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Urbanization and Child Nutritional Outcomes

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Abstract

The implications of urbanization on child nutritional outcomes are investigated using satellite-based nighttime light intensity data as a marker of urbanization with data from two rounds of the Nigeria Demographic and Health Survey. Nighttime light introduces a gradient of urbanization permitting investigation of the implications of urbanization on child nutritional outcomes along an urbanization continuum. Nightlight is found to significantly predict 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 nonlinear 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 benefits of urban agglomeration to larger shares of the population would speed improvements to child nutritional outcomes.

JEL classification: I15, O18

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

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, Ruel, and Morris 2000; Smith, Ruel, and Ndiaye 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, Ruel, and Morris 2000). Nevertheless, the ongoing rapid process of urbanization in Africa (Paciorek et al. 2014) would appear to broadly support progress in improving child nutritional outcomes through the benefits of population agglomeration.

Beyond these generalities, data limitations have restricted what can be concluded with respect to the relationship between urbanization and nutrition. 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 (Calì and

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Menon 2013; Christiaensen and Todo 2014). 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. These two limitations obscure insights into the inter-linkages between urbanization and nutrition.[1] 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; Imhoff et al. 1997; Sutton 1997; Henderson et al. 2003; 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, the relationship between urbanization and child nutritional outcomes is investigated using satellite-based nighttime light intensity data as a proxy for urbanization and urban growth. Geo-referenced and nationally representative data from two rounds (2008 and 2013) of the Demographic and Health Survey (DHS) from Nigeria is employed. The DHS data provide detailed anthropometric measures of child nutritional outcomes along with a series of control variables. These geo-referenced DHS data are merged with nighttime light intensity data for the survey clusters in which the DHS sample households reside. This nighttime light introduces a gradient of urbanization permitting investigation of the implications of urbanization on child nutritional outcomes along an urbanization continuum.

Nightlight is found to significantly predict child nutritional outcomes even after controlling for covariates known to influence child nutrition. Relative to areas with no or very limited nightlight signatures, even relatively low levels of light emission are associated with better child nutritional outcomes, and these positive correlations 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. Consistent with the benefits of agglomeration, even a relatively loose clustering of human settlement is positively associated with childhood nutrition. These results are broadly consistent with recent studies highlighting the implication of urbanization and agglomeration in developing countries (e.g., Christiaensen, de Weerdt, and Todo 2013; 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 and discusses the empirical results. Section 5 provides some concluding remarks.

2. Measuring Urbanization and Child Nutritional Outcomes

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, O'Donnell, and van Doorslaer 2012). As noted earlier, satellite-based collection of nighttime light intensity data has attracted substantial interest given its potential to capture, at least partially, the dynamics of urbanization.

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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.

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 daily nighttime light intensity data from every location on the planet at about a one square-kilometer resolution. 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 defense meteorological satellite program's operational linescan system (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.

Besides being freely available, the nighttime light data have several 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 an index that detects changes in the degree of urbanization, information which is absent from traditional dichotomous rural-urban indicators. Third, the nighttime data allow 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.

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. Second, 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 light sources may not be associated with urban activities, such as in areas of natural gas production where gas flaring may be common (see Elvidge et al. 2009).

Urbanization could influence child nutritional outcomes through different channels. 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, Ruel, and Ndiaye 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 (Bhutta et al. 2013; Black et al. 2013; Hirvonen et al. 2017). These are fundamental determinants of nutritional status that can substantially explain nutritional outcomes for young children as well as their later economic outcomes in adulthood.

3. Data Sources, Measurement, and Descriptive Results

The data sources for this study are the 2008 and 2013 Nigerian DHSs (National Population Commission and ICF Macro 2009; National Population Commission and ICF International 2014). These are nationally representative surveys covering both urban and rural households. As noted, the DHS data provide information on the location (latitude and longitude) of each cluster, which enables merging the nighttime light data from the DMSP-OLS with that on the DHS clusters. The DHS datasets are not panel surveys that follow the same households. Rather, they are repeated cross-sections. Approximate cluster-level panel data are constructed using the cluster location information by assigning the 2008 DHS clusters to the nearest 2013 DHS cluster for each. Using this method, 560 (of 886) 2008 DHS clusters were found to be sufficiently close to a 2013 DHS cluster (see Amare et al. 2017). The unit of analysis for this study are 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

The nutritional outcome variables used are z-scores for height-for-age (HAZ), weight-for-height (WHZ), weight-for-age (WAZ), and related standard indicators for child malnutrition from these continuous HAZ, WHZ, and WAZ measures. 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 WHZ less than -2 is considered wasted, and a child is considered underweight if WAZ for the child is less than -2 (WHO Multicentre Growth Reference Study Group 2006). Stunting in children represents linear growth that has failed to reach genetic potential because a child receives inadequate nutrition over a long period or experiences recurrent or chronic illness (Black et al. 2013). Stunting is a chronic form of malnutrition and measures long-term nutritional deprivation. Wasting is ongoing undernutrition that has resulted in substantial weight loss, usually because of acute food shortage or severe disease. It represents acute malnutrition and measures short-term malnutrition in children. Previous research guided the choices of control variables (e.g., Smith, Ruel, and Ndiaye 2005; Black et al. 2013). Controls are included for detailed child and parental characteristics as well as households' access to various resources, including information.

Descriptive Results

Table 1 provides a descriptive summary of the variables employed in the parametric and conditional regressions. As discussed, the 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 both rounds is 8.98. Figure 1 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 the DHS sample households residing in clusters with ln (nighttime light intensity) of less than 1.5 reduced from 63 percent in 2008 to 56 percent in 2013.

The average values of child HAZ and child WHZ are -1.40 and -0.41, respectively, in the pooled sample (table 1). On average across the two years, about 38 percent of the children in Nigeria are stunted, and 15 percent of them are wasted, highlighting the pervasive levels of child undernutrition in Nigeria.

Nonparametric Associations between Urbanization and Child Nutritional Outcomes

Before considering the parametric and conditional regressions, the results of some nonparametric local polynomial regressions are presented, which explore relationships between nighttime light intensity and child nutritional outcomes.

Figure 2(a) and (b) present nonparametric local polynomial regression plots of HAZ and stunting on ln (nighttime light intensity), respectively, for the pooled sample of children under five. To probe the
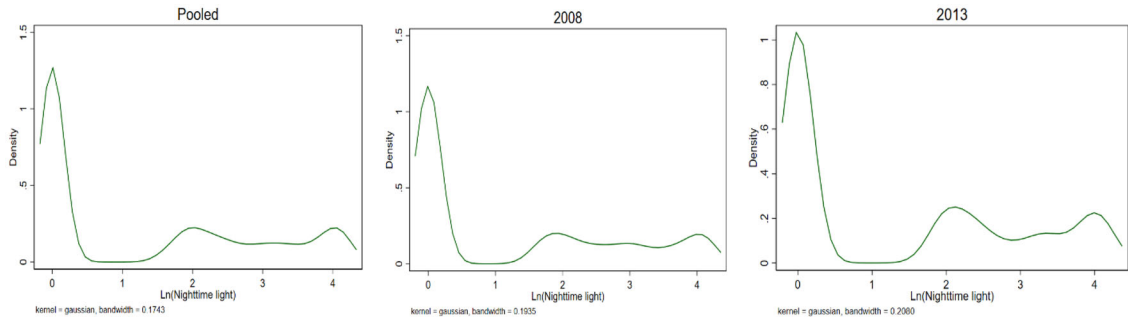
Table 1. Descriptive Statistics of Variables

Variable	Pooled		Year	
	Full sample mean	Standard deviation	2008	2013
Urbanization measure				
Nighttime light intensity (DN)	8.98	16.40	7.96	10.27
ln(nighttime light)	1.12	1.48	1.02	1.26
Outcome variables				
Height-for-age z score	−1.40	2.05	−1.54	−1.32
Child is stunted (HAZ←2), 0/1	0.38	0.49	0.42	0.36
Weight-for-height z score	−0.41	1.64	−0.20	−0.54
Childiswasted(WHZ(2),0/	0.15	0.36	0.14	0.15
Weight-for-age z score	−1.08	1.44	−1.03	−1.16
Child is underweight (WAZ←2), 0/1	0.25	0.43	0.24	0.26
Child and parental characteristics				
Boy child, 0/1	0.49	0.50	0.50	0.50
Age of child, months	28.54	17.21	28.42	28.50
Birth order of child for mother, number	3.90	2.55	3.97	3.90
Mother's educational attainment, years	5.08	5.26	4.57	5.24
Age of mother at first birth, years	19.52	4.33	19.28	19.55
Father's educational attainment, years	6.30	5.77	6.10	6.69
Poorest quintile wealth index, 0/1	0.21	0.41	0.24	0.21
Poorer quintile wealth index, 0/1	0.22	0.41	0.23	0.22
Middle quintile wealth index, 0/1	0.19	0.39	0.20	0.19
Richer quintile wealth index, 0/1	0.19	0.39	0.18	0.19
Richest quintile wealth index, 0/1	0.19	0.39	0.15	0.18
Household has own TV, 0/1	0.42	0.49	0.34	0.45
Reads newspaper, 0/1	0.16	0.37	0.13	0.15
Visited family planning agents, 0/1	0.10	0.30	0.07	0.14
Observations:	33,894		18,888	15,006

Source: Nigerian demographic and health survey (NDHS) 2013, nigerian demographic and health survey (NDHS) 2008, the national geophysical data center (NGDC) of the United States' national oceanic and atmospheric administration (NOAA).

Note: HAZ = Height-for-age z-score; WHZ = Weight-for-height z-score; WAZ = Weight-for-age z-score.
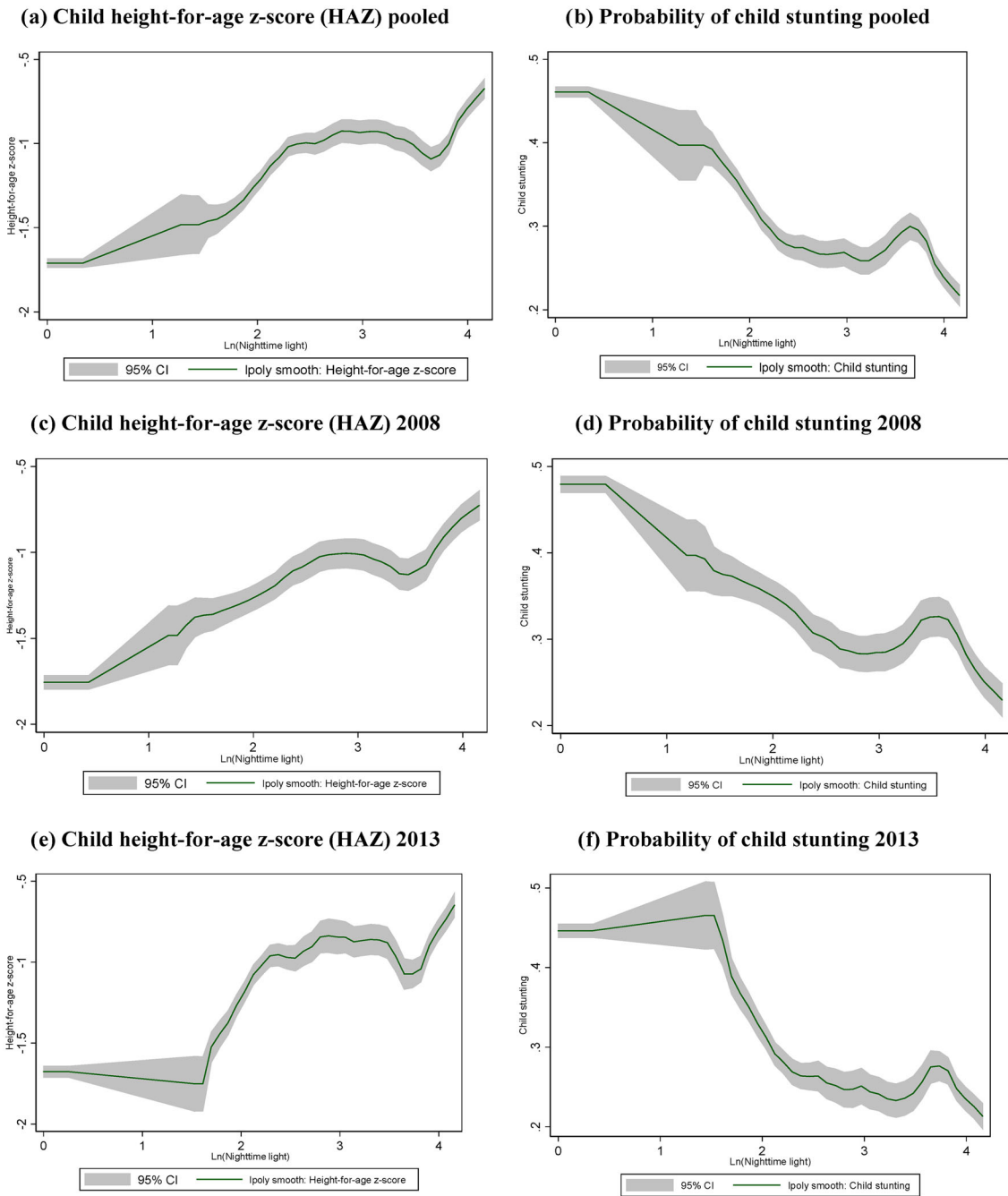
Figure 1. Kernel Density Estimation of ln (nighttime light intensity) in Nigeria in 2008 and 2013

Source: Analysis of nigerian demographic and health survey (NDHS) 2013, nigerian demographic and health survey (NDHS) 2008, the national geophysical data center (NGDC) of the United States' national oceanic and atmospheric administration (NOAA).

stability of the relationships, similar regressions for each year are presented in fig. 2(c)–(f). Overall, these figures show a strong and positive (negative) association between urbanization and HAZ (stunting). Importantly, the magnitude and strength of these relationships vary significantly across the distribution of urbanization intensity as proxied by light intensity. In both figures, the association between nighttime light

Figure 2. Plots of Polynomial Associations between Nighttime Light and Child Height-for-Age z-score (HAZ) and Stunting

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

(b) Probability of child stunting pooled

(c) Child height-for-age z-score (HAZ) 2008

(d) Probability of child stunting 2008

(e) Child height-for-age z-score (HAZ) 2013

(f) Probability of child stunting 2013

Source: Analysis of nigerian demographic and health survey (NDHS) 2013, nigerian demographic and health survey (NDHS) 2008, the national geophysical data center (NGDC) of the United States' national oceanic and atmospheric administration (NOAA).

Note: An Epanechnikov kernel function employing a rule-of-thumb (ROT) bandwidth estimator is used to estimate the nonparametric regressions. The shaded area around each plot represents the 95 percent confidence interval.

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.[2]

Similar patterns are observed for the separate 2008 and 2013 samples, which suggest that the relationship between nightlight and child nutritional outcomes is reasonably stable over time. 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 fig. 2 particularly reveal strong relationships around the middle distribution of nighttime light intensity for the range in ln (nighttime light intensity) between 1.5 and 2.5.[3] Overall, higher nighttime light intensities are associated with better child nutritional outcomes. However, the strength of these relationships varies across different stages of nighttime light intensity.

Nonparametric regressions considering weight-for-height (WHZ) and weight-for-age measures (WAZ), other measures of child nutritional outcomes, were run for the two surveys separately (fig. 3). Similar patterns are observed for children's WAZ as was seen with the HAZ measure, with an increasingly positive relationship between urbanization and WAZ to an intermediate level of urbanization (see fig. 2c and d). These relationships then weaken in the middle of the range before strengthening again at the upper end. The relationship between children's WHZ and night light intensity are less precise and less clear, although broadly similar patterns and some non-linearities in the relationships are observed (see fig. 2a and b). This is not surprising given that WHZ is a more transitory measure of nutritional outcome, while HAZ and WAZ capture relatively longer-term conditions, which can be affected by differential investments in rural and urban areas. HAZ and stunting are related more to food insecurity, which is more common in rural zones (Haddad, Ruel, and Garrett 1999).

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 issues. In view of these empirical challenges and features, alternative econometric approaches were employed that exploit the cross-sectional as well as (approximate) longitudinal variations in the measure of urbanization, by means of nighttime light intensity. Following the preliminary evidence from the nonparametric and unconditional regressions, sufficient nonlinearities in the estimations were allowed for by including higher order polynomial terms associated with nighttime light. Considering a latent nutrition production function, the following longitudinal regression was estimated:
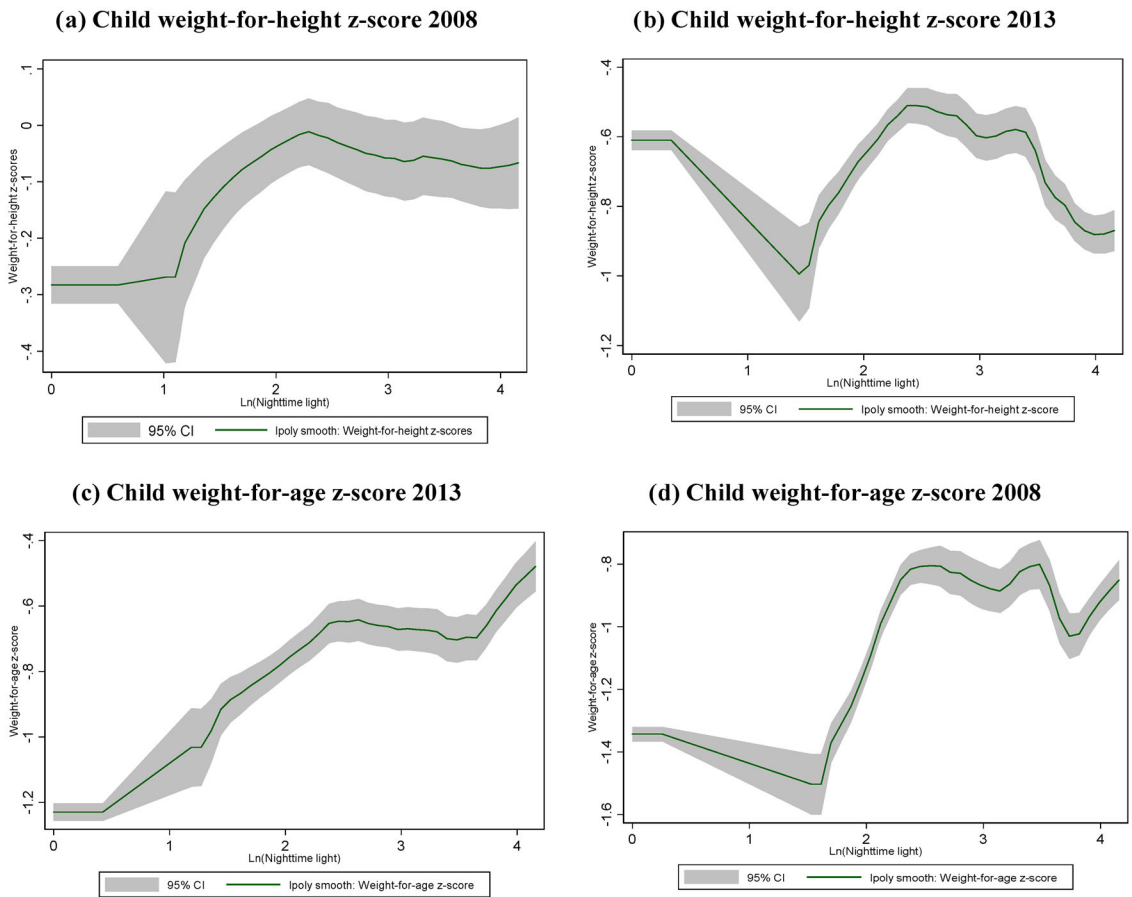
$$Y_{ict} = \sum_{n=1}^{4} \beta_n (ln\_night\_light_{ct})^n + \theta_1 T_{ic} + \theta_2' X_{ict} + \theta_3 (cluster_c) + \varepsilon_{ict} \tag{1}$$

where Y_{ict} stands for a nutritional outcome for child i from cluster (village) c and survey round t. $ln\_night\_light_{ct}$ stands for an index measuring nighttime intensity at cluster level and for the two time periods. To facilitate interpretation of the linear and nonlinear terms, the key variable of interest, the natural

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2   Increasing HAZ is observed up to some level of urbanization with lower or potentially flat returns at more advanced stages and then a reprise at the highest light levels.

3   We investigated 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. A parametric regression is first run on the relationship between child nutritional outcomes and nighttime light focusing on this region of nighttime light intensity. The results appear to be consistent with the nonparametric figures, the correlations in the subsample are much stronger than those based on the full sample. The results are available on request.

Figure 3. Plots of Polynomial Associations between Nighttime Light and Child Weight-for-Height (WHZ) and Weight-for-Age (WAZ) z-scores

Source: Analysis of nigerian demographic and health survey (NDHS) 2013, nigerian demographic and health survey (NDHS) 2008, the national geophysical data center (NGDC) of the United States' national oceanic and atmospheric administration (NOAA).

Note: An Epanechnikov kernel function employing a rule-of-thumb (ROT) bandwidth estimator is used to estimate the nonparametric regressions. The shaded area around each plot represents the 95 percent confidence interval.

logarithmic values of nighttime light, was centered (de-mean).[4] T_{ic} represents year dummies to indicate the year in which the child was suryed, which may capture aggregate shifts in nutritional status or correlated shifts in the explanatory variables. X_{ict} represents a vector of child and parental characteristics that influence child nutrition. *Cluster* represents a set of about 560 enumeration area (EA) dummies that may capture time-invariant differences in nutritional outcomes among children living in different survey clusters. As the main explanatory variable of interest (nighttime light intensity) varies at the EA level and is observed over two periods, the *cluster* dummies in equation (1) implement an EA-level fixed effects estimation.

Table 2 presents regression results for children's HAZ, WHZ, and WAZ. The first, third, and fifth columns are control for detail child and parent characteristics on the pooled sample, while the second, fourth, and sixth columns include cluster-level dummies (village fixed

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4   As the distribution of nighttime light is skewed (fig. 1), an inverse hyperbolic sine function was considered as an alternative transformation for the nighttime light intensity. This transformation provides similar results.

Table 2. Urbanization and Child Nutritional Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Child HAZ		Child WHZ		Child WAZ	
Explanatory variables	Pooled	Cluster fixed-effects	Pooled	Cluster fixed-effects	Pooled	Cluster fixed-effects
ln(nighttime light)-centered	0.447**	0.955***	0.106	−0.368**	0.290*	0.338*
	(0.187)	(0.212)	(0.194)	(0.186)	(0.171)	(0.149)
ln(nighttime light)-centered-square	0.084	0.423***	0.071	−0.056	0.073	0.180***
	(0.061)	(0.070)	(0.060)	(0.061)	(0.054)	(0.049)
ln(nighttime light)-centered-cubic	−0.232**	−0.546***	−0.274**	0.191*	−0.158	−0.141
	(0.109)	(0.124)	(0.116)	(0.109)	(0.102)	(0.087)
ln(nighttime light)-centered-quad	0.058**	0.114***	0.011	−0.053**	0.036	0.020
	(0.026)	(0.030)	(0.029)	(0.027)	(0.025)	(0.021)
Year 2013	0.121***	0.183***	−0.370***	−0.370***	−0.187***	−0.146***
	(0.036)	(0.025)	(0.160)	(0.149)	(0.030)	(0.018)
Child and parental characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−1.125***	−1.495***	−0.784***	−0.339**	−1.323***	−1.223***
	(0.159)	(0.169)	(0.160)	(0.149)	(0.139)	(0.119)
Observations: 33,894						

Source: Analysis of nigerian demographic and health survey (NDHS) 2013, nigerian demographic and health survey (NDHS) 2008, the national geophysical data center (NGDC) of the United States' national oceanic and atmospheric administration (NOAA).

Note: HAZ = Height-for-age z-score; WHZ = Weight-for-height z-score; WAZ = Weight-for-age z-score. Standard errors are clustered at village level and given in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

effects).[5] The estimation results consistently show that urbanization is strongly associated with improved child nutritional outcomes. This holds for all nutritional outcomes and indicators. The coefficients associated with the higher order polynomial terms of nighttime light show substantial nonlinearity in the relationship between urbanization and nutritional outcomes. These nonlinearities are qualitatively consistent across specifications. For instance, the estimates associated with the squared terms for the HAZ estimation in table 2 show that the positive association between nighttime light intensity and HAZ strengthens up to some level of urbanization. Establishing such consistent patterns and relationships between urbanization and child nutritional outcomes across alternative methods and specifications suggests that urban expansion is associated with (non-linear) nutritional transitions.

Interestingly, the non-linear patterns observed in the data are consistent with an emerging literature showing that expansion of towns can be more effective in reducing poverty levels than the expansion of mega-cities (e.g., Christiaensen and Todo 2014; Christiaensen and Kanbur 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. The results appear to be consistent with the nonparametric figures, although the patterns appear to be less clear for child WHZ.

To probe the robustness of the parametric results in table 2 to functional form assumptions, nonparametric conditional regressions for the pooled sample are estimated as well as for each year separately.[6] Estimating these nonparametric regressions involves computing an average derivative associated with a small change in the variable of interest. This corresponds to marginal effects, which is computed as the mean of derivative for continuous covariates or mean of contrasts for discrete covariates (Cattaneo and Jansson 2018).

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5   Estimates for both children's probability of stunting and underweight are consistent with the nonparametric regressions in fig. 2. See Amare et al. (2017) for detailed results.

6   Nonparametric regression outputs report averages of the mean function and the effects of the mean function. An average effect from nonparametric regress may be either (1) an average marginal effect, in the case of the mean of derivatives for continuous covariates or (2) the mean of contrasts for discrete covariates (Cattaneo and Jansson 2018).

Table 3. Nonparametric Regression of Urbanization and Child Nutritional Outcomes

	(1) Pooled	(2) 2008	(3) 2013
Child HAZ			
Child HAZ – Average predictive mean	−1.206***	−1.232***	−1.321***
	(0.015)	(0.026)	(0.022)
ln(nighttime light) − centered: Average derivative	0.166***	0.280***	0.309***
	(0.024)	(0.069)	(0.052)
Child and parental characteristics	Yes	Yes	Yes
Child stunting			
Child stunting: Average predictive mean	0.335***	0.345***	0.359***
	(0.004)	(0.006)	(0.006)
ln(nighttime light)-centered: Average derivative	−0.040***	−0.043***	−0.051***
	(0.009)	(0.011)	(0.012)
Child and parental characteristics	Yes	Yes	Yes
Child WHZ			
Child WHZ: Average predictive mean	−0.383***	−0.068***	−0.575***
	(0.010)	(0.021)	(0.012)
ln(nighttime light)-centered: Average derivative	−0.020	−0.006	0.042*
	(0.013)	(0.024)	(0.022)
Child and parental characteristics	Yes	Yes	Yes
Child wasting			
Child wasting: Average predictive mean	0.146***	0.118***	0.162***
	(0.003)	(0.004)	(0.004)
ln(nighttime light)-centered: Average derivative	−0.005	−0.002	−0.005
	(0.009)	(0.005)	(0.007)
Child and parental characteristics	Yes	Yes	Yes

Source: Analysis of nigerian demographic and health survey (NDHS) 2013, nigerian demographic and health survey (NDHS) 2008, the national geophysical data center (NGDC) of the United States' national oceanic and atmospheric administration (NOAA).

Note: An Epanechnikov kernel function employing a rule-of-thumb (ROT) bandwidth estimator is used to estimate the nonparametric regressions. Effect estimates are averages of derivative. Bootstrap standard errors in parentheses. HAZ = Height-for-age z-score; WHZ = Weight-for-height z-score. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In table 3, these nonparametric regression results are reported for all measures of nutritional outcomes considered. The first set of results are average predictive mean for each outcome, which appears to broadly comparable to the unconditional mean of outcomes in table 1. The most important results in table 3 are those labeled as average derivative, which are marginal effects associated with a small change in nightlight intensity. These results are consistent with the unconditional nonparametric results as well as with the parametric results in table 2. These results are also consistent with previous studies (e.g., Smith, Ruel, and Ndiaye 2005; Paciorek et al. 2014) which show, on average, higher HAZ in urban areas. The statistically insignificant relationship between nightlight intensity and child WHZ are also consistent with previous studies (e.g., Garrett and Ruel 1999; Haddad, Ruel, and Garrett 1999; Smith, Ruel, and Ndiaye 2005) that found a small or negligible rural-urban difference in child WHZ (or prevalence of child wasting).

5. Concluding Remarks

This study investigates the linkages between urbanization and child malnutrition along a gradient of population agglomeration intensity as proxied by nightlight intensity. The empirical analysis reveals several key insights on these links. Most importantly, despite the generally strong positive association between urbanization and child nutritional outcomes, the strength of such relationships varies across stages of

urbanization. The nonparametric and parametric estimations reveal nonlinear relationships between urbanization and child nutritional outcomes. Broadly, strong associations are observed at early stages of urbanization, while such relationships weaken in more advanced stages. These nonlinear relationships are apparent in all of the estimations. From a methodological point of view, these results imply that satellite nightlight data are likely to be preferred for such analyses over rural-urban dichotomous indicators based on census or administrative data.

From a policy vantage point, these patterns hint that achieving even moderate agglomeration of the population may provide welfare benefits-nutritional, in this case. Consistent with the conclusions of Christiaensen and Todo (2014) and Christiaensen, de Weerdt, and Todo (2013), the results suggest that the rural nonfarm 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 could strengthen the improvements in child nutritional outcomes that urbanization provides in Nigeria and likely elsewhere in sub-Saharan Africa.

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