Heterogeneous Effects in the Built Environment

Adam Peterson[1] Brisa Sánchez[2]

[1] University of Michigan Dept. of Biostatistics

[2]Drexel University Dept. of Biostatistics & Epidemiology

Introduction

- The availability of built environment amenities may affect members of the population differently.
- We adapt our previous method, Spatial Temporal Aggregated Predictors [1], to identify these **heterogeneous effects**.
- We examine the relationship between availability of fast food restaurants (FFRs) near schools (a point pattern predictor) and child obesity.

Motivating Data

- Obesity or overweight status of 5th and 7th grade students attending California public schools during 2001-2008 academic year (source: FitnessGram© test[2]).
- Locations of FFRs were obtained though a commercial data source [3].

	Second City[1]	Sub-Urban[1]	Urban[1]
# Schools	5	70	505
# Students	53 (40, 61)	72 (54, 115)	105 (63, 159)
# Obese	30 (22, 35)	28 (20, 57)	56 (34, 91)
% Obese	55 (54, 57)	42 (35, 52)	56 (50, 60)

[1]Statistics presented: median (IQR)

Figure: Example FFR Data in Los Angeles, CA

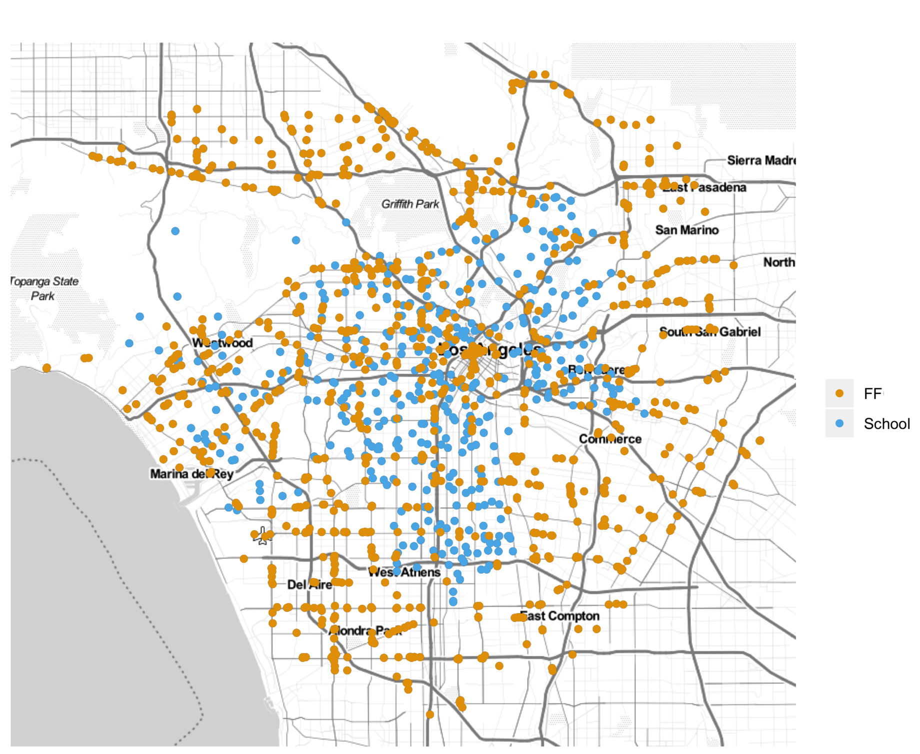
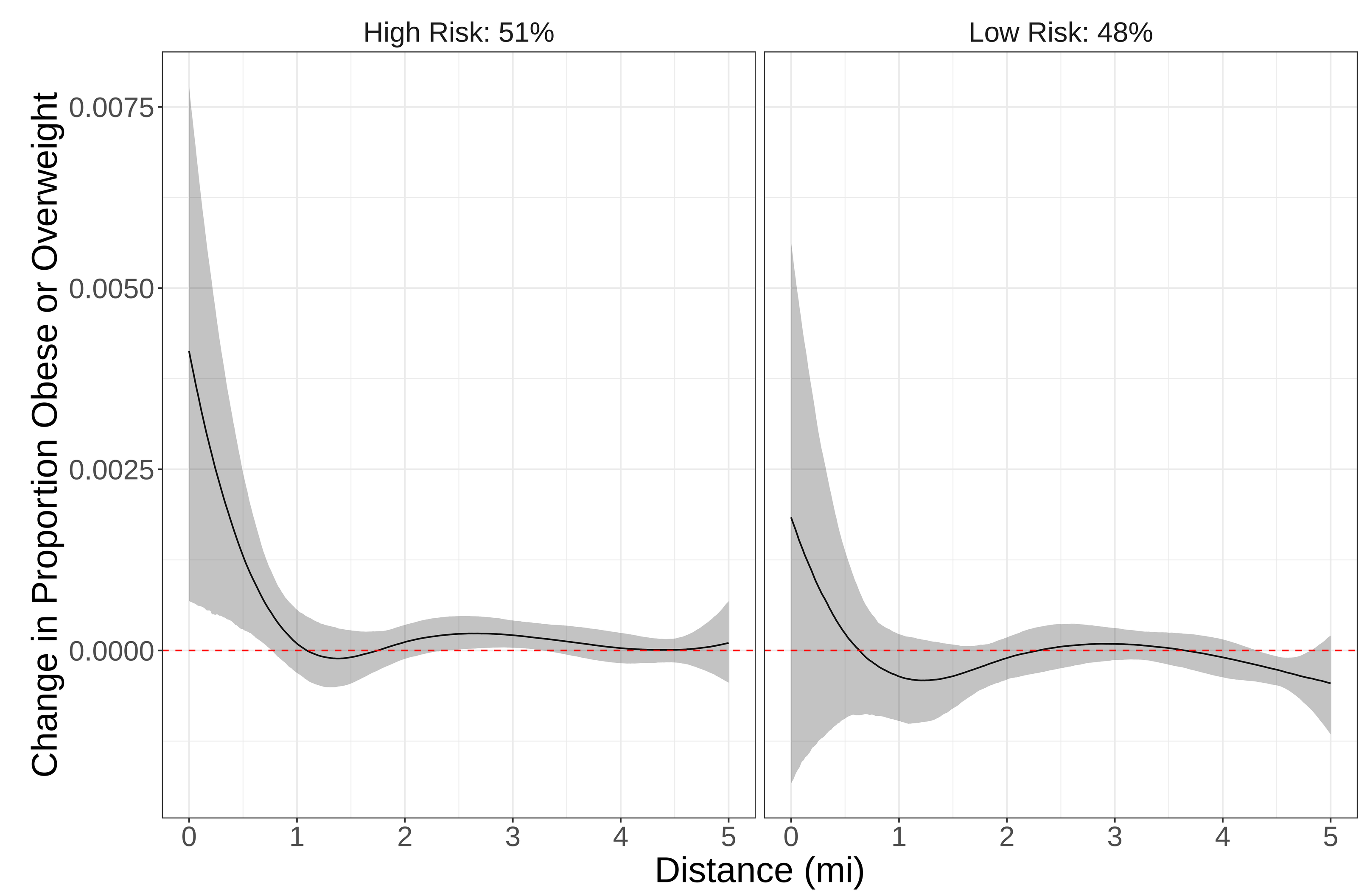


Figure: FFR Heterogeneous Exposure Effects on Childhood Obesity with Median and 95% Credible Intervals



Main takeaways

- FFR exposure effects decompose into two major groups.
- This decomposition reinforces prevailing ideas that different populations interact with and are affected by the built environment in different ways.

Modeling Framework

The STAP-DP model is parameterized in the following manner:

$$E[\%\text{Obese}_{ij}] = \boldsymbol{Z}_{ij}^T\boldsymbol{\delta} + f_i(\text{FFR Exposure}) + b_{i1} + b_{i2}\text{year}_{ij}, \quad i = 1, ..., 604 \tag{1}$$

where

$$\begin{aligned}\boldsymbol{b}_i &\sim MVN_2(\boldsymbol{0}, \Sigma)\\ f_i(\text{FFR Exposure}) &= \sum_{d\in\mathcal{D}_i}\sum_{j=1}^{J} \beta_{ij}\phi_j(d)\\ (\boldsymbol{\beta_i}, \boldsymbol{\tau}_i) &\sim DP(\alpha, G_0)\\ \alpha &\sim \text{Gamma}(a_\alpha, b_\alpha)\\ G_0 &\equiv N(0, \sigma^2\tau) \times \text{Inv-Gamma}(1,1)\end{aligned}$$

- $\boldsymbol{Z}_i$ represents school level covariates and $\boldsymbol{\delta}$, their corresponding effects.
- b_i is a latent school specific intercept that adjusts for within-school correlation.
- $\phi_j(d)$ is a b-spline basis function expansion of the euclidean distance, d, between the FFR and school.
- $\mathcal{D}_i$ is the set of distances between school i and FFRs within 10 miles.
- $DP(\alpha, G_0)$ is a Dirichlet Process with concentration parameter α and base measure G_0.

Group Analysis

Cluster	High Risk	Low Risk
Income[1] (1,000 USD)	35	38
% African American	14	13
% Asian	5	5
% Hispanic	67	66
% White	11	14

Table: Modal Cluster School Characteristics.[1]Median School's Census Tract Income

References

[1] Adam Peterson and Brisa Sanchez. rstap: An R package for spatial temporal aggregated predictor models. *arXiv preprint arXiv:1812.10208*, 2018.

[2] https://www.cde.ca.gov/ta/tg/pf/, Nov 2017.

[3] D Walls. National establishment time-series (nets) database: 2012 database description. *Oakland: Walls & Associates*, 2013.

[4] Ana V Diez Roux, Mahasin S Mujahid, Jana A Hirsch, Kari Moore, and Latetia V Moore. The impact of neighborhoods on cv risk. *Global heart*, 11(3):353–363, 2016.

Contact Information

[1] University of Michigan Dept. of Biostatistics

[2] Drexel University Dept. of Biostatistics & Epidemiology

Acknowledgements

This work was funded by NIH grant R01-HL131610 (PI: Sánchez)