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### Public skate-parks and community well-being: A spatial econometric study

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#### Abstract

With recent growth in skateboarding, it has become more important than ever to consider what effect skateparks have on community well-being. This analysis is a first investigation into the effect of skatepark access on three county-level wellness outcomes: suicide rates, population in juvenile detention, and rates of high-school completion with a novel data set on skatepark locations. In consideration of spatial heterogeneity in the location of skateparks and potential spillovers across space, we use spatial autoregressive (SAR) models to account for potential omitted variable bias and to correct for inefficient estimators in linear models due to spatial autocorrelation. We find a correlation between additional skateparks and increased suicide rates, juvenile detention rates, and high school completion. Returns to education are consistent with past literature on public recreational space, and provide support for further integration of skateboarding in the public space. Unexpected positive correlations between skatepark access and suicide and juvenile detention rates warrant future research.

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## 1. Introduction

On May 7, 2021, the city of Des Moines, Iowa opened Lauridsen Skatepark, the largest skatepark in the United States. For skateboarders in the Midwest, this was seen as a huge boon; a first step toward a more developed skate-infrastructure for those who do not live on the coasts. Proponents of the park’s construction hope that it will generate visitors and tourists to the city, with the expectation that the skatepark would attract 40,000 skaters each year while allowing for the city to additionally attract regional and national skating events.<sup>1</sup>

Shortly following the opening of Lauridsen Skatepark, skateboarding made its debut in the summer Olympics, with both men and women from all over the globe showcasing their talents in both street and park skateboarding. Des Moines hosted the only North American skateboarding qualifying event for the 2021 Olympic Games. Despite this monumental development there is still a long way to go before skateboarding receives public support on the same level as other sports in the U.S., such as baseball, basketball, or football.

The U.S. skateboard market alone is expected to grow from its 2018 value of 532.5 million USD to a value of 649.5 million USD by 2025.<sup>2</sup> This massive expected increase in the consumption of skateboard goods is reflected by a similarly large growth in the population of skateboarders. In 2020, there were an estimated 8.87 million skateboarders in the United States, an increase of 2.26 million from the previous year.<sup>3</sup>

With this growth in skateboarding participation, it has become more important than ever to evaluate the effects that skateparks have on the community. Previous literature broadly addresses the impact of public recreation on community well-being; however, it leaves the effects of specific facilities up for debate. Moreover, the effects of skateboarding have not been addressed in the economics literature, likely due to a dearth of relevant data. This paper addresses these two shortcomings in the literature and bridges the gap between public health and economics to estimate the effects of access to skateparks on county wellness outcomes.

## 2. Public Recreation, Skateboarding, and Well-being

Skateboarders largely have two options as to where they may practice: in designated skateparks or out in the streets. Howell (2001) provides insight on the interplay between surveillance, street skateboarding, and their relationship to urban design. Howell argues that the relationship between skateboarding and defensive architecture is twofold. On the one hand, street skateboarding serves as driving force for the erection of defensive architecture, with various firms such as Skatestoppers emerging with the sole purpose of discouraging street skateboarding. On the other hand, street skateboarding is a relatively new phenomenon, emerging in the 1980s as a response to the closing of skateparks and a national trend of urban redevelopment. With this new form of skateboarding came the “skate and destroy” motto in the early 1990s, signaling recognition that the activity can be destructive to street

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<sup>1</sup><https://www.desmoinesregister.com/story/money/business/development/2019/06/26/downtown-des-moines-lauridsen-skate-park-united-states-largest-riverfront/1572762001/>

<sup>2</sup><https://www.statista.com/statistics/1072008/skateboard-market-value-us/>

<sup>3</sup><https://www.statista.com/statistics/191308/participants-in-skateboarding-in-the-us-since-2006/>

furniture. Lack of respect for these spaces may stem from skate culture which has historically seen a heavy handed and profit-motivated state as inimical to the sport (Batalla, 2021).

While street skateboarding is challenging and beneficial to a skateboarder’s technical progression, it is often met with resistance by the city and comes with many risks that skateboarding in a public skatepark does not. Property owners may see skateboarders as a liability and may ban its practice, citing destruction of property and possibly liability for injury. Private skateboarding prohibition forces skateboarders to practice in public space with little oversight when skateparks are inaccessible. Public provision of skateparks may serve as a means to improve well-being.

While there is currently little empirical research on skateboarding itself, plenty exists regarding public recreation more generally. Robinson (1967) develops an economic perspective for studying outdoor recreation. The author provides a foundation upon which one can empirically study these systems, illustrating the need for an external control scheme to prevent recreational areas from over-crowding. The author argues that, in the long run, public ownership and operation of outdoor recreation is more likely to promote the American idea of “the great out-of-doors,” a public benefit that may be associated with better wellness outcomes.

Improving access to outdoor recreation is likely to promote physical activity among the population. Current research has found a statistically significant positive effect of physical activity on cognitive functioning abilities, particularly in children (Donnelly et al., 2016). Larson et al. (2016) provides empirical evidence that increased access to public parks leads to higher levels of community well-being.

Huhtala and Pouta (2008) studies the effects of public recreation areas on social welfare. The authors provide derivations for the benefit incidence by income group of increases in the supply of public recreation opportunities. The authors also motivate an empirical example using data collected from a national inventory regarding state-protected and recreation areas (SPRAs) in Finland, showing a positive marginal average change in consumer surplus. When inspecting the knock-on effects from a hypothetical policy increasing recreation access on specific income groups, the authors found discrepancies in the gains to the population with income levels below the 1st quartile and those above the third. They find that the value per trip to recreational sites was significantly higher for the latter group than the former. This result raises questions as to the distribution opportunity costs of time spent on recreation and, subsequently, the distribution of benefits of public recreation.

While the effects of outdoor recreation facilities on community well-being have been studied extensively, little research has considered the effects of specific facilities. To address this gap, we focus in on skatepark access in consideration of recent rapid growth in skateboarding beginning with the COVID-19 pandemic.

### 3. Data

To analyze the effects of skatepark access on health and economic outcomes, we collate information from three separate data sets regarding county-level access to skateparks, health measures, and sociodemographic information. The covariate of interest considered in this study is access to skateparks. It is hypothesized that access to skateparks will reduce suicide rates, reduce youth delinquency and populations in juvenile detention, and lead to improved

educational outcomes. We recognize that these benefits of recreational access may have spillovers to neighboring counties, and treat for this autocorrelation with spatial autoregression (SAR) models as will be described in the methods section.

Table I: Summary Statistics

Statistic	Mean	St. Dev.	Min	Max
<b>Dependent Variables</b>				
Suicides per 100,000	41.922	61.875	10	901
Pop. in Juvenile Detention	47.421	160.351	0	4,746
% Less than HS degree	13.374	6.579	1.1	73.6
<b>Independent Variables</b>				
# of Skateparks	1.034	2.636	0	81
<i>Health Measures</i>				
# Short-Term Psych Units	0.132	0.542	0	11
# Long-Term Psych Units	0.046	0.215	0	2
# of ER Visits	44,759	131,431	0	3,075,704
<i>Sociodemographic Controls</i>				
Median Age	40.241	5.037	21.9	62.7
% White	82.660	16.914	2.7	99.2
% Black	9.006	14.515	0	85.7
% Hispanic or Latino	5.109	5.013	0.2	35
% Native American	1.985	7.653	0	96
% Asian	1.143	2.539	0	43.9
% Pacific Islander	0.095	1.281	0	49.3
% > 2 Races	2.009	1.587	0.1	29.5
% Other Race	3.095	4.351	0	31.8
% Pop Residing in Urban Areas	42.533	32.064	0	100
Median HH Income	55,713	14,490	24,732	151,806
Persons Impoverished	12,572	42,564	12	1,319,242
Proportion of Population Impoverished	0.139	0.054	0.027	0.475
# of Households	36,644	110,636	39	3,241,204
# of Single-Parent Households	4,166	13,703	0	412,960
% At Least HS degree	86.626	6.579	26.4	98.9
% of Pop at least a college degree	21.969	9.501	0	77.6

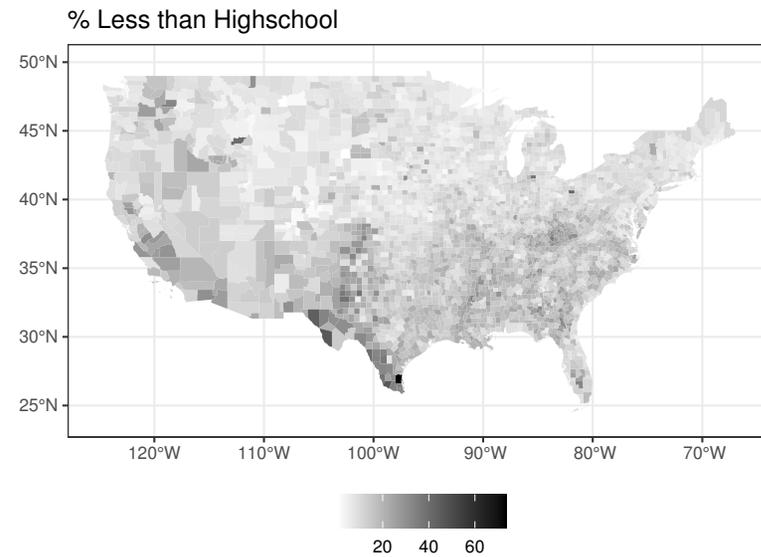
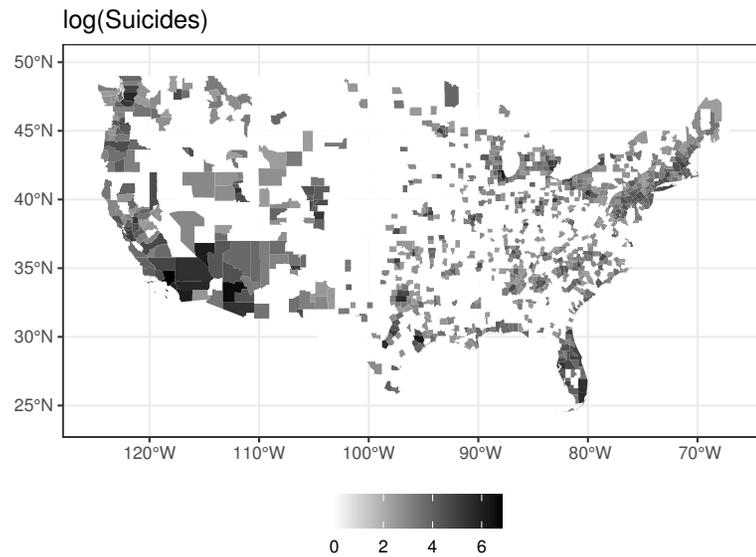
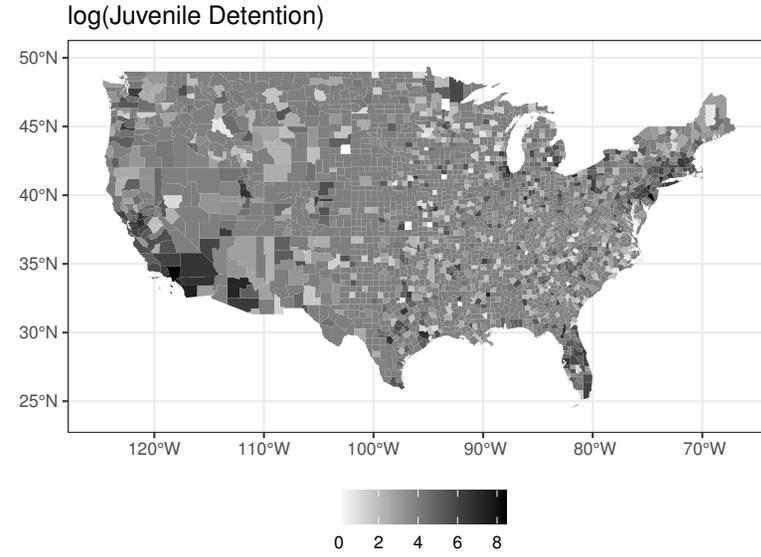
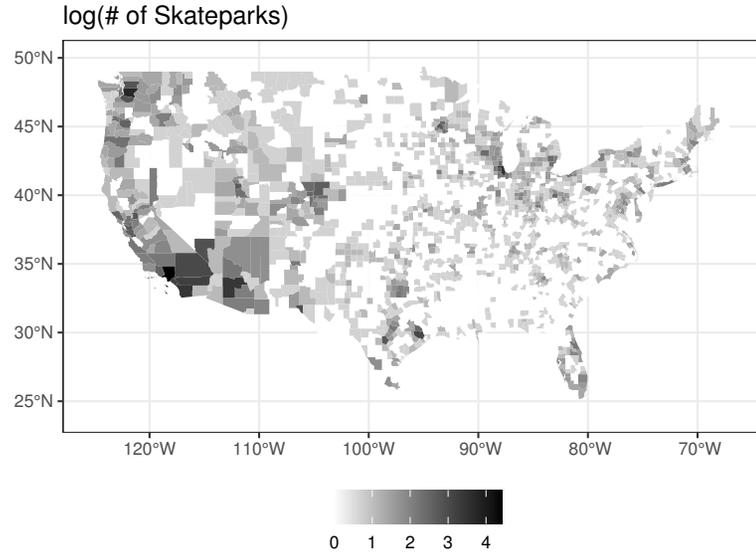


Figure 1: Spatial Distribution of Skateparks and Dependent Variables

To collect information on skatepark locations and attributes, we trained a web scraper to parse HTML from Concrete Disciples’ Skatepark Locator<sup>4</sup>. Concrete Disciples is a website that tracks access to and development of skateparks around the world, amongst other services.

County-level health measures were gathered from the most recent release year of the Area Health Resource File (AHRF) produced by the Health Resources and Services Administration.<sup>5</sup> Data on suicides were sourced from the Center for Disease Control’s (CDC) National Center for Health Statistics Mortality File.<sup>6</sup> The American Hospital Association Survey Database provided data on hospital visits across a variety of health specialties.<sup>7</sup>

Finally, county-level data on demographics, income, juvenile detention rates, poverty, and education were obtained from the U.S. Census Bureau’s American Community Survey. The final data set is a cross-section of counties across the continental United States. Summary statistics are presented in Table I. Spatial distribution of dependent variables suicide rates, juvenile detention rates, and educational outcomes alongside the key covariate of skatepark access are provided in Figure 1.

It is important to note that the majority of counties (2,273 counties) do not have recorded suicide values. In respect of privacy, the exact rate of suicides for counties which record fewer than 10 suicides per 100,000 people are not reported. It can be assumed that missing observations represent counties that experienced relatively few suicides. This lack of reporting creates potential issues of sample selection bias when analyzing related data, as only counties with relatively high rates of suicide are recognized. This potential source of bias will be considered in interpretation of results.

#### 4. Methods

In an effort to model the benefits of skateboarding on well-being, we model suicides as a proxy for mental health outcomes, juvenile detention rates for youth crime, and percentage of county population with less than a high school education in  $Y$ . The estimating equations may be expressed as the following:

$$Y_i = \alpha + \beta_1 \text{skateparks}_i + \gamma X_i + \epsilon_i \tag{1}$$

where *skateparks* is the count of skateparks in county,  $i$ , and  $X$  is a vector of controls.  $\alpha$  represents the intercept and  $\epsilon$  the error term.

Spatial autocorrelation describes the degree to which a variable of interest is correlated to itself across space. Outcomes considered, including suicides, population in juvenile detention, and percent with less than a high school education, are likely correlated across space due to geographic differences in access to hospitals, education opportunities, income, etc. OLS assumes independence between observations, a heroic assumption with expectation of heterogeneity across space. Spatial autocorrelation may result in biased and inconsistent estimates if not properly accounted for (Ullah, 1998; LeSage and Pace, 2009). Spatial de-

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<sup>4</sup><https://www.concretedisciples.com/global-skatepark-directory/usa-skateparks-guide/>

<sup>5</sup><https://data.hrsa.gov/topics/health-workforce/ahrf>

<sup>6</sup><https://www.cdc.gov/nchs/data-linkage/mortality.htm>

<sup>7</sup><https://www.ahadata.com/aha-annual-survey-database>

pendence may be modeled similarly to autoregressive processes in time series with spatial autoregressive (SAR) models.<sup>8</sup> Modifying equation 1 to account for potential bias due to autocorrelation across space yields the following:

$$Y_i = \alpha + \rho W_{ij} Y_i + \beta_1 \text{skateparks}_i + \gamma X_i + \epsilon_i \quad (2)$$

where  $W$  is a row standardized spatial weights matrix indicating the neighboring counties of  $i$ , where  $i \neq j$ . The term  $W_{ij} Y_i$  induces correlation with  $\epsilon_i$  much like an endogenous variable. When  $\rho = 0$ , the spatial lag model reduces to the linear regression model in equation 1, indicating that equation 1 is nested in the more complex SAR model.

While SAR models produce parameter estimates, the interpretation of the parameters in SAR models is more complex than in OLS because the effects of marginal changes to measures extend to neighbors and can feed back to the principle county (Arbia et al., 2020). Following LeSage and Pace (2009), impact measures are derived to account for this potential feedback.

Average direct effects capture the average effect of skateparks, amongst other measures, in county  $i$  on the dependent variable of interest for county  $i$ , in addition to feedback effects due to changes in neighboring measures of the dependent variable of interest from skateparks in county  $i$ . Indirect effects capture spillovers to county  $i$  due to variation in skatepark access in neighboring counties,  $j$ . Finally, average total effects are the sum of direct and indirect effects and measure the entire average effect of skateparks on the dependent variable.

## 5. Results

Estimated county-level effects of an additional skatepark on the three well-being outcomes are provided in Table II. Overall, we find initial evidence of skatepark access being positively correlated with suicide rates, juvenile incarcerations, and high school completion.<sup>9</sup>

Spatial autocorrelation violates the Gauss-Markov spherical errors assumption. While not necessarily leading to bias, this assumption violation due to spatial autocorrelation can lead to inefficient estimators. We next investigate models presented above to examine whether residuals are correlated across space. If residuals are not randomly assigned across counties, then it might be that distributions of the error depend upon some omitted information related to county location.

Moran's  $I$  is a measure of spatial autocorrelation (Moran, 1950). The Moran's  $I$  statistic may be calculated as follows:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^n \sum_{j=1}^n w_{ij}) \sum_{i=1}^n (x_i - \bar{x})^2} \quad (3)$$

where  $n$  is the number of counties,  $\bar{x}$  is the mean of the variable  $x$ ,  $x_i$  is the value of the variable  $x$  in a given county,  $x_j$  the value of the variable at another county, and  $w_{ij}$  is a

<sup>8</sup>e.g. Alexakis et al. (2021); Elhorst et al. (2021); Zhang et al. (2021)

<sup>9</sup>As discussed in the Data section, the exact rate of suicides for counties which record fewer than 10 suicides per 100,000 people are not reported. Models treating counties recording fewer than 10 suicides per 100,000 people as either missing or as an observed category are functionally similar in terms of estimates. These alternative models are available from authors upon request.

Table II: OLS Estimates of Skatepark Access on Well-being

	<i>Dependent variable:</i>		
	Suicides per 100,000	Juvenile Detentions	% Less than HS
# of Skateparks	1.884*** (0.240)	4.382*** (1.339)	-0.244*** (0.044)
Observations	940	3,074	3,074
Controls	Y	Y	Y
Adjusted R <sup>2</sup>	0.927	0.574	0.691

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01  
Standard errors in parentheses

weight matrix indicating location of county  $i$  relative to county  $j$ .

The expected value of Moran's I may be expressed as  $E(I) = \frac{-1}{n-1}$  where, as the sample size gets larger,  $E(I)$  approaches zero. Moran's I values near zero suggest random spatial assignment. Negative values for Moran's I suggest spatial autocorrelation characteristic of dispersion, and positive values suggest spatial autocorrelation where like counties are located nearer by, providing evidence of spatial clustering (Grekousis, 2020). Moran's I statistics calculated for the three models above suggest significant positive spatial autocorrelation, as demonstrated in Table III, indicating that suicide rates, population in juvenile detention, and rates of high school completion are spatially clustered.

Table III: Lagrange Multiplier (LM) Tests for Model Selection

	Suicides	Juvenile Detention	% Less than HS
Moran's I	0.162***	0.036***	0.337***
LM Error (robust)	1.2429	0.005	319.43***
LM Lag (robust)	57.285***	9.393***	87.14***

In light of visual evidence of spatial autocorrelation across all three models, we implement Lagrange Multiplier (LM) tests to detect the existence of spatial correlation following the procedure outlined in Anselin et al. (1996). LM Lag and LM Error tests test for spatial correlation in the dependent variable and error terms, respectively. Both tests produce significant results, so we use robust LM Lag and LM Error tests to test for spatial correlation in the dependent variable and error terms, respectively, conditioned on the presence of spatial correlation in the alternative location, the error term and dependent variable, respectively, as outlined in Florax et al. (2003).

Table III provides results of robust LM tests. Test results across all models show that models incorporating a spatial autoregressive term outperform those failing to model spatial heterogeneity or choosing to model it in the error term, suggesting that spatial autocorrelation may be best modeled with SAR.

Finally, as demonstrated in Equation 2, endogenously modeling spatial autocorrelation requires specification of a spatial weights matrix,  $W$ . Theory does not suggest a particularly likely weights matrix, so we estimate three SAR models for each of the three dependent variables of interest with spatial weights matrices indicating closeness to five- and ten-nearest neighbors as well as all contiguous neighbors (referred to as “queen contiguity”). All spatial weight matrices are row-standardized, where instead of indicating spatial proximity with ones, proximity is indicated by  $1/n$  where  $n$  is the number of neighbors.<sup>10</sup>

Table IV presents results for SAR models estimating suicide rates, juvenile detention rates, and percent of population in each county that did not complete high school. Panels (A), (B), and (C) in each table refer to five nearest neighbors, ten nearest neighbors, and queen contiguity weight matrices. All models indicate significant spatial autocorrelation in  $\rho$ . LR and Wald tests indicate that model fit including the spatial autoregressive term  $\rho W_{ij} Y_i$  lead to statistically improved model fit over models lacking the spatial autoregressive term.

<sup>11</sup>

Inference and interpretation of marginal effects in spatial econometric models is complicated by the presence of the spatial autoregressive term,  $\rho W_{ij} Y_i$ . If  $\rho = 0$ , then a standard linear model is nested in the SAR model, and parameters  $\beta_k$  may be interpreted as the marginal effect of variable  $x_k$  on  $y$ . The impact for every pair of observations in a sample in a linear model can be found by differentiating the vector  $y$  with respect to  $x_k$ . However, in the presence of non-zero  $\rho$  values, inference is made more difficult, as the resulting matrix in a SAR model is neither diagonal nor spherical as in a standard linear model (LeSage and Pace, 2009). Average direct, indirect, and total effects may be calculated to provide the means for proper inference in consideration of estimates modeling spatial dependence.

Table V presents direct, indirect, and total effects from above SAR models estimating suicide rates, juvenile detention rates, and percent of population in each county that did not complete high school. Panels (A), (B), and (C) in each table refer to five- and ten-nearest neighbors and queen contiguity weight matrices. Results across models appear stable regardless of chosen weight matrix, with each reinforcing previously found positive correlations between skateparks and suicide rates, juvenile detentions, and high school completion. Taken together, additional public recreation opportunities from skateparks appear to be associated with worse mental health and behavioral outcomes, but improved educational outcomes.

For both mental health and behavioral proxies, estimates for the direct effects are much smaller than their indirect counterparts, with this difference less pronounced in the case of high school completion rates. The discrepancy in effect sizes is exogenous to the model, and may be explained by noting that the average American skateboarder is younger than the average American, and more likely to experience the effects of an additional proximal skatepark.

Observed pattern of direct effects dominating indirect ones suggests a semi-monotone

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<sup>10</sup>Row-standardization creates proportional weights, helping to alleviate potential bias due to some counties having more neighbors than others and aiding in coefficient interpretation Ullah (1998)

<sup>11</sup>LeSage and Pace (2014) show that well-specified spatial regression models are not particularly sensitive to reasonable spatial weight structures, especially for local cross-sectional connectivity between elements with limited numbers of neighbors (Chudik and Straub, 2017; Elhorst et al., 2021). Additionally investigated but not included in the results are four- and eight-nearest neighbors and rook contiguity spatial weights matrices. All spatial weights matrices produce qualitatively similar estimated marginal effects.

Table IV: SAR Estimates of Skatepark Access on Well-being

	<i>Dependent variable:</i>		
	Suicides	Juvenile Detention	% Less than HS
Panel A: 5-nearest Neighbors Weights Matrix			
# of Skateparks	2.257*** (0.236)	4.886*** (1.284)	-0.166*** (0.044)
Observations	940	3,074	3,074
Controls	Y	Y	Y
$\rho$	0.088321***	0.095776***	0.38972***
Log Likelihood	-3,998.577	-18,704.820	-7,882.369
LR Test	28.476***	21.864***	625.445***
Panel B: 10-nearest Neighbors Weights Matrix			
# of Skateparks	2.299*** (0.237)	5.304*** (1.277)	-0.170*** (0.044)
Observations	940	3,074	3,074
Controls	Y	Y	Y
$\rho$	0.086109***	0.18243***	0.43158***
Log Likelihood	-4,005.811	-18,691.410	-7,876.397
LR Test	14.007***	48.680***	637.390***
Panel C: Queen Contiguity Weights Matrix			
# of Skateparks	2.328*** (0.037)	5.131*** (0.038)	-0.181*** (0.037)
Observations	940	3,074	3,074
Controls	Y	Y	Y
$\rho$	0.064144***	0.064144***	0.40717***
Log Likelihood	-4,002.517	-18,707.170	-7,864.639
LR Test	20.595***	17.154***	660.905***

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01  
Standard errors in parentheses

Table V: Average Direct, Indirect, and Total Impact Measures of Skatepark Access on Well-being from SAR

<i>Dependent Variable</i>	Direct	Indirect	Total
Panel A: 5 Nearest Neighbors			
Suicides	2.260*** (0.0111)	0.216*** (0.0022)	2.476*** (0.012)
Juvenile Detention	4.894*** (0.0584)	0.509*** (0.0087)	5.404*** (0.065)
% Less than HS	-0.171*** (0.0017)	-0.101*** (0.0011)	-0.272*** (0.0028)
Panel B: 10 Nearest Neighbors			
Suicides	2.300*** (0.010)	0.215*** (0.0029)	2.515*** (0.012)
Juvenile Detention	5.322*** (0.056)	1.166*** (0.016)	6.488*** (0.069)
% Less than HS	-0.173*** (0.0016)	-0.125*** (0.0012)	-0.298*** (0.0028)
Panel C: Queen Contiguity			
Suicides	2.331*** (0.011)	0.156*** (0.0018)	2.488*** (0.0113)
Juvenile Detention	5.138*** (0.0589)	0.467*** (0.0074)	5.605*** (0.0639)
% Less than HS	-0.188*** (0.0017)	-0.118*** (0.0011)	-0.305*** (0.0028)

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01  
Standard errors in parentheses

treatment interaction, first mentioned in Manski (2013). Moreover, skatepark construction appears to be a reinforcing effect, as both direct and indirect effects work in the same direction. This points to accessibility to skateparks as a potential cause of these effects.

## 6. Conclusions and Future Research

Across all models, we observe positive correlations between skatepark access and high school completion rates. This finding is in line with the opinion of many educators that participation in physical activities improves student performance. Moreover, the communities which form around these parks may serve as effective support systems for the high school aged population, facilitating completion of their academic goals.

These results make sense when considering the purpose of skateparks. Public skateparks provide an environment for skateboarders to hone their craft and develop greater discipline. To become a more competent skateboarder one must fail repeatedly, instilling a mindset of resilience upon the rider. Rodney Mullen, the godfather of modern technical skateboarding, and inventor of over 30 fundamental tricks, comments on this phenomena in his TEDx Talk, “Pop an Ollie and Innovate”, arguing that the skills developed through skateboarding are the same as those which facilitate academic learning.<sup>12</sup>

For skateboarders, traveling significant distances to skate somewhere interesting is a cultural norm. On warm summer weekends, skateboarders from rural space take joy in traveling to skate somewhere better. Ali (2003) use a spatial-interaction model to investigate a similar phenomena of migration of college students due to heterogeneity of educational opportunities across space. Future research may consider a similar approach to estimate inflows of skateboarders into locations with skateparks, using recent skatepark construction as a statistical treatment.

In some parts of the country, particularly in the Midwest and Pacific Northwest, skateboarders often find their usual spaces unskateable due to weather conditions. Indoor skateparks provide a means for exercise and socialization during cold and wet months where many are trapped indoors. An investigation of the differential effects of indoor and outdoor skateparks is warranted, particularly for such regions.

Finally, future work should consider selection issues within the spatial autoregressive framework for modeling county well-being following recent work by Rabovič and Čížek (2023) on using partial maximum likelihood to estimate spatially lagged latent dependent variables. Issues of selection may also be approached using the theoretical models of McMillen (1995) and Seya et al. (2020) in spatial econometric models to account for the non-random missing values for suicide rates. These techniques should help produce unbiased estimates for model parameters when facing selection bias such as in estimating suicide rates.

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<sup>12</sup>[https://www.ted.com/talks/rodney\\_mullen\\_pop\\_an\\_ollie\\_and\\_innovate?language=en](https://www.ted.com/talks/rodney_mullen_pop_an_ollie_and_innovate?language=en)

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