Strategies and Inequities in Balancing Recreation and COVID Exposure when Visiting Green Spaces

Abstract

Green spaces are beneficial for physical and mental health, especially during and after disasters. The COVID-19 pandemic, however, created a trade-off: parks could be therapeutic but also could expose people to infection. This paradox posed inequities as marginalized populations often have less access to parks and were hit harder by the pandemic. We combined cellphone-generated mobility data with demographic indicators, a neighborhood survey, and local infection rates to examine how residents of Boston, MA, navigated this tradeoff in April – August 2020. We hypothesized that they adopted strategies for mitigating infection exposure—including fewer park visits and prioritizing parks that might have lower infection risk, including larger parks with more opportunity for social distancing and parks near home with fewer unfamiliar faces—but that marginalized populations would have less opportunity to do so. We also introduce a novel measure of exposure per visit based on the volume of other visitors, infection rates, and park size. Bostonians made fewer park visits relative to 2019 and prioritized larger parks and parks closer to home. These strategies varied by community. Experiences of the pandemic were influential, as communities that perceived greater risk or had more infections made more park visits, likely because they were a relatively safe activity. Communities with more infections tended to avoid nearby parks. Inequities were also apparent. Communities with more Black residents and infections had greater infection exposure per visit even when controlling for the types of parks visited, highlighting difficulties in escaping the challenges of the pandemic.

Introduction

Parks and urban green spaces are essential community infrastructure (Kuo, 2011). They create opportunities for visitors to gather, exercise, and relax, thereby providing physical and mental health benefits. Most obviously, parks enable physical activity (Babey et al., 2008; Seltenrich, 2015), which is critical for a healthy lifestyle (World Health Organization, 2020; USDHHS, 2018). This is especially important in urban areas, where dense development makes parks one of the few public spaces suitable for recreation. Green spaces also nurture emotional well-being and diminish stress (Payne et al., 1998; Sturm and Cohen, 2014; Thompson Coon et al., 2011) and are contexts for interaction and relationship-building between community members (Baur and Tynon, 2013). During the early months of the COVID-19 pandemic, however, communities were faced with a crucial tradeoff: visiting parks could alleviate some of the stress and sedentariness caused by the pandemic, but it could also expose people to infection. Here we examine how communities across the greater Boston region navigated these competing considerations.

The trade-off between visiting parks and exposure to COVID-19 was especially challenging because parks can be crucial for coping and recovery following disasters. After Hurricane Katrina, for example, people from flooded areas cited escapism and activity as some of the largest motivators for visiting parks at that time (Rung et al., 2011). Likewise, studies from numerous countries have found that people experienced sharp drops in physical and mental health during the COVID-19 pandemic, especially in the early months (Aknin et al., 2021; Bierman and Schieman, 2020; Holingue et al., 2020; Wang et al., 2020), which could be addressed in part by the use of parks and green spaces (Jackson et al., 2021; Xie et al., 2020). Further, public health guidelines, including restrictions on gatherings and the closure of workplaces and gyms, made parks a unique outlet for exercise. These outlets, however, were still social in nature, potentially convening many people and raising the potential for transmission of the virus. This created a conflict that in fact *lowered* park visitation, partially due to closures. For example, an initial burst in park visitation levels led officials in New Jersey to shut down parks over fears of transmission (Volenec et al., 2021). Similarly, Landry estimated that there was a 26% reduction in trips to outdoor recreation spaces post-COVID-19 in the United States (Landry et al., 2021). That said, once society began reopening in May 2020, park visitations rebounded to pre-COVID levels (Jay et al., 2021).

Aware of the infection risk presented by social activity, people were forced to make choices about how to balance essential needs with potential exposure to COVID-19. This was true in many domains, with some amenities posing more striking trade-offs than others (Benzell et al., 2020). Though we now know that outdoor activities are low-risk, that was not well understood in the early months of the pandemic. Consequently, the strategies that different communities adopted to balance the essential need of outdoor activity against the risk of infection exposure likely impacted their well-being. It also raises important questions about equity and the extent to which some populations were capable of visiting parks while also limiting their exposure to infection. For instance, Jay et al. (2021) have found that park visitation saw a greater rebound in predominantly White communities than in communities of color. It is not yet known, however, why these disparities existed.

The current study takes an urban analytic (or urban informatics; O'Brien, 2018) approach to examining how the residents of Boston, MA’s neighborhoods differed when navigating the trade-off between park visitation and infection exposure in the early months of the pandemic. This entails the analysis of cell phone-generated mobility data provided by SafeGraph, which capture movements between neighborhoods and places of interest, including green spaces, in conjunction with multiple other data sets describing the demographics, infrastructure, perceptions and attitudes, and infection rates of each neighborhood. We test four sets of questions and hypotheses regarding park visitation in the early months of the pandemic. The first two regard the actual patterns of park visitation. The third and fourth go a step further, asking how park visitation patterns did or did not reflect strategies for mitigating exposure to infection.

(1) *How did overall park visitation change during the early months of the pandemic?* We quantify not only the frequency of visitation but also the types of parks visited and

how far people traveled to visit parks. We hypothesize that visits dropped in general but especially at small parks, which are more intimate and may have been perceived as creating greater infection risk. We also hypothesize that people prioritized parks close to home to limit exposure to unfamiliar individuals whose infection status might be uncertain.

(2) *How did patterns of visitation differ across communities with different demographic compositions?* This question is central to understanding equity in the tendency or ability to utilize public green spaces. In doing so, we account for the distribution of parks as previous research has found that historically marginalized communities tend to have less access to parks nearby, which could drive differences in visitation during the pandemic (Abercrombie et al., 2008; Rigolon, 2016). We also control for transportation infrastructure, which can influence the willingness or ability to travel to parks (Zhang and Zhou, 2018),

(3) *How did resident attitudes and experiences during the pandemic explain visitation strategies?* We test this using indicators from a neighborhood-level survey and granular infection rate data. As noted, parks were unique among essential amenities in that they had more visits than previous years in the United States starting in May 2020, reflecting a belief that they were on of the safest options for public activities (Jay et al., 2021). We thus hypothesize that those who perceived COVID-19 as posing a major risk would see themselves as having very few other options for activities, leading them to visit parks more often; meanwhile, communities where residents were comfortable with high-risk behaviors saw themselves as having alternatives, lowering visits. We do, however, hypothesize that those who perceived greater risk prioritized

parks that they believed would have fewer visitors and therefore create less exposure risk (Seong and Hong, 2021)—meaning smaller parks closer to home. We also test the hypothesis that communities with more infections visited parks *further* from home as a way of limiting exposure.

(4) *How did visitation strategies predict different levels of exposure risk when visiting parks?* We present an original calculation of exposure that incorporates: the quantity of visitors to each park; the infection rates of the communities of these visitors; and park size, as a proxy for the ability to socially distance. This goes beyond previous efforts, which have used only a subset of these components (Hong et al., 2021; Sun et al., 2020; Yue et al., 2021). This permits a full assessment not only of the strategies communities adopted for balancing park visitation with infection exposure, but also of how effective they were. In particular, we assess the extent to which variations in exposure were a product of strategy or of certain populations having limited ability to escape high infection rates.

In the analysis that follows, we find consistent evidence that Bostonians did indeed adjust their park visitation strategies in ways that would tend to mitigate infection risk. As hypothesized, these tendencies varied by community, driven in part by greater fear of and exposure to infection locally. Further, there was evidence of inequities as some marginalized populations had difficulty mitigating infection risk *even when* employing strategies intended to do so.

Methods

The study used data from Boston, MA, aggregated to census block groups (CBGs), which are a good proxy for neighborhoods (avg. pop. approx. 1,000 people) and the most granular level of analysis for which many of the key datasets and variables were available. The analysis was limited to 509 CBGs in Boston with at least 250 residents. We compare May-August 2020 with the same period in 2019 as a baseline because it was the earliest part of the pandemic following the reopening of parks.

Data Sources and Measures

We used five data sources: (1) cross-community mobility records derived from cell phone records, generated by SafeGraph, a data company that aggregates anonymized location data from numerous applications to provide insights about physical places, via the Placekey Community; (2) population descriptors from the American Community Survey's 2014-2018 five-year estimates; (3) transportation infrastructure provided by the City of Boston; (4) community perceptions and attitudes during COVID-19 from a strateified random-sample neighborhood survey; and (5) monthly COVID-19 case counts derived from infection records. We accessed or aggregated all data at the CBG level, except where noted. For certain point data we calculated isochrones, or the quantity of locations accessible from the centroid of a CBG within an established amount of time for a given mode of transportation (e.g., 10 minutes walking; using the ORS Tools plug-in for QGIS). Specific details are noted for each dataset. Descriptive statistics for and correlations between all variables are reported in Table 1.

Cellphone-Generated Mobility Records

We used SafeGraph's monthly "Patterns" dataset to measure park visitation patterns. The data are generated by SafeGraph using a panel of GPS pings from anonymous mobile devices. Each device is attributed to an estimated home CBG based on its most common nighttime location. SafeGraph also identifies all stay points of these devices that occur within points of interest (POI), including parks and green spaces among various other amenities, treating them as “visits.” The published data aggregate these pieces of information to generate a mobility matrix of the monthly number of visits by the assumed residents of each CBG to each point of interest. To enhance privacy, SafeGraph suppresses counts of visits from a given CBG to a particular POI if there were fewer than five such visits in a month by setting one or fewer visits equal to 0 and 2-4 visits equal to 4.

We accessed the subset of this matrix that quantified visits from each CBG to each park, defined as POIs fitting the following criteria: (1) categorized by SafeGraph under "Nature Parks and Other Similar Institutions"; (2) merged by spatial join with the OpenSpace dataset provided by the City of Boston (https://data.boston.gov/dataset/open-space); (3) described as "Parks, Playgrounds & Athletic Fields" or "Parkways, Reservations & Beaches" by the OpenSpace dataset or contain “Park” in the name; (4) was not classified as having private ownership. This resulted in 187 green spaces. We accessed this matrix separately for each month April-June. We then calculated three variables for each CBG for each month: *frequency of visits to parks*, as a sum of all visits to all parks by residents; *percentage of visits to large parks*, defined as (>5 acres per OpenSpace; 33.2% of parks); *visits to parks close to home*, defined as <15-minute walk from the CBG’s centroid (measured as a binary variable as 4.5% of CBGs had any such visits during COVID). We then averaged all measures across months for CBG-specific measures. We also calculated average distance traveled to parks for general descriptive analysis.

We acknowledge that these data may give a clearer view of park visitation in some communities than others, dependent on the extent to which residents are represented in SafeGraph’s data. In some studies this would call for controlling for the number of devices per capita identified in each community. In the current case, however, this is unnecessary because we include the same measure in 2019 as a control in all models, thereby measuring shifts in behavior during the pandemic rather than absolute measures. This should account for any biased representation across communities as said bias should be approximately the same between 2019 and 2020.

Census Indicators

We drew population descriptors from the U.S. Census' American Community Survey's 2014-2018 estimates for all CBGs in Massachusetts. Community indicators included total population, ethnic composition (i.e., proportion Asian, proportion Black, proportion Latinx, proportion White), income, homeownership, and commuting characteristics (e.g., proportion commuting by public transit; proportion with a commute greater than an hour).

Transportation

We accessed shapefiles of T stations and bus stops published by the City of Boston (data.boston.gov) and calculated access to each as the count located within a 10-minute walking isochrone from each CBG's centroid.

Survey

The Boston Area Research Initiative at Northeastern University, the Center for Survey Research at University of Massachusetts Boston, and the Boston Public Health Commission conducted the Living in Boston During COVID survey in July 2020. The survey consisted of items measuring respondents' experiences during the first months of the COVID-19 pandemic, including their ability and tendency to follow social distancing recommendations; attitudes towards regulations; and the economic and personal impacts of the pandemic. The survey utilized a stratified random sample design that divided the city of Boston into 25 distinct neighborhoods based on social, demographic, and historical salience. Four neighborhoods with a higher proportion of Black or Latinx populations were oversampled (Hyde Park, Mattapan, Lower Roxbury, and East Boston-Eagle Hill). The survey was also administered online to members of a previously-constructed panel that had been recruited using the same 25 neighborhood stratified sample design. The final sample included 1,626 respondents (response rate = 26.88%). Survey responses were mapped to census tracts, which contain CBGs. We thus calculated tract-level measures by taking the average of a given measure for all resident respondents, weighted for non-response bias within neighborhoods. We then imputed tract-level measures to their CBGs.

We utilized two measures from the survey. Perception of infection risk was measured with 3 items reflecting concern for oneself and family members regarding COVID-19 (e.g., "In your opinion, how much of a risk to your health and well-being is it to be within 6 feet of people in public?"; $\alpha = .82$). High-risk behaviors were measured with 4 items reporting the frequency with which the respondent engaged in behaviors that were likely to place them at elevated risk for exposure to COVID-19 infection during the past 7 days when completing the survey (in summer 2020). These included eating at a restaurant, bar, or club; visiting someone else's home; attending any kind of event where more than ten people were gathered; or having people who do not live with you in your home, either to work or visit ($\alpha = .65$). We aggregated this latter measure as the proportion of individuals who participated in any high-risk behaviors. More on the data collection methodology and items is available in the Supplementary Online Materials.

Infection Cases

BPHC provided daily COVID-19 infection cases mapped to the tract level. We aggregated these monthly for April-August 2020 to estimate the total infection risk in each tract. We then imputed counts from each tract to all CBGs therein.

Estimating Exposure

A major part of the study was to test whether strategies of park visitation did or did not mitigate exposure to infection risk. Total exposure was calculated as follows:

$$Total\ Exposure(h) = \sum_{g} \frac{\sum_{t,g} p_t * v_{t,g}}{A_g} * v_{h,g}$$

where h is the CBG of interest, g is a green space, t is any of the CBGs that visited that park, v is visits from a given CBG to a given park, p_t is infection rate in a given CBG (count divided by total population), and A_g is area in acres of a given park. In this way total exposure sums the estimated the number of individuals visiting the park who might be infected with COVID-19 (per the infection rate of their home neighborhood) for all visits from CBG h to all parks, divided by the area of the park as a proxy for the ability to socially distance. This follows the models of previous studies using place visitation data to estimate risk exposure (Hong et al., 2021; Sun et al., 2020; Yue et al., 2021). Average exposure per visit to park was then derived from this calculation by dividing by the total number of visits made by residents of h, or:

$$Avg.\,Exposure\ per\ trip(h) = \frac{\sum_g \frac{\sum_{t,g} p_t * v_{t,g}}{A_g} * v_{h,g}}{\sum_g v_{h,g}}$$

At the end of the analysis, in order to better understand how exposure results from different contexts, we decompose the measure into three components, all calculated as weighted averages: acreage of parks visited ($\frac{\sum_g A_g * v_{h,g}}{\sum_g v_{h,g}}$), volume of visitors to parks visited ($\frac{\sum_g (\sum_{t,g} v_{t,g}) * v_{h,g}}{\sum_g v_{h,g}}$), and infection load of parks visited ($\frac{\sum_g (\sum_{t,g} p_t * v_{t,g}) * v_{h,g}}{\sum_g v_{h,g}}$).

Analysis

We used generalized linear models to assess the impacts that demographic factors, transportation access, survey-measured perceptions and behaviors, and local infection rates had on park visitation patterns across CBGs. A Poisson (logit) link was used for total visits because it was a count variable with a long tail. A logistic regression was used for having any visits to nearby parks as it was a binary variable. Regressions predicting percentage of visits to large parks, total exposure, average exposure, and the three components of the decomposed exposure measure used a standard linear model; weighted volume of visitors and park size were log-transformed to account for skew.

Results

Descriptive statistics

As illustrated in Figure 1, park visitation in Boston dropped by more than 2/3rds at the onset of the pandemic (compared to February 2020). Meanwhile, the average distance traveled also dropped by approximately half, indicating that people prioritized parks near their homes at this time. They were also more likely to go to larger parks, with proportions quickly rising from 50-60% to nearly 70%. Each of these effects was consistent throughout the remainder of 2020. We also see in Figure 2 that both large and small parks are rather evenly distributed throughout Boston, and do not appear to cluster near neighborhoods predominated by White nor Black or Latinx populations (also see correlations in Table 1). This would suggest that any differences in behavior we observe by neighborhood are not merely driven by access to parks.

Community Variation in Park Visitation Patterns: Demographics

Generalized linear models assessed the impacts of demographic factors and transportation access on park visitation patterns and shifts toward (or away from) local or large parks as ways to mitigate exposure across CBGs (see Analysis for more detail). Each model controlled for the outcome measure pre-COVID and the number of parks within 15 minutes walking to the model (or large parks, as appropriate; all results reported in Table 2).

Communities with a higher proportion of Black residents (ß = 0.15, $p < .001$), Latinx residents (ß = 0.06, $p < .001$), and residents who commuted to work by car (ß = 0.05, $p < .001$) or over 60 minutes (ß = 0.02, $p < .001$), as well as had access to more bus stops (ß = 0.02, $p < .001$), visited parks more often relative to visits pre-COVID (i.e., saw less of a drop in their total visits). CBGs with a higher population density (ß = -36.2, $p < .001$), proportion of Asian residents (ß = -0.02, $p < .01$), median household income (ß = -2.73, $p < .001$), and access to subway stops (ß = -0.02, $p < 0.01$) had fewer visits relative to 2019. The number of nearby parks had no predictive effect, indicating that these effects were independent of the geographic distribution of parks.

In terms of shifts in the types of parks visited, access to bus stops (ß = 0.01, $p < 0.05$) was positively associated with the likelihood of visiting any nearby parks, whereas population density had a negative effect (ß = -0.002, $p < .05$). The shift toward large parks was not predicted by any demographic or transportation features.

Community Variation in Park Visitation Patterns: Perceptions and Experiences

To assess the impact of COVID-related attitudes and experiences on park visitation patterns, we added perceptions of risk, proportion of residents engaging in high-risk behaviors, and local infection rates to the initial models. Communities whose residents perceived more risk of COVID-19 infections (ß = 0.03, $p < .001$) and had more infections in April (ß = 0.68, $p < .001$) also visited parks relatively more often. In contrast, communities where a greater percentage of residents engaged in at least one high-risk activity in the summer (ß = -2.50, $p < .001$) had fewer park visits.

Communities with a higher number of COVID cases in April (ß = -0.006, $p < 0.05$) were less likely to have any visits to nearby parks, as did communities with more residents who engaged in high-risk activities (ß = -0.16, $p < .05$). Those whose residents expressed higher perceived risk from COVID-19, though, were relatively less likely to visit large parks (ß = -0.09, $p < 0.05$).

Exposure

We next explore the extent to which communities experienced different levels of exposure from visiting parks, both in total and per park visit (see Data Sources and Measures for more on calculation; all parameters reported in Table 3). These measures are mapped across communities in Figure 3. Communities with a higher proportion of Black residents (ß = 0.31, $p < .001$), lower income (ß = -0.008, $p < .001$), a higher perceived risk of COVID-19 (ß = 0.54, $p < .01$), and more infections locally (ß = 0.036, $p < .01$) had more total exposure. Each of these factors also predicted higher average exposure per visit, except for median income (% Black: ß = 0.14, $p < .001$; perceived risk: ß = 0.36, $p < .05$; local infections: ß = 0.032, $p < .01$).

To better understand how visitation decisions might have driven exposure, we added percentage of visits to nearby parks and percentage of visits to big parks to the model predicting average exposure per visit. As anticipated, percentage of visits to big parks predicted lower levels of average exposure (ß = -1.98, $p < .001$). The percentage of visits to nearby parks predicted lower average exposure (ß = -0.85, $p < .001$), possibly reflecting greater access to "local" parks in communities with lower infection rates or that certain parks indeed only attracted a small number of local residents. Unexpectedly, total visits, which we included as a robustness check, predicted more exposure per visit (ß = 0.004, $p < .01$). This effect should be absent in an assessment of average exposure but is likely a function of the community-level analytic approach. If a community has many visits to a park, our calculations assume a relatively high number of individuals at that park during any visit.

The addition of measures of park visitation only partially explained the tendency of Black communities and communities with more local infections in April to have greater average exposure per park visit (parameters diminished by 7% and 16%, respectively), suggesting that strategy had limited importance for them. These measures did explain the effect of perceived risk of infection (parameter diminished by 61%, now non-significant). This may be because communities with more perceived risk visited parks more often, raising our estimation of exposure when they are frequenting the same parks, as previously described.

What Drives Exposure?

As a final step, we sought to better specify why certain communities were experiencing more exposure by decomposing the exposure metric into three components, each as a weighted average of visits: acreage of parks visited; volume of visitors at parks visited; and infection density at parks visited (see Methods for equations). We concentrate primarily on the relationships with percentage of Black residents and local infection rates, as these are the two features whose association with average exposure remain unexplained. All other parameters are reported in Table 3.

People from communities with more Black residents tended to visit parks with more acreage (ß = 0.25, $p < .001$), which would in fact be expected to lead to less exposure, all else held equal. Residents of the same communities, however, did tend to visit parks with more visitors (ß = 0.084, $p < .001$) and with higher infection load (ß = 0.03, $p < .001$). People from communities with higher infection rates did not tend to visit smaller parks or parks with more visitors on average (acreage: ß = 0.002, p = *ns*; volume: ß = -0.0004, p = *ns*), but they did tend to visit parks with higher infection load (ß = 0.0008, $p < .001$). It is worth noting that infection loads were also higher for the park visits made by members of communities with more Latinx residents (ß = 0.04, $p < .001$) and lower median income (ß = -0.001, $p < .001$).

Discussion

The results indicate that the residents of Boston shifted their park visitation patterns in ways that strategically balanced recreation against the risk of infection exposure. They not only lowered their trips to parks overall, but also prioritized parks that they might expect to be less risky: parks closer to home, which might have fewer unfamiliar faces whose own infection risk status is unknown; and larger parks, which permit greater space for social distancing. Further, we see that these shifts varied across communities in ways that reflect local perceptions and experiences, validating their interpretation as strategies while also raising crucial concerns of equity. Importantly, these findings were robust when controlling for transportation infrastructure and the distribution of parks, each of which would shape levels of access.

Visiting parks and green spaces was one of the safest activities available during the early months of the pandemic (Benzell et al., 2020), and visitation across the United States in general rebounded to 2019 levels by May, which was not the case for other amenities (Jay et al., 2021). The latter finding was not replicated here as we see an overall drop in park visitation relative to 2019, as well as a shift in the types of parks visited following the initial shutdown, as hypothesized in our first research question. Following our second and third set of hypotheses, the rebound in park visitation varied with the different demographics, perceptions, and experiences of Boston’s neighborhoods. Communities who perceived greater risk from infection or had higher infection counts visited parks more often than expected, presumably because they perceived outdoor activities as the best option for recreation or socialization. This same was true for marginalized populations, including communities with lower income and more Black and Latinx residents. These effects were additive, suggesting that communities suffering from multiple risk factors (e.g., majority-minority, low-income and suffering from high infection rates) leaned even more strongly into green spaces as a relatively safe form of recreation. In contrast, communities where more residents engaged in high-risk behaviors visited parks less than expected, potentially because they believed themselves to have other outlets.

Though green spaces were likely seen as offering a *relatively* safer outlet for recreation during the early days of the pandemic, the scientific and public understanding at that time was that they could still present risks of infection exposure and thus should be navigated carefully. We see this in cross-community variation in how perceptions and experiences shaped the types of parks communities tended to visit, similar to the finding that visitors to national parks during the pandemic who perceived more risk of infection concentrated on less-trafficked trails (Seong and Hong, 2021). The strategic effectiveness of the decisions in this case, however, were mixed. On the positive side, those who lived in communities with higher infection rates were more likely to avoid parks that were nearby, which was probably prudent. Less effective, however, was the tendency of communities who perceived greater risk from infection to prioritize small parks. This may have been the product of faulty reasoning: individuals who perceived greater risk may have been trying to avoid places with more visitors but might not have taken into account that larger parks have more space to spread out and socially distance. Indeed, visiting smaller parks more often predicted more total exposure and more exposure per visit. Also, we see no evidence that those who perceived more risk prioritized local parks, which is noteworthy because such visits generated less exposure on average, holding local infection rates constant.

Last, we see that communities with more individuals participating in high-risk behaviors were less likely to visit nearby parks, which could again be an indication that they felt less reliant on outdoor recreation as a primary activity as they were willing to undertake other activities that might have been more likely to expose them to infection.

We also see how the effectiveness of strategy was undermined by geographic inequities, as anticipated by our fourth set of hypotheses. Communities with a higher proportion of Black residents and more infections locally experienced more exposure at parks, even when accounting for the number of visits. This effect was further intensified for Black communities with high infection rates, which is notable given the substantial correlation between those factors. It is important to note that others have found similar things for mobility more generally (Hong et al., 2021). This previous work, though, was premised on the volume of visitors but did not account for local infection rates of those visitors, nor did it specify a type of amenity. The finding here also goes further by taking into account the different strategies that might have mitigated infection exposure. Most notably, our results indicate that communities with a higher proportion of Black residents and of infections tended to have more exposure when visiting parks *even if* they used these strategies. This points to the difficulty of accessing contexts different from one's own in a city that is de facto racially and socioeconomically segregated (Moro et al., 2021; Phillips et al., 2019; Wang et al., 2018). One might point out that we now understand that green spaces were not major vehicles for transmission during the early stages of the pandemic, but that was not known at the time, as indicated by the closing of green spaces to the public for multiple weeks in many jurisdictions. As such, many residents were in fact trying to limit exposure while visiting green spaces. Nonetheless, infections were concentrated in communities of color and those residents had little recourse to escape what was believed to be the threat of exposure. This is the very definition of inequity.

We do note one finding regarding inequities that differed considerably with other recent work. Jay et al. (2021) found that, across the country, park visitation rebounded less in communities of color. We found the opposite, with communities with more Black and Latinx (but not Asian) residents making more visits to parks than expected. This could be for a few reasons. First, Jay et al. (2021) used parks as the unit of analysis, categorizing them by communities within a 10-minute walk. We instead examine communities, meaning we include visits to parks beyond that catchment area. Second, we treat racial composition as a series of continuous variables rather than categorization, which can reveal more nuanced variations. Third, our regression models include a variety of control variables, thus analyzing differences relative to expectation, whereas their analyses were on absolute change. Last, we only analyzed a single city, which might have its own idiosyncratic dynamics regarding race and access to and usage of parks.

There are a few limitations we must address. First, the study is of a single city, which was necessary given our utilization of unique forms of data, including surveys and infection cases at a granular level. Nonetheless, the behavioral strategies of Bostonians may differ from other regions of the country and it would be important to replicate the findings. Second, SafeGraph is a distinctive and valuable resource for studying human mobility, but it is not without its weaknesses. There may be biases in the data originating from cross-community differences in the use of mobile devices. We believe we have largely controlled for those here by including mobility measures from 2019 in our models, anticipating that these biases were consistent across time. Nonetheless, it is possible that the disturbances of the pandemic altered the biases in some places. In addition, the need to suppress CBG-park visitation counts under 4 obscures an unknown number of visits in non-systematic ways. The hope, though, is that these are few enough relative to the full body of visits to have limited effect. Last, our calculation of exposure at a park is the most sophisticated we know of as it combines elements from multiple previous studies (Hong et al., 2021; Sun et al., 2020; Yue et al., 2021), but it does assume that exposure varies linearly with the size of a park. It might be that not all parts of a big park are actively used by visitors (e.g., large tracts of forest with paths; Yue et al., 2021). Solving this would require more detailed data on the structure of the amenities within each park in the study.

Conclusion

In sum, we see here the importance of parks as a recreation outlet for Bostonians during the early months of the pandemic, especially for communities who experienced and perceived the greatest risk of infection. We also see how visitation tended to be strategic, with the highest-risk communities prioritizing parks that were less likely to expose them to infection. Nonetheless, these strategies saw limitations. Some were simply in error, like the tendency of those who perceived greater risk to frequent smaller parks even though they offered fewer opportunities for social distancing. Others, however, were undermined by local constraints. Try as they might, residents in communities with more Black residents or with more local infections found themselves still experiencing greater exposure to infection when visiting parks, making for yet another inequity in a pandemic that has been characterized by them.

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Table 1. Descriptive statistics for all variables and correlations between them.

	% near	*% big*	*Total*	*Avg. Exp.*	*Tot. Exp.*	*Pop. Den.*	*Near Parks*	*% Big Near*	*% Black*	*% Asian*	*% Lat.*	*HH Inc.*	*% >60 min.*	*% by Car*	*Bus*	*Sub-way*	*Perc. Risk*	*High Risk*	*Inf. Rate*
% visits nearby parks[a]	—	-.11	.11	-.20	.06	-.12	.11	-.03	-.06	.05	-.04	-.02	-.09	-.06	.13	.09	.01	.00	.10
% visits big parks[a]		—	.05	.27	.16	-.24	-.23	.26	.12	-.07	.02	-.10	.12	.27	.07	-.02	-.09	-.02	.13
Total visits[a]			—	.42	.75	-.12	.13	-.13	.52	-.19	.39	-.40	.27	.10	.15	.01	.19	-.13	.32
Exp. per trip[a]				—	.58	-.17	-.08	-.01	.48	-.16	.35	-.34	.32	.19	.00	-.10	.15	-.14	.34
Total Exp.[a]					—	-.20	.07	-.03	.60	-.20	.40	-.45	.35	.15	.16	.01	.27	-.16	.37
Pop. Density[b]						—	.33	-.35	-.18	.15	.04	-.06	-.18	-.51	-.39	-.08	-.10	.02	-.19
Nearby Parks[c]							—	-.56	.01	.07	.04	-.02	-.30	-.45	-.11	.17	.06	.07	-.20
% Big Parks Nearby[c]								—	-.07	-.15	-.08	.12	.18	.49	.11	-.09	-.09	.06	.13
% Black									—	-.30	.16	-.43	.48	.23	.04	-.11	.33	-.13	.37
% Asian										—	-.24	-.15	-.18	-.23	-.06	.15	-.15	.00	-.16
% Lat.											—	-.47	.22	-.04	-.01	-.06	.19	-.20	.33
Med. House Income[d]												—	-.29	.08	.04	.02	-.21	.23	-.22
% Comm. >60 min													—	.17	.07	-.08	.20	-.18	.32
% Comm. by Car														—	.21	-.21	.06	.03	.26
Bus Stops Nearby[e]															—	.17	.09	-.03	.16
Subway Nearby[e]																—	.03	-.01	-.09
Perc. Risk																	—	-.19	.16

High Risk Bhvr																		—	-.13
Inf. Rate (April 2020)[f]																			—
Mean	0.07	0.48	72.81	0.67	254	28.8	7.40	0.38	0.22	0.10	0.19	74.8	0.13	0.46	3.57	0.20	3.16	0.67	5.36
S.D.	0.16	0.26	63.15	0.54	370	22.2	4.91	0.31	0.26	0.13	0.18	39.0	0.10	0.20	3.67	0.71	0.30	0.19	4.64
Range	0 – 1	0 – 1	4 – 369	0 – 3.65	0 – 4225	0.2 – 183.2	1 – 20	0 – 1	0 – 0.96	0 - 0.87	0 – 0.83	9.9 – 218.2	0 – 0.69	0 – 0.94	0 – 27	0 – 8	2.4 – 4.0	0 – 1	0 – 24.3
Corr. w/2019	.75	.42	.82	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—

Note: Sample of 509 census block groups (CBG) in Boston, MA with population >250 residents and values on all variables.

[a] – As calculated from park visitation patterns during April – June 2020.

[b] – In 1,000s per sq. mile.

[c] – Defined as being within a 15-minute walk of the centroid of the CBG.

[d] – In $1,000s.

[e] – Defined as being within a 10-minute walk of the centroid of the CBG.

[f] – Infections in 10s.

Table 2. Parameter estimates from regression models estimating the effects of community demographics, transportation access, perceptions, and infection cases on patterns of park visitation in April-June 2020.

	Total Visits during COVID	*Any Visits to Nearby Parks during COVID*	*Visits to Large Parks during COVID*
Same measure 2019	0.39*** (0.005)	1.62*** (0.091)	0.43*** (0.063)
Population density	-36.2*** (8.4)	-0.002* (0.0008)	-0.001 (0.0006)
# nearby parks[a]	-0.02* (0.007)	0.006 (0.004)	-0.003 (0.003)
% large parks in CBG	-0.02 (0.007)	0.048 (0.056)	0.057 (0.044)
% Black	0.15*** (0.009)	0.012 (0.013)	0.0060 (0.010)
% Asian	-0.02** (0.006)	0.0068 (0.013)	0.0026 (0.010)
% Latinx	0.06*** (0.007)	0.011 (0.014)	-0.011 (0.010)
Med. HH income	-2.73*** (0.80)	-0.0007 (0.0004)	-0.0006 (0.0003)
% commuting >60 min.	0.02*** (0.006)	-0.32* (0.16)	0.019 (0.12)
% commuting by car	0.05*** (0.008)	0.16 (0.094)	0.088 (0.073)
Access to bus[b]	0.02*** (0.005)	0.01* (0.004)	-0.0016 (0.003)
Access to subway[b]	-0.02** (0.006)	0.037 (0.020)	0.019 (0.016)
Perceived infection risk	0.03*** (0.006)	-0.03 (0.048)	-0.09* (0.038)
High-risk behaviors	-2.50*** (0.52)	-0.16* (0.13)	-0.01 (0.08)
Infections	0.68***	-0.006*	.0003

(April 2020)	(0.06)	(0.003)	(.00004)
R^2	0.60	0.34	0.23

* - *p* < .05, ** - *p* < .01, *** - *p* < .001

[a] – Defined as being within a 15-minute walk of the centroid of the CBG.

[b] – Defined as being within a 10-minute walk of the centroid of the CBG.

Note: Sample of 509 census block groups (CBG) in Boston, MA with population >250 residents and values on all variables.

Table 3. Parameter estimates from regression models estimating the effects of community demographics, transportation access, perceptions, and infection cases on infection exposure from park visitation in April-June 2020.

	Total Exposure	*Avg. Exposure*	*Avg. Exposure*	*Avg. Acreage of Visits*	*Avg. # Other Visitors per Visit*	*Avg. Infection Load of Visits*
Total visits to parks (COVID)	-	-	0.004*** (0.001)	-	-	-
% visits to nearby parks (COVID)	-	-	-0.85*** (0.23)	-	-	-
% visits to large parks (COVID)	-	-	-1.98*** (0.15)	-	-	-
Population density[a]	-0.002 (0.003)	0.004 (0.002)	-0.003 (0.002)	-0.007* (0.003)	-0.003* (0.001)	-0.001 (0.0005)
% large parks in CBG	-0.052* (0.21)	-0.25 (0.17)	0.13 (0.15)	0.11 (0.22)	-0.0036 (0.094)	-0.08* (0.03)
% Black	0.31*** (0.049)	0.14*** (0.040)	0.13*** (0.035)	0.25*** (0.053)	0.084*** (0.022)	0.03*** (0.008)
% Asian	-0.027 (0.050)	-0.040 (0.041)	-0.0035 (0.035)	-0.073 (0.054)	-0.067** (0.023)	-0.01 (0.008)
% Latinx	0.12* (0.058)	0.09 (0.047)	0.029 (0.041)	0.0095 (0.063)	-0.0026 (0.026)	0.04*** (0.010)
Med. HH income[b]	-0.008*** (.002)	-0.001 (0.001)	-0.002 (0.001)	-0.004 (0.002)	-0.002* (0.008)	-0.001** (0.0003)
% commuting >60 min.	-0.04 (0.61)	0.25 (0.50)	0.090 (0.42)	0.88 (0.66)	0.20 (0.28)	0.18 (0.10)
% commuting by car	-0.45 (0.36)	-0.47 (0.30)	-0.28 (0.25)	1.72*** (0.40)	0.15 (0.16)	0.03 (0.08)
Access to bus[c]	0.046** (0.016)	-0.002 (0.013)	-0.0076 (0.011)	-0.016 (0.017)	-0.014 (0.007)	-0.003 (-0.003)
Access to subway[c]	0.086 (0.080)	-0.086 (0.065)	-0.079 (0.055)	-0.004 (0.086)	0.028 (0.036)	-0.02 (.014)
Perceived	0.54**	0.36*	0.14	-0.13	-0.10	0.01

risks of COVID	(0.19)	(0.16)	(0.13)	(0.21)	(0.087)	(.03)
High-risk behaviors	0.26 (0.32)	0.16 (0.17)	0.12 (0.19)	-0.58 (0.31)	-0.17 (0.08)	-.04 (.05)
Infections[d] *(April 2020)*	0.036** (0.01)	0.032** (0.01)	0.027** (0.01)	0.002 (0.01)	-0.0004 (0.01)	0.0008*** (.0002)
R^2	0.38	0.18	0.42	0.27	0.17	0.33

* - $p < .05$, ** - $p < .01$, *** - $p < .001$

Note: Sample of 509 census block groups (CBG) in Boston, MA with population >250 residents and values on all variables.

[a] – In 1,000s per sq. mile.

[b] – In $1,000s.

[c] – Defined as being within a 10-minute walk of the centroid of the CBG.

[d] – Infections in 10s.

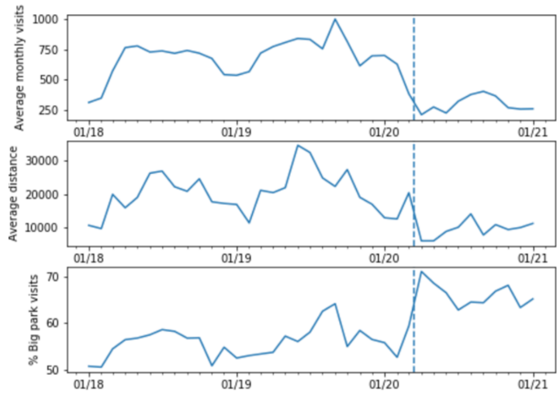

Figure 1. Average monthly visits, distance traveled to parks, and percent of visits to large parks across CBGs in greater Boston from 2018-2020. Vertical line denotes March 2020 and the start of the pandemic in the United States.

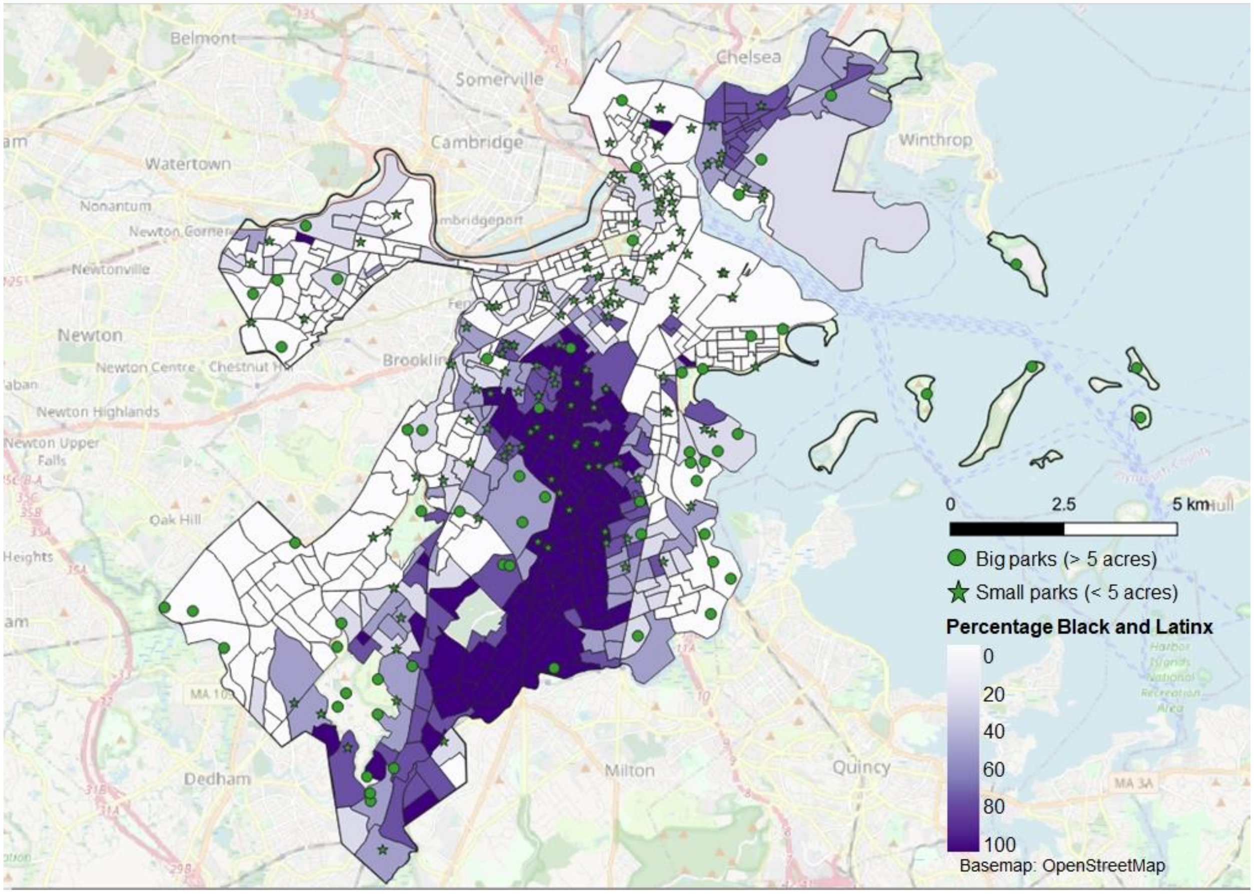

Figure 2. The locations of small (stars) and large (circles) parks in Boston, MA, overlain with the percentage of Black and Latinx residents by census tract.

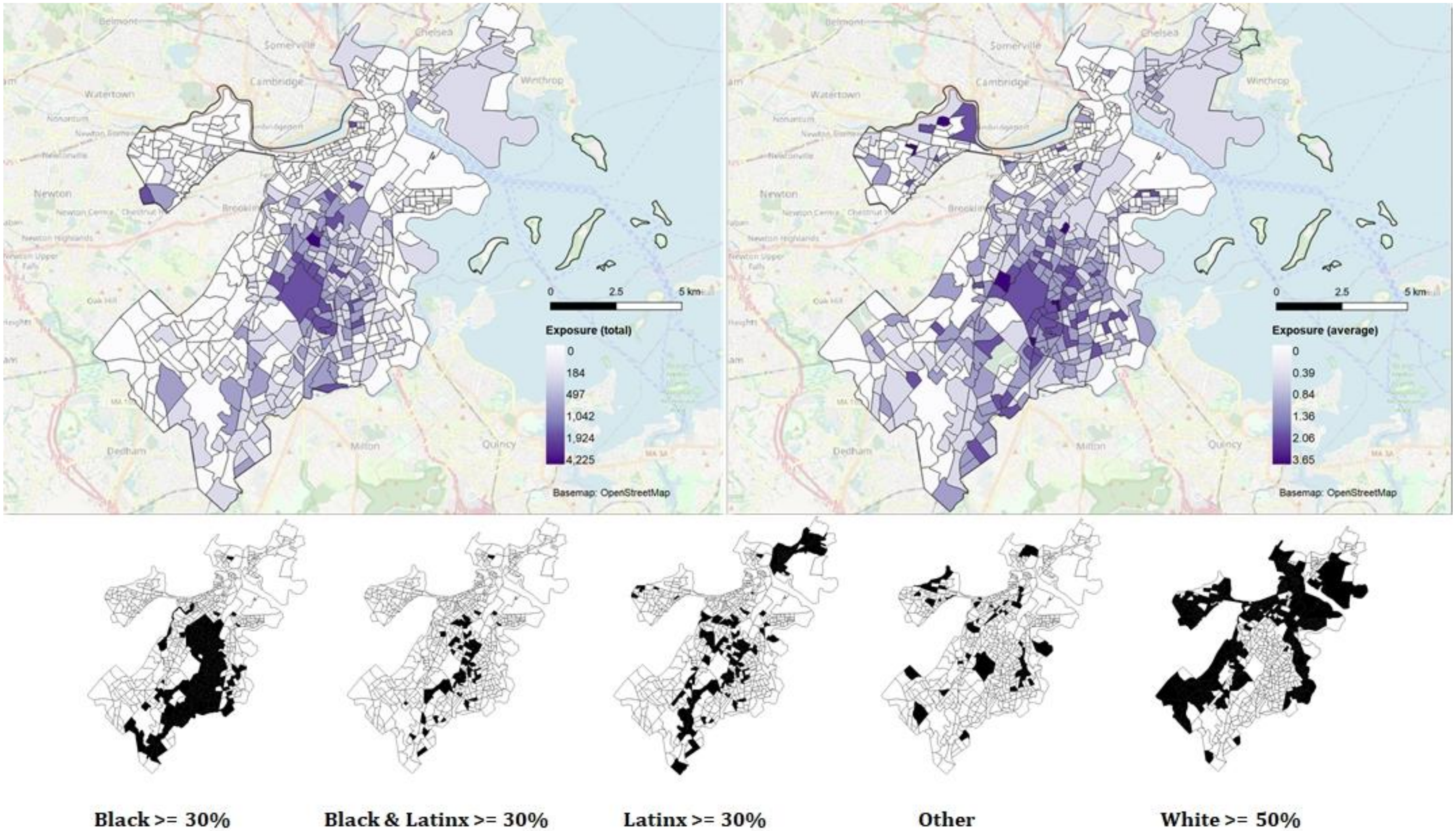

Figure 3. Communities of color experienced more exposure to infection through visits to parks (left) and more exposure per park visit (right).