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Neighborhood street activity and greenspace usage uniquely contribute to predicting crime

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Abstract

Crime is costly economically, socially, and psychologically for all societies, especially in urban areas. While there are many well-studied environmental and social influences on crime such as poverty and marginalization, one less studied, but important factor is the effect of neighborhood greenspace. Prior research has shown that greenspace is negatively associated with crime, but the mechanism of this effect is debated. One suggested mechanism is that greenspaces increase local street activity, which in turn reduces crime, but past work has failed to examine effects of greenspace and street activity together, making it difficult to decouple these factors. Additionally, past research has typically used the static physical presence of greenspace as opposed to determining residents' engagement with and use of greenspace, which may be critical to understanding the potential causal role of greenspace on crime. Here, we examine the association of crime with street activity, physical greenspace presence, and active engagement with greenspace as measured by park visits, in Chicago and New York City, USA. Using novel cell phone mobility data, we quantified street activity and park visits by census tracts. In both cities, we found that park visits and street activity significantly and negatively predicted both violent and non-violent crime after controlling for many socio-demographic factors. Each factor explained unique variance in the model, suggesting multiple pathways for the effects of street activity and greenspace on crime.

Significance Statement

Understanding physical and social characteristics of neighborhoods that may contribute to crime has both practical and theoretical implications. This study covering two major US cities (Chicago and New York City) shows that neighborhood street activity, active engagement with greenspace and physical presence of greenspace all add unique information in predicting lower crime levels, after controlling for socio-demographic factors (e.g., income, education, poverty, crowding, etc.). Park visits and street activity were measured objectively using large cell phone mobility datasets. While it has been proposed that increased social interaction is the mechanism through which greenspace leads to less crime, these findings support the idea of multiple pathways for these effects.

Introduction

Crime is a serious and costly challenge to many urban areas. There is a large heterogeneity in crime rates observed across and within cities. Much work has focused on sociological and economic factors that influence crime such as education (1), job opportunities (2), and poverty (3). Importantly, some of this heterogeneity may be due to the characteristics of the physical and social environments of different neighborhoods. For example, how individuals in a neighborhood engage with their physical environment, in the sense of where they choose to spend time, may also influence crime. In this study, we use neighborhood networks constructed through novel cell phone mobility data to test sociological and psychological hypotheses on the relationship between specific physical environment variables, e.g., greenspace, and sociological variables, e.g., street activity, and their relationship with crime.

There has been a growing body of research examining how physical environment variables impact crime such as climate change (4, 5), vacant lots or buildings (6), ambient and artificial light (7, 8), or visual disorder (9). Another factor that has been much less studied is the impact of urban greenspace (10), though the mechanisms for this effect are unknown. Some research has demonstrated a negative relationship between crime levels and various types of urban greenspace, such as tree canopy (11), vegetation levels (12), and greened lots (13, 14), while others have failed to find a relationship between greenspace and crime at all (15). In at least one case, researchers found a significant *positive* relationship between parks and crime, as crime was found to be clustered in and around greenspace (16). A potential problem is that these studies have used the static physical presence of greenery, either binary or as a quantified amount, as their independent variable. This coarse measure may be leading to equivocal results as it is unclear to what degree residents are interacting with these measured greenspace variables.

Accounting for these differences in consumption of experiential factors may be critical in determining the efficacy of urban greenspace (17).

As such, it becomes important to quantify how individuals interact with greenspace in their city in terms of quality, type, and amount of interaction because such variations likely affect the relationships between greenspace and crime. However, doing so is not trivial and requires unique data and analyses that allow researchers to monitor, *en masse*, how individuals interact with different physical environments in their cities.

It remains unclear why interacting with greenspace may reduce crime. One potential sociological mechanism is that urban greenspaces increase residential street activity. For example, trees and grass can create pleasant public spaces where neighbors can interact and spend time outside (18, 19) and take more walking trips (20). Thus, urban greenspace can motivate individuals to spend more time on the streets of their neighborhood. This increase in "eyes on the street" then can prevent criminal behavior (21, 22), which is in accordance with the theory of crime prevention through environmental design (23). Through the lens of routine activity theory, residents spending time outside within their neighborhood may be effective guardians against crime (24). Additionally, busy streets have been proposed to empower communities by helping promote social cohesion (25), which leads to safer neighborhoods (26).

Another potential mechanism for the relationship between crime and greenspace is psychological, by restoring attentional functioning (27). Long-term and acute exposures to greenspace are associated with improvements in cognitive functioning (28–31). These improvements in attentional functioning resulting from experiencing urban greenspace led to reduced aggression for adults living in public housing projects (32). These results are in accordance with theory suggesting that attention is an underlying psychological resource that influences self-control (27). Therefore, any intervention that might increase attentional capacity, such as interactions with nature, would increase self-control and subsequently reduce crime. This cognitive mechanism suggests that urban greenspaces may contribute two mechanisms to predict crime: 1) an effect of enhancing cognitive resources required for self-control, which then would lead to reduced crime and 2) an effect of increasing social interaction and street activity which would then lead to reduced crime. See Figure 1 for a schematic of these theories.

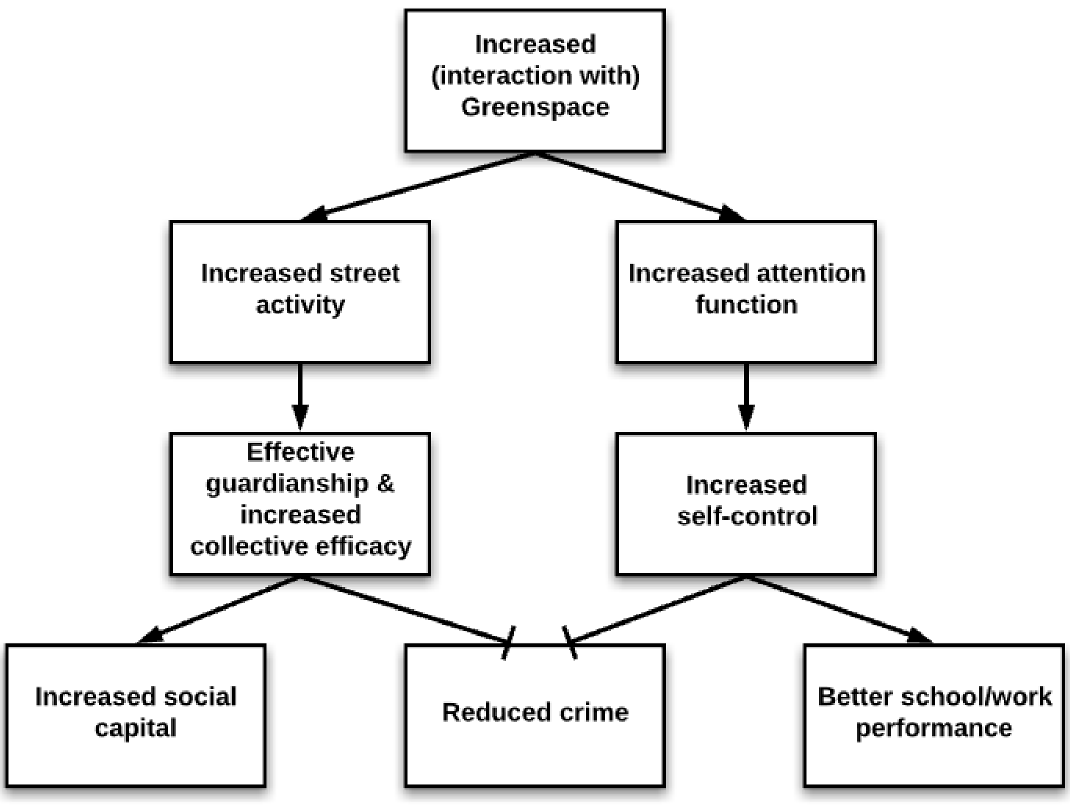

Figure 1. A visualization of theorized pathways between greenspace and crime.

Here we take a novel approach to this problem using unique mobility data from tens of thousands of residents where we can measure the amount of street activity in a neighborhood, and the amount of active engagement that residents have with greenspace through park visits to tease apart each of these factors associations with crime. Additionally, by using these novel large datasets, our park visits information represents realized access to parks, as opposed to using a static variable such as park area, which represents only potential park use. In this study we are able to determine if: 1) street activity and exposure to urban greenspace add unique information to a model predicting crime, and 2) if intentional greenspace exposure (i.e. park visits) and incidental greenspace exposure (i.e. tree canopy) have unique associations with crime. To achieve this, we first analyzed crime data over a 1-year period in Chicago. We then independently repeated the analysis in New York City, in a preregistered report, using three years of crime events to confirm that the relationships found were not specific to Chicago in a particular year. In both cities, we found that park visits, street activity, and neighborhood tree canopy all uniquely and significantly predicted reduced crime (controlling for income, education, and other demographic factors), with park visits having the strongest effect in most models. These results suggest important, independent, and significant roles for the physical and social environments of cities in potentially reducing crime in urban areas.

Results

Chicago. Figure 2 shows choropleth maps for number of park visits, tree canopy, street activity, and crime rates for the city of Chicago. Using a hierarchical linear model with neighborhood units ("Community Areas") as a random intercept, we controlled for unemployment, income, poverty, crowded housing, size of the resident population and working population, and educational attainment. The first model only includes tree canopy, the second model includes tree canopy and park visits, the third model includes tree canopy and street activity, and the fourth model includes all three variables of interest (see Table 1). We find that tree canopy, park visits, and street activity all have significant, negative associations with non-violent crime in each of the models, and the model with all variables has the best fit, as indicated by the lowest Akaike Information Criteria (AIC) (33). Importantly, the model with all variables did not have significant spatial autocorrelation (global Moran's I = 0.03, p = 0.18).

For violent crime, instead, the hierarchical linear model with all variables shows significant spatial autocorrelation (global Moran's I = 0.07, p < 0.001). Lagrange multiplier diagnostics indicated a spatial error model would properly account for the spatial autocorrelation. Using a spatial error model, and controlling for all of our confounding variables, park visits and street activity show significant negative associations with crime, while tree canopy was not significant (see Table 2) across all models. Again, the model of best fit was the model which included all three variables.

As crime was log-transformed and the independent variables were standardized, we can determine the percent change in crime associated with each of the significant predictor variables. For both non-violent and violent crime, an increase in observed average park visits by one visit per month was associated with 14% less crime, while a 5% increase in street activity was associated with 7% less crime. For non-violent crime, a 5% increase in tree canopy was associated with 3% less non-violent crime. As a comparison, 34% less people in poverty is associated with the same reduction in violent crime as an increase in one park visit.

It is possible that visiting any cultural amenity may be related to less crime, which would indicate no special role for a park visit. As such, we also investigated whether museum visits would have the same effect as park visits. In general, we found that museum visits were significantly and negatively associated with less crime when replacing park visits in the model, however this relationship was greatly weakened or made not significant when including both museum visits and park visits in the same model (see Supplementary Table S1 for models).

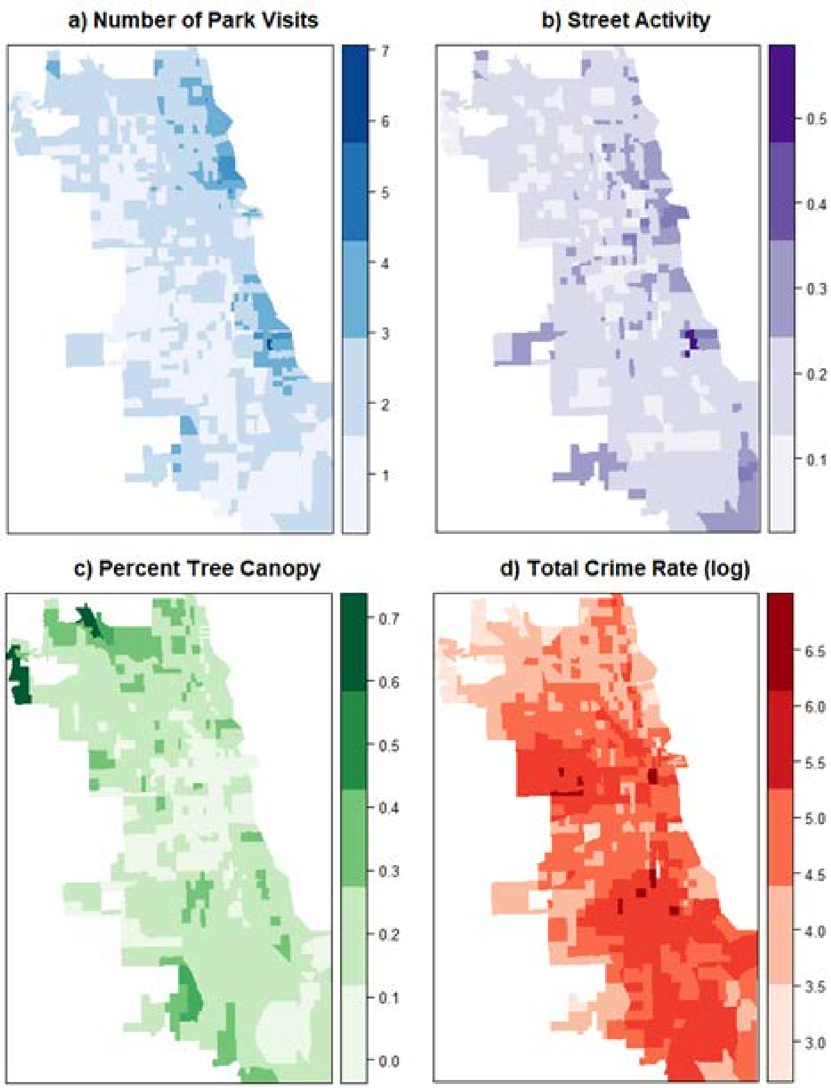

Figure 2. Choropleth maps for a) number of monthly park visits, b) percent tree canopy, c) street activity and d) total crime rate (per 1000 resident population, log-transformed) for the city of Chicago. Airports and census tracts with missing data have been removed. Total crime rate shown for visualization purposes only; all analysis done separately for violent and non-violent crime using crime counts while adjusting for residential and working population.

Table 1. Hierarchical linear models for non-violent crime in Chicago

	(1) Only Physical Greenspace	(2) W/ Park Use	(3) W/ Street Activity	(4) W/ Park Use and Street Activity
Intercept	-0.050 (-0.113, 0.014)	-0.055 (-0.119, 0.008)	-0.047 (-0.111, 0.017)	-0.049 (-0.112, 0.014)
Tree Canopy	-0.056** (-0.090, -0.022)	-0.054** (-0.087, -0.020)	-0.055** (-0.088, -0.021)	-0.053** (-0.086, -0.020)
Grass Coverage	0.006 (-0.025, 0.038)	0.010 (-0.020, 0.041)	-0.005 (-0.036, 0.026)	-0.002 (-0.032, 0.028)
Park Visits		-0.122*** (-0.158, -0.086)		-0.120*** (-0.155, -0.085)
Distance Traveled to Parks		0.021 (-0.016, 0.058)		-0.001 (-0.038, 0.036)
Street Activity			-0.109*** (-0.141, -0.078)	-0.103*** (-0.134, -0.071)
Population (log)	0.374*** (0.345, 0.404)	0.379*** (0.350, 0.407)	0.370*** (0.341, 0.398)	0.375*** (0.348, 0.403)
Working population (log)	0.185*** (0.152, 0.217)	0.171*** (0.139, 0.202)	0.158*** (0.125, 0.190)	0.148*** (0.116, 0.179)
Median Household Income (log)	0.049 (-0.007, 0.105)	0.030 (-0.025, 0.085)	0.038 (-0.016, 0.093)	0.024 (-0.030, 0.077)
Percent Unemployed	0.084*** (0.045, 0.122)	0.081*** (0.043, 0.118)	0.078*** (0.040, 0.116)	0.077*** (0.041, 0.114)
Percent below poverty line	0.072** (0.023, 0.120)	0.063** (0.016, 0.110)	0.059* (0.012, 0.106)	0.052* (0.006, 0.098)
Percent living in crowded housing	0.004 (-0.028, 0.035)	0.004 (-0.026, 0.035)	0.003 (-0.028, 0.034)	0.003 (-0.027, 0.033)
Percent w/ less than high school diploma	-0.018 (-0.069, 0.032)	-0.029 (-0.079, 0.020)	-0.009 (-0.058, 0.040)	-0.023 (-0.071, 0.025)
Percent w/ Bachelor's degree or higher	0.015 (-0.052, 0.081)	0.075* (0.007, 0.142)	0.061 (-0.005, 0.127)	0.106** (0.039, 0.173)
AIC	647.437	601.374	604.2	562.655
Δ AIC from Model (1)		-46.063	-43.237	-84.782

Notes. *p<0.05; **p<0.01; ***p<0.001. 95% CI shown in parentheses.

Table 2. Spatial error models for violent crime in Chicago

	(1) Only Physical Greenspace	(2) W/ Park Use	(3) W/ Street Activity	(4) W/ Park Use and Street Activity
Intercept	-0.028 (-0.092, 0.035)	-0.024 (-0.084, 0.035)	-0.026 (-0.092, 0.040)	-0.022 (-0.083, 0.039)
Tree Canopy	-0.031 (-0.071, 0.009)	-0.033 (-0.072, 0.006)	-0.026 (-0.066, 0.013)	-0.029 (-0.068, 0.009)
Grass Coverage	0.019 (-0.017, 0.055)	0.013 (-0.022, 0.048)	0.008 (-0.028, 0.043)	0.001 (-0.034, 0.036)
Park Visits		-0.125*** (-0.166, -0.084)		-0.117*** (-0.158, -0.076)
Distance Traveled to Parks		-0.0003 (-0.042, 0.042)		-0.019 (-0.061, 0.023)
Street Activity			-0.110*** (-0.147, -0.073)	-0.102*** (-0.139, -0.065)
Population (log)	0.392*** (0.359, 0.425)	0.398*** (0.365, 0.431)	0.383*** (0.350, 0.415)	0.390*** (0.358, 0.422)
Working population (log)	0.162*** (0.126, 0.199)	0.149*** (0.113, 0.185)	0.133*** (0.096, 0.170)	0.124*** (0.087, 0.161)
Median Household Income (log)	-0.024 (-0.088, 0.040)	-0.033 (-0.096, 0.030)	-0.030 (-0.093, 0.033)	-0.036 (-0.098, 0.026)
Percent Unemployed	0.041 (-0.002, 0.083)	0.042* (0.001, 0.084)	0.034 (-0.007, 0.076)	0.038 (-0.003, 0.079)
Percent below poverty line	0.076** (0.022, 0.130)	0.072** (0.020, 0.125)	0.063* (0.010, 0.115)	0.061* (0.009, 0.113)
Percent living in crowded housing	0.013 (-0.023, 0.049)	0.012 (-0.023, 0.048)	0.015 (-0.021, 0.050)	0.013 (-0.022, 0.048)
Percent w/ less than high school diploma	-0.053 (-0.109, 0.003)	-0.069* (-0.125, -0.014)	-0.040 (-0.096, 0.015)	-0.059* (-0.113, -0.004)
Percent w/ Bachelor's degree or higher	-0.056 (-0.128, 0.016)	-0.0002 (-0.075, 0.074)	-0.011 (-0.084, 0.062)	0.029 (-0.045, 0.103)
Lambda	0.57	0.56	0.6	0.58
AIC	812.662	781.747	782.132	755.417
Δ AIC from Model (1)		-30.915	-30.53	-57.245

Notes. *p<0.05; **p<0.01; ***p<0.001. 95% CI shown in parentheses. Lambda is the spatial correlation of error terms.

New York. Figure 3 shows the choropleth maps for number of park visits, tree canopy, street activity, and total crime rate for New York City. For non-violent crime, the hierarchical linear model with neighborhood ("Neighborhood Tabulation Area") as a random intercept has significant spatial autocorrelation (global Moran's I = 0.09, $p < 0.001$). Lagrange multiplier diagnostics indicate that a spatial error model would be appropriate. Controlling for all of our confounding variables we found that park visits and street activity had significant, negative associations with crime, while tree canopy was not significant (see Table 3). Park visits and street activity each added unique information to the model, and the model with all variables provided the best fit. For violent crime, Lagrange multiplier diagnostics also indicated a spatial error model was appropriate. Controlling for all of our confounding variables, tree canopy, park visits, and street activity all had significant, negative associations with crime (see Table 4), and each provided unique information to the model. In the models with all variables included, a 5% increase in street activity was associated with 5.8% and 2.2% reduction in non-violent and violent crime respectively. An increase in observed average park visits by one per month was associated with 5.6% less non-violent crime and 7.5% less violent crime, while a 5% increase in tree canopy was associated with 2.2% less violent crime. To compare the strength of association, 12% fewer people in poverty is associated with the same reduction in violent crime as an increase in one park visit. As in Chicago, we examined if museum visits would have similar effects on crime, however museum visits did not have a significant association with crime in New York (see Supplementary Table S2 for models).

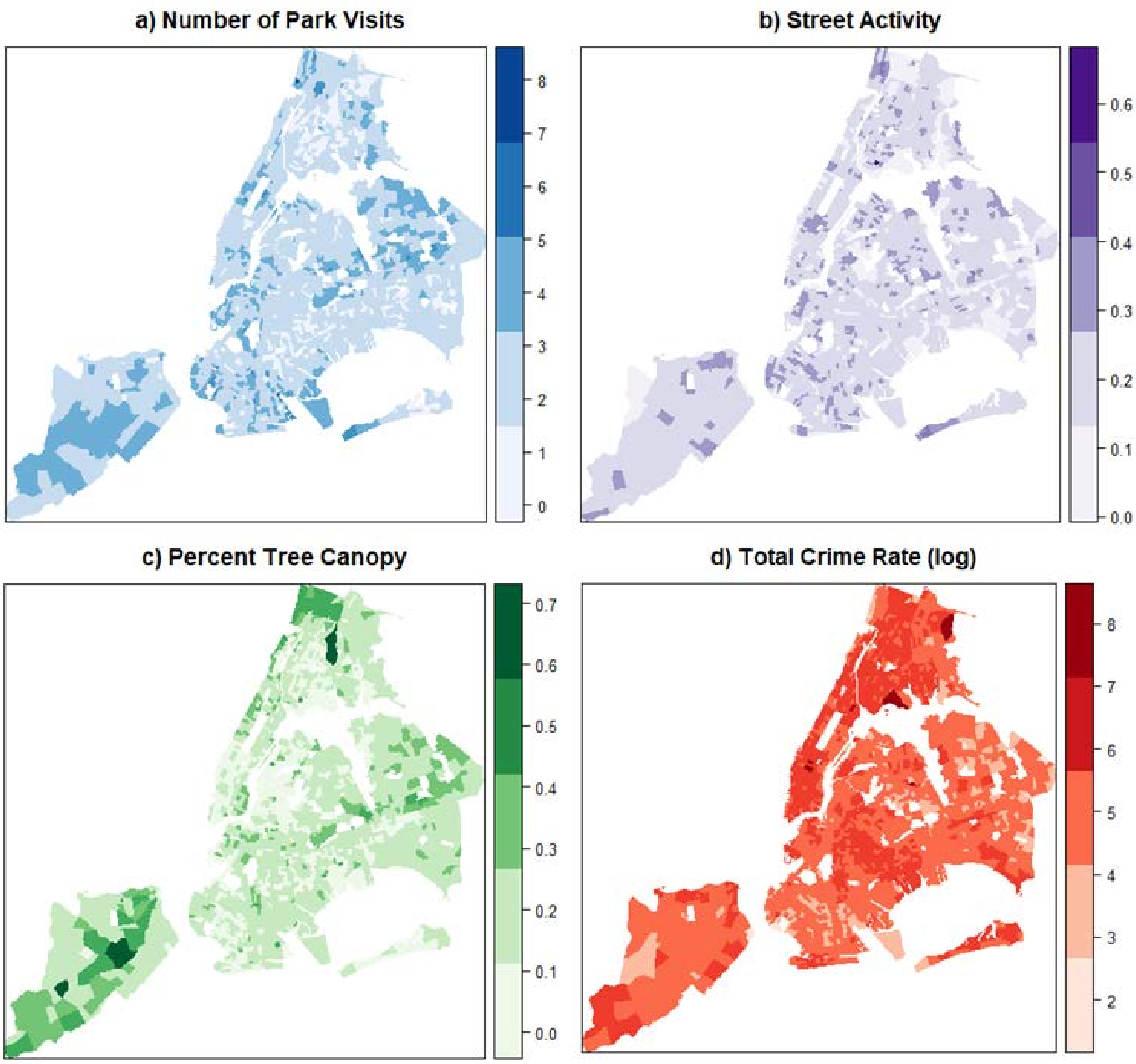

Figure 3. Choropleth maps for a) number of monthly park visits, b) percent tree canopy, c) street activity and d) total crime rate (per 1000 resident population, log-transformed) for the city of New York. Airports and census tracts with missing data have been removed. Total crime rate shown for visualization purposes only; all analysis done separately for violent and non-violent crime using crime counts while adjusting for residential and working population.

Table 3. Spatial error models for non-violent crime in New York City

	(1) Only Physical Greenspace	(2) W/ Park Use	(3) W/ Street Activity	(4) W/ Park Use and Street Activity
Intercept	-0.048* (-0.096, -0.001)	-0.046* (-0.093, -0.0001)	-0.048 (-0.098, 0.001)	-0.046 (-0.094, 0.002)
Tree Canopy	-0.021 (-0.045, 0.004)	-0.021 (-0.046, 0.004)	-0.014 (-0.038, 0.011)	-0.016 (-0.040, 0.009)
Grass Coverage	-0.001 (-0.029, 0.026)	-0.0001 (-0.027, 0.027)	-0.008 (-0.035, 0.019)	-0.007 (-0.034, 0.020)
Park Visits		-0.049*** (-0.072, -0.025)		-0.052*** (-0.075, -0.028)
Distance Traveled to Parks		0.010 (-0.016, 0.037)		-0.003 (-0.030, 0.023)
Street Activity			-0.072*** (-0.094, -0.051)	-0.074*** (-0.095, -0.052)
Population (log)	0.288*** (0.266, 0.309)	0.286*** (0.264, 0.307)	0.284*** (0.263, 0.305)	0.281*** (0.260, 0.303)
Working population (log)	0.239*** (0.216, 0.262)	0.239*** (0.216, 0.262)	0.218*** (0.194, 0.241)	0.218*** (0.194, 0.241)
Median Household Income (log)	0.006 (-0.033, 0.045)	0.013 (-0.026, 0.052)	0.006 (-0.033, 0.044)	0.013 (-0.026, 0.052)
Percent Unemployed	0.076*** (0.055, 0.097)	0.074*** (0.053, 0.095)	0.071*** (0.050, 0.091)	0.069*** (0.048, 0.089)
Percent below poverty line	0.095*** (0.060, 0.130)	0.096*** (0.061, 0.131)	0.094*** (0.059, 0.129)	0.094*** (0.060, 0.129)
Percent living in crowded housing	-0.008 (-0.034, 0.018)	-0.011 (-0.037, 0.015)	-0.007 (-0.033, 0.019)	-0.010 (-0.036, 0.016)
Percent w/ less than high school diploma	-0.006 (-0.044, 0.032)	-0.011 (-0.049, 0.027)	-0.004 (-0.041, 0.034)	-0.010 (-0.048, 0.027)
Percent w/ Bachelor's degree or higher	0.094*** (0.058, 0.131)	0.102*** (0.065, 0.140)	0.093*** (0.057, 0.130)	0.099*** (0.062, 0.136)
Lambda	0.62	0.62	0.64	0.64
AIC	2,467.07	2,453.50	2,426.06	2,411.34
Δ AIC from Model (1)		-13.57	-41.01	-55.73

Notes. *p<0.05; **p<0.01; ***p<0.001. 95% CI shown in parentheses. Lambda is the spatial correlation of error terms.

Table 4. Spatial error models for violent crime in New York City

	(1) Only Physical Greenspace	(2) W/ Park Use	(3) W/ Street Activity	(4) W/ Park Use and Street Activity
Intercept	-0.035 (-0.083, 0.013)	-0.032 (-0.079, 0.014)	-0.033 (-0.081, 0.015)	-0.031 (-0.077, 0.016)
Tree Canopy	-0.037* (-0.068, -0.005)	-0.039* (-0.071, -0.007)	-0.032* (-0.064, -0.001)	-0.036* (-0.067, -0.004)
Grass Coverage	-0.031 (-0.065, 0.004)	-0.029 (-0.063, 0.005)	-0.036* (-0.070, -0.001)	-0.035* (-0.069, -0.0003)
Park Visits		-0.068*** (-0.098, -0.037)		-0.070*** (-0.100, -0.040)
Distance Traveled to Parks		-0.012 (-0.045, 0.021)		-0.022 (-0.056, 0.011)
Street Activity			-0.047*** (-0.075, -0.020)	-0.052*** (-0.080, -0.024)
Population (log)	0.262*** (0.234, 0.290)	0.259*** (0.231, 0.287)	0.259*** (0.231, 0.287)	0.255*** (0.227, 0.283)
Working population (log)	0.208*** (0.178, 0.238)	0.208*** (0.178, 0.237)	0.196*** (0.166, 0.227)	0.195*** (0.165, 0.225)
Median Household Income (log)	0.013 (-0.038, 0.064)	0.021 (-0.030, 0.072)	0.013 (-0.038, 0.063)	0.021 (-0.030, 0.071)
Percent Unemployed	0.049*** (0.021, 0.077)	0.046** (0.018, 0.074)	0.045** (0.018, 0.073)	0.042** (0.014, 0.070)
Percent below poverty line	0.086*** (0.041, 0.132)	0.085*** (0.040, 0.131)	0.088*** (0.042, 0.133)	0.086*** (0.040, 0.131)
Percent living in crowded housing	0.028 (-0.006, 0.061)	0.024 (-0.010, 0.057)	0.027 (-0.006, 0.061)	0.024 (-0.010, 0.057)
Percent w/ less than high school diploma	0.049* (0.001, 0.097)	0.041 (-0.007, 0.089)	0.050* (0.002, 0.098)	0.041 (-0.007, 0.089)
Percent w/ Bachelor's degree or higher	0.120*** (0.074, 0.166)	0.128*** (0.081, 0.175)	0.122*** (0.076, 0.168)	0.128*** (0.081, 0.175)
Lambda	0.52	0.5	0.52	0.5
AIC	3,531.41	3,516.71	3,521.98	3,505.24
Δ AIC from Model (1)		-14.7	-9.43	-26.17

Notes. *p<0.05; **p<0.01; ***p<0.001. 95% CI shown in parentheses. Lambda is the spatial correlation of error terms.

Discussion

We found significant, negative associations between tree canopy, park visits and street activity with crime in Chicago, and then replicated these results in New York City in a preregistered report. By comparing the models, which include park visits, street activity, or both, we see that interaction with greenspace and street activity account for unique variance in predicting crime. This lends support for multiple pathways for the effects of greenspace and street activity on crime and suggests that the greenspace effects may be due to psychological/cognitive mechanisms and not to sociological mechanisms per se. The observation of multiple pathways for these effects will help design future research on interventions to reduce crime. Additionally, we observe that adding park visits to our models does not change the strength of association between tree canopy and crime. This could indicate that long-term passive exposure to natural elements, although having a smaller effect, is not replaceable by short-term active engagement with nature.

The strength of associations for each of these independent variables was stronger in Chicago, where overall crime levels are also higher at the time of the study, compared to New York City. This could be for several reasons. The parks in Chicago and New York City may have different facilities, sizes, and landscaping. Proportions of trees lining streets compared to on private property may also vary, and these may drive differences in the strength of associations as well. The only difference in results between Chicago and New York City was for which crime category tree canopy's influence reached significance, although for both cities tree canopy did predict less violent and non-violent crime. These two cities have very different populations, geographies, and baseline crime levels so the convergence of results in our analysis provides substantial evidence for the consistent influence of these neighborhood characteristics across environments.

Given the observed strength of associations, the results suggest that support for green infrastructure (and its use) and community programs to facilitate local street activity could provide cost-effective ways to address crime, while additionally providing many other socioeconomic and health co-benefits. For those measures to be most effective, it will also be important to understand sociocultural elements that influence how people voluntarily engage with greenspace (34, 35). The cost of crime is difficult to calculate, however one method estimates that the direct and indirect costs for violent crime in Chicago, for example, were $5.31 billion in 2010 (36, 37). Thus, the 14% reduction in violent crime associated with an increase of one park visit on average per month, could save the city $743 million, with approximately $154 million in direct savings.

Future research is needed to investigate more directly the causal nature of the relationship between urban greenspace and crime, as well as determining the mechanisms of this effect. Longitudinal studies examining the physical presence of greenspace lend support to a causal relationship between greenery and lower crime, with less crime being observed after increased greening or tree planting (13, 14, 38), and more crime being observed after a natural event that led to a reduction in trees (e.g., the Emerald Ash Borer infestation that killed many Ash trees (39)). However, the detailed mechanism behind these effects remains unclear (40). A tree-lined street may indicate cues of social order or property that is cared for, indicating territoriality, which could lead to less crime (41, 42). Alternatively, the cognitive benefits attained after exposure to natural elements may lead to less crime, as increased attention functioning has been shown to mediate reduced aggression (27, 28, 32). Natural environments also have been shown to increase positive affect (43) as well as pro-social behavior (44, 45), both of which could translate to lower crime levels in neighborhoods where residents visit parks more or there is greater tree canopy. Future research could also explore what neighborhood characteristics are associated with high levels of street activity (26, 46).

Importantly, these relationships could work in the other direction – i.e., residents may spend less time on the street or visiting parks *because* there is higher crime in their neighborhood. If this were true, there may not be multiple pathways, but rather one pathway in which higher crime causes less use of neighborhood amenities. However, we do not believe reverse causality can fully explain our results, as our park visits observations are not limited to one's home neighborhood, but also include parks visited throughout the city. Longitudinal data for park visits and street activity may be useful in creating causal models to answer these questions. Longitudinal studies could also be used to compare crime levels before and after localized campaigns to increase park usage (47), after verifying the effectiveness of the campaigns.

While exploring a novel large dataset, this study is limited by the sample of smartphone users that create our mobility data in Chicago and New York City. However, these data have been shown to be reasonably representative across census tract populations (48) and constitute a substantial subset of the residents for each of these major cities. Additionally, our measure of street activity could be improved as it does not measure the quality or type of social interactions that residents may engage in while being active in their neighborhood. Certain street activity behaviors, and the resulting social interactions, may be more or less influential on crime levels. Being able to quantify the nature of local social interactions would be of great utility, but is also a very difficult proposition and would require the use of additional datasets.

In addition to providing insights into the relationship between greenspace, street activity, and crime, this study demonstrates how cell phone mobility data – a new, large scale data source - can be leveraged to quantify neighborhood characteristics at scales previously impossible to access (49). These near-continuous empirical measures of mobility behavior can be used to address questions from a range of fields, including urban planning, health sciences, sociology, geography, and psychology and can help to revolutionize how social scientists conduct research.

In conclusion, utilizing cell phone trace data to study human mobility presents a novel framework for examining intentional behaviors in cities that have practical implications for urban planners and policy makers, and theoretical implications for how greenspace and local street activity influence crime. Realized park access, tree canopy and street activity are all associated with safer neighborhoods. Our results support multiple pathways for the effects of greenspace and street activity on crime. These data also support the notion that much of our behavior is determined by environmental factors and is not solely attributable to individual choices (40). Ensuring equitable access to urban greenspace and support for neighborhood amenities to promote local street activity may be ways to help cities reduce crime, leading to more sustainable and inclusive cities, ecologically and socially.

Materials and Methods

Land Cover Data. Light detection and ranging (LiDAR) data for Chicago and New York City were downloaded from the University of Vermont's Spatial Analysis Lab website. LiDAR data, collected in 2010 at 2ft resolution, were classified into seven land cover variables – trees, grass, road/rail, building, bare soil/sand, water, and other pavement. Percent tree canopy and percent grass coverage was calculated for each census tract in ArcGIS, version 10.5.1 (50). Census tract boundaries from 2010 are used.

Cell Phone Trace Data. Cell phone location data were recorded in May 2017 by active applications on users' phones, aggregated by LiveRamp and provided by Carto. Using OpenStreetMaps (51), location points were removed where individuals were in transit, as identified by points within 10 meters of motorways, trunk (e.g. highway), primary or secondary roads, railways, and subways. A home census tract was defined for each user (i.e., device) by its modal location between midnight and 6am. In Chicago, this location could be defined for N = 95,000 users. In New York, this location could be defined for N = 191,000 users. The local street activity for each census tract was defined as the share of residents' locations recorded in the immediate vicinity of their home, following Saxon (48). Locations are normalized by device before averaging by tract. The "vicinity" is defined as a constant-population region of Census tracts surrounding but not including the user's home. The tracts are chosen as the nearest 'n' tracts whose combined population is less than 40,000 people, but for which the next tract ('n+1') would exceed that threshold. This definition is designed to be "node split invariant," that is, to account for census tracts' variable sizes and populations (52). The total activity is corrected for residents' activity in tract 'n+1'. Park and museum visits per user, per month, were calculated by identifying cell phone locations within park and museum boundaries. Number of visits observed is tied to our selection criteria in counting device observations, so these criteria are held constant between cities. These visits were then aggregated by census tract. Park and museum boundaries were extracted from OpenStreetMap data using existing tags. Parks were identified by: *leisure* as park, dog park, playground, nature reserve, garden or golf course, *landuse* as recreation ground, *natural* as beach, or *boundary* as protected area. Museums are classified under the *tourism* tag as museum, zoo, or aquarium, or *amenity* of planetarium. Data were processed using Open Science Grid (53, 54). For more details on the processing of these data, see (48).

Crime data. Crime data for Chicago and New York were downloaded from each city's open data portal (55, 56). Chicago crime data were from 2010 and New York crime data were from 2009-2011. Crimes were categorized as violent or non-violent and then aggregated to the census tract level in ArcGIS. Any crime without location data, or with location listed as the precinct headquarters, was removed. In Chicago, violent crimes included assault, battery, criminal sexual assault, homicide, kidnapping, robbery, and sex offense (28% of total crime). In New York violent crimes included murder and non-negligent manslaughter, homicide, robbery, felony assault, and kidnapping & related offenses (7% of total crime). Locations are not reported for rape and other sex-related crimes in New York data and were thus not included in the crime count. As some census tracts had no reported violent crimes in both Chicago and New York City, all violent crime counts were increased by 1 before completing log-transformation.

Demographics Data. Demographics data were downloaded from the U.S Census Bureau website, American FactFinder, using the 2010 Decennial Census and American Community Survey 5-year estimates (2006-2010). Working population was computed as the total number of jobs in the census tract from the Workplace Area Characteristics table of the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics for 2010 (57). Census tracts with no resident population (e.g. airports) and those missing other demographic data were removed. 792 census tracts in Chicago and 2102 census tracts in New York City were included in the models.

Statistical models. We used a two-step regression for all our models. All independent variables were z-scored, with median household income, population and working population first being log-transformed due to their positive skew. See Supplemental Figures S1 and S2 for the correlation tables of all variables in Chicago and New York City, respectively. Non-violent and violent crime were also log-transformed, and as some census tracts had no reported violent crimes in both Chicago and New York, violent crime counts were increased by 1 before completing log-transformation. We first regressed out percent Black population and percent Hispanic population from crime, either non-violent or violent, using a simple linear model. This allows us to statistically adjust for previously shown associations between race/ethnicity and crime, for which there is no theoretical justification, but rather are proxies which can indicate forms of residential inequality which are unable to be directly measured. Given the spatial nature of the data, we then ran all models as hierarchical linear models with neighborhood as a random intercept, using the residuals of the first linear regression as the dependent variable. In Chicago, neighborhoods are officially called Community Areas (58), while in New York City the equivalent areas are defined as Neighborhood Tabulation Areas (59). If the hierarchical model had significant spatial autocorrelation as indicated by global Moran's I, we then conducted Lagrange multiplier diagnostics to determine whether a spatial lag model or spatial error model was more appropriate. All models were computed in R, version 3.3.3 (60). R packages used for data processing, visualization, and analysis were: apaTables, corrplot, dplyr, ggplot2, gridExtra, lme4, lmerTest, RColorBrewer, rgdal, spdep, and stargazer. Land cover, demographics, and crime data are available on Open Science Framework (https://osf.io/dx5ce/). Cell phone mobility data is not available as it is owned by Carto.

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Supporting Information Appendix

Table S1. Hierarchical and spatial error models comparing museum and park visits in Chicago

	Non-Violent Crime		Violent Crime	
	W/ Museum Visits	W/ Park Visits and Museum Visits	W/ Museum Visits	W/ Park Visits and Museum Visits
Intercept	-0.055 (-0.121, 0.011)	-0.053 (-0.117, 0.011)	-0.026 (-0.091, 0.040)	-0.022 (-0.083, 0.039)
Tree Canopy	-0.054** (-0.087, -0.021)	-0.053** (-0.086, -0.021)	-0.027 (-0.066, 0.012)	-0.030 (-0.068, 0.009)
Grass Coverage	-0.009 (-0.039, 0.022)	-0.005 (-0.035, 0.026)	0.004 (-0.031, 0.040)	0.0004 (-0.035, 0.035)
Museum Visits	-0.086*** (-0.119, -0.054)	-0.046* (-0.081, -0.010)	-0.055** (-0.095, -0.015)	-0.014 (-0.057, 0.029)
Park Visits		-0.099*** (-0.137, -0.060)		-0.112*** (-0.156, -0.067)
Distance Traveled to Parks		-0.002 (-0.039, 0.034)		-0.019 (-0.062, 0.023)
Street Activity	-0.108*** (-0.138, -0.077)	-0.103*** (-0.134, -0.072)	-0.106*** (-0.143, -0.069)	-0.102*** (-0.139, -0.064)
Population (log)	0.372*** (0.344, 0.400)	0.376*** (0.348, 0.403)	0.383*** (0.350, 0.415)	0.390*** (0.358, 0.422)
Working population (log)	0.157*** (0.125, 0.189)	0.149*** (0.117, 0.181)	0.134*** (0.097, 0.171)	0.125*** (0.088, 0.162)
Median Household Income (log)	0.025 (-0.029, 0.079)	0.020 (-0.034, 0.073)	-0.031 (-0.093, 0.032)	-0.036 (-0.097, 0.026)
Percent Unemployed	0.081*** (0.044, 0.118)	0.079*** (0.043, 0.116)	0.036 (-0.005, 0.078)	0.039 (-0.002, 0.080)
Percent below poverty line	0.044 (-0.003, 0.090)	0.045 (-0.001, 0.091)	0.060* (0.007, 0.112)	0.061* (0.009, 0.113)
Percent living in crowded housing	0.004 (-0.027, 0.034)	0.004 (-0.026, 0.033)	0.014 (-0.022, 0.049)	0.013 (-0.022, 0.047)
Percent w/ less than high school diploma	-0.013 (-0.061, 0.035)	-0.023 (-0.070, 0.025)	-0.041 (-0.096, 0.014)	-0.058* (-0.113, -0.003)
Percent w/ Bachelor's degree or higher	0.092** (0.025, 0.158)	0.113*** (0.047, 0.180)	0.011 (-0.064, 0.085)	0.032 (-0.043, 0.107)
Lambda			0.6	0.58
AIC	580.02	558.51	776.82	757.01

Notes. *p<0.05; **p<0.01; ***p<0.001. 95% CI shown in parentheses. Lambda is the spatial correlation of error terms.

Table S2. Spatial error models comparing museum and park visits in New York City

	Non-Violent Crime		Violent Crime	
	W/ Museum Visits	W/ Park Visits and Museum Visits	W/ Museum Visits	W/ Park Visits and Museum Visits
Intercept	-0.047 (-0.097, 0.002)	-0.045 (-0.093, 0.003)	-0.033 (-0.082, 0.015)	-0.031 (-0.078, 0.016)
Tree Canopy	-0.012 (-0.036, 0.012)	-0.013 (-0.038, 0.011)	-0.031 (-0.062, 0.001)	-0.033* (-0.065, -0.002)
Grass Coverage	-0.010 (-0.038, 0.017)	-0.009 (-0.036, 0.018)	-0.040* (-0.075, -0.005)	-0.038* (-0.073, -0.004)
Museum Visits	0.007 (-0.018, 0.032)	0.021 (-0.004, 0.047)	0.001 (-0.031, 0.033)	0.017 (-0.015, 0.050)
Park Visits		-0.055*** (-0.079, -0.031)		-0.074*** (-0.105, -0.043)
Distance Traveled to Parks		0.0005 (-0.026, 0.027)		-0.019 (-0.053, 0.014)
Street Activity	-0.070*** (-0.092, -0.049)	-0.071*** (-0.093, -0.050)	-0.049*** (-0.076, -0.021)	-0.053*** (-0.080, -0.025)
Population (log)	0.280*** (0.259, 0.301)	0.278*** (0.257, 0.299)	0.256*** (0.228, 0.284)	0.252*** (0.224, 0.280)
Working population (log)	0.219*** (0.196, 0.243)	0.219*** (0.196, 0.243)	0.197*** (0.166, 0.227)	0.195*** (0.164, 0.225)
Median Household Income (log)	0.003 (-0.036, 0.041)	0.008 (-0.031, 0.047)	0.015 (-0.036, 0.066)	0.020 (-0.031, 0.071)
Percent Unemployed	0.070*** (0.050, 0.091)	0.069*** (0.048, 0.089)	0.046** (0.019, 0.074)	0.043** (0.016, 0.071)
Percent below poverty line	0.096*** (0.061, 0.130)	0.095*** (0.060, 0.130)	0.092*** (0.046, 0.137)	0.088*** (0.042, 0.133)
Percent living in crowded housing	-0.007 (-0.033, 0.019)	-0.011 (-0.037, 0.015)	0.028 (-0.006, 0.062)	0.024 (-0.010, 0.057)
Percent w/ less than high school diploma	-0.008 (-0.045, 0.030)	-0.013 (-0.050, 0.024)	0.048 (-0.0004, 0.096)	0.040 (-0.008, 0.088)
Percent w/ Bachelor's degree or higher	0.094*** (0.058, 0.131)	0.099*** (0.062, 0.136)	0.121*** (0.074, 0.167)	0.125*** (0.077, 0.172)
Lambda	0.65	0.64	0.52	0.51
AIC	2,425.26	2,408.93	3,522.01	3,504.13

Notes. *p<0.05; **p<0.01; ***p<0.001. 95% CI shown in parentheses. Lambda is the spatial correlation of error terms.

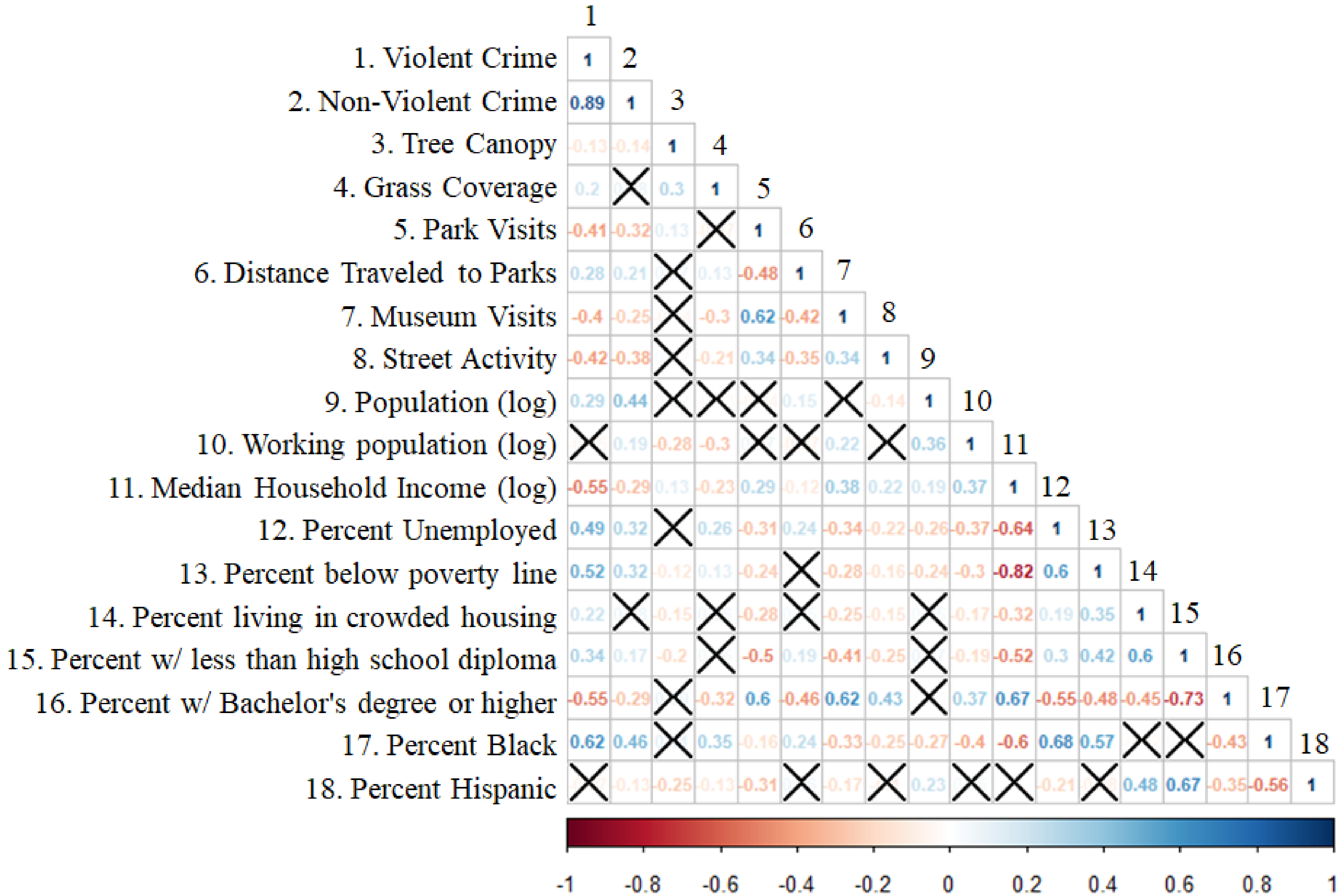

Figure S1. Correlation Matrix of all variables for Chicago. "X" indicates correlations not significant at p=0.001.

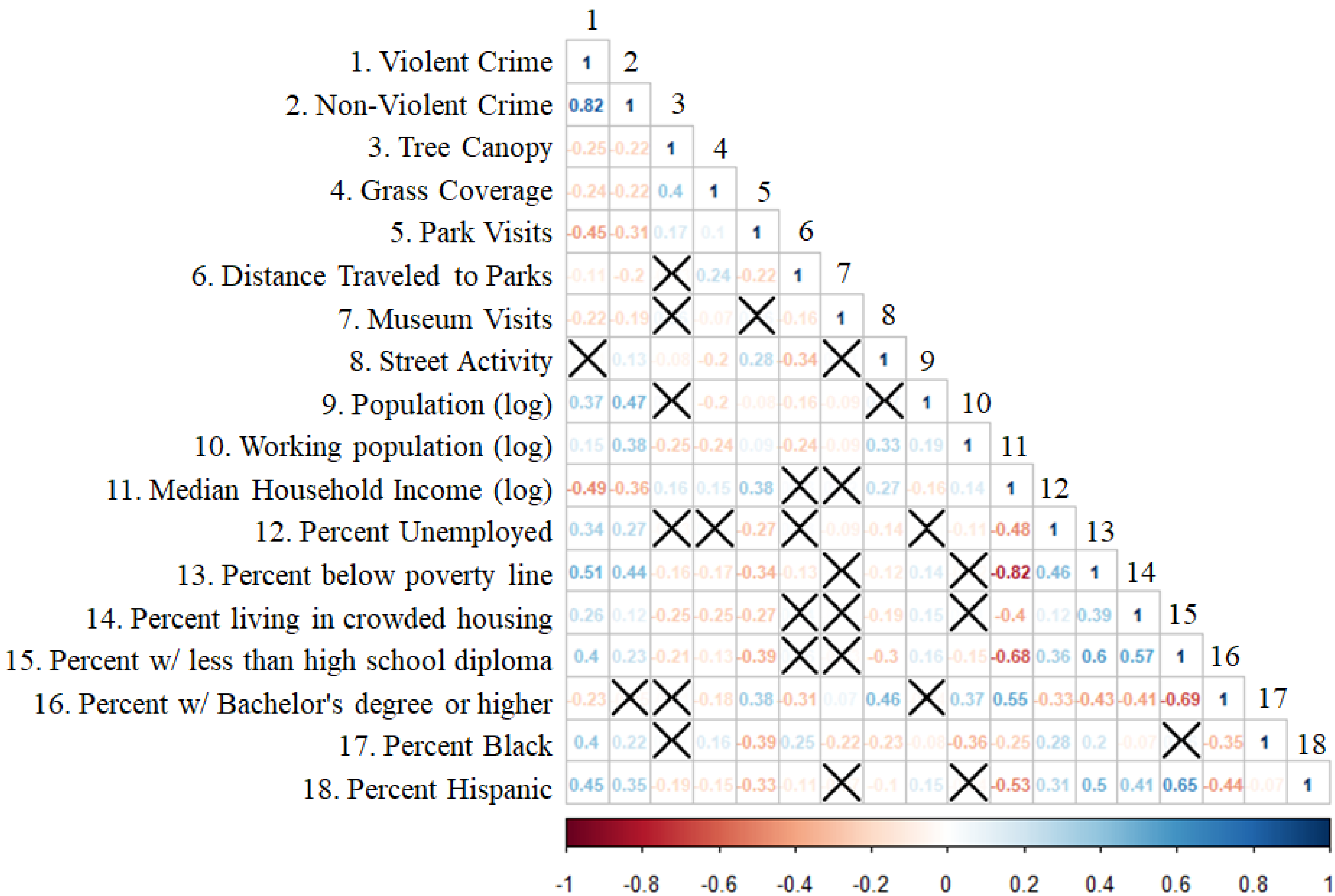

Figure S2. Correlation Matrix of all variables for New York City. “X” indicates correlations not significant at p=0.001.