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## Disparities in trajectories of changes in the unhealthy food environment in New York City: a latent class growth analysis, 1990–2010

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### Abstract

Disparities in availability to food retailers in the residential environment may help explain racial/ethnic and socio-economic differences in obesity risk. Research is needed that describes whether food environment dynamics may contribute to equalizing conditions across neighborhoods or to amplifying existing inequalities over time. This study improves the understanding of how the BMI-unhealthy food environment has evolved over time in New York City. We use longitudinal census tract-level data from the National Establishment Time-Series (NETS) for New York City in

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Ethics approval

Ethics approval is unnecessary. No human subjects' data was used for this paper.

the period 1990–2010 and implement latent class growth analysis (LCGA) to (1) examine trajectories of change in the number of unhealthy food outlets (characterized as selling calorie-dense foods such as pizza and pastries) at the census tract level, and (2) examine how trajectories are related to socio-demographic characteristics of the census tract. Overall, the number of BMI-unhealthy food outlets increased between 1990 and 2010. We summarized trajectories of evolutions with a 5-class model that indicates a pattern of fanning out, such that census tracts with a higher initial number of BMI-unhealthy food outlets in 1990 experienced a more rapid increase over time. Finally, fully adjusted logistic regression models reveal a greater increase in BMI-unhealthy food outlets in census tracts with: higher baseline population size, lower baseline income, and lower proportion of Black residents. Greater BMI-unhealthy food outlet increases were also noted in the context of census tracts change suggestive of urbanization (increasing population density) or increasing purchasing power (increasing income).

### Keywords

New York City; neighborhood; inequalities; trajectory; retail environment; National Establishment Time-Series; latent class growth analysis; food environment

### Introduction

Although the prevalence of obesity has increased in all population groups, low-income, Black and Hispanic populations face higher risk of obesity (Flegal et al., 2016; Krueger and Reither, 2015). Differences in availability of food retailers in the residential environment may help explain these differences. Past studies of racial, ethnic and socio-economic disparities in neighborhood food environments have focused on single business categories like fast food (Larson et al., 2009). However, multiple business categories prominently selling energy-dense, nutrient-poor foods, such as fast food outlets, convenience stores, and candy stores often cluster together, for instance near transportation hubs like subway and bus stops. In addition, in lower-income neighborhoods where national fast food chains often have lower penetration, corner convenience stores- sometimes referred to as bodegas- often occupy the same niche in the food environment as fast food outlets (Neckerman et al., 2014). A food environment metric previously referred to as “BMI-unhealthy food outlets” was developed to provide a more comprehensive picture of the presence of food outlets selling energy dense, nutrient poor foods than can be assessed by focusing on a single business category such as fast food (Rundle et al., 2009).

A few recent contributions have stressed the importance of how places - and change in places - might affect health over the life course (Lekkas et al., 2017; Pearce et al., 2016). Yet, despite the growing availability of commercial and non-commercial historical datasets on contextual variables (Kaufman et al., 2015), few studies have attempted to understand how the local food environment is changing over time (Boone-Heinonen and Gordon-Larsen, 2012; Hedman et al., 2015; Sharkey and Faber, 2014). In particular, there is currently an incomplete understanding of *where* and *for whom* changes in the food environment are occurring. Cross-sectional studies have indicated that low-income and racial/ethnic minority groups tend to be more exposed to worse food environments, typified

by high concentrations of fast food and convenience stores, and a shortage of large grocery stores (Beaulac et al., 2009; Larson et al., 2009). Whether food environment dynamics may contribute to equalizing conditions across neighborhoods or to amplifying existing inequalities over time remains unknown.

The goal of this study is to improve our understanding of how the BMI-unhealthy food environment has evolved over time. We use longitudinal data from the National Establishment Time-Series (NETS) for New York City census tracts for the period from 1990 to 2010 and implement LCGA to (1) examine trajectories of change in the number of BMI-unhealthy food outlets (characterized as selling calorie-dense foods such as pizza and pastries) at the census tract level, and (2) examine how such trajectories relate to census socio-demographic characteristics of the residents at baseline and over time.

## Methods

### 1. Study population

We treated 2010 US census tracts in the five boroughs of New York City as units of analysis. Previous studies relating neighborhood environment and health have used the same spatial units. Census tracts contain on average 4,000 inhabitants and are redrawn every ten years. Local jurisdictions have input on the spatial boundaries that help them reflect popular knowledge of neighborhoods. To ensure our analysis used consistent spatial units over time, we used census data regularized to 2010 tract boundaries, as defined in the Longitudinal Tract Data Base (Logan et al., 2016, 2014).

### 2. Food environment measure

We derived our food environment measure from the National Establishment Time-Series (NETS) database obtained from Walls & Associates for the years 1990 to 2010 (Kaufman et al., 2015). NETS is made up of annual snapshots of Dun & Bradstreet's business establishment data taken every January, and is considered to be the most comprehensive longitudinal establishment source available (Kaufman et al., 2015). The data include business name, geocoded location, street address, sales volume, number of employees, and detailed Standard Industrial Classification (SIC) codes (Kaufman et al., 2015). All retail businesses were re-geocoded to improve consistency over time and minimize missing or low quality geocodes. Following previous research (Rundle et al., 2009), businesses considered to provide BMI-unhealthy food were classified using mutually exclusive food outlets categories, defined a priori using SIC codes and other fields such as business names (Kaufman et al., 2005). Six categories of BMI-unhealthy food outlets were identified: convenience stores (Morland et al., 2006), "bodegas" or very small grocery stores (Kaufman and Karpati, 2007; Neckerman et al., 2014), fast food restaurants (Befort et al., 2006; French et al., 2001), pizza restaurants, bakery or candy/confectionary stores, and meat markets (Gillis and Bar-Or, 2003). A single classification for any given business establishment across all years was sought using information from the whole time series, as opposed to SIC codes of individual years. We used the most frequently reported SIC if it was consistently reported for at least 75% of the years; for the 4% of businesses that did not meet this criterion we used the most recently reported SIC. In addition, food outlets that were assigned to a same

category and were co-located in the same year were collapsed to a single record to avoid potential duplicate records. Thus a location with multiple unhealthy food sources, or with multiple records listed in a given year for the same business would be counted only once that year. Food outlets were aggregated by category at the census-tract level using 2010 boundaries. A tract-level summary variable counting all unique BMI-unhealthy food outlet locations was created for subsequent analysis. Data were available for all census tracts ( $n=2,167$ ) at each year. More details on the NETS data processing and re-geocoding are available elsewhere (Kaufman et al., 2015).

### 3. Census tract socio-demographic data

Data from the 1990, 2000 and 2010 Census were obtained from the Longitudinal Tract Data Base (Logan et al., 2016, 2014), a longitudinal dataset of census tracts with values reported for consistent geographic boundaries based on the 2010 definitions. Tract-level socio-demographic characteristics are our primary independent variables, including 1990 total population size, inflation-adjusted median household income (base month = July 2010), percent Black residents, and percent Hispanic residents. We used 1990 measures and assessed change in these variables between 1990 and 2010. Census socio-demographic data were available for 2,047 out of 2,167 census tracts. Tracts with missing census variables are usually uninhabited (e.g. parks, cemeteries, and airports).

### 4. Statistical Model

**Latent class growth model**—We identified class trajectories of counts of BMI-unhealthy retail stores in tracts over the 1990 to 2010 period using LCGA (for more details on LCGA see Jung and Wickrama, 2008; Muthén and Asparouhov, 2009; Nagin, 2005). LCGA is appealing in its ability to simplify a complex collection of observed trajectories into a few intelligible and easily communicated latent classes/trajectories (Nagin, 2005).

For this analysis, the outcome  $Y_{ij}$  is the number of BMI-unhealthy food outlets in the census tract  $i$  in year  $j$ . We used a zero-inflated Poisson model with a categorical latent variable  $C$  ( $C=1, \dots, K$ ) to predict for each latent class the number of BMI-unhealthy food outlets within the census tract as a function of time. For time point  $j$  in census tract  $i$

$$Y_{ij}|C_i = k = \begin{cases} 0 & \text{with probability } \pi_{ij}, \\ \text{Poisson}(\lambda_{ijk}) & \text{with probability } 1 - \pi_{ij}. \end{cases}$$

where  $\lambda$  is the Poisson rate. The LCGA zero-inflated Poisson model for these data is expressed in terms of the log-rate as

$$\ln(\lambda_{ij}|C_i = k) = \eta_{0k} + \eta_{1k}t_j + \eta_{2k}t_j^2,$$

$$\eta_{0k} = \beta_{0k},$$

$$\eta_{1k} = \beta_{1k}$$

$$\eta_{2k} = \beta_{2k}$$

In each latent class  $k$ , the log-rate is defined using a linear slope factor  $\eta_1$  and a quadratic slope factor  $\eta_2$  that allows for non-linear trajectories. All time points were equally spaced. It was expected that the number of BMI-unhealthy food outlets could grow, remain constant or even slightly decrease over time. Cubic terms did not improve model fit and were not included in the final model. The LCGA model specifies zero within-class variance in the growth factors so that the  $\eta$  s do not vary across census tracts within the  $k$ th group, but only across the  $K$  groups of census tracts captured by the latent class variables. The  $\eta$  s are estimated using only fixed coefficients  $\beta$ .

Latent class membership for a given census tract is assigned based on which latent class  $k$  has the highest likelihood of producing the data trajectory observed, given that it belonged to that class.

We estimated models for successive numbers of latent classes by the maximum likelihood estimator using the EM algorithm using Mplus 7.4 (Muthén and Muthén, 2015). A file containing the syntax of the final model is available in Supplementary Material.

**Decision on the number of latent classes**—To decide on the number of latent classes, we assessed models with successive numbers of classes to identify the model with a combination of the lowest Bayesian information criterion (BIC) value, low Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test (VLMR –LRT) (Lo et al., 2001), and high entropy. The bootstrap likelihood ratio test, which has been shown to outperform BIC and VLMR-LRT (Asparouhov and Muthén, 2012; Nylund et al., 2007), could not be calculated for the complex models fitted in this analysis. Ultimately, the decision on the number of latent classes was guided by the interpretability of the results (van de Schoot et al., 2017). We examined the similarity between models with one more trajectory and one fewer in order to confirm the robustness of the results to specified number of classes (Bader and Warkentien, 2016) (Supplementary Figures S2-S3).

**Logistic regression**—Most likely class membership was subsequently predicted (predicted probabilities with 95% CI) by census-tract level socio-demographic variables, using logistic regression models. The standard 3-step method was used as entropy was greater than 0.9 (Asparouhov and Muthén, 2014; van de Schoot et al., 2017). Due to the large number of latent classes, we illustrated dissimilarities between latent classes by selecting a pair of latent classes, representing two contrasting types of census tracts with respect to food environment trajectories. Models were adjusted for four baseline (1990) socio-demographic variables: population size, median household income, proportion of Black residents, and proportion of Hispanic residents. Changes between 1990 and 2010 in

these census tract-level variables were also considered. Only change in median household income and change in population size indicated evidence of association and were retained in the final models. Results from a fully adjusted multinomial logistic regression with all latent classes as the outcome are available in Supplementary Table S2. Analyses were conducted using Stata version 14 (StataCorp, 2015). For sensitivity purposes we replicated the analysis using the 3-step approach in Mplus with adjustment for classification errors (Asparouhov and Muthén, 2014; Muthén and Muthén, 2015) (Supplementary Table S3).

## Results

### Sample description

The mean number of BMI-unhealthy food outlets doubled from about 3 outlets per tract in 1990 to about 6 in 2010 (Table 1). Bodegas were the most common type of BMI-unhealthy food outlet, and convenience stores the least common. Variability between census tracts also increased over time: the SD of BMI-unhealthy food outlets was 3.1 in 1990 and 5.4 in 2010. Increases in mean and variance were greatest for bodegas, and moderate for convenience stores, fast food restaurants, and bakeries. During the 1990 to 2010 period mean population size and proportion of Hispanic residents increased slightly, while other census tract variables maintained similar distributions.

### Model selection

LCGA models with 1 to 12 latent classes successfully converged (Supplementary Table S1). Model summary statistics indicated a continuous decrease in BIC as the number of latent classes increased. Vuong-Lo-Mendell-Rubin adjusted LRT p-values were close to or less than 0.05 for the models with 3–5 latent classes, indicating a gradual improvement in model fit up to five classes. Classification accuracy, captured by entropy, slightly decreased as the number of classes increased but remained high up to the 12-class model (0.92). Results suggested that the 5-class model had the best fit and provided well-identified and interpretable classes (Figure 1).

### Interpretation of the LCGA model

The 5-class model displays very distinct latent classes in terms of trajectory of evolution (Figure 1). Overall, the number of BMI-unhealthy food outlets increased between 1990 and 2010. A general pattern of fanning-out was observed: the higher the number of BMI-unhealthy food outlets in 1990, the steeper the increase over time. In classes 2–5, the average number of food outlets doubled during the study period. Class 1 “Always low” (14.6%) includes census tracts with no food outlets throughout the period. Class 2 “Low with slow growth” (28.4%) contains census tracts with on average 1.1 food outlets in 1990 and 2.6 in 2010. Class 3 “Moderate with moderate growth” (31.4%) represents census tracts with 2.7 BMI-unhealthy food outlets on average in 1990 and a mean increase to 5.7 outlets in 2010. Class 4 “High with rapid growth” (20.8%) includes census tracts with an average starting value of 5.4 food outlets, and an increase to more than 10 food outlets. Class 5 “Very high with very rapid growth” (4.9%) contains an average of about 11 food outlets in 1990, an increase to 25.6 in 2008 and a decrease to 21.2 in 2010.

Variation in the average count of BMI-unhealthy food outlets across years was observed somewhat in parallel for all classes, corresponding roughly to economic cycles. Recessions in 1990–91 and 2001 were followed by increases in the number of food outlets, and the “Great Recession” of 2007–09 was followed by a rapid decrease near the end of the observation period (2010).

### Census variables predict selected trajectories

Using selected contrasting latent classes from the LCGA, we assessed whether latent classes of BMI unhealthy census tracts differed in terms of census characteristics (Figure 2). Census tracts assigned to class 2 “Low with slow growth” and class 4 “High with rapid growth” had divergent characteristics. Census tracts with greater population size, lower median household income and a lower proportion of Black residents were more likely to belong to the latent class 4 with many food outlets and a rapid increase over time, as compared to the class 2 with few food outlets and slow increase. No association was observed with the proportion of Hispanic residents. Increases in population size and in median household income between 1990 and 2010 were associated with an increased probability of belonging to the class with more BMI-unhealthy food outlets (class 4). Results from the comparison of other pairs of latent classes have a similar interpretation (Supplementary Table S2). Results from a 3-step approach with adjustment for classification errors are similar; point estimates are unchanged and confidence intervals are only marginally wider (Supplementary Table S3).

### Discussion

In this study, we examined disparities in trajectories of changes in the unhealthy food environment. Using retail business data for New York City, we showed an overall increase in the number of BMI-unhealthy food outlets during the period 1990 to 2010. We summarized trajectories of evolutions with a 5-class model that indicates a pattern of fanning out, such that census tracts with a higher initial number of BMI-unhealthy food outlets in 1990 experienced a more rapid increase over time. Using fully adjusted logistic regression models, we then examined socio-demographic disparities in those trajectories. Our results reveal a greater increase in BMI-unhealthy food outlets in census tracts with higher population size, lower baseline household income, and lower proportion of Black residents. Greater BMI-unhealthy food outlets increases were also noted in the context of census tract change suggestive of urbanization (increasing population density) or purchasing power (increasing median household income).

To our knowledge, this is the first study to examine differences in neighborhood trajectories in an aspect of the retail environment relevant to health. A few studies have described historical trends in the food environment and in the broader retail environment, but none have explored differences in trajectories. James et al. (2017) used multiple data sources, including Dun & Bradstreet, to characterize the home, workplace and commute food environments of participants of the Framingham Heart Study Offspring and Omni cohorts in four Massachusetts towns between 1971 and 2008. They reported an average increase in proximity and density of fast food restaurants, full service restaurants, convenient stores and bakeries over the study period. The trends were relatively similar in the home, work and

commute environments. Richardson et al. (2014) also found an increase in the availability of fast food and full-service restaurants, supermarkets, and convenience stores between 1985 and 2006 in four US cities. Gibson (2011) used the US Census Bureau ZIP code Business Pattern data to characterize the changing neighborhood food environment for participants of the National Longitudinal Survey of Youth 1998–2004. The author reported a small overall decrease in the density of supermarkets, grocery stores, convenience stores and specialty food stores, limited-service restaurants and full-service restaurants, which suggests the need to include settings with a range of population densities in future work.

Multiple studies have examined socio-economic disparities in the food environment, usually focusing on single outlet categories like fast food (Black et al., 2014; Fleischhacker et al., 2011; Hilmers et al., 2012). Cross-sectional evidence has indicated that higher-poverty neighborhoods and communities of color tend to have greater access to convenience stores, which are important sources of unhealthy food. The evidence linking neighborhood disadvantage to fast food access is mixed, however (Lovasi et al., 2009). Some studies reported more fast food restaurants in neighborhoods with a higher proportion of Black residents (e.g. Kwate et al. (2009) in New York City), while others found the opposite (e.g. Powell et al. (2007)). Our study provides a more comprehensive measure of the presence of food outlets selling energy-dense, nutrient-poor foods than an assessment focusing on just a single business category such as fast food. We found BMI-unhealthy food outlets to be less frequent in census tracts of New York City with higher proportions of Black residents.

Fewer studies have examined the socio-demographic predictors of change in the food environment. James et al. (2017) found that census tract household income disparities in proximity to fast food by tract-level household income diminished over time in Massachusetts towns. This seems consistent, to some extent, with our study which found that some census tracts with a higher chance of an increase in BMI-unhealthy food outlets were poorer areas that experienced an increase in purchasing power (median household income) and in urbanization (population size). Thus, in addition to the disparate exposure of less affluent population neighborhoods to unhealthy food, we found that in areas where the purchasing power increased over time, the exposure to unhealthy sources of food also increased over time. In contrast, Richardson et al. (2014) found that neighborhoods with downward or low stable socio-economic conditions were the most likely to experience increase in access to convenience stores. We additionally examined change in the food environment in function of racial/ethnic composition, which has not been documented before. We found a protective effect for census tracts with higher proportion of Black residents having fewer BMI-unhealthy stores.

Despite the disparities observed, the implications of increasing exposure to unhealthy food environments need careful consideration. On the one hand, our study joins other recent studies finding widening socio-economic disparities in access to health-promoting neighborhoods across American cities. Hirsch et al. (2016), for example, showed unequal distribution in access to destination for social engagement, walking and physical activity over the past decade. On the other hand, evidence of a causal link between access to unhealthy food outlets and dietary intake or weight has been mixed; in fact, previous research in New York City found that greater access to fast food restaurants was negatively



associated with obesity in youth (Bader et al., 2013). The research suggested that more fast food restaurants could be a marker for retail investment more generally, which could have positive health consequences for neighborhood residents. The density of retail firms may provide employment, “eyes on the street” to mitigate crime (Browning et al., 2010), and financial and political capital to help improve city services (Laveist, 1993; Logan and Molotch, 1987). Our observation that the number of BMI-unhealthy food outlets increased over time in areas where household income also increases, might therefore reflect rising neighborhood income and business investment, with potentially overall health benefits, despite a greater exposure to unhealthy food. Additional analyses from NETS data indeed indicate both an increase in the proportion of BMI-unhealthy to all food outlets over time (from 52% in 1990 to 59% in 2010), and greater increase in the number of stores in latent classes experiencing faster increases in BMI-unhealthy stores. These trends seem to be confirmed by a report from the New York City Comptroller Scott M. Stringer (2017) showing that business growth between 2000 and 2015 was more pronounced outside of the Manhattan core, leading to a dispersion of the economic activity in the city. In particular, entrepreneurial activity in lower income communities experienced a 41% increase in business establishment during that period. Further work on the dynamics of the broader retail environment and its impact on health is therefore encouraged.

Although NETS is considered one of the most comprehensive databases of business establishments, it has several limitations. First, it has restricted ability to include short-lived and seasonal businesses (Kaufman et al., 2015). Second, although the data used were re-geocoded to minimize positional error, classification leveraged data from all available years to limit noise, and potential duplicates were identified and removed (Kaufman et al., 2015), NETS is vulnerable to missing data and misclassification which might differ by neighborhood deprivation level. Third, the data provider, Walls and Associate, imputed some of the historical variables to create the time series, and that the longer an outlet is present in the dataset the more likely data were imputed which could introduce inconsistencies between places that are relatively stable versus changing rapidly. Our results might also be sensitive to the level at which we aggregated data. Census tracts might not reflect the most relevant neighborhood boundaries, yet they provide an available proxy for which we could obtain reliable geographical information on retail businesses and socio-demographic characteristics. A further limitation is that our analysis only provided compositional characteristics of the residential neighborhood, which might differ from the commute and work environments to which individuals are exposed (Cummins et al., 2007). It should also be mentioned that this study is restricted to unhealthy food sources. Analysis of trajectories and disparities in healthier food sources could further improve the understanding of the contextual drivers of obesity (Cummins et al., 2017). Finally, results from our trajectory analyses have limited external validity due to the specificity of the urban environment of New York City. Further work should investigate whether different patterns of growth in the food environment would be observed in different US cities as well as in rural areas. The pattern of rapid economic and residential growth starting in central districts then dispersing over the period through gentrification has been seen in other metropolitan areas in the United States (Richardson, et al. 2019).

## Conclusion

Evidence from this study suggests that overall exposure to BMI-unhealthy food outlets increased in New York City between 1990 and 2010. The use of LCGA enabled the identification of different trajectories of exposure, indicating that the extent of growth depended on the initial level of unhealthy stores present in the census tract. Exposure to BMI-unhealthy environments appeared to differ by census tract socio-demographic characteristics. Initiatives to reduce neighborhood exposure to unhealthy food should focus on disadvantaged neighborhoods in order to reduce environmental and health disparities. Attention should be given to the broader retail business context to ensure changes do not have the unintended consequence of increased health disparities.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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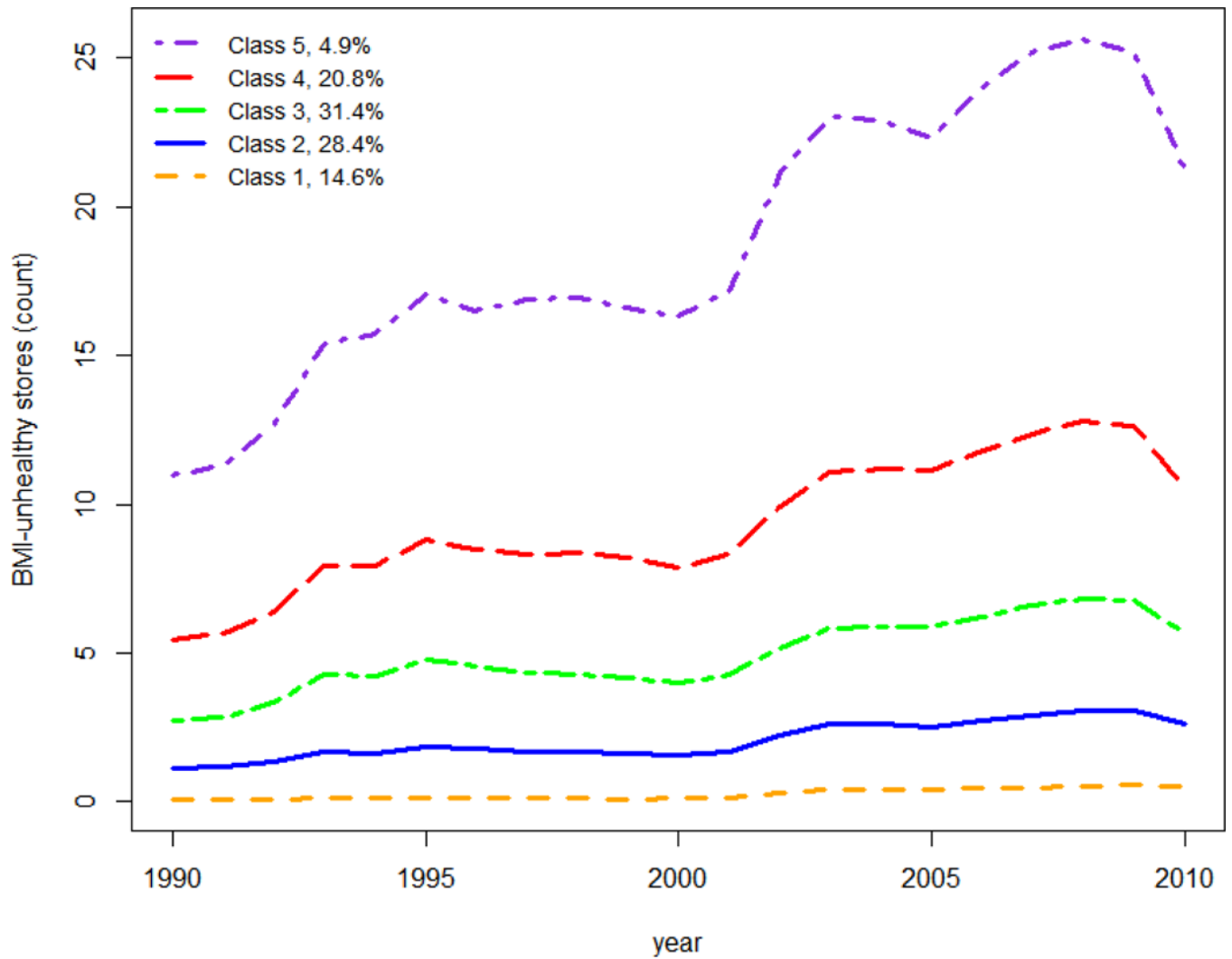
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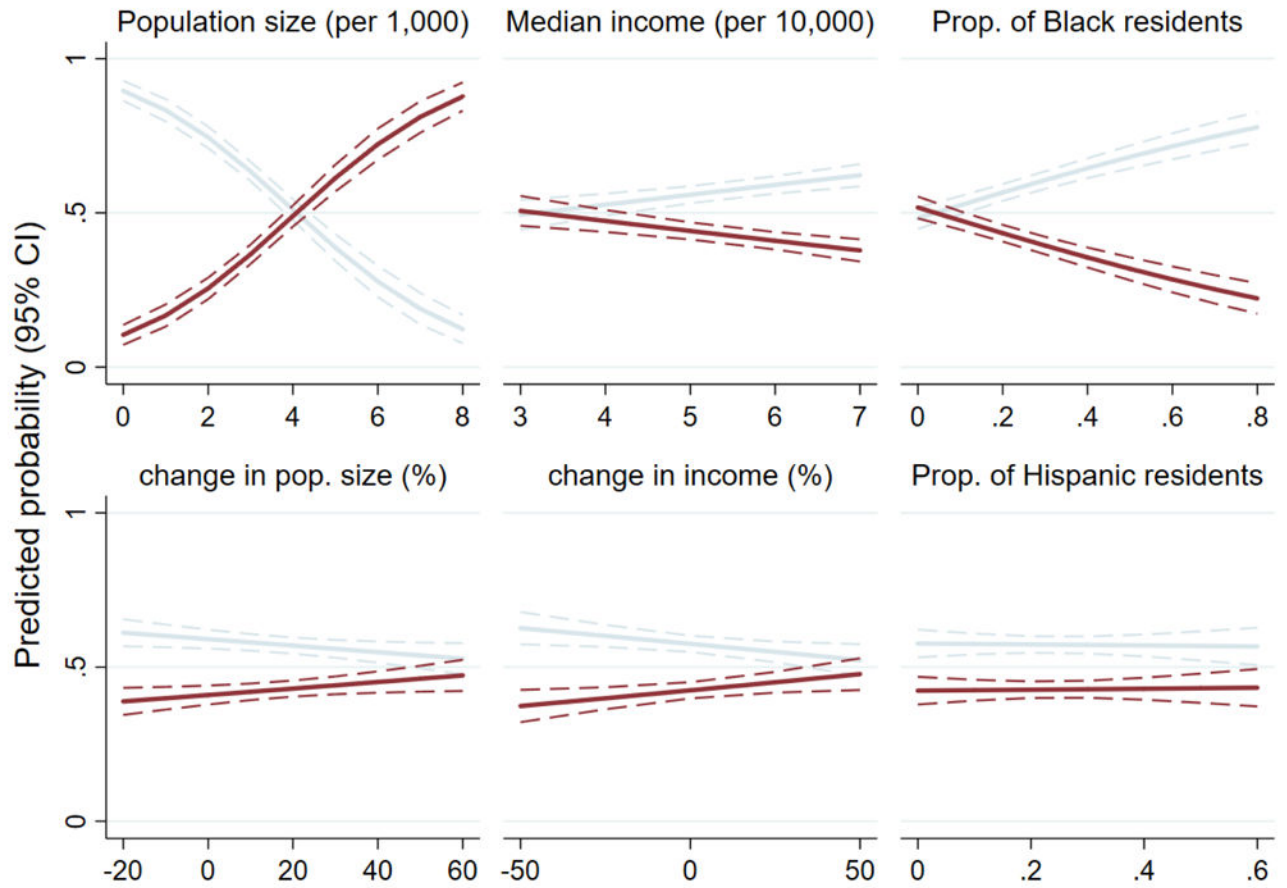
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**Figure 1 -** Five Class-solution representing trajectories of the number of BMI-unhealthy food outlets at census tract level in New York City. Results are from Latent Class Growth Analysis with a 5-class solution, a quadratic growth function and a zero-inflated Poisson distribution (n=2,167).



**Figure 2 -** Predicted probabilities of belonging to class 4 “High with rapid growth” (bold red) and class 2 “Low with slow growth” (blue) of the 5-class solution by 1990 census socio-demographic variables and their evolution between 1990 and 2010. Results are from logistic regression adjusting for all 6 census variables (n=1,025).

**Table 1**

Descriptive characteristics of the census tracts of New York City 1990–2010 (n=2,167)

	Mean $\pm$ SD (10 <sup>th</sup> – 90 <sup>th</sup> percentiles)		
	1990	2000	2010
<b>Number of food outlets</b>			
All BMI-unhealthy stores	2.9 $\pm$ 3.1 (0 – 7)	4.2 $\pm$ 4.2 (0 – 9)	5.8 $\pm$ 5.4 (1 – 12)
Convenience stores	0.1 $\pm$ 0.3 (0 – 1)	0.2 $\pm$ 0.5 (0 – 1)	0.4 $\pm$ 0.7 (0 – 1)
Bodegas	1.4 $\pm$ 1.5 (0 – 3)	2.0 $\pm$ 2.0 (0 – 5)	3.2 $\pm$ 3.0 (0 – 7)
Pizza restaurants	0.4 $\pm$ 0.8 (0 – 1)	0.6 $\pm$ 1.0 (0 – 2)	0.5 $\pm$ 0.9 (0 – 2)
Other fast food restaurants	0.2 $\pm$ 0.6 (0 – 1)	0.4 $\pm$ 0.9 (0 – 1)	0.5 $\pm$ 1.1 (0 – 1)
Bakeries and candy/ confectionary stores	0.5 $\pm$ 0.9 (0 – 2)	0.7 $\pm$ 1.2 (0 – 2)	1.0 $\pm$ 1.4 (0 – 3)
Meat markets	0.3 $\pm$ 0.6 (0 – 1)	0.2 $\pm$ 0.6 (0 – 1)	0.3 $\pm$ 0.6 (0 – 1)
<b>Census variables*</b>			
Population size	3,453 $\pm$ 2,038 (1,422 – 6,051)	3,781 $\pm$ 2,065 (1,608 – 6,571)	3,856 $\pm$ 2,045 (1,675 – 6,529)
Inflation-adjusted <sup>†</sup> median annual household income (per \$ 1,000)	55.0 $\pm$ 24.5 (25.3 – 83.7)	53.3 $\pm$ 24.9 (25.0 – 83.2)	54.7 $\pm$ 26.4 (25.7 – 87.1)
Proportion in poverty (%)	18.3 $\pm$ 15.0 (3.9 – 42.1)	20.4 $\pm$ 13.5 (5.7 – 41.0)	18.2 $\pm$ 13.0 (4.1 – 37.1)
Proportion of Black residents (%)	25.6 $\pm$ 32.1 (0.3 – 86.5)	27.1 $\pm$ 32.0 (0.6 – 86.3)	25.5 $\pm$ 30.2 (1.0 – 80.7)
Proportion of Hispanic residents (%)	22.9 $\pm$ 21.9 (4.0 – 59.5)	25.3 $\pm$ 22.5 (4.6 – 63.3)	26.9 $\pm$ 22.4 (5.9 – 64.8)

\* Descriptive characteristics restricted to the 2,047 census tracts for which all census variables were available.

<sup>†</sup> Base month= July 2010.