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Birth Intervals and Stunting in Bangladesh

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This paper analyses the relation between birth intervals and stunting of under-five children in Bangladesh. The main novelty of this study compared to the existing literature is that we use an econometric panel data model that accounts for the birth interval's potential endogeneity and for potentially correlated unobserved heterogeneity in the stunting and birth interval equations. The model is estimated using data on 7,849 children under five of birth order two and higher in the 2017-18 Bangladesh Demographic and Health Survey. We find that a ten percent increase in the preceding birth interval reduces the probability of stunting by 2.17 percentage points for an average observation, ceteris paribus. This effect is more than five times larger than the effect found with a standard model not accounting for endogeneity. Simulations of counterfactuals using the complete model show how household wealth, parental education, and regional differences drive birth intervals and stunting. For example, the estimated indirect regional effect on stunting through birth spacing moving from Dhaka to Sylhet is almost 5%-points. On the other hand, the direct effect (keeping birth intervals constant) is even larger: 12%-points. This leads to important conclusions for policies to bring down stunting by lengthening birth intervals.

Keywords: *Stunting, under-five, causality, birth intervals, Bangladesh*

Introduction

According to the World Health Organization (WHO), a child is stunted if its height-for-age is more than two standard deviations below the WHO Child Growth Standards median (WHO, 2014). The stunting percentage is often seen as the best single indicator of well-being for children under five years and is one of the indicators of malnutrition in the context of the sustainable development goal to end hunger, achieve food security, improve nutrition and promote sustainable agriculture (UNICEF/WHO/World Bank Group Joint Child Malnutrition Estimates, 2020). Grantham-McGregor et al. (2007) propose stunting as one of the two leading indicators of poor child development, together with absolute poverty. Stunting often occurs in children who live in low-income countries, as they are less likely to have access to safe drinking water, adequate sanitation and hygiene, nutritious food, and

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good health care. As a consequence, these children become susceptible to diseases and infections such as malaria, diarrhea, and pneumonia (Black et al., 2003), and are exposed to malnutrition and stunting. Strong associations are observed between stunting and lack of schooling and reduced economic productivity. For instance, Grantham-McGregor et al. (2007, Table 6) estimated that stunting results in an educational performance deficit of 2.91 years causing a 19.8% loss in adult income. This damage can also affect future generations, creating a persistent poverty trap (Prendergast and Humphrey, 2014).

A study in Bangladesh has confirmed there is a robust intergenerational linkage between short maternal stature and offspring stunting (Khatun et al., 2019). Globally in 2019, approximately 21.3% of all children under the age of five years are affected by stunting (UNICEF/WHO/World Bank Group Joint Child Malnutrition Estimates, 2020). According to data from the Bangladesh Demographic Health Survey (BDHS) 2019, 31% of all children under the age of five were stunted in 2017 - 2018. The level of stunting among children under five has declined from 43% in 2007 to 31% in 2017 - a reduction of 1.2 percentage points per year. The Health Population and Nutrition Sector Development Program (HPNSDP) in Bangladesh aimed to reduce the stunting levels to 25% by 2025. To achieve this goal, it is essential to analyze the risk factors for stunting to help design effective policies and public health interventions.

Determinants of stunting in Bangladesh identified in the literature include parental education, maternal nutrition, household socio-economic status, size of the baby at birth, birth order, place of residence and preceding birth interval (Faruque et al. 2008; Das et al. 2009; Jesmin et al. 2011; Heady et al., 2015; Islam et al,2018; Saha et al., 2019; Svefors et al., 2019; Saha et al., 2020; Saha and Wesenbeeck, 2021). In the current study we focus on the role of birth spacing. A short preceding birth interval (less than two years) can place the child at risk for several reasons. First, the fact that the mother has not yet recovered from the previous birth can lead to low birth weight of the next born child. Second, the time that mothers can devote to a newborn child can be less if there is another infant (Chungkham et al., 2020). It is also possible that the household is exposed to food insecurity since more mouths must be fed.

In the existing literature, the risk factors were included as exogenous variables. Some of them, and birth spacing in particular, might however depend on unobserved mother or household characteristics that also drive the likelihood of stunting. For example, birth spacing can be affected by the same community values, customs and beliefs driving child nutrition. This implies that a risk factor like the space between two births may be endogenous so that its association with stunting does not necessarily have a causal interpretation. This is a limitation from a policy perspective, since evaluating the effectiveness of a policy or intervention to overcome malnutrition requires identifying causal effects rather than estimating associations (cf. Moffitt, 2005).

The main novelty of our analysis is that our model accounts for potential endogeneity of the birth interval in the equation for stunting. To achieve this, we will use instrumental variables related to the gender composition of the family (the gender of the previously born child, dummy variables for the lack of sons and daughters among previous children). In many developing countries including

Bangladesh, short birth intervals are a consequence of gender preferences and family planning. For Bangladesh, Rahman and Da Vanzo (1993) found that son preference is vital in determining family planning and family composition -- the likelihood and timing of a subsequent birth are related to the number of sons. On the other hand, women also want to give birth to a girl when they already have several sons. We show that in our data, these instruments are indeed correlated with birth intervals, in line with gender favoritism.

We use data on 7,849 children under five of birth order two and higher in the 2017-18 Bangladesh Demographic and Health Survey. Our model consists of a probit equation for the binary stunting outcome and a linear equation for the log birth interval, with error terms that can be correlated. An additional novelty compared to existing studies is that we incorporate unobserved mother specific heterogeneity in both of these equations. This is feasible because for many mothers, we have observations on more than one child, allowing us to use a panel data model with random unobserved heterogeneity terms. The unobserved heterogeneity terms in both equations are also allowed to be correlated.

We find that the model with endogenous birth intervals is supported by the data -- exogeneity of the birth interval is rejected and validity of the instruments is not rejected. With this model, we find that a ten percent increase in the preceding birth interval reduces the probability of stunting by 2.17 percentage points for an average observation, keeping other regressors constant. This effect is much larger than the estimated effects in models that do not account for endogenous birth intervals.

Literature Review

There are many channels through which birth intervals can affect malnutrition and stunting in infants and young children. The literature distinguishes prenatal and postnatal mechanisms.

The prenatal channel relates to the nutritional basis that a woman requires before conception. A pregnant woman needs substantially more protein, vitamins and minerals than a non-pregnant woman (Del Valle et al., 2011). If the birth interval is short, women may not have regained the initial nutritional bases of, e.g., calcium and iron, which are needed to support fetal development (Pebley and Da Vanzo, 1993). Insufficient food intake may accelerate the mothers' nutritional health problems and thus hamper fetus development and increase the risk of stunting (King, 2003). In a recent study, Svefors et al. (2019) emphasize the need to address prenatal risk factors to reduce stunting in Bangladesh.

Previous studies on the relation between stunting and birth intervals focused on associations rather than trying to find causal relationships. Rutstein (2005) analyzed stunting on panel data from 17 developing countries. The key independent variable was the length of the preceding birth interval. The study found a significant negative association between stunting and the preceding birth interval. In particular, children born after a birth interval shorter than 18 months faced a 43% higher risk of stunting than children born after an interval of 60 months or longer. Aerts et al. (2004) analyzed the risk of stunting among children under five in the city of Porto Alegre, Brazil, and found an odds ratio of 1.69 for birth intervals shorter than 24 months.

Fink et al. (2014) estimated the effect of birth spacing on stunting using a pooled cross-section of Demographic Health Surveys conducted between 1990 and 2011 in 61 countries, including Bangladesh. They found relative risks of short birth intervals that are significantly different from 1 but much smaller than the ones in Aerts et al. (2004): 1.09 and 1.06 for birth intervals less than 12 months and between 12 and 23 months, respectively, compared to a 24–35 months inter-pregnancy interval. Miller and Karra (2020) used longitudinal data on children born between 2002 and 2013 in Ethiopia, India, Peru, and Vietnam. They found a strong and significant positive association between birth spacing and child height for young children, but the difference falls as children age. If the relation can be interpreted as a causal effect of birth intervals on stunting, this suggests that children born after a short interval catch up when they get older.

The post-natal channel mainly relates to cultural aspects and gender preferences driving fertility. Gender preference may lead to more births and children who get less parental attention and compete for scarce family resources such as food (Sulloway, 1996). As a result, higher order births more often suffer from various health hazards including stunting (see, e.g., Shapiro-Mendoza et al., 2005, and Jayachandran and Pande, 2017). For Bangladesh, Rahman (2016) found that children of birth order three, four, or five and higher are 24%, 30%, and 72% more likely to be stunted than first-born children, controlling for mother's weight and height and socio-economic and demographic characteristics of the household. Akram et al. (2018) found a larger prevalence of stunting among children born after an interval of less than 48 months than among children born after a longer birth interval, in both urban and rural areas. They did not control for the birth interval in their multiple regressions of stunting, however. Studies that consider the role of birth spacing for stunting specific for Bangladesh are scarce. Because of this, the overview article of Islam et al. (2020) does not even consider the risk factor birth interval.

Again, the existing studies find associations that are sometimes interpreted as causal, but do not aim at isolating causal effects from confounding factors that may explain the associations since they affect both birth intervals and stunting. In the current study, we address this gap by developing a two-equations model in which the birth interval can be endogenous to the stunting outcome. Moreover, another novelty compared to the existing literature is that we exploit the fact that for some mothers we have two or more children in the data set, allowing us to use random mother specific effects in both equations, possibly correlated and thus creating another source of endogeneity.

Data

This study uses data from the Bangladesh Demographic Health Survey (BDHS) 2017,[1] a nationally representative survey that collects information on a wide range of sociodemographic variables and health indicators. The dataset has height-for-age z-scores (HAZ) for 7,902 children under the age of five, as well as many other variables at various levels: child, parents, household, and community. Among the 7,902 children,

[1]Children recode file: BDKR7Fl.DTA

53 cases were dropped due to inconsistent values (flagged cases). The final sample for our analysis includes 7,849 children of ages 0 to 59 months. They have 6989 different mothers, ranging in age from 15 to 49 years. The data also allows identifying the gender of the older siblings,[2] as well as the total number of girls and boys each mother gave birth to and who survived till the day of survey interview date.

The overall stunting rate in this sample is 31.4%. This is higher than the 28% average for all developing countries reported by Grantham-McGregor et al. (2007, Table 4) but smaller than their figure of 39% for South Asia. Table 1 shows that stunting is more common among higher birth orders. It is substantially (and significantly) lower among first born children (28.6%) than among children of higher birth order (33.1%), in line with the findings in the literature.

Table 1. *Stunting Rates (in %) by Birth Order*

Birth order	Number of observations	Percentage stunting
1	2997	28.6
2	2556	29.4
3	1320	33.4
4	565	38.8
5	246	45.5
6	95	49.5
7	40	50.0
8 or more	30	46.7
All	7,849	31.4

Table 2 shows some descriptive statistics of the explanatory variables that we will use in our analysis. Considering the literature (cf. Section 2), variables that are related to the probability of stunting include the gender of the child, religious affiliation, birth order, and the mother's and father's education levels. More than 91% of the sample are Muslims. Mothers tend to be higher educated than fathers: Among husbands, 14.6% are non-educated, 33.8% and 49.7% have primary and secondary and above education, respectively, while among mothers, only 7.1% are non-educated, 29% have primary education, and 63.8 have at least some secondary education. The national survey data in Bangladesh suggests that women's education levels continue to increase over the years (NIPORT and ICF, 2019).

Another important socio-economic variable is the wealth index quintile, a composite measure of a household's cumulative living standard.[3] Most variables have 7,849 observations. Exceptions are the variables *Birth interval:* the preceding birth intervals in months, and *Distnhc:* distance to the nearest health clinic in which 25 observations were found missing. The preceding birth interval in months has only 4,830 observations because it is not defined for firstborn children (2,997 observations). Moreover, there are 22 observations of birth order two where the birth interval is missing.

[2]The file 'Individual Recode: BDIR7FL.DTA'

[3]According to the DHS documentation, the wealth index is calculated using principal components analysis from data on household ownership of selected assets, such as televisions and bicycles, and materials used for housing construction; and types of water access and sanitation facilities. See Standard Recode Manual for DHS7 [DHSG4] (dhsprogram.com), p.25.

We include variables indicating that the mother is short or has low weight, as well as the mother's age at birth of the child. In addition, we include the community level variable distance to the nearest health center (in km) and a dummy for living in a rural area. Almost 66% of the households in the sample live in a rural area. We also include dummies for the divisions of Bangladesh. Like stunting rates, differences in birth intervals across administrative divisions are large, with the medians varying from 39 months in Sylhet to 68 months in Khulna (cf. Saha et al., 2019).

Table 2. *Descriptive Statistics*

VARIABLES	Mean	St. dev.	Min	Max
Age of child (mos.)				
Agech1 (0-5)	0.119	0.324	0	1
Agech2 (6-11)	0.099	0.299	0	1
Agech3 (12-23)	0.205	0.404	0	1
Agech4 (24-35)	0.193	0.395	0	1
Agech5 (36-47)	0.186	0.389	0	1
Agech6 (48-59)	0.198	0.399	0	1
Wealth_index	3.000	1.414	1	5
Birth order	2.124	1.264	1	11
Birth interval (months)	60.90	34.17	8	256
Barisal	0.105	0.307	0	1
Chittagong	0.161	0.368	0	1
Dhaka	0.142	0.349	0	1
Khulna	0.106	0.308	0	1
Mymensingh	0.119	0.324	0	1
Rajshahi	0.104	0.305	0	1
Rangpur	0.115	0.319	0	1
Sylhet	0.148	0.355	0	1
Rural	0.658	0.474	0	1
Mother no education	0.071	0.258	0	1
Mother primary education	0.290	0.454	0	1
Mother secondary+ education	0.638	0.480	0	1
Father no education	0.146	0.353	0	1
Father primary education	0.338	0.473	0	1
Father secondary+ education	0.497	0.500	0	1
Muslim	0.914	0.280	0	1
Child is male	0.521	0.500	0	1
Mother age at birth	23.776	5.497	13.00	48.42
Mother_lowbmi[4]	0.160	0.367	0	1
Mother_small[5]	0.133	0.339	0	1
Distnhc	5.400	4.432	0	31.06
Noboy	0.306	0.461	0	1
Nogirl	0.321	0.466	0	1
Previous child is male	0.301	0.458	0	1

[4]Body mass index ≤ 18.5 kg/m^2.

[5]Height ≤ 145 cm.

Figure 1 presents the distribution of preceding birth intervals. The median preceding birth interval is 54 months. It is 56 in families with at least one living son and one daughter, 530 if there is a son but no daughter, and 51 if there is one daughter but no son. The differences suggest that, in particular, not having a son speeds up the next birth, in line with a preference for having sons. This suggests that we can use the gender composition variables as instruments: they have a direct effect on the birth interval, but it seems plausible that they do not have a direct effect on stunting.

Figure 1. *Histogram of preceding Birth Intervals*

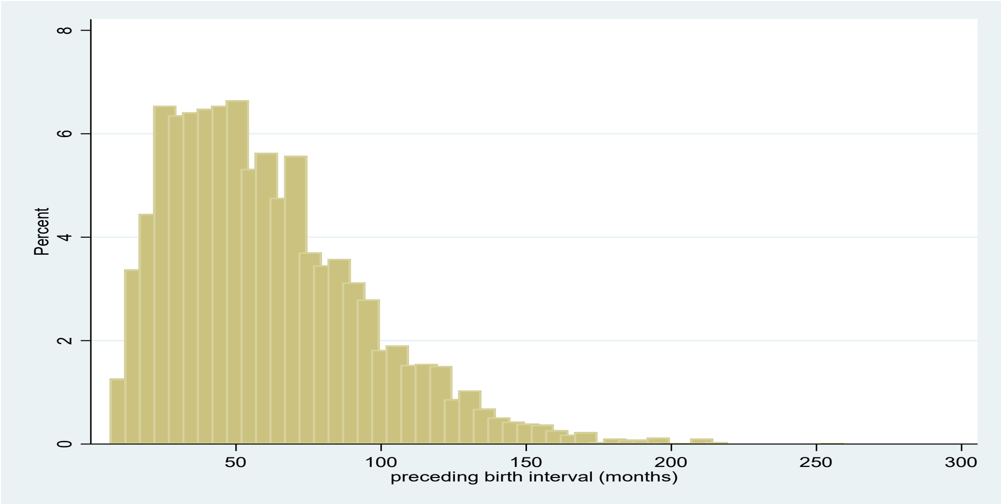
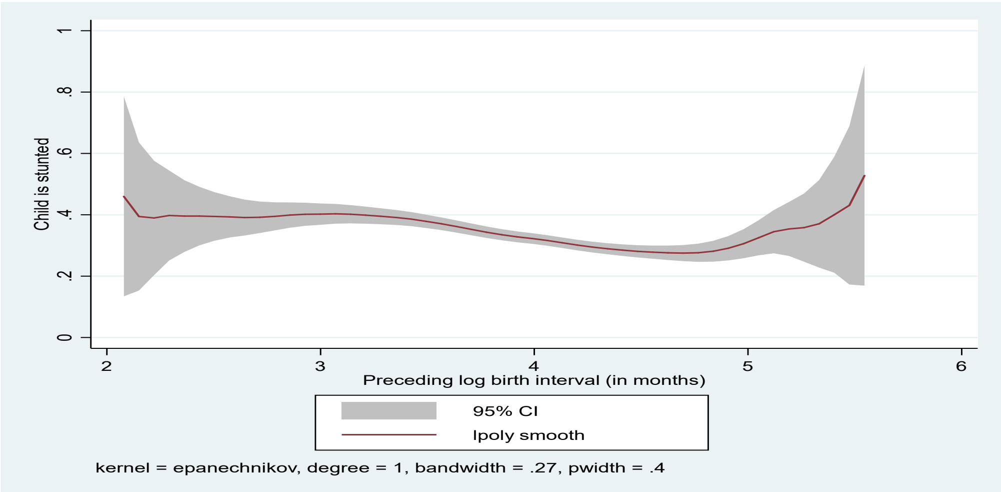


Figure 2 presents a nonparametric regression of stunting on the log of the preceding birth interval, with 95% confidence bands. (First born children are excluded.) It clearly illustrates the negative association between the two: a longer birth interval is associated with a smaller probability of stunting. The main goal of our study is to establish whether this can be given a causal interpretation or not.

Figure 2. *Non-parametric Regression of Stunting on the Log Preceding Birth Interval with 95% Confidence Intervals*



Empirical Model

To identify the causal effect of birth spacing on stunting, we account for unobserved common factors that drive birth intervals and have a direct effect on stunting (keeping other explanatory variables constant). Since some mothers have two children under five in our data set, we can distinguish between unobserved factors that are specific to the mother ("mother specific unobserved heterogeneity" in terms of panel data models; cf., e.g., Arulampalam and Bhalotra, 2008) and child specific unobserved factors that are independent across children ("error terms").[6] We consider the following multilevel two equations model:

$$S_{it}^{*} = X_{it}\beta + \gamma\, ln(B_{it}) + \alpha_{si} + u_{it}\,;\; S_{it} = 1 \text{ if } S_{it}^{*} > 0 \text{ and } S_{it} = 0 \text{ if } S_{it}^{*} \leq 0 \qquad (1)$$
$$ln(B_{it}) = X_{it}\delta + Z_{it}\eta + \alpha_{bi} + v_{it} \qquad (2)$$

$(u_{it}, v_{it}) \sim_{iid} N_2(0, \Sigma)$ independent of all X_{it} and Z_{it}, with $\Sigma(1,1)=1$
$(\alpha_{si}, \alpha_{bi}) \sim_{iid} N_2(0, \Omega)$ independent of all X_{it}, Z_{it} and (u_{it}, v_{it})

Equation (1) is a probit equation for stunting: $S_{it} = 1$ if child t of mother i is stunted, $S_{it} = 0$ otherwise. The covariates X_{it} include socio-economic status indicators and other household and local community characteristics (see Table 2) other than the preceding birth interval. All variables in X_{it} are assumed to be exogenous. On the other hand, the log preceding birth interval $ln(B_{it})$ is allowed to be endogenous. This is because it can be correlated with unobserved household characteristics that also affect birth intervals. For example, lack of knowledge of contraceptives, limited access to contraceptives, or the reluctancy to use contraceptives can be correlated to nutrition habits or other behaviors affecting stunting. To some extent this problem will be mitigated by including a rich set of socioeconomic household and community characteristics, but other factors may not be captured by the covariates observed in the data.

To capture these potential correlations between unobserved factors affecting birth intervals and stunting, Equation (2) is added to the model. This is a linear equation for the log birth interval $ln(B_{it})$. The birth interval can depend on the same covariates X_{it} but may also depend on exogenous variables Z_{it} ("instruments") that do not have a direct effect on S_{it}. For Z_{it} we use variables determined by the family composition before the birth of index child t (presence of boys, presence of girls, gender of the previous sibling). This is in line with the work on the effect of birth intervals on infant mortality by, e.g., van Soest and Saha (2018), who show that the gender composition affects birth spacing and family planning in Bangladesh but argue that it is plausible that it has no direct effect on mortality. Since mortality and stunting are both indicators of child health, the assumption that the gender composition does not directly affect mortality has similar intuitive appeal as the assumption that gender composition does not affect stunting.

[6]Mothers (or households) are treated as a random sample (from the Bangladesh population of mothers (households) with children younger than five), so events related to different mothers are assumed to be independent.

Still, this assumption is not beyond dispute. In particular, Jayachandran and Pande (2017) argue that in India, a country with very strong son preference, limited resources might be allocated to sons rather than daughters, so that children with brothers rather than sisters are disadvantaged and more susceptible to stunting. Since this plays a lesser role for Muslims than for Hindus, it may be less relevant in our sample data where Muslims are majority. Moreover, as a sensitivity check, we will also consider models that do not use these (or other) exclusion restrictions.

The mother or family-specific effects α_{si} and α_{bi} capture the unobserved mother level factors like genetics or preferences for family size that do not vary over time. As argued above, there are good arguments why α_{si} and α_{bi} may be correlated with each other, so we allow for a nonzero covariance $\Omega(1,2)$ between the two.

The idiosyncratic errors (u_{it}, v_{it}) capture child specific shocks, such as temporary health shocks to the mother that increase the probability of stunting (u_{it}) but might also delay getting pregnant or speed up birth when a woman is pregnant (v_{it}). In the most general specification, we allow for a nonzero covariance $\Sigma(1,2)$ between u_{it} and v_{it}, though the need for this is less clear than the need to allow for a nonzero correlation between α_{si} and α_{bi}.

The log birth interval is endogenous in the stunting equation if either α_{si} and α_{bi} are correlated or if u_{it} and v_{it} are correlated, or both. If both correlations are zero, we do not need to estimate the equations jointly and can estimate a random effects probit model for stunting (allowing for correlation between unobservable factors that drive stunting of different children of the same mother). if α_{si} and α_{bi} are correlated but u_{it} and v_{it} are not, we can use the panel structure of the data to identify γ and we do not need exclusion restrictions in the stunting equation for identification. If α_{si} and α_{bi} are correlated and u_{it} and v_{it} are also correlated, the model is technically still identified due to its nonlinear nature, but exclusion restrictions are needed to get a more solid basis for identification. In the next section, we will discuss the estimates of several versions of the model. Considering loglikelihoods and several tests for model specification and selection, we will conclude that the model with exclusion restrictions and correlation between error terms as well as mother specific heterogeneity terms gets most support from the data.

The model is estimated by maximum likelihood, using the generalized structural equation model estimation (GSEM) routine in Stata. The likelihood contributions are a product of normal probabilities and densities, mixed with the density of the mother specific effects. Mixing (i.e., bivariate numerical integration) is performed using Gauss-Hermite quadrature.

Results

Table 3 presents the estimates of some standard models for stunting. The first column presents the results of a standard probit model for first born children, where there is no preceding birth interval. The second column considers a probit model for children of birth order two and higher, allowing for correlation between error terms for different children of the same mother. This model accounts for mother specific unobserved heterogeneity, but both the unobserved heterogeneity term and the remaining error term are independent of the birth interval. The results reveal a significant negative association between log birth intervals and stunting, keeping other observed factors constant. This result is in line with the existing literature. The estimated coefficient of -0.092 implies that, on average, a 10% increase of the birth interval is associated with a reduction in stunting of about 0.33%-points, *ceteris paribus*.[7]

For many of the other covariates, the estimates for first born children are qualitatively similar to those for higher order births. For example, the likelihood of stunting falls with mother's age at birth. Stunting is substantially more likely if the mother is short herself and somewhat more likely if the mother is underweight. Community characteristics are not significant. There is a strong and significant negative wealth gradient: Compared to the poorest wealth quintile, the richest group has a 10%-points lower probability of stunting for higher order births, on average. For first order births, the estimated difference is even somewhat larger (21%-points). Keeping wealth and other variables constant, the association with the father's education level is significant for higher order births but not for the first child.

Table 3. *Models for Risk Factors associated with Stunting in Under-five Children*

Covariate	**Subsample: first-born children (birth order =1); Standard probit model**		**Subsample: other than first born children (birth order >1); Probit model**		**Subsample: other than first-born children (birth order >1); Quasi fixed effects probit model**	
	coeffic.	s.e.	coeffic.	s.e.	coeffic.	s.e.
Child level factors						
Child's age 6-11 months	-0.049	0.117	0.065	0.091	0.066	0.091
12-23 months	0.387**	0.095	0.576**	0.075	0.577**	0.075
24-36 months	0.453**	0.094	0.674 **	0.076	0.672**	0.076
37-47 months	0.194*	0. 098	0.628**	0.076	0.626**	0.076
48-59 months	0.009	0.099	0.375**	0.075	0.371**	0.076
Gender of child, male	-0.001	0.051	0.007	0.039	0.007	0.039
Religion of child, Muslim	0.050	0.087	-0.021	0.076	-0.022	0.0756
Birth order	-	-	0.070*	0.024	0.069**	0.024
Preceding log birth interval	-	-	-0.092*	0.041	-0.009	0.125
Mean log birth interval	-	-	-	-	-0.093	0.132
Mother level factors						
Age of mother at childbirth (continuous)	-0.029	0.008	-0.004	0.006	-0.003	0.006
Mother is short (height<=145 cm)	0.609**	0.077	0.653**	0.054	0.653**	0.054
Mother is thin (body mass index<=18.5 kg/m^2)	0.102	0.065	0.208**	0.056	0.207**	0.056
Mother has primary education	-0.061	0.148	0.001	0.072	0.002	.071
Mother has secondary+ education	-0.264	0.147	-0.031	0.077	-0.030	0.077
Family level factors						
Father has primary education	-0.050	0.087	-0.031	0.055	-0.031	0.055

[7]The marginal effect for an observation with stunting probability equal to the sample average (0.314) is equal to $-0.092\,\phi(\Phi^{-1}(0.314)) = -0.0033$.

Father has secondary+ education	-0.175	0.088	-0.232**	0.062	-0.232**	0.062
Family wealth score						
Poorer (2nd quintile)	-0.007	0.083	0.061	0.058	0.062	0.058
Middle (3rd quintile)	-0.125	0.085	-0.068	0.063	-0.067	0.063
Richer (4th quintile)	-0.220*	0.091	-0.155*	0.068	-0.154*	0.068
Richest (5th quintile)	-0.592**	0.107	0.280**	0.081	-0.280**	0.081
Community level factors						
Rural area	-0.068	0.064	0.026	0.049	0.026	0.049
Barisal	-0.071	0.106	0.231**	0.085	0.232**	0.085
Chittagong	0.088	0.095	0.255**	0.075	0.254**	0.075
Mymensingh	-0.109	0.102	0.256**	0.082	0.256**	0.082
Khulna	-0.157	0.103	0.146	0.087	0.147	.087
Rajshahi	0.008	0.102	0.067	0.087	0.068	0.087
Rangpur	-0.075	0.105	0.020	0.084	0.020	0.084
Sylhet	0.162	0.098	0.388**	0.076	0.386**	0.076
Distance to nearest health Centre	0.009	0.006	0.007	0.005	0.007	0.005
Constant	0.151	0.272	0.796**	0.209	-0.772**	0.212
Observations	2994		4808		4808	

Notes: Standard errors (s.e.) clustered at mother level; * $p<=0.05$; ** $p<=0.01$.
Source: BDHS 20117/18.

Column 3 in Table 3 is a first step towards allowing for a correlation between the log birth interval and mother specific unobserved heterogeneity, following the approach of Mundlak (1978) for quasi-fixed effects panel data models. The error term in the stunting equation (consisting of an idiosyncratic error and a mother specific effect) is decomposed as $\varepsilon_{it} + \lambda$ *mean*[$ln(B_{i.})$], where *mean*[$ln(B_{i.})$] is the mean of the log birth intervals for mother *i* over all her children of birth order larger than one observed in the data, and ε_{it} is a standard normally distributed error term, independent of the log birth intervals and other explanatory variables. In this way, the correlation between the mother specific effect and the log birth interval is explicitly modeled and is present if $\lambda \neq 0$. Column 3 shows that λ is not significant. The effect of the log birth interval is somewhat smaller in absolute value than in column 2 and less precise. It remains negative and not significant. The other estimates hardly change.

We now turn to the two equations model for stunting and preceding birth intervals for children of birth order higher than one, introduced in Section 4. We estimated several specifications of this model. Log likelihoods and values of goodness of fit measures AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) are presented in Table 4. Note that a lower value of AIC or BIC indicates a better fit.

Table 4 shows that, according to both AIC and BIC, the models imposing exclusion restrictions (models 1 and 3) perform better than their respective counterparts models 2 and 4, which also add the variables in Z_{it} (gender of the previous child and dummies for no boys and no girls) in the stunting equation. Model 3 has the lowest BIC and AIC. Moreover, the estimate of $\Sigma(1,2)$ is significant (see Table 5 below). It therefore seems justified to consider model 3 as our favorite model, and we will refer to it as the benchmark model. To illustrate the importance of accounting for endogeneity of the birth interval, we will, however, also discuss some results of model 1.

Table 4. *Goodness of Fit Criteria for Several Model Specifications*

Model	Number of parameters	Log likelihood	AIC	BIC
1. Independent errors, exclusion restrictions	54	-5995.4	12098.816	12189.73
2. Independent errors, No exclusion restrictions	57	-5995.4	12104.816	12200.79
3. Correlated errors, exclusion restrictions	58	-5982.38	12080.77	12188.75
4. Correlated errors, no exclusion restrictions	61	-5982.02	12086.03	12202.32

Note: different specifications of the model in Section 4. Independent errors means *Σ(1,2)* is set to zero. No exclusion restrictions means that Z_{it} in equation (2) is also added to equation (1).

Table 5. *RE and Two-equations Model for Stunting (children of birth order larger than 1)*

Covariate	Random Effects (RE)		Generalized Structural Equation Model (GSEM)			
	Stunting		stunting		Log birth interval	
	Coefficients	s.e.	Coefficients	s.e.	Coefficients	s.e.
Child level factors						
Child age 6-11 months	0.084	0.112	0.079	0.109	-	-
12-23 months	0.689**	0.101	0.667**	0.100	-	-
24-36 months	0.811**	0.106	0.784**	0.104	-	-
37-47 months	0.755**	0.105	0.729**	0.103	-	-
48-59 months	0.458**	0.098	0.439**	0.096	-	-
Gender of child male	0.014	0.047	0.017	0.046	-	-
Religion of child, Muslim	-0.021	0.088	-0.012	0.087	0.017	0.027
Birth order	0.084**	0.029	-0.021	0.051	-0.211**	0.009
Preceding log birth interval	-0.108*	0.049	-0.611**	0.196	-	-
Mother level factors						
Age of mother at childbirth	-0.005	0.007	0.035*	0.017	0.078*	0.002
Mother is short (height<=145cm)	0.771**	0.078	0.747**	0.078	-	-
Mother is thin (body mass index<=18.5 kg/m^2)	0.259**	0.070	0.250**	0.067	-	-
Mother primary education	-0.002	0.086	0.020	0.085	0.041	0.028
Mother secondary+ educ.	-0.039	0.093	-0.044	0.091	-0.0156	0.030
Family level factors						
Father primary education	-0.039	0.068	-0.032	0.068	0.015	0.020
Father secondary+ educ.	-0.284**	0.079	-0.286**	0.078	-0.019	0.022

Family wealth score						
Poorer (2^{nd} quintile)	0.071	0.070	0.080	0.069	0.024	0.021
Middle (3^{rd} quintile)	-0.078	0.076	-0.069	0.075	0.015	0.022
Richer (4^{th} quintile)	-0.175*	0.083	-0.159*	0.082	0.024	0.024
Richest (5^{th} quintile)	-0.330**	0.110	-0.336**	0.098	-0.032	0.028
Community level factors						
Rural area	0.037	0.061	0.038	0.058	0.005	0.017
Barisal	0.278**	0.105	0.270**	0.104**	0.002	0.029
Chittagong	0.303**	0.093	0.268**	0.092	-0.053*	0.025
Mymensingh	0.306**	0.102	0.281**	0.101	-0.027	0.028
Khulna	0.176	0.105	0.220*	0.105	0.097**	0.029
Rajshahi	0.081	0.106	0.130	0.106	0.103**	0.029
Rangpur	0.031	0.102	0.063	0.102	0.068*	0.028
Sylhet	0.468**	0.097	0.338**	0.109	-0.227**	0.027
Distance to health center	0.008	0.006	0.008	0.006	-	-
Gender composition						
Previous child male	-	-	-	-	-0.012	0.017
No surviving boy	-	-	-	-	-0.060**	0.019
No surviving girl					-0.053*	0.021
Constant	-0.967**	0.255	0.306	0.551	2.503**	0.063
Observations	4808		4808		4830	

Notes: Standard errors (s.e.) clustered at mother level; * p<=0.05; ** p<=0.01.
Source: BDHS 20117/18.

Table 5. *continued*

	RE Model		GSEM			
	Stunting		Stunting		Ln(birth interval)	
	coeffic.	s.e.	coeffic.	s.e.	coeffic.	s.e.
St. dev. (error term)	1	-	1	-	0.440	0.011**
St. dev. (ind. effect)	0.652	0.125**	0.630	0.124**	0.164	0.025**
				coeffic.	s.e.	
Corr.(u_{it}, v_{it})				0.396	0.020**	
Corr.$(\alpha_{si}, \alpha_{bi})$				0.249	0.078**	
Observations	4808		4808		4830	

Notes: Standard errors (s.e.) clustered at mother level; * p<0.05; ** p<0.01.
Source: BDHS 2017/2018.

Table 5 presents the main results. First, for comparison, the first column shows the estimates of a random effects probit model for stunting, where the random effects are mother specific (capturing time persistent unobserved heterogeneity across mothers and their households) and birth intervals are treated as exogenous. The other columns present the estimates of our benchmark specification of the bivariate model, model 3 in Table 4. Column 2 presents the parameter estimates of the stunting equation (eq. 1) and Column 3 presents the results for the equation for the log birth interval (eq. 2). The main difference between the results for the complete model and the probit equation in column 1 is the coefficient on the log birth interval. The effect of the log birth interval is significantly negative in both models, but the effect is much larger in the bivariate model than according to the random effects probit equation. A Hausman test based upon comparing the two estimates confirms that the difference is significant (test statistic -2.7, p-value 0.000).[8] This implies that exogeneity of the log birth interval is rejected and the bivariate model with endogenous birth intervals outperforms the random effects probit model in which birth intervals are assumed to be exogenous.

The finding that birth intervals are endogenous is also confirmed by the estimated covariance structure of the error terms and the mother specific effects in the two equations model. The estimated correlations between u_{it} and v_{it} and between α_{si} and α_{bi} are 0.396 and 0.249, respectively (see the bottom of the table). Both are significantly positive, and they are also jointly significant. Only if both were zero, the birth interval would be exogenous.

We therefore conclude that exogeneity of the birth intervals is rejected. Moreover, the estimates show that assuming exogeneity leads to a substantial underestimation of the importance of the preceding birth interval for stunting. We will therefore focus on the bivariate model in the remainder of this study.

The effect of the birth interval is not only statistically significant, but also substantively relevant: For an average observation (with stunting probability 0.314), keeping other characteristics (including unobserved characteristics α_{si}), a 10% increase of the birth interval reduces the probability of stunting by approximately 2.17 percentage points.[9] Going from the 25th percentile (33 months) to the median of all birth intervals (52 months) would reduce the probability of stunting by approximately 9.9 percentage points,[10] keeping other variables constant.

For the other explanatory variables in the stunting equation, the estimated coefficients generally do not differ much between the univariate model in column 1 and the bivariate model in column 2, as expected. They are also in line with the probit estimates in Table 2 and with earlier findings in the literature (see, e.g., Saha et al. 2019). The probability of stunting falls with the mother's age at previous birth[11] until approximately age 31 (the 90th percentile of mother's age at birth). It rises with birth order over most of the birth order range, in line with the stunting rates by birth order in Table 1. Neither the gender of the index child nor the religion of the family is significant.[12] Stunting is also more likely if the mother is unusually short. The stunting probability falls substantially with the education levels of both the father and the mother, but also with household wealth. As already emphasized

[8] $(-0.611 - (-0.108))/\sqrt{(0.196^2 - 0.049^2)} = -2.7$; Under the null that the birth intervals are exogenous, the test statistic follows a standard normal distribution.

[9] $- 0.611\ \phi(\Phi^{-1}(0.314))\ 0.1 = -0.0217$.

[10] $- 0.611\ \phi(\Phi^{-1}(0.314))\ \ln(52/33) = -0.099$.

[11] In this model we use age of the mother at previous birth, before the start of the birth interval.

[12] The positive sign of the dummy for a male child is in line with Thurstans et al. (2020).

by Saha et al. (2019), regional differences are substantial, with the largest stunting probability in Barisal, *ceteris paribus*.

The estimate of $\Omega(1,1)$ is 0.652 and significant, implying that almost one third ($0.652^2/0.652^2+1$) of the unexplained variance in (the latent variable that drives) stunting is captured by mother specific effects, while the other two thirds reflect unsystematic variation that is independent across children.

The third column of Table 5 presents the estimates of the log birth interval equation. The most interesting coefficients are those on the three instruments. Two of them are significant at the 5% level. Importantly, the three instruments are jointly significant (Chi2 value 13.76; p-value 0.0008), confirming relevance of the set of instruments as a whole. If the household either only has boys or only has girls, this significantly reduces the length of the birth interval, consistent with the notion that families desire a "complete family" with at least one boy and one girl, a stylized fact that has also been observed in developed countries (see, e.g., Angrist and Evans, 1998). The size of the reduction is 6% if there are no boys and 5.3% if there are no girls, and the small difference implies hardly any sign of son preference in this respect. The third instrument, gender of the previously born child, is not significant once the numbers of boys and girls (and other covariates) are kept constant.

The estimates for the other coefficients in the birth interval equation are largely in line with, e.g., van Soest and Saha (2018). Birth interval length falls with birth order but increases with the mother's age at her previous childbirth. Birth intervals are shortest in Sylhet, where stunting is relatively common. They are relatively long in Khulna and Rajshahi, divisions with relatively low prevalence of stunting. On the other hand, wealth status of the household itself and education of the father and mother play no significant role for birth spacing. This suggests that regional economic welfare (and associated cultural norms) are more important for birth spacing than the individual household's socioeconomic status.

The estimated variance of α_{bi} is 0.027 and significant, but much smaller than the variance of the error term in the same equation (v_{it}). Mother specific heterogeneity therefore plays a modest role here: it captures only 12% of the unsystematic variation in birth intervals.

Discussion and Conclusion

The large literature on determinants of stunting reports that age and gender of the child, birth weight and birth interval, mother's education and nutritional status, household economic status and family size, and place of residence are significant predictors of stunting (see for example, Abdullah et al., 2023; Saha et al., 2019; 2020; Heady et al., 2015). Our study largely confirms these existing findings. Not all these associations necessarily reflect causal effects. In particular, birth intervals and stunting may be affects by similar unobserved cultural, hygienic or economic factors, that make birth intervals endogenous in an equation for stunting. Our study focuses on estimating the causal effect of preceding birth intervals on stunting among children of birth order two and higher. It is the first of its kind to explicitly account for endogeneity of the preceding birth interval, as well as for mother specific unobserved heterogeneity in stunting as well as birth spacing.

Our main result is the large negative causal effect of birth spacing on the probability that a child of birth order larger than one is stunted: an increase of the birth interval by 10% leads to a reduction of the stunting probability by 2.17 percentage points for an average observation, keeping other covariates constant. Previous studies using the BDHS surveys found adverse effects of birth intervals on the probability that a child is stunted, but they treated the birth interval as an exogenous variable (Kamal and Moniruzzaman, 2021; Khokon 2019). Our study shows clear evidence of endogeneity of birth intervals in the stunting equation and demonstrates that accounting for endogeneity leads to a much larger estimate of the birth interval effect on stunting. It fills a gap in the literature in showing that an appropriate econometric model can lead to quite different conclusions about the importance of birth spacing policy for stunting.

olicy measures that improve socioeconomic status (wealth and education) have direct negative effects on stunting, keeping birth intervals constant. For example, compared to no education, secondary + education of the father reduces stunting by 10 %-points on average. And the ceteris paribus difference between the lowest and highest wealth quintiles is almost 12 %-points. On the other hand, improving socioeconomic status does not significantly increase birth intervals, so there is no evidence that the reduction of stunting works through the mechanism of longer birth intervals.

The large wealth effect is in line with descriptive results of Saha et al. (2019), who found that "when 20% children of the richest household were stunted in 2014, higher levels of stunting were observed among children in the poorest household during that period (56%)". Also, Saha et al, 2020 found a best scenario of the reduction of stunting with a step-wise improvement of wealth quintiles, parental education, household food security and eliminating large household size. Heady et al., 2015 showed factors that correlated with the decline in stunting in Bangladesh are: a rise in household assets; improvements in parental education; a reduction in open defecation; prenatal and birth delivery care; birth order and birth intervals; and maternal height. However, past studies have rarely quantified such effects keeping birth intervals constant.

We find that family composition influences birth spacing: The estimates suggest that families desire at least one daughter and at least one son, rather than a preference for boys. This seems to offer guidance for policy measures to educate couples towards gender preference. The existing demographic literature using data from India and Taiwan also showed evidence of a preference for a balanced sex composition (Pande, 2003; Lin 2009), but a son preference among Iranian women (Dehesh et al., 2020).

The other main driving factor of variation in birth intervals is formed by region specific factors where Sylhet is the hotspot of short birth intervals (Islam et al., 2022). Existing studies already revealed large variation in stunting across divisions. For example, children from Sylhet are much more likely to be stunted than the children of Dhaka division (Chowdhury et al., 2020). Short birth intervals are one of the reasons explaining this large stunting rate. The estimated indirect regional effect on stunting through birth spacing moving from Dhaka to Sylhet is almost 5%-

points.[13] On the other hand, the direct effect (keeping birth intervals constant) is even larger: 12%-points. This is an important finding for policy measures that can bring down stunting in a high-stunting division like Sylhet. Existing studies discuss the regional differences in stunting probabilities emphasizing differences in food supply due to agricultural productivity differences caused by the type of soil, for example (National Encyclopaedia of Bangladesh; Quddus et al.,2004), differences in Social Safety Net Program and for Government, non-Government aid (Chowdhury et al., 2020), differences in fertility levels and differences in women's autonomy and decision-making capacity (Saha et al. 2019; Basu et al., 2000; Amin et al., 2002; Chottopadhaya et al., 2007). Different from other studies, our study quantifies the effects and shows how household wealth, parental education, and regional differences drive birth intervals and stunting. Better understanding the risk factors including short birth intervals that drive stunting probabilities in under-five children may help to attain the Sustainable Development Goal (SDG) in maternal and child health in Bangladesh.

References

Abdullah F, Azizur R, Hossain Md M (2023) Prevalence and risk predictors of childhood stunting in Bangladesh, *Plos one* 18(1): e0279901. doi: 10.1371/journal.pone.0279901.

Aerts D, de Lourdes Drachler M, Regina Justo Giugliani ER (2004) Determinants of growth retardation in southern Brazil, *Cadernos Saude Publica* 20(5): 1182 - 1190.

Akram R, Sultana M, Ali N, Sheikh N, Razzaque Sarker A (2018) Prevalence and determinants of stunting among preschool children and Its urban–rural disparities in Bangladesh, *Food and Nutrition Bulletin* 39(4): 521-535.

Amin S, Lloyd SB (2002) Women's lives and rapid fertility decline: Some lessons from Bangladesh and Egypt. *Population Research and Policy Review* 4(21):275–317.

Arulampalam W, Bhalotra S (2008) The linked survival prospects of siblings: Evidence for the Indian states, *Population Studies* 62(2):171-190.

Basu AM, Amin S (2000) Conditioning Factors for Fertility Decline in Bengal: History, Language Identity, and Openness to Innovations, *Population Development Review* 26(4):761–794.

Black RE, Morris SS, Bryce J (2003) Where and why are 10 million children dying every year? *The Lancet* 361(9376): 2226 – 2234.

Chottopadhyay A, Goswami B (2007) Status of women in two Bengals: Evidence from large scale surveys. *Journal of Biosocial Science* 39:267-86.

Chowdhury MK, Bairagi R (1990) Son preference and fertility in Bangladesh, *Population and Development Review* 16(4): 749 - 757.

Chowdhury TR, Chakrabarty S, Rakib M, Afrin S, Saltmarsh S, Winn S (2020) Factors associated with stunting and wasting in children under 2 years in Bangladesh, *Helion* 6(9): https://doi.org/10.1016/j.heliyon.2020.e04849;

Chungkham HS, Sahoo H, Marbaniang SP (2020) Birth interval and childhood undernutrition: Evidence from a large-scale survey in India, *Clinical Epidemiology and Global Health* 8(4): 1189 – 1194.

Das SK, Jobayer Chisti M, Abdul Malek M, Das J, Abdus Salam M, Ahmed T, Al Mamun A, Golam Faruque AS (2015) Changing childhood malnutrition in Bangladesh: trends

[13] - 0.611 $\phi(\Phi^{-1}(0.314))$ x -0.227 = 0.0492.

over the last two decades in urban–rural differentials (1993–2012), *Public Health Nutrition* 18(10):1718–1727.

Ross AC, Taylor CL, aktine AL, Del Valle HB (2011) *Dietary Reference Intakes for Calcium and Vitamin D*, *National Academies Press* Washington DC.: Available https://pubmed.ncbi.nlm.nih.gov/21796828/

Dehesh T, Salarpour E, Malekmohammadi N, Arjomand Kermani S (2020) Associated factors of pregnancy spacing among women of reproductive age Group in South of Iran: cross-sectional study, *BMC Pregnancy and Childbirth* 20: 554.

Faruque ASG, Shamsir Ahmed AM, Ahmed T, Munirul Islam M, Md. Hossain I, Roy SK, Alam N, Kabir I, Sacks DA (2008) Nutrition: Basis for Healthy Children and Mothers in Bangladesh, *Journal of Health, Population and Nutrition*26(3):325-339.

Fink G, Sudfeld CR, Danaei G, Ezzati M, Fawzi WW (2014) Scaling-up access to family planning may improve linear growth and child development in low and middle income countries, *PLoS ONE* 9(7): e102391.

Grantham-McGregor S, Cheung YB, Cueto S, Glewwe P, Richter L, Strupp B, International Child Development Steering Group, et al. (2007) Developmental potential in the first 5 years for children in developing countries, *The Lancet* 369(9555): 60-70.

Headey D, Hoddinott J, Ali D, Tesfaye R, Dereje M (2015) The other Asian enigma: explaining the rapid reduction of undernutrition in Bangladesh, *World Development* 66:749–761.

Islam MM, Istiaque Sanin K, Mahfuz M, Shamsir Ahmed AM, Mondal D, Haque D, Ahmed T (2018) Risk factors of stunting among children living in an urban slum of Bangladesh: findings of a prospective cohort study, *BMC Public Health* 8: 197.

Islam Md S, Zafar Ullah AN, Mainali S, Imam Md A, Hasan Md I (2020) Determinants of stunting during the first 1,000 days of life in Bangladesh: A review, *Food Science and Nutrition,* 8(9), 4685-4696.

Islam MZ, Islam MM, Rahman Md M, Khan Md. N (2022) Exploring hot spots of short birth intervals and associated factors using a nationally representative survey in Bangladesh, *Scientific Reports* https://doi.org/10.1038/s41598-022-13193-2.

Jesmin A, Yamamoto SS, Azam Malik A, Haque Md A (2011) Prevalence and Determinants of Chronic Malnutrition among Preschool Children: A Cross-sectional Study in Dhaka City, Bangladesh, *Journal of Health Population and Nutrition* 29(5):494-9.

Jayachandran S, Pande R (2017) Why are Indian Children so short? The role of birth order and son preference, *American Economic Review* 107(9): 2600 – 2629.

Kamal S, Moniruzzaman M (2021) Birth Interval and its Association with Adverse Childhood Nutritional Outcomes Among Under-Five Children in Bangladesh: A Longitudinal Study, *Journal of Nepal Pediatric Society* 41(3):327-335.

Wajiha K, Rasheed S, Alam A, Huda TM, Dibley MJ (2019) Assessing the Intergenerational Linkage between Short Maternal Stature and Under-Five Stunting and Wasting in Bangladesh. Nutrients, 11(8**):** 1818 doi: 10.3390/nu11081818

Khokon MR (2019) The Effects of Birth Spacing on Nutritional Status in the form of Stunting of Under Five Children in Bangladesh: Evidence Based on BDHS, 2014 Data, *Dhaka University Journal of Science* 67(2): 139-144.

King JC (2003) The risk of maternal nutritional depletion and poor outcomes increases in early or closely spaced pregnancies, *The Journal of Nutrition* 133(5): 1732S - 1736S. doi:10.1093/jn/133.5.1732S.

Lin T-C (2009) The decline of son preference and rise of gender indifference in Taiwan since 1990. *Demographic Research* 20(1): 377-402.

Miller R, Karra M (2020) Birth spacing and child health trajectories, *Population and Development Review*, 46(2): 347-371.

Moffitt R (2005) Remarks on the analysis of causal relationships in population research, *Demography* 42, 91-108.

Mundlak Y (1978) On the pooling of time series and cross section data, *Eonometrica* 46, 69-85.

National Encyclopedia of Bangladesh; Bangladesh Soil (2021) Available at http://en.banglapedia.org/index.php?title=Bangladesh_Soil

National Institute of Population Research and Training (NIPORT), and ICF. (2019) Bangladesh Demographic and Health Survey 2017-18: Key Indicators. Dhaka, Bangladesh, and Rockville, Maryland, USA: NIPORT, and ICF.

Pande RP (2003) Selective Gender Differences in Childhood Nutrition and Immunization in Rural India: The Role of Siblings, *Demography* 40 (3): 395-418.

Pebley AR, DaVanzo J (1993) *Maternal Depletion and Child Survival in Guatemala and Malaysia*, *RAND Corporation*, *Santa Monica CA.*

Prendergast AJ, Humphrey JH (2014) The stunting syndrome in developing countries, *Paediatrics and International Child Health* 34(4): 250 – 265.

Quddus MA, Sen K, Salimullah M (2004) Performance of crop production in Bangladesh: Growth and regional Disparities, Research Note. Bangladesh *Journal of Agriculture Economics,* 27(2): 57-74.

Mosfequr R (2016) Association between order of birth and chronic malnutrition of children: a study of nationally representative Bangladeshi sample, *Cadernos de Saude Publica* 32: e00011215.

Rahman M, DaVanzo J (1993) Gender preference and birth spacing in Matlab, Bangladesh, *Demography* 30(3): 315 - 332.

Rutstein SO (2005) Effects of preceding birth Intervals on neonatal, infant and under-five years mortality and nutritional status in developing countries: Evidence from the Demographic and Health Surveys, *International Journal of Gynecology & Obstetrics* 89: S7 - S24.

Saha UR, Chattopadhyay A, Hendrik Richardus J (2019) Trends, prevalence and determinants of childhood chronic undernutrition in regional divisions of Bangladesh: Evidence from Demographic Health Surveys, 2011 and 2014, *PloS ONE* 14(8): e0220062.

Saha UR, van den Boom B, Hendrik Richardus J (2020) Risk factors and spatial variation of stunting among under-fives in Bangladesh: Challenges to reach to the sustainable development goal. In book: Population Dynamics in Eastern India and Bangladesh. doi: 10.1007/978-981-15-3045-6_19

Shapiro-Mendoza BJS, Smith DP, Sanderson M (2005) Parental pregnancy intention and early childhood stunting: Findings from Bolivia, *International Journal of Epidemiology* 34(2): 387 - 396.

Sulloway FJ (1996) *Born to Rebel: Birth order, Family Dynamics, and Creative Lives,* Pantheon Books, New York.

Svefors P, Sysoev O, Ekstrom EC, Ake Persson L, Arifeen SE, Naved RT, et al. (2019) Relative importance of prenatal and postnatal determinants of stunting: Data Mining approaches to the MINIM at cohort, Bangladesh, *BMJ Open* 9(8):e025154. doi: 10.1136/bmjopen-2018-025154.

UNICEF/WHO/World Bank Group Joint Child Malnutrition Estimates (2020) Levels and trends in child malnutrition, https://apps.who.int/iris/bitstream/handle/10665/331621/9789240003576-eng.pdf?sequence=1&isAllowed=y.

WHO (2014) Global nutrition targets 2025: Stunting policy brief, World Health Organization WHO Reference Number WHO/NMH/NHD/14.3, Global nutrition targets 2025: stunting policy brief (who.int)

Van Soest A, Saha UR (2018) Relationships between infant mortality, birth spacing and fertility in Matlab, Bangladesh, *PLoS ONE* 13(4), 1-21.