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Urbanization and Child Nutritional Outcomes

Mulubrhan Amare, Channing Arndt, Kibrom A. Abay, and Todd Benson

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ABSTRACT

We investigate the implications of urbanization on child nutritional outcomes using satellite-based nighttime light intensity data as a marker of urbanization using two-rounds of Demographic and Health Survey data from Nigeria. We find that nightlight significantly predicts child nutritional outcomes even after controlling for observable covariates known to influence child nutrition. In all specifications, improvements in child nutrition outcomes onset with relatively low levels of light emissions and continue rapidly as nightlight intensity increases before largely leveling off. These non-linear relationships highlight the value of nightlight as a population agglomeration indicator relative to traditional binary rural-urban indicators. Consistent with other recent work, patterns of urbanization influence welfare outcomes. At least for Nigeria, a pattern that extends the rapid onset agglomeration benefits to larger shares of the population would speed improvements to child nutritional outcomes that the general urbanization trend provides.

Keywords: child nutritional outcomes, malnutrition, urbanization, nighttime light.

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1. INTRODUCTION

Existing studies almost invariably find that child nutritional outcomes are better on average in urban than in rural areas of developing countries (Garrett and Ruel 1999; Menon et al. 2000; Smith et al. 2005; Paciorek et al. 2014). This remains largely the case even after controlling for a series of observable related factors, though children from the lowest socioeconomic quintile often have similar stunting rates in rural and urban areas (Garrett and Ruel 1999; Menon et al. 2000). Nevertheless, the rapid process of urbanization ongoing in Africa (Paciorek et al. 2014) would appear to broadly support progress in improving child nutritional outcomes through benefits of population agglomeration.

Data has limited what can be said with respect to the relationship between urbanization and nutrition beyond these generalities. Two data limitations are in focus here. First, key surveys, such as the Demographic and Health Surveys, employ census- or survey-based (normally binary) measures of urbanization. These measures fail to fully capture the heterogeneity of urban areas. Rather than a binary phenomenon, urbanization is a continuum reflecting a rural-to-urban transformation process (Christiaensen and Todo 2014; Calì and Menon 2013). The typical binary rural/urban indicator inhibits micro-level analysis of the implications of urbanization and limits understanding of the potentially complex nature of the relationship between urbanization and child nutritional outcomes. Second, these measures are often very poor at capturing the dynamics of urbanization. In developing countries, dichotomous census-based indicators of urbanization are at best obtained at 10-year intervals.[1] These two limitations obscure insights into the inter-linkages between urbanization and nutrition. For instance, it is unclear whether nutritional improvements onset rapidly at a low level of urban intensity and then level off or whether the gains emerge essentially linearly with increasing urbanization.

The advent of satellite-based nighttime light data offers interesting potentials to measure urbanization and urban expansion. Based on the notion that light intensity per unit area corresponds to a reasonable measure of degree of urbanization, nighttime light intensity is argued to be a valid marker of urbanization and urban settlements (Elvidge et al. 1997; Henderson et al. 2003; Imhoff et al. 1997; Sutton 1997; Storeygard 2016). A key benefit of nighttime light is that it is measured with consistent quality. In addition, longer time series data are coming into place.

In this paper, we investigate the implications of urbanization on child nutritional outcomes using satellite-based nighttime light intensity data as a proxy for urbanization and urban growth. We employ two rounds (2008 and 2013) of geo-referenced and nationally representative Demographic and Health Survey (DHS) data from Nigeria. The DHS data provide detailed anthropometric measures of child nutritional outcomes along with a series of control variables. We merge these geo-referenced DHS data with nighttime light intensity data for the survey clusters in which the DHS sample households reside. This nighttime light introduces a continuous gradient of urbanization permitting investigation of the implications of urbanization on child nutritional outcomes along an urbanization continuum.

We find that nightlight is a highly significant determinant of child nutritional outcomes even after controlling for covariates known to influence child nutrition. Relative to areas with no nightlight signatures, improvements in child nutrition outcomes are observed in areas with relatively low levels of light emission, and these improvements continue rapidly as nightlight intensity increases before largely leveling off. This is true of both the simple bivariate relationship between nighttime light intensity and nutrition and when controlling for observable factors associated with child nutritional status. This implies that benefits of agglomeration arise even from a relatively loose clustering of human settlement with positive implications

[1] A third important limitation, though not in focus here, is that the criteria and definition of urbanization often varies across countries, which limits cross-country comparisons.

for childhood nutrition. These results are broadly consistent with those of Christiaensen et al. (2013) and Christiaensen and Todo (2014).

The remainder of the paper is organized as follows. Section 2 discusses alternative measures of urbanization and the advantages and limitations of using nighttime light data. Section 3 presents the key variables used in the empirical analysis. Section 4 presents the empirical model and estimation strategy. Section 5 presents and discusses the empirical results. Section 6 concludes that a pattern of urbanization that extends the rapid onset agglomeration benefits of urbanization to larger shares of the population would speed improvements to child nutritional outcomes in Nigeria, and likely most countries in sub-Saharan Africa, that the general urbanization trend provides.

2. MEASURING URBANIZATION AND ITS LINKAGE WITH CHILD NUTRITIONAL OUTCOMES

Measuring urbanization

The measurement problems related to urbanization have prompted researchers and urban planners to seek alternative measures of urbanization. Recent efforts have focused on constructing continuous and disaggregated indexes that capture micro-level variations in urban expansion (Van de Poel et al. 2012). Satellite-based collection of nighttime light intensity data has attracted substantial interest given its potential to capture, at least partially, the dynamics of urbanization. As urban areas are expected to have higher nightlight intensities than rural areas, satellite-based nighttime light intensity has been employed as a valid marker of urbanization and urban settlements (Imhoff et al. 1997; Elvidge et al. 1997; Sutton 1997; Sutton et al. 2010; Henderson et al. 2003).

The satellite-based nighttime light intensity data come from the Operational Linescan System (OLS) sensors of the Defense Meteorological Satellite Program (DMSP) of the United States Air Force. These satellite-based remote sensors collect nighttime light intensity data from every location on the planet at about a one square-kilometer resolution daily. The National Geophysical Data Center (NGDC) of the National Oceanic and Atmospheric Administration (NOAA) processes the raw data. This processing involves averaging of light intensities over time (monthly or annually) and removing any natural dimness arising from clouds, leaving lights from human activities. The NGDC then distributes these processed data for research and public use. The DMSP-OLS provides the nighttime light intensity data as digital numbers (DN) ranging from 0 (no light) to 63 (highest light) for one km^2 pixels. Due to this scaling, some areas of the world characterized by high and intense lighting may be censored at 63.

The DHS data provide information on GPS-coordinates of clusters, which enables merging the nighttime light and DHS clusters. To maintain the anonymity of survey participants and their communities, the coordinates of each survey cluster have been randomly displaced by up to two kilometers in any direction for urban areas, and up to five kilometers for rural areas, with one percent of all survey clusters randomly displaced by up to 10 kilometers. However, since the nightlight data is at a 1 km^2 resolution and higher values for nightlights are clustered, so the displacement is likely to only cause a small error in the nightlight value assigned households in that cluster from what the true value was.

Besides being freely available, the nighttime light data have attractive features for measuring urbanization and related human activities. First, the availability of the data at a high spatial resolution allows constructing spatially-detailed measures of urbanization. This makes it an attractive proxy indicator compared to the census and survey-based measures commonly used. Second, the nighttime light data provide a continuous index for detecting changes in the degree of urbanization, information which is absent from traditional dichotomous rural-urban indicators. Third, the nighttime data allows us to trace the dynamics of urbanization across time, a process which otherwise requires frequently repeated censuses and surveys. The DMSP-OLS data provide monthly nighttime light intensities. Using these nighttime light intensities enables monitoring and tracing of short-term dynamics in urbanization and differentiates urban areas by light intensity.

Early literature employed these data for delineating urban areas and urban settlements. These studies validated the use of nighttime imagery data to delineate urban settlements in the United States by comparing these data with census-based statistics (Imhoff et al. 1997, Sutton et al. 2010). Other researchers have used nighttime data as a marker of urbanization and related outcomes in different parts of the globe (e.g., Henderson et al 2003; Sutton et al. 2010; Storeygard 2016).

Despite the widespread and increasing use of the DMSP-OLS nighttime light intensity to approximate the levels and dynamics of urbanization, there are some caveats to the use of these data. First, because of the censoring of light intensities, the index may understate the level of light intensities for a small fraction of areas with high levels of lighting. Secondly, the nighttime light measure does not distinguish differences in light intensity caused by variations in infrastructures (e.g., factories and transportation hubs) or differences in energy conservation across areas. This implies that nighttime light data may not accurately capture levels of urbanization in areas where artificial lights are frequent, such as in areas of natural gas production where gas flaring may be common (see Elvidge et al. 2009). To address these potential problems with the use of night light data for Nigeria, we estimate our equations including and excluding the states of Nigeria that have major infrastructure complexes or are major gas and oil producers. Finally, although night light represents one of the fundamental urban amenities and, hence, can serve as a good proxy for urbanization, nighttime light intensity also captures general trends in economic activities (e.g., Chen and Nordhaus 2011; Henderson et al. 2012). These trends in local economic and infrastructural growth affect child nutritional outcomes and should be accounted for.

Although some studies use nighttime lighting for measuring urbanization, we are not aware of studies using nighttime light data for studying the implication of urbanization on child nutritional outcomes.

Urbanization and child nutritional outcomes

The link between urbanization and child nutritional outcomes, can be established within the UNICEF conceptual framework of the determinants of nutritional status in young children (UNICEF, 1990). The framework presents the immediate determinants of child nutritional which directly links the level of dietary intake and the health status, and nutritional outcomes of the young child. The quality of these immediate determinants, in turn, is determined by the underlying factors including quality of care, access to health services and food security status of the household. The framework also links these underlying factors as a function of how society is organized in terms of economic structure, political and ideological expectations, and the institutions through which activities within society are regulated, social values are met, and potential resources are converted into actual resources. Urbanization could influence child nutritional outcomes through its effect on the immediate, underlying and basic determinants of child nutritional outcomes.

First, urbanization may improve nutritional outcomes by shaping basic determinants such as institutions and economic structure. Urbanization may improve public infrastructure and technology to facilitate distribution of or access to a greater variety of foods and enables better resources for health facilities (Ruel et al., 2017; Stifel and Minten, 2017). Urbanization improves households' access to markets (by reducing transportation and transaction costs), information and technologies that can directly influence the underlying determinants of young child nutritional status. Nevertheless, asymmetries in urban dwellers' access to medical and related public health services could imply limited benefits to children in urban poor households (World Bank, 2013).

Second, urbanization may improve the well-being of households, thereby increasing the quality and quantity of diets. For example, Hirvonen (2016) finds that most of the rural-urban differences in dietary diversity can be explained by rural-urban differences in socioeconomic characteristics of households.

Third, urbanization may also improve child malnutrition by influencing more ''proximate'' and immediate causes of child nutritional status (e.g., Smith et al. 2005). Urbanization can enhance households' knowledge and caregiving practices, including feeding and child care practices. Some studies find that improving caregivers' nutritional knowledge can improve children's dietary diversity, particularly if complemented with access to markets (Black et al. 2013; Bhutta et al. 2013; Hirvonen et al. 2017). These are fundamental determinants of nutritional status which can substantially explain child nutritional outcomes as well as later economic outcomes in adulthood.

3. DATA SOURCES, MEASUREMENT AND DESCRIPTIVE RESULTS

Data sources

The data sources for this study are the 2008 and 2013 Nigerian DHSs. These are nationally representative surveys covering both urban and rural households.[2] As noted, the DHS data provide information on GIS coordinate data (latitude and longitude) of each cluster, which enables merging the nighttime light data from the DMSP-OLS and DHS clusters. The DHS datasets are not panel surveys that follow-up on the same households. Rather, they are repeated cross-sections. To address the change in urbanization and its implication on child nutrition, we construct cluster panel data using cluster GIS coordinate data and assign a 2008 DHS cluster to 2013 DHS households that are in the 2013 DHS clusters nearest to the 2008 DHS cluster. We use the Stata routine *geonear* to assign 2008 DHS cluster to the nearest clusters 2013 DHS cluster[3], using this method we find 560 from 886 clusters that appear in both years.[4] Original cluster coordinates of each survey cluster have been randomly displaced by up to two kilometers in any direction for urban areas, and up to five kilometers for rural areas, with one percent of all survey clusters randomly displaced by up to 10 kilometers. Overall, highlighting this displacement is just raising the issue that the locations are imprecisely specified, so one should not expect too much precision. Moreover, that urbanization and nightlights are both clustered phenomena reduce the significance on standard errors of any estimates due to the random displacement of cluster locations. The units of analysis for this study are all children under five years of age. The final sample comprises 18,888 children from the 2008 survey and 15,006 children from the 2013 survey.

Measurement of outcome variables used in the analysis

We employ height-for-age z-score (HAZ), weight-for-age z-score (WAZ), and related standard indicators for child malnutrition from these continuous HAZ and WAZ measures.[5] A child is considered stunted if the HAZ for the child is less than -2 (two standard deviations below the median measurement for the reference group), while a child with WAZ less than -2 is considered underweight (WHO 2006).

We follow the UNICEF framework and previous research to guide our choice of control variables. We control for detailed child and parental characteristics as well as households' access to various resources, including information. Specifically, our parametric empirical analysis controls for the sex and age of the child; the number of siblings in the household; detailed parental characteristics, including mother's

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[2]See the 2008 and 2013 NDHS reports for details on sampling strategies.

[3]We use 10 kilometers the average distance between the 2008 DHS clusters and the nearest 2013 DHS cluster

[4]We assume they are the same cluster if the distance between the 2008 and 2013 cluster points is less than 10 kilometers.

[5]Stunted or chronically malnourished children have experienced deficient linear growth that has failed to reach genetic potential. This results from the child receiving an inadequate diet over a long period or experiencing recurrent or chronic illness. A child being underweight can reflect a combination of experience of both chronic and acute nutritional shocks.

educational attainment, mother's age at first birth, and father's educational attainment; household's wealth index; and household's access to media, information and public health services. The household wealth index is constructed using principal components that combine ownership of durable goods, such as radio, bicycle, car, and housing characteristics (Rutstein and Johnson 2004).

Descriptive results

Table 1 provides a descriptive summary of the variables employed in our parametric and conditional regressions. The average values of child HAZ and child WAZ are -1.40 and -1.08, respectively in the pooled sample. On average across the two years, about 38 percent of the children in Nigeria are stunted and 25 percent of them are underweight, highlighting the pervasive levels of child undernutrition in Nigeria.

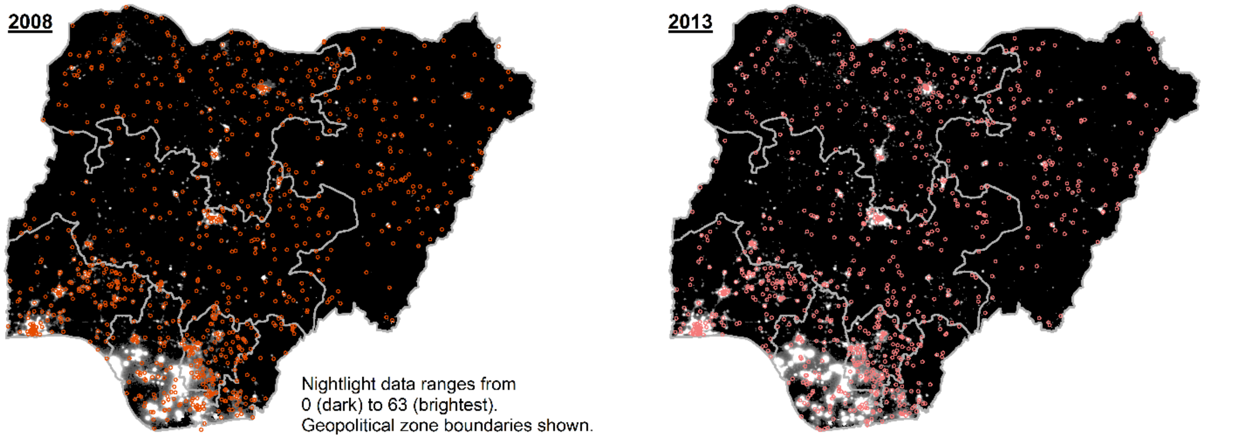
Table 1: Descriptive statistics of variables

Variable	Full sample mean (standard deviation)
Urbanization measure	
Nighttime light intensity (DN)	11.19 (18.48)
Outcome variables	
Height-for-age z score	-1.40 (2.05)
Child is stunted (HAZ<-2), 0/1	0.38 (0.49)
Weight-for-age z score	-1.08 (1.44)
Child is underweight (WAZ<-2), 0/1	0.25 (0.43)
Child and parental characteristics	
Boy child, 0/1	0.49 (0.50)
Age of child, months	28.54 (17.21)
Birth order of child for mother, number	3.90 (2.55)
Mother's educational attainment, years	5.08 (5.26)
Age of mother at first birth, years	19.52 (4.33)
Father's educational attainment, years	6.30 (5.77)
Wealth indicator	
Poorest quintile wealth index, 0/1	0.21 (0.41)
Poorer quintile wealth index, 0/1	0.22 (0.41)
Middle quintile wealth index, 0/1	0.19 (0.39)
Richer quintile wealth index, 0/1	0.19 (0.39)
Richest quintile wealth index, 0/1	0.19 (0.39)
Access to water, sanitation, electricity and health facilities	
Household has own TV, 0/1	0.42 (0.49)
Reads newspaper, 0/1	0.16 (0.37)
Visited family planning agents, 0/1	0.10 (0.30)
Observations	33,850

Source: NDHS 2013, NDHS 2008, NOAA's National Geophysical Data Center
Note: standard deviations in parentheses.

As discussed, our measure of urbanization (nighttime light intensity) is reported as a digital number (DN), an integer ranging from 0 to 63. Average nighttime light intensity for Nigeria across the two years, 2008 and 2013, is 11.19 DN. Figure 1 presents the geographic distribution of nighttime light (measured at the NDHS cluster levels) for 2008 and 2013. The nighttime light increases as we move from north to south in Nigeria.

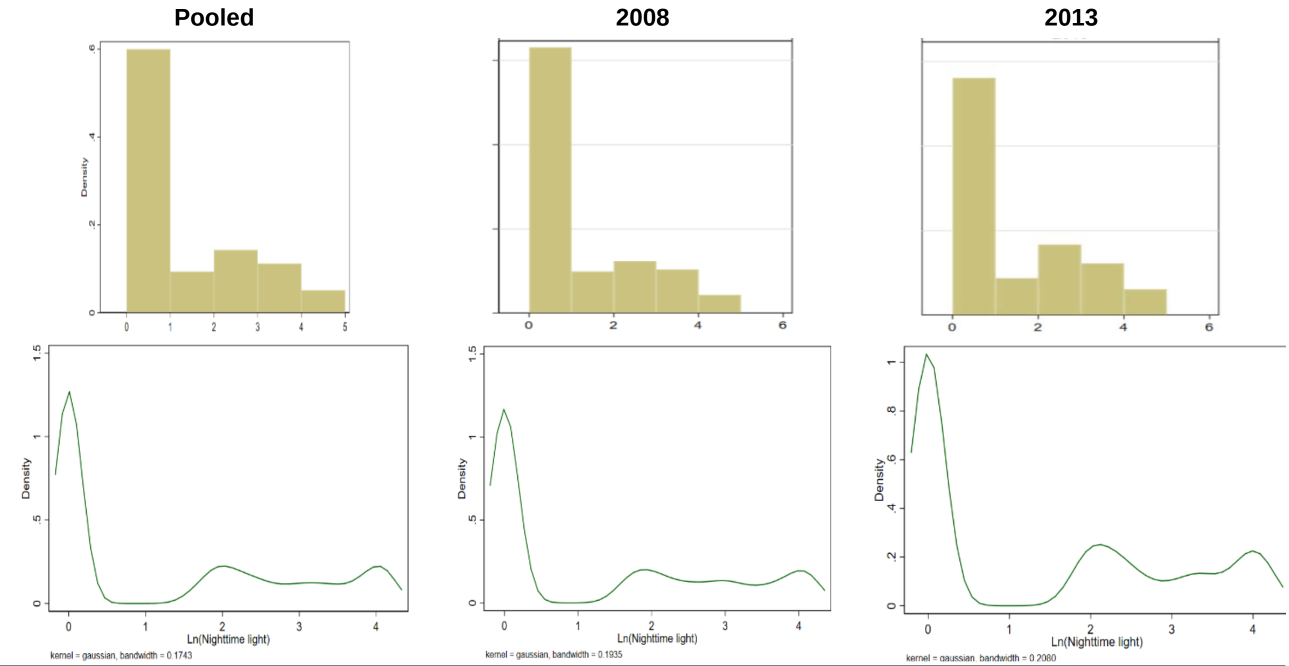
Figure 1: Nightlight intensity and Nigeria DHS survey cluster locations for both years, 2008 and 2013



Source: Image and data processing by NOAA's National Geophysical Data Center. DMSP data collected by the United States Air Force Weather Agency.

Figure 2 provides the distribution of nighttime light intensities across both years. Average nighttime light intensity across Nigeria increased by about 23 percent from 2008 to 2013. The proportion of households with ln(nighttime light intensity) less than 1.5 reduced from 63 percent in 2008 to 56 percent in 2013.

Figure 2: Distribution and kernel density estimation of nighttime light intensity (ln(nighttime light intensity DN)) in Nigeria in 2008 and 2013 and pooled

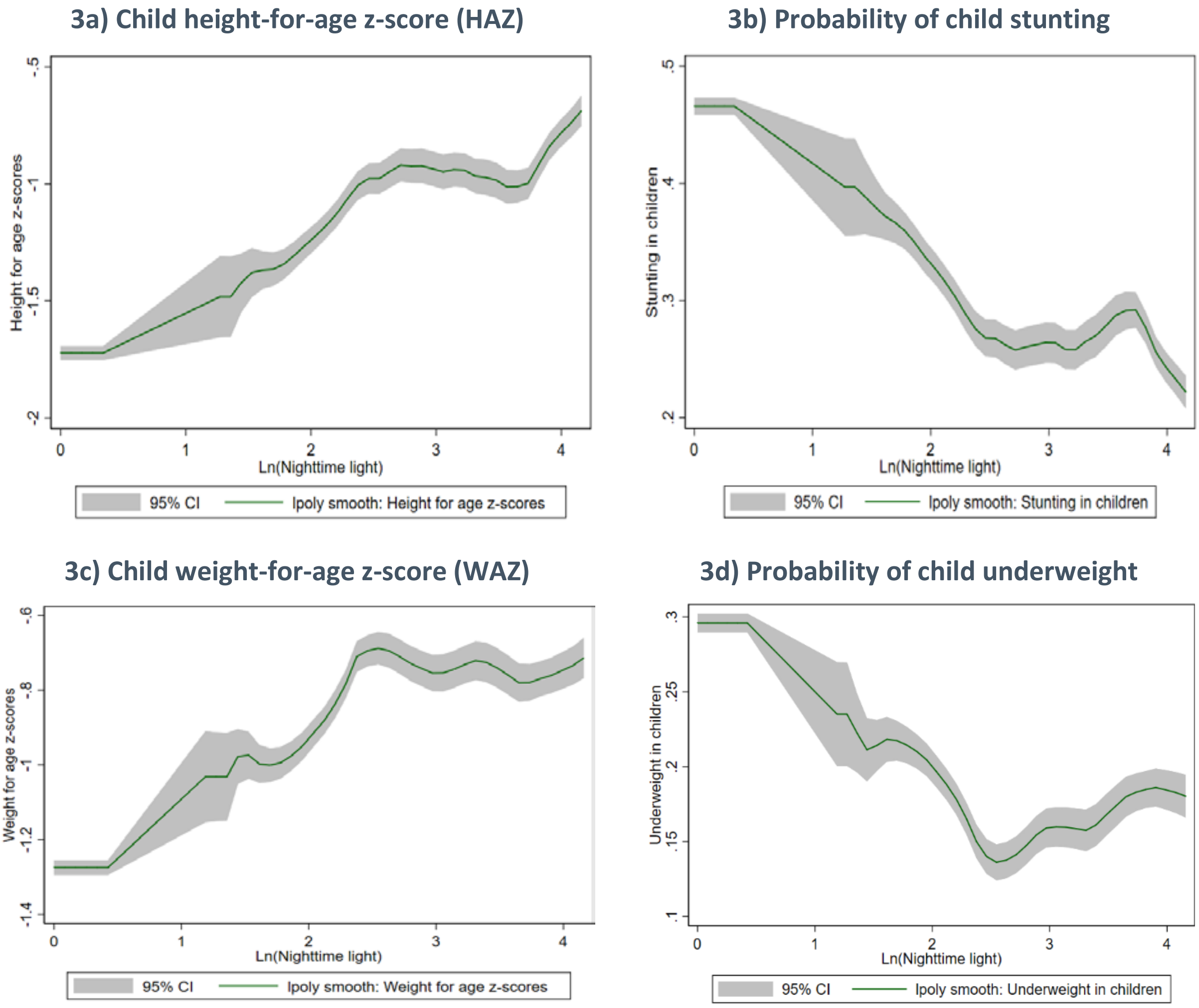


Source: Authors' analysis of NDHS 2008, NDHS 2013, NOAA's National Geophysical Data Center.

Nonparametric associations between urbanization and child nutritional outcomes

Before considering parametric and conditional regressions, we present some nonparametric and unconditional regressions characterizing the relationship between urbanization as proxied by nightlight and child nutritional outcomes. These exercises help us uncover potential nonlinearities in these relationships. For this purpose, we employ nonparametric local polynomial regressions and threshold estimation techniques to explore relationships between nighttime light intensity and child nutritional outcomes. The threshold estimation technique enables the detection of thresholds that identify linear regression coefficients that statistically differ across the distribution of the nighttime lights measure of urbanization.[6] Figure 3 illustrates nonparametric local polynomial regression results for four child nutritional outcomes – HAZ, stunting, WAZ, and underweight.

Figure 3: Plots of polynomial associations between nighttime light and child nutrition indicators



Source: Analysis of NDHS 2013, NDHS 2008, NOAA's National Geophysical Data Center.

Figure 3a plots associations between HAZ and urbanization, while Figure 3b provides similar plots for the relationship between (probability of) stunting and urbanization. These figures show a strong and positive (negative) association between urbanization and HAZ (stunting). Importantly, the magnitude and strength of these relationships varies significantly across the distribution (range) of urbanization as proxied by light intensity. In both figures, the association between nighttime light intensity and improved nutritional outcomes is strongly positive up to an intermediate stage. Thereafter, the relationship weakens before again reemerging towards the end of the distribution of nighttime light intensity. Similar patterns are observed for children's WAZ and probability of underweight with an increasingly positive (negative) relationship between urbanization and WAZ (probability of underweight) up to an intermediate level of urbanization (Figures 3c and 3d). These relationships then weaken in the middle of the range before strengthening again at the upper end.

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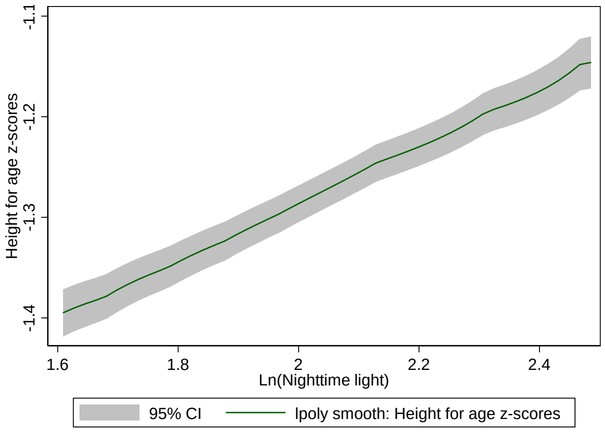
[6]In this approach, we use Hansen's threshold estimation techniques to test for the presence of the threshold(s) that split urbanization into different stages (Hansen 2000). This threshold estimation selects the optimal number of thresholds based on model fit and the usual information criteria.

These nonparametric local polynomial regression results imply nonlinear relationships between urbanization and child nutritional outcomes across various stages of urbanization. The consistent patterns observed in Figure 3 suggest a strong relationship between urbanization and ln(nighttime light) between 1.5 and 2.5 and then milder associations for the range thereafter. Overall, we find that child nutrition outcomes improve as nighttime light intensities increase though at different rates depending on the nighttime light intensity level.

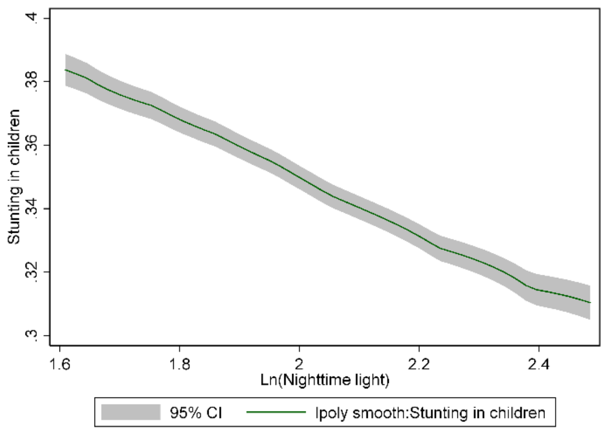
We further investigate whether this strong relationship between urbanization and nighttime light intensity between ln nighttime light) from 1.5 to 2.5 is driven by smoothing between values or whether the region where the gradient appears steep is because it has a lot of mass. We first run non-parametric local polynomial regression on the relationship between child nutritional outcomes and nighttime light focusing on this region. The nonparametric results in Figure 4 imply a strong and positive (negative) association between urbanization and HAZ (stunting).

Figure 4: Plots of polynomial associations between nighttime light and child nutrition indicators for ln(nighttime light) between 1.5 and 2.5

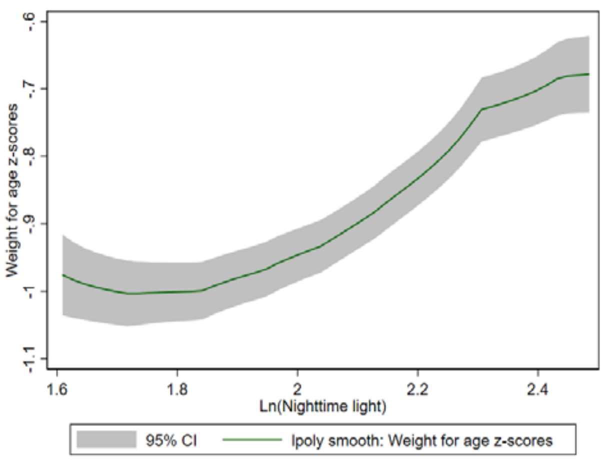
4a) Child height-for-age z-score (HAZ)



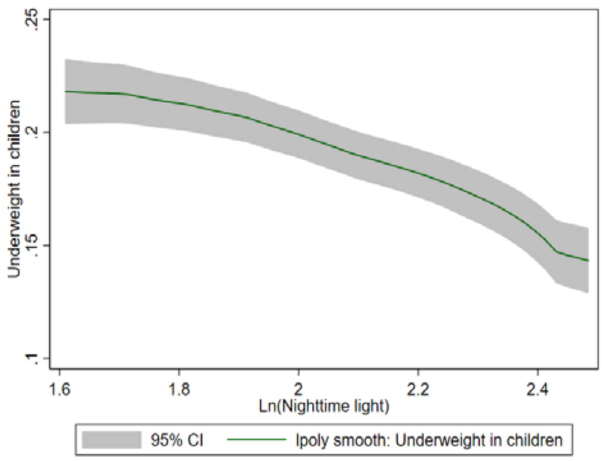
4b) Probability of child stunting



4c) Child weight-for-age z-score (WAZ)



4d) Probability of child underweight



Source: Analysis of NDHS 2013, NDHS 2008, NOAA's National Geophysical Data Center.

Similarly, we also estimate simple parametric regressions of urbanization and child nutritional outcomes, both for the full sample as well as for subsample of this region where ln (Nighttime light) ranges from 1.5 to 2.5. The subsample is about 18 percent of the total sample of the study. The results (Table 2) indicate strong and robust relationship between levels of urbanization and child nutritional outcomes.

Table 2: Urbanization and child HAZ and child stunting for ln(nighttime light) between 1.5 to 2.5

	Pooled	1.5 to 2.5 ln(nighttime light)	Pooled	1.5 to 2.5 ln(nighttime light)
	Child HAZ		Child stunting	
ln(nighttime light)	0.247***	0.757***	-0.060***	-0.186***
	(0.016)	(0.166)	(0.003)	(0.039)
Constant	-1.720***	-2.736***	0.461***	0.700***
	(0.031)	(0.326)	(0.006)	(0.081)
Observations	33,850	6,153	33,850	6,153
	Child WAZ		Child underweight	
ln(nighttime light)	0.159***	0.521***	-0.038***	-0.139***
	(0.011)	(0.157)	(0.004)	(0.035)
Constant	-1.265***	-1.948***	0.292***	0.473***
	(0.019)	(0.336)	(0.007)	(0.074)
Observations	33,850	6,153	33,850	6,153

Sources: Analysis of NDHS 2013, NDHS 2008, NOAA's National Geophysical Data Center.
Notes: Standard errors are clustered at village level and given in parentheses. *** p<0.01; ** p<0.05; * p<0.10

Threshold estimations, shown in Table 3, identify three thresholds and split the sample into four segments for all outcome variables. For child HAZ, urbanization is associated with increased child HAZ in all four segments with the strength of relationship varying across segments. For HAZ, the slope in the second segment of the distribution is about six times the slope in the first segment of the urbanization distribution, while the slope in the fourth segment is almost five times the coefficient in the third segment of the distribution. Similar patterns are observed for the remaining outcomes measuring child nutritional outcomes.[7]

[7]We can translate the thresholds estimated in Table 3 into nighttime light intensities.

Table 3: Threshold estimation on the relationship between urbanization and child nutrition

	Height-for-age Z-score	Stunting in child	Weight -for-age Z- score	Underweight in child
Threshold 1	1.71	1.69	1.79	1.79
Threshold 2	2.71	2.64	2.08	2.08
Threshold 3	3.56	3.56	3.47	3.47
Segment 1	**Coefficients**	**Coefficients**	**Coefficients**	**Coefficients**
ln(nighttime light)	0.209***	-0.059***	0.187***	-0.054***
	(0.018)	(0.004)	(0.021)	(0.006)
Constant	-1.724***	0.463***	-1.275***	0.296***
	(0.014)	(0.003)	(0.010)	(0.003)
Segment 2				
ln(nighttime light)	0.400*	-0.113*	1.443***	-0.424***
	(0.215)	(0.058)	(0.452)	(0.138)
Constant	-1.861***	0.526***	-3.902***	1.070***
	(0.518)	(0.138)	(0.902)	(0.275)
Segment 3				
ln(nighttime light)	0.220	-0.055	-0.027	0.006
	(0.156)	(0.034)	(0.042)	(0.014)
Constant	-1.658***	0.439***	-0.633***	0.129***
	(0.496)	(0.106)	(0.118)	(0.039)
Segment 4				
ln(nighttime light)	1.112***	-0.281***	0.450***	-0.049
	(0.206)	(0.049)	(0.143)	(0.035)
Constant	-5.221***	1.370***	-2.536***	0.378***
	(0.816)	(0.195)	(0.569)	(0.137)

Source: Analysis of NDHS 2013, NDHS 2008, NOAA's National Geophysical Data Center.
Notes: Observations: 33,850. Standard errors are clustered at village level and given in parentheses. *** p<0.01; ** p<0.05; * p<0.10

Following the above nonparametric and threshold estimation, we roughly classify and compare the distribution of child nutritional outcomes and other observable covariates across three stages of urbanization (Table 4). This is pursued in the interest of comparing the distribution of socioeconomic determinants of child nutritional outcomes in the spirit of similar empirical exercises in the literature (e.g., Garrett and Ruel 1999; Smith et al. 2005; Hirvonen 2016). The first stage of urbanization is in areas with a logarithmic nighttime light intensity below ln(DN)1.5 – we refer to this as ''rural''. The second stage includes areas with logarithmic nighttime light intensity between 1.5 and 2.5, which we refer to as ''urbanizing'', while the third stage covers areas with logarithmic nighttime light intensity above 2.5, which we refer to as ''urbanized''. Comparing the distribution of our outcomes as well as their socioeconomic determinants across these three stages of urbanization show that early stages of urbanization may more strongly influence child nutritional outcomes than more advanced levels of urbanization. We can observe that the differences in our outcomes and their socioeconomic determinants are stronger for relatively early stage urbanization than for more advanced stages of urbanization.

Table 4: Distribution of outcomes and covariates across stages of urbanization

Variable	Rural	Urbanizing	Urban	Difference between rural and urbanizing	Difference between urban and urbanizing
Urbanization measure					
Nighttime light (DN)	0.00	7.04	37.92	-7.04***	-30.88***
Ln(nighttime light (DN))	0.00	2.05	3.54	-2.05***	-1.49***
Outcome variables					
Height-for-age z score	-1.72	-1.21	-0.87	-0.52***	-0.34***
Child is stunted (HAZ<-2), 0/1	0.47	0.33	0.25	0.14***	0.07***
Weight-for-age z score	-1.30	-0.89	-0.74	-0.41***	-0.15***
Child is underweight (WAZ<-2), 0/1	0.31	0.19	0.17	0.12***	0.01***
Child and parental characteristics					
Child is boy, 0/1	0.49	0.50	0.49	0.00	0.01
Age of child, months	28.29	28.64	29.03	-0.35***	-0.38***
Birth order of child for mother, number	4.19	3.73	3.40	0.46**	0.33**
Mother's educational attainment, years	2.73	6.68	8.95	-3.95***	-2.28**
Age of mother at first birth, years	18.47	20.03	21.38	-1.56***	-1.35**
Father's educational attainment, years	4.27	7.98	10.32	-3.71***	-2.35**
Wealth indicator					
Poorest quintile wealth index, 0/1	0.36	0.06	0.01	0.30***	0.06*
Poorer quintile wealth index, 0/1	0.33	0.14	0.03	0.18***	0.12**
Middle quintile wealth index, 0/1	0.20	0.26	0.10	-0.06*	0.16***
Richer quintile wealth index, 0/1	0.09	0.34	0.30	-0.26***	0.05**
Richest quintile wealth index, 0/1	0.02	0.19	0.56	-0.17***	-0.38***
Access to water, sanitation, electricity & health facilities					
Household has own TV, 0/1	0.18	0.55	0.83	-0.38***	-0.27***
Reads newspaper, 0/1	0.05	0.21	0.36	-0.16***	-0.15***
Visited family planning agents, 0/1	0.06	0.13	0.17	-0.07***	-0.04*

Source: Analysis of NDHS 2013, NDHS 2008, NOAA's National Geophysical Data Center
Notes: Standard errors are clustered at village-level. *** p<0.01; ** p<0.05; * p<0.10

4. PARAMETRIC AND CONDITIONAL REGRESSIONS

Urbanization is a complex process that is not amenable to imposed randomization and for which natural experiments generating exogenous variations are, at best, rare. Thus, quantifying the overall effects of urbanization may suffer from endogeneity problems arising from omitted attributes and measurement problems. In view of these empirical challenges and features, we employ alternative econometric approaches that exploit the cross-sectional as well as longitudinal variations in our measure of urbanization (nighttime light intensity). Following the preliminary evidence from our previous nonparametric and unconditional regressions, we allow for sufficient nonlinearities in our estimations by including higher order polynomial terms associated with nighttime light. Considering a latent nutrition production function, we estimate the following longitudinal regression:

$$Y_{ict} = \sum_{n=1}^{4} \beta_n (ln\_night\_light_{ct})^n + \theta_1 T_{ic} + \theta_2' X_{ict} + \theta_3(cluster_c) + \varepsilon_{ict} \quad (1)$$

Where $\mathrm{X_{ict}}$$Y_{ict}$ stands for nutritional outcome of child *i* from cluster (village) *c* and round *t*. *ln_night_light*$_{ct}$ $\mathrm{X_{ict}}$stands for an index measuring nighttime intensity at cluster level and for two time periods. To facilitate interpretation of our linear and nonlinear terms in our regressions, we first centered (de-mean) our key variable of interest, the natural logarithmic values of nighttime light.[8] T_{ic} represents year dummies to indicate the year in which the child was surveyed, which may capture aggregate shifts in nutritional status or correlated shifts in our explanatory variables. $\mathrm{X_{ict}}X_{ict}$ represents the aforementioned vector of child and parental characteristics that influence child nutrition. *Cluster* represents a set of (more than 56) enumeration area (EA) dummies that may capture time-invariant differences in nutritional outcomes among children living in different EAs. As our main explanatory variable of interest (nighttime light intensity) varies at the EA level and we observe these at two periods, the *cluster* dummies in equation (1) implement EA-level fixed effects estimation. Thus, the parameters associated with nighttime light in equation (1) identify the implication of potential dynamics in urbanization on nutritional outcomes of children, effectively exploiting longitudinal variations in nighttime light intensity.

The estimation process involves a progressive inclusion of important variables. We first run regressions of children's nutrition outcomes as a function of nightlight, and later extend the specification by adding child and parental characteristics as well as EA fixed effects. By doing so, we gain insights on the role of some of the potential channels through which urbanization can affect child nutrition. For instance, by including or excluding household socioeconomic and wealth status, we may judge covariations between households' wealth and urbanization as proxied by nightlight and, hence, their implications for the relationships between urbanization and child nutrition. Children living in the same village are exposed to similar markets for food and infrastructure, implying that they may share some unobservable effects. Thus, we cluster standard errors by EA.

5. RESULTS AND DISCUSSION

Table 5 presents pooled regression results for children's HAZ. We also generate indicator (dummy) variables for those children who are stunted and provide linear probability model estimates for this outcome in Table 6. In the first columns of Tables 5 and 6, we run simple unconditional regressions of children's HAZ score on nighttime light intensity and the time dummy capturing the survey round for the sample child. We then extend this specification by including a long-list of child-level and household-level characteristics. The first two columns are based on pooled regressions while the last two columns include cluster-level fixed effects.

The estimation results in Tables 5 and 6 consistently show that urbanization is strongly associated with improved nutritional outcomes. In all estimations, nighttime light intensity strongly and consistently predicts children's HAZ score as well as children's probability of stunting.[9] The coefficients associated with the higher order polynomial terms of nighttime light show substantial nonlinearity in the relationship between urbanization and children's growth measured by HAZ and prevalence of stunting. These nonlinearities are consistent both in the cross-sectional and longitudinal variations of nighttime light data as well as across both measures of child growth. For instance, the estimates associated with the linear term in the fixed-effects models presented in Table 6 (columns 3 and 4) imply that an increase in the sample average level of urbanization by 10 percent is associated with a 1.9 to 2.4 percentage point reduction in the probability of stunting.

The estimates associated with the higher-order polynomial terms indicate the strength and direction of these associations across various distributions of urbanization. For instance, the estimates associated with the quadratic terms in Table 5 (Table 6) show that the positive (negative) association

[8] As we have a skewed distribution of nighttime light (see Figure 2), we also considered inverse hyperbolic sine as an alternative transformation for the nighttime light intensity. Using this transformation provides similar results.

[9] These results are also robust across a battery of robustness exercises, including sample exclusion of major states with major infrastructures as well as those states running major oil productions.

between nighttime light intensity and HAZ (stunting) strengthens up to some level of urbanization. The third and fourth order polynomials in Tables 5 and 6 imply that this pattern then slows with increasing urbanization. These patterns are also broadly consistent across both measures of child growth.

Table 5: Urbanization and child height-for-age z-score (HAZ)

	(1)	(2)	(3)	(4)
Explanatory variables	**Pooled**	**Pooled**	**Village fixed-effects**	**Village fixed-effects**
ln(nightlight)-centered	1.083***	0.447**	1.109***	0.955***
	(0.220)	(0.187)	(0.221)	(0.212)
ln(nightlight)-centered-square	0.199***	0.084	0.460***	0.423***
	(0.069)	(0.061)	(0.073)	(0.070)
ln(nightlight)-centered-cubic	-0.489***	-0.232**	-0.574***	-0.546***
	(0.129)	(0.109)	(0.130)	(0.124)
ln(nightlight)-centered-quad	0.120***	0.058**	0.120***	0.114***
	(0.032)	(0.026)	(0.032)	(0.030)
Year 2013	0.142***	0.121***	0.226***	0.183***
	(0.042)	(0.036)	(0.026)	(0.025)
Boy		-0.212***		-0.224***
		(0.020)		(0.020)
Age child		-0.100***		-0.101***
		(0.003)		(0.002)
Age child square		0.132***		0.133***
		(0.005)		(0.004)
Birth order of child (for mother)		0.011		0.007
		(0.007)		(0.006)
Mother’s educational attainment		0.040***		0.022***
		(0.004)		(0.004)
Mother’s age at first birth		0.017***		0.010***
		(0.003)		(0.003)
Father’s educational attainment		0.004		0.005**
		(0.003)		(0.003)
Poorer quintile wealth index		0.151***		0.137***
		(0.043)		(0.034)
Middle quintile wealth index		0.321***		0.281***
		(0.050)		(0.041)
Richer quintile wealth index		0.430***		0.374***
		(0.063)		(0.058)
Richest quintile wealth index		0.649***		0.555***
		(0.076)		(0.071)
Household has own TV		0.003		0.021
		(0.042)		(0.037)
Reads newspaper		0.107***		0.108***
		(0.038)		(0.037)
Visited by family planning worker		0.089**		0.048
		(0.039)		(0.038)
Constant	-2.005***	-1.125***	-2.472***	-1.495***
	(0.154)	(0.159)	(0.162)	(0.169)

Source: Analysis of NDHS 2013, NDHS 2008, NOAA’s National Geophysical Data Center.
Notes: Observations: 33,850. Standard errors are clustered at village level and given in parentheses. *** p<0.01; ** p<0.05; * p<0.10

Table 6: Urbanization and stunting in children

Explanatory variables	(1) Pooled	(2) Pooled	(3) Village fixed-effects	(4) Village fixed-effects
ln(nightlight)-centered	-0.262***	-0.103**	-0.231***	-0.188***
	(0.049)	(0.040)	(0.053)	(0.052)
ln(nightlight)-centered-square	-0.045***	-0.017	-0.090***	-0.079***
	(0.016)	(0.013)	(0.017)	(0.017)
ln(nightlight)-centered-cubic	0.116***	0.053**	0.110***	0.102***
	(0.029)	(0.023)	(0.031)	(0.030)
ln(nightlight)-centered-quad	-0.028***	-0.013**	-0.022***	-0.021***
	(0.007)	(0.006)	(0.008)	(0.007)
Year 2013	-0.047***	-0.041***	-0.064***	-0.054***
	(0.010)	(0.008)	(0.006)	(0.006)
Boy child		0.042***		0.045***
		(0.005)		(0.005)
Age child		0.019***		0.019***
		(0.001)		(0.001)
Age child square		-0.027***		-0.027***
		(0.001)		(0.001)
Birth order of child (for mother)		-0.002		-0.002
		(0.002)		(0.002)
Mother’s educational attainment		-0.011***		-0.007***
		(0.001)		(0.001)
Mother’s age at first birth		-0.004***		-0.002***
		(0.001)		(0.001)
Father’s educational attainment		-0.001*		-0.001*
		(0.001)		(0.001)
Poorer quintile wealth index		-0.039***		-0.036***
		(0.010)		(0.008)
Middle quintile wealth index		-0.083***		-0.073***
		(0.012)		(0.010)
Richer quintile wealth index		-0.125***		-0.116***
		(0.015)		(0.014)
Richest quintile wealth index		-0.155***		-0.143***
		(0.018)		(0.017)
Household owns TV		0.002		-0.002
		(0.010)		(0.009)
Reads newspaper		-0.007		-0.009
		(0.009)		(0.009)
Visited by family planning worker		-0.028***		-0.016*
		(0.009)		(0.009)
Constant	0.523***	0.419***	0.594***	0.462***
	(0.035)	(0.034)	(0.039)	(0.041)

Source: Analysis of NDHS 2013, NDHS 2008, NOAA’s National Geophysical Data Center.
Notes: Observations: 33,850. Standard errors are clustered at village level and given in parentheses. *** p<0.01; ** p<0.05; * p<0.10

Establishing such consistent patterns and relationships between urbanization and child nutritional outcomes across alternative methods and specifications may suggest that urban expansion induces (nonlinear) nutritional transitions. Interestingly, the non-linear patterns we observe in our data are consistent with evolving evidence on the effectiveness of secondary towns and big cities. Evolving studies are showing that expansion of towns can be more effective in reducing poverty levels than those of mega cities (e.g., Christiaensen and Todo 2014; Christiaensen and Kanbur 2017; Gibson et al. 2017). Using similar night light data for measuring levels of urbanization, Gibson et al. (2017) show that growth of towns is more effective in reducing national poverty than the growth of big cities.

Comparing the unconditional and conditional estimates in Table 5 and 6 provides insights on potential mechanisms through which urbanization can lead to higher nutritional outcomes. For instance, the estimates on the effect of nightlight intensity in the pooled regressions almost halve when we control for socioeconomic and wealth indicators, suggesting, as expected, that part of the link between urbanization and child nutrition is mediated through these channels. This is consistent with previous evidence highlighting that much of the rural-urban differences in child nutritional outcomes can be explained by differences in socioeconomic characteristics of in rural and urban areas (e.g., Smith et al. 2005; Hirvonen 2016; O'Donnell et al. 2009). Nevertheless, the estimated coefficients on the nightlight polynomial terms remain sizeable and strongly statistically significant even after controlling for these socioeconomic characteristics.

The magnitude and precision of the estimates are plausibly related to the precision with which nightlight proxies urbanization as compared with a simply rural/urban dummy variable. As noted in the Introduction, a rural/urban dummy captures only one step in an essentially continuous urbanization process. Also, rural/urban definitions are frequently out of date.[10] These measurement errors may generate significant attenuation bias, which nightlight avoids. The result strengthens the conclusion that children are, on average, better nourished in urban zones even after controlling for a host of observables, such as education of parents and household wealth. Nightlight is proxying for a series of difficult to observe environmental and caregiving factors that lead to improved child nutrition.

The remaining associations between child nutritional outcomes and parent characteristics are intuitive and consistent with previous evidence. For instance, girls have generally higher HAZ than boys, which is a common finding (e.g., Black et al. 2013, Alderman and Headey 2017a). Consistent with the existing literature on child nutrition in developing countries, older children are more likely to have lower nutritional outcomes (e.g., Behrman and Taubman 1986). We also find mother’s age at first birth is strongly and positively associated with improved nutritional outcomes (e.g., Fall et al. 2015).

Tables 5 and 6 further document the importance of parental characteristics. Education may, among other contributions, enable women to provide appropriate care for their children (Alderman and Headey 2017). We find significant association between parents’ educational attainment and child nutritional outcomes. As expected, wealth of parents significantly predicts higher nutritional outcomes for children. Finally, parents’ access to media and health services are positively associated with higher HAZ.

We also run these estimations by splitting the sample using children’s age (0-5 months; 6-23 months; 24-59 months). We observe similar patterns for those children aged 24-59 months, but not for those children aged 0-5 months (see Appendix Table 1). This suggests that children aged 0-5 months may not realize the direct dietary benefits of urbanization, as they are probably consuming only breastmilk (Alderman and Headey 2017b). This is consistent with the evidence in Figure 4 which highlights that slightly older children benefit more from urban amenities and infrastructures.

In Tables 7 and 8 we run conditional and unconditional regressions of children’s WAZ on our measure of urbanization and its higher order polynomial terms. The results in Table 7 employ continuous values of WAZ score, while those in Table 8 use an indicator variable for children who are underweight. Both tables show that urbanization strongly predicts children’s WAZ and probability of being underweight.

[10]Inconsistent definitions of rural and urban zones across countries provide an additional source of measurement error in cross country analysis that nightlight would avoid.

Table 7: Urbanization and child weight-for-age z-score (WAZ)

Explanatory variables	(1) Pooled	(2) Pooled	(3) Village fixed-effects	(4) Village fixed-effects
ln(nightlight)-centered	0.810***	0.290*	0.367**	0.338*
	(0.208)	(0.171)	(0.152)	(0.149)
ln(nightlight)-centered-square	0.159**	0.073	0.217***	0.180***
	(0.064)	(0.054)	(0.050)	(0.049)
ln(nightlight)-centered-cubic	-0.365***	-0.158	-0.169*	-0.141
	(0.124)	(0.102)	(0.089)	(0.087)
ln(nightlight)-centered-quad	0.085***	0.036	0.025	0.020
	(0.031)	(0.025)	(0.022)	(0.021)
Year (round) dummy	-0.173***	-0.187***	-0.112***	-0.146***
	(0.037)	(0.030)	(0.018)	(0.018)
Child is boy		-0.113***		-0.117***
		(0.015)		(0.014)
Age child		-0.036***		-0.037***
		(0.002)		(0.002)
Age child squared		0.046***		0.048***
		(0.003)		(0.003)
Birth order of child (for mother)		-0.008*		-0.008*
		(0.005)		(0.005)
Mother's educational attainment		0.042***		0.025***
		(0.003)		(0.002)
Mother's age at first birth		0.013***		0.007***
		(0.002)		(0.002)
Father's educational attainment		0.010***		0.008***
		(0.002)		(0.002)
Poorer quintile wealth index		0.146***		0.100***
		(0.034)		(0.024)
Middle quintile wealth index		0.282***		0.237***
		(0.040)		(0.029)
Richer quintile wealth index		0.297***		0.261***
		(0.052)		(0.041)
Richest quintile wealth index		0.418***		0.372***
		(0.062)		(0.050)
Household owns TV		0.011		0.041
		(0.030)		(0.026)
Reads newspaper		0.020		0.033
		(0.028)		(0.026)
Visited by family planning worker		0.027		0.011
		(0.030)		(0.027)
Constant	-1.374***	-1.323***	-1.398***	-1.223***
	(0.149)	(0.139)	(0.111)	(0.119)

Source: Analysis of NDHS 2013, NDHS 2008, NOAA's National Geophysical Data Center.
Notes: Observations: 33,850. Standard errors are clustered at village level and given in parentheses. *** p<0.01; ** p<0.05; * p<0.10

Table 8: Urbanization and underweight in children

Explanatory variables	(1) Pooled	(2) Pooled	(3) Village fixed-effects	(4) Village fixed-effects
ln(nightlight)-centered	-0.201***	-0.066	-0.099**	-0.065
	(0.054)	(0.044)	(0.047)	(0.047)
ln(nightlight)-centered-square	-0.039**	-0.018	-0.055***	-0.046***
	(0.016)	(0.013)	(0.015)	(0.015)
ln(nightlight)-centered-cubic	0.088***	0.036	0.045	0.039
	(0.032)	(0.026)	(0.028)	(0.027)
ln(nightlight)-centered-quad	-0.020**	-0.007	-0.006	-0.005
	(0.008)	(0.007)	(0.007)	(0.007)
Year (round) dummy	0.026**	0.030***	0.008	0.017***
	(0.010)	(0.009)	(0.005)	(0.005)
Child is boy		0.025***		0.027***
		(0.005)		(0.005)
Age of child		0.006***		0.007***
		(0.001)		(0.001)
Age of child square		-0.009***		-0.010***
		(0.001)		(0.001)
Birth order of child (for mother)		0.004**		0.004**
		(0.002)		(0.001)
Mother's educational attainment		-0.012***		-0.007***
		(0.001)		(0.001)
Mother's age at first birth		-0.003***		-0.001**
		(0.001)		(0.001)
Father's educational attainment		-0.003***		-0.002***
		(0.001)		(0.001)
Poorer quintile wealth index		-0.049***		-0.034***
		(0.010)		(0.007)
Middle quintile wealth index		-0.087***		-0.074***
		(0.012)		(0.009)
Richer quintile wealth index		-0.098***		-0.083***
		(0.015)		(0.013)
Richest quintile wealth index		-0.114***		-0.104***
		(0.017)		(0.016)
Household owns TV		0.003		-0.005
		(0.009)		(0.008)
Reads newspaper		0.022***		0.013
		(0.007)		(0.008)
Visited by family planning worker		-0.021**		-0.011
		(0.008)		(0.008)
Constant	0.318***	0.373***	0.332***	0.340***
	(0.038)	(0.036)	(0.034)	(0.037)

Source: Analysis of NDHS 2013, NDHS 2008, NOAA's National Geophysical Data Center.
Notes: Observations: 33,850. Standard errors are clustered at village level and given in parentheses. *** p<0.01; ** p<0.05; * p<0.10

However, as with children's height, the relationship involves significant nonlinearities, indicating that that these types of nonlinearities and dynamics are evident across alternative measures of child growth and nutritional outcomes. These results are robust across a battery of robustness exercises, including excluding from the analysis those states of Nigeria with significant gas flaring affecting the nightlight data captured.[11]

6. CONCLUDING REMARKS

This study investigates the linkages between urbanization and child malnutrition along a gradient of population agglomeration intensity as proxied by nightlight. Our empirical analysis reveals several key insights on these links. Most importantly, despite the generally strong positive association between urbanization and child nutritional outcomes, every stage of urbanization is not equally important in producing improved nutritional outcomes. Our non-parametric and parametric estimations uncover nonlinear relationships between urbanization and child nutritional outcomes. Broadly, high returns to urbanization are present at early stages, with relatively low returns to more advanced stages of urbanization. These nonlinear relationships are apparent in all our estimations.

From a methodological point of view, these results imply that satellite nightlight data is likely to be preferred over rural-urban dichotomous indicators based on census or administrative data. From a policy vantage point, achieving even moderate agglomeration of the population appears to provide benefits. Consistent with the conclusions of Christiaensen and Todo (2014) and Christiaensen et al. (2013), the results suggest that the rural non-farm economy and secondary towns deserve serious consideration as governments consider investments likely to influence the pattern of urbanization. Channeling the pattern of urbanization such that larger shares of the population attain the rapid agglomeration gains from early-stage urbanization should strengthen the improvements in child nutritional outcomes that urbanization provides in Nigeria and likely elsewhere in sub-Saharan Africa.

[11]We rerun the model by excluding six states in Nigeria in which gas flaring from Nigeria's petroleum production occurs - Akwa Ibom, Delta, Rivers, Bayelsa, Ondo, and Lagos. The results are available from the authors on request.

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APPENDIX

Appendix Table 1: Urbanization and child height-for-age z-score (HAZ) for children aged 0 to 5 months, 6 to 23 months, and 24 to 59 months

Explanatory variables	0 to 5 months	6 to 23 months	24 to 59 months
ln(nightlight)-centered	-0.637	0.504	1.398***
	(0.918)	(0.423)	(0.262)
ln(nightlight)-centered-square	0.068	0.304**	0.527***
	(0.309)	(0.139)	(0.086)
ln(nightlight)-centered-cubic	0.331	-0.294	-0.777***
	(0.537)	(0.248)	(0.153)
ln(nightlight)-centered-quad	-0.102	0.053	0.169***
	(0.130)	(0.060)	(0.037)
Year 2013, 0/1	0.422***	0.350***	0.081***
	(0.105)	(0.049)	(0.031)
Boy, 0/1	-0.242***	-0.364***	-0.134***
	(0.084)	(0.041)	(0.025)
Age child, months	-0.364***	-0.241***	0.023**
	(0.108)	(0.025)	(0.011)
Age child square	3.990**	0.538***	-0.024*
	(1.893)	(0.086)	(0.013)
Birth order of child (for mother)	0.025	0.004	-0.000
	(0.026)	(0.012)	(0.008)
Mother's educational attainment, years of education	-0.013	0.027***	0.027***
	(0.015)	(0.007)	(0.004)
Mother's age at first birth, years	0.019	0.011**	0.008**
	(0.012)	(0.006)	(0.003)
Father's educational attainment, years of education	0.014	0.010*	0.001
	(0.011)	(0.005)	(0.003)
Poorer quintile wealth index, 0/1	0.082	0.107	0.157***
	(0.134)	(0.066)	(0.042)
Middle quintile wealth index, 0/1	0.337**	0.248***	0.307***
	(0.168)	(0.082)	(0.051)
Richer quintile wealth index, 0/1	0.432*	0.238**	0.436***
	(0.240)	(0.115)	(0.072)
Richest quintile wealth index, 0/1	0.524*	0.478***	0.593***
	(0.294)	(0.142)	(0.088)
Household has own TV, 0/1	0.005	0.009	0.005
	(0.152)	(0.076)	(0.046)
Reads newspaper, 0/1	0.066	0.062	0.128***
	(0.156)	(0.073)	(0.046)
Visited by family planning worker, 0/1	-0.129	0.125*	0.008
	(0.150)	(0.073)	(0.048)
Constant	-0.183	-0.301	-3.955***
	(0.740)	(0.373)	(0.298)
Observations	3,224	10,107	18,886

Sources: Analysis of NDHS 2013, NDHS 2008, NOAA's National Geophysical Data Center.
Notes: All models include village fixed-effects. Standard errors are clustered at village level and given in parentheses. *** p<0.01; ** p<0.05; * p<0.10

About the Author(s)

Mulubrhan Amare is an Associate Research Fellow with IFPRI's Nigeria Strategy Support Program, based in Washington, DC, USA. **Channing Arndt** and **Todd Benson** both are Senior Research Fellows in IFPRI's Development Strategy and Governance Division based in Washington, DC. **Kibrom A. Abay** is a Post-doctoral Fellow at the University of Copenhagen in Denmark.

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INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
1201 Eye Street, NW | Washington, DC 20005-3915 USA
T: +1.202.862.5600 | F: +1.202.862.5606
Email: ifpri@cgiar.org | www.ifpri.org

IFPRI-ABUJA
c/o International Fertilizer Development Center
No.6 Ogbagi Street | Off Oro-Ago Crescent, Garki II
Abuja | Nigeria
ifpri-nigeria@cgiar.org | nssp.ifpri.org

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