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Urbanization and Women's Body Weight

Evidence from Nigeria

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Urbanization and Women's Body Weight: Evidence from Nigeria

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Abstract

The prevalence of overweight and obesity are increasing in many African countries and hence becoming regional public health challenges. We employ satellite-based night light intensity data as a proxy for urbanization to investigate the relationship between urbanization and women's body weight. We use two rounds of the Demographic and Health Survey data from Nigeria. We employ both nonparametric and parametric estimation approaches that exploit both the cross-sectional and longitudinal variations in night light intensities. Our empirical analysis reveals nonlinear relationships between night light intensity and women's body weight measures. Doubling the sample's average level of night light intensity is associated with up to a ten-percentage point increase in the probability of overweight. However, despite the generally positive relationship between night light intensity and women's body weight, the strength of the relationship varies across the assorted stages of night light intensity. Early stages of night light intensity are not significantly associated with women's body weight, while higher stages of nightlight intensities are associated with higher rates of overweight and obesity. Given that night lights are strong predictors of urbanization and related economic activities, our results hint at nonlinear relationships between various stages of urbanization and women's body weight.

Keywords: Nighttime light, Urbanization, BMI, overweight, obesity, Nigeria

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1. Introduction

In the last few decades, many developing countries have been experiencing unprecedented levels of urbanization and economic growth. African nations, in particular, over the last two decades have experienced their highest-ever rate urban growth, and their economies have sustained unprecedented rates of overall growth. The share of urban population has quadrupled since 1950, rising from about 10 percent to about 40 percent in 2014. This rapid urbanization is changing the continent's demographic and nutritional landscapes, presenting both new opportunities and challenges for urban dwellers. Although urbanization improves access to health facilities and improved nutrition, it is also associated with major risk factors that may promote unhealthy lifestyles. It is commonly associated with a sedentary lifestyle, whose limited physical activities may lead to unhealthy weight gain and related cardiovascular diseases (Popkin, 1999; Harpham et al., 2004; Monda et al., 2007). This transition in lifestyle is commonly coupled with a nutritional transition, which involves a shift to more processed and fatty foods (Popkin, 2003; Popkin and Du, 2003; Popkin et al., 2012). Because of these transitions in lifestyle and nutrition, urbanization is commonly associated with a rise in noncommunicable diseases and associated mortality, mainly stemming from rises in the risk factors of overweight and obesity.

Due to these multifaceted attributes, contemporary urban expansion, on the one hand, has received a somewhat positive response from many economists and social scientists and, on the other hand, has been regarded more negatively in the public health and epidemiology literature (Leon, 2008). Indeed, the World Health Organization (WHO) classifies urbanization as a key threat to public health (WHO, 2007).[1] Given this mix of positive and negative externalities, it is important to identify the overall public health implication of urbanization to regulate and monitor contemporary urban expansions in developing countries.

Previous attempts to investigate the implications of urbanization have commonly employed dichotomous indicators of urbanization.[2] These aggregate indicators of urbanization mask enormous

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[1] Unregulated urbanization is commonly associated with urban slums and informal settlements. Because of this, a third of global urban dwellers live in urban slums and informal settlements without adequate access to safe water and sanitation (WHO, 2007). In Africa, 62 percent of urban residents live in slums without adequate health and sanitation facilities (World Bank, 2013).

[2] There are some exceptions to this characterization. For instance, Van de Poel et al. (2009) and Van de Poel et al. (2012) construct and employ a continuous urbanicity index using community-based characteristics. This index ranks communities based on various attributes and characteristics related to urbanization.

heterogeneities across communities and villages.[3] For instance, the indicators are commonly census- or survey-based, and as such cannot capture the enormous heterogeneities among urban areas and the rapid dynamics of urbanization (McDade and Adair, 2001; Vlahov and Galea, 2002; Dahly and Adair, 2007; Van de Poel et al., 2012). Rather than being a binary phenomenon, urbanization involves a continuum of rural-to-urban transformation at various stages and paces. Aggregate and binary indicators cannot uncover nonlinear relationships between urbanization and public health outcomes, and hence are not well suited for microlevel and dynamic analyses.[4] Thus, researchers and urban planners are exploring alternative metrics that can sufficiently inform the dynamics and levels of urbanization.

The advent of satellite-based night light data offers a unique opportunity and potential to capture urban expansion. Based on the notion that light intensity per unit area corresponds to a reasonable measure of the degree of urbanization, night light intensity is proved to be a valid marker of urban expansion (Elvidge et al., 1997; Imhoff et al., 1997; Sutton, 1997; Henderson et al., 2003; Sutton et al., 2010; Storeygard, 2016). Night light data are measured with consistent quality across countries, regardless of different institutional capacities, allowing consistent measurement of urban growth across various communities and regions. For these reasons, night light data are increasingly being used as a proxy for urban expansion.

In this paper, we employ satellite-based night light intensity data as a proxy for urbanization and related economic activities. We thus investigate the relationship between night light intensity and women's body weight outcomes. Despite the increasing use of night light for measuring urbanization, we are not aware of any study using night light data to study individuals' body weight outcomes.[5] Thus, unlike previous studies that employed binary rural-urban indicators, we employ night lights as a continuous, disaggregated, and objective proxy for urbanization. This allows the detection of relatively small variations and uncovers potentially nonlinear relationships between night light and body weight.

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[3] Similarly, studies exploring the relationship between economic growth and public outcomes (such as the prevalence of obesity) are also based on aggregate national figures (e.g., Egger et al., 2012; Goryakin and Suhrcke, 2014), an approach that may mask significant asymmetries across regions and communities.

[4] Furthermore, most of these indicators are based on varying definitions of urbanization across countries and regions, making cross-country and regional comparisons difficult.

[5] The most relevant studies we can find are those using satellite sensor imagery to study the relationship between urbanization and outbreak of epidemic disease (e.g., Tatem and Hay, 2004; Hay et al., 2005; Liu and Weng, 2012) and those exploring the implications of urbanization for mental health (Chen et al., 2014).

We focus the study on Nigeria, a country that provides an interesting context to address our research question for several important reasons. Nigeria is going through rapid urban expansion, concurrent with reasonably increasing trends of overweight and obesity. In 2000 about 44 percent of the Nigerian population used to live in urban areas, while recent predictions show that the urban population will hit 65 percent by 2020. The prevalence as well as trends of adult overweight and obesity are also increasing overtime (Chukwuonye et al., 2013).[6] The rates of overweight and obesity in our sample period (2008 to 2013) increased by about 24 and 40 percent, respectively. These trends reinforce the need for careful analysis of the distribution and determinants of body weight outcomes. We focus on women's overweight and obesity trends, since these two indicators are commonly associated with a higher risk of noncommunicable diseases and associated mortality.

We employ two rounds (2008 and 2013) of georeferenced and nationally representative Demographic and Health Survey (DHS) data from Nigeria. The DHS data provide detailed public health indicators and body weight outcomes for both urban and rural dwellers. We merge these georeferenced DHS data with night light intensity data for the survey clusters in which the DHS sample households reside. We employ both nonparametric and parametric estimation approaches that exploit the cross-sectional and longitudinal variations in night light intensity. Thus, the longitudinal nature of the night light data allows us to examine potential dynamic relationships between night light intensity and women's body weight.

The remainder of the paper is organized as follows: In section 2 we discuss alternative measures of urbanization and potential advantages of using night light data. In Section 3 we present the key variables used in the empirical analysis. Section 4 presents the empirical model and estimation strategy. We present and discuss the empirical results in Section 5. Section 6 provides concluding remarks and policy implications.

2. Measuring Urbanization and Its Implications for Public Health

2.1 Measuring urbanization

While the globe continues to register unprecedented levels of rural-to-urban transformations, we still lack an accurate measure of the level and dynamics of urbanization. Most urban expansions in developing countries are accompanied by local economic, infrastructural, and technological developments. While we have standard measures of this economic progress in the aggregate,

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[6] Similar trends in overweight and obesity have been observed for many other African countries (e.g., Siervo et al., 2006; Ziraba et al., 2009; Neupane et al., 2016).

especially at national and regional levels, it is difficult to measure at the disaggregated level, such as the community and village level. Thus, we lack not only accurate measures of urbanization but also accurate measures of associated local economic progress. Most measures of urbanization are based on censuses and self-reported survey responses, but these measures are too coarse to sufficiently capture the rapid dynamics in urban expansion. Furthermore, most of these indicators are aggregated at higher levels, inhibiting microlevel analysis of urbanization's implications. Although this measurement problem can be more acute in developing countries, even in the United States and Europe census-based indicators may be insufficient to inform the dynamics of urbanization (Imhoff et al., 1997).

Due to these measurement problems, researchers and urban planners are actively looking for alternative measures or markers of urbanization. Recent efforts have focused on constructing continuous indexes that capture microlevel variations in urban expansion.[7] In this regard, the satellite-based night light intensity data is believed to reasonably capture, at least partially, the dynamics of urbanization and related economic activities. Because urban areas are expected to have higher night light intensity than rural areas, satellite-based night light intensity has been commonly used as a marker of urbanization (Elvidge et al., 1997; Imhoff et al., 1997; Sutton, 1997; Henderson et al., 2003; Sutton et al., 2010; Zhang and Seto, 2011; Storeygard, 2016).

The satellite-based night light intensity data that we use come from the Defense Meteorological Satellite Program (DMSP) of the United States Air Force. The DMSP collects daily night light intensity data from every location on the planet at about a one square-kilometer resolution. The National Geophysical Data Center (NGDC) of the United States' National Oceanic and Atmospheric Administration (NOAA) processes and avails the raw data for public use. The night light data series begins in 1992. It measures and expresses light intensity in digital numbers (DNs) ranging from 0 (no light) to 63 (highest light) for each square-kilometer pixel.[8]

These night light intensity data have novel features that are helpful in mapping urbanization. First, due to the availability of the data at high spatial resolution, we can construct spatially detailed and continuous measures of urbanization. This makes it an attractive proxy for mapping urban growth, compared to the aggregate census and survey-based, dichotomous rural-urban indicators commonly used. Second, the longitudinal nature of the data allows us to trace the

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[7] For instance, Van de Poel et al. (2012) employ factor analysis to construct a continuous index of urbanization using information on a large set of community characteristics.

[8] These values can be further averaged for every geographic area of interest (e.g., village, district, state, or country).

dynamics of urbanization. This is particularly attractive, since most census-based measures and indicators of urbanization are usually conducted at 10-year intervals. Thus, the light-intensity data enable us to monitor and regulate short-term dynamics in urbanization, a process that would otherwise require frequently repeated censuses and surveys. Because of these novel features, early literature employed these data for delineating urban areas and urban settlements. For instance, Imhoff et al. (1997) employ the nightlight intensity data to delineate urban settlements in the United States by comparing these data with census-based statistics.

2.2. Urbanization and body weight

To explore the potential link between urbanization and body weight, we need to understand the components of a comprehensive body weight production function and its determinants. This body weight production function is potentially complex and involves several causal chains among various inputs. Toward this end, Northridge et al. (2003) provide a simplified conceptual representation of three potential factors that may affect body weight and related health outcomes, which they classify as macro-, community-, and individual-level factors.

The macrolevel factors include natural, environmental, institutional, and social factors that may influence body weight outcomes either directly or indirectly by influencing those immediate and community-level attributes that in turn affect individuals' lifestyles. For instance, urbanization may influence body weight by shaping the environment and amenities associated with individuals' livelihoods (Hill and Peters, 1998; Gong et al., 2012). Urbanization commonly involves a transition in lifestyle, as people shift into more sedentary livelihoods involving limited physical activities, which in turn may lead to unhealthy weight gain and hence related cardiovascular diseases (Popkin, 1999; Harpham et al., 2004; Monda et al., 2007). At the individual level, urbanization may shape individuals' dietary practices and health-related decisions. Urbanization is commonly associated with a nutritional transition into more processed and fatty food items (Popkin, 2001, 2003; Popkin and Du, 2003). For instance, several studies show that socioeconomic characteristics of households markedly vary between rural and urban areas (e.g., Garrett and Ruel, 1999; Smith et al., 2005; Hirvonen, 2016). These underlying socioeconomic factors are expected to influence individuals' dietary practices and related health decisions.

It is worth noting that identifying and disentangling one or more of these channels is not straightforward and goes beyond the scope of this paper. However, we aim to control for observable factors at each level to gain some insight into the potential of these channels in explaining variations in body weight outcomes.

3. Data Sources, Measurement, and Descriptive Results

3.1 Data sources

The main data source for this study is the Nigerian Demographic and Health Survey (NDHS). We employ two rounds of these surveys (2008 and 2013), which are nationally representative surveys covering both urban and rural households. The sampling design involves a three-stage stratified sampling strategy. In the first stage, localities were selected with probability proportional to population size and independent of selection in each sampling stratum. In the second stage, enumeration areas were randomly selected. Finally, a fixed number of households were selected in every selected urban and rural cluster through random sampling.

Interestingly, the DHS data provide information on the location (latitude and longitude) of each cluster, which enables us to merge these clusters with the night light data from the DMSP. The DHS datasets are not panel surveys that follow the same households; rather, they are repeated cross-sections with a possibility of following the same clusters. Using the cluster location information, we construct cluster-level panel data by assigning the 2008 DHS clusters to the nearest 2013 DHS cluster. Following this approach, we find 560 (of 886) clusters that are sufficiently close or appear in both years (see Amare et al., 2017). For those clusters appearing in both rounds, we then merge the NDHS data from the two surveys with the village-level night light intensity data from the DMSP for the relevant years. These enumeration areas (clusters) are small enough for the night light intensities to reasonably capture broader human activities at high spatial resolution. We focus on women between ages 15 and 49. The final sample comprises 18,667 women from the 2008 survey and 14,919 women from the 2013 survey.

3.2 Measurement of variables used in the analysis

Our outcome variables are based on women’s body weight measures (for all women between ages 15 and 49). We measure women’s body weight using body mass index (BMI) as well as indicator variables for those with BMIs above standard thresholds. The World Health Organization (WHO) defines a person to be overweight if his or her BMI is 25 or above, while individuals with a BMI of 30 or above are referred to as obese (WHO, 2000). We use these thresholds to assign individuals as overweight (BMI ≥ 25) or obese (BMI ≥ 30). We follow previous research to guide our choice of control variables (Popkin, 1999; Northridge et al., 2003; Monda et al. 2007; Van de Poel et al., 2012).

We control for detailed individual and household characteristics as well as households' access to various resources, including information. More specifically, our empirical analysis controls for women's detailed characteristics, including age, educational attainment, occupation, household's wealth index, and household's access to media and public health services. The household wealth index is constructed using a principal component analysis that combines ownership of durable goods—such as radio, bicycle, car, and other items—including housing characteristics (Rutstein and Johnson, 2004).

3.3 Descriptive results

In Table 1 we provide descriptive statistics associated with the dependent and independent variables employed in our analysis. Our key outcome variables are BMI (kg/m^2) and indicator variables for overweight and obesity. The table indicates that the average value of women's BMI is 22.82. One out of four women of childbearing age is overweight in Nigeria. On average, about 6 percent of the sampled women in Nigeria are obese. Disaggregating across time, the rate of overweight increased by 22 percent (from about 21 percent in 2008 to 26 percent in 2013). Similarly, the rate of obesity increased by 40 percent (from 5 percent in 2008 to 7 percent in 2013). These trends highlight the increasingly pervasive rates of overweight and obesity in Nigeria.

Table 1. Descriptive statistics for variables

	Pooled		2008	2013	
Variable	Mean	Std. Dev.	Mean	Mean	Mean difference test
Outcome variables (Women health)					
BMI-women	22.82	4.29	22.52	23.19	-0.67***
Ln (BMI)	3.11	0.17	3.10	3.13	-0.03***
Overweight-women	0.23	0.42	0.21	0.26	-0.05***
Obesity-women	0.06	0.24	0.05	0.07	-0.02***
Height-women	1.58	0.07	1.58	1.59	-0.01***
Weight-women			56.26	58.27	-2.01***
Urbanization (Night light intensity)					
Night light	8.99	16.40	7.98	10.26	-2.28***
Ln (night light)	1.13	1.48	1.02	1.26	-0.24***
Stage 0 (about 0–50th percentile):	0.61	0.49	0.64	0.57	0.07***
Stage 1 (about 50–75th percentile)	0.19	0.40	0.18	0.22	-0.04***
Stage 2 (about 75–90th percentile)	0.13	0.34	0.13	0.13	0.00***
Stage 3 (above 90th percentile)	0.07	0.25	0.05	0.08	-0.03**
Explanatory variables					
Educational attainment	4.88	5.20	4.59	5.25	-0.66***
Age	29.52	6.94	29.45	29.61	-0.16*
Marital status (married)	0.96	0.20	0.96	0.96	0.00
Household chores	0.29	0.45	0.30	0.28	0.02*
Agriculture	0.18	0.38	0.21	0.13	0.08**
Nonagricultural	0.39	0.49	0.36	0.44	-0.08**
Professional	0.14	0.35	0.14	0.15	-0.01
Wealth: Poorest quintile	0.23	0.42	0.24	0.21	0.03*
Poorer quintile	0.23	0.42	0.23	0.22	0.01
Middle quintile	0.20	0.40	0.20	0.19	0.01
Richer quintile	0.18	0.39	0.18	0.19	-0.01
Richest quintile	0.16	0.37	0.15	0.18	-0.03**
Household owns TV	0.39	0.49	0.34	0.45	-0.11**
Reads newspaper	0.14	0.35	0.13	0.15	-0.02**
Visited by health officer	0.10	0.30	0.07	0.14	-0.07**
No. observations	33,586		18,667	14,919	

Sources: Analysis of NDHS 2013, NDHS 2008, NOAA's National Geophysical Data Center.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As discussed earlier, night light intensity is reported in digital numbers (DN), ranging from 0 (darkest) to 63 (brightest). Table 1 shows that the average night light intensity is 8.99 DN. Figure 1 presents the geographic distribution of night light (measured at the NDHS clusters) for 2008 and 2013. The night light increases as we move from north to south in Nigeria. Figure 2 provides the distribution of night light intensities across both years. Night light intensity increased by about 28 percent from 2008 to 2013.

We also generate indicator variables for various stages of night light intensity and present the distribution of these variables in Table 1. This classification is based on the distribution of the night light intensities: the initial stage (Stage 0) represents clusters with 0 DN, and the next stages are based on the 50th, 75th, and 90th percentile thresholds. We use these ranges as robustness exercises to corroborate our main analysis based on continuous night light intensity.

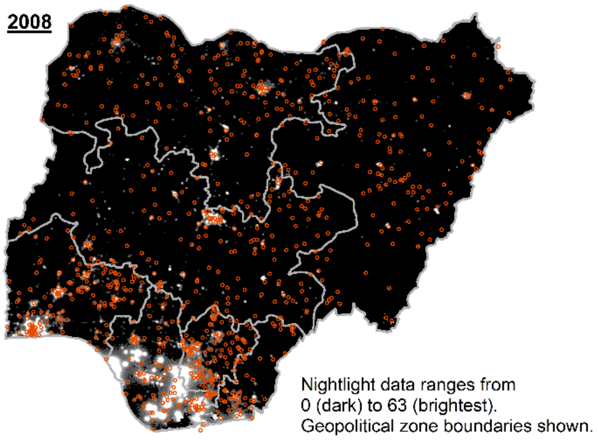

Figure 1: Night light intensity (at NDHS clusters) for both years, 2008 and 2013. Sources: Image and data processing by NOAA's National Geophysical Data Center. DMSP data collected by the United States Air Force Weather Agency.

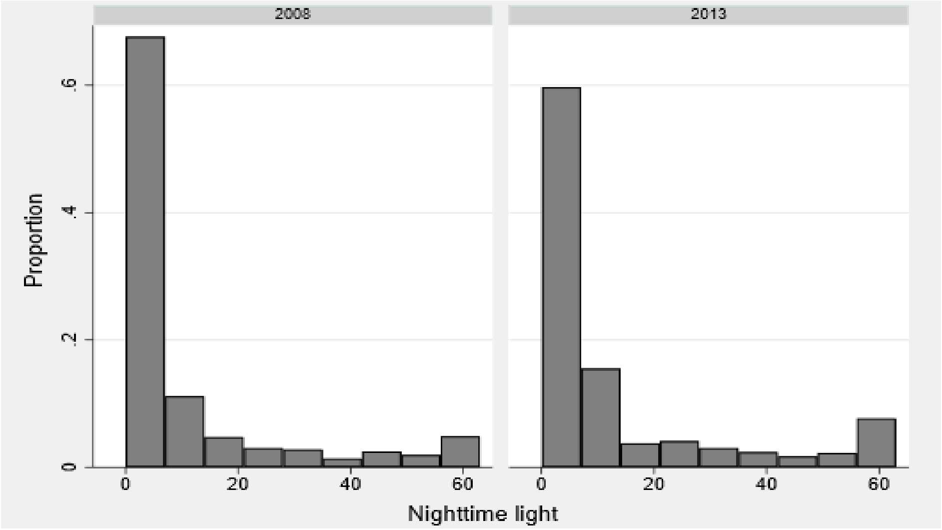

Figure 2. Distribution of night light intensity by year, 2008 and 2013. Sources: Analysis of NDHS 2013, NDHS 2008, NOAA's National Geophysical Data Center.

3.4. Nonparametric associations between night light intensities and women's body weight

Before estimating our main equations, we conduct nonparametric and unconditional regressions characterizing the relationship between night light intensities and women's body weight measures. 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 night light intensity and women's body weight outcomes. The threshold estimation technique enables us to detect the thresholds that identify statistically different linear regression coefficients across the distribution of the night light intensity. We particularly employ Hansen's (2000) threshold estimation technique to test for the presence of threshold(s) that split night light intensities into different ranges. This estimation selects the optimal number of thresholds based on model fitness (using the usual information criteria). We do these empirical exercises for the three key body weight measures: BMI, overweight, and obesity.

In Figure 3 we plot polynomial associations between nightlight light and body weight outcomes. These graphs show strong and mostly positive associations between nightlight light and women's body weight measures. However, the magnitude and strength of these relationships vary across the distribution of night light intensities. This implies that the relationship between night light intensity and women's body weight is potentially nonlinear.

These nonlinear patterns are more visible in our threshold estimations (Table 2), which identify three optimal thresholds and split the sample into four segments. The threshold estimations in column 1 of Table 2 show that the magnitudes of the relationships (slopes) significantly vary across the four stages of night light intensity. For instance, the slope in the fourth segment of the distribution is about ten times steeper than the slope in the first segment of night light intensity. Similar patterns are observed for the remaining outcomes measuring women's body weight, overweight, and obesity. The threshold estimations for overweight (obesity) identify two (one) optimal thresholds and hence provide regression coefficients for three (two) regions (segments).[9] These estimations (columns 2 and 3 of Table 2) indicate that the early stages of night light intensity are weakly associated with the probability of overweight and obesity, while higher levels of night light intensity are strongly associated with higher risk of overweight and obesity. However, we note that these threshold estimations are based on unconditional regressions, and one may suspect that these nonlinearities could be driven by observable and unobservable heterogeneities among

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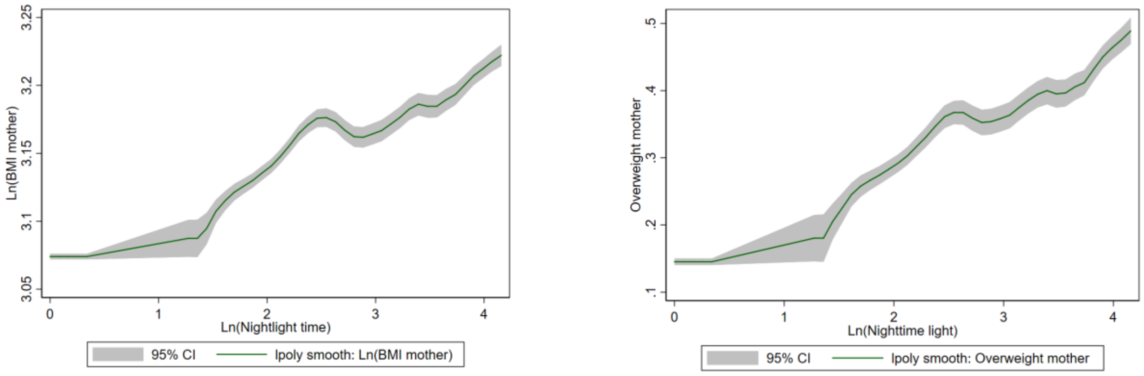
[9] We also run these threshold estimations using the raw values of nighttime light intensities and confirm the patterns in Figure 3.

households or villages (clusters). Our parametric and conditional regressions in Section 4 aim to explore these issues further. In addition, Section 5.2 provides estimates from conditional regressions using categorical variables for the various "stages" of night light intensity.



3a) Night light and body mass index (BMI)

3b) Night light and probability of overweight

3c) Night light and probability of obesity

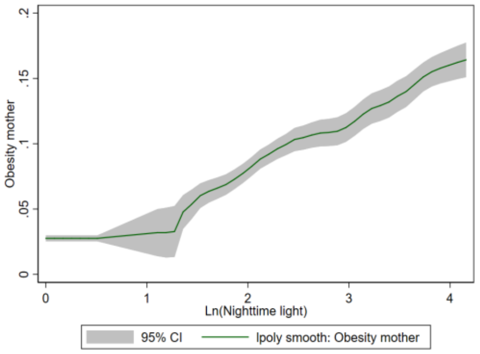


Figure 3. Nonparametric associations between night light and body weight measures. Sources: Analysis of NDHS 2013, NDHS 2008, NOAA's National Geophysical Data **Center**.

Table 2. Threshold estimations of the relationship between night light and body weight outcomes

	(1) Ln (BMI)	(2) Overweight	(3) Obesity
Threshold 1	1.61	1.61	1.61
Threshold 2	2.56	2.71	2.48
Threshold 3	3.56	3.56	
Region 1			
Ln (night light)	0.008*	0.022**	0.003
	(0.005)	(0.011)	(0.006)
Constant	3.074***	0.145***	0.028***
	(0.001)	(0.003)	(0.002)
Region 2			
Ln (night light)	0.090***	0.153***	0.102***
	(0.009)	(0.018)	(0.015)
Constant	2.961***	-0.013	-0.123***
	(0.019)	(0.039)	(0.030)
Region 3			
Ln (night light)	0.045***	0.165***	0.037***
	(0.010)	(0.032)	(0.008)
Constant	3.033***	-0.147	0.014
	(0.030)	(0.101)	(0.030)
Region 4			
Ln (night light)	0.120***	0.353***	
	(0.017)	(0.042)	
Constant	2.732***	-0.944***	
	(0.067)	(0.165)	
No. observations	33,586	33,586	33,586

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

Notes: Standard errors are clustered at the village level and given in parentheses.

*** p < 0.01; ** p < 0.05; * p < 0.10.

4. Parametric and Conditional Regressions

Estimating the relationship between night light intensity and body weight requires recalling the potential determinants of body weight we discussed in Section 2.2. Furthermore, quantifying the overall effects of urbanization on body weight may suffer from endogeneity problems arising from omitted attributes. This is plausible given that urbanization programs and trends are accompanied by rapid economic and infrastructural growth, which can affect livelihoods and body weight. Thus, the relationship we estimate in this paper is more correlational than causal. But that is less of a concern than it otherwise might be, because many urbanization programs and urban expansions are apparently accompanied by reasonable levels of local economic and infrastructural development.

We employ alternative econometric approaches that exploit the cross-sectional as well as longitudinal variations in night light intensity. Following the preliminary evidence from our polynomial regressions, we allow for sufficient nonlinearities in our estimations by including higher-order polynomial terms associated with night light. We consider and estimate a body weight production function of the following type:

$$Y_{ict} = \beta_0 + \sum_{n=1}^{N} \beta_n (\log\_night\_light_{ct})^n + \theta_1 T_{ic} + \theta_2' X_{ict} + \theta_3 (cluster_c) + \varepsilon_{ict} \ , \qquad (1)$$

where Y_{ict} stands for body weight outcomes, including BMI and indicator variables for overweight and obesity for each woman *i* from cluster (village) *c* and round *t*. The variable $night\_light_{ct}$ stands for night light intensity measured at the cluster level and for various time periods.

To facilitate interpretation of the linear and nonlinear terms in our regressions, we first centered (demeaned) our key variable of interest, the logarithmic value of night light.[10] This implies that the linear terms in β_1 can be interpreted as relationships and slopes at the sample mean of night light. T_{ic} stands for round dummies to indicate the year in which the woman was surveyed. X_{ict} represents a vector of individual and household characteristics that may explain the body weight production function. *Cluster* represents a large set of (more than 560) village-level dummies that may capture time-invariant differences in body weight outcomes of women living in different villages. As our main explanatory variable of interest (night light intensity) varies at the village level, the cluster dummies in equation (1) implement village-level fixed effects estimation. Thus, for some of our estimations the parameters associated with night light in equation (1) capture dynamic relationships between night light intensity and body weight. As a robustness exercise, we also estimate equation (1) using categorical variables standing for night light intensity at various stages.

We first run unconditional regressions and later extend the specification by including individual- and household-level characteristics as well as village-level fixed effects. We mainly focus on exploiting longitudinal variations in our measure of urbanization (night light intensity). This is a more robust empirical strategy, since it helps cancel out time-invariant differences across villages. Women living in the same village are exposed to a similar environment and infrastructure, which may imply potential correlations in unobservable effects. To account for such correlations in error terms, we cluster standard errors at the village level. For this purpose (clustering of standard errors), we focus on linear regression approaches, even though some of our outcomes assume a binary nature.

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[10] Since we have a skewed distribution of nighttime light (see Figure 2), we also consider inverse hyperbolic sine transformations and confirm our results.

5. Results and Discussion

Before discussing our results, it is worth clarifying how to interpret our estimates. Although we are exploiting longitudinal variations in night light intensity, so that time-invariant unobserved heterogeneities are innocuous, our estimates might not sufficiently inform causal inference due to the endogeneity problems arising from omitted attributes discussed in Section 4. Furthermore, night light might capture not only rural-urban transformations but also accompanying local economic developments and spatial variations in these developments. Although we may observe some of these trends in income using household-level socioeconomic and wealth characteristics, we cannot completely disentangle these trends from trends in urbanization and local economic development.

Despite these drawbacks, our empirical analysis provides important insights for several reasons. Importantly, the associational evidence between potential dynamics in night light intensity and body weight allows for predicting women's health trends in the face of contemporary urban expansions in developing countries.

5.1 Main results

Table 3 presents estimates for women's body mass index (BMI) based on cross-sectional and longitudinal variations in night light intensity. The first column presents pooled regression results, while the second and third columns provide estimates controlling for village (cluster) fixed effects. In the first column of Tables 3, we report unconditional regressions of women's BMI on night light intensity and a time dummy capturing the wave of the sample. We then extend this specification by including a long list of individual and household-level characteristics. Due to our transformations (demeaning), the linear terms can be interpreted as relationships (slopes) between night light and women's body weight around the sample mean of night light. Significant higher-order polynomials in these regressions can inform the direction and steepness of curvatures in the relationship between night light intensity and women's body weight outcomes.

Table 3. Night light intensity and body mass index (BMI)

	Pooled	Village fixed effects	
	(1)	(2)	(3)
Explanatory variables	Ln (BMI)	Ln (BMI)	Ln (BMI)
Ln (night light)-centered	0.050***	0.045**	0.030**
	(0.012)	(0.018)	(0.015)
Ln (night light)-centered-square	0.011***	0.017***	0.011***
	(0.003)	(0.005)	(0.004)
Ln (night light)-centered-cubic	-0.013**	-0.013	-0.013*
	(0.006)	(0.009)	(0.007)
Ln (night light)-centered-quadruple	0.003*	0.002	0.003
	(0.002)	(0.002)	(0.002)
Year (round) dummy	0.022***	0.027***	0.021***
	(0.002)	(0.002)	(0.002)
Educational attainment			0.004***
			(0.000)
Age			-0.011***
			(0.001)
Age square			0.011***
			(0.001)
Marital status			0.018***
			(0.004)
Occupation: Base (household chores)			
Agriculture			0.003
			(0.003)
Nonagricultural			0.010***
			(0.002)
Professional			-0.006**
			(0.003)
Wealth index: Base (poorest quintile)			
Poorer quintile			0.008***
			(0.003)
Middle quintile			0.026***
			(0.003)
Richer quintile			0.034***
			(0.005)
Richest quintile			0.073***
			(0.006)
Household owns TV			0.016***
			(0.003)
Reads newspaper			0.018***
			(0.003)
Visited by health officers			0.003
			(0.003)
Constant	3.104***	3.080***	2.804***
	(0.004)	(0.006)	(0.016)
R^2	0.19	0.09	0.18
No. observations	33,586	33,586	33,586

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

Notes: Standard errors are clustered at village level and given in parentheses. The base occupation is household chores, while the base wealth is the poorest quintile.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

The estimation results in Table 3 show that night light intensity significantly predicts women's body mass index. The coefficients associated with the higher-order polynomial terms of night light show substantial nonlinearity in the relationship between night light intensity and body mass index. These nonlinear trends are apparent both in the cross-sectional and longitudinal variations of night light. These associations and relationships are strong and of appreciable magnitude. For instance, the linear terms in columns 2 and 3 of Table 3 show an average elasticity of 0.03–0.05. The estimates associated with the higher-order polynomial terms indicate the strength and direction of these associations across the distributions (stages) of night light intensity. For instance, the estimates associated with the quadratic terms in Table 3 show that the positive association between night light intensity and BMI strengthens, up to some level of night light intensity, before it weakens toward the end of the distribution. This is consistent with the polynomial associations shown in Figure 3 and with the notion that relatively higher levels of night light intensity and hence urbanization may be more consequential for body weight gains.

We also generate indicator (dummy) variables for overweight and obesity for women with BMI ≥ 25 and BMI ≥ 30, respectively. Tables 4 and 5 provide linear probability model estimates for these binary outcomes. The estimation results in Table 4 and 5 show similar nonlinear relationships between night light and prevalence of overweight (obesity). For instance, the results in Table 4 show that doubling the sample's average level of night light intensity is associated with up to a ten-percentage point increase in the probability of overweight.

Table 4. Night light intensity and probability of overweight

Explanatory variables	Pooled	Village fixed effects	
	(1)	(2)	(3)
	Overweight	Overweight	Overweight
Ln (night light)-centered	0.249***	0.166***	0.095**
	(0.026)	(0.045)	(0.044)
Ln (night light)-centered-square	0.042***	0.063***	0.045***
	(0.008)	(0.015)	(0.015)
Ln (night light)-centered-cubic	-0.104***	-0.067**	-0.046*
	(0.016)	(0.026)	(0.026)
Ln (night light)-centered-quadruple	0.026***	0.015**	0.010
	(0.004)	(0.006)	(0.006)
Year (round) dummy	0.025***	0.037***	0.025***
	(0.004)	(0.005)	(0.005)
Educational attainment			0.006***
			(0.001)
Age			0.022***
			(0.002)
Age square			-0.000***
			(0.000)
Marital status			0.037***
			(0.011)
Occupation: Base (household chores)			
Agriculture			-0.013*
			(0.008)
Nonagricultural			0.020***
			(0.006)
Professional			-0.005
			(0.007)
Wealth index: Base (poorest quintile)			
Poorer quintile			0.013*
			(0.007)
Middle quintile			0.052***
			(0.009)
Richer quintile			0.066***
			(0.012)
Richest quintile			0.147***
			(0.015)
Household owns TV			0.037***
			(0.008)
Reads newspaper			0.050***
			(0.008)
Visited by health officers			0.004
			(0.008)
Constant	0.108***	0.084**	-0.461***
	(0.019)	(0.033)	(0.049)
R^2	0.14	0.08	0.15
No. observations	33,586	33,586	33,586

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

Notes: Standard errors are clustered at village level and given in parentheses. The base occupation is household chores, while the base wealth is the poorest quintile.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

The estimates in Table 5 show consistent evidence of a generally positive but nonlinear relationship between night light intensity and women's risk of obesity. The quadratic terms associated with night light intensities in Table 5 reinforce the finding that the strength of the relationship between night light intensity and body weight increases with higher levels of night light intensity. This is consistent with our threshold estimations in Table 2, which show that lower levels of night light intensity are not statistically correlated with women's rates of overweight and obesity.

The above types of nonlinear relationships are apparent in all the estimations—those that exploit cross-sectional as well as longitudinal variations in night light. We note that these types of nonlinear relationships cannot be uncovered using the binary rural-urban indicators commonly used in the literature. On the other hand, similar nonlinear relationships between urbanization and other public health outcomes have been documented by few other studies employing continuous measures of urban growth (Van de Poel et al., 2012; Chen et al., 2014). For instance, Van de Poel et al. (2012) show that the negative public health impacts of urban expansion are more pronounced after advanced stages of urbanization. More pertinently, Amare et al. (2017) find similar relationships between night light intensity and child nutritional outcomes. They indicate that higher night light intensity is associated with better child nutritional outcomes, despite substantial variation in the strength of these relationships across different stages of night light intensity.

Given the potential of night light intensity to capture dynamic and continuous rural-urban transformations, these pieces of evidence hint that urbanization should be understood as a continuum process, with different stages having varying implications on alternative outcomes of interest. These patterns are consistent with the view that higher levels of urbanization can trigger changes in lifestyles (such as physical activity and mobility) and nutrition transition, which both contribute to unhealthy weight gains. Ruel et al. (2017) argue that up to a certain stage, urbanization may reduce undernutrition, while advanced stages of urbanization may encourage unhealthy lifestyles in a way that may induce overweight and obesity.

By comparing the unconditional and conditional estimates in Tables 3–5, we may provide suggestive evidence on some of the potential mechanisms through which night light intensity (or the implied level of urbanization) can lead to higher body weight. For instance, the size of the estimates in all regressions substantially shrinks when we control for socioeconomic and wealth indicators, suggesting that part of the link between night light (urbanization) and women's body weight could be mediated through these channels. This is consistent with previous evidence highlighting substantial rural-urban differences in socioeconomic characteristics of households living in rural and urban areas (e.g., Smith et al., 2005; Hirvonen, 2016). Along this line, Hirvonen (2016) documents that much of the rural-urban differences in child nutritional outcomes can be captured by socioeconomic differences. However, our estimates remain sizeable even after we control for these socioeconomic characteristics, implying that other mechanisms may also be at play.

The remaining associations between body weight outcomes of women and their individual and household characteristics are consistent with previous evidence. For instance, we can observe that older and married women have higher body mass index and higher probability of overweight (e.g., Siervo et al., 2006; Asfaw, 2007; Ziraba et al., 2009). Consistent with the existing literature on overweight and obesity in developing countries, we find that wealthier women are associated with higher BMI and higher probability of overweight and obesity (e.g., Siervo et al., 2006; Asfaw, 2007; Ziraba et al., 2009; Abdulai, 2010).

The positive associations between body weight outcomes and socioeconomic status reflect the additional challenges to reduce overweight and obesity in African countries. In most African countries, higher body weight is commonly associated with improved (urban) livelihood and higher socioeconomic status (Popkin, 1999, 2003; Siervo et al., 2006). This is consistent with the view that higher socioeconomic status is associated with lower risk of overweight and obesity in developed countries, but the reverse holds in developing countries (Kim et al., 2004; Tafreschi, 2015).[11] Intuitively, this may imply that strategies and campaigns that are effective at reducing the pandemic of overweight and obesity in developed countries may not necessarily curb unhealthy weight gains and related public health outcomes in African countries. This further highlights the challenges associated with reducing the epidemics of overweight and obesity in African countries as doing so may require addressing sociocultural barriers (Neupane et al., 2016).

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[11] Other recent studies show some dynamism in these relationships. For instance, Monteiro et al. (2004) document that as countries grow, the burden of overweight and obesity shifts across various groups of society. They show that as countries experience higher levels of economic growth, the burden of obesity shifts to the poor. Tafreschi (2015) reports similar results and reversal of the relationship between income and rates of obesity.

Table 5. Night light intensity and probability of obesity

	Pooled	Village fixed effects	
Explanatory variables	(1)	(2)	(3)
	Obesity	Obesity	Obesity
Ln (night light)-centered	0.028^{***}	0.018^{***}	0.004^{*}
	(0.001)	(0.002)	(0.002)
Ln (night light)-centered-square	0.004^{***}	0.009^{***}	0.005^{***}
	(0.001)	(0.001)	(0.001)
Year (round) dummy	0.010^{***}	0.014^{***}	0.010^{***}
	(0.003)	(0.003)	(0.003)
Educational attainment			0.003^{***}
			(0.000)
Age			-0.008^{***}
			(0.002)
Age square			0.008^{***}
			(0.001)
Marital status			0.001
			(0.007)
Occupation: Base (household chores)			
Agriculture			-0.013^{***}
			(0.005)
Nonagricultural			0.004
			(0.003)
Professional			-0.002
			(0.004)
Wealth index: Base (poorest quintile)			
Poorer quintile			0.004
			(0.004)
Middle quintile			0.015^{***}
			(0.005)
Richer quintile			0.022^{***}
			(0.007)
Richest quintile			0.075^{***}
			(0.009)
Household owns TV			0.008^{*}
			(0.005)
Reads newspaper			0.012^{***}
			(0.005)
Visited by health officers			-0.004
			(0.005)
Constant	0.052^{***}	0.036^{***}	-0.163^{***}
	(0.003)	(0.004)	(0.022)
R^2	0.13	0.05	0.11
No. observations	33,586	33,586	33,586

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

Notes: Standard errors are clustered at village level and given in parentheses. The base occupation is household chores, while the base wealth is the poorest quintile.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

5.2 Alternative specifications and robustness exercises

To probe the robustness of our main results, we conduct alternative specifications and robustness exercises. The first exercise involves estimating the relationship between night light intensity and women's body weight using categorical variables for the various levels of night light intensity. This is an alternative way to detect nonlinearities in the relationship between night light intensity (or the implied level of urbanization) and body weight without imposing any functional form assumptions on these relationships. To do so, we generate four categories based on the distribution of night light intensity. The benchmark or Stage 0 stands for those clusters with 0 DN and covers about half of our sample (see Table 1), while the next ranges are based on the 75th and 90th percentile thresholds.

Table 6 provides the estimates using these categories, with the initial range (those clusters with almost no light) serving as base outcome. Consistent with our threshold estimations, Table 6 shows that compared to the Stage 0, the Stage 1 of night light intensity is not significantly associated with women's body weight, while Stages 2 and 3 are positively correlated with women's risk of overweight and obesity. This suggests that the threshold estimation results and those main results we established in section 5.1 are not driven by the choice of function forms.

We also explore whether these types of nonlinear relationships extend beyond body weight outcomes. We consider height measures and investigate whether night light intensity explains a portion of the variation in women's height and weight separately. The estimates are given in Table A1 in the appendix. Overall, we can observe a significantly positive relationship between night light intensity and women's height and weight. This is not surprising given that night light intensity can capture long-term as well as short-term economic activities, which can affect both short-term nutritional outcomes (such as body weight) and longer-term nutritional outcomes (such as height). However, the magnitude of the association between night light and women's height is much weaker than the association between night light intensity and women's body weight. This result resonates with the notion that height is a measure of long-term nutritional status and less likely to be strongly correlated with recent night light intensity, while body weight may respond or strongly correlate with recent trends in night light intensity. We finally estimate our empirical specifications excluding major states with major infrastructure as well as those states that are running major oil productions. These exercises confirm our main results.[12]

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[12] We do so because the night light measure does not distinguish differences in light intensity caused by human activities and those caused by artificial lights from, for example, gas flaring (Elvidge et al., 2009). We rerun our models by excluding six major oil-producing states in Nigeria, including Akwa Ibom, Delta, Rivers, Bayelsa, Ondo, and Logos. These results are consistent with the main estimates and they are available from the authors upon request.

Table 6. Night light intensity and body weight measures

	(1) Ln (BMI)	(2) Overweight	(3) Obesity
Base: Stage 0			
Stage 1	0.012*	0.022	0.008
	(0.007)	(0.017)	(0.009)
Stage 2	0.024***	0.080***	0.025**
	(0.008)	(0.019)	(0.012)
Stage 3	0.047***	0.147***	0.054***
	(0.011)	(0.028)	(0.017)
Year (round) dummy	0.021***	0.025***	0.010**
	(0.004)	(0.008)	(0.004)
Socioeconomic characteristics	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes
Constant	2.809***	-0.389***	-0.160***
	(0.018)	(0.044)	(0.022)
R^2	0.20	0.15	0.09
No. observations	33,586	33,586	33,586

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

Notes: Standard errors are clustered at village level and given in parentheses. The base occupation is household chores, while the base wealth is the poorest quintile.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

6. Concluding Remarks

Overweight and obesity are increasingly becoming major public health problems in African urban centers. These trends have been particularly rapid in the last two decades, just as many African countries have been experiencing their highest-ever urban growth. Thus, many attributes these trends in body weight to contemporary urban expansion and associated nutritional transitions and changes in lifestyle. Indeed, there exists an evolving interest in unpacking the role of urbanization in driving these trends in overweight and obesity, although these efforts are partly inhibited by the lack of objective measures of urbanization. In this paper, we employ satellite-based night light intensity data as a proxy for urbanization to investigate the relationship between urbanization and women's body weight (measured by BMI, overweight, and obesity). We particularly explore whether potential dynamics in night light intensity predicts women's body weight and trends in overweight and obesity. Our parametric and nonparametric estimations reveal some important insights into the linkage between night light intensity and body weight. Most importantly, our nonparametric and parametric estimations show that the relationship between night light intensity and body weight is potentially nonlinear.

We find that early stages of night light intensity are weakly correlated with women's risk of overweight and obesity, while higher levels of night light intensity are strongly associated with adverse body weight outcomes. These nonlinear relationships are apparent in all our estimations and across all measures and indicators of body weight. These pieces of evidence are consistent with previous findings and may relate to the substantial heterogeneity in urban livelihood and associated amenities (Menon et al., 2000; World Bank, 2013). For example, some recent studies find significant asymmetries in urban dwellers' access to medical and related public health services (World Bank, 2013). These types of patterns and nonlinear relationships cannot be detected using the rural-urban binary indicators commonly used to study the effect of urbanization. Interestingly, similar patterns and nonlinear relationships between urbanization and some public health indicators have been documented by recent studies that employ continuous proxies for urbanization (e.g., Van de Poel et al., 2012). Our results, along with these studies, hint that the urbanization and body weight outcomes might be more complex than suggested in the literature.

The remaining associations between women's body weight and household characteristics further reinforce the need for more-tailored efforts to reduce the epidemics of overweight and obesity in Africa. As documented by other studies, potential determinants of overweight and obesity in Western and African countries are distinct (Kim et al., 2004). Consistent with previous evidence, we find that higher socioeconomic and wealth status is associated with a higher probability of overweight and obesity. This may be attributed to sociocultural attitudes of societies, with higher body weight commonly perceived as an indicator of higher socioeconomic status in many African countries (Siervo et al., 2006). This in turn implies that many instruments that are proved to be effective in improving public health outcomes in Western countries may not necessarily be effective in these African countries.

References

Abdulai, A. 2010. Socio-economic characteristics and obesity in underdeveloped economies: Does income really matter? *Applied Economics, 42*(1–3), 157–69.

Amare, M., Arndt, C., Abay, K. A., & Benson, T. 2017. Urbanization and child nutritional outcomes. NSSP Working Paper 49 v2. Washington, D.C.: International Food Policy Research Institute (IFPRI).

Asfaw, A. 2007. Do government food price policies affect the prevalence of obesity? Empirical evidence from Egypt. *World Development, 35*, 687–701.

Chen, J., Chen, S., Landry, P. F., & Davis, D. S. 2014. How dynamics of urbanization affect physical and mental health in urban China. *The China Quarterly, 220*, 988–1011.

Chukwuonye, I. L, Chuku, A., John, C., et al. 2013. Prevalence of overweight and obesity in adult Nigerians – a systematic review. *Diabetes, Metabolic Syndrome and Obesity: Targets and Therapy, 6*, 43–47.

Dahly, L. D., & Adair, L. S. 2007. Quantifying the urban environment: A scale measure of urbanicity outperforms the urban–rural dichotomy. *Social Science and Medicine, 64*, 1407–1419.

Egger, G., Swinburn, B., & Amirul Islam, F. 2012. Economic growth and obesity: an interesting relationship with world-wide implications. *Economics and Human Biology, 10*, 147–153.

Elvidge, C. D., Baugh, K. E., Kihn, E. A., Kroehl, H. W., Davis, E. R., & Davis, C. W. 1997. Relation between satellite observed visible-near infrared emissions, population, and energy consumption. *International Journal of Remote Sensing, 18*, 1373–1379.

Elvidge, C. D., Ziskin, D., Baugh, K. E., Tuttle, B. T., Ghosh, T., Pack, D. W., Erwin, E. H., & Zhizhin, M. 2009. A fifteen-year record of global natural gas flaring derived from satellite data. *Energies, 2*(3), 595–622.

Garrett, J. L., & Ruel, M. T. 1999. Are determinants of rural and urban food security and nutritional status different? Some insights from Mozambique. *World Development, 27*, 1955–1575.

Gong, P., Liang, S., Carlton, E. J., Jiang, Q., Wu, J., Wang, L., et al. 2012. Urbanisation and health in China. *The Lancet, 379*(9818), 843–852.

Goryakin, Y., & Suhrcke, M., 2014. Economic development, urbanization, technological change and overweight: what do we learn from 244 demographic and health surveys? *Economics and Human Biology*, *14*, 109–127.

Hansen, B. E. 2000. Sample splitting and threshold estimation. *Econometrica, 68*, 575–603.

Harpham, T., Reed, H., Montgomery, M., Satterthwaite, D., Moser, C., & Cohen, B. 2004. Mortality and morbidity: Is city life good for your health? In Montgomery, M. R., Stren, R., Cohen, B., & Reed, H. E. (Eds.), *Cities transformed: demographic change and its implications in the developing world* (259–99). London: Earthscan.

Hay, S. I., et al. 2005. Urbanization, malaria transmission and disease burden in Africa. *Nature reviews. Microbiology, 3.1*, 81.

Henderson, M., Yeh, E. T., Gong, P., Elvidge, C., & Baugh, K. 2003. Validation of urban boundaries derived from global night time satellite imagery. *International Journal of Remote Sensing, 24*(3), 595–609.

Hill, J. O., & Peters, J. C. 1998. Environmental contributions to the obesity epidemic. *Science, 280*, 1371–1374.

Hirvonen, K. 2016. Rural-urban differences in children's dietary diversity in Ethiopia: A Poisson decomposition analysis. *Economics Letters, 147*, 12–15.

Imhoff, M. L., Lawrence, W. T., Stutzer, D. C. & Elvidge, C. D. 1997. A technique for using composite DMSP/OLS city lights satellite data to map urban area. *Remote Sensing of Environment, 61*(3), 361–370.

Kim, S., Symons, M., & Popkin, B. 2004. Contrasting socioeconomic profiles related to healthier lifestyles in China and the United States. *American Journal of Epidemiology, 159*, 184–191.

Leon, D. A. 2008. Cities, urbanization and health. *International Journal of Epidemiology*, *37*, 4–8.

Liu, H., & Weng, Q. 2012. Enhancing temporal resolution of satellite imagery for public health studies: A case study of West Nile Virus outbreak in Los Angeles in 2007. *Remote Sensing of Environment*, *117*, 57–71.

McDade, T. W., & Adair, L. S. 2001. Defining the "urban" in urbanization and health: A factor analysis approach. *Social Science and Medicine*, *53,* 55–70.

Menon, P., Ruel, M. T., & Morris, S. S. 2000. Socio-economic differentials in child stunting are consistently larger in urban than rural areas: Analysis of 10 DHS data sets. *Food Nutrition Bulletin, 21*, 282–289.

Monda, K. L., Gordon-Larsen, P., Stevens, J., & Popkin, B. M. 2007. China's transition: The effect of rapid urbanization on adult occupational activity. *Social Science and Medicine*, *64*(4), 858–870.

Monteiro, C. A., Moura, E. C., Conde, W. L., & Popkin, B. M. 2004. Socioeconomic status and obesity in adult populations of developing countries: A review. *Bulletin of the World Health Organization, 82*, 940–946.

Neupane, S., Prakash, K. C., & Doku, D. T. 2016. Overweight and obesity among women: Analysis of demographic and health survey data from 32 Sub-Saharan African Countries. *BMC Public Health, 13*(1), 16–30.

Northridge, M. E., Sclar, E. D., & Biswas, P. 2003. Sorting out the connections between the built environment and health: A conceptual framework for navigating pathways and planning healthy cities. *Journal of Urban Health, 80,* 556–568.

Popkin, B. 1999. Urbanization, lifestyle changes and the nutrition transition. *World Development, 27,* 1905–1916.

______. 2001. The nutrition transition and obesity in the developing world. *The Journal of Nutrition, 131,* 871S–873S.

______. 2003. The nutrition transition in the developing world. *Development Policy Review, 21*, 581–597.

Popkin, B. M., & Du, S. 2003. Dynamics of the nutrition transition toward the animal foods sector in China and its implications: A worried perspective. *Journal of Nutrition*, *133*, 3898–3906.

Popkin, B. M., Adair, L. S. & Ng, S. W. 2012. Global nutrition transition and the pandemic of obesity in developing countries. *Nutrition reviews*, 70(1), 3–21.

Ruel M. T, Garrett J., Yosef S., & Olivier M. 2017. Urbanization, food security and nutrition. *Nutrition and Health in a Developing World*, 705–735.

Rutstein, S. O., & Johnson, K. 2004. *The DHS Wealth Index, DHS Comparative Reports*, Calverton, MD, USA: ORC Macro, No. 6.

Siervo, M., Grey, P., Nyan, O., & Prentice, A. 2006. Urbanization and Obesity in The Gambia: A Country in the Early Stages of the Demographic Transition. *European Journal of Clinical Nutrition*, *6*: 455–463

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

Storeygard, A. 2016. Farther on down the road: Transport costs, trade and urban growth in sub-Saharan Africa. *Review of Economic Studies*, *83*, 1263–1295.

Sutton, P. C. 1997. Modeling population density with nighttime satellite imagery and GIS. *Computers, Environment, and Urban Systems*, *21*(3/4), 227–244.

Sutton, P. C., Taylor, M. J., & Elvidge, C. D. 2010. Using DMSP OLS imagery to characterize urban populations in developed and developing countries. In Rashed, T., Jurgens, C., & Meer, F. D. (Eds.), *Remote Sensing of Urban and Suburban Areas*: *Remote Sensing and Digital Image Processing*, *10*, 329–348.

Tafreschi, D. 2015. The income body weight gradients in the developing economy of China. *Economics & Human Biology*, *16*(1), 115–134.

Tatem, A. J., & Simon, I. H. 2004. Measuring urbanization pattern and extent for malaria research: A review of remote sensing approaches. *Journal of Urban Health*, *81*(3), 363–376.

Van de Poel, E., O'Donnell, O., & Van Doorslaer, E. 2009. Urbanization and the spread of diseases of affluence in China. *Economics and Human Biology*, *7*(2), 200–216.

______. 2012. Is there a health penalty of China's rapid urbanization? *Health Economics*, *21*(4), 367–385.

Vlahov, D., & Galea, S. 2002. Urbanization, urbanicity, and health. *Journal of Urban Health*, *79*, S1–S12.

World Bank. 2013. *Global monitoring report 2013: Rural-urban dynamics and the millennium development goals*. Washington, DC.

WHO (World Health Organization). 2000. *WHO obesity: Preventing and managing the global epidemic*. Technical Report No. 894. Geneva.

______. 2007. *World health report 2007: A safer future—global public health security in the 21st century*. Geneva.

Zhang, Q., & Seto, K. C. 2011. Mapping urbanization dynamics at regional and global scales using multi-temporal DMSP/OLS night light data. *Remote Sensing Environment*, *115*, 2320–2329.

Ziraba, A., Fotso, J., & Ochako, R. 2009. Overweight and obesity in urban Africa: a problem of the rich or the poor? *BMC Public Health*, *9*, 465.

Appendix

Table A1. Night light intensity and women's height and body weight

	(1) Ln (height)	(2) Ln (height)	(3) Ln (weight)	(4) Ln (weight)
Ln (Night light)-centered	0.013***	0.009*	0.081***	0.039**
	(0.005)	(0.005)	(0.020)	(0.019)
Ln (Night light)-centered-square	0.005***	0.004***	0.029***	0.018***
	(0.001)	(0.001)	(0.006)	(0.006)
Ln (Night light)-centered-cubic	-0.007**	-0.005**	-0.031***	-0.020*
	(0.003)	(0.003)	(0.011)	(0.011)
Ln (Night light)-centered-quadruple	0.001**	0.001*	0.007**	0.004
	(0.001)	(0.001)	(0.003)	(0.003)
Year (round) dummy	0.003***	0.002***	0.032***	0.025***
	(0.001)	(0.001)	(0.002)	(0.002)
Educational attainment		0.001***		0.005***
		(0.000)		(0.000)
Age		-0.000***		-0.000***
		(0.000)		(0.000)
Age square		0.002***		0.015***
		(0.000)		(0.001)
Marital status		0.001		0.019***
		(0.001)		(0.005)
Occupation: Base (Household chores)				
Agriculture		0.001		0.004
		(0.001)		(0.003)
Non-agricultural		0.000		0.011***
		(0.001)		(0.002)
Professional		-0.001		-0.008**
		(0.001)		(0.003)
Wealth index: Base (Poorest quintile)				
Poorer quintile		0.004***		0.016***
		(0.001)		(0.003)
Middle quintile		0.005***		0.037***
		(0.001)		(0.004)
Richer quintile		0.008***		0.051***
		(0.001)		(0.005)
Richest quintile		0.011***		0.096***
		(0.001)		(0.006)
Household owns TV		-0.001		0.015***
		(0.001)		(0.003)
Reads newspaper		0.002***		0.023***
		(0.001)		(0.003)
Visited by health officers		0.002***		0.009***
		(0.001)		(0.003)
Constant	0.446***	0.397***	-0.651***	-1.017***
	(0.003)	(0.005)	(0.014)	(0.021)
N	33586	33586	33586	33586

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

Notes: Standard errors are clustered at village level and given in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. The base occupation is household chores, while the base wealth is the poorest quintile.

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