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## Original Contribution

# Spatial-Temporal Modeling of Neighborhood Sociodemographic Characteristics and Food Stores

**Archana P. Lamichhane, Joshua L. Warren, Marc Peterson, Pasquale Rummo, and Penny Gordon-Larsen***

* Correspondence to Dr. Penny Gordon-Larsen, Department of Nutrition, Gillings School of Global Public Health, University of North Carolina, 137 East Franklin Street, Campus Box 8120, Chapel Hill, NC 27514 (e-mail: pglarsen@email.unc.edu).

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The literature on food stores, neighborhood poverty, and race/ethnicity is mixed and lacks methods of accounting for complex spatial and temporal clustering of food resources. We used quarterly data on supermarket and convenience store locations from Nielsen TDLinx (Nielsen Holdings N.V., New York, New York) spanning 7 years (2006–2012) and census tract–based neighborhood sociodemographic data from the American Community Survey (2006–2010) to assess associations between neighborhood sociodemographic characteristics and food store distributions in the Metropolitan Statistical Areas (MSAs) of 4 US cities (Birmingham, Alabama; Chicago, Illinois; Minneapolis, Minnesota; and San Francisco, California). We fitted a space-time Poisson regression model that accounted for the complex spatial-temporal correlation structure of store locations by introducing space-time random effects in an intrinsic conditionally autoregressive model within a Bayesian framework. After accounting for census tract–level area, population, their interaction, and spatial and temporal variability, census tract poverty was significantly and positively associated with increasing expected numbers of supermarkets among tracts in all 4 MSAs. A similar positive association was observed for convenience stores in Birmingham, Minneapolis, and San Francisco; in Chicago, a positive association was observed only for predominantly white and predominantly black tracts. Our findings suggest a positive association between greater numbers of food stores and higher neighborhood poverty, with implications for policy approaches related to food store access by neighborhood poverty.

food availability; food stores; intrinsic conditionally autoregressive model; neighborhood characteristics; poverty; sociodemographic factors; spatial-temporal modeling; supermarkets

Abbreviation: MSA, Metropolitan Statistical Area.

While neighborhood food environments are associated with diet-related health outcomes, vulnerable subpopulations may be particularly at risk (1–3), given observed differential access to food resources (4–10) and associations with dietary intake and weight (11–13). However, the evidence base is inconsistent (3, 14, 15), which might be an artifact of the clustering of food stores and individual- and neighborhood-level sociodemographic characteristics across geographic space. The current literature base is largely cross-sectional in nature and does not account for spatial and temporal patterning, leaving the temporal and spatial dynamics of this relationship fundamentally unaddressed.

New methodologies that account for spatial and temporal clustering in neighborhood sociodemographic characteristics and spatial distribution of food stores are needed. Spatial-temporal modeling has become increasingly common in air pollution research (16–18), to account for placement of monitoring stations and assumptions about consistency of risk across space. These models are applicable to studies of the food environment, as there is clear spatial and temporal clustering of food stores related to zoning, demand, and competition.

To this end, we used quarterly data on supermarket and convenience store locations spanning a 7-year period (2006–2012) and census tract–based sociodemographic data from the same period to examine food store accessibility in 4 geographically and economically diverse US cities emblematic of distinct historical development patterns. We used a space-time Poisson regression model implemented by Waller et al.

(19) to introduce space-time random effects using a conditionally autoregressive model within a Bayesian framework. We assessed whether neighborhood racial/ethnic composition moderated the relationship between neighborhood poverty and numbers of stores, accounting for spatial and temporal correlation. To our knowledge, our study is the first to have used these advanced Bayesian models to account for the complex spatial-temporal correlation structure of food store accessibility.

## METHODS

### Study area

The geographic areas included in this study were the US Census Metropolitan Statistical Areas (MSAs) of Birmingham, Alabama; Chicago, Illinois; Minneapolis, Minnesota; and San Francisco, California (20). Using unit boundaries from the 2010 Census, each MSA was comprised of multiple census tracts (Birmingham: 264 tracts; Chicago: 2,210 tracts; Minneapolis: 772 tracts; San Francisco: 975 tracts).

### Food store data

We used quarterly supermarket and convenience store data from 2006 through the third quarter of 2012 (27 quarters) obtained from Nielsen TDLinx (21), a commercial database of stores selling consumer packaged goods in the United States (Nielsen Holdings N.V., New York, New York). Nielsen TDLinx uses official industry-standard definitions for food store categories when available or its own rigorously developed definitions of trade channels and subchannels supported by trade associations and trade publications. We combined TDLinx subchannel categories to form 3 food store groups: 1) supermarkets—defined as natural/gourmet food stores, superettes, and conventional supermarkets and supercenters (stores selling both food and nonfood items, including dry grocery goods, canned goods, and perishable items) with an annual sales volume greater than or equal to $1,000,000; 2) convenience stores—defined as conventional convenience stores and gas stations/kiosks with a limited selection of confectionary items, snacks, and beverages; and 3) other—defined as warehouse stores, military commissaries, and wholesale clubs. We performed extensive data-cleaning to correct more than 20,000 spelling and address errors and formatting problems and then geocoded all addresses using ArcGIS 10 software (Esri, Redlands, California) and StreetMap 2010 Premium (Esri) as the reference street network database, finding higher reliability than locations provided by Nielsen. Of 261,239 TDLinx data points, 96.8% ($n = 252{,}996$) were successfully geocoded with ArcGIS and 0.3% ($n = 723$) were located through Internet searches; Nielsen-provided geocodes were used for the remaining 2.7% ($n = 6{,}939$). We excluded 581 (0.2%) erroneous or unresolvable observations.

### Census tract characteristics

We obtained census tract–level data on total population, total area, percentage of the population living below the federal poverty level, and race/ethnicity from the American Community Survey (2006–2010) within each MSA (22). Continuous measures were used, with tertiles of percentage of the population living below the federal poverty level being used in some analyses. We defined the racial/ethnic composition of census tracts according to the method of Powell et al. (23): predominantly white (≥70% of residents non-Hispanic white), predominantly black (≥70% of residents non-Hispanic black), predominantly Asian (≥70% of residents Asian/Pacific Islander), predominantly Hispanic (≥70% of residents Hispanic), or racially mixed (not meeting any of the above criteria); racial/ethnic groups were combined into an “other” category when the sample size was insufficient for analysis. We ensured that sample sizes were adequate to fit statistical models for white-versus-nonwhite comparisons, combining racial/ethnic groups when necessary. To address structural confounding (24), we ensured sufficient racial diversity across levels of neighborhood poverty and did not extrapolate outside of observed poverty rates for each racial group.

### Analysis

*Descriptive analysis.* Census tract characteristics and numbers and densities of food stores (counts per 10,000 population) were compared across the 4 MSAs using analysis of variance and $\chi^2$ tests for continuous variables and categorical variables, respectively. We performed separate analyses to compare densities of food stores according to census tract–level poverty for each MSA, using SAS statistical software, version 9.3 (SAS Institute, Inc., Cary, North Carolina).

*Spatial-temporal Poisson regression analysis.* Poisson regression analyses were used to examine the associations between neighborhood characteristics and separate quarterly counts of supermarkets and convenience stores by store type. The 4 MSAs were modeled separately due to the great distances between cities and to allow for varying relationships between store counts and sociodemographic characteristics by city.

Because of spatial and temporal correlation in store counts between census tracts, we introduced the statistical models within a Bayesian framework which allowed for the efficient fitting of advanced space-time models. We modeled counts of a specific store type (dependent variable) at the census tract level using a multivariable log-linear Poisson regression model which accounted for variation in counts across space and time, to assess whether neighborhood racial/ethnic composition moderated the relationship between neighborhood poverty and store counts. The model is given as

$$Y(\boldsymbol{s}_i, t)|\lambda(\boldsymbol{s}_i, t) \sim \text{Poisson}\{\lambda(\boldsymbol{s}_i, t)\},$$
$$\ln\{\lambda(\boldsymbol{s}_i, t)\} = \mathbf{x}_i^T\boldsymbol{\beta} + \beta_{p+1}t + \beta_{p+2}t^2 + \phi_t(\boldsymbol{s}_i) + \theta(\boldsymbol{s}_i, t),$$

where $Y(\boldsymbol{s}_i, t)$ is the store count in census tract $\boldsymbol{s}_i$ at time $t$ and $\lambda(\boldsymbol{s}_i, t)$ represents the expected count of the store type at the same location and time. We assumed that the logarithm of the expected count was a linear function of covariates and more general error terms which control the observed counts in a tract across time. Specifically, we allowed $\mathbf{x}_i$ to be a vector of tract-level covariates (including an intercept term) that included the poverty level, racial/ethnic composition, area, and population size of census tract $s_i$. Interactions between racial/ethnic composition and poverty and between tract area and population were also included as covariates. To control for time, we included flexible linear and quadratic time parameters, $\beta_{p+1}$ and $\beta_{p+2}$, that accounted for any broad temporal changes in observed counts across all tracts. We allowed for more local time adjustments (tract-specific) by modeling the extra Poisson variability and allowing for changing spatial relationships over time. Thus, we accounted both for large-scale temporal changes that were similar across all tracts and for small-scale changes that possibly varied spatially. We introduced 2 additional terms into the usual log-linear Poisson regression analysis. The form of our model was originally introduced in the disease mapping setting by Waller et al. (19) and is commonly used in the spatial-temporal modeling of count data (25). The introduced $\phi_t(s_i)$ parameters account for spatial clustering of expected counts at a specified time point, capturing the local clustering trend and leading to similar expected counts in neighboring census tracts. In contrast, the $\theta(s_i, t)$ parameters capture region-wide heterogeneity over the entire study site of interest. These parameters together represent the extra Poisson variability contained in the data due to overdispersion caused by the spatially and temporally correlated tract counts. Failing to account for overdispersion in a Poisson regression can lead to standard errors of parameter estimates which are incorrectly too small and can result in misguided statistical conclusions. Our approach of modeling the extra Poisson variability in the form of the spatial-temporal and non–spatial-temporal components allowed the probability of observing a zero count to be higher in certain tracts/quarters if necessary. Details on model fit are shown in the Web Appendix (available at http://aje.oxfordjournals.org/).

*Prior information.* Specification of the Bayesian model was completed by assigning prior distributions to the model parameters. The introduced spatial-temporal parameters were given a prior distribution allowing for a flexible spatial-temporal relationship between expected counts of neighboring census tracts across time. We used a nested (in time) intrinsic conditionally autoregressive (ICAR) model (26) to specify the prior distribution, such that

$$\boldsymbol{\phi}_t = \{\phi_t(\boldsymbol{s}_1), \ldots, \phi_t(\boldsymbol{s}_m)\}^T,$$

$m$ = number of census tracts in the specified MSA,

$$\boldsymbol{\phi}_t \sim \mathrm{ICAR}(\sigma^2_{\phi_t}),$$

$$\phi_t(\boldsymbol{s}_i)|\boldsymbol{\phi}_t(-\boldsymbol{s}_i) \sim \mathrm{N}\left(\sum_j \frac{w_{ij}}{w_{i+}}\phi_t(\boldsymbol{s}_j), \frac{\sigma^2_{\phi_t}}{w_{i+}}\right),$$

where $\boldsymbol{\phi}_t(-\boldsymbol{s}_i) = \{\phi_t(\boldsymbol{s}_1), \ldots, \phi_t(\boldsymbol{s}_{i-1}), \phi_t(\boldsymbol{s}_{i+1}), \ldots, \phi_t(\boldsymbol{s}_m)\}^T$, $w_{ij}$ is equal to 1 if tracts $s_i$ and $s_j$ are neighbors (touching borders) and 0 otherwise, and $w_{i+}$ is the number of neighbors of tract $s_i$. Locations are not considered to be neighbors of themselves, resulting in $w_{ii} = 0$ for all $i$. In the proposed prior distribution, the spatial parameters were nested within time, with independence assumed between times. We allowed $\sigma^2_{\phi_t}$, the unknown variance component at each time point, to change across time. This allowed the spatial relationship to change and allowed for the possibility of spatial-temporal interaction, increasing the flexibility of the model.

The regression covariate parameters were given vague yet proper prior distributions, such that $\beta_j \sim N(0, \sigma^2_\beta)$ with $\sigma^2_\beta$ fixed at a large value. The error terms that controlled the region-wide heterogeneity at a specified time point were given exchangeable prior distributions, such that $\theta(s_i, t) \sim N(0, \sigma^2_{\theta_t})$. These variance parameters were also allowed to change over time, allowing for the possibility of space-time interaction and a more flexible model in general. The variance parameters were assigned independent inverse gamma prior distributions, such that $\sigma^2_{\phi_t} \sim$ inverse gamma$(1.00, 0.35)$ and $\sigma^2_{\theta_t} \sim$ inverse gamma$(1.00, 0.35)$. We selected "fair" priors, as described by Banerjee et al. (27), which allowed the extra Poisson variability to be equally partitioned between the region-wide heterogeneity and spatial clustering parameters a priori. Details regarding the transformation of variables are included in the Web Appendix. All analyses were carried out using R statistical software (R Foundation for Statistical Computing, Vienna, Austria).

## RESULTS

### Descriptive analysis

Chicago had the largest total number of tracts and total area, and San Francisco had the smallest total area but the largest population density (Table 1). San Francisco had the highest median household income, and Birmingham was the least affluent. Birmingham had the highest proportion of tracts with at least 1 supermarket or convenience store in comparison with the other MSAs.

There was variation in the proportion of tracts with at least 1 store by census tract poverty (Table 2). There was variation in the density of supermarkets (Table 3) and convenience stores (Table 4) by poverty across all years, with variation in $P$ values and number of tracts in each MSA. In general, higher densities of supermarkets and convenience stores were found in higher-poverty tracts.

### Spatial-temporal Poisson regression analysis

Comparison of the expected predicted deviance values from the basic and spatial-temporal Poisson regression models showed smaller expected predicted deviances and improved overall fit of the data for the latter models across all MSA and store-type combinations (Web Table 1). Hence, we present and discuss results from the space-time models. All results are based on 15,000 draws from the posterior distribution of the model parameters after a burn-in period of 15,000 draws. Posterior means and 95% credible intervals for supermarket and convenience store models are shown in Tables 5 and 6, respectively, and model results for the basic Poisson regressions are shown in Web Tables 2 and 3. While point estimates were similar in the space-time models and standard models, the widths of the 95% credible intervals differed as expected.

After accounting for tract-level area, population, area × population interaction, and spatial and temporal variability, census tract poverty (empirically logit-transformed, corresponding

**Table 1.** Sociodemographic characteristics of 4 US Metropolitan Statistical Areas, 2006–2012[a]

| Characteristic | MSA | | | | | | | | | | | | P Value[b] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Birmingham, Alabama | | | Chicago, Illinois | | | Minneapolis, Minnesota | | | San Francisco, California | | | |
| | No. | % | Mean (SD) | No. | % | Mean (SD) | No. | % | Mean (SD) | No. | % | Mean (SD) | |
| Total no. of census tracts | 264 | | | 2,210 | | | 772 | | | 975 | | | |
| Total area, square miles[c] | 5,279.5 | | | 7,196.8 | | | 6,027.2 | | | 2,470.5 | | | |
| Tract area, square miles | | | 20.0 (34.6) | | | 3.25 (11.9) | | | 7.80 (19.6) | | | 2.52 (12.9) | <0.0001 |
| Total population | | | 4,225.5 (1,872.3) | | | 4,246.4 (1,933.6) | | | 4,182.9 (1,859.2) | | | 4,353.73 (1,679.8) | 0.26 |
| Population per square mile | | | 1,434.7 (1,506.5) | | | 9,467. 8 (15,152.5) | | | 3,779.9 (3,646.2) | | | 12,054.6 (14,002.9) | <0.0001 |
| Median annual household income, dollars | | | 50,288 (25,197) | | | 62,508 (29,527) | | | 66,441 (24,917) | | | 81,507 (35,577) | <0.0001 |
| Tract racial/ethnic composition[d] | | | | | | | | | | | | | <0.0001 |
| Predominantly white | | 56.8 | | | 41.4 | | | 76.3 | | | 20.7 | | |
| Predominantly black | | 22.3 | | | 15.6 | | | 0.4 | | | 0.3 | | |
| Other | | 20.4 | | | 42.7 | | | 23.2 | | | 78.8 | | |
| Tertile of tract-level poverty[e] | | | | | | | | | | | | | <0.0001 |
| Low | | 27.3 | | | 42.6 | | | 54.8 | | | 51.7 | | |
| Medium | | 37.9 | | | 26.7 | | | 24.7 | | | 28.8 | | |
| High | | 34.5 | | | 30.4 | | | 20.1 | | | 19.2 | | |
| % of tracts with ≥1 food outlet (2006–2012)[f] | | | | | | | | | | | | | |
| Supermarkets[g] | | 52.3 | | | 41.5 | | | 34.7 | | | 50.1 | | <0.0001 |
| Convenience stores[h] | | 90.2 | | | 73.2 | | | 75.8 | | | 65.6 | | <0.0001 |
| Total no. of food outlets (2006–2012)[f] | 1,139 | | | 5,009 | | | 1,594 | | | 2,352 | | | |
| Type of food outlet | | | | | | | | | | | | | |
| Supermarkets | | 16.8 | | | 24.6 | | | 21.2 | | | 33.2 | | <0.0001 |
| Convenience stores | | 82.0 | | | 71.2 | | | 76.6 | | | 64.7 | | |
| Other[i] | | 1.2 | | | 4.2 | | | 2.2 | | | 2.1 | | |

Abbreviations: MSA, Metropolitan Statistical Area; SD, standard deviation.

[a] Percentages may not total 100 because of missing data.

[b] *P* value from analysis of variance or $\chi^2$ test.

[c] 1 mile = 0.61 km.

[d] Predominantly white or predominantly black tracts were defined as tracts with ≥70% of the tract population of a specific race/ethnicity. All other racial/ethnic categories, such as predominantly Hispanic, predominantly Asian, or racially mixed, were lumped together in the “other” category, given the small sample sizes available for analysis.

[e] Percentage of the population living below the federal poverty level.

[f] Mean value for the entire study period (2006–2012).

[g] The supermarket category included natural/gourmet food stores, superettes, conventional supermarkets, and supercenters.

[h] The convenience store category included conventional convenience stores and gas stations/kiosks.

[i] The “other” outlet type category included limited-assortment supermarkets, warehouse grocery stores, wholesale clubs, and military commissaries.

**Table 2.** Percentages of Census Tracts With at Least 1 Supermarket and at Least 1 Convenience Store in 4 US Metropolitan Statistical Areas, by Tertile of Census-Tract Poverty Level, 2006–2010

| Outlet Type and MSA[a] | Tertile of Census-Tract Poverty Level | | | | | | P Value[b] |
|---|---|---|---|---|---|---|---|
| | Low | | Medium | | High | | |
| | Total No. of Tracts | % With ≥1 Store[c] | Total No. of Tracts | % With ≥1 Store[c] | Total No. of Tracts | % With ≥1 Store[c] | |
| Supermarkets | | | | | | | |
| Birmingham, AL | 72 | 50.6 | 100 | 53.4 | 91 | 52.6 | 0.6174 |
| Chicago, IL | 942 | 38.7 | 590 | 42.0 | 671 | 45.4 | <0.0001 |
| Minneapolis, MN | 423 | 28.8 | 191 | 43.9 | 155 | 40.0 | <0.0001 |
| San Francisco, CA | 504 | 43.8 | 281 | 52.9 | 187 | 63.2 | <0.0001 |
| Convenience stores | | | | | | | |
| Birmingham, AL | 72 | 79.0 | 100 | 95.9 | 91 | 93.7 | <0.0001 |
| Chicago, IL | 942 | 73.7 | 590 | 79.2 | 671 | 67.9 | <0.0001 |
| Minneapolis, MN | 423 | 72.8 | 191 | 84.4 | 155 | 74.8 | <0.0001 |
| San Francisco, CA | 504 | 58.6 | 281 | 73.0 | 187 | 74.6 | <0.0001 |

Abbreviations: AL, Alabama; CA, California; IL, Illinois; MN, Minnesota; MSA, Metropolitan Statistical Area.

[a] Numbers of census tracts (2010 census tract boundaries) falling within the MSAs: Birmingham, 264; Chicago, 2,210; Minneapolis, 772; San Francisco, 975.

[b] P value from $\chi^2$ test.

[c] Mean proportion for the entire study period (2006–2010).

to increasing poverty) was significantly positively associated with an increase in the log of expected counts of supermarkets (corresponding to increasing numbers) among tracts of all different racial/ethnic compositions in all 4 MSAs (interaction plots shown in Figure 1; interaction estimates presented in Web Table 4). Therefore, the results suggest an association between increased poverty and increased numbers of supermarkets.

Comparison of expected numbers of supermarkets according to combinations of census tract racial/ethnic composition and poverty in Birmingham and Chicago suggested that predominantly black tracts had the largest estimated increases in supermarket counts with increasing tract-level poverty, followed by tracts of "other" race/ethnicity and then predominantly white tracts (Table 5). For instance, in the Birmingham MSA, the slope was larger for the black (versus white) racial/ethnic group. Every unit increase in the transformed poverty variable was associated with a 0.28, 0.22, and 0.13 increase in the log of expected supermarket counts in predominantly black, "all other" racial composition, and predominantly white census tracts, respectively, whereas there was not a statistically significant difference between predominantly white and "other" census tracts in Minneapolis and San Francisco (Table 5).

Figure 1 shows the interaction between poverty and race/ethnicity for all 4 MSAs, including average tract area and population specific to each MSA in the model. The interactions between census tract racial composition and poverty were highly statistically significant for Birmingham and Chicago, while no significant interaction was observed between race/ethnicity and poverty for supermarkets in Minneapolis and San Francisco (albeit with increased uncertainty in San Francisco), as can be seen from the different slopes for the racial/ethnic groups.

Similarly, census tract poverty was significantly positively associated with an increase in the log of expected numbers of convenience stores among tracts of all different racial/ethnic compositions in Birmingham, Minneapolis, and San Francisco (interaction plots shown in Figure 2; interaction estimates presented in Web Table 5). In Birmingham, tracts of "other" race/ethnic composition had the largest estimated increase in convenience store counts with increasing tract-level poverty, followed by predominantly black tracts and then predominantly white tracts (increases in log expected convenience store counts of 0.49, 0.28, and 0.13, respectively); predominantly white tracts had the largest estimated increase in convenience store counts as compared with tracts with "all other" racial composition in Minneapolis and San Francisco (Table 6). Chicago, which required a categorical poverty variable due to an increasing and then decreasing expected store count with increasing poverty levels for one of the racial/ethnic groups, also showed statistically significant interaction between racial composition and poverty, with estimated increasing numbers of convenience stores from low-poverty tracts to medium-poverty tracts to high-poverty tracts for predominantly white and predominantly black tracts (Figure 2). The largest estimated black-white differences were observed at the lower end of poverty, with decreasing differences as tract-level poverty increased. Among the low-poverty census tracts, we observed significantly more convenience stores in predominantly black (vs. predominantly white) tracts; this association was reversed for medium- and high-poverty tracts, with predominantly white (vs. black) tracts having more estimated convenience stores (Figure 2).

## DISCUSSION

Our findings suggest variation in numbers of supermarkets and convenience stores by neighborhood sociodemographic characteristics in Birmingham, Chicago, Minneapolis, and

**Table 3.** Density of Supermarkets[a] (Mean Number (SD) per 10,000 Population) in 4 US Metropolitan Statistical Areas, by Year and Tertile of Census-Tract Poverty Level, 2006–2012

| MSA[b] and Year | Tertile of Census-Tract Poverty Level | | | *P* Value[c] |
|---|---|---|---|---|
| | Low | Medium | High | |
| Birmingham, Alabama | | | | |
| 2006 | 2.69 (1.40) | 3.52 (2.20) | 4.56 (3.66) | 0.0061 |
| 2007 | 2.63 (1.48) | 3.81 (3.07) | 4.58 (3.01) | 0.0054 |
| 2008 | 2.75 (1.56) | 3.74 (3.10) | 4.46 (2.99) | 0.0178 |
| 2009 | 2.72 (1.55) | 3.73 (3.10) | 4.55 (3.16) | 0.0132 |
| 2010 | 2.75 (1.51) | 3.53 (3.02) | 4.33 (3.09) | 0.0381 |
| 2011 | 2.77 (1.54) | 3.49 (3.02) | 4.26 (3.08) | 0.0509 |
| 2012 | 2.75 (1.56) | 3.45 (3.00) | 4.13 (2.68) | 0.0565 |
| Chicago, Illinois | | | | |
| 2006 | 2.93 (1.63) | 3.38 (1.87) | 3.99 (2.52) | <0.0001 |
| 2007 | 2.97 (1.66) | 3.34 (1.83) | 3.88 (2.42) | <0.0001 |
| 2008 | 2.98 (1.66) | 3.36 (1.92) | 3.90 (2.47) | <0.0001 |
| 2009 | 2.93 (1.57) | 3.33 (1.91) | 3.78 (2.45) | <0.0001 |
| 2010 | 2.96 (1.58) | 3.33 (2.00) | 3.73 (2.48) | <0.0001 |
| 2011 | 2.95 (1.59) | 3.41 (2.09) | 3.76 (2.38) | <0.0001 |
| 2012 | 2.96 (1.61) | 3.38 (2.06) | 3.73 (2.38) | <0.0001 |
| Minneapolis, Minnesota | | | | |
| 2006 | 2.84 (1.47) | 3.19 (2.03) | 4.36 (2.30) | <0.0001 |
| 2007 | 2.85 (1.46) | 3.08 (1.67) | 4.32 (2.55) | <0.0001 |
| 2008 | 2.72 (1.30) | 3.15 (1.66) | 4.35 (2.53) | <0.0001 |
| 2009 | 2.70 (1.29) | 3.15 (1.65) | 4.30 (2.27) | <0.0001 |
| 2010 | 2.74 (1.31) | 3.15 (1.52) | 4.21 (2.17) | <0.0001 |
| 2011 | 2.75 (1.37) | 3.25 (1.64) | 4.23 (2.17) | <0.0001 |
| 2012 | 2.71 (1.39) | 3.23 (1.74) | 5.05 (7.07) | 0.0002 |
| San Francisco, California | | | | |
| 2006 | 3.30 (2.31) | 4.26 (3.44) | 5.20 (4.33) | <0.0001 |
| 2007 | 3.33 (2.29) | 4.15 (3.18) | 5.25 (4.35) | <0.0001 |
| 2008 | 3.38 (2.41) | 4.20 (3.30) | 5.12 (4.29) | <0.0001 |
| 2009 | 3.47 (2.43) | 4.19 (3.30) | 5.15 (4.28) | <0.0001 |
| 2010 | 3.54 (2.55) | 4.30 (3.47) | 5.18 (4.32) | 0.0001 |
| 2011 | 3.55 (2.53) | 4.35 (3.41) | 5.12 (4.25) | 0.0001 |
| 2012 | 3.54 (2.57) | 4.22 (3.32) | 5.02 (4.25) | 0.0004 |

Abbreviations: MSA, Metropolitan Statistical Area; SD, standard deviation.

[a] The supermarket category included natural/gourmet food stores, superettes, conventional supermarkets, and supercenters.

[b] Numbers of census tracts (2010 census tract boundaries) falling within the MSAs: Birmingham, 264; Chicago, 2,210; Minneapolis, 772; San Francisco, 975.

[c] *P* value from regression analysis.

San Francisco from 2006 to 2012. Model evaluation suggested spatial and temporal dependencies requiring an approach to account for spatial-temporal clustering of food stores over time. After accounting for tract area, population, their interaction, and spatial and temporal variability, tract-level poverty was significantly and positively associated with an increase in expected numbers of supermarkets among tracts of all different racial/ethnic compositions in all 4 MSAs. A similar positive association was observed for convenience stores in Birmingham, Minneapolis, and San Francisco; in Chicago, a positive association was observed only for predominantly white and predominantly black tracts. Thus, our findings suggest a positive association between numbers of food stores and greater neighborhood poverty, which could have implications for health, particularly for residents of disadvantaged areas.

In contrast to several other studies (6, 9, 28–30), we found greater numbers of supermarkets in high-poverty areas than in

**Table 4.** Density of Convenience Stores[a] (Mean Number (SD) per 10,000 Population) in 4 US Metropolitan Statistical Areas, by Year and Tertile of Census-Tract Poverty Level, 2006–2012

| MSA[b] and Year | Tertile of Census-Tract Poverty Level | | | *P* Value[c] |
|---|---|---|---|---|
| | Low | Medium | High | |
| Birmingham, Alabama | | | | |
| 2006 | 6.99 (4.66) | 10.65 (7.74) | 12.47 (7.37) | <0.0001 |
| 2007 | 6.76 (4.99) | 10.52 (7.19) | 12.65 (7.45) | <0.0001 |
| 2008 | 6.70 (4.43) | 10.30 (7.13) | 12.86 (7.80) | <0.0001 |
| 2009 | 6.84 (4.50) | 10.12 (7.11) | 12.65 (7.72) | <0.0001 |
| 2010 | 6.80 (4.50) | 10.13 (7.15) | 12.60 (7.69) | <0.0001 |
| 2011 | 7.03 (4.75) | 9.91 (7.09) | 12.44 (7.54) | <0.0001 |
| 2012 | 6.92 (4.67) | 9.91 (7.36) | 12.37 (7.76) | <0.0001 |
| Chicago, Illinois | | | | |
| 2006 | 4.99 (4.12) | 5.76 (3.77) | 6.16 (4.39) | <0.0001 |
| 2007 | 4.93 (4.10) | 5.80 (3.97) | 6.24 (4.38) | <0.0001 |
| 2008 | 4.88 (4.03) | 5.79 (4.05) | 6.17 (4.24) | <0.0001 |
| 2009 | 4.85 (4.04) | 5.81 (4.17) | 6.12 (4.30) | <0.0001 |
| 2010 | 4.82 (4.03) | 5.76 (4.26) | 6.06 (4.23) | <0.0001 |
| 2011 | 4.87 (4.06) | 5.69 (4.41) | 6.16 (4.32) | <0.0001 |
| 2012 | 4.89 (4.07) | 5.68 (4.41) | 6.15 (4.31) | <0.0001 |
| Minneapolis, Minnesota | | | | |
| 2006 | 4.81 (3.32) | 5.48 (3.19) | 6.87 (6.48) | <0.0001 |
| 2007 | 4.89 (3.50) | 5.35 (3.02) | 7.00 (6.85) | <0.0001 |
| 2008 | 4.81 (3.23) | 5.45 (3.07) | 6.90 (6.49) | <0.0001 |
| 2009 | 4.69 (3.05) | 5.37 (3.26) | 6.66 (6.24) | <0.0001 |
| 2010 | 4.65 (3.08) | 5.21 (3.43) | 6.67 (6.48) | <0.0001 |
| 2011 | 4.64 (3.02) | 5.16 (3.27) | 6.80 (6.53) | <0.0001 |
| 2012 | 4.66 (2.99) | 5.14 (3.26) | 6.40 (6.04) | 0.0002 |
| San Francisco, California | | | | |
| 2006 | 5.16 (4.19) | 6.22 (7.22) | 7.85 (15.62) | 0.0120 |
| 2007 | 5.19 (4.18) | 6.41 (9.13) | 7.78 (15.49) | 0.0229 |
| 2008 | 5.24 (4.19) | 6.41 (9.14) | 7.78 (15.58) | 0.0275 |
| 2009 | 5.26 (4.19) | 6.28 (9.12) | 7.70 (15.70) | 0.0402 |
| 2010 | 5.23 (4.18) | 6.24 (9.13) | 7.88 (15.94) | 0.0263 |
| 2011 | 5.27 (4.32) | 6.37 (9.11) | 8.06 (15.81) | 0.0166 |
| 2012 | 5.26 (4.33) | 6.38 (9.09) | 7.94 (15.86) | 0.0225 |

Abbreviations: MSA, Metropolitan Statistical Area; SD, standard deviation.
[a] The convenience store category included conventional convenience stores and gas stations/kiosks.
[b] Numbers of census tracts (2010 census tract boundaries) falling within the MSAs: Birmingham, 264; Chicago, 2,210; Minneapolis, 772; San Francisco, 975.
[c] *P* value from regression analysis.

low-poverty areas. Our finding of a greater number of convenience stores in high-poverty areas versus low-poverty areas is similar to published literature (6, 29, 31, 32). Differences in findings might relate to our modeling strategy, the quality of the Nielsen TDLinx data, or our use of temporal data.

Previous studies examining the association between neighborhood sociodemographic characteristics and food stores have examined neighborhood poverty (6, 9, 29) and neighborhood race/ethnicity (6, 9, 29, 30) separately. Only a few studies have examined interactions between neighborhood poverty and race/ethnicity (28, 31). Our findings suggest heterogeneity in the positive association between census tract poverty and numbers of food stores by census tract race/ethnicity, even with overlapping 95% credible intervals for supermarkets in 3 of the 4 cities. For supermarkets, we found the strongest positive associations in Birmingham and Chicago (predominantly black race/ethnicity vs. "other"), whereas for convenience stores we found comparatively stronger positive associations in Minneapolis and San Francisco (predominantly white race/ethnicity vs. "other"),

**Table 5.** Associations of Census Tract–Level Poverty and Racial/Ethnic Composition With Numbers of Supermarkets per Tract in 4 Metropolitan Statistical Areas, 2006–2012[a]

| Parameter | MSA[b] | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Birmingham, Alabama | | Chicago, Illinois | | Minneapolis, Minnesota | | San Francisco, California | |
| | PM | 95% CrI | PM | 95% CrI | PM | 95% CrI | PM | 95% CrI |
| Intercept | −0.33 | −0.54, −0.15 | −7.12 | −7.27, −7.00 | −5.67 | −6.16, −5.11 | −0.73 | −0.87, −0.46 |
| Logit poverty | 0.13 | 0.09, 0.18 | 0.09 | 0.07, 0.11 | 0.27 | 0.24, 0.30 | 0.14 | 0.10, 0.22 |
| Racial/ethnic composition[c] | | | | | | | | |
| Predominantly black vs. white | −0.24 | −0.45, −0.03 | 0.13 | 0.05, 0.21 | | | | |
| Other vs. white | −0.05 | −0.25, 0.15 | 0.21 | 0.14, 0.28 | −0.09 | −0.22, 0.04 | 0.13 | −0.12, 0.24 |
| Poverty × racial composition | | | | | | | | |
| Poverty × predominantly black vs. white | 0.15 | 0.03, 0.28 | 0.13 | 0.09, 0.18 | | | | |
| Poverty × other vs. white | 0.08 | −0.01, 0.17 | 0.12 | 0.10, 0.15 | 0.02 | −0.05, 0.08 | 0.07 | −0.01, 0.11 |
| Area[d] | −0.27 | −0.32, −0.21 | 0.48 | 0.40, 0.58 | −0.14 | −0.17, −0.12 | −0.06 | −0.10, −0.03 |
| Population[d] | 0.11 | 0.08, 0.14 | 0.79 | 0.78, 0.81 | 0.65 | 0.59, 0.70 | 0.13 | 0.12, 0.14 |
| Area × population | 0.03 | 0.02, 0.04 | −0.05 | −0.06, −0.04 | 0.01 | 0.01, 0.02 | 0.0005 | −0.006, 0.007 |
| Time (linear) | 0.004 | −0.01, 0.02 | 0.005 | −0.006, 0.01 | 0.007 | −0.01, 0.02 | 0.008 | 0.001, 0.01 |
| Time (quadratic) | −0.0003 | −0.0008, 0.0002 | −0.0001 | −0.0003, −0.00008 | −0.0002 | −0.0006, 0.0005 | −0.0002 | −0.0005, −0.00002 |

Abbreviations: CrI, credible interval; MSA, Metropolitan Statistical Area; PM, posterior mean.

[a] Results were derived from a spatial-temporal multivariable Poisson regression model accounting for region-wide heterogeneity in the 4 MSAs.

[b] Numbers of census tracts (2010 census tract boundaries) falling within the MSAs: Birmingham, 264; Chicago, 2,210; Minneapolis, 772; San Francisco, 975.

[c] Reference group: white. Predominantly white or predominantly black tracts were defined as tracts with ≥70% of the tract population of a specific race/ethnicity. All other racial/ethnic categories, such as predominantly Hispanic, predominantly Asian, or racially mixed, were lumped together in the “other” category, given the small sample sizes available for analysis.

[d] Log-transformed area was used for the Birmingham, Chicago, and San Francisco MSAs, while an untransformed area variable was used for the Minneapolis site. Similarly, a population/1,000 transformation was used for the Birmingham and San Francisco MSAs, while a log-transformed population variable was used for the Chicago and Minneapolis MSAs.

**Table 6.** Associations of Census Tract–Level Poverty and Racial/Ethnic Composition With Numbers of Convenience Stores per Tract in 4 Metropolitan Statistical Areas, 2006–2012[a]

| Parameter | MSA[b] | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Birmingham, Alabama | | Chicago, Illinois | | Minneapolis, Minnesota | | San Francisco, California | |
| | PM | 95% CrI | PM | 95% CrI | PM | 95% CrI | PM | 95% CrI |
| Intercept | 0.46 | 0.33, 0.57 | −3.98 | −4.09, −3.77 | −4.67 | −4.87, −4.47 | 0.30 | 0.08, 0.42 |
| Logit poverty[c] | 0.13 | 0.11, 0.16 | | | 0.23 | 0.22, 0.25 | 0.41 | 0.34, 0.46 |
| Poverty level[c] | | | | | | | | |
| High vs. low | | | 0.32 | 0.29, 0.35 | | | | |
| Medium vs. low | | | 0.37 | 0.32, 0.44 | | | | |
| Racial/ethnic composition[d] | | | | | | | | |
| Predominantly black vs. white | 0.46 | 0.36, 0.58 | 0.24 | 0.13, 0.35 | | | | |
| Other vs. white | 0.97 | 0.86, 1.09 | 0.16 | 0.13, 0.18 | −0.37 | −0.43, −0.30 | −0.47 | −0.60, −0.22 |
| Poverty × racial/ethnic composition | | | | | | | | |
| Poverty × predominantly black vs. white | 0.15 | 0.09, 0.21 | | | | | | |
| Poverty × other vs. white | 0.36 | 0.31, 0.41 | | | −0.22 | −0.25, −0.18 | −0.22 | −0.27, −0.15 |
| Poverty level × racial/ethnic composition | | | | | | | | |
| High poverty × predominantly black | | | −0.28 | −0.41, −0.16 | | | | |
| Medium poverty × predominantly black | | | −0.31 | −0.43, −0.18 | | | | |
| High poverty × other | | | −0.30 | −0.37, −0.24 | | | | |
| Medium poverty × other | | | −0.13 | −0.17, −0.09 | | | | |
| Area[e] | 0.09 | 0.06, 0.12 | 0.63 | 0.57, 0.70 | 0.23 | 0.21, 0.25 | 0.09 | 0.07, 0.12 |
| Population[e] | 0.13 | 0.11, 0.15 | 0.48 | 0.45, 0.49 | 0.67 | 0.64, 0.69 | 0.15 | 0.14, 0.16 |
| Area × population | 0.0005 | −0.005, 0.005 | −0.05 | −0.06, −0.04 | 0.03 | 0.02, 0.05 | −0.01 | −0.02, −0.008 |
| Time (linear) | 0.007 | 0.002, 0.01 | 0.02 | 0.01, 0.02 | 0.005 | −0.002, 0.01 | 0.03 | 0.02, 0.03 |
| Time (quadratic) | −0.0002 | −0.0004, −0.00002 | −0.0006 | −0.0008, −0.0005 | −0.0002 | −0.0004, −0.00004 | −0.0008 | −0.001, −0.0006 |

Abbreviations: CrI, credible interval; MSA, Metropolitan Statistical Area; PM, posterior mean.

[a] Results were derived from a spatial-temporal multivariable Poisson regression model accounting for region-wide heterogeneity in the 4 MSAs.

[b] Numbers of census tracts (2010 census tract boundaries) falling within the MSAs: Birmingham, 264; Chicago, 2,210; Minneapolis, 772; San Francisco, 975.

except Chicago, where tertiles of the poverty variable (representing low, medium, and high poverty levels)

[c] The poverty variable was continuous (percentage of the population living below the federal poverty level) for Birmingham, Minneapolis, and San Francisco and categorical (tertile of census-tract poverty level) for Chicago.

[d] Reference group: white. Predominantly white or predominantly black tracts were defined as tracts with ≥70% of the tract population of a specific race/ethnicity. All other racial/ethnic categories, such as predominantly Hispanic, predominantly Asian, or racially mixed, were lumped together in the “other” category, given the small sample sizes available for analysis.

[e] Log-transformed area was used for all 4 MSAs. A population/1,000 transformation was used for the Birmingham and San Francisco MSAs, while a log-transformed population variable was used for the Chicago and Minneapolis MSAs.

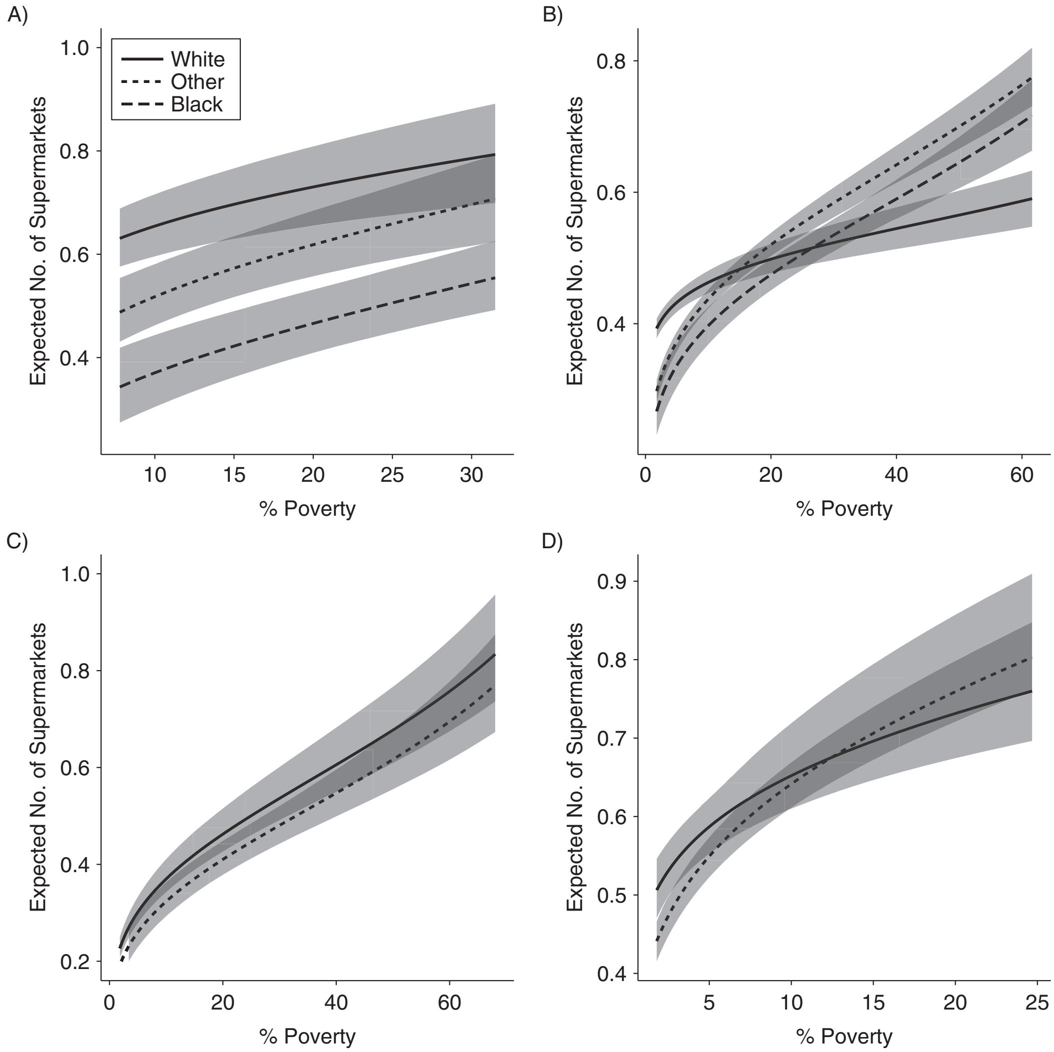


**Figure 1.** Estimated numbers of supermarkets in the Birmingham, Alabama (A), Chicago, Illinois (B), Minneapolis, Minnesota (C), and San Francisco, California (D), Metropolitan Statistical Areas (MSAs), by census tract poverty (percentage of the population living below the federally defined poverty level) and racial/ethnic composition, 2006–2012. Numbers of census tracts (2010 census tract boundaries) falling within the MSAs: Birmingham, 264; Chicago, 2,210; Minneapolis, 772; San Francisco, 975. Predominantly white or predominantly black tracts were defined as tracts with ≥70% of the tract population of a specific race/ethnicity. All other racial/ethnic categories, such as predominantly Hispanic, predominantly Asian, or racially mixed, were lumped together in the "other" category, given the small sample sizes available for analysis. Average tract area and population specific to each MSA were included in the space-time Poisson regression models to generate realistic supermarket counts. Continuous variables worked well with the regression models for all 4 MSAs. The shaded band indicates the 95% credible interval.

Birmingham ("other" race/ethnicity vs. white), and Chicago (in the low-poverty stratum for black race/ethnicity vs. "other"). Population density might influence this racial/ethnic heterogeneity, as the higher-poverty census tracts had higher population densities. Thus, it is possible that population demand related to greater population density might influence the observed distribution of food stores.

Despite increased minority participation in the urban planning process in the past decade, policies in Birmingham, Chicago, and San Francisco have led to inequitable distribution of racial/ethnic minorities (albeit with variation) across these cities (33–36). For example, racial diversity increased in Chicago between 1980 and 2000 (37), and Minneapolis was the least economically and racially diverse city in our sample (36, 38, 39). There may be unmeasured macro-level factors that influence the distributions of neighborhood poverty and food store locations and bias results. Our analysis spanned the period of the US financial and housing crises (2006–2012), and it is possible that characteristics of the housing market played a role in neighborhood poverty and the locations of food stores. Our models can handle spatial correlation between tracts and allow for varying relationships between store counts and sociodemographic characteristics by city.

Our model testing suggested that accounting for spatial and temporal dependencies is needed to contend with clustering in food stores across time and geographic space.

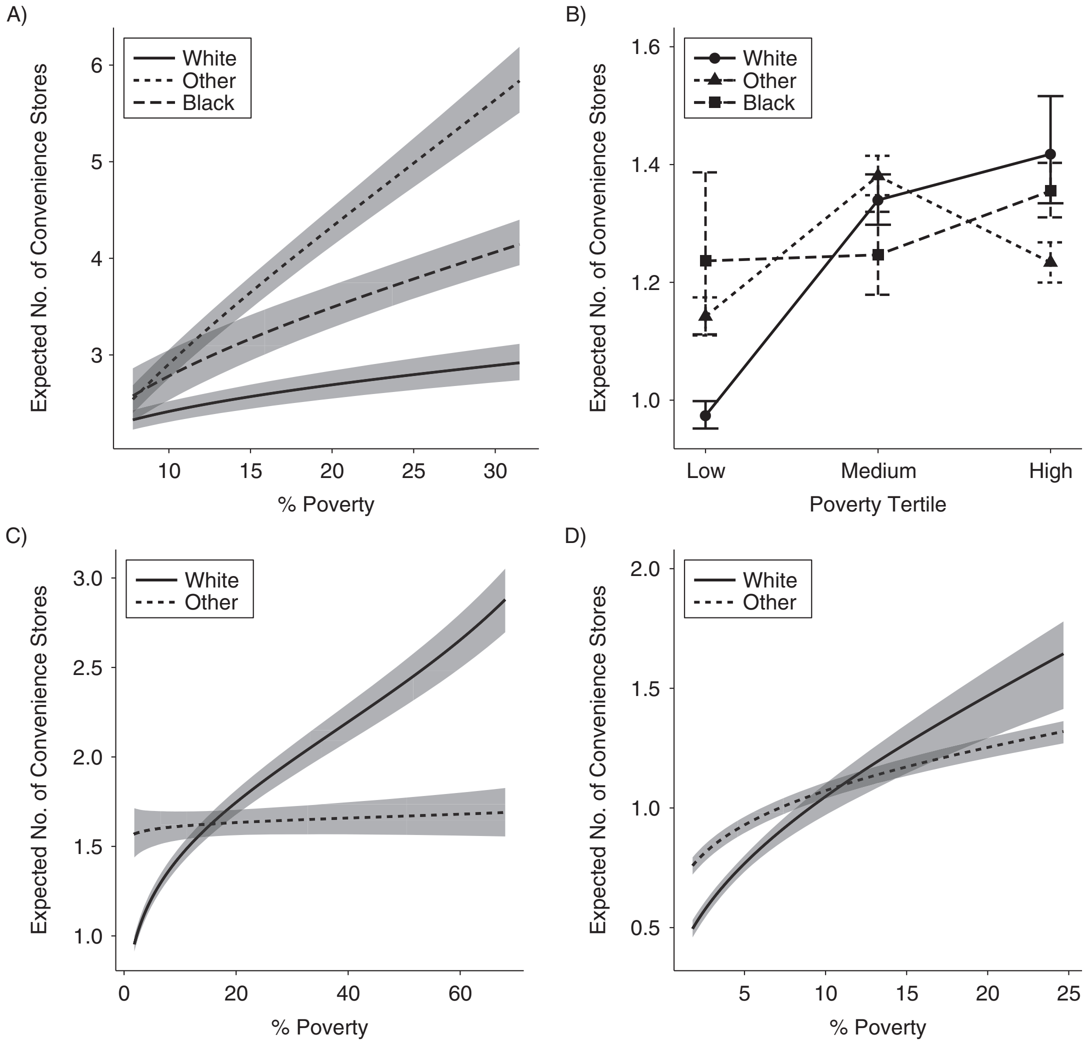


**Figure 2.** Estimated numbers of convenience stores in the Birmingham, Alabama (A), Chicago, Illinois (B), Minneapolis, Minnesota (C), and San Francisco, California (D), Metropolitan Statistical Areas (MSAs), by census tract poverty (percentage of the population living below the federally defined poverty level) and racial/ethnic composition, 2006–2012. Numbers of census tracts (2010 census tract boundaries) falling within the MSAs: Birmingham, 264; Chicago, 2,210; Minneapolis, 772; San Francisco, 975. Predominantly white or predominantly black tracts were defined as tracts with ≥70% of the tract population of a specific race/ethnicity. All other racial/ethnic categories, such as predominantly Hispanic, predominantly Asian, or racially mixed, were lumped together in the "other" category, given the small sample sizes available for analysis. Average tract area and population specific to each MSA were included in the space-time Poisson regression models to generate realistic counts of convenience stores. Continuous variables worked well with the regression models for all MSAs except Chicago (part B), where tertiles of the poverty variable (representing low, medium, and high poverty levels) were used (bars, standard error). The shaded band indicates the 95% credible interval.

However, in comparing the spatiotemporal model results with those from the standard models, the estimates were similar. We expected the point estimates from both models to be similar, with the main differences occurring for the posterior standard deviations and 95% credible interval widths (which can be incorrectly and inaccurately small when overdispersion is not addressed). Thus, we found that the 95% credible intervals from the space-time models were wider for almost all of the presented parameter estimates, and in a few instances the parameter was no longer statistically significant as a result. The fact that we did not observe major differences between the spatiotemporal model results and those from the standard models with respect to the point estimates provides evidence that important spatially varying confounders were not excluded from the analyses (40).

While there are many strengths of our approach, limitations must be noted. First, like other investigators, we used census tracts to assess the spatial availability of food stores, despite lack of information about the relevant spatial units for local food shopping (41, 42). However, we used a full census of each of the 4 MSAs and as such made no assumptions about the context for individual food shopping. Further, we performed sensitivity tests to consider whether census block groups would be more appropriate, finding similarity in direction and strength of estimated effects with tracts. Given the cumbersome nature of the spatial-temporal models with large numbers of smaller geographic units, we opted for census tracts. In addition, the low temporal resolution of census data is a limitation. Second, most studies have relied on Dun & Bradstreet (Dun & Bradstreet, Inc., Short Hills, New Jersey) and InfoUSA (Infogroup, Papillion, Nebraska) data sources to characterize the retail food environment (32, 43–47), although there is only moderate agreement between these data sources and ground-level observations (43, 45–49). In contrast, Nielsen TDLinx data are known to be of higher quality (44) and are updated monthly, capturing changes in store openings/closings, categorization, ownership, and name (http://www.nielsen.com/us/en.html), and thus may be a more accurate source of data on food store availability over time, with the caveat that small and independent food outlets may not be as well captured as larger stores (50). Our approach of characterizing census tracts as predominately single-race using a 70% cutpoint allowed us to examine racial/ethnic composition in areas with sufficient concentrations, but it did not allow study of more nuanced combinations in racially/ethnically diverse tracts. Unmeasured confounding and endogenicity of neighborhood poverty remain possible, as we did not use causal models, though we allowed for the possibility of spatial correlation between the regions. The standard errors for the fixed effects were adjusted appropriately with inclusion of the spatially correlated effects (40, 51, 52).

In conclusion, our findings suggest that there are greater numbers of supermarkets and convenience stores in areas with higher census tract–level poverty, after accounting for tract-level area, population, their interaction, and spatial and temporal variability, which suggests potential to influence behavior to the extent that availability of neighborhood food stores is associated with dietary behaviors. The positive association between poverty and supermarkets held true for census tracts of all racial/ethnic compositions in all 4 MSAs, albeit with variation by tract race/ethnicity. For convenience stores, there were substantial racial/ethnic disparities as poverty level increased, with higher numbers of convenience stores at high poverty levels in predominantly nonwhite tracts versus predominantly white tracts in Birmingham and in white tracts versus nonwhite tracts in Minneapolis and San Francisco, and comparatively stronger positive associations (black tracts vs. white tracts) at low poverty levels in Chicago. Differences in the associations between neighborhood poverty/race and food stores suggest variation in access to unhealthy food options in poor and/or high-minority neighborhoods (53, 54), where residents are at disproportionate risk for diet-related chronic diseases (55–57). The fact that the associations vary over geographic space confirms the need for context-specific analyses (14). Health-related policies designed to reduce spatial inequalities in access to healthy foods may need to be context-specific and to consider neighborhood race/ethnicity and income level.

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Author affiliations: Department of Nutrition, Gillings School of Global Public Health, University of North Carolina at Chapel Hill, Chapel Hill, North Carolina (Archana P. Lamichhane, Pasquale Rummo, Penny Gordon-Larsen); Department of Biostatistics, Gillings School of Global Public Health, University of North Carolina at Chapel Hill, Chapel Hill, North Carolina (Joshua L. Warren); Department of Biostatistics, Yale School of Public Health, New Haven, Connecticut (Joshua L. Warren); and Carolina Population Center, University of North Carolina at Chapel Hill, Chapel Hill, North Carolina (Marc Peterson).

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