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# Modeling the impacts of park access on health outcomes: a utility-based accessibility approach

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## Abstract

Recent research has underscored the potential for public green spaces to influence individual and societal health outcomes, but empirical measurements of such influences have yielded mixed results to date, with particular disagreement surrounding how access to parks ought to be defined while controlling for alternate explanations. In this paper we apply a comprehensive measure of park accessibility drawn from random utility choice theory, which avoids arbitrary assertions of proximity while incorporating potentially numerous amenities and attributes of both the parks and the population. We apply this utility-based accessibility measure to correlate Census tract-level obesity and physical activity rate estimates from the Centers for Disease Control and Prevention's 500 Cities project with tract-level American Community Survey socioeconomic data in New York City, paired with geographic open space data from New York City. Controlling for the socioeconomic variables and spatially correlated error terms, we show a positive and significant relationship between park access and physical activity rates. The data also suggest a negative relationship between park access and obesity rates, beyond what is expected through physical activity and socioeconomic factors. In doing so, this research contributes a more comprehensive modeling approach for measuring the impact of park access on health, and may improve our understanding of the role parks and access to them can serve in furthering public health objectives.

## Keywords

Accessibility; Green Space

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## Introduction

The United States and other developed nations face an epidemic of obesity and chronic diseases, including cardiovascular diseases, chronic respiratory diseases, diabetes, stroke, joint and bone diseases, and cancer. These diseases can severely limit the lifespan of affected individuals (World Health Organization, 2014), with substantial financial costs for treatment borne both privately and socially (Finkelstein et al., 2009). Though a moderate amount of regular physical activity has been established as an effective strategy for reducing and managing obesity and many of the aforementioned chronic diseases (Centers for Disease Control and Prevention, 2009; Durstine et al., 2013), a large portion of U.S. adults do not participate in sufficient physical activity (Wolf, 2008).

Historically, most large-scale health promotion efforts focused on individual-level interventions intended to educate people about healthy lifestyles and behaviors, touching on topics including diet and exercise. Over the last several years a new *social* model of health has evolved, described by Duhl and Sanchez (1999) “as an outcome of the effects of socioeconomic status, culture, environmental conditions, housing, employment and community influences” (1999, p.7). In this new paradigm, resources provided via civil infrastructure — in particular parks and other public green spaces — play a crucial role in promoting and sustaining public health (Bedimo-Rung et al., 2005; Wells et al., 2007; Coutts, 2008). After all, it does little to educate individuals on the importance of exercise if their community is designed and built in such a way that such exercise is expensive, unenjoyable, or unsafe. It is similarly necessary for urban planners to identify which neighborhoods have access to quality green space, and which neighborhoods need intervention in the form of new or rehabilitated green space, or improved transportation access to existing quality green space.

But in spite of the potential for green spaces to influence public health outcomes and numerous studies attempting to empirically estimate the strength of these outcomes, evidence to date has been mixed. A major challenge researchers have faced is a proliferation of techniques for measuring access to green spaces, of which many are plausible but lack robust theoretical bases.

In this paper, we apply a holistic and flexible measurement for park accessibility based in activity location choice theory. This utility-based accessibility measure compares the continuous distance to all parks in the region, weighted against the sizes of each park and its other assorted amenities. We apply this

measure to study the link between park accessibility and attractiveness and census tract-level aggregate physical activity participation and obesity rates in New York City, controlling for spatially correlated unobserved effects, spatial spillovers of covariates, and tract-level socioeconomic characteristics. We also demonstrate how the utility-based accessibility metric can potentially be expanded to account for other measures of a park’s attractiveness in the form of various park amenities. The paper concludes with a discussion of opportunities for future research.

## Literature Review

The question of how green space in the urban environment affects the physical, emotional, and mental well-being of urban residents is not new to the academic literature. Comprehensive reviews and analysis of this literature up to 2007 can be had from Tzoulas et al. (2007), and for the subsequent decade from Kabisch et al. (2015). In spite of the depth of this research arena — or perhaps because of it — quantitative approaches for assessing both health outcomes and access to green space vary widely. It is therefore not surprising that in a meta-analysis of 20 recent peer reviewed journal articles exploring the relationship between access to parks and objectively measured physical activity, Bancroft et al. (2015) found that five studies reported a significant positive association, six studies produced mixed results, and nine studies found no association at all.

Loosely defined, the *accessibility* of an arbitrary place describes the ease with which people can accomplish activities there. Accessibility is an abstract concept with tempting quantifiability (Handy and Niemeier, 1997), but objective quantification may not be strictly necessary. For example, Takano et al. (2002) showed improved survival rates among senior citizens in Japan who self-reported having access to qualitatively good walking spaces. Though encouraging, this result could simply reveal self-selection: Those seniors who felt the walking space was good were those who chose to enjoy it. Urban planners seeking to evaluate which residents have good access to quality green space may desire objective and therefore comparable measures.

Dong et al. (2006) present a helpful mathematical hierarchy of common quantitative mechanisms for calculating access, which we follow here. Consider a person residing at point  $i$  in a city with parks  $j \in 1 \dots J$ . An analyst might consider point  $i$  as “having access” to a park if the distance to the park  $d_{ij}$  is within an “isochrone,” or a geometric buffer defined by some threshold  $D$ ,

$$A_i = \begin{cases} 1 & d_{ij} \leq D \\ 0 & d_{ij} > D \end{cases} \quad (1)$$

Applications of this isochrone-based framework are easily derived and relatively common. ParkScore (Trust for Public Land, 2019) is a sophisticated application of this approach where  $D$  is a carefully calculated 10-minute network-bound walk, paired with a demographic analysis of areas within and outside of this threshold. de Vries et al. (2003) showed the amount of greenspace within a 3-kilometer radius was positively associated with a suite of self-reported health outcomes. Similarly, de Vries et al. (2013) showed that streetscape greenery within 500 meters of a residence was associated with perceived general health. Conversely, Carlson et al. (2012) found no relationship between the health of senior citizens and the number of parks within 500 meters.

Another common access measure fits in this category, where distance-based isochrones are replaced with political, geographical, or statistical boundaries. For example, Mitchell and Popham (2008) find that inequalities in health outcomes attributable to income are mitigated in statistical areas with a greater percentage of green space. Stark et al. (2014) found a significant relationship in New York City between the percent of a residential ZIP code that is park space and objectively measured body mass index (BMI). Political or regional boundaries are especially common in comparative macroscopic studies, such as the positive relationships found by West et al. (2012) between density of park land in a metropolitan area and self-reported population health indicators derived from the Behavioral Risk Factor Surveillance System (BRFSS). On the other hand, Larson et al. (2016) found no relationship between physical health and park quantity, quality, and accessibility in 44 U.S. cities and self-reported scores on the Gallup-Healthways Wellbeing Index. It is also possible to attenuate an isochrone with various factors; for instance, Dias et al. (2019) considered road safety perception as an extenuating factor in the effective distance to a park.

In spite of the flexibility of adapted isochrone techniques, the arbitrary definitions necessarily imposed by researchers in its application can inhibit holistic analysis (Logan et al., 2019). A somewhat more complete approach is the so-called “gravity” accessibility statistic. In this case the accessibility of point  $i$  is the denominator of the gravity formulation of a trip distribution model,

$$A_i = \sum_{j=1}^J S_j f(d_{ij}) \quad (2)$$

where  $S_j$  is the “size” of each park literally (i.e. acres) or abstractly (i.e. trip attractions) and  $f(d_{ij})$  is a monotonically decreasing cost function, usually a negative exponential. Dong et al. (2006) note that the isochrone framework is a special case of the gravity model where  $f(d_{ij})$  is a binary function and  $S_j = 1$ . Giles-Corti et al. (2005) compare various gravity-based accessibility scores with an isochrone specification and show that the former are more predictive of walking behavior; that is, the attributes of a park influence walking more than merely the distance to it. Hillsdon et al. (2006) found no relationship between a gravity-based accessibility term and self-reported physical activity among middle-aged individuals in Norwich, England. Zhang et al. (2011) developed a population-weighted, gravity-based accessibility to parks metric with a national scope, though they do not examine its correlation with health outcomes.

A third accessibility mechanism is a utility-based specification, termed as such for being derived from random utility choice theory. Consider that an individual living at point  $i$  is choosing a park for a recreation activity. If we apply the multinomial logit model (McFadden, 1974), the expected consumer surplus enjoyed by this individual can be shown to be

$$A_i = \ln \left( \sum_{j=1}^J \exp(V_{ij}) \right) + C \quad (3)$$

where parks are differentiated from each other by their relative measurable *utilities*,  $V_{ij}$ .  $C$  is an unknown constant, but the difference in consumer surplus between two points  $i$  and  $k$  can be quantitatively compared as  $A_i - A_k$  (Bruce, 1977). In principle,  $V$  may include any measurable attributes of either the choice maker or the park, and is typically represented as a linear-in-parameters function of destination attributes  $X_j$  and the travel cost  $d_{ij}$ ,

$$V_{ij} = X_j \beta + \beta_d * d_{ij} \quad (4)$$

The coefficients  $\beta$  are frequently estimated from household surveys, though in the absence of a survey we may assert reasonable values.

Note that the gravity formulation is itself a special case of the utility-based specification where  $\exp(X_j \beta + \beta_d d_{ij}) = X_j f(d_{ij})$  (Daly, 1982). The distinction between gravity and utility-based specification is meaningful, however. Primarily, it becomes possible to construct accessibility statistics based on revealed behavioral preferences rather than calibrated or asserted values (Handy and Niemeier, 1997). Kinnell et al. (2006) collected a choice-based survey sufficient to construct a utility-based measure, though they

do not do so. Similarly, Kaczynski et al. (2016) present what is effectively a utility-based score called “ParkIndex”, with the explicit motivation of developing a uniformly applicable park accessibility statistic, though they limit this statistic as a way to add heterogeneity within an isochrone analysis.

Both gravity and utility-based specifications hold several advantages relative to isochrone-based accessibility metrics more commonly found in the literature. First, all individuals are defined as having some access to all parks, rather than an arbitrary cutoff asserted by the researcher. This allows for the fact that some people are more or less sensitive to distances, and that distance is a continuous, non-binary phenomenon. It defies reason to assume a person living 11 minutes via walking from a park always has meaningfully different accessibility than someone living 9 minutes away. Second, the random utility formulation allows the researcher to include – in principle – any attribute of the park as part of its utility specification. This suggests that not all parks are equal, and that a large park with many amenities such as Central Park in Manhattan may provide health and activity benefits over a much larger area than a smaller community square.

In spite of its flexibility and basis in choice theory, utility-based accessibility measures have not received much application in the accessibility literature compared with distance-based or even gravity-based measures. Vale et al. (2016) present a descriptive classification of active accessibility techniques, and explicitly dismiss utility-based metrics for incorporating randomness. The accessibility formula presented in Equation 3 is the expectation of a random utility process, and is not in and of itself random any more than the gravity model is random. Utility-based accessibility metrics are commonly used, however, in alternatives analyses of transit infrastructure improvements (de Jong et al., 2007). A reason for this is likely that a regional travel demand model is available to the analysts, thus making calibrated and multimodal logsums readily available (Geurs et al., 2010).

## Empirical Application

In this section, we develop a model with data for New York City, where we compute a set of utility-based accessibility to parks scores for each tract and model the relationship between this measure and physical activity rates, controlling for spatial effects and socioeconomic factors. We subsequently model the effect of the accessibility metric on obesity rates, accounting for physical activity and the other controls.

## Data

This study uses data available to the public from a variety of federal and state data agencies\*. The Centers for Disease Control and Prevention makes small-area estimates on key health indicators available through its 500 Cities data program (Centers for Disease Control and Prevention, 2016). The indicators are multilevel aggregations and imputations of BRFSS responses (Wang et al., 2018, 2017), and have been recently used to study the tract-level link between gentrification and urban health (Gibbons et al., 2018). We use two indicators as our dependent variables in this study: the share of adults in a Census tract who are obese, and the share of adults who participate in no leisure-time physical activity. To improve clarity in our interpretation, we use the complement of the second variable — the share of tract adults who participate in *some* physical activity — even if the amount may not be sufficient to affect overall health. Both indicators are obtained for the year 2016.

To the health data, we join socioeconomic data collected through the Census Bureau API via the `tidycensus` package for R (Walker, 2019). The primary dataset is a geographic polygons layer of Census tracts in the five boroughs of New York City. We append to each Census tract relevant socioeconomic data for each tract from the American Community Survey 2013-2017 5-year estimates. For a small handful of tracts in our sample, Census suppressed the median income estimate; these appear to be primarily wealthy tracts and in almost all cases the CDC estimates of obesity and physical activity are missing as well. After removing these tracts from the estimation dataset, we have 2,102 complete cases. Table 1 presents key descriptive statistics for these data.

In a destination choice framework, the tracts represent the “origins” and the “destinations” are parks and green spaces in New York City. We retrieved a polygons layer of public parks and greenspaces within New York City’s municipal boundaries and checked it for accuracy and relevance (City of New York, 2018). Upon inspection, we removed several facilities that do not qualify as publicly accessible green space, such as Yankee Stadium, Citi Field, and their surrounding parking lots. We also removed parks of less than half an acre in size, as these appear to be predominantly planted medians rather than legitimate public green space. We consolidated individual geographic polygons

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\*The datasets, as well as the analysis code, are available on GitHub at <https://github.com/XXXX>.

comprising a single facility — as is the case in Flushing Meadows — and eliminated sub-facilities such as tennis courts or baseball fields included within larger park facilities. Instead of these distinct sub-facilities, we created variables for each containing park indicating the presence of sports courts, playgrounds, and trails.

To this dataset of parks and regularized green spaces, we add a polygons layer of cemeteries in New York that are open to the public. Cemeteries are important green spaces that can be used for many types of physical activity. These operations leave us with 1,277 distinct green spaces; for simplicity we will refer to both parks and cemeteries as “parks” going forward. For each park, we calculate the size of the park in acres.

### Accessibility

We calculate a pair of utility-based accessibility statistics for each tract in New York City. The most basic utility specification includes only the park size in acres and the Euclidean distance from the population-weighted tract centroid to the nearest boundary of the park in miles,

$$V_{ij} = \lambda_s * \log(size_j) + \lambda_d * \log(distance_{ij}) \quad (5)$$

There are a few cases where the population-weighted tract centroid lies on or within the boundary of a park; for these cases we assert that the minimum possible distance is one tenth of a mile. The logarithmic transform allows for diminishing marginal utility of distance and park size: A 1-mile increase to a trip matters more for a 1-mile trip than a 10-mile trip. Macfarlane and Tapia (2020) estimated destination choice parameters for park trips in Alameda County (Oakland), California by applying this utility specification to passively collected mobile device data, obtaining values of  $\lambda_s = 0.373$  and  $\lambda_d = -1.76$ . The ratio of these estimates implies people are willing to travel roughly six times further to reach a park twice as large. We do not have access to the necessary data to repeat the Macfarlane and Tapia (2020) methodology in New York, and the public parks datasets in Alameda County are not sufficiently detailed to perform the present accessibility analysis there. In the absence of park trip destination choice coefficients in New York City, we adopt these previous estimates.

Kinnell et al. (2006) surveyed park users in New Jersey and applied a multinomial logit model to determine which factors influence a park’s perceived utility as a park trip destination. By transferring estimates of common variables between our data and this survey-based model, we can create a second utility

specification as

$$V_{ij} = \lambda_s * \log(size_j) + \lambda_d * \log(distance_{ij}) + \lambda_t * trails + \lambda_c * courts + \lambda_p * playgrounds \quad (6)$$

with  $\lambda_t = 0.99$ ,  $\lambda_c = 0.43$ , and  $\lambda_p = 0.26$ . Kinnell et al. did not transform their size and distance estimates, so we retain the previously estimated and applied values. We assume that the other covariates in the model which we do not have available to us (e.g., boat launches, picnic areas) are orthogonal to the included parameters and leaving them out will not affect the values of the included coefficients.

We then calculate the utility-based accessibility of each tract  $A_i$  as defined in Equation 3 under each utility specification. Recall that the total value of the accessibility is relative to an unknown scalar  $C$ ; for this reason we standardize the accessibility values for all tracts within each utility specification,

$$A'_i = \frac{A_i - \bar{A}}{\sigma_A} \quad (7)$$

Figure 1 shows a map of New York City with each tract highlighted based on its relative size and distance utility-based accessibility score (Equation 5). The most continuous region of good park access is in upper Manhattan and the Bronx, bracketed by Central Park and the Bronx River. Conversely, some of the poorest-accessibility areas are in Brooklyn tracts not immediately adjacent to Prospect Park. Because the accessibility statistic is normalized, the worst values are slightly below  $-3$ , the best somewhere above  $3$ .

For comparative purposes, we also employ an isochrone analysis using the 10-minute walk threshold calculated for ParkScore (Trust for Public Land, 2019). If the population-weighted centroid of a tract is within a 10-minute walk of a green space as defined by ParkScore, the tract is considered as having “access” to a park. The centroid is necessary as all tracts in New York City have at least *some* intersection with the 10-minute walk buffer; as it is, only 24 of the 2,102 tract centroids are not located within this buffer.

### Model

We predict either the physical activity or the obesity rate ( $y$ ) in a census tract as a linear function of the tract’s sociodemographic characteristics  $X$  and accessibility to parks  $A$ ,

$$y = X\beta + \beta_a A + \varepsilon \quad (8)$$

where  $X$  is a matrix of dimension  $n \times p$  where  $n$  is the number of observations and  $p$  is the number



**Table 1.** Descriptive Statistics of Tract and Park Variables

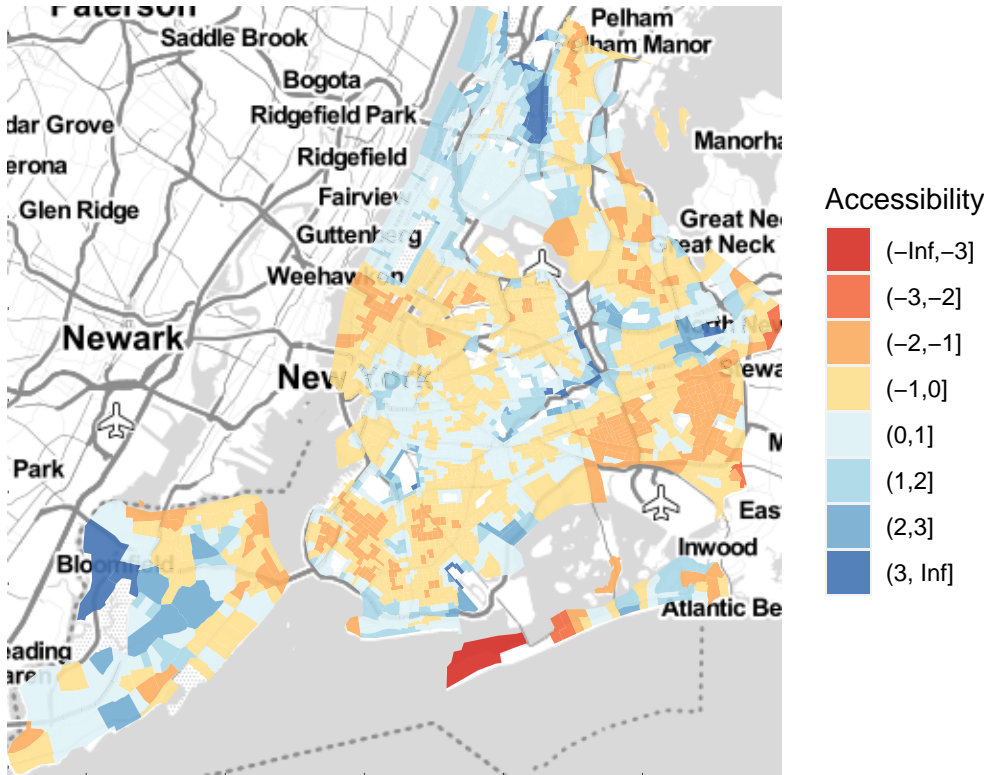
	Description	Minimum	Median (IQR)	Maximum	Source
<b>Tract Variables, N = 2102</b>					
Obesity	Share of adults over 18 who are obese	9.60	24.50 (19.60, 30.50)	44.20	CDC 500 Cities
Physical Activity	Share of adults over 18 who engage in some leisure-time physical activity	48.10	69.50 (64.70, 74.60)	89.10	CDC 500 Cities
Income	Median tract income	9053.00	59,592.50 (41,928.25, 79,092.75)	250001.00	ACS
Density	Households per square kilometer	9.20	5,848.46 (3,173.62, 9,674.36)	43621.52	ACS
Fulltime	Share of adults over 18 with full-time work	8.80	49.48 (44.45, 55.29)	100.00	ACS
College	Share of adults over 24 with a college degree	0.61	16.30 (12.37, 20.11)	44.94	ACS
Single	Share of adults over 18 living alone or in a non-partnership household	16.38	59.39 (50.30, 68.65)	100.00	ACS
Youth	Share of population under 18	0.00	20.54 (16.79, 24.92)	64.07	ACS
Young adults	Share of population between 18 and 34	0.00	25.73 (21.66, 29.98)	86.75	ACS
Seniors	Share of population who are 65 and over	0.00	12.83 (9.47, 16.88)	89.88	ACS
Black	Share of population who is black	0.00	10.03 (2.13, 44.62)	220.65	ACS
Asian	Share of population who is Asian	0.00	7.66 (2.40, 20.78)	88.07	ACS
Hispanic	Share of population who is Hispanic	0.00	19.07 (9.39, 41.07)	96.27	ACS
Other	Share of population who belong to other minority groups	0.00	0.00 (0.00, 0.53)	19.47	ACS
<b>Park Variables, N = 1277</b>					
Size	Park size in acres	0.50	1.66 (0.95, 5.62)	1961.00	NYC
Courts	Presence of sport courts / ball fields	0.00	0.00 (0.00, 0.00)	1.00	NYC
Playgrounds	Presence of playgrounds	0.00	0.00 (0.00, 1.00)	1.00	NYC
Trails	Presence of trails	0.00	0.00 (0.00, 0.00)	1.00	NYC

of predictor variables, and  $\beta$  is a  $p \times 1$  vector of estimated parameters. The accessibility vector  $\mathbf{A}$  influences physical activity or obesity rates by the single estimated parameter  $\beta_a$ , and a vector  $\varepsilon$  represents the model residual as a random variable.

As the observations are related to each other spatially, it is likely that this process involves spatial spillovers of one kind or another. A complete treatment of spatial econometrics is not warranted here; the

reader is directed to [LeSage and Pace \(2009\)](#) as well as [LeSage and Pace \(2014\)](#). Suffice it to say that the presence of spatial data generating processes can negatively affect econometric interpretation in a variety of ways. Each of these processes rely on spatial autoregression, where elements of some random variable  $x$  are spatially dependent on other elements,

$$\mathbf{x} = \rho W \mathbf{x} + \varepsilon \quad (9)$$



**Figure 1.** Normalized utility-based park accessibility values in New York City.

with the strength of dependence an estimated parameter  $\rho$ , the structure of spatial dependence governed by the asserted matrix  $W$  (details of  $W$  follow below), and some random uncorrelated residual  $\varepsilon$ . A collection of models is available to represent spatial autodependence in the model residuals, the independent variables, and the dependent variable.

The specific spatial model applied is both an econometric choice — as improperly specified spatial models can lead to inconsistent estimates of model parameters and standard errors — as well as a philosophical choice about the likely structure of spillovers in the problem at hand. In case of physical activity and obesity rates, we believe that the outcomes are locally dependent: That is, a particular individual decides whether or not to participate in physical activity independently of whether his or her neighbors participate in physical activity. This does not mean that we think it impossible that the socioeconomic variables of neighboring tracts do not play a role. Mathematically, we assert that the autodependence relationship on the dependent variable  $y = \rho W y + \dots$  has  $\rho = 0$  in the current case.

With this relationship ruled out, it remains a possibility that the model residuals are spatially

dependent,

$$y = X\beta + \beta_a A + u; u = \lambda W u + \varepsilon \quad (10)$$

that the outcome is partially dependent on the socioeconomic variables in *neighboring* tracts,

$$y = X\beta + \beta_a A + W X \gamma + \varepsilon \quad (11)$$

or a linear combination of both.

$$y = X\beta + \beta_a A + W X \gamma + u; u = \lambda W u + \varepsilon \quad (12)$$

These models are referred as the spatial error model (SEM), the spatial lag of  $X$  model (SLX), and the spatial Durbin error model (SDEM). [Pace and LeSage \(2008\)](#) suggest that a Hausman-style test of the estimates of  $\beta$  derived from the OLS (Equation 8) and SEM (Equation 10) can identify whether the estimates are consistent. If the  $\beta$  estimates are dissimilar, both specifications are inappropriate as they contain untreated omitted variables. Similarly, if the SLX and SDEM estimates are dissimilar it is an indication of missing variables in that specification. On the other hand if the estimates of both pairs of models are similar and the residual correlation parameter  $\lambda$  is non-zero, the model accounting for spatially dependent residuals

will produce proper estimates of the model standard errors.

Note that in the lag- $X$  specifications (SLX and SDEM) we exclude the accessibility component  $\mathbf{A}$ , that is we do *not* consider that the accessibility in a neighboring zone will have an effect on physical activity or obesity rates. In a practical sense, this is because the accessibility term  $\mathbf{A}$  is itself spatially determined.

**Spatial Weights** The spatial weights matrix  $W$  is constructed of individual elements where  $w_{ij} = 0$  if observations  $i$  and  $j$  are spatially independent of each other, and  $w_{ij} > 0$  if  $i$  and  $j$  are spatially related in some way. [Dubin \(1998\)](#) presents details on constructing  $W$ , but in this study we assume that tracts sharing at least one common border point are neighbors of each other<sup>†</sup>. The elements of  $W$  are then row-standardized so that each observation has an equal total influence from all its neighbors.

## Results

To determine which spatial effects specification was appropriate, we estimated SLX and SDEM models of physical activity participation rates as a function of tract covariates and accessibility. These two models are presented in Table 2. With only a few exceptions, the SLX and SDEM coefficient estimates for corresponding covariates lie within the 95% confidence intervals of the other model. A Hausman-style test ([Pace and LeSage, 2008](#)) on the coefficients assumes a null hypothesis that the coefficients are equivalent; this test produces  $p$ -value of only  $1.307e - 23$ . Though this statistic is well beneath a common hypothesis test threshold of  $\alpha = 0.05$ , we elect to retain the null hypothesis that the coefficients are equivalent, as the differences are at no point practically different from each other. The consequences of rejecting the null hypothesis in this case would be to suggest a model with spatial dependence of the dependent variable; as stated above, we feel that such a relationship is unreasonable. As a consequence of these analyses, we adopt the SDEM specification moving forward as the spatial lag of the errors is significant and the overall log likelihood of the SDEM is higher than the SLX specification.

The coefficients in the SDEM model are of two general types: the direct effect resulting from a tract's own attributes and the indirect effect ( $\gamma$ ) resulting from the spatially-weighted attributes of its neighbors. For example, a percentage point increase in the share of young adults in a tract increases the expected physical activity rate in a tract by 0.02947 percentage points, and a percentage point increase in the share of young adults *in neighboring tracts* increases the expected physical activity rate by an

additional 0.08417 percentage points. This opportunity to examine spatial spillovers of attributes is a key benefit of using a spatial model.

For the most part the direct coefficients are highly significant and of the expected sign. Tracts with higher shares of full-time workers, college-educated adults, young adults, and high-income households all show a greater share of individuals engaging in regular physical activity. Conversely, tracts with greater population density and a greater share of single adults, children, seniors, minorities, and low income households all have lower modeled expected rates of physical activity. The indirect coefficients are less clearly significant, with only density, median tract income, some age groups, and some minority groups showing an indirect effect.

Table 3 presents the estimated spatial lag and accessibility coefficients for three models using different specifications of the utility equation, as well as the ten-minute walk buffer calculated by ParkScore. Note that the model called "Size and Distance" is precisely the model labeled "SDEM" in Table 2. The controlling covariates are suppressed for clarity but do not change meaningfully across the four specifications. Complete model estimates are available in the Appendix. Each of the three utility-based specifications is significant at the  $\alpha = 0.05$  level or lower, and is of the hypothesized directionality. That is, residents living in tracts with increased utility-based accessibility to green spaces show a significantly higher physical activity participation rate. Taking the rough mean of the 2 estimated utility-based coefficients, moving from the least-accessible tract ( $A_i = -3$ ) to the most-accessible tract ( $A_i = 3$ ) is expected to raise the physical activity rate by 0.9 percentage points. With the understanding of the full 95% confidence interval, we could suggest that the true effect of excellent versus poor park access is anywhere between 0.06 and 1.8 percentage points.

The 10-minute walk buffer is considerably less useful at isolating the effects of park "access" on physical activity rates. As so few tracts are located outside of the buffer, the standard error of the estimated effect is large and implies an effect on activity rates anywhere from a loss of 1.08 percentage points to a gain of 8.1.

We now consider the impacts of a model where the dependent variable is the *obesity* rate in a tract, and physical activity becomes an independent covariate alongside the controlling variables and the accessibility metrics. Table 4 presents estimates of the effect of

<sup>†</sup>We also considered a distance-discounted weights matrix, which produced similar results. This matrix is selected for simplicity.



**Table 2.** Comparison of SLX and SDEM Coefficients

	SLX			SDEM		
	Estimate	95% Conf.Int.		Estimate	95% Conf.Int.	
(Intercept)	-15.8424	-26.8735	-4.8112	-24.9740	-41.8930	-8.0549
log(Density)	0.0484	-0.1314	0.2282	0.1775	0.0384	0.3166
log(Income)	5.8210	5.2977	6.3443	5.9985	5.5746	6.4224
Fulltime	0.1150	0.0936	0.1365	0.1275	0.1090	0.1460
College-educated	0.0012	-0.0272	0.0297	0.0076	-0.0158	0.0309
Single Adults	-0.0433	-0.0623	-0.0244	-0.0362	-0.0526	-0.0198
Youth (0-17)	-0.1511	-0.1830	-0.1192	-0.1310	-0.1576	-0.1045
Young adults (18-34)	0.0257	0.0008	0.0505	0.0295	0.0094	0.0496
Seniors (65+)	0.0137	-0.0185	0.0459	0.0403	0.0130	0.0677
Black population share	-0.0465	-0.0584	-0.0346	-0.0499	-0.0586	-0.0411
Asian population share	-0.0686	-0.0832	-0.0541	-0.0767	-0.0873	-0.0662
Hispanic population share	-0.1017	-0.1140	-0.0894	-0.1025	-0.1116	-0.0934
Other Minorities	0.0368	-0.0643	0.1378	0.0037	-0.0849	0.0923
$\gamma$ : log(Density)	1.2594	0.9413	1.5774	1.0985	0.7155	1.4815
$\gamma$ : log(Income)	2.3930	1.5476	3.2383	1.9742	0.9465	3.0020
$\gamma$ : Fulltime	-0.1398	-0.1804	-0.0991	-0.0397	-0.0869	0.0076
$\gamma$ : College-educated	-0.1312	-0.1806	-0.0818	-0.0710	-0.1305	-0.0115
$\gamma$ : Single Adults	-0.0480	-0.0821	-0.0140	-0.0082	-0.0504	0.0339
$\gamma$ : Youth (0-17)	-0.1031	-0.1618	-0.0445	-0.0108	-0.0798	0.0583
$\gamma$ : Young adults (18-34)	0.1191	0.0762	0.1619	0.0842	0.0335	0.1349
$\gamma$ : Seniors (65+)	0.0108	-0.0479	0.0695	0.0590	-0.0102	0.1282
$\gamma$ : Black population share	0.0096	-0.0054	0.0247	0.0010	-0.0151	0.0172
$\gamma$ : Asian population share	-0.0661	-0.0840	-0.0483	-0.0397	-0.0583	-0.0210
$\gamma$ : Hispanic population share	-0.0060	-0.0216	0.0097	-0.0010	-0.0182	0.0162
$\gamma$ : Other Minorities	0.1868	-0.0508	0.4244	0.0726	-0.1845	0.3297
Accessibility	0.5430	0.4195	0.6666	0.1663	0.0277	0.3048
$\lambda$ : spatial correlation				0.6905	0.6513	0.7296
Log Likelihood	-4831.974			-4435.507		
Num.Obs.	2099			2099		

**Table 3.** Estimated Effect of Accessibility on Physical Activity Rates

	Size and Distance	Amenities	10-Minute Walk
Accessibility	0.1663*	0.1493*	0.5865
	[0.0277; 0.3048]	[0.0073; 0.2914]	[-0.1778; 1.3508]
Num. obs.	2099	2099	2099
Parameters	28	28	28
Log Likelihood	-4435.3869	-4436.0034	-4436.9264

\* 0 outside the confidence interval 95% confidence interval in brackets.  $y$  = tract-level physical activity rate.

all three utility-based accessibility measures as well as the 10-minute walk buffer. As before, the estimates of the other variables are available in the Appendix. The correlation between physical activity rates and obesity is clear; for every percentage point increase in physical activity rate, the expected obesity rate drops by 0.43 percentage points in all four accessibility specifications.

The indirect effect of physical activity rates on obesity in neighboring zones is inconsequential, supporting our methodological assertion that public health variables are not spatially dependent, though the factors leading to them may be.

As far as the accessibility values are concerned, none of the three utility-based specifications nor the

ParkScore 10-minute walk buffer are correlated with obesity rates at the traditional 95% confidence interval. It is important to consider the implications of the full range of the confidence interval, however (Amrhein et al., 2019). The results suggest that after controlling for tract socioeconomic variables, physical activity rates, and spatially correlated error terms, obesity rates in tracts with excellent park accessibility are expected to be between 0.72 percentage points lower and 0.21 percentage points higher than tracts with poor park accessibility. This range of values suggests that accessibility to parks may have obesity-reducing effects beyond the effect of accessibility on physical activity rates worth further study.

## Limitations and Future Research Direction

We readily acknowledge limitations in this study. As in any study conducted with areal data, we are at risk of falling victim to the ecological inference fallacy, where aggregate statistics mask or contradict disaggregated or individual-level trends. The socioeconomic and public health data used in this study are only available at the tract level; projecting the tract-level data to the block group level and computing more spatially precise accessibility logsums proved infeasible as the spatial lags of the independent variables introduced substantial collinearity in the model equations. A large-sample survey of individuals in New York City, including measured physical activities and obesity would always be preferable to the tract-level data used in this study. An ideal survey to address the question would incorporate both sets of questions: physical activity and health data on one hand and park use (including which parks were used and how frequently) on the other. As no such dataset exists to our knowledge, this tract-level aggregate analysis with asserted and transferred utility coefficients is the possibility that remains.

This paper applies a previously-presented but little-used accessibility statistic that could, in theory, accommodate many attributes of the destination parks as well as the people who might use them. As an illustration: the park-going population could be separated into at least four delineated clusters, each preferring different amenities of a park:

- runners and cyclists: long, interesting trail systems
- sports players: soccer fields, basketball courts, or baseball diamonds
- families with small children: water features and playgrounds

- casual users: water features, gardens, performances, etc.

An analyst could then compute the utility-based accessibility for each cluster with different utility values for each park’s amenities, and obtain a measure of a neighborhood’s accessibility to park features that its residents most care about. In this paper, we proceed only incrementally towards this by adding some selected park amenities as an element of each park’s attractiveness above and beyond its size. The set of amenities we included in the utility calculation — and the contribution of each amenity to the overall utility — was dictated by the availability of data on the park amenities in New York City and our ability to find comparable prior studies with transferrable utility parameters. We can envision a study where mobile device data revealing the home locations of park users would be paired with more detailed park amenities and use data (e.g. geolocated Twitter data *a la Roberts (2017)*) to estimate the utility contribution of these features. This could in turn provide a more nuanced understanding of the relationship between park accessibility, use, and health outcomes.

As a travel impedance measure, we used the Euclidean distance between each tract’s population-weighted centroid and the nearest point on the edge of a park’s border. Euclidean distances have well-rehearsed limitations regarding their fidelity with the underlying infrastructure network, etc. Network-based distances can also suffer from challenges when applied to multimodal problems; these challenges are exacerbated when the non-highway mode share is high, as is likely when considering access to parks. We examined replacing the Euclidean distance with a network-based distance; the choice of distance metric appeared inconsequential to our larger findings in this case while substantially increasing the computational load required. Additionally, we could not verify the accuracy of the underlying network data at the scale of this analysis. We therefore retain the Euclidean distance for simplicity. A better metric of travel impedance may be a mode choice model logsum, which weights all alternative travel alternatives against each other. We leave this as a recommendation for future research.

We compared our utility-based accessibility to a well-constructed isochrone that has attracted attention in the literature. That said, virtually all tracts in New York City are within this specific isochrone. It is possible that this isochrone may be more discriminating of park access in other cities, or that a different definition would yield different results in New York City. This observation however reinforces

**Table 4.** Estimated Effect of Accessibility on Obesity Rates

	Size and Distance	Amenities	10-Minute Walk
Physical Activity	−0.4802* [−0.5043; −0.4561]	−0.4802* [−0.5043; −0.4561]	−0.4803* [−0.5044; −0.4562]
$\gamma$ : Physical Activity	0.0197 [−0.0380; 0.0775]	0.0198 [−0.0380; 0.0775]	0.0173 [−0.0404; 0.0750]
Accessibility	−0.0403 [−0.1158; 0.0351]	−0.0429 [−0.1210; 0.0352]	−0.2630 [−0.6491; 0.1232]
Num. obs.	2099	2099	2099
Parameters	30	30	30
Log Likelihood	−3113.8451	−3113.8136	−3113.5028

\* 0 outside the confidence interval 95% confidence interval in brackets.  $y$  = tract-level obesity rate.

our suggestion that a measure explicitly based in the utility of access is warranted.

Finally, this study is primarily focused on the hypothesis that accessibility to parks encourages physical activity, which in turn reduces obesity. There are a multitude of other hypotheses that might be proposed and tested with the basic methodology we have employed here, or competing explanations for the outcomes we have observed. It is distinctly possible, for instance, that individuals who wish to exercise regularly in parks choose to live near them. Given that the CDC models informing the small-area obesity and physical activity estimates presumably include variables likely to influence such preferences (income, etc.), our investigation cannot isolate the preferences from the effect. Controlling for such a self-selection effect would be necessary to isolate the exogenous impacts of park access on obesity or other health outcomes. And regarding these other variables: this study did not consider potential relationships between park access and hospitalization rates, life expectancy, respiratory disease, mental health, or any number of potential beneficial outcomes hypothesized or explored in the existing literature. [The COVID-19 pandemic and its associated social distancing behaviors in many regions of the world has also drawn attention to problems of park access, use, and equity.](#) Exploring these connections and their underlying mechanisms should be a priority as city planners and urban architects attempt to improve the quality of life of urban residents in the future.

## Conclusion

Increased physical activity and decreased obesity rates are critical measures of improvement in public health. Although many have theorized the link between park accessibility and these metrics, previous literature has produced mixed findings, perhaps owing to the range

of variables modeled and the coarse spatial scale of the analyses. Using New York City as a case study, we presented a holistic and flexible measurement for park accessibility that compares the continuous distance to all parks in the region, weighted against the size of the park and its other amenities, with weights determinable through revealed preferences. In terms of physical activity, we found a positive relationship where the least park-accessible tracts have an expected physical activity participation rate between 0.06 and 1.8 percentage points lower than the most accessible tracts. We also found a suggestive though not significant relationship between park accessibility and expected obesity rates *in addition to* the effect of physical activity participation.

In both cases a common, isochrone-based analysis estimated a statistically weak relationship with greater uncertainty. Isochrone analyses are relatively common in the literature, perhaps because of the widespread availability of and training in GIS software. In spite of their widespread use, isochrones are relatively limited in terms of both their theoretical underpinnings and their flexibility to accommodate attributes of parks beyond their proximity. And even proximity may not be adequately handled, as the isochrone threshold may be arbitrarily asserted by the researcher. The model we apply in this paper extends a more comprehensive and flexible approach for measuring the impact of park access on health outcomes. Adopting utility-based accessibilities of the kind used in this study will allow researchers to encompass the full range of park amenities in their accessibility analyses, and to separate the definition of access from the study of its effects. This will in turn enhance the ability of planners to consider how multiple attributes of a park — from its location to its size to its amenities and beyond — benefit the health of the community the park serves.

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## Appendix

In this appendix we present the complete estimation results for the models relating different definitions of access to physical activity (in Table 5) and to obesity (in Table 6). In each case we also present a base model with no accessibility statistics for comparison.

**Table 5.** Estimated Effect of Accessibility on Physical Activity Rates

	No Access	Size and Distance	Amenities	10-minute Walk
(Intercept)	−24.5190*	−24.8266*	−24.8920*	−24.7176*
	[−41.5947; −7.4433]	[−41.7445; −7.9087]	[−41.8372; −7.9468]	[−41.7891; −7.6461]
log(Density)	0.1740*	0.1766*	0.1757*	0.1686*
	[0.0348; 0.3132]	[0.0375; 0.3156]	[0.0366; 0.3148]	[0.0293; 0.3079]
log(Income)	5.9786*	5.9976*	5.9964*	5.9767*
	[5.5540; 6.4032]	[5.5737; 6.4215]	[5.5723; 6.4205]	[5.5523; 6.4011]
Fulltime	0.1283*	0.1275*	0.1275*	0.1285*
	[0.1098; 0.1468]	[0.1090; 0.1460]	[0.1090; 0.1460]	[0.1100; 0.1470]
College-educated	0.0075	0.0076	0.0073	0.0083
	[−0.0159; 0.0310]	[−0.0158; 0.0309]	[−0.0161; 0.0306]	[−0.0152; 0.0317]
Single Adults	−0.0363*	−0.0362*	−0.0360*	−0.0366*
	[−0.0527; −0.0198]	[−0.0526; −0.0198]	[−0.0524; −0.0196]	[−0.0530; −0.0201]
Youth (0-17)	−0.1306*	−0.1311*	−0.1310*	−0.1311*
	[−0.1572; −0.1040]	[−0.1576; −0.1046]	[−0.1576; −0.1045]	[−0.1577; −0.1045]
Young adults (18-34)	0.0283*	0.0293*	0.0294*	0.0281*
	[0.0081; 0.0484]	[0.0092; 0.0495]	[0.0092; 0.0495]	[0.0079; 0.0482]
Seniors (65+)	0.0430*	0.0403*	0.0408*	0.0427*
	[0.0157; 0.0704]	[0.0130; 0.0677]	[0.0135; 0.0682]	[0.0153; 0.0700]
Black population share	−0.0499*	−0.0499*	−0.0498*	−0.0497*
	[−0.0587; −0.0412]	[−0.0586; −0.0412]	[−0.0585; −0.0411]	[−0.0584; −0.0409]
Asian population share	−0.0772*	−0.0767*	−0.0768*	−0.0774*
	[−0.0877; −0.0666]	[−0.0873; −0.0662]	[−0.0874; −0.0663]	[−0.0879; −0.0669]
Hispanic population share	−0.1021*	−0.1025*	−0.1025*	−0.1020*
	[−0.1112; −0.0929]	[−0.1116; −0.0934]	[−0.1116; −0.0934]	[−0.1111; −0.0928]
Other Minorities	0.0006	0.0035	0.0037	−0.0005
	[−0.0882; 0.0894]	[−0.0851; 0.0921]	[−0.0850; 0.0923]	[−0.0893; 0.0883]
$\gamma$ : log(Density)	1.1105*	1.0987*	1.1030*	1.0928*
	[0.7245; 1.4964]	[0.7156; 1.4817]	[0.7196; 1.4865]	[0.7063; 1.4793]
$\gamma$ : log(Income)	1.9269*	1.9646*	1.9570*	1.9189*
	[0.8913; 2.9625]	[0.9370; 2.9922]	[0.9282; 2.9857]	[0.8836; 2.9541]
$\gamma$ : Fulltime	−0.0360	−0.0396	−0.0388	−0.0363
	[−0.0835; 0.0115]	[−0.0869; 0.0076]	[−0.0861; 0.0085]	[−0.0837; 0.0112]
$\gamma$ : College-educated	−0.0707*	−0.0711*	−0.0721*	−0.0731*
	[−0.1307; −0.0107]	[−0.1306; −0.0116]	[−0.1317; −0.0125]	[−0.1332; −0.0131]
$\gamma$ : Single Adults	−0.0081	−0.0085	−0.0077	−0.0076
	[−0.0506; 0.0344]	[−0.0507; 0.0336]	[−0.0499; 0.0345]	[−0.0501; 0.0348]
$\gamma$ : Youth (0-17)	−0.0111	−0.0111	−0.0101	−0.0120
	[−0.0806; 0.0585]	[−0.0802; 0.0579]	[−0.0793; 0.0591]	[−0.0815; 0.0575]
$\gamma$ : Young adults (18-34)	0.0806*	0.0842*	0.0848*	0.0801*
	[0.0296; 0.1317]	[0.0335; 0.1349]	[0.0339; 0.1356]	[0.0291; 0.1311]
$\gamma$ : Seniors (65+)	0.0625	0.0589	0.0603	0.0623
	[−0.0071; 0.1322]	[−0.0103; 0.1282]	[−0.0090; 0.1296]	[−0.0073; 0.1319]
$\gamma$ : Black population share	0.0006	0.0011	0.0008	0.0006
	[−0.0157; 0.0168]	[−0.0151; 0.0172]	[−0.0153; 0.0170]	[−0.0157; 0.0168]
$\gamma$ : Asian population share	−0.0410*	−0.0398*	−0.0401*	−0.0409*
	[−0.0597; −0.0223]	[−0.0584; −0.0212]	[−0.0587; −0.0215]	[−0.0596; −0.0222]
$\gamma$ : Hispanic population share	0.0009	−0.0009	−0.0008	0.0008
	[−0.0164; 0.0182]	[−0.0181; 0.0163]	[−0.0181; 0.0164]	[−0.0165; 0.0181]
$\gamma$ : Other Minorities	0.0656	0.0715	0.0710	0.0716
	[−0.1926; 0.3239]	[−0.1856; 0.3287]	[−0.1863; 0.3284]	[−0.1866; 0.3299]
Accessibility		0.1610*	0.1472*	0.5865
		[0.0238; 0.2982]	[0.0058; 0.2886]	[−0.1778; 1.3508]
$\lambda$ : spatial correlation	0.6985*	0.6906*	0.6917*	0.6987*
	[0.6600; 0.7370]	[0.6514; 0.7297]	[0.6526; 0.7307]	[0.6602; 0.7372]
Num. obs.	2099	2099	2099	2099
Parameters	27	28	28	28
Log Likelihood	−4438.0569	−4435.5066	−4436.0465	−4436.9264

\* 0 outside the confidence interval. 95% confidence interval in brackets.

**Table 6.** Estimated Effect of Accessibility on Obesity Rates

	No Access	Size and Distance	Amenities	10-minute Walk
(Intercept)	71.6539*	71.7489*	71.7525*	71.7182*
	[61.1144; 82.1933]	[61.2170; 82.2809]	[61.2164; 82.2887]	[61.1846; 82.2518]
log(Density)	-0.0294	-0.0307	-0.0306	-0.0266
	[-0.1037; 0.0448]	[-0.1050; 0.0436]	[-0.1049; 0.0437]	[-0.1009; 0.0478]
log(Income)	-0.4849*	-0.4907*	-0.4908*	-0.4861*
	[-0.7612; -0.2085]	[-0.7672; -0.2141]	[-0.7674; -0.2142]	[-0.7623; -0.2098]
Fulltime	-0.0137*	-0.0137*	-0.0137*	-0.0139*
	[-0.0244; -0.0031]	[-0.0244; -0.0030]	[-0.0244; -0.0030]	[-0.0246; -0.0032]
College-educated	0.0343*	0.0343*	0.0343*	0.0340*
	[0.0211; 0.0474]	[0.0211; 0.0474]	[0.0211; 0.0474]	[0.0208; 0.0471]
Single Adults	0.0010	0.0010	0.0010	0.0012
	[-0.0082; 0.0103]	[-0.0083; 0.0103]	[-0.0083; 0.0102]	[-0.0081; 0.0104]
Youth (0-17)	0.0051	0.0052	0.0052	0.0054
	[-0.0099; 0.0201]	[-0.0098; 0.0202]	[-0.0098; 0.0202]	[-0.0096; 0.0204]
Young adults (18-34)	-0.0095	-0.0097	-0.0098	-0.0094
	[-0.0206; 0.0016]	[-0.0209; 0.0014]	[-0.0209; 0.0014]	[-0.0205; 0.0017]
Seniors (65+)	-0.0826*	-0.0821*	-0.0821*	-0.0825*
	[-0.0977; -0.0675]	[-0.0973; -0.0669]	[-0.0973; -0.0670]	[-0.0976; -0.0673]
Black population share	0.0462*	0.0462*	0.0462*	0.0461*
	[0.0414; 0.0511]	[0.0414; 0.0511]	[0.0414; 0.0510]	[0.0413; 0.0510]
Asian population share	-0.1010*	-0.1010*	-0.1010*	-0.1009*
	[-0.1069; -0.0950]	[-0.1070; -0.0951]	[-0.1070; -0.0951]	[-0.1068; -0.0949]
Hispanic population share	-0.0062*	-0.0061*	-0.0061*	-0.0062*
	[-0.0118; -0.0007]	[-0.0116; -0.0006]	[-0.0116; -0.0006]	[-0.0117; -0.0007]
Other Minorities	-0.0642*	-0.0646*	-0.0647*	-0.0637*
	[-0.1127; -0.0156]	[-0.1132; -0.0161]	[-0.1133; -0.0162]	[-0.1122; -0.0151]
$\gamma$ : log(Density)	-0.5545*	-0.5565*	-0.5567*	-0.5445*
	[-0.7908; -0.3182]	[-0.7927; -0.3203]	[-0.7929; -0.3204]	[-0.7812; -0.3079]
$\gamma$ : log(Income)	-0.0863	-0.1004	-0.0987	-0.0783
	[-0.7966; 0.6240]	[-0.8108; 0.6100]	[-0.8091; 0.6118]	[-0.7883; 0.6317]
$\gamma$ : Fulltime	-0.0118	-0.0115	-0.0116	-0.0116
	[-0.0404; 0.0169]	[-0.0402; 0.0172]	[-0.0402; 0.0171]	[-0.0402; 0.0171]
$\gamma$ : College-educated	0.0698*	0.0698*	0.0699*	0.0710*
	[0.0334; 0.1062]	[0.0334; 0.1062]	[0.0335; 0.1063]	[0.0346; 0.1075]
$\gamma$ : Single Adults	-0.0114	-0.0113	-0.0114	-0.0117
	[-0.0368; 0.0140]	[-0.0367; 0.0140]	[-0.0368; 0.0140]	[-0.0371; 0.0137]
$\gamma$ : Youth (0-17)	-0.0330	-0.0330	-0.0332	-0.0326
	[-0.0748; 0.0088]	[-0.0748; 0.0088]	[-0.0750; 0.0086]	[-0.0744; 0.0092]
$\gamma$ : Young adults (18-34)	-0.0238	-0.0247	-0.0248	-0.0235
	[-0.0545; 0.0069]	[-0.0554; 0.0060]	[-0.0555; 0.0059]	[-0.0542; 0.0071]
$\gamma$ : Seniors (65+)	-0.0222	-0.0217	-0.0218	-0.0222
	[-0.0629; 0.0185]	[-0.0624; 0.0190]	[-0.0625; 0.0189]	[-0.0628; 0.0185]
$\gamma$ : Black population share	0.0186*	0.0186*	0.0186*	0.0185*
	[0.0080; 0.0292]	[0.0080; 0.0292]	[0.0080; 0.0292]	[0.0079; 0.0291]
$\gamma$ : Asian population share	-0.0460*	-0.0462*	-0.0461*	-0.0461*
	[-0.0594; -0.0325]	[-0.0596; -0.0327]	[-0.0596; -0.0327]	[-0.0595; -0.0327]
$\gamma$ : Hispanic population share	0.0257*	0.0263*	0.0263*	0.0258*
	[0.0129; 0.0386]	[0.0134; 0.0392]	[0.0134; 0.0391]	[0.0130; 0.0386]
$\gamma$ : Other Minorities	0.0794	0.0789	0.0790	0.0767
	[-0.0648; 0.2236]	[-0.0652; 0.2230]	[-0.0652; 0.2231]	[-0.0674; 0.2209]
Physical Activity	-0.4807*	-0.4803*	-0.4803*	-0.4803*
	[-0.5048; -0.4566]	[-0.5044; -0.4561]	[-0.5044; -0.4562]	[-0.5044; -0.4562]
$\gamma$ : Physical Activity	0.0180	0.0195	0.0194	0.0173
	[-0.0397; 0.0757]	[-0.0383; 0.0772]	[-0.0383; 0.0772]	[-0.0404; 0.0750]
Accessibility		-0.0349	-0.0352	-0.2630
		[-0.1095; 0.0397]	[-0.1129; 0.0425]	[-0.6491; 0.1232]
$\lambda$ : spatial correlation	0.8363*	0.8357*	0.8360*	0.8361*
	[0.8101; 0.8625]	[0.8094; 0.8620]	[0.8098; 0.8622]	[0.8099; 0.8624]
Num. obs.	2099	2099	2099	2099
Parameters	29	30	30	30
Log Likelihood	-3114.3931	-3113.9742	-3113.9998	-3113.5028

\* 0 outside the confidence interval. 95% confidence interval in brackets.