*(0.0851)*
Weight at birth	0.274**	0.357**	0.471***	0.150	0.229**	0.253**
	(0.112)	*(0.180)*	*(0.141)*	*(0.127)*	*(0.102)*	*(0.107)*
Empowerment & educ.						
Mother's schooling	−0.0515	0.0501*	0.0537**	0.0617***	−0.0358	0.0572**
	(0.0317)	*(0.0261)*	*(0.0240)*	*(0.0138)*	*(0.0269)*	*(0.0250)*
Age at first marriage	0.0102	0.0173	−0.00213	−0.00569	0.0452**	0.0403***
	(0.0218)	*(0.0177)*	*(0.0166)*	*(0.0112)*	*(0.0190)*	*(0.0151)*
Mother's nutrition						
Mother's HAZ	0.221***	0.291***	0.346***	0.317***	0.332***	0.317***
	(0.0655)	*(0.0429)*	*(0.0453)*	*(0.0278)*	*(0.0537)*	*(0.0489)*
Mother anemic	−0.0265	−0.326***	−0.380***	−0.107	−0.0868	−0.197*
	(0.175)	*(0.0963)*	*(0.107)*	*(0.0665)*	*(0.122)*	*(0.110)*
Assets (non-agric.)						
Electricity	−0.112	−0.0101	0.0880	0.223***	0.314**	0.229**
	(0.207)	*(0.112)*	*(0.0964)*	*(0.0653)*	*(0.141)*	*(0.115)*
TV	−0.189	0.264*	0.0619	0.0535	0.118	−0.0939
	(0.147)	*(0.136)*	*(0.124)*	*(0.0689)*	*(0.126)*	*(0.137)*
Fridge	0.545	−0.251	0.185	0.251	0.149	−0.235
	(0.414)	*(0.250)*	*(0.244)*	*(0.180)*	*(0.215)*	*(0.249)*
Scooter	0.0706	0.293	0.182	0.203**	0.110	0.322*
	(0.185)	*(0.189)*	*(0.165)*	*(0.0892)*	*(0.160)*	*(0.178)*
Car	−0.875	1.053**	−0.0552	−0.138	0.154	−0.858
	(0.855)	*(0.507)*	*(0.632)*	*(0.358)*	*(0.441)*	*(0.653)*

(*continued on next page*)

Table 5 (*continued*)

Variables	TN	Bihar	MP	UP	Gujarat	Odisha
Mother's employment						
Mother unemployed	0.0977	−0.283	0.507	−0.103	0.0373	0.159
	(0.302)	*(0.240)*	*(0.312)*	*(0.208)*	*(0.260)*	*(0.220)*
Mother manual labor	0.0956	−0.459	0.448	−0.383	−0.293	0.289
	(0.357)	*(0.360)*	*(0.321)*	*(0.245)*	*(0.304)*	*(0.285)*
Mother in agriculture	−0.115	−0.408	0.572*	−0.121	0.0246	0.0633
	(0.327)	*(0.248)*	*(0.313)*	*(0.212)*	*(0.266)*	*(0.236)*
Assets (agricultural)						
Own land	0.196	0.228**	0.192	0.245***	0.171	−0.0338
	(0.302)	*(0.109)*	*(0.170)*	*(0.0850)*	*(0.209)*	*(0.146)*
Irrigation	−0.174	0.0187	−0.279*	0.00930	−0.185	−0.0230
	(0.319)	*(0.113)*	*(0.160)*	*(0.0747)*	*(0.202)*	*(0.136)*
Cows	0.0945	0.0519	0.136	0.00157	0.00354	0.0768
	(0.170)	*(0.0838)*	*(0.102)*	*(0.0615)*	*(0.124)*	*(0.0960)*
Goats	0.241	−0.115	−0.177	−0.000144	−0.0541	0.0596
	(0.215)	*(0.0823)*	*(0.109)*	*(0.0581)*	*(0.139)*	*(0.112)*
Chickens	0.0221	−0.345***	−0.0315	−0.0803	0.235	−0.0268
	(0.175)	*(0.109)*	*(0.140)*	*(0.101)*	*(0.175)*	*(0.102)*
Sanitation & environment						
Open defecation (household)	−0.481**	−0.116	−0.0631	0.00271	−0.350**	−0.107
	(0.219)	*(0.132)*	*(0.193)*	*(0.0903)*	*(0.163)*	*(0.167)*
Open defecation (village)	−0.626	−0.105	0.0579	−0.0628	−0.169	−0.808**
	(0.410)	*(0.356)*	*(0.336)*	*(0.157)*	*(0.261)*	*(0.326)*
Clean Fuel	−0.0139	0.158	0.106	0.0841	0.159	−0.0436
	(0.226)	*(0.261)*	*(0.286)*	*(0.165)*	*(0.198)*	*(0.323)*
Constant	0.281	−0.906	−1.674**	−0.239	−1.523**	−1.167*
	(0.833)	*(0.719)*	*(0.684)*	*(0.503)*	*(0.632)*	*(0.608)*
Demographics						
Children under age six (prop.)	−0.182	0.233	−0.437	−0.284	−0.259	0.549
	(0.485)	(0.340)	(0.370)	(0.220)	(0.426)	(0.688)
Household size	−0.00344	0.000378	−0.0197	−0.00973	−0.0440**	−0.0812**
	(0.0443)	(0.0126)	(0.0172)	(0.00775)	(0.0182)	(0.0356)
Observations	696	1,380	1,471	3,460	849	1,141
R^2	0.119	0.234	0.167	0.215	0.194	0.170

Standard errors in parentheses. Asterisks denote the level of significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Regression also includes a dummy variable control for missing data for the birth weight variable.

Table 6. *Tests of equality of coefficients between each state and TN:* H_0*:* $\beta^{TN} = \beta^{COMPARISON\ STATE}$

Comparison	Statistic	*P*-value
TN and Bihar	$F(29, 2018) = 3.65$	0.000
TN and MP	$F(29, 2019) = 2.85$	0.000
TN and UP	$F(29, 4098) = 4.39$	0.000
TN and Gujarat	$F(29, 1487) = 3.72$	0.000
TN and Odisha	$F(29, 1779) = 1.85$	0.003

Table 7. *Detailed Oaxaca–Blinder decompositions: Tamil Nadu and Bihar*

	Covariate	$P > z$	Coefficient	$P > z$
	Explained		*Unexplained*	
Open defecation (household)	0.002	0.739	−0.306	0.13
Open defecation (village)	0.002	0.529	−0.435	0.295
Birthorder	−0.005	0.476	−0.145	0.462
Female	0.000	0.882	0.173	0.011
Age	−0.125	0.118	1.501	0.009
Age squared	0.083	0.198	−0.740	0.037
Mother's HAZ	0.090	0	0.147	0.356
Mother's schooling	0.025	0.552	−0.236	0.005
Age at first marriage	0.032	0.421	−0.114	0.808
Mother anemic	0.009	0.074	0.050	0.12
Clean fuel	−0.003	0.838	−0.002	0.898
Electricity	−0.020	0.765	−0.077	0.654
TV	0.012	0.699	−0.134	0.018
Fridge	0.000	0.89	0.021	0.053
Scooter	0.018	0.236	−0.022	0.411
Car	0.000	0.989	−0.011	0.078
Mother unemployed	0.004	0.639	0.233	0.306
Mother manual laborer	−0.006	0.732	0.024	0.346
Mother in agriculture	0.014	0.256	0.087	0.45
Weight at birth	0.618	0.002	−0.040	0.803
Own land	−0.050	0.026	−0.010	0.94
Irrigation	0.006	0.482	−0.061	0.551
Cows	−0.026	0.242	0.020	0.718
Goats	0.027	0.205	0.041	0.223
Chickens	−0.005	0.235	0.062	0.067
Children less than age 6	0.005	0.506	−0.116	0.439
Household size	−0.023	0.455	0.003	0.99
Constant			1.186	0.261
Total	0.033	0.797	0.954	0

Table 8. *Detailed Oaxaca–Blinder decompositions: Tamil Nadu and MP*

	Covariate	$P > z$	Coefficient	$P > z$
	Explained		*Unexplained*	
Open defecation (household)	0.019	0.083	−0.362	0.117
Open defecation (village)	0.013	0.446	−0.587	0.16
Birthorder	−0.014	0.122	−0.235	0.239
Female	−0.002	0.566	0.078	0.275
Age	−0.018	0.81	1.199	0.045
Age squared	−0.004	0.947	−0.575	0.122
Mother's HAZ	−0.013	0.313	0.240	0.115
Mother's schooling	0.032	0.329	−0.267	0.007
Age at first marriage	0.020	0.571	0.207	0.672
Mother anemic	0.008	0.112	0.059	0.072
Clean fuel	0.000	0.989	−0.005	0.821
Electricity	0.007	0.723	−0.163	0.438
TV	−0.002	0.936	−0.099	0.15
Fridge	−0.004	0.295	0.012	0.289
Scooter	0.010	0.282	−0.016	0.645
Car	0.000	0.788	−0.004	0.312
Mother unemployed	0.060	0.119	−0.192	0.256
Mother manual laborer	−0.018	0.251	−0.050	0.336
Mother in agriculture	−0.050	0.11	−0.230	0.075
Weight at birth	0.673	0	−0.226	0.284
Own land	−0.066	0.165	0.008	0.961
Irrigation	0.070	0.067	0.030	0.812
Cows	−0.058	0.131	−0.011	0.865
Goats	0.012	0.191	0.048	0.099
Chickens	−0.002	0.784	0.009	0.768
Children less than age 6	−0.007	0.371	0.068	0.676
Household size	0.030	0.364	0.091	0.721
Constant			1.954	0.05
Total	0.091	0.347	0.762	0

Table 9. *Detailed Oaxaca–Blinder decompositions: Tamil Nadu and UP*

	Covariate	$P > z$	Coefficient	$P > z$
	Explained		*Unexplained*	
Open defecation (household)	0.000	0.965	−0.403	0.029
Open defecation (village)	0.000	0.758	−0.469	0.153
Birthorder	−0.011	0.053	−0.156	0.38
Female	0.000	0.996	0.136	0.033
Age	−0.186	0.026	1.875	0
Age squared	0.149	0.031	−0.995	0.003
Mother's HAZ	0.077	0	0.193	0.167
Mother's schooling	0.086	0	−0.326	0.001
Age at first marriage	−0.003	0.916	0.287	0.51
Mother anemic	0.002	0.282	0.013	0.654
Clean fuel	0.008	0.498	−0.013	0.575
Electricity	0.113	0.002	−0.282	0.154
TV	0.002	0.834	−0.103	0.132
Fridge	0.001	0.628	0.008	0.391
Scooter	0.011	0.043	−0.023	0.486
Car	0.000	0.864	−0.004	0.286
Mother unemployed	0.002	0.827	0.123	0.529
Mother manual laborer	−0.010	0.353	0.033	0.259
Mother in agriculture	0.001	0.701	0.003	0.977
Weight at birth	0.480	0.007	0.158	0.355
Own land	−0.080	0.011	−0.030	0.809
Irrigation	0.003	0.903	−0.055	0.585
Cows	−0.012	0.647	0.032	0.53
Goats	0.000	0.987	0.025	0.333
Chickens	−0.007	0.437	0.017	0.562
Children less than age 6	−0.007	0.269	0.027	0.846
Household size	0.018	0.409	0.042	0.855
Constant			0.520	0.56
Total	0.156	0.125	0.884	0

Table 10. *Detailed Oaxaca–Blinder decompositions: Tamil Nadu and Gujarat*

	Covariate	$P > z$	Coefficient	$P > z$
	Explained		*Unexplained*	
Open defecation (household)	−0.033	0.011	−0.105	0.598
Open defecation (village)	−0.034	0.133	−0.366	0.295
Birthorder	−0.001	0.872	−0.007	0.976
Female	0.002	0.688	0.043	0.561
Age	−0.094	0.144	0.391	0.529
Age squared	0.065	0.231	−0.295	0.443
Mother's HAZ	−0.015	0.261	0.213	0.185
Mother's schooling	−0.048	0.062	−0.047	0.653
Age at first marriage	0.042	0.051	−0.630	0.212
Mother anemic	0.004	0.457	0.010	0.787
Clean fuel	0.000	0.933	−0.024	0.508
Electricity	0.008	0.309	−0.365	0.127
TV	−0.003	0.793	−0.123	0.105
Fridge	−0.030	0.031	0.029	0.112
Scooter	0.000	0.868	−0.007	0.861
Car	0.001	0.761	−0.008	0.158
Mother unemployed	0.018	0.411	0.023	0.893
Mother manual laborer	0.000	0.88	0.032	0.344
Mother in agriculture	−0.010	0.729	−0.032	0.789
Weight at birth	0.302	0.001	0.086	0.739
Own land	−0.043	0.331	0.009	0.959
Irrigation	0.042	0.249	−0.001	0.994
Cows	−0.009	0.75	0.029	0.697
Goats	0.000	0.992	0.034	0.283
Chickens	0.011	0.285	−0.029	0.362
Children less than age 6	−0.006	0.426	0.022	0.896
Household size	0.060	0.044	0.222	0.384
Constant			1.803	0.058
Total	−0.058	0.471	0.999	0

Table 11. *Detailed Oaxaca–Blinder decompositions: Tamil Nadu and Odisha*

	Covariate	$P > z$	Coefficient	$P > z$
	Explained		*Unexplained*	
Open defecation (household)	0.015	0.064	−0.321	0.134
Open defecation (village)	0.034	0.009	0.158	0.700
Birthorder	0.000	0.762	−0.074	0.709
Female	0.001	0.695	0.202	0.005
Age	−0.071	0.185	−0.041	0.944
Age squared	0.048	0.288	−0.016	0.965
Mother's HAZ	0.065	0.000	0.198	0.218
Mother's schooling	0.015	0.543	−0.281	0.005
Age at first marriage	0.037	0.011	−0.553	0.228
Mother anemic	0.004	0.303	0.029	0.393
Clean fuel	−0.008	0.650	0.007	0.713
Electricity	0.093	0.046	−0.284	0.139
TV	−0.028	0.185	−0.036	0.585
Fridge	−0.001	0.625	0.025	0.049
Scooter	0.016	0.139	−0.033	0.290
Car	−0.001	0.704	0.000	0.949
Mother unemployed	−0.011	0.294	−0.034	0.869
Mother manual laborer	0.009	0.293	−0.016	0.617
Mother in agriculture	0.000	0.841	−0.047	0.626
Weight at birth	0.380	0.000	0.034	0.886
Own land	−0.008	0.869	0.096	0.524
Irrigation	0.019	0.552	−0.055	0.643
Cows	−0.029	0.314	0.007	0.913
Goats	−0.006	0.514	0.019	0.524
Chickens	0.003	0.794	0.009	0.826
Children less than age 6	0.000	0.966	−0.100	0.538
Household size	−0.018	0.411	−0.063	0.806
Constant			1.448	0.124
Total	0.227	0.003	0.377	0.000

Table 12. *Quantile regression coefficients: Tamil Nadu*

	10th	25th	50th	75th	90th
Open defecation (household)	−0.362	−0.117	−0.105	−0.164	−0.541
Open defecation (village)	−0.157	−0.519	−0.083	−0.714	-2.098^{*}
Birth order	−0.074	0.093	0.088	−0.116	0.124
Female	0.242	0.346^{***}	0.194^{*}	0.164	−0.291
Age	−0.030	-0.063^{***}	-0.072^{***}	-0.082^{***}	-0.113^{**}
Age^2	0.000	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{**}
Mother's HAZ	0.158^{*}	0.265^{***}	0.296^{***}	0.268^{***}	0.071
Mother's schooling	−0.004	0.001	0.013	−0.001	0.006
Age at first marriage	0.084^{***}	0.048^{**}	0.029	−0.039	−0.045
Mother anemic	−0.001	−0.003	−0.105	−0.160	−0.100
Clean fuel	0.430	0.273	−0.024	−0.144	−0.354
Electricity	−0.107	−0.111	0.138	−0.280	−0.442
TV	−0.325	-0.272^{*}	-0.231^{*}	0.067	0.134
Refrigerator	1.155^{*}	1.046^{**}	0.699^{*}	0.737	0.079
Motorcycle	−0.078	0.010	0.249	0.250	−0.307
Car	−0.656	−0.930	-1.393^{*}	-2.191^{*}	−0.066
Mother unemployed	0.015	−0.170	0.020	−0.315	−0.239
Mother manual labor	−0.086	−0.055	−0.188	−0.107	0.689
Mother in agriculture	0.185	−0.026	−0.084	−0.486	−0.314
Birth weight	0.190	0.207^{*}	0.305^{***}	0.378^{**}	0.396
Own land	0.682^{**}	0.623^{***}	0.208	0.154	−0.157
Irrigation	-0.008^{**}	-0.006^{**}	-0.005^{**}	−0.002	0.000
Cows	−0.004	−0.063	0.061	−0.023	0.076
Goats	0.208	0.189	−0.120	0.185	0.639
Chickens	0.305	0.133	0.304^{**}	−0.062	0.250
Children under age six	−0.550	-0.820^{*}	−0.601	−0.612	−0.036
Household size	0.062	−0.046	-0.076^{**}	−0.019	−0.114
Constant	-4.043^{***}	-1.665^{*}	−0.875	2.415^{**}	5.575^{**}

Table 13. *Quantile regression coefficients: Bihar*

	10th	25th	50th	75th	90th
Open defecation (household)	−0.116	−0.115	0.199	−0.105	−0.559**
Open defecation (village)	−0.412	0.044	−0.519	−0.225	0.073
Birth order	0.072	0.255**	0.228**	0.193	0.04
Female	−0.15	−0.141	−0.177**	−0.036	−0.047
Age	0.100***	0.101***	0.120***	0.124***	0.121***
Age2	0.001***	0.001***	0.002***	0.002***	0.002***
Mother's HAZ	0.274***	0.276***	0.306***	0.265***	0.238***
Mother's schooling	0.052**	0.060***	0.032**	−0.009	−0.023
Age at first marriage	0.01	0.013	0.045**	0.024	0.024
Mother anemic	−0.172	−0.268**	−0.269**	0.387***	−0.351*
Clean fuel	0.138	0.239	0.155	−0.044	−0.203
Electricity	0.252	0.165	−0.052	−0.023	−0.169
TV	0.091	0.144	0.295**	0.410**	0.194
Refrigerator	−0.483	−0.579*	−0.082	−0.302	−0.175
Motorcycle	0.789**	0.398	0.483**	0.228	0.006
Car	−0.016	1.222*	0.793	0.648	2.863***
Mother unemployed	−0.162	0.129	−0.191	−0.438	−0.73
Mother manual labor	−0.825	−0.075	−0.423	−0.614	−1.191
Mother in agriculture	−0.383	−0.012	−0.438	−0.652*	−0.582
Birth weight	0.299	0.487**	0.472**	0.633**	0.173
Own land	0.165	0.638**	0.507**	0.571**	0.114
Irrigation	0.001	−0.004	−0.002	−0.003	0.001
Cows	0.139	0.12	−0.027	−0.019	0.052
Goats	−0.118	0.038	−0.058	−0.273**	−0.235
Chickens	−0.485**	−0.360**	0.367***	−0.391**	−0.156
Children under age six	0.58	0.491	0.202	0.118	0.257
Household size	0.009	0.003	−0.018	0.005	0.01
Constant	−2.627**	3.286***	−1.693**	−0.767	1.997

Table 14. *Quantile regression coefficients: Madhya Pradesh*

	10th	25th	50th	75th	90th
Open defecation (household)	0.236	0.362	−0.194	0	−0.09
Open defecation (village)	−0.468	−0.201	0.53	0.254	−0.493
Birth order	0.271	0.384***	0.14	0.206*	0.123
Female	0.156	0.028	0.025	0.145	0.053
Age	−0.110***	−0.099***	−0.108***	−0.099***	−0.102***
Age2	0.001***	0.001***	0.001***	0.001***	0.001***
Mother's HAZ	0.309***	0.373***	0.409***	0.363***	0.367***
Mother's schooling	0.059**	0.043**	0.034**	0.041**	0.029
Age at first marriage	−0.028	−0.019	−0.002	−0.026	0.017
Mother anemic	−0.356*	−0.343**	−0.375***	−0.382***	−0.507**
Clean fuel	−0.385	0.123	0.149	−0.059	0.31
Electricity	0.330*	0.144	0.09	0.066	−0.089
TV	0.083	0.102	0.064	−0.084	−0.029
Refrigerator	0.201	0.372	0.026	0.203	−0.139
Motorcycle	−0.014	0.511**	0.261	0.357*	−0.176
Car	−0.696	0.325	0.223	0.095	−0.141
Mother unemployed	0.063	0.307	0.23	0.499	1.092
Mother manual labor	0.226	0.436	0.149	0.461	0.823
Mother in agriculture	0.315	0.366	0.336	0.54	1.066
Birth weight	0.263	0.368**	0.340**	0.522***	0.926***
Own land	−0.21	−0.113	−0.143	0.05	0.166
Irrigation	0.003	0.001	0.001	−0.001	−0.001
Cows	0.197	0.280**	0.161	−0.037	−0.069
Goats	−0.296	−0.086	−0.19	−0.259*	−0.12
Chickens	0.42	0.172	0.03	−0.215	−0.135
Children under age six	0.027	−0.632	−0.476	−1.035**	−1.203
Household size	−0.018	−0.055**	−0.018	−0.021	−0.008
Constant	−2.673**	−2.244**	−1.207	−0.551	−0.893

Table 15. *Quantile regression coefficients: Gujarat*

	10th	25th	50th	75th	90th
Open defecation (household)	−0.959***	−0.522**	−0.328**	−0.147	−0.013
Open defecation (village)	0.141	−0.181	−0.21	−0.218	−0.26
Birth order	0.278	−0.045	−0.062	−0.042	0.371*
Female	0.377**	0.305**	0.107	−0.004	−0.222
Age	−0.106***	−0.115***	−0.088***	−0.073***	−0.068***
Age2	0.001***	0.002***	0.001***	0.001***	0.001*
Mother's HAZ	0.365***	0.296***	0.263***	0.349***	0.448***
Mother's schooling	−0.03	0.008	−0.013	−0.028	−0.042
Age at first marriage	0.034	0.032	0.052***	0.057**	0.078*
Mother anemic	0.124	−0.297*	−0.123	−0.144	−0.016
Clean fuel	0.21	0.143	0.179	0.209	0.48
Electricity	0.561**	0.679***	0.407***	0.066	0.007
TV	0.228	−0.087	0.055	0.096	−0.056
Refrigerator	0.025	0.135	0.196	0.221	0.42
Motorcycle	0.333	−0.055	−0.006	0.138	0.48
Car	0.531	0.271	−−0.014	0.26	−0.219
Mother unemployed	−0.186	−0.367	−0.177	0.171	0.388
Mother manual labor	−0.465	−0.728*	−0.532*	−0.243	0.024
Mother in agriculture	0.013	−0.374	−0.276	0.105	0.313
Birth weight	−0.073	0.126	0.309***	0.330**	0.314
Own land	−0.19	−0.219	0.177	0.211	0.2
Irrigation	0.001	0.003	0	−0.002	−0.008**
Cows	−0.127	−0.049	−0.086	0.066	0.642**
Goats	−0.112	−0.109	0.042	−0.165	−0.258
Chickens	0.087	0.376	0.328*	0.245	0.336
Children under age six	−0.19	0.305	−0.823*	−0.401	−0.623
Household size	−0.03	0.002	−0.036*	−0.042*	−0.109***
Constant	−2.056*	−1.715**	−1.600**	−1.07	−0.421

Table 16. *Quantile regression results: Odisha*

	10th	25th	50th	75th	90th
Open defecation (household)	0.105	0.075	−0.175	−0.166	−0.083
Open defecation (village)	−0.554	−1.004**	−0.717**	−0.870*	−0.419
Birth order	−0.031	0.131	0.134	0.134	0.238
Female	−0.064	−0.153	−0.275***	−0.262**	−0.409**
Age	−0.047***	−0.062***	−0.069***	−0.079***	−0.075***
Age2	0.001***	0.001***	0.001***	0.001***	0.001**
Mother's HAZ	0.296***	0.291***	0.322***	0.396***	0.361***
Mother's schooling	0.090***	0.073***	0.054***	0.014	0.005
Age at first marriage	0.017	0.019	0.035**	0.051**	0.034
Mother anemic	−0.096	−0.077	−0.257**	−0.22	−0.135
Clean fuel	0.809	0.248	−0.113	−0.221	0.025
Electricity	0.223	0.281**	0.178	0.199	0.113
TV	−0.17	−0.205	−0.300**	−0.127	−0.133
Refrigerator	−0.522	−0.685**	−0.218	0.32	0.592
Motorcycle	0.054	0.28	0.293	0.261	0.431
Car	−0.953	−1.771**	−0.974	−0.18	−0.504
Mother unemployed	0.024	0.134	0.087	0.321	0.263
Mother manual labor	0.486	0.328	0.235	0.246	0.089
Mother in agriculture	−0.277	−0.039	−0.082	0.368	0.481
Birth weight	0.149	0.185	0.146	0.308**	0.444**
Own land	−0.064	−0.048	−0.083	−0.213	−0.26
Irrigation	0.004**	0.002	0.003**	0.002	0.003
Cows	0.051	−0.061	0.13	0.029	0.21
Goats	0.054	0.127	0.037	0.092	−0.06
Chickens	−0.042	−0.057	0.076	0.003	−0.269
Children under age six	−0.512	−0.007	0.21	0.411	0.481
Household size	0.032	0.011	−0.005	0.016	0.048
Constant	−2.898***	−1.732**	−0.771	−0.432	−0.362

Table 17. *Quantile regression results: UP*

	10th	25th	50th	75th	90th
Open defecation (household)	0.045	−0.016	0.059	−0.017	0.03
Open defecation (village)	−0.039	0.065	−0.117	−0.009	−0.163
Birth order	0.139	0.150**	0.130**	0.103	0.153
Female	0.012	−0.112*	−0.071	−0.02	−0.075
Age	−0.117***	−0.117***	−0.125***	−0.126***	−0.133***
Age2	0.002***	0.002***	0.002***	0.002***	0.002***
Mother's HAZ	0.244***	0.326***	0.317***	0.308***	0.331***
Mother's schooling	0.071***	0.044***	0.030***	0.021**	0.016
Age at first marriage	0.01	0.011	−0.019	−0.008	−0.026
Mother anemic	0.062	−0.026	−0.109	−0.257***	−0.197
Clean fuel	−0.065	0.177	0.198	−0.105	−0.04
Electricity	0.238*	0.195**	0.258***	0.308***	0.111
TV	0.07	0.028	0.037	−0.006	−0.024
Refrigerator	0.441	0.316	0.108	0.127	0.061
Motorcycle	−0.002	0.216**	0.350***	0.233**	0.311*
Car	0.187	0.001	−0.393	−0.338	0.26
Mother unemployed	−0.482	0.006	0.036	0.104	−0.016
Mother manual labor	−0.721	−0.676**	−0.278	−0.212	−0.133
Mother in agriculture	−0.512	−0.033	0.028	0.038	−0.001
Birth weight	0.429*	0.306**	0.297**	0.025	−0.022
Own land	0.540*	0.268	0.589***	0.599***	0.690**
Irrigation	−0.002	−0.001	−0.003	−0.004*	−0.004
Cows	0.045	0.005	−0.04	−0.036	−0.027
Goats	0.022	0.01	−0.002	−0.075	0.038
Chickens	0.049	0.003	−0.139	−0.331**	0.034
Children under age six	0.38	−0.132	−0.671***	−0.740***	−0.307
Household size	−0.009	−0.001	−0.017*	−0.017	−0.015
Constant	−3.597***	−2.298***	−0.51	1.166*	2.577**

Table 18. *Some priority areas for policy and program development in the comparison states*

	Key policy/programmatic areas of focus suggested by this research	Key other recommendations from wider literature
Madhya Pradesh	Maternal nutrition has a strong association with child HAZ throughout the HAZ distribution in MP. Bose et al. (2014) report strong stakeholder support in MP for adopting a life-cycle approach to nutrition in the ICDS that integrates improvements in maternal nutrition, birthweight, and nutrition of girls	Bose et al. (2014) note: *ICDS and the National Rural Health Mission programs in MP need to be better integrated with other relevant departments/programs in the state, including Agriculture, Water and Sanitation and the PDS *A strategy for knowledge-sharing is required that would put nutrition more prominently on the state's policy agenda, involving enhanced participation of civil society and media
Bihar	Mother's schooling as well as nutrition co-vary positively and strongly with child HAZ in Bihar, particularly in the lower half of the conditional HAZ distribution. Bihar has introduced a raft of policy measures on this front over the last decade, cash incentives to delay marriage, free school supplies for adolescent girls, etc. As a consequence the percentage of girls aged 11 to 14 that out of school has declined from 17.6% in 2006 to 4.6% in 2013 (ASER, 2014). Noznesky, Ramakrishnan, and Martorell (2012) suggest more could be done, including targeting interventions to newlywed women and providing cash incentives to delay pregnancy until after 18	Noznesky et al. (2012) suggest that the Bihar government can build on impressive policy achievements over the last decade by (among other aspects): *Improving currently weak M&E systems for programs such as nutrition supplementation and nutrition education *Empowering Panchayati Raj institutions to develop local initiatives for nutrition *Facilitating the integration of nutrition education into the activities of livelihood-based self-help groups
Uttar Pradesh	While growth faltering, reflected in a negative relationship between child age and HAZ, is observed in many Indian states, our results indicate it to be particularly acute in UP. This is consistent with Menon's (2014) report based on stakeholder interviews in UP that a lack of technical capacity in the state ICDS has led to a breakdown of growth monitoring. Building technical capacity on this and other fronts may be a priority. As in other states, maternal nutrition and education have strong positive associations with the lower tail of child HAZ in UP. Menon et al. suggest a large gap between ICDS service availability and usage; the reasons for this gap need to be studied and acted on	Menon (2014) also emphasize, among other aspects: *It is important to capitalize on the high profile that nutrition is currently enjoying, marked by the launch of a new Nutrition Mission in the State *While there is experience in implementing individual nutrition interventions, there is little comprehension of how the multiple causes of malnutrition can be tackled simultaneously to enable impact at scale. A strategic approach that pools the strengths of development partners in key areas of relevance to nutrition is needed

Table 18 (*continued*)

	Key policy/programmatic areas of focus suggested by this research	Key other recommendations from wider literature
Odisha	Odisha has made great strides in nutrition programing and policymaking, as outlined in the main text. Notions of inter-departmental convergence and a life-cycle approach to nutrition that have been suggested as recommendation for other states are already well-embedded in Odisha's approach. Thus Odisha's need is to build on this impressive base, with maternal nutrition and education indicated as key areas of focus by our research	
Gujarat	This research suggests a very strong relationship between improved sanitation and child HAZ in Gujarat. One of the Total Sanitation Campaign's strategies has been to provide toilet facilities at Anganwadi centers to discourage open defecation habits from an early age. However, the Comptroller and Auditor General's audit of Gujarat has highlighted the state's gap between target and implementation. This is an area that needs priority attention	