Policy Research Working Paper 8798

Accounting for Regional Differences in Mother and Child Health

Bangladesh, West Bengal, Bihar, and Jharkhand

Susmita Dasgupta
David Wheeler

WORLD BANK GROUP
Development Economics
Development Research Group
March 2019

Policy Research Working Paper 8798

Abstract

Using recent Demographic Health Survey data for Bangladesh and the neighboring Indian states of Bihar, Jharkhand, and West Bengal, this paper reexamines the determinants of child wasting and maternal anemia. The findings bear out the importance of commonly cited factors, such as mother's education and age, household wealth, and child birth order. However, the findings also highlight significant and large regional differences between Indian states and Bangladeshi provinces. For example, the results for Jharkhand state in India and Barisal province in Bangladesh indicate that controlling for those commonly cited determinants, the poorest, least-educated mothers and their children in Barisal have better health outcomes than the wealthiest, best-educated counterparts in Jharkhand. Mapping analysis of the spatial variations in child wasting and maternal anemia shows clear patterns of clustering over large areas that frequently overlap state/province and national boundaries. Possible sources of these striking differences include spatially differentiated prices and availability of critical nutrients; dietary preferences related to religion and ethnicity; nutrition education; and administration of public health and nutrition policy.

This paper is a product of the Development Research Group, Development Economics. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/research. The authors may be contacted at sdasgupta@worldbank.org.

Accounting for Regional Differences in Mother and Child Health: Bangladesh, West Bengal, Bihar, and Jharkhand

Susmita Dasgupta*
David Wheeler

Key Words: Child wasting, maternal anemia, Bangladesh, Eastern India, spatial differences

JEL Classification: I120; I150.

This research was conducted under the South Asia Water Initiative - Sundarbans Landscape.

*Authors' names are in alphabetical order.

The authors are respectively Lead Environmental Economist, Development Research Group, World Bank; United States; and Senior Fellow, World Resources Institute.

We are grateful to Indrani Gupta, Subhendu Roy, Dinesh Nair and Mainul Huq for their review comments on this paper. We would like to extend our special thanks to Stuti Khemani, Tamer Samah Rabie and Michael Toman for their expert opinion. We are also thankful to Siobhan Murray for her valuable help with the maps.

1. Introduction

In this paper, we use information from recent Demographic and Health Surveys (DHS) for India and Bangladesh to identify regional differences in measures of maternal and child health that are not explained by commonly cited socioeconomic determinants. Our analysis assesses the health status of mothers and children using the incidence of anemia and wasting, respectively. These measures have two advantages for our purposes: They are widely cited as critical health indicators, and they are the best-recorded health measures in the DHS surveys.

Wasting, or a substandard weight/height ratio,[1] indicates nutritional deficiencies that significantly increase the risk of child morbidity and mortality. These risks are well-documented in the literature (Ghosh-Jerath et al. 2017; Tickell et al. 2017), and are attributable to diverse factors, including weight loss from infectious disease; loss of muscle and fat tissue from inadequate diets (Lenters et al. 2013); associated chronic infections (Bhutta et al. 2017; Scrimshaw 2016); and other forms of developmental impairment (Menon et al. 2012; Kara and Dolan, 2014). Wasting afflicts more than 50 million children worldwide (Harding, et al. 2018, citing UNICEF 2017) and causes about 875,000 preventable deaths annually (13% of the total) for children less than five years of age (Black et al. 2013). More than half of the children with wasting are in South Asia (Harding et al. 2018), where IFPRI (2016) identifies wasting as a critical public health problem because its incidence surpasses the 15% threshold. In related work, Galasso and Wagstaff (2018) find that stunting (substandard height/age ratio), another nutritional deficiency measure, has a significant impact on adult wages through its effects on schooling, cognitive skills and height. For developing countries, they estimate that the associated per capita income penalty from stunting is around 7 percent.

[1] Wasting is technically defined as a weight-for-height Z-score (WHZ) less than -2, based on WHO's Child Growth Standards (WHO, 2006).

Maternal anemia has been identified as the world's most common nutrition-related health problem (Kalaivani, 2009). Recent estimates suggest that about half of the pregnant women in low-income countries are anemic (Daru et al. 2018; Stevens et al. 2013; Balarajan et al. 2011; WHO 2004). The high incidence of anemia is attributed to factors that include dietary iron deficiency, hemoglobinopathies,[2] macronutrient deficiencies, and infections such as malaria, HIV, and hookworm infestation (McLean et al. 2009). Ezzati et al. (2002) find that South Asia accounts for about one-half of global maternal deaths due to anemia, and India accounts for about 80% of the South Asian total. In 1990, 19% of the maternal deaths in India were related to anemia (Anand, 1995), which also contributes to maternal deaths caused by hemorrhage, septicemia, and eclampsia (Rukuni et al. 2016).

We perform our analysis with a pooled sample of data from the just-published India National Family Health Survey for 2015-16 and the most recent Bangladesh DHS (2011) that includes measures of maternal anemia. We fit appropriate regression models to observations on child wasting and maternal anemia, using independent variables that have been identified by published empirical studies for Indian and Bangladeshi women and children. To ensure comparability, we use measures that are identical in the two national surveys. The results enable us to assess the health impacts of several determinants that are commonly cited in the literature: mothers' education and age, children's birth order, household wealth, and seasonal factors. We investigate the potential importance of unobserved geographic factors by incorporating fixed effects for Indian states and Bangladeshi provinces in our regression models. Then we re-estimate the models without regional effects and search for spatial clusters by computing and mapping mean regression residuals for the 197 districts in Bangladesh, West Bengal, Bihar and Jharkhand.

[2] Hemoglobinopathies are abnormally-structured globin chains of the hemoglobin molecule.

The remainder of the paper is organized as follows. In Section 2, we draw on the empirical literature to specify regression models for child wasting and maternal anemia. We introduce the data in Section 3 and present our regression results in Section 4. Section 5 uses the results to explore the impact magnitudes of the regression variables; state/province differences in regression predictions; and district-level spatial clustering of regression residuals. Given the striking spatial clusters revealed by this exercise, Section 6 offers some initial thoughts about their sources. Section 7 summarizes and concludes the paper.

2. Model Specification

The DHS data record individual conditions that relate to maternal and child health outcomes, and individual and household characteristics and behaviors that are directly or indirectly linked to health outcomes. These links are frequently explored in empirical research based on DHS variables, or equivalent variables from other sample-based surveys. Such exercises implicitly rely on a model of interdependent household utility, in which adult caretakers make decisions about food, sanitation and health treatments that will benefit themselves and children in their care, subject to limited household financial resources; cultural preferences; the costs of food, sanitation and health measures; knowledge of expected links between their decisions and health outcomes; and uncertainty about the strength of those links.

DHS surveys provide information on some of the requisite variables for a full analysis of health-related decisions and outcomes, including maternal and child health measures, household financial resources, sanitation measures, demographics, religion, foods given to children, health-related knowledge (proxied by schooling), and interactions with health treatment facilities. They do not provide information on relative prices, the effectiveness of health and nutrition education, the efficiency of available treatment facilities, or the myriad micro-actions that influence the translation of caregivers' health-related intentions into health outcomes. In consequence, these potentially-critical variables are generally excluded from statistical assessments of relationships between DHS-recorded variables and health outcomes .

In South Asia, many empirical studies based on the DHS and local sampling exercises have found that health outcomes are improved when parents (usually mothers) are better-educated, wealthier and more mature. Supporting evidence for wasting can be found in Vollmer et al. (2017), Harding et al. (2018), Martorell and Young (2012), Black et al. (2018), IFPRI (2014), Frongillo et al. (1997) and Fernandez et al. (2002). Similar results for maternal anemia can be found in Dutta and Sengupta (2017), Mangla (2016), Gogoi et al. (2016), Chowdhury et al. (2015), Mithra et al. (2014), Arlappa et al. (2014), Singh and Chaudhary (2015), and Tayade et al. (2018).

Other studies have suggested that culture-based preferences can also play a significant role. For example, associations between child gender, birth order and wasting have been explored by Harding et al. (2018), Hill and Upchurch (1995), and Pillai and Ortiz-Rodriguez (2015). In a study of child feeding practices, Dasgupta et al. (2018) find a perverse "education bias": Cultural preferences seem to dictate a negative association between maternal education and the share of fish among animal protein sources, even though fish is both less expensive and nutritionally superior.

With these studies as background, we specify regression models for child wasting and maternal anemia in equations (1) and (2) below. All regression variables are based on identical measures in the DHS surveys for India and Bangladesh. We posit that child wasting probability is a function of mother's education,[3] household wealth, mother's age, child birth order and child birth month.[4] We also incorporate controls for survey months, and fixed effects for Indian states [Bihar, Jharkhand, West

[3] We have also tested husband's education, which is statistically insignificant in all cases.
[4] We include birth month to incorporate the potential effects of seasonal food supply fluctuations on mothers' post-partum nutrient intake. This follows Dasgupta et al. (2018), who find that child health measures in Bangladesh are higher for birth dates in September - December, when monsoon floods sharply increase the availability of fish protein.

Bengal]; and Bangladeshi provinces [Rajshahi, Dhaka, Sylhet, Khulna, Barisal, Chittagong]). Our maternal anemia equation drops child birth order and child birth month, but is otherwise identical.

(1) $P_W = \alpha_0 + \sum_{i=1}^{4} \delta_i E_i + \sum_{j=1}^{4} \theta_j W_j + \alpha_1 A + \alpha_2 O + \sum \sigma_p D_p + \sum \gamma_{sm} D_{sm} + \sum \vartheta_{bm} D_{bm} + \varepsilon$

(2) $P_A = \beta_0 + \sum_{i=1}^{4} \mu_i E_i + \sum_{j=1}^{4} \rho_j W_j + \beta_1 A + \sum \tau_p D_p + \sum \varphi_{sm} D_{sm} + \varepsilon$

To avoid total collinearity, we exclude dummy variables for mother's education class 0; household asset class 0; Bihar state (India); February survey month[5]; and January birth month.

where

P_W	=	Probability of child wasting
P_A	=	Probability of maternal anemia
E_i	=	Mother's years of formal education by group (1 [1-6]; 2 [7-9]; 3 [10-12]; 4 [13+]
W_j	=	Total household assets (1 [1-2]; 2 [3-4]; 3 [5-6]; 4[7-9])[6]
A	=	Mother's age
O	=	Child's birth order
Dsm	=	Dummy variable for survey month (March - December)
D_{bm}	=	Dummy variable for child birth month (February - December)
ε	=	Stochastic error term

Our prior expectations are as follows:

Mother's education: $\delta_4<\delta_3<\delta_2<\delta_1<0$; $\mu_4<\mu_3<\mu_2<\mu_1<0$
Household assets: $\theta_4<\theta_3<\theta_2<\theta_1<0$; $\rho_4<\rho_3<\rho_2<\rho_1<0$
Mother's age: $\alpha_1<0$; $\beta_1<0$
Birth order: $\alpha_2 > 0$

[5] Survey data for January are not available.
[6] See the following section for a detailed description of this variable.

3. Data

Our data come from two recently-administered surveys that incorporate the methodology of the global Demographic and Health Surveys (DHS): the India National Family Health Survey (NFHS-4), 2015-16 (IIPS 2017) and the Bangladesh Demographic and Health Survey 2011 (NIPORT 2013). We have used Bangladesh DHS 2011 instead of DHS 2014 because the latter does not include maternal anemia measures. Table 1 displays summary statistics by province/state for DHS clusters in the regression data set. Overall, the sample contains data on 124,327 individuals in 4,241 DHS clusters. Figure 1 displays the cluster locations.

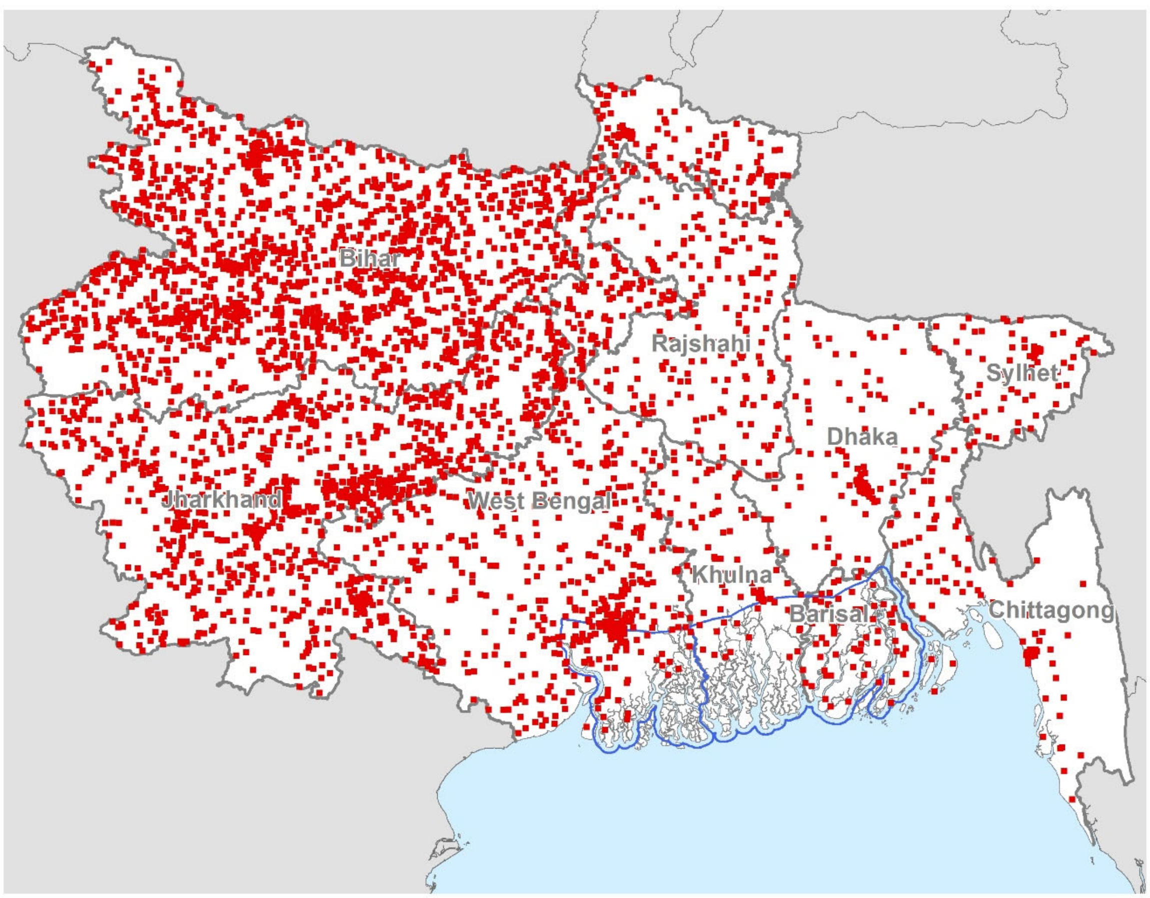
Our child and maternal health variables are measured identically in the two surveys. Wasting is based on child weight-for-height measures converted to Z-scores, based on WHO's Child Growth Standards (WHO, 2006).[7] Using a standard cutoff criterion, we define our child wasting variable as 1 for Z-scores less than -2.0 and 0 otherwise. Anemia is based on the measured hemoglobin (h) level (in grams/deciliter) in a droplet of blood. After adjustment for altitude and rounding to one decimal place, women are assigned to anemia categories as follows: severe ($h \leq 7.0$ g/dl); moderate ($7.1 \leq h \leq 9.9$); mild ($10.0 \leq h \leq 10.9$ [pregnant women], $10.0 \leq h \leq 11.9$ [other adult women]; non-anemic ($h \geq 11.0$ [pregnant women], $h \geq 12.0$ [other adult women]. Using these categories, we define our maternal anemia variable as 1 for severe and moderate anemia and 0 otherwise.

[7] Z-scores are calculated from tables standardized for age and gender, so we do not include these variables in our regression equations.

Table 1: Regression data set statistics

Country	Province/State	DHS Clusters	Sample Size
Bangladesh	Barisal	72	2,171
	Chittagong	92	3,221
	Dhaka	109	3,278
	Khulna	85	2,745
	Rajshahi	171	5,294
	Sylhet	70	2,436
India	Bihar	1677	54,404
	Jharkhand	1231	31,887
	West_Bengal	734	18,891
Total		4,241	124,327

Figure 1: Regression sample DHS clusters



We draw variables directly from the surveys for mother's formal education in years, mother's age, child birth order, birth month and survey month. Our measure of total household assets is the sum of nine variables defined as 1 if the household has the asset and 0 otherwise. The nine included assets are: (1) electricity; (2) television; (3) bicycle; (4) motorcycle or motor scooter; (5) water piped to dwelling or yard/plot; (6) flush toilet; (7) floor material in DHS quality classes 31+ (parquet, polished wood, vinyl, asphalt strips, ceramic tiles, cement, carpet, polished stone/marble/granite); (8) wall material in DHS quality classes 32+ (stone with lime/cement, burnt bricks, cement blocks, wood planks/shingles, gi/metal/asbestos sheets); (9) roof material in DHS quality classes 31+ (metal/gi, wood, calamine/cement fibre, asbestos sheets, rcc/rbc/cement/concrete, roofing shingles, tiles, slate, burnt brick).

4. Results

Table 2 presents our logit estimation results. For each case, we present estimates that incorporate classical and robust standard errors, as well as standard errors adjusted for DHS clusters. The patterns of statistical significance are invariant to estimation mode in all cases. We have checked the robustness of our estimates with several exercises whose results are available from the authors on request. We have repeated the exercise with probit estimation and find no meaningful differences. Although the available Stata software does not support spatial logit estimation for such large samples, we have computed HAC standard errors for linear probability models fitted to equations (1) and (2). The patterns of statistical significance are unchanged, suggesting that cluster-level spatial autocorrelation is not a problem.[8] Noting the spatial imbalance between Indian and Bangladeshi clusters in Table 1, we have also performed the logit estimation exercise with a sample in which the Indian observations have been

[8] All households in single clusters are assigned the same geographic coordinates. Reported DHS cluster locations are randomly varied to preserve anonymity. Urban clusters are displaced from 0 to 2 km; 99% of rural clusters from 0 to 5 km; 1% of rural clusters from 0 to 10 km.

randomly culled to achieve parity with the Bangladeshi observations in overall cluster density per unit area. Again, the results are essentially unchanged.

Overall, our results confirm the previously-cited empirical studies while adding precision in the measurement of independent variable effects. As expected, child wasting probability and maternal anemia decline as the mother's education increases. Our results suggest two discrete drops for wasting (no formal education => [primary, middle] => [secondary, post-secondary], but a continuous decline with increased education for anemia. For household assets, our wasting results suggest a significant, constant reduction for Classes 3 and 4, while the anemia results suggest a continuous decline as household assets increase.

The results for mother's age and child birth order strongly support previous empirical findings, with high significance in all cases. Wasting and anemia probabilities both decline significantly with maternal age, and wasting probability increases significantly with birth order.

Our control for interview month suggests significant seasonality for both wasting and anemia, although the patterns are somewhat different. The monthly increment to wasting probability rises steadily from spring to a peak in July-August, and then falls through the end of the year. For maternal anemia, the results suggest two seasons in which the probability increment is roughly the same: lower from April to October, and higher for the rest of the year.

Drawing on previously-cited work by Dasgupta et al. (2018), we have tested the effect of child birth month on wasting. We also find a highly-significant reduction in wasting probability for children born during the monsoon season (September - November), as well as the prior month.

Finally, and most critically for this exercise, we introduce state\province fixed effects to test for regional differences that are not explained by the variables in equations (1) and (2). We find striking

Table 2: Logit results: child wasting and maternal anemia

	Child Wasting			Maternal Anemia		
	Std. Logit	Robust	DHS Cluster	Std. Logit	Robust	DHS Cluster
Mother's Education (dummy for no formal education excluded)						
Primary	-0.075	-0.075	-0.075	-0.086	-0.086	-0.086
	(2.25)*	(2.26)*	(2.20)*	(3.28)**	(3.26)**	(2.70)**
Middle	-0.075	-0.075	-0.075	-0.160	-0.160	-0.160
	(2.13)*	(2.13)*	(2.06)*	(6.08)**	(6.02)**	(5.08)**
Secondary	-0.181	-0.181	-0.181	-0.213	-0.213	-0.213
	(4.54)**	(4.53)**	(4.37)**	(7.43)**	(7.36)**	(6.26)**
Post_Secondary	-0.195	-0.195	-0.195	-0.321	-0.321	-0.321
	(3.03)**	(3.03)**	(2.94)**	(7.03)**	(7.01)**	(6.34)**
Household Assets (of 9) (dummy for 0 assets excluded)						
Class 1 [1- 2]	0.032	0.032	0.032	-0.152	-0.152	-0.152
	(0.44)	(0.44)	(0.41)	(2.59)**	(2.59)**	(2.10)*
Class 2 [3 - 4]	-0.099	-0.099	-0.099	-0.174	-0.174	-0.174
	(1.38)	(1.38)	(1.27)	(2.98)**	(2.98)**	(2.40)*
Class 3 [5 - 6]	-0.238	-0.238	-0.238	-0.288	-0.288	-0.288
	(3.16)**	(3.17)**	(2.91)**	(4.77)**	(4.78)**	(3.84)**
Class 4 [7 - 9]	-0.229	-0.229	-0.229	-0.373	-0.373	-0.373
	(2.82)**	(2.83)**	(2.58)**	(5.89)**	(5.90)**	(4.76)**
Mother's Age	-0.014	-0.014	-0.014	-0.005	-0.005	-0.005
	(4.65)**	(4.56)**	(4.34)**	(4.60)**	(4.58)**	(4.15)**
Birth Order	0.038	0.038	0.038			
	(3.64)**	(3.66)**	(3.49)**			
State/Province (dummy for India/Bihar excluded)						
India						
Jharkhand	0.529	0.529	0.529	0.271	0.271	0.271
	(15.75)**	(15.72)**	(13.05)**	(11.08)**	(11.06)**	(7.46)**
West_Bengal	0.135	0.135	0.135	-0.014	-0.014	-0.014
	(3.23)**	(3.23)**	(2.76)**	(0.53)	(0.53)	(0.36)
Bangladesh						
Rajshahi	-0.314	-0.314	-0.314	-0.749	-0.749	-0.749
	(4.10)**	(4.07)**	(3.24)**	(7.42)**	(7.55)**	(5.66)**
Dhaka	-0.086	-0.086	-0.086	-0.900	-0.900	-0.900
	(0.94)	(0.95)	(0.86)	(6.48)**	(6.42)**	(5.04)**
Sylhet	-0.193	-0.193	-0.193	-0.436	-0.436	-0.436
	(2.31)*	(2.30)*	(2.06)*	(3.49)**	(3.50)**	(2.74)**
Khulna	-0.139	-0.139	-0.139	-1.361	-1.361	-1.361
	(1.27)	(1.27)	(1.05)	(7.86)**	(7.71)**	(7.37)**
Barisal	-0.473	-0.473	-0.473	-0.650	-0.650	-0.650
	(4.53)**	(4.54)**	(4.55)**	(4.46)**	(4.46)**	(4.44)**
Chittagong	-0.327	-0.327	-0.327	-0.967	-0.967	-0.967
	(4.06)**	(4.10)**	(3.31)**	(7.17)**	(7.08)**	(6.50)**

	Child Wasting			Maternal Anemia		
	Std. Logit	Robust	DHS Cluster	Std. Logit	Robust	DHS Cluster
Survey Month (January NA; dummy for February excluded						
March	0.312	0.312	0.312	-0.105	-0.105	-0.105
	(1.23)	(1.22)	(1.23)	(0.90)	(0.90)	(0.61)
April	0.270	0.270	0.270	-0.489	-0.489	-0.489
	(1.07)	(1.06)	(1.07)	(4.18)**	(4.18)**	(2.84)**
May	0.532	0.532	0.532	-0.324	-0.324	-0.324
	(2.11)*	(2.09)*	(2.11)*	(2.78)**	(2.78)**	(1.89)
June	0.686	0.686	0.686	-0.468	-0.468	-0.468
	(2.72)**	(2.70)**	(2.73)**	(4.01)**	(4.01)**	(2.72)**
July	0.705	0.705	0.705	-0.535	-0.535	-0.535
	(2.79)**	(2.76)**	(2.79)**	(4.55)**	(4.55)**	(3.10)**
August	0.562	0.562	0.562	-0.534	-0.534	-0.534
	(2.20)*	(2.18)*	(2.19)*	(4.39)**	(4.39)**	(3.00)**
September	0.402	0.402	0.402	-0.631	-0.631	-0.631
	(1.57)	(1.55)	(1.57)	(5.16)**	(5.17)**	(3.51)**
October	0.388	0.388	0.388	-0.570	-0.570	-0.570
	(1.51)	(1.50)	(1.50)	(4.62)**	(4.62)**	(3.16)**
November	0.131	0.131	0.131	-0.165	-0.165	-0.165
	(0.49)	(0.49)	(0.48)	(1.11)	(1.11)	(0.79)
December	-0.143	-0.143	-0.143	-0.396	-0.396	-0.396
	(0.52)	(0.51)	(0.52)	(2.17)*	(2.17)*	(1.65)
Birth Month (dummy for January excluded)						
February	-0.003	-0.003	-0.003			
	(0.05)	(0.05)	(0.05)			
March	-0.019	-0.019	-0.019			
	(0.34)	(0.34)	(0.34)			
April	-0.004	-0.004	-0.004			
	(0.07)	(0.07)	(0.07)			
May	-0.049	-0.049	-0.049			
	(0.86)	(0.86)	(0.86)			
June	-0.024	-0.024	-0.024			
	(0.42)	(0.42)	(0.41)			
July	-0.131	-0.131	-0.131			
	(2.37)*	(2.37)*	(2.41)*			
August	-0.161	-0.161	-0.161			
	(3.08)**	(3.08)**	(3.04)**			
September	-0.163	-0.163	-0.163			
	(2.99)**	(3.00)**	(3.00)**			
October	-0.144	-0.144	-0.144			
	(2.72)**	(2.72)**	(2.72)**			
November	-0.176	-0.176	-0.176			
	(3.24)**	(3.24)**	(3.17)**			
December	-0.023	-0.023	-0.023			
	(0.43)	(0.43)	(0.42)			
Constant	-1.330	-1.330	-1.330	-0.904	-0.904	-0.904
	(4.90)**	(4.85)**	(4.80)**	(6.84)**	(6.83)**	(4.84)**
Observations	45,199	45,199	45,199	109,817	109,817	109,817

Absolute value of t statistics in parentheses
* significant at 5%; ** significant at 1%

and broadly-similar patterns of regional divergence for the unexplained components of child wasting and maternal anemia. Here it is worth recalling that the results measure deviations from Bihar, whose dummy variable is excluded from the regressions. For Jharkhand, the wasting and anemia effects (relative to Bihar) are both positive, relatively large in magnitude and statistically significant. The wasting effect for West Bengal is also positive and significant, while the anemia effect is essentially equivalent to Bihar's. In contrast, all effects are negative for all Bangladeshi provinces; four are highly-significant for child wasting and all six are highly significant for maternal anemia. We draw two broad conclusions from these results. First, child wasting and maternal anemia probabilities in Bangladeshi provinces are lower than the probabilities predicted by our jointly-estimated model, while they are higher in the Indian states. Second, our results indicate substantial variation within each country.

In the following section, we perform two exercises to explore the implications of these regional variations. First, we assess their empirical importance by using our regression results to predict wasting and anemia probabilities for representative individuals in different regions. Then we re-estimate models (1) and (2) without state/province effects and map average residuals at the district level to explore the patterns of spatial variation that have produced the state/province differences.

5. Regional Differences

5.1 Predicted Risks

We use regression predictions to explore the magnitudes of the regional differences captured by estimated state/province effects in Table 2. We compute tables of predicted wasting and anemia probabilities for all education and income groups under the following conditions: observation month April; mother's age 28 (to allow for the possibility of post-secondary education); child's birth order 2 and birth month June. Tables 3a and 3b display predictions for child wasting and maternal anemia, respectively.

The variations across education and income in Tables 3a and 3b illustrate the magnitude of their estimated effects in Table 2. For Jharkhand and Barisal, wasting probability declines by about 14% and 16%, respectively, when a mother's education level increases from 0 to post-secondary, holding asset group constant.[9] Holding education constant, wasting probability declines by about 16% and 18%, respectively, when household asset status increases from group 0 to group 4. When education and asset status both change from minimum to maximum levels, wasting probability declines by about 27% in Jharkhand and 31% in Barisal.

For Jharkhand and Barisal, anemia probability declines by about 23% and 26%, respectively, when a mother's education level increases from 0 to post-secondary, holding asset group constant. Holding education constant, anemia probability declines by 27% and 29%, respectively, when household asset status increases from group 0 to group 4. When education and asset status change from minimum to maximum levels, anemia probability declines by about 44% in Jharkhand and 47% in Barisal.

Overall, our results strongly confirm the critical roles played by education and household wealth in improving mother/child health. For Jharkhand and Barisal together, improvements in education and wealth can account for reductions of about 30% in child wasting probability and 45% in maternal anemia.

---

[9] The percent changes cited in this paragraph and the following one represent typical results across 5 columns (for education) and 5 rows (for assets), when percent changes from lowest to highest group are calculated. To illustrate: For education in Jharkhand, for each asset group column, we calculate the percent reductions in wasting probability when education changes from lowest to highest group. The results by asset group column are (0) 13.2% (1) 13.1% (2) 13.5% (3) 14.0% (4) 13.9%. These results yield our summary estimate of about 14%.

Table 3: Predicted child wasting and anemia probabilities by education and asset class Jharkhand (India) and Barisal (Bangladesh)

(Mother age 28; child birth month June; child birth order 2; interview month April)

(3a) Child wasting probability

Jharkhand					
	Asset Class				
Education	0	1	2	3	4
0	29.57	30.23	27.55	24.86	25.04
Primary	28.04	28.68	26.09	23.49	23.66
Middle	28.03	28.67	26.08	23.48	23.66
Secondary	25.94	26.55	24.08	21.63	21.79
Post-Secondary	25.67	26.28	23.83	21.39	21.56
Barisal					
	0	1	2	3	4
0	13.35	13.72	12.25	10.83	10.92
Primary	12.51	12.86	11.47	10.12	10.21
Middle	12.5	12.86	11.46	10.12	10.21
Secondary	11.39	11.71	10.43	9.19	9.28
Post-Secondary	11.25	11.57	10.3	9.08	9.16

(3b) Maternal anemia probability

Jharkhand					
	Asset Class				
Education	0	1	2	3	4
0	22.19	19.67	19.33	17.62	16.41
Primary	20.74	18.35	18.03	16.4	15.27
Middle	19.55	17.27	16.96	15.42	14.34
Secondary	18.72	16.52	16.22	14.73	13.69
Post-Secondary	17.15	15.09	14.82	13.43	12.47
Barisal					
	0	1	2	3	4
0	10.19	8.88	8.71	7.84	7.25
Primary	9.43	8.21	8.05	7.24	6.69
Middle	8.82	7.67	7.52	6.76	6.24
Secondary	8.4	7.3	7.16	6.43	5.94
Post-Secondary	7.61	6.61	6.47	5.82	5.37

While these results are striking, so are the regional differences displayed by Table 2: *For both child wasting and maternal anemia, the education/wealth tables for Jharkhand and Barisal do not even overlap.* Remarkably, our results suggest that, for both wasting and anemia, the risks for Barisal women and children in the poorest, least educated group are lower than the risks for Jharkhand women in the wealthiest, best-educated group. Overall, for any education or wealth group, the risk in Barisal is about 56% lower than in Jharkhand.

We readily acknowledge that more elaborate, interactive specifications of equations (1) and (2) might well yield more nuanced results, with more complex patterns of variation than those reported in Tables 3a and 3b. For example, there might be significant differences in the estimated marginal effects of education and wealth by state/province, or in the estimated marginal effect of education in different wealth groups (and conversely). Even if this were the case, however, the regional differences in marginal effects would also warrant explanation. Thus, the results from more complex, interactive models would simply rephrase the basic message in our results: Across neighboring regions of India and Bangladesh, very large differences in health outcomes for women and children are not explained by a model that incorporates the variables that are commonly identified as significant determinants in the empirical literature.

5.2 District-Level Differences

The regional risk differentials illustrated in Table 3 reflect our estimation of fixed effects at a high level of regional aggregation. It is entirely possible, however, that these estimated average differences in state/province effects mask more complex patterns of spatial variation at more disaggregated levels. To explore this possibility, we re-estimate equations (1) and (2) without state/province fixed effects; compute mean regression residuals for districts; standardize the mean residuals (from most negative to most positive) in the range 0-100; and map the results. Figures 2 - 4 display our maps for wasting, anemia, and a combined mother-child health index computed from the average of the wasting and anemia index values. Low index numbers correspond to cases where wasting and anemia probabilities are lower than predicted, while the converse is true for high index numbers. We color-code in five quintiles: light yellow (the "healthiest" outliers), yellow, orange, dark orange and red (the "unhealthiest" outliers).

Figure 2 displays residual index values for child wasting. Several spatial patterns are evident. The first is a large contiguous red area from western Jharkhand, through southern Jharkhand, into the western region of West Bengal. To the north, this is abutted by an dark orange region that spans most of remaining Jharkhand and a large region in southern Bihar. To the north, a broad band from northwest Bihar through northern West Bengal into northern Rajshahi includes districts that are orange, yellow and, more rarely, light yellow. From northern Rajshahi, a broad band of yellow and light yellow extends eastward to Sylhet and southward to eastern West Bengal, Khulna and Barisal.

Residual index values for maternal anemia are displayed in Figure 3. Here the map displays mixed district colors from red to yellow in Jharkhand and West Bengal. In contrast, the map is dominated by orange, yellow and light yellow in Bihar, southern Rajshahi, Khulna, Dhaka and Chittagong. Figure 3 displays more district-level variation within states than Figure 2, with the notable exceptions of Bihar, Khulna and Chittagong.

Figure 4 displays an overall index of mother-child health, which we construct from mean values for the wasting and anemia indices by district. By this measure, the healthiest districts dominate southern Rajshahi and northern Dhaka, with substantial representation in eastern West Bengal, Khulna, Barisal and Chittagong. Much of Bihar is also orange or yellow. In contrast, we find a very large cluster of red districts along an axis canted toward the northeast from a base in southern Jharkhand and western West Bengal, extending into northern Jharkhand, West Bengal and Rajshahi. The red districts are flanked by broad dark orange regions to the west in Jharkhand and Bihar.

Figures 2 - 4 provide a disaggregated interpretation of the estimated state/province effects in Table 1. To illustrate, Rajshahi, Dhaka, Khulna and Barisol are generally best-off in Figure 4, while Sylhet, Chittagong and Bihar rank somewhat lower, West Bengal lower still, and Jharkhand last. However, as the maps show, aggregative results mask substantial variation at the district level, with broad bands of similar color extending across states/province boundaries, both within and across the two countries.

In summary, our analysis reveals strong spatial clustering, both within and across states/provinces, that reflects unaccounted factors large enough to dominate variations attributable to commonly-cited determinants of mother-child health such as education, wealth, age, birth order and seasonality.

5.3 The Sundarbans Region

We provide an example of local variation by focusing on the Sundarbans, which are of particular interest to our research. The Sundarbans region, shared by India and Bangladesh, is the world's largest mangrove delta and a wetland of international importance whose conservation is mandated by international conventions and treaties. The Sundarbans region is also home to some of the world's poorest and the most vulnerable communities. Figure 5 refocuses Figures 2 - 4 on the Sundarbans core forest zone and the neighboring coastal regions in India (West Bengal), and Bangladesh (Khulna and Barisal).

In Figure 5a, the mean residuals index for child wasting exhibits the full range of variation, from red to light yellow. Districts in West Bengal are in the middle spectrum, varying from dark orange to yellow. In contrast, variation on the Bangladesh side is more extreme, varying from red in the frontier district to light yellow in most of Barisal's coastal region.

Figure 2: Child wasting, mean residual index by district

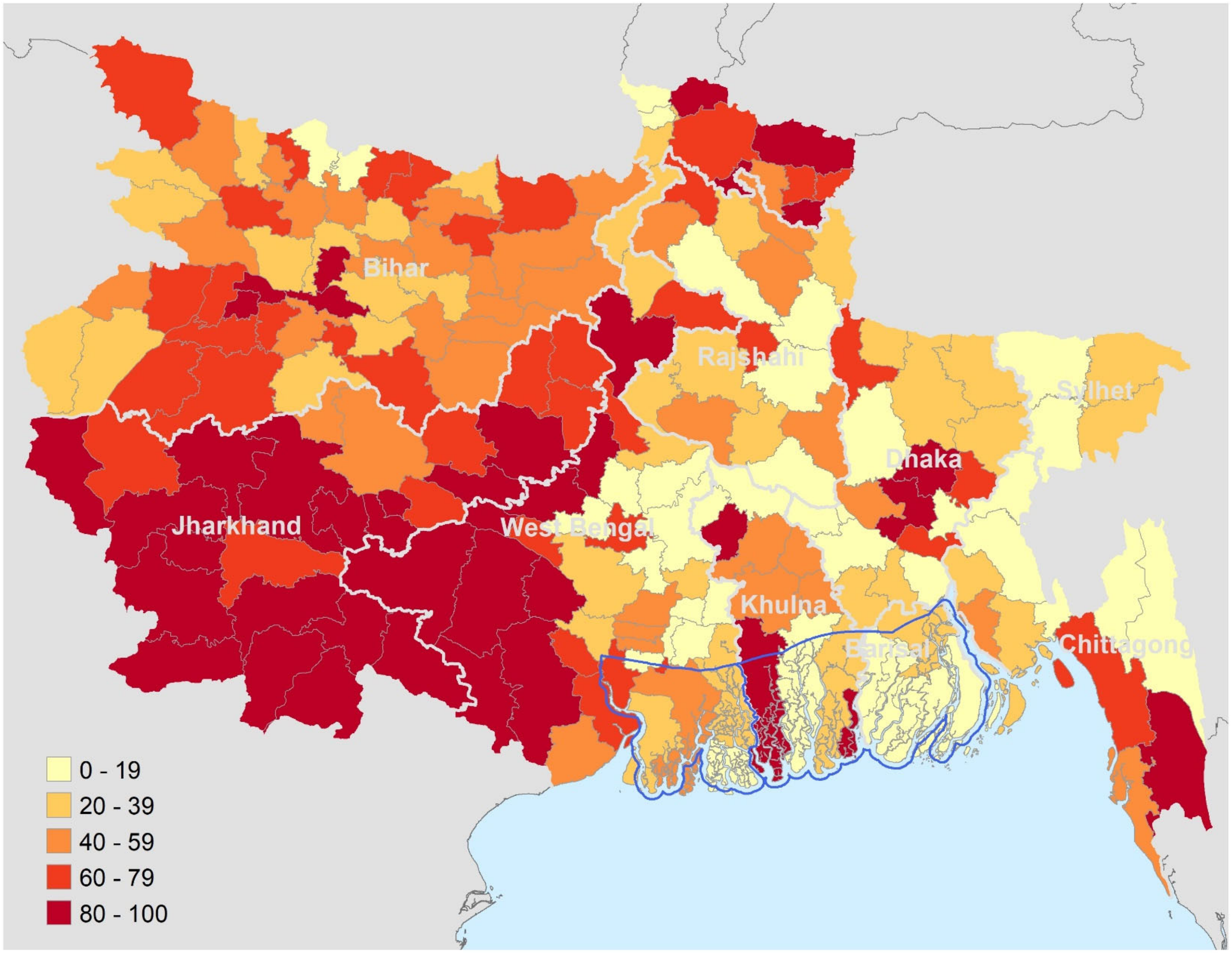


Figure 3: Maternal anemia, mean residual index by district

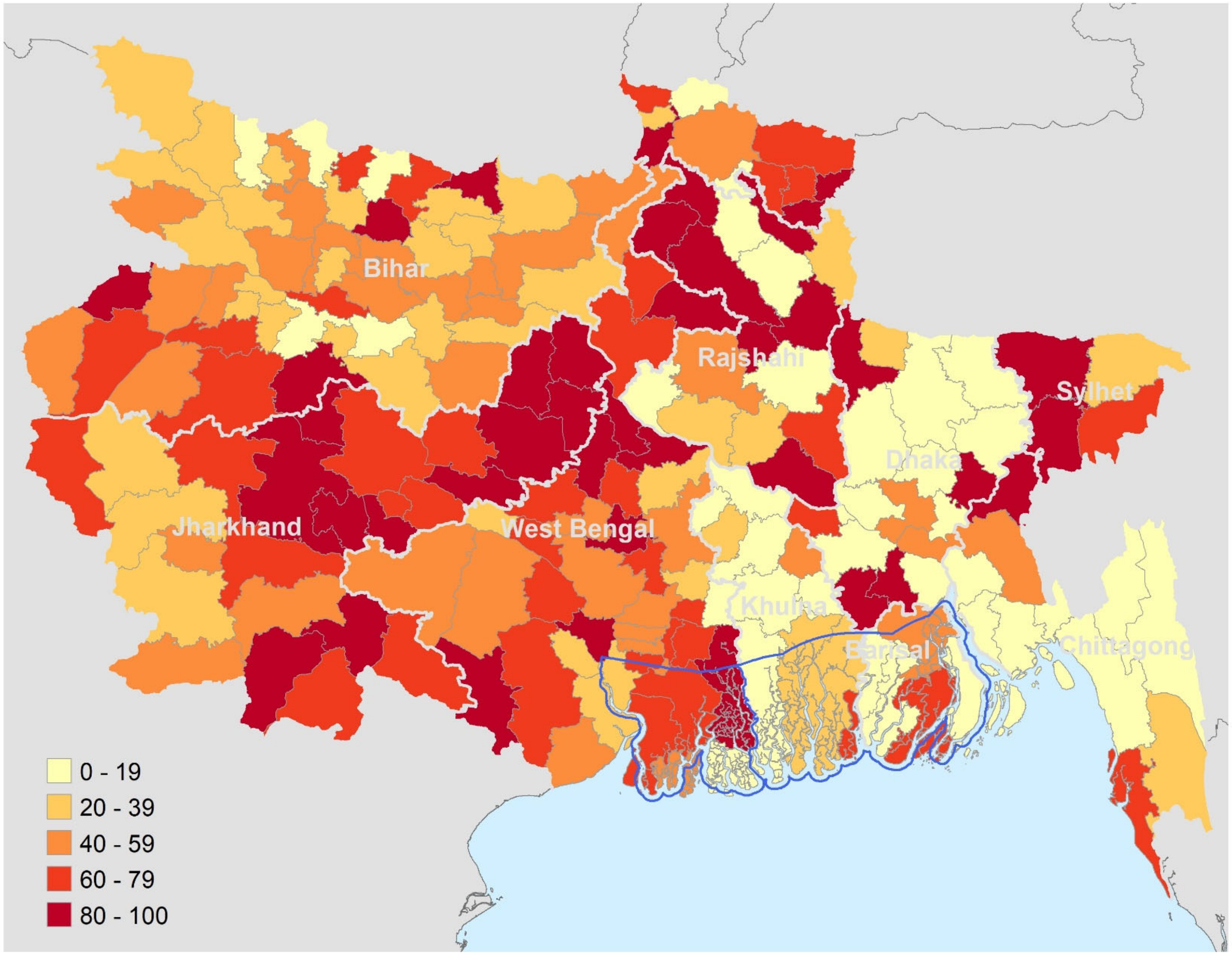
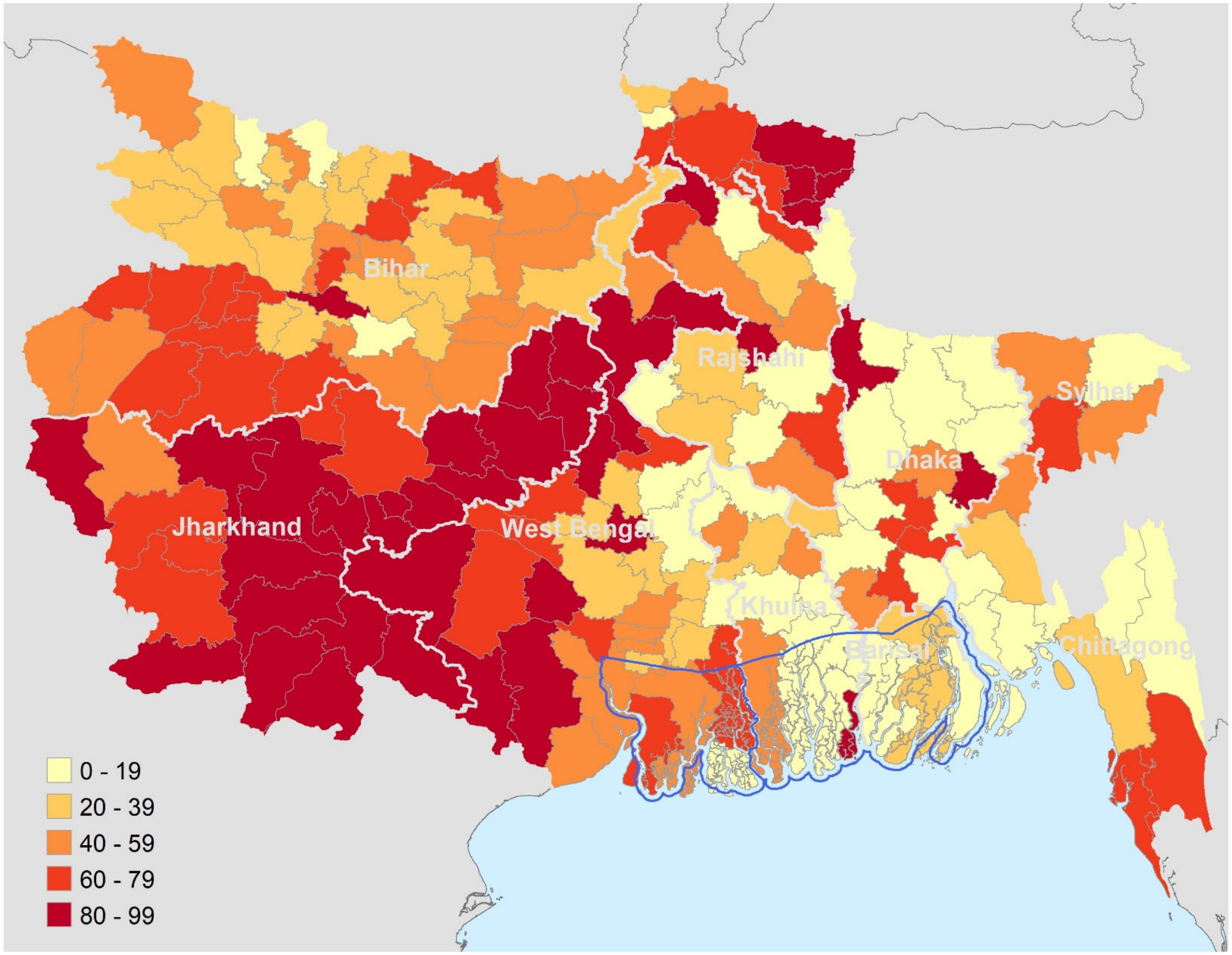


Figure 4: Mother-child combined residual index by district.



The international contrast is more visible in Figure 5b, which displays variations in the maternal anemia index. In West Bengal, most of the area is either red (in the district next to Bangladesh) or dark orange. On the Bangladesh side, in contrast, most districts are either yellow or light yellow.

The mother-child health index in Figure 5c displays the average for the wasting and anemia indexes. In this summary measure, the greater Sundarbans region in West Bengal is predominantly orange and dark orange. The neighboring region in Bangladesh is dominated by light yellow and yellow, with the exception of the orange district on the frontier with West Bengal and a small red area near the coast in southern coastal Khulna. Since the mean residual for the latter area is computed for a sample from one DHS cluster, we suspect that the red result may reflect random variation rather than a systematic deviation from the rest of the sub-region.

6. Potential Sources of Unexplained Variance

While our regression results indicate high significance and substantial impacts for the commonly-cited determinants of child wasting and maternal anemia, they also reveal an intriguing spatial pattern in the residuals -- the unexplained components of variation in these key health indicators. Estimated state/province fixed effects are so widely varied that they completely dominate the effects of the commonly-cited determinants in some cases. The maps in Figures 2 - 4 also show that the district-level patterns of spatial variation are far from random. Large clusters are evident, spanning both state/province boundaries within countries and the boundary between the two countries.

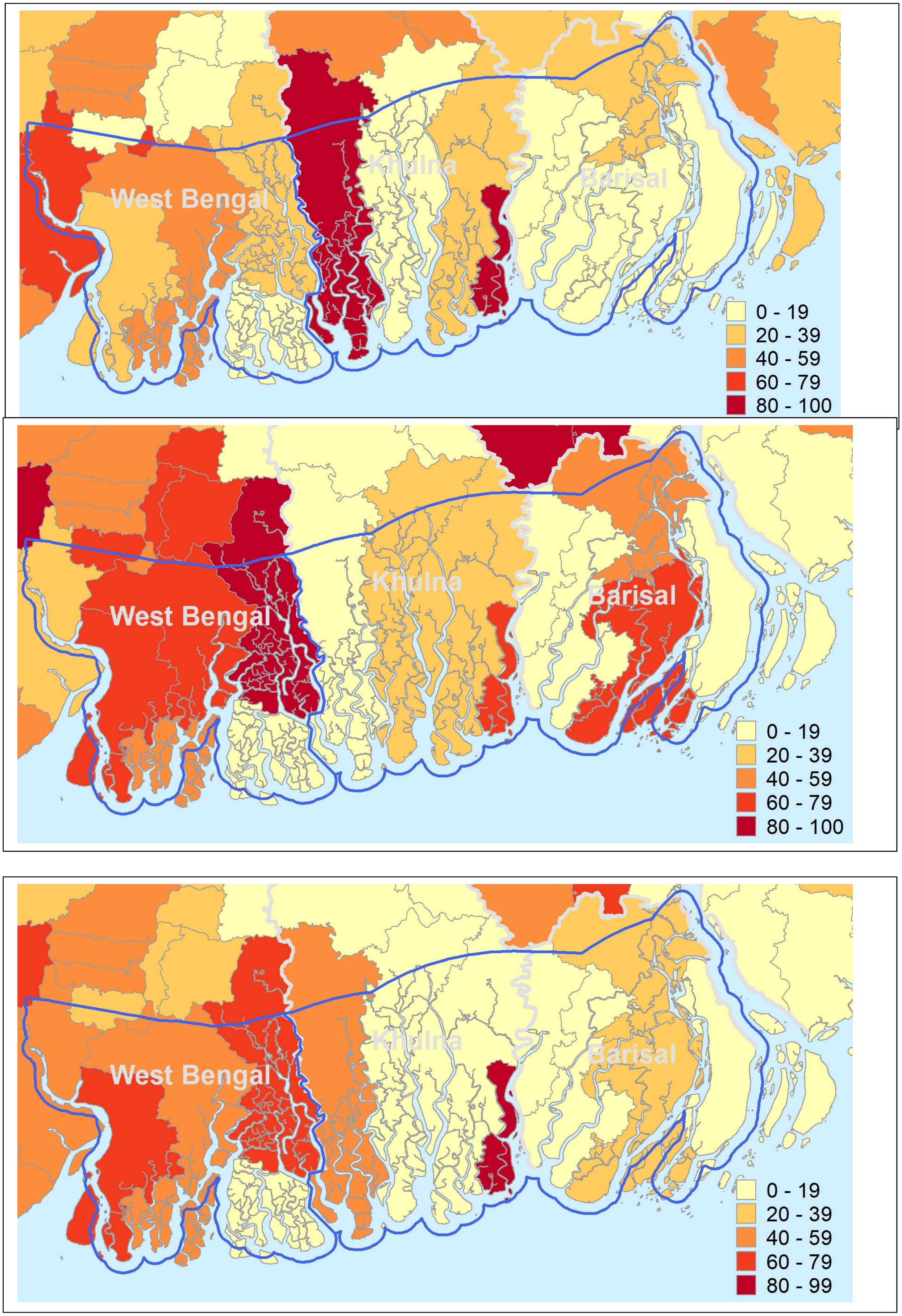
Figure 5: Sundarbans residuals index: wasting, anemia and mother-child health

Sundarbans Region

(5a) Wasting

(5b) Anemia

(5c) Mother-Child Health



These spatial clustering patterns are challenging for policy analysis, because they reveal how much variation in maternal and child health cannot be explained by the commonly-cited determinants. They are also intriguing, because the unaccounted spatial factors may provide clues for policy interventions to improve health outcomes. In this section, we offer some initial hypotheses about factors that may help account for the observed spatial clustering. They will be explored in depth in the next round of research.

First, it seems sensible to consider conditions in the food sector. Both wasting and anemia reflect nutritional factors, so food provides an initial point of reference. Dietary variation across individuals and households is undoubtedly affected by spatial variations in food supplies and prices. This may well explain our birth month results for child wasting in Table 2, which reflect similar findings for Bangladesh reported in Dasgupta et al. (2018). The latter research identifies regional variations in fish supplies over the monsoon flood cycle as an important determinant of child protein consumption. In the same vein, part of the spatial clustering identified in Table 2 and Figures 2 - 4 may well reflect geographic differences in the cost and availability of various nutritionally-critical foods. It is probably not accidental that many Bangladeshi districts colored yellow in Figures 2 - 4 are also prone to heavy annual flooding. Differential fish supplies may well be part of the larger story told by these maps.

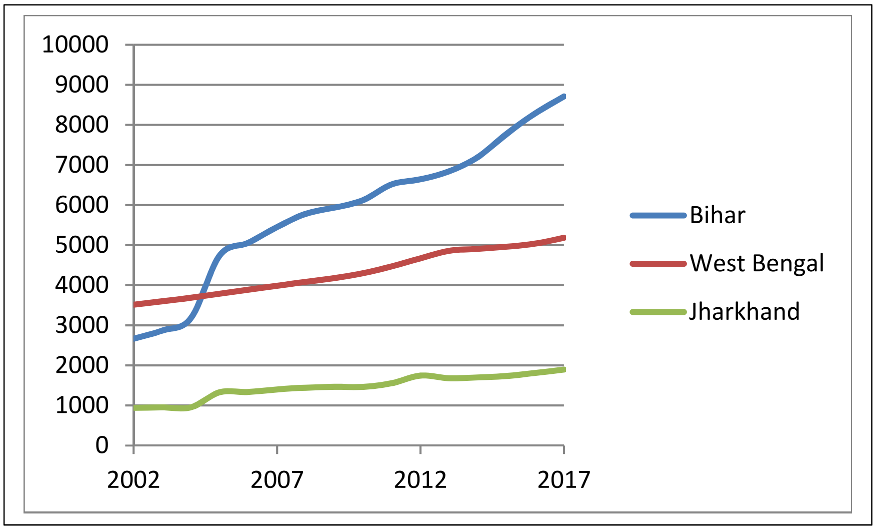
Another significant role could be played by dairy production. An important clue may be provided by regional variations in India's "white revolution" -- the rapid rise of milk production that is due in part to Operation Flood, India's promotion program supported by the World Bank and other development institutions (Kurien 2004; Cunningham, 2009). While Operation Flood has been national in scope, Figure 6 indicates that its impact has been quite different in our three focal states: Milk production growth from 2002 to 2017 in Bihar (227%) was much faster than in Jharkhand and West Bengal (100% and 47% respectively). By implication, farmers in Bihar have been more prone to diversify away from traditional crops to milk production. At the same time, Bihar is much more flood-prone than the other two states. Thus, it is at least possible that farmers' incentive to diversify is greater in areas where traditional cropping is subject to the stochastic occurrence of flooding. If so, then annual flooding may account for significant differences in local supplies and prices of both fish and milk, two important sources of animal protein.[10]

Religious culture may be a second source of nutritionally-significant differences in diet. The three Indian states are predominantly Hindu, while Bangladesh is predominantly Muslim. Many Hindus are vegetarians, with potentially-important implications for the role of diet in the incidence of child wasting and maternal anemia. Although it is perfectly possible to compensate for the lack of animal protein in vegetarian diets, this may require nutrition education, incentives and provision of diet additives which are sometimes difficult to achieve in practice.

A third, related factor involves nutrition education. At this point, we have no information on regional differences in nutrition education at different levels of schooling. However, we should note an important difference in the India and Bangladesh surveys that may have related implications. Both surveys ask detailed questions about mothers' child-feeding practices. However, Bangladesh DHS 2011 asks specifically about meat (beef, pork, lamb, chicken, etc.), while India National Family Health Survey 2015-16 excludes this question. This is pure speculation on our part, but the exclusion may reflect a sensitivity about dietary issues in India that affects school instruction in nutrition. And, of course, there may well be differences in nutrition education across regions that reflect other factors.

[10] As noted by Dasgupta et al. (2018), fish are a particularly important source of micronutrients that are critical for child health. Fish are also an important source of dietary iron, which is critical for the prevention of anemia.

Figure 6: Milk production in Bihar, Jharkhand and West Bengal, 2002 - 2017 ('000 tonnes)



Source: India National Dairy Development Board (2018)

Fourth, it is entirely possible that some spatial clustering is due to differences in the administration of public health and nutrition policy. These may include differences in the staffing and provision of clinical facilities and medical and nutritional outreach programs, the extension of such programs to rural areas, and the administrative efficiency of operations.

In summary, many valuable insights about the sources of spatial variation in mother-child health outcomes may come from further inquiry into the roles of food market conditions, cultural preferences, nutrition education and the administration of health/nutrition. The next phase of the research will focus on exploration of these issues, with possible inclusion of a survey that will target outlier (red and light yellow) districts for both wasting and anemia that have been identified by the regression, tabulation and mapping exercises in this paper.

7. Summary and Conclusions

The empirical literature on determinants of child wasting and maternal anemia is plentiful for South Asia. In this paper, we have used recent DHS data for Bangladesh and the neighboring Indian states of Bihar, Jharkhand and West Bengal to confirm the importance of commonly-cited determinants such as mother's education, mother's age, household wealth, and child birth order. We have extended the literature by linking variations in mother-child health to seasonal fluctuations in the price and availability of critical nutrients. But all this is a prelude to the main objective of the paper, which is a spatial analysis of variations in health outcomes that are not explained by the commonly-cited determinants.

Our analysis employs logistic regression models that link the probabilities of child wasting and maternal anemia to the determinants noted above. We initially explore the spatial structure of the residuals using estimated state/province effects, which suggest great spatial variation. To illustrate, we compare Jharkhand state, India and Barisal province, Bangladesh. Remarkably, our results (controlling for mother's age, child birth month and seasonal factors) suggest that the poorest, least-educated mothers and their children in Barisal have better health outcomes than their wealthiest, best-educated counterparts in Jharkhand.

We explore the implications by re-estimating our logistic models without state/province effects and mapping mean regression residuals at the district level. We find clear patterns of spatial clustering over large areas that frequently overlap state/province and national boundaries. Although our results for child wasting and maternal anemia reveal some differences, the common clustering patterns are sufficiently evident to warrant creation of a composite mother-child health index from an equal-weighted combination of the separate indices. This brings the spatial clustering pattern into sharp relief, with particularly stark contrasts between Jharkhand and Bihar on the Indian side, and between Bangladeshi and Indian districts more generally.

In the concluding section of the paper, we offer some initial thoughts about possible sources of such striking differences. These include spatially-differentiated prices and availability of critical nutrients; preferences related to religious culture; nutrition education; and administration of public health and nutrition policy. Our next round of research will involve in-depth investigation of these factors. At the same time, we are very interested in hearing from colleagues whose experience in the region may suggest additional factors, or more insightful interpretations of the spatial clustering patterns in our maps. Ultimately, we hope that better understanding of these patterns will suggest policy measures for narrowing the remaining gaps in health outcomes.

References

Anand A. 1995. Anaemia -- a major cause of maternal death. Indian Med Trib. 3(1):5, 8.

Arlappa, N., I. Meshram, N. Balakrishna, R. Harikumar, K. Rao, and A. Laxmaiah. 2014. Prevalence of anaemia among different physiological groups in the rural areas of Maharashtra. Indian Journal of Community Health. 26: 278-284.

Balarajan., Y, U. Ramakrishnan, E. Ozaltin, A. Shankar and S. Subramanian. 2011. Anaemia in low-income and middle-income countries. Lancet 378: 2123–35.

Bhutta Z., J. Berkley, R. Bandsma, M. Kerac, I. Trehan I and A. Briend. 2017. Severe childhood malnutrition. Nat Rev Dis Primers. 3:17067.

Black, R., C. Victora, S. Walker, Z. Bhutta, P. Christian, M. de Onis M, et al. 2018. Maternal and child undernutrition and overweight in low-income and middle-income countries. Lancet. 382(9890):427–51.

Chowdhury, H., A. Kazi, F. Jebunnesa, J. Akter, S. Hossein and M. Shahjahan. 2015. Factors associated with maternal anaemia among pregnant women in Dhaka city. BMC women's health. 15, 77.

Cunningham, K. 2009. Rural and Urban Linkages: Operation Flood's Role in India's Dairy Development. International Food Policy Research Institute Discussion Paper 00924. November.

Daru, J., J. Zamora, B. Fernández-Félix, J. Vogel, O. Oladapo, N. Morisaki, Ö.Tunçalp, M. Torloni, S. Mittal, K. Jayaratne, P. Lumbiganon, G. Togoobaatar, S.Thangaratinam and K. Khan. 2018. Risk of maternal mortality in women with severe anaemia during pregnancy and post partum: a multilevel analysis. Lancet Glob Health 6: e548–54.

Dasgupta, S., M. Mustafa, T. Paul and D. Wheeler. 2017. The Socioeconomics of Fish Consumption and Child Health in Bangladesh. World Bank Policy Research Working Paper #8217. October.

Dutta, P. and B. Sengupta. 2017. Socioeconomic Determinants of Maternal Anemia: A Disaggregated Level Analysis from Assam, India. Proceeding of the 3rd International Conference on Public Health. 3: 71-87.

Ezzati M., A. Lopus, A. Dogers, H. Vander and C.Murray C. 2002. Selected major risk factors and global and regional burden of disease. Lancet 360 : 1347-60.

Fernandez I., J. Himes and M. de Onis. 2002. Prevalence of nutritional wasting in populations: building explanatory models using secondary data. Bull World Health Organ. 80(4):282–91.

Frongillo, E., M. de Onis and K. Hanson. 1997, Socioeconomic and demographic factors are associated with worldwide patterns of stunting and wasting of children. J Nutr. 127(12):2302–9.

Galasso, E. and A.Wagstaff. 2018. The Aggregate Income Losses from Childhood Stunting and the Returns to a Nutrition Intervention Aimed at Reducing Stunting. World Bank Policy Research Working Paper #8536. August.

Ghosh-Jerath, S., A. Singh, N. Jerath, S. Gupta, and E. Racine. 2017. Undernutrition and severe acute malnutrition in children. BMJ. 359.

Gogoi, I., T. Mahanta, S. Mahanta, P. Gogoi, P. Ratna and H. Saikia. 2016. Prevalence and socio-demographic factors affecting anaemia in pregnant women of Dibrugarh District, Assam, India. Indian Journal of Community Health. 28: 202-207.

Harding, K., V. Aguayo and P. Webb. 2018. Factors associated with wasting among children under five years old in South Asia: Implications for action. PLoS ONE 13(7).

Hill, K. and D. Upchurch DM. 1995. Gender Differences in Child Health: Evidence from the Demographic and Health Surveys. Popul Dev Rev. 21(1):127–51.

IFPRI (International Food Policy Research Institute). 2014. Global Nutrition Report 2014: Actions and Accountability to Accelerate the World's Progress on Nutrition. IFPRI: Washington, DC.

IFPRI (International Food Policy Research Institute. 2016. Global Nutrition Report 2016: From Promise to Impact: Ending Malnutrition by 2030. IFPRI: Washington, DC.

IIPS (International Institute for Population Sciences) and ICF. 2017. National Family Health Survey (NFHS-4), 2015-16: India. Mumbai: IIPS.

India National Dairy Development Board. 2018. Milk Production by States. Data available online at https://www.nddb.coop/information/stats/milkprodstate.

Kalaivani, K. 2009. Prevalence & consequences of anaemia in pregnancy/ Indian J Med Res 130: 627-633.

Khara, T. and C. Dolan. 2014. Technical Briefing Paper: Associations between Wasting and Stunting, policy, programming and research implications.

Kurien, V. 2004. India's Milk Revolution: Investing in Rural Producer Organizations.
Scaling Up Poverty Reduction: A Global Learning Process and Conference
Shanghai, May.

Lakew, Y., S. Biadgilign and D. Haile. 2015. Anaemia prevalence and associated factors among lactating mothers in Ethiopia: evidence from the 2005 and 2011 demographic and health surveys. BMJ open. 5.

Lenters L., K. Wazny, P. Webb, T. Ahmed and Z. Bhutta. 2013. Treatment of severe and moderate acute malnutrition in low- and middle-income settings: a systematic review, meta-analysis and Delphi process. BMC Public Health. 13 Suppl 3:S23.

Mangla, M.. 2016. Prevalence of anaemia among pregnant women in rural India: a longitudinal observational study. Int J Reprod Contracept Obstet Gynecol. 2016: 3500-3505.

Martorell, R. and M. Young. 2012. Patterns of Stunting and Wasting: Potential Explanatory Factors Advances in Nutrition. 3(2): 227–233.

McLean E., M. Cogswell, I. Egli, D. Wojdyla and B. de Benoist. 2009. Worldwide prevalence of anaemia, WHO vitamin and mineral nutrition information system, 1993–2005. Public Health Nutr 12: 444–54.

Menon, P. and R. Stoltzfus. 2012. Building convergence in science, programs, and policy actions on child undernutrition: symposium rationale and overview. Adv Nutr. 3(2):224–6.

Mithra, P., B. Unnikrishnan, R. Thapar, K. Nithin, K. Mohan, V. Kulkarni, R. Holla, R. and D. Agarwal. 2014. Compliance with Iron-folic acid (IFA) therapy among pregnant women in an urban area of South India. African health sciences. 14, 10.

NIPORT (National Institute of Population Research and Training), Mitra and Associates, ICF International. 2011. Bangladesh Demographic and Health Survey 2011. Dhaka and Calverton, Md, USA: NIPORT/Mitra and Associates/ICF International, 2013.

Pillai, V. and J. Ortiz-Rodriguez J. 2015. Child Malnutrition and Gender Preference in India: The Role of Culture. Health Science Journal. 9(6:8).

Rukuni R., S. Bhattacharya, M. Murphy, D. Roberts, S. Stanworth and M. Knight. 2016. Maternal and neonatal outcomes of antenatal anemia in a Scottish population: a retrospective cohort study. Acta Obstet Gynecol Scand 95: 555–64.

Scrimshaw, N. 2003. Historical concepts of interactions, synergism and antagonism between nutrition and infection. J Nutr. 133(1):316S–21S.

Singh, P. and V. Chaudhary. 2015. Prevalence of anaemia and its socio demographic determinants among pregnant women in Bareilly district, Uttar Pradesh. Indian Journal of Community Health. 26: 348-352.

Stevens, G., M. Finucane, L. De-Regil, et al. 2013. Global, regional,and national trends in haemoglobin concentration and prevalence of total and severe anaemia in children and pregnant and non-pregnant women for 1995–2011: a systematic analysis of population-representative data. Lancet Glob Health 1: e16–25.

Tayade, S., R. Singh, J. Kore, N. Gangane and N. Singh. 2018. Maternal hemoglobin: socio-demographic and obstetric determinants in rural Central India. International Journal of Reproduction, Contraception, Obstetrics and Gynecology. 7(3).

Tickell K., P. Pavlinac, G. John-Stewart, D. Denno, B. Richardson, J. Naulikha, et al. 2017. Impact of Childhood Nutritional Status on Pathogen Prevalence and Severity of Acute Diarrhea. Am J Trop Med Hyg. 97(5):1337–44.

UNICEF, WHO, World Bank. 2017. Joint Child Malnutrition Estimates Database.

Vollmer, S., C. Bommer, A. Krishna, K. Harttgen and S. Subramanian. 2017. The association of parental education with childhood undernutrition in low- and middle-income countries: comparing the role of paternal and maternal education International Journal of Epidemiology. 46 (1): 312–323.

WHO Multicentre Growth Reference Study Group. WHO Child Growth Standards based on length/height, weight and age. Acta Paediatr Suppl. 2006;450:76–85.

WHO. 2004. Micronutrient deficiency: Battling iron deficiency anaemia: the challenge.