RESEARCH ARTICLE

Disaggregating the longitudinal association between urbanization and body weight in Chinese adults over 1991 – 2015

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Abstract

Urbanization is widely viewed as a major contextual force behind the rising prevalence of overweight and obese people in developing countries. Research in China often conflates between-community difference and within-community change - two separate processes of urbanization that are related to body weight gain. Capitalizing on longitudinal and multilevel data from the 1991 to 2015 China Health and Nutrition Survey, the present study disaggregated the association between change in a community-level urbanicity index and change in individual-level body weight status over time in Chinese adults aged 18–65 years. A positive longitudinal relationship was confirmed between urbanicity and body weight in men, but varied in women by the choice of anthropometric measure. However, for both men and women, such an overall association was largely driven by preexisting between-community differences in the level of urbanization rather than an intrinsic within-community urbanization process. This pattern is robust against two different disaggregation methods. These findings together confirm the inadequate simplicity of the conventional model of community effects on health and nutrition.

Keywords: Community; Overweight; Obesity

1. Introduction

Being overweight or obese has raised a public health concern for the Chinese population (Ng et al., 2014). According to disease surveillance data collected by the Chinese Center for Disease Control and Prevention, the overweight rate among Chinese adults aged 18 years and older nearly doubled from 16.4% in 1992 to 30.1% in 2012, and the obese rate more than tripled from 3.6% to 11.9% during the same period (Chinese CDC, 2015; Wang, 2005). Reasons for population-level weight gain in China are multifaceted and the subject of considerable debate among scholars. Nonetheless, prior research suggests that rising incomes, higher-fat diets, reduced physical activity, and cultural ideals regarding desirable weight all play a role. Because higher levels of urbanization are likely to include a shift from occupations requiring strenuous physical activities to those with more sedentary activities, an increase in automotive use for job commuting and daily activities, more affordable food markets for meat and cooking oil, and easier access to Western fast-food restaurants, many weight-gain-related changes in China are thought
to stem from urbanization, one of the most dramatically changing features of communities in contemporary China (Monda et al., 2007; Monda et al., 2008; Xu et al., 2013).

In China, urbanization can be driven by flows of migrants from rural villages to cities for better life opportunities, resulting in rapid increases in population size and density in existing urban areas. Meanwhile, rural villages can experience in situ urbanization fueled by the development of township and village enterprises and the inflow of foreign investment. In situ village urbanization involves changes in the economic structure, wherein the labor force shifts from agricultural activities to activities in manufacturing and service sectors. In situ village urbanization also includes changes in the built environment, wherein previously rural areas of farmland and farmhouses are converted into urban areas with modern roads designed for automobiles, factories, and residential and commercial centers (Zhu, 2000; Zhu, 2002).

In situ urbanization involves within-community longitudinal changes in demographics, socioeconomic conditions, and built environment, while urbanization through rural-to-urban migration can be seen as between-community cross-sectional differences in these characteristics. Therefore, in situ urbanization is the context often related to the conventional wisdom about the effects of changing community characteristics on individual-level weight gain. That is, increasing in situ urbanization in China is thought to have a strong impact on altering individual physical activity patterns in the urbanized areas, which, in turn, is thought to drive the increasing prevalence of overweight and obesity in China (Monda et al., 2007; Monda et al., 2008). As part of the urbanization process, local food environment is also likely to shift, usually from a high-fiber, low-fat, and low-energy diet to a low-fiber, high-fat, and high-energy diet, contributing to the so-called “obesogenic environments” – contexts that promote obesity by encouraging both physical inactivity and excessive energy intake (Swinburn et al., 1999; Mehta & Chang, 2008).

Investigation into the in situ urbanization process and its implications for within-community weight gain requires longitudinal data at both the individual and community levels. The China Health and Nutrition Survey (CHNS) has been a valuable data source in this regard. However, as reviewed below, previous analyses of the CHNS data focused on an overall association between community-level urbanization and individual-level body weight status without making either a conceptual or an analytical distinction between within-community urbanization processes and pre-existing between-community differences. Thus, an observed overall association can be theoretically misleading because it may be largely driven by between-community differences, including substantial pre-existing gaps in urbanization levels between rural and urban areas and an uneven pace of urbanization across the entire country (Xie & Hannum, 1996; Yeh et al., 2011).

This study seeks to improve our understanding about the overall association between urbanization and weight gain in Chinese adults by disaggregating it into two components: (1) the between-community component that captures differences in level of urbanization at baseline and rate of urbanization over time across communities; and (2) the within-community component that reflects the in situ urbanization process and corresponds to the conventional theory of neighborhood effects on health (Roux, 2004; Entwisle, 2007). Drawing on longitudinal and multilevel data from the CHNS, the present study prospectively examines body weight changes in Chinese adults from 1991 to 2015. The analysis of weight change relies on both general adiposity and abdominal adiposity with physically measured anthropometric data, minimizing simplistic erroneous inference that can result from sole reliance on body weight measures (Xu et al., 2013). Two disaggregation methods are compared in assessing the relative strengths of between- and within-community components in explaining the longitudinal association between urbanization and weight gain.

2. Prior research and limitations
An ongoing longitudinal panel study first conducted in 1989, the CHNS now includes more than 7000 households across 15 provinces and municipal cities in contemporary China that vary substantially in geography, economic development, public resources, and health indicators. In addition, detailed community-level data are collected from local officials. The long survey period makes the CHNS data extremely valuable for studying the relation between urbanization and body weight status, not only because it usually takes some time for community characteristics to evolve as a result of human activities but also because the study period of the CHNS (1990s and 2000s) is when China experienced unprecedented social changes and urbanization. Therefore, it is not surprising that previous research on community-level urbanization and weight gain in China heavily relies on analyses of the CHNS data.

That being said, a few studies using the CHNS data examined only cross-sectional associations between urbanization and body weight status. For example, Van de Poel et al. (2009) performed separate cross-sectional analyses of respondents aged 16 years and older from the 1991 and 2004 waves of CHNS. They found that, compared with residents of communities in the bottom tercile of an urbanicity index, the risk of being overweight (body mass
index [BMI ≥25] was significantly higher for residents of communities in the top tercile. Thompson et al. (2015), who analyzed the adult sample from the 2009 wave of the CHNS, found that living in a community in the top tercile of an urbanicity index was associated with a greater likelihood of having a high waist-to-height ratio (WHtR) (>0.5) than living in a community in the bottom tercile for men but not for women. The cross-sectional nature of these studies means that the findings are based on between-community differences only.

The most common approach for longitudinal analyses of the urbanization-weight association is to estimate a hierarchical linear model (for continuous measures of body weight) or logistic model (for dichotomous measures of body weight) that adjusts for the multilevel data structure in CHNS, nesting measurement occasions (level 1) within individuals (level 2), who, in turn, are nested within communities (level 3). Applying this approach to the adult sample (ages 18–59) in 1991–2009 CHNS, Jaacks et al. (2013) found that a two standard deviation increase in community urbanization was related to a 0.23 unit (kg/m²) increase in BMI and a 3% increase in the odds of being overweight (BMI ≥25). The same approach has also been applied to examining the diet and physical activity mediators through which urbanization affects body weight status. For example, using 1991–1997 CHNS data, Monda et al. (2007) found that a 1-unit change in urbanization score was related to a 7% and a 6% increase in the odds of light or moderate (versus heavy) occupational activity for men and women ages 18–55, respectively. Using the 1991–2011 CHNS data, Ng et al. (2014) measured physical activity for adults aged 18–60 at work and at home using the metabolic equivalent of task hours per week. They found that higher urbanization scores were associated with lower occupational physical activity for both men and women, and lower domestic physical activity for women, but higher domestic physical activity for men.

However, alternative model specifications have led to inconclusive findings. Focusing on a subset of women who had their BMI measured in both the 1991 and 2004 waves of the CHNS, and who were not overweight or obese in 1991, Jones-Smith and Popkin (2010) estimated a logistic model with robust standard errors and found significantly greater odds of being overweight (BMI ≥25) for women in communities with greater increases in urbanization scores over the study period than for women in communities within the lowest quintile of urbanization in 1991 and that experienced no increase over time. In contrast, applying a difference-in-differences estimator with fixed-effects to the 1991–2004 CHNS data, Van de Poel et al. (2012) found no significant association between urbanization (defined as movement from below to above the median of an urbanicity index) and obesity (BMI >30) among adults aged 18 years and older. Gordon-Larsen et al. (2014) identified latent class trajectories of adult BMI in the 1991–2011 CHNS data and found that baseline urbanicity was not associated with upward BMI trajectories for men or women. After dividing communities into terciles of urbanicity scores, they found a positive association between the 10-year change in community urbanicity scores and residents’ rate of being overweight (BMI ≥25) in the least urbanized communities at the baseline, but a negative association in the most urbanized communities at the baseline.

Despite using these different estimation strategies, the previous research has paid little attention to explicitly modeling the within-community process of urbanization separately from between-community differences in the baseline level or the rate of urbanization. The mixed findings in the literature may be partially explained by different estimation strategies that make inferences about different components of the urbanization process that are related to body weight status in different ways. For example, the hierarchical modeling approach draws inference from pooling together within- and between-community variability over time (Monda et al., 2007; Jaacks et al., 2013; Ng et al., 2014), whereas the difference-in-differences approach and its variant adopted by other researchers (Jones-Smith & Popkin, 2010; Van de Poel et al., 2012; Gordon-Larsen et al., 2014) adjusts for between-community difference in the baseline level of urbanization but leveraged on between-community difference in the rate of urbanization.

The disaggregation analysis in this study will shed new light on the methodological issues (different modeling strategies that may or may not correctly specify different processes of urbanization) that lead to inconsistent findings obtained from the same data source in the literature. More importantly, it will help clarify the mismatch between the conceptual model of within-community process (i.e., in situ urbanization) and the statistical model that conflates within- and between-community processes. The disaggregation of between- and within-community components permits a precise and unambiguous test of the longitudinal association between in situ urbanization and weight gain.

3. Data and methods
3.1. Sample
Subjects for this study were adults ages 18–65 in the CHNS. Although the CHNS data are not nationally representative, households were randomly selected from a diverse set of nine provinces in northeast, central, and south China. Together, these nine provinces are home to more than
40% of China's population, or 549 million people. Survey communities were drawn through a stratified, multistage random sampling process from cities, suburbs, towns, and villages designated by China’s National Bureau of Statistics. In each community, 20 households were randomly selected and all household members were interviewed. The response rate at the individual level is 88%. In addition to individual-level data, the CHNS collects background characteristics of the survey communities. Details on the design and sampling of the CHNS are available elsewhere (Popkin et al., 2010).

This study draws on data from nine waves of the survey (1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011, and 2015) that span more than 20 years. Three municipal cities were added to the sampling frame in 2011 and three more provinces were added in 2015. Respondents from these new sites were excluded, because they might obscure the long-time trends in the other provinces since 1991. A total number of 69,582 (93.5%) out of 74,419 age-eligible person-year observations had valid values of body weight and height between 1991 and 2015 (69,175), or valid values of waist circumference (WC) between 1993 (see the next section) and 2015 (60,760), or both (60,353). Among them, 1818 (2.6%) observations were excluded due to missing data on covariates. The overall analytical sample consisted of 67,764 person-year observations (35,255 females and 32,509 males) contributed by 21,029 individual adults (10,983 female and 10,046 male) from 241 communities. To maximize the statistical power, the final sample size was allowed to vary depending on the number of valid values of each outcome variable.

3.2. Measures

The dependent variable, body weight status, is captured in two ways: (1) BMI, calculated from body weight (in kilograms) and height (in centimeters), which taps general obesity and (2) WC, waist-to-hip ratio (WHpR), and WHtR, all of which tap abdominal obesity. All the anthropometric measures were taken by experienced healthcare workers. While widely used as an indicator for measuring whole-body obesity, BMI is not the best measure for abdominal fat accumulation. In several populations, measures of abdominal obesity, such as WC, WHpR, and WHtR, were found to be superior to BMI for predicting cardiovascular disease risk and for obesity screening (Yusuf et al., 2004; Li et al., 2006; Knowles et al., 2011).

We also examine dichotomous outcomes of body weight status. Overweight status is defined as a BMI ≥ 24 kg/m², using the Chinese Center for Disease Control and Prevention guidelines (2003). Abdominal obesity is defined as a WC ≥ 90 cm for men and WC ≥ 85 cm for women (JCDCG, 2007); a WHpR ≥ 0.9 for men and WHpR ≥ 0.85 for women (the World Health Organization, 2008); or a WHtR > 0.5 (Browning et al., 2010). As a robustness check, overweight is also defined as a BMI ≥ 25 kg/m², using the World Health Organization guidelines (1998) and abdominal obesity is WC ≥ 90 cm for men and WC ≥ 80 cm for women according to the International Diabetes Federation guidelines (IDF, 2006). The CHNS did not collect data on WC until 1993, and thus, all measures of body weight status that involve WC are from solely the 1993–2015 period.

The primary independent variable of interest is a community-level urbanicity index designed specifically for the CHNS data (Jones-Smith & Popkin, 2010). Capitalizing on the rich community-level data in the CHNS, the urbanicity index captures 12 dimensions of urbanization for each community in each wave, including population density, economic activity, traditional markets, modern markets, transportation infrastructure, environmental sanitation, communications, housing conditions, average education level, socioeconomic diversity, health infrastructure, and social services. Each of these dimensions is measured by one or multiple variables and assigned ten possible points, resulting in a maximum value of 120 points summed across the 12 dimensions, with higher values indicating greater urbanization. Detailed information on this index is available elsewhere (Monda et al., 2007; Jones-Smith & Popkin, 2010).

To account for biological differences in body weight status and weight gain trajectory, the full sample is divided into female and male subsamples. Other demographic control variables include age (in years), age-squared, and marital status. Socioeconomic backgrounds are captured by respondents’ educational attainment (no formal education, primary school, middle school, high school, or college and above) and annual household per capita income (adjusted for inflation and divided into quartiles). Dummy variables indexing provinces and survey waves are included to adjust for spatial and temporal fixed effects, respectively.

3.3. Methods

To assess the robustness of the findings, two methods that vary in their strengths and limitations were employed to disaggregate between- and within-community components of the urbanization-body weight associations. The first, standard method is to rescale the time-varying urbanicity index by community-specific mean centering. Borrowing the notations from Curran and Bauer (2011), let \( z_j \) be the urbanicity index score for community \( j \) at time \( t \), the mean-centered score, denoted by \( \mu_j \), can be calculated as:

\[
\hat{z}_j = z_j - \bar{z}_j
\]
where $\bar{z}_{jt}$ is the observed sample mean urbanicity index score for community $j$ throughout its entire observation period. Estimates of disaggregated within- and between-community differences can be obtained by regressing the outcome variable on $z_{jt}$ and $\bar{z}_{jt}$. Let $y_{ijt}$ be a continuous body weight measure for individual $i$ living in community $j$ at time $t$, and $X_{ij}$ be a set of individual- and household-level control variables. A three-level random effects model is fitted to incorporating the hierarchical data structure as the following:

$$y_{ijt} = \beta_0 + \beta X_{ij} + \gamma_j \bar{z}_{jt} + \gamma_z z_{jt} + u_j + u_{ij} + e_{ijt} \tag{2}$$

where $\beta_0$ is an intercept, $u_i$ and $u_j$ represent person- and community-level random intercepts, respectively, and $e_{ijt}$ denotes residues. The coefficient $\gamma_j$ captures the relation between average levels of urbanicity index and average levels of body weight measures pooling over communities. In contrast, the coefficient $\gamma_z$ captures the mean relation between a given community’s time-specific deviation in urbanization (from its overall level of urbanization) and the time-specific body weight status among the residents living in that community.

The validity of the standard method relies on the assumption that the community-level urbanicity index is unrelated to time (Curran & Bauer, 2011). In other words, it assumes potential growth in the body weight outcome (i.e., $y_{ijt}$), but no systematic change in urbanization itself, aside from random variations, with the passage of time. This assumption is unlikely to hold because not only has China been one of the fastest urbanizing countries in the world since the 1980s (United Nations, 2015) but also the sampled communities in CHNS have gained considerable growth in their urbanicity index scores between 1991 and 2015 (see the results section).

The second method, referred to as growth curve disaggregation, allows the community-level urbanicity index to change as a function of time and allows the rates of change to vary randomly over communities. These assumptions represent a more realistic scenario, in which the initial level of urbanicity and the pace of urbanization over time differ across communities. A growth curve model for the relationship between the time-varying community-level urbanicity index and time can be specified as the following:

$$z_{jt} = \alpha_0 + \alpha_1 T_{jt} + \delta_{0j} + \hat{\delta}_{ij} T_{jt} + r_{jt}$$

$$= (\alpha_0 + \delta_{0j}) + (\alpha_1 + \hat{\delta}_{ij}) T_{jt} + r_{jt} \tag{3}$$

where $T_{jt}$ is the measure of time at time $t$ for community $j$, which permits the possibility that all the sampled communities are not surveyed at all of the same points in time (i.e., unbalanced longitudinal data with respect to time); $\alpha_0$ is the mean intercept, indicating the average urbanicity index across all communities and all time points; $\alpha_1$ is the mean slope, indicating the average rate of change in urbanization over time; $\delta_{0j}$ represents the deviation of community $j$’s intercept from the grand mean $\alpha_0$, $\hat{\delta}_{ij}$ represents the deviation of community $j$’s slope from the mean slope $\alpha_1$, and the residual term $r_{jt}$ captures the within-community variability of urbanization around the community-specific mean. Between-community differences at any given point in time are determined by both between-community variability in the intercept ($\delta_{0j}$) and between-community variability in the slope ($\hat{\delta}_{ij}$). Instead of centering at the observed community-specific mean as in Equation (1), each community- and time-specific $z_{jt}$ can be deviated from its model’s implied value (Curran & Bauer, 2011):

$$\hat{r}_{jt} = z_{jt} - (\hat{\alpha}_0 + \hat{\delta}_{0j}) - (\hat{\alpha}_1 + \hat{\delta}_{ij}) T_{jt} \tag{4}$$

where $\hat{\alpha}_0$, $\hat{\delta}_{0j}$, $\hat{\alpha}_1$, $\hat{\delta}_{ij}$, and $\hat{r}_{jt}$ are the estimates of the coefficients defined in Equation (3). Between-community differences averaged over time can be represented by:

$$\hat{\delta}_{0j} = \bar{x}_j - \hat{\alpha}_0 - (\hat{\alpha}_1 + \hat{\delta}_{ij}) \bar{T}_j \tag{5}$$

where $\bar{r}$ is the mean value of time for community $j$ and allows unbalanced time structure. The values of $\hat{\delta}_{0j}$ and $\hat{r}_{jt}$ can then be substituted into Equation (2) for $\bar{z}_j$ and $\hat{z}_{jt}$, respectively.

Three multilevel random-intercept models, in which repeated measures (level-1) were nested within individuals (level-2) which, in turn, were nested within communities (level-3), were fitted to each outcome variable. Model 1 assessed the overall association between body weight status and the urbanicity index. Model 2 applied the standard method to rescaling urbanicity index scores and disaggregating the overall association into between- and within-community differences. Model 3 adopted the growth curve disaggregation method instead. Multilevel linear models were estimated for continuous measures of body weight status, while multilevel logistic models were estimated for binary measures of body weight status.

### 4. Results

#### 4.1. Descriptive statistics of body weight status

The gender-stratified secular trends of the continuous and dichotomous measures of body weight status presented in Figures 1 and 2, indicate that both Chinese men and women have grown heavier over two decades. For example, Figure 1 shows that the average BMI increased...
from 21.9 in 1991 to 24.1 in 2015 for women and from 21.5 to 24.6 during the same period for men (Table S1 in Supplementary File). For both men and women, the 95% confidence intervals of the sample average BMI in 2015 do not overlap with those in 1991, suggesting statistically significant secular increases. Figure 2 shows that using a cutoff of BMI ≥24 kg/m², the sample percentage of overweight women nearly doubled from 22.1% in 1991 to
45.7% in 2015 (Table S2 in Supplementary File). During the same period, the sample percentage of overweight men more than doubled from 14.8% to 51.4%. Weight changes are also seen in the measures related to abdominal obesity. For example, the average WC increased by about 8% from 74.9 cm in 1993 to 80.6 cm in 2015 for women and by about 12% from 76.4 cm to 85.4 cm for men during the same period. Using WC ≥90 cm for men and WC ≥85 cm for women as cutoffs, the sample percentage of abdominal obesity grew by more than 150% from 14.8% in 1993 to 38.1% in 2015 for women and more than tripled from 8.3% to 38.3% for men during the same period.

The secular trend of gender gap in weight gain varies across different measures of body weight status. Among the continuous measures depicted in Figure 1, men had on average significantly lower BMI and WHtR than women in the early 1990s, but the gender gaps narrowed over time. In fact, the gender gap in average BMI lost its statistical significance by 2000 and men’s average BMI gradually surpassed that of women thereafter. Men had on average significantly higher WC and WHpR than women in the early 1990s, with the gender gap growing for WC but remaining relatively stable for WHpR in the study period. In contrast, men had generally lower rates of abdominal obesity according to WC and WHpR cutoffs between 1993 and 2015, but the gender gap in WC-based rate of abdominal obesity converged by 2006 (Figure 2). The gendered patterns across measures of weight growth between the continuous and dichotomous measures of WC and WHpR may be attributed to gender-specific cutoffs of abdominal obesity.

### 4.2. Descriptive statistics of independent variables

Figure 3 shows the trends of average urbanicity index values and the associated 95% confidence intervals, stratified by four community types used in the CHNS sampling stage. Rapid urbanization took place in the sampled communities, with the average urbanicity index score growing by almost 50% from 46.4 in 1991 to 71.5 in 2015 (Table S3 in Supplementary File). The pace of urbanization was fastest in village communities, where the average urbanicity index score rose by nearly 70% from 34.8 to 59 over two decades. Nevertheless, Figure 3 indicates that the average level of urbanization in village communities remained significantly lower than in any other type of community throughout the period of 1991-2015. In addition, the average level of urbanization in suburban communities was significantly lower than that in city communities throughout the same period, and significantly lower than that in town communities during most of the period. These findings suggest that despite a growing urbanicity within each type of community, the pace of urbanization was uneven across different types of communities – sustaining the between-community gaps in the level of urbanization over two decades, which might be attributable to public policies and investments in favor of urban development during China’s reform era (Xie & Hannum, 1996). Therefore, the observed growth in population-level body weight described above could have been driven by both within- and between-community differences in urbanization.

Table 1 shows that the average age of the respondents was around 42 years; more than 80% were married; and most had completed elementary or middle school education, with men on average having a higher level of education than women. The person-year observations in the analytical sample were by and large evenly distributed across household income quartiles, provinces, and survey waves.

### 4.3. Regression results for continuous outcomes

Table 2 reports multilevel regression disaggregation results for the longitudinal associations between urbanization and continuous measures of body weight status. To preserve the space, only the main coefficient estimates of interest were presented. Full regression estimates from selected models can be found in Table S4 in Supplementary File and full results from other models can be requested from the author. In the female subsample, the urbanicity index score was significantly associated with BMI and WC (Model 1), but unrelated to WHpR or WHtR. Both associations were attributed to between-community difference but not within-community difference in urbanicity index, regardless of which disaggregation method was employed (Models 2 and 3). After disaggregation, WHpR was not associated with either between- or within-community difference in urbanicity index; neither was WHtR.
The patterns were different for men. Urbanicity index was significantly and positively related to all the four continuous measures of body weight status. For WC, WHpR, and WHtR, the overall associations were completely attributable to between-community difference in urbanization, regardless of the choice of disaggregation method. For BMI, the overall association was driven by both between- and within-community differences, although the latter played a relatively minor role and was only marginally significant at $\alpha = 0.1$ level. For example, according to the standard disaggregation, BMI would increase by 0.024 unit for every one-unit increase in between-community difference in urbanicity index, but only by 0.005 unit for every one-unit increase in within-community difference. The results were almost identical according to the growth curve disaggregation.

### 4.4. Regression results for overweight and abdominal obesity

Table 3 reports multilevel regression disaggregation results for the longitudinal associations of urbanization with the overweight and abdominal obesity measures. In the female subsample, urbanicity index was positively associated with both overweight- and WC-based abdominal obesity measures, but unrelated to WHpR or WThR (Model 1). The standard disaggregation showed the association between urbanicity index score and the overweight measure being driven by both between- and within-community differences (Model 2), whereas the growth curve disaggregation suggested that within-community difference did not play any significant role (Model 3). In contrast, the two disaggregation methods consistently showed that the association between urbanicity index score and the WC-based abdominal obesity measure was entirely driven by between-community difference in urbanization.

In the male subsample, urbanicity index score was again significantly and positively related to all the four measures of overweight and abdominal obesity. For abdominal obesity, the two disaggregation methods found that the association was attributed to between- but not within-community difference, regardless of which measure was used. For the overweight measure, between-community difference again played a much stronger role than within-community difference (i.e., log odds = 0.048 vs. 0.011 according to the standard disaggregation, and 0.051 versus 0.01 according to the growth curve disaggregation).

### 4.5. Sensitivity analysis

Two sensitivity analyses were conducted. First, Table S5 in Supplementary File shows that similar results were obtained when alternative cutoff points were used to classify overweight (BMI $\geq 25$ vs. 24 kg/m$^2$) and abdominal obesity (WC $\geq 80$ cm in women). For both men and women, urbanicity index was positively related to the risks of being overweight and having abdominal obesity, and these associations were mainly driven by between- rather than within-community difference. Second, Table S6 in Supplementary File reports coefficient estimates from growth curve models of the continuous

<table>
<thead>
<tr>
<th>Control variables</th>
<th>Women</th>
<th>Men</th>
</tr>
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<tbody>
<tr>
<td>Age in years (mean [SD])</td>
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<td>42.1 (13.0)</td>
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<tr>
<td>Marital status (%)</td>
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<tr>
<td>Never married</td>
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<td>Married</td>
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<td>Divorced/widowed</td>
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<td>Educational attainment (%)</td>
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<td></td>
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<td>College or above</td>
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<td>Per capita household income (%)</td>
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<td>4th quartile</td>
<td>24.8</td>
<td>25.6</td>
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<tr>
<td>Province (%)</td>
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<td>Guizhou</td>
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<td>12.0</td>
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<td>1993</td>
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<td>2000</td>
<td>11.0</td>
<td>11.0</td>
</tr>
<tr>
<td>2004</td>
<td>11.4</td>
<td>11.4</td>
</tr>
<tr>
<td>2006</td>
<td>11.2</td>
<td>11.0</td>
</tr>
<tr>
<td>2009</td>
<td>11.3</td>
<td>11.3</td>
</tr>
<tr>
<td>2011</td>
<td>10.7</td>
<td>10.4</td>
</tr>
<tr>
<td>2015</td>
<td>11.1</td>
<td>11.2</td>
</tr>
<tr>
<td>N of person-year observations</td>
<td>32,573</td>
<td>30,880</td>
</tr>
</tbody>
</table>
measures of body weight status. These growth curve models include not only random intercepts that capture intra-person correlation (of repeated measurements) and intra-community correlation (of clustered individuals) but also random coefficients for age that capture heterogeneous age effect. Despite slight changes in certain coefficient estimates and standard errors, the results are qualitatively the same as those reported in Table 2. Unfortunately, similar specification of growth curve models for dichotomous measures of body weight status failed to converge.

5. Discussion

Urbanization is widely viewed as a major contextual force behind the rising prevalence of obesity in developing countries (Hoffman, 2001; Ng et al., 2014). China, a developing country in the midst of rapid urbanization and nutrition transition, is an ideal setting to assess the impact of urbanization on excess weight gain. Higher levels of urbanization are likely to include a shift from occupations requiring strenuous physical activities to those with more sedentary activities, an increase in automotive use for job commuting and daily activities, more affordable food markets for meat and cooking oil, and easier access to Western fast-food restaurants – all factors increasing body weight status. However, the previous research has reported inconsistent findings on the relationship between urbanization at the community level and body weight status at the individual level. More important, the previous research usually does not make a conceptual distinction between different forms
Table 3. Three-level random-intercept logistic models of longitudinal associations of urbanicity with overweight and abdominal obesity in Chinese adults (18–65 years).

<table>
<thead>
<tr>
<th>Key predictors</th>
<th>Overweight (N=35,065)</th>
<th>Abdominal obesity based on WC (N=30,709)</th>
<th>WHpR (N=30,203)</th>
<th>WHtR (N=30,661)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1: Urbanicity index</td>
<td>0.014*** (0.003)</td>
<td>0.008** (0.003)</td>
<td>−0.002 (0.002)</td>
<td>0.002 (0.003)</td>
</tr>
<tr>
<td>Model 2: Standard disaggregation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between-community component</td>
<td>0.021*** (0.004)</td>
<td>0.012*** (0.003)</td>
<td>−0.004 (0.002)</td>
<td>0.002 (0.003)</td>
</tr>
<tr>
<td>Within-community component</td>
<td>0.010* (0.004)</td>
<td>0.004 (0.005)</td>
<td>−0.001 (0.003)</td>
<td>0.002 (0.004)</td>
</tr>
<tr>
<td>Model 3: Growth curve disaggregation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between-community component</td>
<td>0.025*** (0.004)</td>
<td>0.014*** (0.003)</td>
<td>−0.004 (0.002)</td>
<td>0.004 (0.003)</td>
</tr>
<tr>
<td>Within-community component</td>
<td>0.007 (0.005)</td>
<td>0.002 (0.005)</td>
<td>−0.001 (0.004)</td>
<td>0.001 (0.004)</td>
</tr>
<tr>
<td>Male sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1: Urbanicity index</td>
<td>0.029*** (0.003)</td>
<td>0.021*** (0.003)</td>
<td>0.007*** (0.002)</td>
<td>0.015 (0.003)</td>
</tr>
<tr>
<td>Model 2: Standard disaggregation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between-community component</td>
<td>0.048*** (0.003)</td>
<td>0.035*** (0.003)</td>
<td>0.012*** (0.002)</td>
<td>0.023*** (0.003)</td>
</tr>
<tr>
<td>Within-community component</td>
<td>0.011* (0.005)</td>
<td>0.005 (0.005)</td>
<td>0.002 (0.004)</td>
<td>0.007* (0.004)</td>
</tr>
<tr>
<td>Model 3: Growth curve disaggregation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between-community component</td>
<td>*** (0.004)</td>
<td>0.039*** (0.003)</td>
<td>0.013*** (0.002)</td>
<td>0.026*** (0.003)</td>
</tr>
<tr>
<td>Within-community component</td>
<td>0.010† (0.005)</td>
<td>0.002 (0.005)</td>
<td>0.000 (0.004)</td>
<td>0.004 (0.004)</td>
</tr>
</tbody>
</table>

Overweight if body mass index≥24 kg/m\(^2\). Abdominal obesity if waist circumference (WC) ≥90 cm in men or ≥85 cm in women; waist-to-hip ratio (WHpR) ≥0.9 in men or ≥0.85 in women; or waist-to-height ratio (WHtR) >0.5. Robust standard errors are in parentheses. All the models adjusted for age, marital status, education, household income, provincial fixed effects, and time fixed effects. †P<0.1; *P<0.05; **P<0.01; ***P<0.001.

of urbanization (i.e., in situ urbanization of community environment versus rural-to-urban migration) and thus empirically conflates preexisting between-community difference and intrinsic within-community change in relation to body weight gain. From the perspective of place effects on health, it is the within-community urban development that has a direct bearing on the conventional hypothesis about the relationship between urbanization and body weight changes. In contrast, between-community difference may encompass gaps in communities’ baseline levels and rates of urbanization in relation to weight gain.

With prospective, longitudinal, and multilevel data, this study documented considerable weight gain among Chinese adults with respect to their average body size and fat distribution, as well as remarkable within-community urbanization over two decades. After taking into account individual- and household-level demographic and socioeconomic factors, regression estimates confirmed a positive longitudinal association between community-level urbanicity and individual-level body weight status, with noteworthy gender differences. For Chinese men, the positive weight gain-urbanization association holds irrespective of body weight measure (continuous or dichotomous, general overweight or abdominal obesity). For Chinese women, the statistical significance is sensitive to the choice of body weight measure.

Through disaggregation analysis, the overall longitudinal association between community-level urbanicity and
individuals' body weight was found to be largely driven by between-community difference. This finding holds for both men and women and is robust against the choice of disaggregation method or body weight measure. In other words, contrary to the conventional theory, little evidence supports that an increase in the level of urbanization within a community was related to weight gain among its residents. The observed positive association between urbanization and body weight status was heavily inferred from disparities between individuals living in different communities that differed in their baseline and trajectory of urbanization.

The lack of association between within-community urbanization and weight gain might reflect insufficient statistical power. For example, as evident in Figure 3 and in Supplementary File Table S3, the cross-sectional between-community variation in the urbanicity index score at any time point was considerably larger than the longitudinal within-community variation over any two consecutive waves of the CHNS. As a result, the CHNS data provided greater statistical power for researchers to detect potential between-community effect than within-community effect. In essence, this is similar to the drawback of fixed-effects models being less efficient than random-effects models of longitudinal data.

To be comparable with previous research, the present study did not disentangle the multiple dimensions of urbanization. The urbanicity index provides a single composite measure of 12 distinct aspects of urbanization and, hence, does not allow researchers to identify the heterogeneity in the process of urbanization that may have diverse implications for people's weight gain. For example, when a village develops into a town, not only would its transportation infrastructure and food environment change substantially but also more importantly, new urban social and economic structures would be established in place of the old rural ones. Agricultural work would be replaced by manufacture or service industry, and a physically active lifestyle might be replaced by a sedentary lifestyle, making villagers more susceptible to changes in body weight status than, say, city dwellers whose lifestyles would change less drastically as their urban community experiences such gradual changes as the opening of a new supermarket or subway station. Therefore, future research should develop and test theories that identify specific aspects of urbanization related to weight gain. Furthermore, the present study does not examine intermediate diet and physical activity outcomes that lie in the pathway to weight gain. However, the CHNS has made some changes in questionnaire design related to self-reported measures of diet and physical activities, making longitudinal analysis difficult. Future research using the CHNS data may specify a shorter study period during which consistent measures are available to decompose the associations between urbanization and these intermediate outcomes.

Despite these limitations, findings from this study highlight complex patterns of body weight changes in relation to urbanization as the Chinese society transitions from an old era of poverty and under-nutrition to a new one of affluence and over-nutrition. The findings also challenge the adequacy of the simple conventional model of community effects on health (Averett & Korenman, 1999; Entwisle, 2007). Understanding risks for obesity in adults depends not only on whether they live in urbanized communities but also on how obesogenic environments evolve as a result of human activities. In terms of policy implications, the findings suggest that limited public health resources to address the rising prevalence of obesity should not be evenly distributed but targeted at city and town communities where the level of urbanization continues to be high and migrants from rural areas are about to adopt new lifestyles.

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Conflict of interest

No conflicts of interest were reported by the author.

Author contributions

This is a sole-authored study.

Ethics approval and consent to participate

This study does not involve human subjects as defined by CUNY Human Research Protection Program (HRPP) because it only involves analysis of publicly available, secondary survey data. Therefore, this study does not require CUNY HRPP or IRB review.
Consent for publication

Not applicable.

Availability of data

The data used in this study are drawn from the CHNS and publicly available at the CHNS website: https://www.cpc.unc.edu/projects/china.

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