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The Effect of Neighborhood Crime Rates on Childhood Obesity in Los Angeles County

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Abstract

This thesis examines the effect of neighborhood crime rates on childhood obesity in Los Angeles County over a five-year period 2012-2016. Using yearly pooled cross-sectional geocoded data from the University of Southern California (USC) Price Center for Social Innovation Neighborhood Data for Social Change (NDSC) interactive platform, I run multiple ordinary least squares regressions using different measures of crime to determine if neighborhoods with higher crime rates influence the unhealthy percentage of 5th, 7th, and 9th grade public school students. I hypothesize that crime influences obesity, violent crime has a stronger correlation than property crime, and that greater parks access reduces obesity. My regression results fail to support hypotheses one and two. Hypothesis three is supported by the available data.

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I. Introduction

Obesity is among the leading causes of a vast array of health problems including: premature death, coronary heart disease, high blood pressure, unhealthy levels of blood cholesterol, stroke, type 2 diabetes, gallbladder disease, osteoarthritis, sleep apnea, certain types of cancer, depression, anxiety, and difficulty with normal bodily functioning.[1,2] Fundamentally, the human body is not designed for the substantial excess weight which has become normalized because of its ubiquity, especially in the United States. As of 2016, an estimated 36.2% of Americans (nearly 120 million) are obese.[3] According to the World Health Organization, "obesity is one of today's most blatantly visible – yet most neglected – public health problems." This is not a cosmetic issue: public health United States needs a systemic overhaul; obesity is only one of its manifestations.

As of 2017, the US Census Bureau reports that LA County has an estimated population of 10.16 million people.[4] Among its residents, the 2015 LA County Community Health Survey reports that 23.5% (1.7 million) of the total 10.16 million are obese, while 35.9% (2.6 million) are overweight.[5] These rates have outpaced population growth over the past two decades, mirroring nationwide and global trends. In the United

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[1] "Adult Obesity Causes & Consequences," Centers for Disease Control and Prevention, last modified August 29, 2017, https://www.cdc.gov/obesity/adult/causes.html.
[2] "Controlling the Global Obesity Epidemic," World Health Organization, https://www.who.int/nutrition/topics/obesity/en/.
[3] "The World Fact Book: United States," Central Intelligence Agency, https://www.cia.gov/library/publications/resources/the-world-factbook/geos/us.html.
[4] "QuickFacts Los Angeles County, California; California," *U.S. Census Bureau*, July 1, 2017, https://www.census.gov/quickfacts/fact/table/losangelescountycalifornia,ca/PST045217.
[5] "2015 LA County Health Survey - Topics & Data: Obesity," Los Angeles County Department of Public Health, accessed April 8, 2019, http://www.publichealth.lacounty.gov/ha/LACHSDataTopics2015.htm#O.

States, “obesity prevalence has doubled among adults and tripled among children” over the past three decades.[6] In LA County, adult obesity rates have increased from 13.6% in 1999, 22.7% in 2007, to 23.5% in 2015.[7] These rates have similarly increased among school aged children from 18.9% in 1999 to 23.0% in 2008.[8] These statistics vary significantly based on gender, age, race/ethnicity, education, income, and disability status.

These public health concerns are not strictly born by individuals: the medical costs of obesity in the US exceed $150 billion USD annually.[9] Obesity has profound economic consequences: not only does it drive up medical costs, it can also lead to lower workplace productivity and increased absenteeism.[10] However, the complexity of its multifactorial causes makes it an extremely difficult issue to address. Although obesity has been at the forefront of public health concerns over the past several decades, Americans continue to grow larger every year.

The majority of nutrition and health economics literature that focuses on the underlying causes of obesity comes up with two primary conclusions: poor dietary quality and lack of physical activity lead to weight gain. Additionally, certain genetic factors can predispose individuals to lower metabolic rates and thus higher likelihood for obesity.

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[6] Jonathan Fielding, “Obesity and Related Mortality in Los Angeles County,” September 2011, 9, http://publichealth.lacounty.gov/ha/reports/habriefs/2007/obese_cities/obesity_2011fs.pdf.
[7] Ibid.
[8] Ibid.
[9] “Adult Obesity Causes & Consequences,” Centers for Disease Control and Prevention.
[10] Ibid.

There are profound systemic obstacles that have facilitated this societal transformation. Although dietary choices are not always rational, healthy food is often unaffordable and geographically inaccessible. Whilst physical activity also has certain behavioral and psychological explanations, an increasing body of literature is focused on neighborhood factors such as sidewalk access, parks access, bike lane access, and neighborhood safety. Recent literature suggests that concerns about neighborhood safety play into these behavioral and psychological explanations and may reduce individual propensity to exercise in high-crime communities.

This thesis builds upon existing literature by examining the relationship between crime and physical activity. I hypothesize that crime influences obesity, violent crime has a stronger correlation than property crime, and that greater access to parks reduces obesity. My results are inconsistent with my first two hypotheses but support my third hypothesis.

II. Literature Review

A. Individual and Societal Explanations for Obesity

Within the fields of nutrition and health economics, a substantial literature exists on the principal determinants and underlying causes of obesity. According to the US Centers for Disease Control and Prevention (CDC), obesity is a multifactorial consequence of genetic predispositions, individual behavior, and societal conditions.[11]

McAllister, et al. (2009) conclude that the individual factors most frequently cited by both mass media and public health advocates form a hegemonic argument that obesity is primarily a result of poor dietary quality and lack of physical activity. Although these "big two" explanations are indisputably significant, McAllister, et al. (2009) argue that the obesity epidemic is a much more complex narrative than many perceive it to be. The oversimplification of individual behavioral to a mere caloric calculation prevents a truly comprehensive analysis on the conditions that determine both diet and physical activity. Consequently, there may be an insufficient body of research into other potentially significant root causes and alternative explanations for obesity.

Excluding behavioral and psychological factors, there are varying financial, geographic, and educational constraints that influence or otherwise determine dietary quality. Similarly, physical activity or inactivity has behavioral, psychological, and environmental explanations. The environmental explanations include factors such as proximity to local parks, public spaces, hiking trails, as well as the local "built

[11] "Adult Obesity Causes & Consequences," Centers for Disease Control and Prevention, last modified August 29, 2017, https://www.cdc.gov/obesity/adult/causes.html.

environment," which includes sidewalk access, bike lane access, and infrastructure, among others.

B. Neighborhood Explanations for Obesity

While many studies link poor dietary quality and lack of physical activity to weight gain, recent literature seeks to determine if certain exogenous neighborhood factors negatively influence an individual's likelihood to be overweight or obese. Numerous studies examine the interaction between neighborhood factors and physical activity. Cubbin, Hadden, and Winkleby (2001) study the effect of "material neighborhood deprivation," as measured by factors such as unemployment and education, on physical activity and BMI. They find that as neighborhood deprivation increases, BMI and obesity also increase. Importantly, however, crime is excluded from their definition of neighborhood deprivation.

The majority of health economics literature that focuses on aspects of the built environment and neighborhood factors does not specifically study the effects of neighborhood safety. Evidence suggests that neighborhood crime and perceived safety may impact obesity through reluctance to physical activity. According to Yu and Lippert (2010): "Historically, neighborhood poverty has been closely correlated with the local crime rate and closer scrutiny of this connection and its effect on exercise and obesity may help explain how neighborhood-level factors are related to body weight" (188). Yu and Lippert (2010) find that these associations are stronger for females than males due to a greater reported fear of victimization. In a study in Northwest England, Valentine and McKendrick (1997) find parental anxieties about neighborhood safety to be more determinant of their children's physical activity than the availability and quality of playgrounds.

Richardson, et al. (2017) test for the pathways through which perceived neighborhood safety and crime influence obesity. Their analysis uses a combination of self-reported body mass index (BMI), physical activity, and perceived safety data from low-income neighborhoods in Pittsburgh. This was coupled with secondary police-reported neighborhood crime data to determine the effect of crime on perceived safety, BMI, and physical activity. Richardson, et al. (2017) find a statistically significant and positive correlation between both crime and lack of perceived safety, as well as lack of perceived safety and BMI.

Tung, et al. (2018) use cross-sectional patient health data and geocoded crime counts to determine the effects of various types of police-recorded crime on obesity and cardiometabolic health in Chicago. Moreover, their analysis distinguishes between violent crime, which includes "assault, battery, criminal sexual assault, robbery, or homicide," and nonviolent crime, which includes "theft or criminal property crime" (3). Each census tract measured is ordered by crime rate quartiles, ranging from low to very high, with existence of homicide as a stand-alone independent binary variable. Covariates include demographic classifications including age, sex, ethnicity, insurance status, and neighborhood characteristics such as median household income, unemployment rates, and average educational attainment. Tung, et al. (2018) find that the sample population included in the highest quartiles of violent crime and nonviolent crime have 53% and 41% higher adjusted odds of obesity, respectively, than the sample population in the lowest quartiles. Moreover, these effects are stronger among women in the medium, high, and very high quartiles.

Although multiple studies indicate a positive correlation between neighborhood safety factors and BMI, physical activity, and obesity, the effect is less clear among children and youth. Yu and Lippert (2016) performed an exhaustive review of academic articles related to the effect of neighborhood crime rates on physical activity, BMI, and obesity rates for adults and children. Among the 18 studies that specifically study adult BMI, eight find a positive relationship while the remaining ten find no degree of statistical significance. Similarly, only six out of eleven studies that focus on youth claim a positive association. The remaining five studies find no degree of statistical significance.

Burdette and Whitaker (2004) seek to determine the relationship between the safety of low-income preschool children's neighborhoods and their likelihood to be overweight. Within the sample size, they find no significant relationship between level of neighborhood crime and likelihood to be overweight. Similarly, Showell et al. (2019) find no association between crime and increased likelihood to be overweight or obese for preschoolers in Baltimore.

Sandy, et. al (2013) examine the effect of neighborhood factors such as accessibility of walking trails and local crime statistics on children's BMI and obesity status. They find that nearby walking trails reduce children's BMI; however, the strength of the reduction depends on local violent crime rates.

C. Hypothesis Formation

Despite the varying results of existing literature, I did not come across any studies that suggest a negatively inverse relationship between crime rates and BMI for either adults or children. Most studies of childhood obesity focus exclusively on preschool aged children. Additional studies are otherwise limited through the use of small sample sizes. Moreover, the relationship between crime and childhood obesity has not been extensively reviewed across the United States, and I am not aware of any studies that test this relationship in Los Angeles County. However, according to an official report on obesity published by the Los Angeles County of Public Health Office of Health Assessment and Epidemiology, "Results of the 2007 LACHS [Los Angeles County Health Survey] suggest that concerns about crime and public safety may be another important barrier to physical activity in [low-income] communities."[12]

I attempt to contribute to this growing body of literature by examining the effect of police-reported property crimes and violent crimes on childhood obesity for 5th, 7th, and 9th grade students across neighborhoods in Los Angeles County over a five-year period from 2012 through 2016. I build upon existing studies by using a more robust data set and including neighborhood covariates such as parks access and grocery store access. Demographic covariates include neighborhood unemployment rate, median household income, educational attainment, and race and ethnicity.

If neighborhood safety risks are factored heavily into parents' decisions about whether or not to allow their children to play or exercise outdoors, then I suspect that neighborhoods with higher crime rates would have disproportionately higher rates of

[12] Fielding, "Obesity."

overweight and obese children than more safe neighborhoods, even after controlling for income and demographic differences. Moreover, based off the results of Tung, et al. (2018), I expect the relationship between obesity and neighborhood crime to be stronger for police-reported violent crime than property crime. Finally, I expect that parks are a primary facilitator of physical activity; thus, I hypothesize that neighborhoods with greater access to parks to have lower rates of childhood obesity.

III. Data

A. Overview: Los Angeles County Descriptive Statistics

This study utilizes a combination of yearly pooled cross-sectional geocoded data across 202 “neighborhoods” in Los Angeles County over a 5-year period from 2012 to 2016. This is collected from the University of Southern California (USC) Price Center for Social Innovation Neighborhood Data for Social Change (NDSC) interactive platform, which aggregates a variety of unique data sources across the 2344 census tracts, 272 neighborhoods, and 88 incorporated cities within the County of Los Angeles. After manually eliminating neighborhoods where data is unavailable for some or all variables, I end up with 202 neighborhoods and 1009 observations. One included neighborhood only has 4 years of data available; this accounts for the total 1009 observations rather than 1010 (202*5).

Given that one’s neighborhood is largely determined by income, which is correlated to factors such as education and race/ethnicity, among others, there are significant variations in obesity rates among neighborhoods in LA County. Since 2000, neighborhoods in Los Angeles County are increasingly racially heterogenous.[13] According to Clark, et. al (2015): “In 2000, about 40 percent of the population in Los Angeles lived in strongly segregated neighborhoods. Ten years later, in 2010, only a third of the population was still living in such neighborhoods… Almost every other inhabitant lives in a neighborhood that has experienced significant shifts in the ethno-racial

[13] William Clark et al., “In Los Angeles, Increasing Neighborhood Diversity Means That Segregation Is on the Decline, London School of Economics, October 13, 2015, https://blogs.lse.ac.uk/usappblog/2015/10/13/in-los-angeles-an-increase-in-neighborhood-diversity-means-that-segregation-is-on-the-decline/.

composition of its population during the last decade and a half."[14] Given the sheer size of its population and increasing neighborhood diversity, Los Angeles provides a uniquely representative lens through which I contribute to a growing body of literature regarding the effect of neighborhood crime rates on childhood obesity.

B. Metrics: Neighborhoods vs. Census Tracts

Although the USC NDSC platform also disseminates more specific census tract data, neighborhoods are a more useful comparative metric for all intents and purposes of discussion in this study. For example, neighborhoods such as "Westwood" within LA County are more comprehensible to the average reader than the numbers (2653.01 and 2652.02) assigned to its census tracts. Excluding Tung, et al. (2018), which orders 324 census tracts in Chicago into crime rate quartiles, this statistical technique is consistent with much of the existing literature.

According to the Los Angeles Times "mapping LA" project: "Census tracts are drawn by the U.S. Census Bureau and used for tabulating demographic information, including income and ethnicity. The shapes of the tracts are frequently out of sync with the geographical, historic and socioeconomic associations that define communities."[15] Perhaps surprisingly, however, there are no official boundaries to the names of Los Angeles communities and neighborhoods.[16] Neighborhood council maps, chamber of commerce maps, and improvement district maps, for example, are often inconsistent. In many places, competing neighborhood councils and homeowner associations claim

[14] Ibid.
[15] "About Mapping LA," *Los Angeles Times*, accessed April 9, 2019, http://maps.latimes.com/about/.
[16] Ibid.

informal jurisdiction over the same territory.[17] Zip codes do not provide the necessary clarification over neighborhood boundaries because smaller incorporated cities such as the city of Santa Monica often have a proportionally higher number of zip codes than similarly sized geographic zones within the neighboring city of Los Angeles.[18] Within Los Angeles, and perhaps many other cities and counties, contemporary applications such as Google Maps and Apple Maps display differing "neighborhoods" based on subjective human data input, often with increasing regularity and new entries.

The LA Times "mapping LA" resource is a collaborative and data-driven effort to adjust and merge census tracts to appropriately define communities and neighborhood boundaries through consensus mapping. My analysis utilizes the USC NDSC platform which aggregates a variety of data sources into 272 distinct "neighborhoods" as defined by the Los Angeles Times. For the purposes of consistency, both the LA Times and my discussion use the term "neighborhood" even when referring to smaller standalone cities (such as Beverly Hills or Santa Monica) and other unincorporated areas within LA County.

Whilst census tracts provide a higher number of observations, and thus a more granular data set, geospatial analysis suggests that crime rates are largely similar between adjacent census tracts over time. Given that neighborhoods in LA County are still a relatively small metric comprised of no more than a few adjacent census tracts, and that my analysis aggregates data over a 5-year period, I mitigate the risk of inappropriately claiming a geographic correlation between aggregated neighborhood crime rates and

[17] Ibid.
[18] Ibid.

childhood obesity. Additionally, children's physical activity outside their immediate homes may largely take place outside the boundaries of their census tract but within the geographic confines of their neighborhood. Given this, neighborhood crime is likely a more effective measurement of this hypothesized correlation. Additional studies could examine the relationship on a census tract level.

C. Variables

I use three different independent variables in my analysis. These include the number of part I property crimes, number of part I violent crimes, and the sum of part I property and violent crimes committed per 1000 people per year across all 202 neighborhoods studied in LA County. The USC Neighborhood Data for Social Change (NDSC) platform collects crime statistics over a 5-year period (2012-2016) from the Los Angeles Police Department (LAPD) and the Los Angeles County Sheriff's Department (LASD). These crimes are reported according to federal standards established by the Uniform Crime Reporting (UCR) program of the FBI, which delineates crime into two distinct categories: part I and part II crimes. Part I crimes are further broken into part I property crimes and part I violent crimes. Part I property crimes "include burglary, larceny theft, motor vehicle theft, and arson," whereas part I violent crimes include "murder and non-negligent manslaughter, forcible rape, aggravated assault, and robbery."[19] Part II crimes are considered less serious offenses; they "include approximately 21 categories of offenses ranging from simple assault to forgery and fraud

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[19] USC Price Center for Social Innovation, "Learn More: Part I Crimes (LA)," Neighborhood Data for Social Change, accessed April 9, 2019, https://usc.data.socrata.com/stories/s/h3ea-qrq9/.

to drug possession."[20] Because of this, part II crimes are considered less indicative of neighborhood safety than part I crimes. Therefore, I regress part I property crime, part I violent crime, and total part I crime against childhood obesity for my analysis. Regressions for part II crimes and the total crime count (sum of part I and part II) are also included in the appendix.

The primary dependent variable of interest relates to childhood obesity. The USC NDSC platform aggregates data from the California Department of Education Ed-Data/Data Quest over an 8-year period (2009/2010 – 2016/2017). I restrict this data to a 5-year period (2012-2016) to match the available independent crime data. The childhood obesity metric is taken by measuring the "unhealthy percentage" of 5th, 7th, and 9th grade public school students who are "not within the "Healthy Fitness Zone" of the Body Mass Index portion of the FitnessGram test. The FitnessGram test was developed by the Cooper Institute "to improve school physical education programs and children's health."[21] It has been used by the California Department of Education across all public schools since 1996. The test evaluates students on aspects such as "their aerobic capacity, strength, body composition, and flexibility."[22] Whilst not all students who fail to meet criteria of the "healthy fitness zone" are necessarily obese, they are "considered to be at risk for future health problems, including obesity."[23] According to the USC NDSC

[20] USC Price Center for Social Innovation, "Learn More: Part II Crimes (LA)," Neighborhood Data for Social Change, accessed April 9, 2019, https://usc.data.socrata.com/stories/s/bvrs-x7wm/.
[21] USC Price Center for Social Innovation, "Learn More: Childhood Obesity (LA)," Neighborhood Data for Social Change, accessed April 9, 2019, https://usc.data.socrata.com/stories/s/iy69-gcuf/.
[22] Ibid.
[23] Megan Goulding, "Childhood Health and Food Access in South Los Angeles," Neighborhood Data for Social Change, accessed April 9, 2019, https://usc.data.socrata.com/stories/s/Childhood-Health-and-Food-Access-in-South-Los-Ange/njbg-yxn2.

platform, these health indicators are significantly worse for children who live in low-income communities.[24]

Given the hypothesized correlation between both neighborhood crime and obesity and certain demographic factors, I attempt to include meaningful controls to mitigate the risk of omitted variable bias. The following control variables account for neighborhood specific factors that influence childhood obesity. Unless otherwise specified, each of these are 5-year estimates collected by the American Community Survey and aggregated to the neighborhood level by the USC NDSC platform. I use five different 5-year estimates (2008-12, 2009-13, 2010-14, 2011-15, and 2012-16) to match the 5-year (2012-2016) data. Due to concerns of multicollinearity, some of these variables have been omitted from my final regressions. Appendix D - Tables 3.1 and 3.2 show correlation matrices.

Socioeconomic Controls (4 metrics):	These include: unemployment rate, median household income, and the percentage of households earning below 100% and 200% of the federal poverty threshold.
Educational Attainment (2 metrics):	These include: the percentage of the population ages 25 and older with a university bachelor's degree and those without a high-school diploma.[25]

[24] Ibid.
[25] USC Price Center for Social Innovation, "Learn More: Educational Attainment (LA)," Neighborhood Data for Social Change, accessed April 9, 2019, https://usc.data.socrata.com/stories/s/juyq-ixr9/.

Youth Opportunity (YO) (single metric):	This is defined by the USC NDSC platform as "the percent of youth ages 16 to 24 who are neither working nor in school."[26]
Food Insecurity (FI) (2 metrics):	This includes the percentage of students in each neighborhood who receive free or reduced priced lunches through the National School Lunch program (NSLP) and the number of grocery stores that accept the Supplemental Nutrition Assistance Program (SNAP). SNAP data is collected by the US Department of Agriculture and aggregated by the USC NDSC platform to the neighborhood level.[27][28]
Parks Access (PA) (single metric):	This is collected by the LA Times is defined as "the number of acres of parks and green space per 1,000 people."[29] Given that some "neighborhoods" are unincorporated mountain ranges, my regressions use the natural log of parks access to reduce the effect of extreme outliers.

[26] USC Price Center for Social Innovation, "Learn More: Opportunity Youth (LA)," Neighborhood Data for Social Change, accessed April 9, 2019, https://usc.data.socrata.com/stories/s/jsrt-6dku.
[27] USC Price Center for Social Innovation, "Learn More: Free/Reduced-Price Lunch (LA)," Neighborhood Data for Social Change, accessed April 9, 2019, https://usc.data.socrata.com/stories/s/rdaz-4vu4/.
[28] USC Price Center for Social Innovation, "Learn More: SNAP Acceptance (LA)," Neighborhood Data for Social Change, accessed April 9, 2019, https://usc.data.socrata.com/stories/s/wiaw-xwq3/.
[29] USC Price Center for Social Innovation, "Acres of Parks per 1,000 people," Neighborhood Data for Social Change, accessed April 9, 2019.

Race and Ethnicity (4 metrics):	These include the percentage of the population who identify as White, Hispanic, Asian, or Black.[30]
Interaction Terms (5 metrics)	Each regression includes an interaction term for unemployment with a dummy variable for each of the highest crime rate quartile covariates.

Reference Appendix C – Tables 2.1-2.6 for data summary statistics.

[30] USC Price Center for Social Innovation, "Learn More: Race & Ethnicity (LA)," Neighborhood Data for Social Change, accessed April 9, 2019, https://usc.data.socrata.com/stories/s/pd65-xuak/.

IV. Estimation Strategy and Results

A. Estimation Strategy

This study examines the effect of crime rates on childhood obesity across 202 neighborhoods in LA County over the five-year time period 2012-2016. Using a combination of yearly pooled cross-sectional geocoded data from the USC NDSC platform, I run multiple ordinary least squares regressions using different measures of crime to determine if neighborhoods with higher crime rates influence the unhealthy percentage of 5^{th}, 7^{th}, and 9^{th} grade public school students. I primarily analyze part I property crime, part I violent crime, and total part I crime (sum of part I property and part I violent crimes). Regressions for part II crime and the sum of part I and part II crimes are included in the appendix (models 4 and 5). Because each of these crime statistics are highly correlated with each other (reference table 3.2), I run separate regressions for each independent crime variable.

I test three hypotheses: crime influences obesity, violent crime has a stronger correlation than property crime, and that greater parks access reduces obesity. Under Gauss-Markov assumptions, the ordinary least squares estimator is the best (minimum variance) linear unbiased estimator. To reduce econometric concerns of multicollinearity, I run a correlation matrix (tables 3.1, 3.2) to determine which covariates are highly correlated and omit the following from my final regressions: median household income, the percentage of the population earning below 200% of the federal poverty threshold, and the percentage of the population with no high-school degree. Median household income is highly correlated with important control variables including: the percentage of the population earning below the federal poverty threshold, the percentage of the population with a college degree, the percentage with no high-school degree, the percentage of students who receive federally subsidized school lunches, and the percentage of white residents. Therefore, I include the percentage of households earning below 100% of the federal poverty threshold; this serves as a proxy for income and it is less correlated with other covariates than median household income (reference table 3.2).

I include control variables related to socioeconomic factors, educational attainment, youth opportunity, food insecurity, parks access, ethnicity, and an interaction term using unemployment and a dummy variable for the highest crime rate quartiles of each crime measure. The interaction term tests for the partial effect of the dependent variable (childhood obesity) with respect to unemployment depending on the magnitude of crime. I test for statistical significance at the standard 95% confidence interval.

Each model includes a series of three regressions to determine the explanatory power and statistical significance of each measure of crime as additional control variables are added. Regression (A) of each model is intentionally minimalistic and does not include any control variables. Regression (B) includes all control variables except for ethnicity and the interaction term between unemployment and high crime quartiles. Regression (C) includes all control variables. The intention is to create an increasingly sophisticated model where I demonstrate that perceived statistical significance from a low standard error in (A) might be inaccurate after controlling for other variables (regressions B & C).

OLS regression results for each model are calculated by the following equations:

Model 1 (A):
$$Y(Unhealthy\ Percentage) = \beta_0 + \beta_1 PropertyCrime + \varepsilon$$

Model 1 (B):
$$Y(Unhealthy\ Percentage) = \beta_0 + \beta_1 PropertyCrime + \beta_2 Unemployment + \beta_3 PovertyThreshold100 + \beta_4 College + \beta_5 YouthOpportunity + \beta_6 SnapInstitutions + \beta_7 SchoolLunchProgram + \beta_8 LnParkAccess + \varepsilon$$

Model 1 (C):
$$Y(Unhealthy\ Percentage) = \beta_0 + \beta_1 PropertyCrime + \beta_2 Unemployment + \beta_3 PovertyThreshold100 + \beta_4 College + \beta_5 YouthOpportunity + \beta_6 SnapInstitutions + \beta_7 SchoolLunchProgram + \beta_8 LnParkAccess + \beta_9 White + \beta_{10} Hispanic + \beta_{11} Asian + \beta_{12} Black + \beta_{13} UnemploymentHighPropCrime + \varepsilon$$

Model 2 (A):
$$Y(Unhealthy\ Percentage) = \beta_0 + \beta_1 ViolentCrime + \varepsilon$$

Model 2 (B):
$$Y(Unhealthy\ Percentage) = \beta_0 + \beta_1 ViolentCrime + \beta_2 Unemployment + \beta_3 PovertyThreshold100 + \beta_4 College + \beta_5 YouthOpportunity + \beta_6 SnapInstitutions + \beta_7 SchoolLunchProgram + \beta_8 LnParkAccess + \varepsilon$$

Model 2 (C):
$$Y(Unhealthy\ Percentage) = \beta_0 + \beta_1 ViolentCrime + \beta_2 Unemployment + \beta_3 PovertyThreshold100 + \beta_4 College + \beta_5 YouthOpportunity + \beta_6 SnapInstitutions + \beta_7 SchoolLunchProgram + \beta_8 LnParkAccess + \beta_9 White + \beta_{10} Hispanic + \beta_{11} Asian + \beta_{12} Black + \beta_{13} UnemploymentHighViolentCrime + \varepsilon$$

Model 3 (A):
$$Y(Unhealthy\ Percentage) = \beta_0 + \beta_1 TotalPartICrime + \varepsilon$$

Model 3 (B):
$$Y(Unhealthy\ Percentage) = \beta_0 + \beta_1 TotalPartICrime + \beta_2 Unemployment + \beta_3 PovertyThreshold100 + \beta_4 College + \beta_5 YouthOpportunity + \beta_6 SnapInstitutions + \beta_7 SchoolLunchProgram + \beta_8 LnParkAccess + \varepsilon$$

Model 3 (C):
$$Y(Unhealthy\ Percentage) = \beta_0 + \beta_1 TotalPartICrime + \beta_2 Unemployment + \beta_3 PovertyThreshold100 + \beta_4 College + \beta_5 YouthOpportunity + \beta_6 SnapInstitutions + \beta_7 SchoolLunchProgram + \beta_8 LnParkAccess + \beta_9 White + \beta_{10} Hispanic + \beta_{11} Asian + \beta_{12} Black + \beta_{13} UnemploymentHighPartICrime + \varepsilon$$

These equations are consistent with the standard linear regression model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon$$

Y is the dependent variable measured by the unhealthy percentage of 5^{th}, 7^{th}, and 9^{th} grade students in each neighborhood. Each β is the coefficient to the independent variables $X_1 - X_n$ and represents the parameters and strength of the covariates. β_0 is the constant term. The residual, ε accounts for standard random error from each unit in the sample population. The results of these regression results are shown in the appendix.

B. Results

The first regression technique is represented in columns A. The results from each initial regression suggest a statistically significant ($p<0.01$) relationship between varying measures of crime and childhood obesity. I represent this graphically with a series of three histograms (Figures 1.1 – 1.3). However, the regressions shown by technique A are intentionally unsophisticated and at risk of omitted variable bias. Given that statistical significance is dependent on including necessary control variables, these regressions alone are insufficient to either accept or reject the null hypothesis. However, this simple regression tells us that ratio of total variation in y (unhealthy percentage) explained by x (crime) in the model is strongest for violent crime, which has an R-squared value of 11%.

Initially perceived statistical significance disappears for each crime metric when necessary control variables are included in the model as shown by techniques B and C. Based off the results of Columns C (Models 1 – 3), neither property nor violent crime have a statistically significant effect on the unhealthy percentage of 5^{th}, 7^{th}, and 9^{th} grade public school students in LA County. These results fail to support my first and second hypotheses. Column B of Model 2 refutes both hypotheses and suggests a statistically significant yet inverse relationship between violent crime and childhood obesity. However, the significance of this metric disappears when additional controls for race and ethnicity are included.

My results are consistent with my third hypothesis: greater access to parks appears to reduce obesity. Model 3 – Column C implies that a one-percent increase in parks and green space per 1,000 people reduces childhood obesity by 0.006 units. This result becomes more consequential depending on the magnitude of the percentage increase in parks and green space. For example, a 100% increase in parks and green space per 1,000 people could reduce childhood obesity by 6%. However, the scalability of this estimation remains uncertain.

Although I reject my first and second hypothesis, my regression results show statistically significant relationships between several control variables and childhood obesity. For example, Model 3 – Column C indicates that a unit increase in the percentage of households earning below 100% of the federal poverty threshold increases the “unhealthy percentage” metric by 0.11 units (in this case measured by percent). Additionally, a unit increase in educational attainment appears to have a statistically significant reduction on rates of childhood obesity.

C. Analysis & Policy Implications

Except for parks access, each of the statistically significant covariates is highly correlated with median household income (reference correlation matrix – table 3.1). These include: the percentage of households earning below 100% of the federal poverty threshold, the percentage of the population ages 25 and older with a university bachelor's degree, youth opportunity, the number of grocery stores that accept SNAP benefits, and the percentage of students in each neighborhood who receive free or reduced priced lunches. These covariates are statistically significant using both regression techniques B and C for each of the models. Except for college education, these effectively serve as proxies for low-income neighborhoods. Thus, I can reasonably deduce that obesity is largely a symptom of socioeconomic factors. Both measures of food insecurity (SNAP institutions and school lunch program) are statistically significant indicators of the relationship between poverty and obesity.

Although the results of this study suggest that crime does not have a statistically significantly effect on childhood obesity, certain findings exogenous to my initial hypotheses may have economic significance and corresponding policy implications. The overarching argument posed by nutritional scientists is that poor dietary quality and sedentary activity increase the likelihood of obesity. Similarly, there is a reverse causality effect between obesity and lethargy. An estimated 70% of our caloric consumption is accounted for by our resting metabolic rate. The abundance of conflicting dietary advise often ignores the fact that not all calories are equivalent in their nutritional value. For example, the body and brain metabolize sugar differently than nutrients derived from fruits and vegetables. The most effective path to individual weight-loss couples an increase in physical activity with an increase in dietary quality. If crime is not a statistically significant obstacle to physical activity, then the national debate surrounding obesity is largely focused on the right topics of improving dietary quality.

Beyond certain behavioral and genetic factors, there are significant financial and often geographic obstacles to maintaining a healthy diet. My regressions are consistent with this existing literature given that each proxy for income has a statistically significant impact on the unhealthy percentage metric. Although SNAP institutions and the federal school lunch program importantly help food-insecure households, more work can be done to improve the availability of healthy yet affordable food in low-income communities. According to the results of a 2016 report published by the U.S. Department of Agriculture: "SNAP households spend about 10 percent of food dollars on sugary drinks, which is about three times more than the amount they spend on milk. In New York City alone, as we've reported, this translates into more than $75 million in sugary drink purchases each year that are subsidized by U.S. taxpayers."[31] Although these purchasing habits extend beyond SNAP households, certain state and local governments have started to provide financial incentives to SNAP recipients for purchasing fruits and vegetables.[32] The healthy incentives pilot program administered by the USDA is a preliminary example of how financial incentives may serve to increase the consumption of more nutritious foods among food-insecure households.[33] Additional studies can examine if programs designed to improve dietary quality can effectively reduce obesity among target populations.

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[31] Allison Aubrey, "Food Stamps for Soda: Time to End Billion-Dollar Subsidy for Sugary Drinks?" *NPR*, October 29, 2018, https://www.npr.org/sections/thesalt/2018/10/29/659634119/food-stamps-for-soda-time-to-end-billion-dollar-subsidy-for-sugary-drinks.
[32] Courtney Perkes, "Food Stamp Program Makes Fresh Produce More Affordable," *NPR*, January 16, 2018, https://www.npr.org/sections/health-shots/2018/01/16/577662116/food-stamp-program-makes-fresh-produce-more-affordable.
[33] "Healthy Incentives Pilot Final Evaluation Report," US Department of Agriculture, last modified May 8, 2018, https://www.fns.usda.gov/snap/healthy-incentives-pilot-final-evaluation-report.

Although physical inactivity may not necessarily be determined by neighborhood crime, my results are consistent with my third hypothesis that greater access to parks and green space can reduce childhood obesity. Whilst the behavioral and psychological explanations for physical activity are largely outside the realm of public policy, state and local governments can work to improve environmental conditions. In LA County, this may include initiatives to increase inner-city access to safe parks, improved public transportation to areas with greater outdoors access, improved sidewalk access, and the addition of more bike lanes. Additional studies more closely examine the relationship between aspects of the neighborhood built-environment and physical activity in LA County.

D. Additional Considerations

Although the results of my regressions are inconsistent with my first and second hypotheses, additional studies could re-examine the perceived relationship between crime and childhood obesity using a more robust and granular data set. My study is restricted by the “unhealthy percentage” metric; this includes students who may not necessarily be obese but who are at risk for developing obesity. This is not necessarily the most accurate statistical representation of obese children across neighborhoods in LA County. It excludes students who may be enrolled in private institutions. Considering that school choice is often determined by income, and that high-income areas often have disproportionately lower crime rates, further data collection on obesity in high versus low income communities would enable a more comprehensive analysis on this subject. Additionally, further analysis could collect gender specific data to determine if there are stronger correlations for women than for men. This finding would be consistent with Yu and Lippert (2010), who hypothesize that a greater reported fear of victimization may account for lesser physical activity among women in high crime neighborhoods. The control variables also present certain drawbacks: further studies could try to collect additional covariates related to aspects of the neighborhood built-environment including the strength of public infrastructure, sidewalk access, and bike-lane access.

V. Conclusion

My regression analysis does not determine a statistically significant relationship between varying crime measures and the unhealthy percentage of 5^{th}, 7^{th}, and 9^{th} grade public school students in LA County. Therefore, I reject hypotheses one and two. Additional studies could examine this relationship using a more robust data set. Although there are potentially significant alternative explanations for obesity that can still be explored, a specific focus on crime ignores the bigger picture. Thus, my regression results are potentially economically significant despite their statistical insignificance.

The overarching consensus among health economists, nutritionists, and other experts is that the most effective solution to the obesity epidemic is to improve the dietary quality of Americans and to encourage greater physical activity. Each of my models is consistent with hypothesis three: neighborhoods with greater access to parks to have lower rates of childhood obesity. This would suggest that parks facilitate physical activity. Local governments can seek to improve existing public green space or attempt to create new parks in inner-city communities.

My contribution to this growing field is potentially economically significant in reinforcing that the focus should primarily remain on strategies to improve both dietary quality and physical activity. Specific policy recommendations include reform of the agriculture sector to restrict the amount of sugar and artificial products advertised as food. Since these often disproportionately affect the nutritious options of food insecure households, I recommend local policies to financially incentivize purchasing fresh fruits and vegetables among SNAP recipients. Additionally, further reform is needed of the dietary standards that govern the federal school lunch program. There is an abundance of innovation and traction around healthy-eating that will hopefully democratize the current unaffordability of certain recommended diets for lower-income Americans.

VI. Resources

"About Mapping L.A." Los Angeles Times. Accessed April 9, 2019. http://maps.latimes.com/about/.

"Adult Obesity Causes & Consequences." Centers for Disease Control and Prevention. Last modified August 29, 2017. Accessed April 8, 2019. https://www.cdc.gov/obesity/adult/causes.html.

Aubrey, Allison. "Food Stamps For Soda: Time To End Billion-Dollar Subsidy For Sugary Drinks." NPR. Last modified October 29, 2018. https://www.npr.org/sections/thesalt/2018/10/29/659634119/food-stamps-for-soda-time-to-end-billion-dollar-subsidy-for-sugary-drinks.

Burdette, Hillary L., and Robert C. Whitaker. "Neighborhood Playgrounds, Fast Food Festaurants, and Crime: Relationships to Overweight in Low-Income Preschool Children." *Preventive Medicine* 38, no. 1 (January 2004). http://doi.org/10.1016/j.ypmed.2003.09.029.

Clark, William, Eva Andersson, John Osth, and Bo Malmberg. "In Los Angeles, Increasing Neighborhood Diversity Means That Segregation Is on the Decline." London School of Economics. Last modified October 13, 2015. https://blogs.lse.ac.uk/usappblog/2015/10/13/in-los-angeles-an-increase-in-neighborhood-diversity-means-that-segregation-is-on-the-decline/.

"Controlling the Global Obesity Epidemic." World Health Organization. Accessed April 20, 2019. https://www.who.int/nutrition/topics/obesity/en/.

Cubbin, Catherine & Hadden, Wilbur & Winkleby, Marilyn. (2001). Neighborhood Context and Cardiovascular Disease Risk Factors: The Contribution of Material Deprivation. Ethnicity & disease. 11. 687-700.

Emily J. McAllister, Nikhil V. Dhurandhar, Scott W. Keith, Louis J. Aronne, Jamie Barger, Monica Baskin, Ruth M. Benca, Joseph Biggio, Mary M. Boggiano, Joe C. Eisenmann, Mai Elobeid, Kevin R. Fontaine, Peter Gluckman, Erin C. Hanlon, Peter Katzmarzyk, Angelo Pietrobelli, David T. Redden, Douglas M. Ruden, Chenxi Wang, Robert A. Waterland, Suzanne M. Wright & David B. Allison (2009) Ten Putative Contributors to the Obesity Epidemic, Critical Reviews in Food Science and Nutrition, 49:10, 868-913, DOI: 10.1080/10408390903372599

Fielding, Jonathan. *Obesity and Related Mortality in Los Angeles County*. September 2011. Accessed April 8, 2019. http://publichealth.lacounty.gov/ha/reports/habriefs/2007/obese_cities/obesity_2011fs.pdf.

Galperin, Ron. "The GOP's Tax Plan Is Terrible for Los Angeles." *Los Angeles Times*, November 29, 2017. Accessed April 8, 2019. https://www.latimes.com/opinion/op-ed/la-oe-galperin-gop-tax-plan-20171129-story.html.

Goulding, Megan. "Childhood Health and Food Access in South Los Angeles." Neighborhood Data for Social Change. Accessed April 9, 2019. https://usc.data.socrata.com/stories/s/Childhood-Health-and-Food-Access-in-South-Los-Ange/njbg-yxn2.

"Healthy Incentives Pilot Final Evaluation Report." US Department of Agriculture. Last modified May 8, 2018. https://www.fns.usda.gov/snap/healthy-incentives-pilot-final-evaluation-report.

Perkes, Courtney. "Food Stamp Program Makes Fresh Produce More Affordable." Last modified January 16, 2018. https://www.npr.org/sections/health-shots/2018/01/16/577662116/food-stamp-program-makes-fresh-produce-more-affordable.

"QuickFacts Los Angeles County, California; California." In *U.S. Census Bureau*. Last modified July 1, 2017. Accessed April 8, 2019. https://www.census.gov/quickfacts/fact/table/losangelescountycalifornia,ca/PST045217.

Richardson, Andrea S., Wendy M. Troxel, Madhumita Ghosh-Dastidar, Gerald P. Hunter, Robin Beckman, Natalie Colabianchi, Rebecca L. Collins, and Tamara Dubowitz. "Pathways through Which Higher Neighborhood Crime Is Longitudinally Associated with Greater Body Mass Index." *International Journal of Behavioral Nutrition and Physical Activity* 14, no. 1 (2017). Accessed April 9, 2019. https://ijbnpa.biomedcentral.com/articles/10.1186/s12966-017-0611-y.

Sandy R, Tchernis R, Wilson J, Liu G, Zhou X. Effects of the built environment on childhood obesity: the case of urban recreational trails and crime. *Econ Hum Biol*. 2012;11(1):18–29. doi:10.1016/j.ehb.2012.02.005

Showell NN, Jennings JM, Johnson KA, Perin J, Thornton RLJ. Where Children Live: Examining Whether Neighborhood Crime and Poverty Is Associated With Overweight and Obesity Among Low-Income Preschool-Aged Primary Care Patients. *Front Pediatr*. 2019;6:433. Published 2019 Jan 22. doi:10.3389/fped.2018.00433

Tung EL, Wroblewski KE, Boyd K, Makelarski JA, Peek ME, Lindau ST. Police-Recorded Crime and Disparities in Obesity and Blood Pressure Status in Chicago. *J Am Heart Assoc*. 2018. Published 2018 Mar 24. doi:10.1161/JAHA.117.008030

"2015 LA County Health Survey - Topics & Data: Obesity." Los Angeles County Department of Public Health. Last modified 2015. Accessed April 8, 2019. http://www.publichealth.lacounty.gov/ha/LACHSDataTopics2015.htm#O.

USC Price Center for Social Innovation. "Acres of Parks per 1,000 People." Neighborhood Data for Social Change. Accessed April 9, 2019. https://ladata.myneighborhooddata.org/#!/dashboard?places=&categories=29:89%3D1&start_date=2015-01-01&end_date=2015-12-31&lat=34.068128208226995&lng=-118.17459466611962&zoom=9&shapeIds=&shapeGroupId=nm6n-sgfb&mapType=ChoroplethMap&listViewTab=Data&overlayLayers=Neighborhoods&search_field=&search_value=&autoUpdate=false&heatFilters=&statusFilter=&choroplethField=thematic_attribute_2_jrjz_rr9e&choroplethCategory=&searchType=.

———. "Learn More: Childhood Obesity (LA)." Neighborhood Data for Social Change. Accessed April 9, 2019. https://usc.data.socrata.com/stories/s/iy69-gcuf/.

———. "Learn More: Educational Attainment (LA)." Neighborhood Data for Social Change. Accessed April 9, 2019. https://usc.data.socrata.com/stories/s/juyq-ixr9/.

———. "Learn More: Employment (LA)." Neighborhood Data for Social Change. Accessed April 9, 2019. https://usc.data.socrata.com/stories/s/3qpn-46hd/.

———. "Learn More: Free/Reduced-Price Lunch (LA)." Neighborhood Data for Social Change. Accessed April 9, 2019. https://usc.data.socrata.com/stories/s/rdaz-4vu4/.

———. "Learn More: Income (LA)." Neighborhood Data for Social Change. Accessed April 9, 2019. https://usc.data.socrata.com/stories/s/u9tw-axc2/.

———. "Learn More: Opportunity Youth (LA)." Neighborhood Data for Social Change. Accessed April 9, 2019. https://usc.data.socrata.com/stories/s/jsrt-6dku.

———. "Learn More: Part I Crimes (LA)." Neighborhood Data for Social Change. Accessed April 9, 2019. https://usc.data.socrata.com/stories/s/h3ea-qrq9/.

———. "Learn More: Part II Crimes (LA)." Neighborhood Data for Social Change. Accessed April 9, 2019. https://usc.data.socrata.com/stories/s/bvrs-x7wm/.

———. "Learn More: Poverty (LA)." Neighborhood Data for Social Change. Accessed April 9, 2019. https://usc.data.socrata.com/stories/s/ta5g-62u8/.

———. "Learn More: Race & Ethnicity (LA)." Neighborhood Data for Social Change. Accessed April 9, 2019. https://usc.data.socrata.com/stories/s/pd65-xuak/.

———. "Learn More: SNAP Acceptance." Neighborhood Data for Social Change. Accessed April 9, 2019. https://usc.data.socrata.com/stories/s/wiaw-xwq3/.

"The USC Price Center for Social Innovation - Neighborhood Data for Social Change." Accessed April 9, 2019. https://ladata.myneighborhooddata.org/#!/dashboard?places=&categories=31:62%3D1&start_date=2017-01-01&end_date=2017-12-31&lat=34.0522&lng=-118.24369999999999&zoom=9&shapeIds=&shapeGroupId=nm6n-sgfb&mapType=ChoroplethMap&listViewTab=Data&overlayLayers=Neighborhoods&search_field=&search_value=&autoUpdate=false&heatFilters=&statusFilter=&choroplethField=thematic_attribute_1_jrjz_rr9e&choroplethCategory=&searchType.

Valentine, Gill, and John McKendrick. "Children's Outdoor Play: Concerns about Children's Safety and the Changing Nature of Childhood." *Geoforum* 28, no. 2 (1997). Accessed April 9, 2019. https://pdfs.semanticscholar.org/fa98/ccca8b7a123e50412166ab0c2bd2e98c1588.pdf.

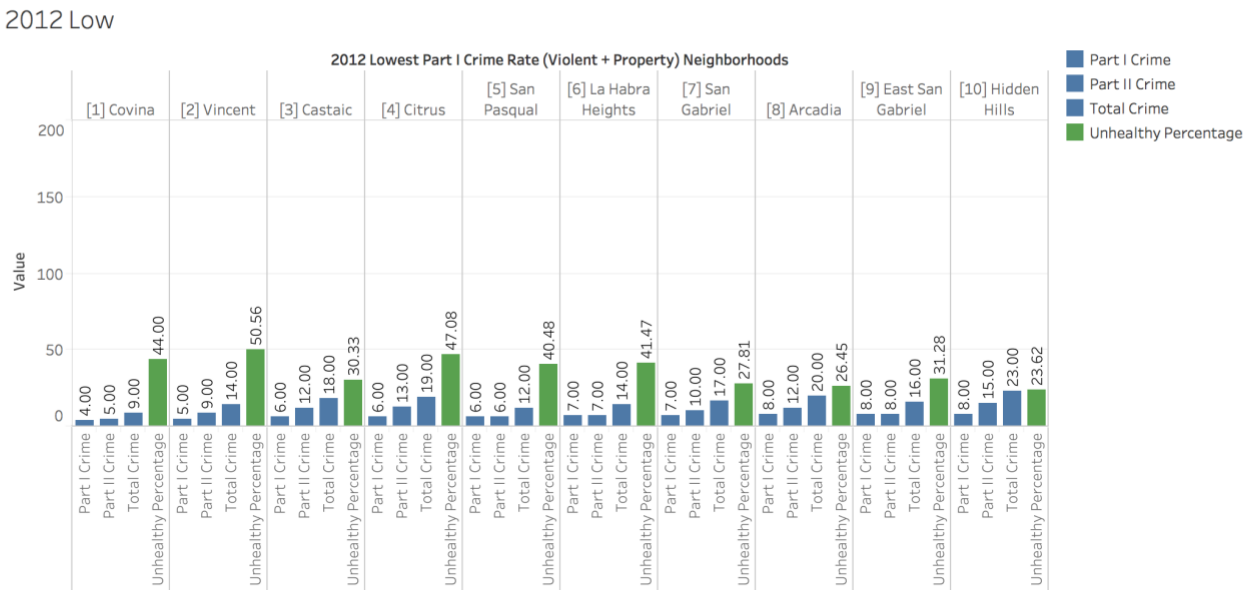
"The World Fact Book: United States." Central Intelligence Agency. https://www.cia.gov/library/publications/resources/the-world-factbook/geos/us.html.

Yu, Edward, and Adam M. Lippert. "Neighborhood Crime Rate, Weight-Related Behaviors, and Obesity: A Systematic Review of the Literature." *Sociology Compass* 10, no. 3 (March 2016). https://onlinelibrary.wiley.com/doi/pdf/10.1111/soc4.12356.

VII. Appendix

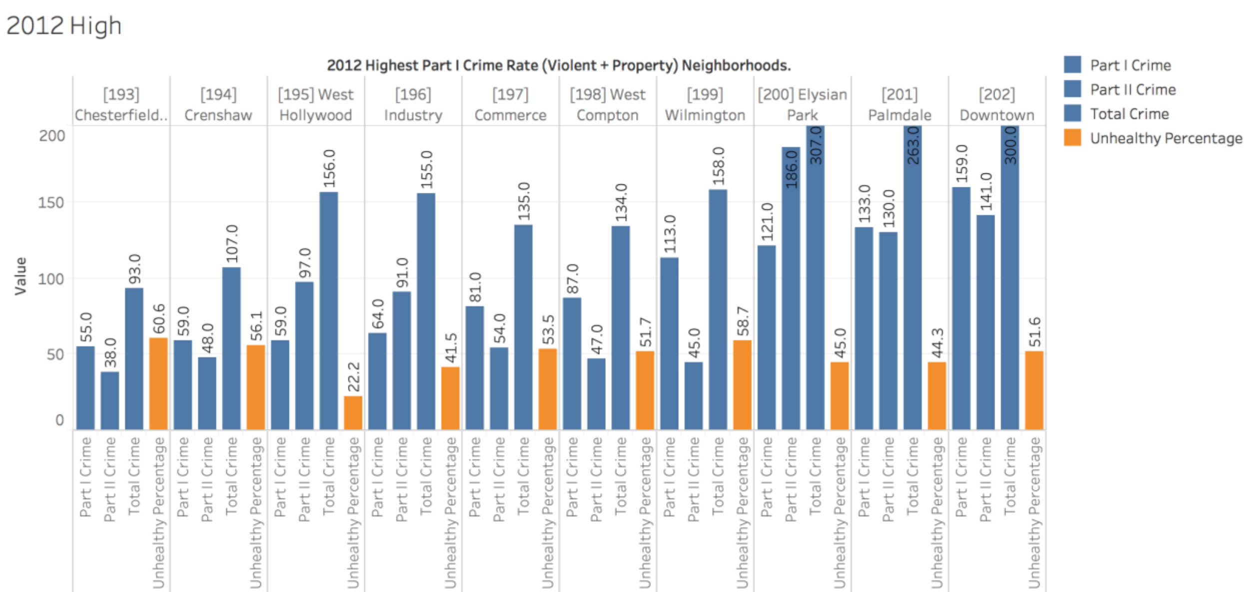
A. Appendix A: Charts – Crime & Childhood Obesity (Unhealthy Percentage)

Figure 1.1: 2012 Lowest Part I Crime Rate (Violent & Property) Neighborhoods



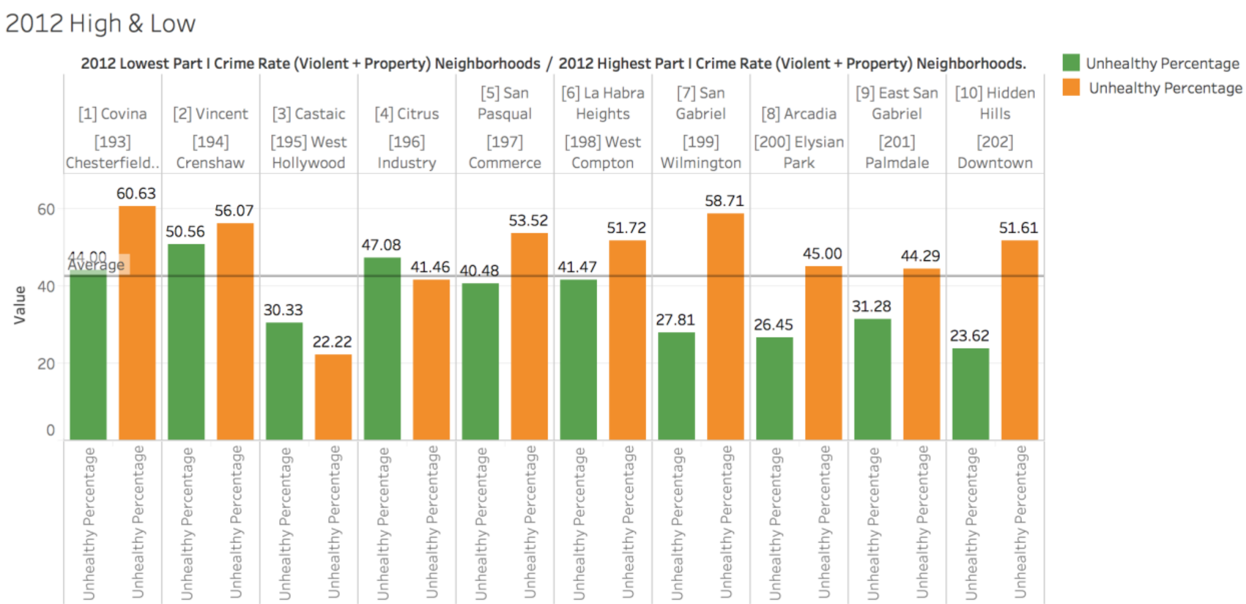
Histogram showing Part I Crime, Part II Crime, Total Crime and Unhealthy Percentage for each of the 10 Lowest Part I Crime Rate (Violent + Property) Neighborhoods in 2012.

Figure 1.2: 2012 Highest Part I Crime Rate (Violent & Property) Neighborhoods



Histogram showing Part I Crime, Part II Crime, Total Crime and Unhealthy Percentage for each of the 10 Highest Part I Crime Rate (Violent + Property) Neighborhoods in 2012.

Figure 1.3: 2012 Lowest & Highest Part I Crime (Violent & Property) Neighborhoods



Histogram showing Unhealthy Percentages for each 2012 Lowest Part I Crime Rate (Violent + Property) Neighborhood and 2012 Highest Part I Crime Rate (Violent + Property) Neighborhood. Lowest crime rate neighborhoods [1-10] are represented by the left-hand side "Unhealthy Percentage" on the x-axis; highest crime rate neighborhoods [193-202] are represented by the right-hand side "Unhealthy Percentage" on the x-axis.

B. Appendix B: List of LA County Neighborhoods Studied

Table 1: LA County Neighborhoods (alphabetized)

Acton	Hancock Park	Ramona
Adams-Normandie	Harbor City	Rancho Palos Verdes
Agoura Hills	Harbor Gateway	Rancho Park
Agua Dulce	Harvard Heights	Reseda
Alondra Park	Harvard Park	Ridge Route
Altadena	Hawaiian Gardens	Rolling Hills
Arcadia	Hidden Hills	Rolling Hills Estates
Arleta	Highland Park	Rosemead
Arlington Heights	Historic South-Central	Rowland Heights
Artesia	Hollywood	San Dimas
Athens	Hollywood Hills	San Gabriel
Atwater Village	Hollywood Hills West	San Pasqual
Avocado Heights	Huntington Park	San Pedro
Baldwin Hills/Crenshaw	Hyde Park	Santa Clarita
Bel-Air	Industry	Sawtelle
Bellflower	Jefferson Park	Shadow Hills
Beverly Crest	Koreatown	Sherman Oaks
Beverly Grove	La Canada Flintridge	Silver Lake
Beverly Hills	La Crescenta-Montrose	South El Monte
Beverlywood	La Habra Heights	South Park
Boyle Heights	La Mirada	South San Gabriel
Bradbury	La Puente	South San Jose Hills
Brentwood	Ladera Heights	South Whittier
Broadway-Manchester	Lake Balboa	Southeast Antelope Valley
Calabasas	Lake View Terrace	Studio City
Canoga Park	Lakewood	Sun Valley
Carson	Lancaster	Sunland
Carthay	Larchmont	Sylmar
Castaic	Lawndale	Tarzana
Castaic Canyons	Leimert Park	Temple City
Central-Alameda	Lennox	Toluca Lake
Cerritos	Leona Valley	Topanga
Charter Oak	Lincoln Heights	Tujunga
Chatsworth	Lomita	Santa Monica Mountains
Chesterfield Square	Lopez/Kagel Canyons	Santa Susana Mountains
Cheviot Hills	Los Feliz	University Park
Chinatown	Lynwood	Valley Glen
Citrus	Manchester Square	Valley Village
Commerce	Mar Vista	Van Nuys
Compton	Marina del Rey	Venice

Covina	Mayflower Village	Vermont Knolls
Cypress Park	Mid-City	Vermont Square
Del Aire	Mid-Wilshire	Vermont Vista
Del Rey	Mission Hills	Vermont-Slauson
Diamond Bar	Monrovia	View Park-Windsor Hills
Downey	Montecito Heights	Vincent
Downtown	Mount Washington	Walnut
Duarte	North Hills	Walnut Park
Eagle Rock	North Hollywood	Watts
East Hollywood	North Whittier	West Adams
East La Mirada	Northeast Antelope Valley	West Carson
East Los Angeles	Northridge	West Compton
East San Gabriel	Northwest Antelope Valley	West Hills
Echo Park	Northwest Palmdale	West Hollywood
El Sereno	Norwalk	West Los Angeles
Elysian Park	Pacific Palisades	West Puente Valley
Elysian Valley	Pacoima	West Whittier-Los Nietos
Encino	Palmdale	Westchester
Exposition Park	Palms	Westlake
Fairfax	Panorama City	Westlake Village
Florence	Pasadena	Westmont
Florence-Firestone	Pico Rivera	Westwood
Gardena	Pico-Robertson	Whittier Narrows
Glassell Park	Pico-Union	Willowbrook
Gramercy Park	Playa Vista	Wilmington
Granada Hills	Porter Ranch	Windsor Square
Green Meadows	Quartz Hill	Winnetka

C. Appendix C: Summary Statistics

Table 2.1: 2012 Summary Statistics

2012	***Mean***	***Median***	***St. Dev***	***Minimum***	***Maximum***	***Count***
Part I Property Crime	22.84	19.00	17.16	4.00	124.00	202
Part I Violent Crime	4.37	3.00	4.47	0.00	36.00	202
Total Part I Crime	27.21	23.00	19.84	4.00	159.00	202
Part II Crime	27.92	23.00	21.17	4.00	186.00	202
Total Crime (I & II)	55.13	45.50	38.90	9.00	307.00	202
Unhealthy %	42.41	44.29	12.22	4.76	62.85	202
Native American	0.17	0.13	0.19	0.00	1.62	202
Asian	13.14	8.90	13.65	0.00	65.64	202
Black	9.56	3.62	15.23	0.00	80.34	202
Hispanic	42.47	38.33	27.07	2.45	97.82	202
Pacific Islander	0.20	0.08	0.36	0.00	2.89	202
White	32.05	26.82	27.13	0.28	89.52	202
Other	0.29	0.19	0.39	0.00	3.34	202
College Graduation	31.11	26.31	20.31	2.41	76.89	202
High School	22.57	18.98	16.86	1.23	64.86	202
Median House Income	66821.36	62004.50	32221.53	16707.00	231648.00	202
Unemployment	10.54	10.22	3.15	3.19	23.67	202
Youth Opportunity	13.88	14.35	5.71	1.32	33.33	202
Poverty Threshold (100)	16.65	13.42	10.77	0.98	56.10	202
School Lunch Program	63.77	69.95	24.89	0.00	93.46	202
SNAP Institutions	24.35	16.00	26.90	0.00	151.00	202
Park Access	101.07	1.19	578.90	0.00	5738.31	202

Table 2.2: 2013 Summary Statistics

2013	***Mean***	***Median***	***St. Dev***	***Minimum***	***Maximum***	***Count***
Part I Property Crime	22.45	19.00	18.61	4.00	215.00	202
Part I Violent Crime	4.01	3.00	4.07	0.00	27.00	202
Total Part I Crime	26.46	21.50	20.70	4.00	221.00	202
Part II Crime Rate	27.29	21.00	28.62	5.00	342.00	202
Total Crime (I & II)	53.75	43.00	47.70	9.00	563.00	202
Unhealthy Percentage	41.74	43.69	12.55	4.63	64.40	202
Native American	0.18	0.13	0.22	0.00	2.08	202
Asian	13.33	8.98	13.67	0.03	64.97	202
Black	9.41	3.75	14.76	0.00	77.45	202
Hispanic	42.84	38.71	27.00	1.69	97.55	202
Pacific Islander	0.20	0.08	0.39	0.00	3.37	202
White	31.48	25.14	26.63	0.39	88.37	202
Other	0.27	0.19	0.32	0.00	2.85	202
College Graduation	31.41	25.47	20.48	3.01	76.42	202
High School	22.35	18.71	16.64	1.29	64.62	202
Median House Income	65899.88	61380.00	31122.07	17618.00	207031.00	202
Unemployment	11.17	11.02	3.32	2.72	24.00	202
Youth Opportunity	13.88	14.28	5.70	1.05	30.74	202
Poverty Threshold (100)	17.04	13.71	10.40	1.46	55.91	202
School Lunch Program	64.77	71.41	25.11	1.58	95.41	202
SNAP Institutions	24.35	16.00	26.90	0.00	151.00	202
Park Access	101.07	1.19	578.90	0.00	5738.31	202

Table 2.3: 2014 Summary Statistics

2014	***Mean***	***Median***	***St. Dev***	***Minimum***	***Maximum***	***Count***
Part I Property Crime	21.40	19.00	16.32	4.00	167.00	202
Part I Violent Crime	4.42	3.00	4.60	0.00	32.00	202
Total Part I Crime	25.81	22.00	19.49	5.00	187.00	202
Part II Crime	27.50	21.00	27.97	5.00	294.00	202
Total Crime (I & II)	53.31	43.00	45.27	10.00	481.00	202
Unhealthy Percentage	34.69	36.40	13.04	2.59	61.95	202
Native American	0.16	0.12	0.21	0.00	1.97	202
Asian	13.53	9.57	13.74	0.01	66.00	202
Black	9.38	3.64	14.73	0.00	78.94	202
Hispanic	42.88	37.88	27.03	2.42	97.34	202
Pacific Islander	0.22	0.10	0.43	0.00	3.86	202
White	31.25	24.25	26.57	0.37	87.46	202
Other	0.30	0.21	0.31	0.00	1.68	202
College Graduation	31.76	25.93	20.71	2.88	77.86	202
High School	22.07	18.24	16.48	1.16	66.57	202
Median House Income	65750.68	60508.50	31299.08	17308.00	218583.00	202
Unemployment	10.81	10.79	3.19	2.33	20.13	202
Youth Opportunity	13.96	14.55	5.61	0.00	36.77	202
Poverty Threshold (100)	17.55	14.63	10.51	2.08	56.59	202
School Lunch Program	65.63	73.56	24.22	1.62	95.41	202
SNAP Institutions	24.35	16.00	26.90	0.00	151.00	202
Park Access	101.07	1.19	578.90	0.00	5738.31	202

Table 2.4: 2015 Summary Statistics

2015	***Mean***	***Median***	***St. Dev***	***Minimum***	***Maximum***	***Count***
Part I Property Crime	23.68	20.00	19.34	5.00	199	202
Part I Violent Crime	5.18	3.00	5.79	0.00	46	202
Total Part I Crime	28.86	23.00	23.63	5.00	229	202
Part II Crime	27.42	22.00	22.36	4.00	227	202
Total Crime (I & II)	56.28	46.00	44.18	10.00	456	202
Unhealthy Percentage	34.66	36.45	12.95	1.61	59.61	202
Native American	0.17	0.12	0.22	0.00	1.77	202
Asian	13.71	9.52	13.86	0.00	65.46	202
Black	9.29	3.80	14.41	0.00	77.86	202
Hispanic	42.95	38.12	26.89	2.23	97.01	202
Pacific Islander	0.22	0.10	0.42	0.00	2.92	202
White	31.11	24.22	26.51	0.45	84.79	202
Other	0.31	0.23	0.31	0.00	1.98	202
College Graduation	32.21	27.31	20.76	2.99	78.19	202
High School	21.63	18.14	16.18	1.39	64.08	202
Median House Income	66318.90	61016.00	31057.40	18633.00	216458	202
Unemployment	9.87	9.37	3.02	2.93	18.66	202
Youth Opportunity	13.33	13.29	5.70	1.50	49.23	202
Poverty Threshold (100)	16.89	14.07	10.16	1.63	57.21	202
School Lunch Program	63.86	72.07	24.58	1.42	97.4	202
SNAP Institutions	24.35	16.00	26.90	0.00	151.00	202
Park Access	101.07	1.19	578.90	0.00	5738.31	202

Table 2.5: 2016 Summary Statistics

2016	***Mean***	***Median***	***St. Dev***	***Minimum***	***Maximum***	***Count***
Part I Property Crime	24.93	21.00	21.31	3.00	234.00	201
Part I Violent Crime	5.78	4.00	7.53	0.00	74.00	201
Total Part I Crime	30.70	25.00	27.56	4.00	308.00	201
Part II Crime	28.00	23.00	24.29	5.00	275.00	201
Total Crime (I & II)	58.70	50.00	50.25	9.00	583.00	201
Unhealthy Percentage	34.27	35.14	13.15	2.35	60.51	201
Native American	0.19	0.13	0.22	0.00	1.60	201
Asian	13.32	9.55	13.32	0.00	65.46	201
Black	9.44	3.82	14.95	0.00	78.53	201
Hispanic	41.94	37.26	26.91	2.17	98.16	201
Pacific Islander	0.17	0.06	0.33	0.00	2.63	201
White	32.59	26.53	27.09	0.37	87.00	201
Other	0.28	0.18	0.36	0.00	3.09	201
College Graduation	32.66	27.84	20.82	3.22	78.86	201
High School	21.22	17.85	15.81	1.57	61.97	201
Median House Income	68304.29	62895.00	32396.70	19313.00	220764.00	201
Unemployment	8.85	8.48	3.09	2.07	24.55	201
Youth Opportunity	12.43	12.46	4.89	2.43	33.33	201
Poverty Threshold (100)	16.61	13.64	9.99	1.99	58.92	201
School Lunch Program	65.48	73.70	25.38	1.81	95.56	201
SNAP Institutions	24.44	16.00	26.94	0.00	151.00	201
Park Access	101.54	1.18	580.4	0.00	5738.31	201

Table 2.6: Total 2012-2016 Summary Statistics

Total	***Mean***	***Median***	***St. Dev***	***Minimum***	***Maximum***	***Count***
Part I Property Crime	23.06	19.00	18.63	3.00	234.00	1009
Part I Violent Crime	4.75	3.00	5.46	0.00	74.00	1009
Total Part I Crime	27.80	23.00	22.47	4.00	308.00	1009
Part II Crime	27.63	22.00	25.01	4.00	342.00	1009
Total Crime (I & II)	55.43	46.00	45.37	9.00	583.00	1009
Unhealthy Percentage	37.56	38.83	13.29	1.61	64.40	1009
Native American	0.18	0.13	0.21	0.00	2.08	1009
Asian	13.41	9.33	13.62	0.00	66.00	1009
Black	9.42	3.74	14.79	0.00	80.34	1009
Hispanic	42.62	38.14	26.93	1.69	98.16	1009
Pacific Islander	0.20	0.08	0.39	0.00	3.86	1009
White	31.69	25.38	26.74	0.28	89.52	1009
Other	0.29	0.20	0.34	0.00	3.34	1009
College Graduation	31.83	26.68	20.58	2.41	78.86	1009
High School	21.97	18.39	16.37	1.16	66.57	1009
Median House Income	66617.35	61639.00	31574.35	16707.00	231648.00	1009
Unemployment	10.25	9.98	3.25	2.07	24.55	1009
Youth Opportunity	13.50	13.61	5.55	0.00	49.23	1009
Poverty Threshold (100)	16.95	13.85	10.35	0.98	58.92	1009
School Lunch Program	64.70	71.97	24.80	0.00	97.40	1009
SNAP Institutions	24.36	16.00	26.86	0.00	151.00	1009
Park Access	101.16	1.18	578.10	0.00	5738.31	1009

D. Appendix D: Correlation Matrix

Table 3.1: Correlation Matrix 1

	Prop	Violent	PT I	UE	MHI	100%	200%	COL	HS	YO	SNAP	SLP	PA	WH	HN	AZ	BL
Property	1.00																
Violent	0.63	1.00															
Total Part I Crime	0.05	0.05	1.00														
Unemployment	0.03	0.10	0.21	1.00													
Med House Income	-0.02	-0.06	-0.34	-0.55	1.00												
Poverty Threshold 100%	0.03	0.05	0.39	0.58	-0.71	1.00											
Poverty Threshold 200%	0.02	0.05	0.33	0.62	-0.79	0.93	1.00										
College Degree	-0.01	-0.06	-0.17	-0.54	0.76	-0.58	-0.71	1.00									
No High School	0.02	0.04	0.24	0.49	-0.73	0.73	0.83	-0.86	1.00								
Youth Opportunity	0.01	0.06	0.30	0.30	-0.35	0.32	0.35	-0.29	0.34	1.00							
SNAP	0.03	0.00	0.18	0.32	-0.44	0.45	0.49	-0.43	0.50	0.18	1.00						
School Lunch Program	0.03	0.06	0.28	0.51	-0.79	0.63	0.73	-0.73	0.77	0.33	0.41	1.00					
Ln Park Access	0.09	-0.19	-0.02	-0.01	0.06	0.00	-0.02	0.03	-0.01	-0.01	-0.01	-0.06	1.00				
White	0.00	-0.02	-0.17	-0.41	0.61	-0.51	-0.61	0.68	-0.69	-0.28	-0.33	-0.63	0.03	1.00			
Hispanic	0.02	0.02	0.07	0.35	-0.51	0.43	0.55	-0.69	0.73	0.24	0.37	0.59	-0.03	-0.79	1.00		
Asian	-0.06	-0.03	-0.06	-0.26	0.10	-0.11	-0.12	0.23	-0.19	-0.15	-0.11	-0.22	-0.03	-0.05	-0.31	1.00	
Black	0.01	0.04	0.24	0.37	-0.29	0.27	0.26	-0.25	0.16	0.23	0.05	0.30	0.04	-0.39	-0.02	-0.29	1.00

Table 3.2: Correlation Matrix 2

I eliminated three control variables because of multicollinearity: median household income, the percentage of the population earning beneath 200% of the federal poverty threshold, and the percentage of the population with no high school degree.

	Prop	Violent	PT I	PT II	I & II	UE	100%	COL	YO	SNAP	SLP	PA	WH	HN	AZ	BL
Property	1.00															
Violent	0.63	1.00														
Total Part I Crime	0.05	0.05	1.00													
Total Part II Crime	0.01	0.01	0.83	1.00												
Total Crime (I & II)	0.03	0.03	0.95	0.96	1.00											
Unemployment	0.03	0.10	0.21	0.20	0.21	1.00										
Poverty Threshold 100%	0.03	0.05	0.39	0.39	0.41	0.58	1.00									
College Degree	-0.01	-0.06	-0.17	-0.26	-0.23	-0.54	-0.58	1.00								
Youth Opportunity	0.01	0.06	0.30	0.31	0.32	0.30	0.32	-0.29	1.00							
SNAP	0.03	0.00	0.18	0.19	0.19	0.32	0.45	-0.43	0.18	1.00						
School Lunch Program	0.03	0.06	0.28	0.23	0.26	0.51	0.63	-0.73	0.33	0.41	1.00					
Ln Park Access	0.09	-0.19	-0.02	-0.02	-0.02	-0.01	0.00	0.03	-0.01	-0.01	-0.06	1.00				
White	0.00	-0.02	-0.17	-0.19	-0.19	-0.41	-0.51	0.68	-0.28	-0.33	-0.63	0.03	1.00			
Hispanic	0.02	0.02	0.07	0.13	0.11	0.35	0.43	-0.69	0.24	0.37	0.59	-0.03	-0.79	1.00		
Asian	-0.06	-0.03	-0.06	-0.06	-0.06	-0.26	-0.11	0.23	-0.15	-0.11	-0.22	-0.03	-0.05	-0.31	1.00	
Black	0.01	0.04	0.24	0.17	0.21	0.37	0.27	-0.25	0.23	0.05	0.30	0.04	-0.39	-0.02	-0.29	1.00

E. Appendix E: Regression Results

Model 1 (A, B, C): Part I Property Crime

VARIABLES	(A) Unhealthy %	(B) Unhealthy %	(C) Unhealthy %
Part I Property Crime	0.0806***	-0.00265	0.0259
	(0.0223)	(0.0161)	(0.0187)
Unemployment		-0.126	0.0773
		(0.111)	(0.115)
Poverty Threshold 100%		0.111***	0.104***
		(0.0395)	(0.0389)
College Graduation		-0.260***	-0.195***
		(0.0223)	(0.0241)
Youth Opportunity		0.102*	0.111**
		(0.0540)	(0.0529)
SNAP Institutions		0.0349***	0.0198*
		(0.0116)	(0.0114)
School Lunch Program		0.137***	0.125***
		(0.0192)	(0.0188)
Ln Park Access		-0.457***	-0.586***
		(0.134)	(0.135)
White			-0.00840
			(0.234)
Hispanic			0.0767
			(0.223)
Asian			-0.00976
			(0.231)
Black			-0.0876
			(0.234)
Unemployment_HighPartIProperty			-0.0773
			(0.0693)
Constant	35.70***	34.83***	29.50
	(0.662)	(2.165)	(22.41)
Observations	1,009	939	939
R-squared	0.013	0.586	0.617

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Model 2 (A, B, C): Part I Violent Crime

VARIABLES	(A) Unhealthy %	(B) Unhealthy %	(C) Unhealthy %
Part I Violent Crime	0.795***	-0.205***	-0.0722
	(0.0724)	(0.0624)	(0.0720)
Unemployment		-0.142	0.0162
		(0.110)	(0.117)
Poverty Threshold 100%		0.160***	0.126***
		(0.0410)	(0.0412)
College Graduation		-0.261***	-0.194***
		(0.0218)	(0.0240)
Youth Opportunity		0.142***	0.124**
		(0.0543)	(0.0535)
SNAP Institutions		0.0362***	0.0210*
		(0.0116)	(0.0116)
School Lunch Program		0.143***	0.131***
		(0.0189)	(0.0187)
Ln Park Access		-0.433***	-0.511***
		(0.129)	(0.129)
White			-0.0262
			(0.236)
Hispanic			0.0592
			(0.226)
Asian			-0.0239
			(0.233)
Black			-0.107
			(0.238)
Unemployment_HighPartIViolent			0.0334
			(0.0765)
Constant	33.78***	34.14***	31.31
	(0.524)	(2.145)	(22.69)
Observations	1,009	939	939
R-squared	0.107	0.591	0.617

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Model 3 (A, B, C): Total Part I Crimes (Property & Violent)

VARIABLES	(A) Unhealthy %	(B) Unhealthy %	(C) Unhealthy %
Total Part I Crimes	0.102***	-0.0118	0.0103
	(0.0184)	(0.0137)	(0.0158)
Unemployment		-0.127	0.0531
		(0.111)	(0.115)
Poverty Threshold 100%		0.120***	0.108***
		(0.0400)	(0.0394)
College Graduation		-0.258***	-0.195***
		(0.0222)	(0.0241)
Youth Opportunity		0.110**	0.111**
		(0.0543)	(0.0535)
SNAP Institutions		0.0353***	0.0201*
		(0.0116)	(0.0115)
School Lunch Program		0.140***	0.127***
		(0.0191)	(0.0189)
Ln Park Access		-0.434***	-0.553***
		(0.133)	(0.134)
White			-0.0165
			(0.235)
Hispanic			0.0700
			(0.225)
Asian			-0.0152
			(0.232)
Black			-0.0996
			(0.236)
Unemployment_HighPartICrime			-0.0191
			(0.0718)
Constant	34.71***	34.62***	30.39
	(0.656)	(2.165)	(22.54)
Observations	1,009	939	939
R-squared	0.030	0.586	0.617

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Model 4 (A, B, C): Total Part II Crimes

VARIABLES	(A) Unhealthy %	(B) Unhealthy %	(C) Unhealthy %
Part II Crime Rate	0.0848***	-0.0396***	-0.0172
	(0.0165)	(0.0126)	(0.0137)
Unemployment		-0.152	0.0701
		(0.111)	(0.117)
Poverty Threshold 100%		0.150***	0.137***
		(0.0402)	(0.0396)
College Graduation		-0.263***	-0.203***
		(0.0219)	(0.0244)
Youth Opportunity		0.142***	0.146***
		(0.0545)	(0.0534)
SNAP Institutions		0.0365***	0.0245**
		(0.0116)	(0.0115)
School Lunch Program		0.139***	0.127***
		(0.0188)	(0.0186)
Ln Park Access		-0.315**	-0.424***
		(0.137)	(0.136)
White			0.0458
			(0.236)
Hispanic			0.125
			(0.225)
Asian			0.0445
			(0.233)
Black			-0.0220
			(0.237)
Unemployment_HighPartIICrime			-0.0978
			(0.0702)
Constant	35.21***	34.80***	24.45
	(0.616)	(2.134)	(22.57)
Observations	1,009	939	939
R-squared	0.025	0.590	0.619

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Model 5 (A, B, C): Total Crime (Part I & Part II)

VARIABLES	(A) Unhealthy %	(B) Unhealthy %	(C) Unhealthy %
Total Crime Rate	0.0509***	-0.0149**	-0.00115
	(0.00909)	(0.00695)	(0.00774)
Unemployment		-0.138	0.0711
		(0.111)	(0.116)
PovThreshold100		0.138***	0.125***
		(0.0403)	(0.0397)
College Graduation		-0.258***	-0.195***
		(0.0219)	(0.0240)
Youth Opportunity		0.129**	0.132**
		(0.0546)	(0.0536)
SNAP Institutions		0.0361***	0.0224*
		(0.0116)	(0.0115)
School Lunch Program		0.141***	0.128***
		(0.0189)	(0.0187)
Ln Park Access		-0.371***	-0.503***
		(0.136)	(0.136)
White			0.0251
			(0.236)
Hispanic			0.106
			(0.225)
Asian			0.0227
			(0.233)
Black			-0.0470
			(0.237)
Unemployment_HighTotalCrime			-0.0878
			(0.0716)
Constant	34.74***	34.52***	26.12
	(0.651)	(2.146)	(22.64)
Observations	1,009	939	939
R-squared	0.030	0.588	0.617

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1