Connecting Disadvantaged Communities with Green Space:

Towards Better Policy Design

by

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ABSTRACT

Recent advancements in mobile sensing technologies and big data analytics have spurred a "mobility turn" in green space exposure studies, emphasizing the importance of human movement and visitation patterns. However, existing environmental justice (EJ) literature on green spaces predominantly highlights inequities in fixed-location exposures or spatial access rather than accounting for how people use and interact with green spaces. Leveraging large-scale human mobility data collected from mobile phones, this dissertation sheds light on the crucial but underexplored dimension of use or visitation-related inequity in EJ. It employs geospatial analyses and quasi-experimental methods to examine the influence of COVID-19 and transportation infrastructures on green space visitation patterns in Phoenix, Arizona. The first essay analyzes the effect of COVID-19 pandemic on Phoenix residents' visits to parks in the United States. During the early stages of the pandemic, when strict mobility restrictions (e.g., stay-at-home orders) were in effect, park visits decreased by 40.2% compared to 2019 levels. Notably, the reduction was significantly higher in lower-income communities. The second essay examines how highways interrupt visits to nearby parks within walking distance. In 2019, Phoenix residents made 55% fewer visits to local parks when their trips were interrupted by highways compared to trips to parks without such interruptions. The third essay investigates the impact of public transportation on visits to South Mountain in Phoenix. By comparing 2019 visit frequencies between neighborhoods connected to the mountain's trailheads by transit and those with similar characteristics but lacking such connections, the findings show that public transportation increases visits, especially in

neighborhoods without nearby parks and those closer to the mountain. Collectively, this dissertation highlights the complex challenges that arise when policies in one domain—such as public health emergencies or transportation planning—unintentionally have adverse effects on another, particularly in the context of environmental justice related to green spaces. Therefore, it calls for adaptive policy solutions that modify or enhance existing policies to address unintended cross-domain impacts, simultaneously advancing public health, infrastructure development, and environmental justice to foster sustainable and equitable urban environments.

DEDICATION

Dedicated to my family. I am deeply grateful for my family's unwavering support and the sacrifices they have made throughout my doctoral journey.

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CHAPTER 1

INTRODUCTION

Green spaces offer more than just their physical presence; their true benefits come from how people interact and experience them—whether by connecting with nature, spending time alone, or participating in social activities. These interactions enhance individual well-being and foster community cohesion, contributing significantly to the quality of urban life (Bratman et al., 2019; Frumkin et al., 2017; Jimenez et al., 2021; Lee & Maheswaran, 2011). However, existing environmental justice (EJ) literature on green spaces predominantly focuses on their spatial distribution without considering whether people actually use them (Boone et al., 2009; D. Liu et al., 2021). Metrics, such as proximity—how close green spaces are to residents—and availability of green spaces in a given area are often used to assess equity in terms of spatial distribution (Nesbitt et al., 2019; Rigolon, 2016; Wen et al., 2013).

Existing research assumes that physical access leads to usage, overlooking complex social, economic, and infrastructural factors that significantly influence green space visitation (Y. Kim et al., 2023; Nelson et al., 2024; Yoo & Roberts, 2022; L. Zhang et al., 2018; Zheng et al., 2024). Recognizing these limitations, recent studies have initiated a "mobility-turn" in measuring people's exposure to green spaces (Y. Liu et al., 2023). This approach shifts focus from static, residence-based assessments to dynamic,

mobility-based evaluations that consider individuals' actual movements and interactions with green spaces.

Traditional fixed-location exposure measures use potential exposure or access metrics within static spatial units like home buffers or administrative areas, relying on data from land-use databases and satellite images. In contrast, mobility-based exposure measures actual exposure by accounting for contact frequency and duration, using dynamic spatial units informed by travel diaries, surveys, interviews, and smartphone GPS data. This comparison is summarized in Table 1.1. By integrating mobility into exposure assessments, researchers achieve a more nuanced understanding of how people interact with green spaces throughout their daily lives. This paradigm acknowledges that exposure is not solely determined by nearby green spaces but also by the dynamic aspects of individuals' movements.

Table 1.1. Comparison of Green Space Exposure Measures

	Fixed Location Exposure	**Mobility-based Exposure**
Focus	Potential exposure or access (e.g., cumulative opportunity, proximity)	Actual exposure (e.g., contact frequency, duration)
Spatial Unit	Buffer zone around home location, administrative area	Individual movement trajectories
Temporal Context	Static	Dynamic
Exposure Accuracy	Less accurate	More accurate
Data Source	Land-use databases, satellite images	Travel diary, survey, interview, smartphone GPS data

Source: Y. Liu et al. (2023); Yoo & Roberts (2022); Zheng et al., (2024)

Building upon this emerging "mobility-turn", this dissertation positions itself at the forefront of this new paradigm in measuring people's exposure to green spaces. To achieve this, it leverages large-scale human mobility datasets collected from smartphone location tracking. Innovations in mobile sensing technologies and big data analytics have enabled the precise and comprehensive quantification of individuals' interactions with green spaces (Zheng et al., 2024). Data sources such as mobile phone geolocation data, smartphone application telemetry, geotagged social media check-ins, and transit card transaction records provide highly detailed spatial and temporal information on human movement patterns (Pappalardo et al., 2023; R. Wang et al., 2022). By utilizing smartphone mobility datasets, the dissertation moves beyond the simplistic assumption that availability and proximity automatically lead to usage, gaining deeper insights into the usage dimension of environmental justice concerning green spaces.

The first essay examines how the early stages of the COVID-19 pandemic—specifically when strict mobility restrictions like stay-at-home orders and park shutdowns were implemented by the state of Arizona and the Phoenix city government—impacted green space usage among different social groups. While these policies were effective in mitigating the spread of the virus, they may have unintentionally exacerbated existing green space inequity. Disadvantaged groups often have limited access to private outdoor spaces and rely more heavily on public parks for recreation and well-being (Astell-Burt et al., 2014; Barbosa et al., 2007). Mobility restrictions can disproportionately hinder their ability to visit green spaces, intensifying disparities in physical and mental health benefits derived from green space usage (Berdejo-Espinola et al., 2021; Venter et al., 2020;

Volenec et al., 2021). This essay analyzes how COVID-19 and mobility restrictions have differentially affected various social groups by comparing park visitation frequencies between 2019 and 2020 using a difference-in-differences design.

The second essay examines the impact of highways on green space visitation. The Federal Aid Highway Act of 1956, along with subsequent federal funding, significantly expanded the interstate highway system (Gilbert & Pearl, 2007). This expansion resulted in serious unintended consequences known as "community severance" or the "barrier effect," wherein transport infrastructures like highways disrupt the movement of local residents to key destinations such as parks (P. R. Anciaes, Boniface, et al., 2016; Benavides et al., 2024; van Eldijk et al., 2022a). This phenomenon raises critical environmental justice concerns because disadvantaged neighborhoods often reside near highways (Rowangould, 2013), which physically interrupt their walking trips to nearby green spaces within walking distance. Recognizing the severity of this issue, the barrier effect has garnered significant policy attention at the federal level, prompting initiatives such as the U.S. Department of Transportation's Reconnecting Communities Pilot Program (Halimi et al., 2024). In this essay, I assess the barrier effect by examining how highways reduce park visitation in nearby neighborhoods, comparing the frequency of visits to parks located on the same side of the highway with those on the opposite side.

In contrast to the first two essays, which explore factors that exacerbate environmental disparities on green space usage, the third essay examines public transportation as a policy tool to ameliorate these disparities. By providing affordable and reliable transit options, public transportation has a potential to increase visits to green

spaces, particularly for underserved neighborhoods that lack green spaces within walking distance (Chen & Chang, 2015; Fan et al., 2017; Park et al., 2021). Recognizing this potential, policymakers in the United States have launched initiatives such as the Transit to Parks Initiative and the proposed Transit to Trails Act, aimed at connecting urban residents to natural environments (Y. Wang et al., 2024). This essay investigates the impact of transportation connectors on visits to South Mountain Preserve in Phoenix, Arizona, using propensity score matching. The study explores how public transportation can improve access to green spaces, especially for underserved neighborhoods, thereby reducing green space inequities.

Collectively, these essays offer a comprehensive and nuanced understanding of how policy decisions and infrastructural developments shape the utilization of green spaces, often resulting in unintended consequences that exacerbate environmental injustices. By examining both the barriers—such as COVID-19 and infrastructural obstacles—and facilitators—like supportive public transportation systems—that affect green space utilization, this dissertation advances environmental justice scholarship by highlighting the critical usage dimension of environmental justice on green spaces.

CHAPTER 2

EFFECTS OF COVID-19 ON GREEN SPACE VISITATION: A CASE OF PHOENIX, ARIZONA RESIDENTS

2.1 Introduction

Several scholars have previously explored how exposure to nature is associated with increased psychological well-being and stress relief (Berman et al., 2008; Bratman et al., 2012; Dobson et al., 2021; Hartig, Mitchell, De Vries, et al., 2014; Logan & Selhub, 2012; Nutsford et al., 2013; A. E. van den Berg et al., 2010; M. van den Berg et al., 2016). For example, Hunter and colleagues (2019) found that the time spent in nature is correlated with the amount of stress reduction experienced. Shanahan and colleagues (2016) found that people who visited green space for longer times had lower rates of depression and high blood pressure. Additionally, higher levels of physical activities were linked to both duration and frequency of green space visits (Shanahan et al., 2016). The quality of parks and urban green spaces (and associated amenities) can have a significant impact on the promotion of human physical health as well. For example, Costigan and colleagues (2017) found that the characteristics of park quality (e.g., park maintenance, feelings of safety in the park, a relaxing atmosphere in the park, easy accessibility, and the presence of shady) are important for increasing physical activity in parks. The benefits of green spaces on people's well-being and health have been well-documented, including linkages between exposure to green space and positive mental

health benefits (Francis et al., 2012; Sugiyama et al., 2016; Wen et al., 2013). Additionally, recreation resources in parks can contribute to higher physical activity and more positive health outcomes among residents (Bai et al., 2013; Wen et al., 2013). Nature exposure as a promising pathway to mental health and well-being became even more critical during COVID-19 (Labib et al., 2022).

However, the allocation of public parks (and other urban green spaces) within metropolitan areas has been the subject of controversy, with recent research demonstrating striking inequalities across socio-economic status groups (Ahn et al., 2020). For example, more affluent communities usually have access to increased acreage and higher quality green spaces (Rigolon, 2016; J. R. Wolch et al., 2014). These inequalities mean that less affluent communities often have access to lower quality green spaces with fewer amenities. COVID-19 pandemic could have aggravated such inequalities (The Trust for Public Land, 2020). For example, during the beginning of the COVID-19 pandemic, outdoor activities in green spaces were encouraged with physical distancing, but residents living in communities with smaller and lower quality green spaces would have had significantly limited access to green spaces during this time. Traveling to larger and higher quality parks would also not have been easy under the mobility restriction order. Therefore, low socio-economic status communities could have been less likely than wealthier communities to have harnessed the benefits of green space during the COVID-19 pandemic.

We analyzed the impacts of COVID-19 on the visits to green spaces for residents living in urban communities by asking the following research questions:

1. To what extent did COVID-19 impact park visits by residents in an urban city?
2. Was the effect of COVID-19 different across communities with different socio-economic characteristics?

To answer these research questions, we examined Phoenix residents' visits to parks in the U.S. Using data from SafeGraph's weekly park visit patterns, we tracked park visit counts among Phoenix residents at the census block group level between January 2019 and December 2020 (i.e., over a two-year period). We also linked these SafeGraph data with U.S. Census data to identify the demographic and socio-economic characteristics of each census block group in Phoenix. We compared park visitation patterns during the early stages of the COVID-19 pandemic to those from 2019, the year before the pandemic began. We also investigated whether the impact of COVID-19 on park visits differed among various communities based on race, ethnicity, age group, or income. In the next section, we will provide an overview of the literature in this area before presenting our methods and results.

2.2 Green Space Inequality and COVID-19 Pandemic

The existing environmental justice literature has largely focused on inequalities in access to green spaces. Through a comprehensive review of 49 park access studies, for

example, Rigolon (2016) concluded that low socioeconomic and ethnic minority groups were disadvantaged in terms of the size and quality of parks that they could access. These groups tended to have access to smaller, lower quality parks, compared to higher socioeconomic status groups. This literature illustrates that people who need the mental and physical health benefits of urban green space the most may have the least access to it, even before the COVID-19 pandemic started. Many existing studies of green space inequities focus on proximity to green space as a key measure of access. To reap the mental and physical benefits of green spaces, however, people must visit the parks (and, preferably, a high-quality park). Since the distance between green spaces and communities does not change due to an external event like COVID-19, access measured by proximity would not change as a result of the pandemic. Nevertheless, a pandemic can affect green space inequalities by impacting people's park visit behavior, which is a form of nature exposure, but different from access (Bratman et al., 2019).

In the literature, the study of green space inequality focusing on visit behavior is limited. The shortcomings of data collection methods such as self-reporting and park use surveys have presented challenges for tracking park visitation by different social groups or communities. New sources of data that help us understand people's mobility have recently become available for the public from data companies such as SafeGraph and Google. These data have been used to examine people's visits to various Place-Of-Interests (POIs), such as parks during the COVID-19 period. Using SafeGraph data, for example, Jay and colleagues (2022) estimated a roughly 36% park visit reduction between March 2020 and November 2020 compared to the prior 2018 and 2019 trends.

Ding and colleagues (2022) found that the greener a park is, the smaller the decrease in park visitation in Harris County, TX during the Stay-At-Home Order (SAHO) period (compared to before the SAHO period). Other scholars have examined park visit patterns by different socio-economic status communities. For example, Dass and colleagues (2022) found that park visits by African American and Hispanic residents in Boston from April to August 2022 increased compared to the same period in 2019. Larson and colleagues (2021) observed that park visitation by North Carolina residents declined in July 2020 compared to July 2019, with BIPOC (black, indigenous, or people of color) and low-income individuals experiencing a higher decline. Challenges in data collection and analysis remain, however. Haraguchi and colleagues (2022) emphasize the scarcity of human mobility data and analysis studies that examine the impact of public policy and planning for evidence-based policymaking.

2.2.1 Individual Decisions during the COVID-19 Pandemic in Arizona

State and local governments implemented various measures to mitigate the spread of COVID-19. The public health emergency declaration was the first state-level government action taken during the COVID-19 pandemic and set the stage for additional state policies. For instance, Arizona issued the declaration on March 11, 2020, coming in as the 23rd U.S. state to adopt it (Wellenius et al., 2021). Three weeks after the declaration in Arizona, the governor issued an Executive Order (EO; 2020-18) effective March 31, 2020 at 5:00 pm, titled “Stay home, Stay healthy, Stay connected.” The policy limited the movements of all individuals in the State of Arizona outside of their homes,

but did not entirely restrict all movement. There were several activities that were exempt from this mobility restriction. For example, participation in essential activities (e.g., visiting parks) was still allowed under the executive order. Also, a variety of outdoor activities (such as walking, hiking, running, biking, walking dogs or golfing) were still allowed under the condition that appropriate physical distancing (six-feet distance following the CDC guideline) would be used at all times. The EO 2020-18 stated that before any enforcement would occur, the person would be noticed and provided with an opportunity to comply.

Table 2.1. COVID-19 Policies by State of Arizona and City of Phoenix

Effective date*	Government	Policy	Restrictions	Exemptions
Mar 11, 2020 – May 30, 2022	State of Arizona	Public health emergency declaration	Emergency measures to mitigate the spread of disease	–
Mar 13 – Jun 7	City of Phoenix	Park closure	All classes and programs (e.g., youth and adult sports leagues)	–
Mar 16 – Jun 7	City of Phoenix	Park closure	All indoor recreational facilities	–
Mar 31 – May 16	State of Arizona	Stay at home order (EO 2020-18)	Outside home activities	Essential activities (e.g., outdoor exercise activities), functions, businesses
Mar 31 – Oct 8	City of Phoenix	Park closure	Amenities (e.g., playground, restrooms, picnic tables, basketball courts)	Green space, walking path, dog parks
Apr 9 – May 12	State of Arizona	Travel restriction	14-day quarantine requirement for out-of-state visitors from areas with widespread COVID-19 cases	People traveling for essential functions (e.g., airline employees and healthcare workers)

*All dates are in 2020 except for public health emergency that ended in Arizona on May 30, 2022.

As shown in Table 2.1, the executive order (SAHO) in Arizona contained a variety of exceptions and exemptions. Essential or non-essential services were classified, and exceptions from mobility restrictions were allowed for essential services and activities. Park visits were an exception in states such as Arizona, Illinois, and Florida if visitors adhered to the social distancing guideline. Therefore, these policies allowed individuals to make their own decisions about traveling to parks, based on their individual health status and risk assessment. People who lived near high quality green spaces (as well as those with more money and time to travel) could have had an advantage in harnessing green space benefits compared with those who did not live close to large and high-quality green spaces (or those who did not have the resources to travel). In fact, Taff and colleagues (2021) found that survey respondents who were active in outdoor recreation before COVID-19, but not during COVID-19, had lower incomes and were more likely to be people of color. In contrast, respondents who increased their outdoor recreation activity during COVID-19 had higher incomes and were more likely to be White. In addition, Mateer and colleagues (2021) reported that psychosocial factors such as perceived risk, social norms, recommendations from authority, health benefits, and lifestyle adjustments significantly impacted individuals' outdoor recreational behavior during COVID-19. Given existing green space inequalities even before COVID-19, it is important to examine which groups took advantage of visits to parks for physical and mental health benefits during the COVID-19 policies.

Based on the developing literature (Souza et al., 2021; Spano et al., 2021; Volenec et al., 2021), we expect that COVID-19 pandemic and associated government

policies would disproportionately impact some communities over others. For example, parking areas for some city parks were closed by local governments to discourage overcrowding. This policy would favor park visits by residents who live close-by and can walk to those parks. Even after parks in some cities reopened following the initial lockdown, amenities (especially those related to sports) within the parks were still off-limits. Also, a majority of parks and trails in the most populous cities were partially closed or trails were kept open while playgrounds and other park areas were closed (Hussain, 2020). These closures (and partial closures) might have been less problematic for affluent communities, because those communities tend to have access to higher quality green spaces in their home environments and in the surrounding areas (near larger parks). In less affluent communities, however, visits to green spaces would have been constrained by the limited availability of high-quality green space nearby, as well as transit limitations during the lockdown. In sum, COVID-19 pandemic might have had disparate effects on different communities (and possibly exacerbated existing green space inequalities). Now we will turn to an explanation of our data collection and analysis.

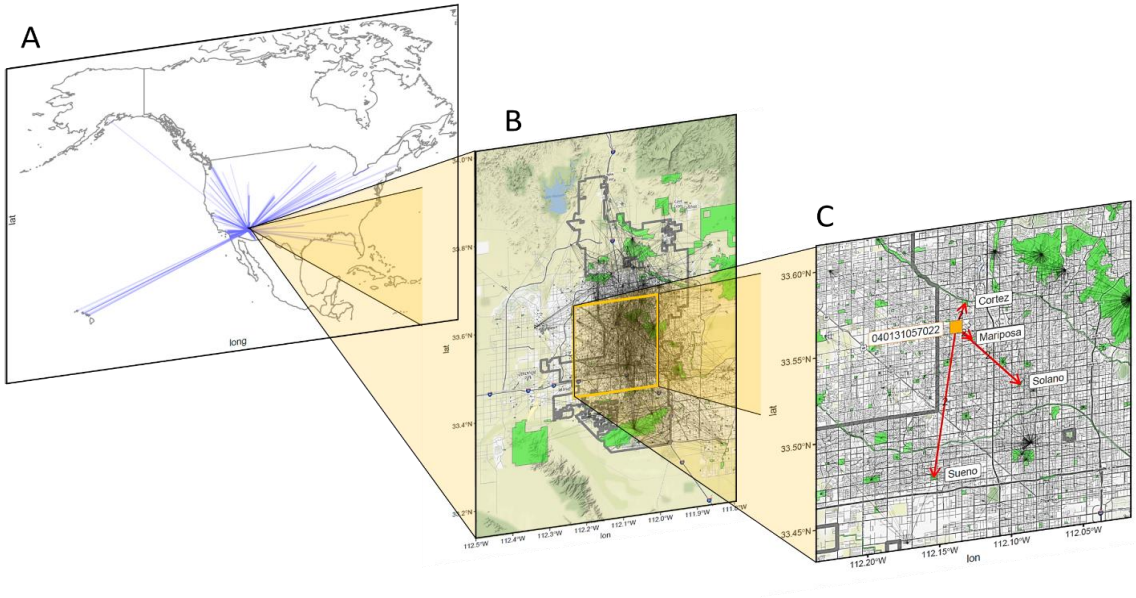
2.3 Data and Methods

2.3.1 Study Context: Phoenix, Arizona

We focus on park visits by residents in the City of Phoenix, Arizona. Phoenix is home to 1.6 million people, 75.6 percent of whom are white, and 37.0 percent of whom are Hispanic (U.S. Census Bureau, 2020). As of 2020, there were 215 parks within

Phoenix's administrative boundaries, including neighborhood parks, mountain preserves, trails, canals, community & recreation centers, and public golf courses (Trust for Public Land, 2019). These parks are especially vital in Phoenix, where the hot weather and arid climate make it challenging for naturally vegetated spaces (such as motorway verges and vacant lots) to grow grass and other green plants (Rupprecht et al., 2015).

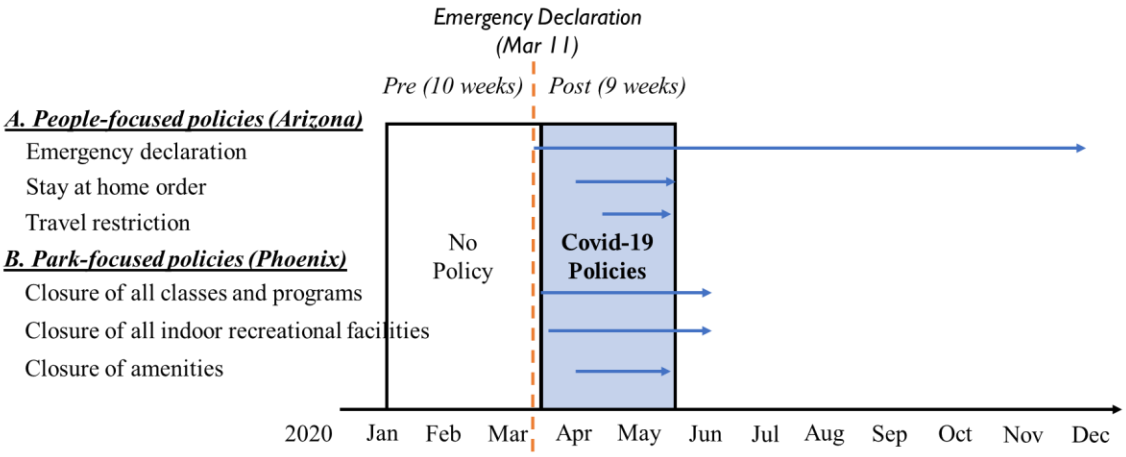
Figure 2.1. Park Visits by Phoenix Residents during March 16 to 22, 2020



Notes: Each line shows visits from a census block group to a park during the third week of March 2020 (March 16 to March 22). The line connects the centroid of the census block group for the residence with the centroid of the park visited. Panel A shows all visits to parks in the United States (blue line). Panel B shows cross city and within city visits. The city boundary (thick gray line) and the park boundary (green polygon) layers added to the map. The network of black lines shows the pattern of park visitation within the city and across the city. Panel C shows visits for a census block group (with FIPS code 40131057022, orange square box) as one example. From this block group, two devices visited each of four parks (red arrow). These device counts are used to calculate park visits using the equation (1).

Using the SafeGraph data (which we explain below), we found that the residents of Phoenix visited parks approximately 36 million times in 2019 (22.2 visit counts per person in a year). Roughly 41.5 percent of these visits took place within the city limits, but residents also visited parks in other cities in Arizona (45.5 percent) and other states (5.6 percent).[1] The geographical scope of this study, which visualizes Phoenix residents' park visits on a map, is illustrated in Figure 2.1.

Figure 2.2. Timeline of COVID-19 Policies



For the analyses, we focused on early stage of the pandemic after the emergency declaration. As Figure 2.2 illustrates, the post-treatment period started one week after the implementation of the emergency declaration of Arizona and continued until the end of SAHO (i.e., from March 16 to May 16, 2020). The pre-treatment period for this study

[1] The SafeGraph dataset contains data for mobility associated with domestic travel only. So, travels to other countries from Phoenix are outside the scope of this study.

begins on January 1, 2020 and continues until March 15, 2020. Note that several policies were implemented around the same time that might have impacted park visitation in this study.

2.3.2 Data

For this study, we tracked park visits using SafeGraph data, which is increasingly used to study human mobility during disaster situations such as COVID-19 (Jay et al., 2022) and hurricanes (Yabe et al., 2021). The SafeGraph dataset contains data for approximately 10% of the total population of the United States and is known to be well represented across demographic and socio-economic categories (Squire, 2021). The dataset includes information about devices that visited Places of Interest (POI) in the United States over a time range (day, week, or month). Our dataset includes the number of mobile devices that visited POIs, such as parks, on a weekly basis between 2019 and 2020, using a weekly pattern dataset from SafeGraph. A visit to a POI is defined as a ping that is detected inside the POI polygon boundary.[2] These data also include the visitors' primary residence at the Census Block Group (CBG) level.[3] When combined with Census data, the information can identify demographic and socioeconomic backgrounds of visitors because each device holder's residential location is detected at the

[2] Duration of a visit should be longer than 4 minutes to be classified as a visit. A density-based clustering algorithm (DBSCAN) are used by to determine visits from location data by SafeGraph team (SafeGraph, 2021).

[3] Home location of devices are determined based on past six weeks of common night-time location (SafeGraph, 2021).

census block group level. We then combined these two datasets (i.e., SafeGraph data and Census data) with other datasets, including: the American Community Survey (ACS) 2015-19 five-year dataset, the gridMet dataset for weather estimates. The key variables, definitions, data sources included in our analyses are listed in Table 2.2.

Table 2.2. Variables and Data Sources

Variables	Variable definitions	Data source	Type
Park visits	The number of mobile devices detected at least 4 minutes within a park boundary.	SafeGraph Weekly Pattern (SafeGraph, 2021)	Weekly
Social distancing policies	Beginning and end dates of social distancing measures of Arizona state	University of Washington (Nancy Fullman et al., 2021)	Weekly
Park closure policies	Beginning and end dates of city-level park closure policies	City of Phoenix Parks and Recreation Department	Weekly
Population	CBG population estimates	American Community Survey 2015-2019 (U.S. Census Bureau, 2020)	5-yr average estimate
Weather conditions	Weather conditions	gridMET (Abatzoglou, 2013)	Weekly

Phoenix consists of 974 CBGs with an average of 1,661 people per CBG (see Table 2.3 for the descriptive statistics). The dataset includes park visits for each CBG from the 1st to the 19th week of each year, comprising 18,506 observations (=974*19). There are two census block groups in the city of Phoenix with no population (IDs: 40131125132 and 40131138021). These are industrial areas and Sky Harbor International

airport, respectively, and there are no residential buildings in these areas. We omitted these two block groups when calculating other variables. We also include Phoenix CBGs' demographic information and weather conditions for 2019 and 2020.

Table 2.3. Descriptive Statistics

Variables	N	Mean	SD	Min	Max
Park Visits per CBG (weekly)					
Visits in 2019	18,506	703.1	496.9	0	5,081.9
Visits in 2020	18,506	662.4	500.5	0	6,039.9
Community Characteristics (2015-2019 5-yr estimates)					
Population	974	1,660.8	758.3	0	5,975.0
Proportion Non-White (%)	972	24.4	15.9	0	85.4
Proportion Hispanic (%)	972	37.0	28.2	0	100.0
Per Capita Income ($)	971	32,213.4	19,746.7	1,175.0	168,302.0
Proportion Under 18 (%)	972	23.7	9.9	0	51.0
Weather Conditions in Maricopa County in 2019 (daily)					
Precipitation (mm)	365	0.8	3.2	0	30.7
Maximum temperature (°F)	365	83.3	16.8	33.3	111.7
Mean wind speed (mph)	365	6.6	2.4	2.4	17.4
Weather Conditions in Maricopa County in 2020 (daily)					
Precipitation (mm)	366	0.4	2.3	0	26.1
Maximum temperature (°F)	366	86.7	17.1	47.4	115.6
Mean wind speed (mph)	366	6.5	2.3	2.0	17.4

2.3.3 Measuring Park Visits

We examined Phoenix residents' weekly park visits as an outcome variable. Since SafeGraph provides the number of devices instead of visit counts in the dataset, we performed an additional procedure before moving forward with the analysis (hereafter called *normalization*) developed by (SafeGraph, 2020). In the equation (1), $Normalized\ Visits_{iyt}$, park visit of census block group i during year y and week t, is

the summation of $Normalized\ Visits_{ijyt}$, visit to park j by residents of census block group i during year y and week t over all US park j.

$$Normalized\ Visit_{iyt} = \sum_{j} Normalized\ Visit_{ijyt} \quad (1)$$

$$Normalized\ Visit_{ijyt} = \underbrace{\frac{Device\ Count_{ijyt}}{\#\ Device\ Residing_{iyt}} \times Census\ Population_{i}}_{Normalized\ Visitor_{ijyt}} \times \frac{\#\ Visit_{jyt}}{\#\ Visitor_{jyt}} \quad (2)$$

To calculate $Normalized\ Visits_{ijyt}$, we first divide $Device\ Count_{ijyt}$, the number of devices from census block group i detected in park j by the number of devices residing in a census block group i. We repeated this normalization procedure for all U.S. parks that the block group *i* visited during year *y* and week *t* to calculate the $Normalized\ Visit_{ijyt}$. This is summed up over all park *j* to get total park visits from block group *i* during year *y* and week *t*, $Normalized\ Visit_{iyt}$ which is the dependent variable.

2.3.4 Difference-in-Differences (DD) Model

We assess the effect of the COVID-19 pandemic on park visitation using a difference-in-differences (DD) approach. Specifically, weekly CBG-level park visits in 2019 are used as the comparison group for weekly CBG-level park visits in 2020. The DD design assumes that the park visit trend in 2019 is the same for the park visit trend in 2020, without the COVID-19 pandemic and related interventions (i.e., a parallel-trend

assumption). An issue that could potentially violate this assumption would be any significant weather differences between 2019 and 2020. To address this issue, seven-day moving averages of weather conditions (e.g., precipitation and temperature) are controlled.

The estimation model is presented in the equation (3).

$$y_{iyt} = \alpha_i + \beta_1 W11to19_t + \beta_2 Year2020_y + \beta_3 W11to19_t \times Year2020_y + \beta_4 Weather_{yt} + \varepsilon_{iyt} \quad (3)$$

In this equation, subscript i, y, and t represent the census block group, year of observations, and week-of-year, respectively. y_{iyt} indicates the log of normalized visits defined in the previous section, that is, $y_{iyt} = ln(Normalized\ Visits_{iyt} + 1)$. Park visits are log transformed to address the right-skewed distribution of park visits and to suppress the influence of a few very high visit counts. We also added the number one to address zero visit counts. We set the pre-treatment period from 1st to 10th week and the post-treatment period from 11th to 19th week (see Figure 2.2). $Year2020$ equals one for observations in 2020, and zero for observations in 2019. α_i is the census block group fixed effects controlling unobserved, time invariant factors of census block groups (e.g., distance to nearest parks) that might affect park visitation. $Weather_{yt}$ is a vector of county-level weekly weather conditions such as precipitation, temperature and wind speed. Other time-invariant covariates are controlled using block group fixed effects.

Given that our dependent variable was the log of park visits count, we converted the estimates into meaningful units before interpreting the results. In this log-linear model, a one-unit change in an independent variable is associated with $(100 \times \hat{\beta})$ % change in y_{iyt} (Stock & Watson, 2015). Because β_3 is the coefficient of the interaction term between two variables (i.e., Year2020 and Week11to19), the interpretation of β_3 is the percentage changes of park visit counts between pre- and post-treatment period in 2020 minus the percentage changes of park visit counts between pre- and post-treatment in 2019, within a census block group on average. For instance, if park visits rose by 20% in the post-treatment period in 2019 compared to the pre-treatment period and fell by 30% over the same period in 2020, the DD estimate is -50%, which is the net percentage point change in park visits.

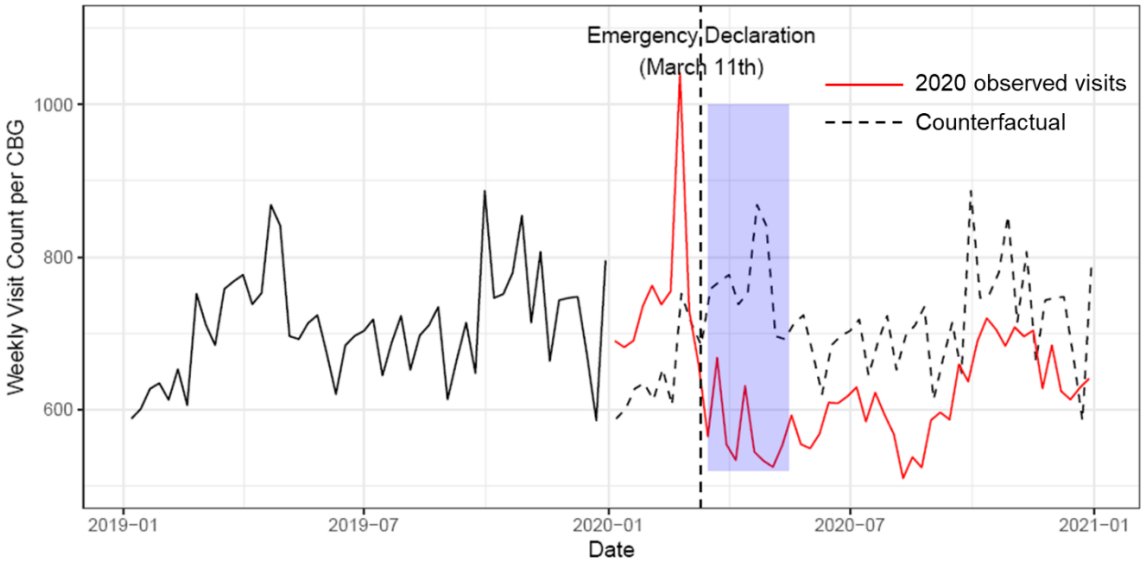
We also performed an event study analysis to assure the assumption of parallel trend before the treatment. The event study results indicate percentage changes in park visit counts relative to week 10, compared to the corresponding change in 2019 when observable characteristics are controlled (Table A1). The estimates in the first two periods (before the policies were implemented) were not significantly different from zero, indicating that the 2019 pre-intervention trend and 2020 pre-intervention trend is statistically indistinguishable.

2.4 Results

On average, Phoenix residents in CBGs visited parks in the U.S. about 600-800 times per week (see Figure 2.3). In both years, park visits decreased during the summer

and increased in the winter due to the hot summer and mild winter in Phoenix. In the Spring of 2020, a noticeable drop in park visits was observed around week 10, contrary to a rise at the same time period in 2019. This was due to the COVID-19 outbreak and the corresponding COVID-19 policies. Also, this is the same month when the Emergency Declaration was announced (March 11, 2020).

Figure 2.3. Phoenix Residents' Park Visit Trends in 2019 and 2020



2.4.1 Difference-in-Differences (DD) Estimates

The estimates of the effect of COVID-19 on park visits are reported in Table 2.4. We present the results from a regression model with CBG fixed effects using only 2020 data in model (1). The coefficient of the variable Week11to19 (-0.542) shows that there was a 54.2 percent decline in average park visitation from the 11th to the 19th week of 2020 in comparison to the 1st to the 10th week. However, we are unable to determine how much of the 2020 reduction is due to COVID-19 and how much is attributable to a park visit trend that might still exist even in the absence of a COVID-19 pandemic. We

introduced an interaction term between the post-treatment dummy (Week11to19) and the treatment group dummy (Year2020) variable in model (2), to set park visits in 2019 as the comparison group for park visits in 2020 (i.e., difference-in-difference design). This model shows that park visits decreased 77.3% in 2020 compared to the change during the same period in 2019. The decline of 77.3 percent represents the net changes after taking into account the 54.2 percent reduction in 2020 and the upward trend of 23.1 percent that would have occurred in the absence of COVID-19, which coincides with the coefficient of Week11to19 (0.231) in model (2).

Table 2.4. Effects of COVID-19 Pandemic on Park Visitation

DV: Log (Park Visits)	(1)	(2)	(3)
Main Estimates (Reference: Week 1 to 10)			
Week 11 to 19	-0.542***	0.231***	0.248***
	(0.019)	(0.018)	(0.026)
Year 2020		0.182***	0.193***
		(0.017)	(0.018)
Year 2020 * Week 11 to 19		-0.773***	-0.781***
		(0.025)	(0.026)
Weather Conditions (Weekly Average)			
Daily Precipitation (mm)			-0.025***
			(0.004)
Maximum Daily Temperature (°F)			-0.003***
			(0.001)
Mean Daily Wind Speed (mph)			0.002
			(0.006)
Block Group FE	Yes	Yes	Yes
Observations	18,506	37,012	37,012
R^2	0.043	0.036	0.037
F Statistic	786.65***	449.70***	232.04***

Notes: *p<0.05; **p<0.01; ***p<0.001. Only 2020 data was used to create model (1). Model (2-4) used 2019 park visits as the comparison group for 2020 park visits.

Even after controlling for the naturally occurring park visitation trend, model (2) does not control for time-varying confounding factors (such as the weather difference between 2019 and 2020 and COVID-19 cases and deaths), potentially violating the parallel trend assumption and producing biased estimates. Therefore, in model (3), we added the weather variables. The DD estimate decreases to -0.781 (i.e., the park visits dropped 78.1% in 2020 compared to the change during the same period in 2019) for this model. The coefficients of the weather variables tend to have minus signs as expected. We found that one-millimeter more of daily precipitation corresponds with a 2.5% decrease in weekly park visitation on average.

2.4.2 Heterogeneous COVID-19 Effects for Communities

We further examined whether the effects of COVID-19 on park visits differed as the proportion of disadvantaged populations (i.e., non-White, Hispanic, children under 18, and low-income) in a community increased. To do this, we interacted the community characteristics (X) in each of the four models with the treatment variable (Year2020*Week11to19) in Table 2.5. The resulting three-way interaction variable (Year2020*Week11to19*X) quantifies the moderating effect of the selected community characteristics variables on the treatment effect. Except for per capita income, the moderating effects were not statistically significant for the other three community characteristics variables (race, ethnicity, and children population). In other words, the effects were not different across communities with smaller or larger proportions of non-White, Hispanic, or children under 18.

Table 2.5. Heterogeneous Effects of COVID-19 Pandemic for Different Communities

	Dependent Variable (Y) = Log (Park Visits)											
	(1) X = % Non-White			(2) X = % Hispanic			(3) X = Log (Per Capita Income)			(4) X = % Under 18		
	Coef.	SE	Stat. Sig.	Coef.	SE	Stat. Sig.	Coef.	SE	Stat. Sig.	Coef.	SE	Stat. Sig.
DD Estimates with Heterogeneous Effect (Reference: Week 1 to 10)												
Year2020	0.143	0.032	***	0.136	0.029	***	1.632	0.308	***	0.124	0.045	**
Week11to19	0.217	0.038	***	0.236	0.035	***	0.927	0.317	**	0.253	0.050	***
Year2020 * Week11to19	-0.739	0.046	***	-0.744	0.042	***	-2.322	0.447	***	-0.784	0.065	***
Year2020 * X	0.205	0.108		0.154	0.061	*	-0.141	0.030	***	0.293	0.174	
Week11to19 * X	0.131	0.111		0.035	0.062		-0.066	0.031	*	-0.020	0.178	
Year2020 * Week11to19 * X	-0.177	0.157		-0.104	0.088		0.151	0.044	***	0.008	0.252	
Weather Conditions (Weekly Average)												
Daily Precipitation (mm)	-0.025	0.004	***	-0.025	0.004	***	-0.025	0.004	***	-0.025	0.004	***
Max Daily Temperature (°F)	-0.003	0.001	**	-0.003	0.001	**	-0.003	0.001	**	-0.003	0.001	**
Mean Daily Wind Speed (mph)	0.002	0.006		0.002	0.006		0.002	0.006		0.002	0.006	
Observations	36,936			36,936			36,898			36,936		
R^2	0.037			0.037			0.038			0.037		
F Statistic	155.150*** (df = 9; 35955)			155.518*** (df = 9; 35955)			157.028*** (df = 9; 35918)			155.337*** (df = 9; 35955)		

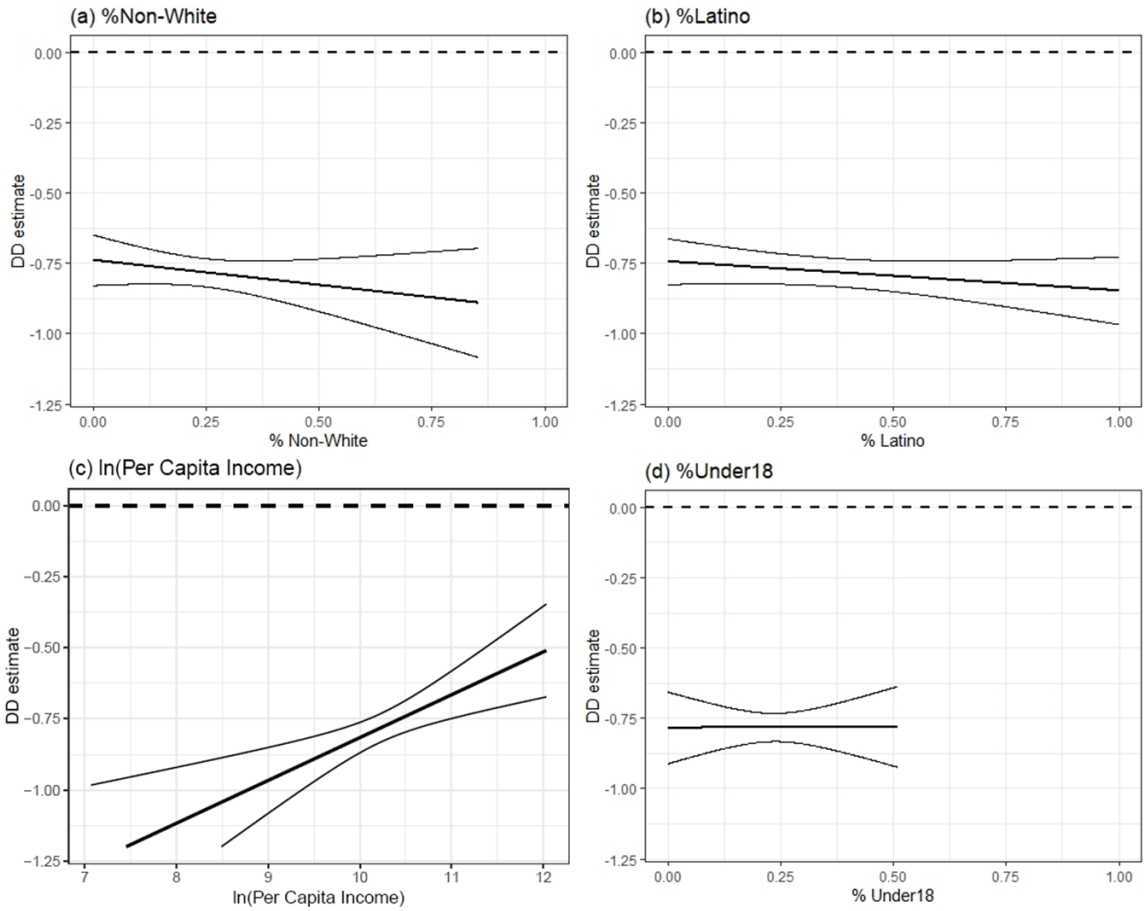
Notes: *p<0.05; **p<0.01; ***p<0.001

In sum, we did not find any heterogeneous policy effects for these groups. Rather, due to COVID-19 pandemic, the reduction of park visits was found to be significantly lower as community income level increases. We found that a 1% increase in per capita income is associated with a 0.15% less reduction of park visits. Since there is a continuous moderator in each model, the effect of COVID-19 can be predicted using three pieces of information: the coefficient of Year2020*Week11to19*X, the coefficient of Year2020*Week11to19, and the value of community variable. For instance, the impact of COVID-19 for a community where non-Whites make up half the population is -82.8% (=-0.739-0.177*0.5).

Figure 2.4 shows the predicted treatment effects at each value of community characteristics (i.e., marginal effect), which helps with interpreting the coefficients from the preceding table. The predicted treatment effect was negative for every range of community attribute, as shown by all the panels, but the degree of negativity varied. The percent Non-White and percent Hispanic slopes in panels (a) and (b) were both negative, but they were not statistically different from zero, indicating that the moderating effect of community characteristics is not statistically significant. The treatment effect slightly increased (park visits reduction became larger) as the proportion of non-White or Hispanic in a community increased, but the effect was not statistically significantly regardless of the proportion. In panel (c), the slope of per capita income is positive and significantly different from zero. As per capita income in a community increases, the effect of the treatment (i.e., park visit reduction) is significantly reduced. Therefore, COVID-19 policy effect on park visits significantly differed by community's income

level. The slope in panel (d) is almost flat and not significantly different from zero. No difference in the predicted treatment effect by the proportion of children under 18 in a community was found.

Figure 2.4. Marginal Effects by Community Characteristics



Notes: 95% confidence intervals are shown.

2.5 Discussion

Our results demonstrate that park visits by Phoenix residents during the study period were reduced in 2020 to almost half of the 2019 visitation level (40.2%). We also found that the effect of the COVID-19 pandemic on park visits during the period was significantly moderated by per capita income. That is, the reduction of park visits due to the COVID-19 pandemic was significantly smaller as per capita income in communities increased (i.e., the higher income communities were less impacted). We did not find heterogeneous policy effects across other socioeconomic status variables, such as race, ethnicity, and children population.

There are a growing number of empirical studies that show the impact of COVID-19 on park visits (Souza et al., 2021; Spano et al., 2021; Volenec et al., 2021; Xie et al., 2020). While these studies have been successful in determining how overall visits have changed, these existing studies have not explored in detail how the effect plays out in communities with different socioeconomic conditions (such as different income levels) for park visitation data. Also, there are conflicting explanations within the existing literature. On the one hand, parks in disadvantaged communities are more crowded because of their small size, making them less appealing to use due to the higher risk of infection during a pandemic (Johnson et al., 2021; Venter et al., 2020). However, people with lower incomes might not be flexible with their time (often due to long working hours) and have fewer financial resources for recreational outdoor activities (Kinder & Stateler, 2021). According to these findings, the gap between high-income and low-income groups in terms of park visitation was widened during the COVID-19 pandemic.

Our study provides empirical evidence that the effect of the COVID-19 pandemic became larger (i.e., fewer visits) as community's per capita income decreased (less affluent communities) at least at the early stage of the pandemic, significantly lowering their visits to parks, compared to affluent communities. The many exceptions applied to the mobility restriction policy (i.e., SAHO) by governments allowed for individuals to make their own decisions on where to go and what to do during the COVID-19 pandemic. The way the exceptions were applied individually could vary across different groups of people. The heterogenous treatment effect results suggest that residents in higher income communities were more likely to travel to in (and out of) parks in Phoenix to escape the stay-at-home order while not exposing themselves to people in an indoor environment. The travel patterns for park visits under the COVID-19 mobility restrictions might have been influenced by available individual or family-oriented resources (such as money), but also because of time (e.g., white collar workers were more likely to be able to work from home or take time off work than blue collar workers). Our findings also suggest that differential park visits by community's income level could be a serious concern of policy-makers and urban planners for future emergency events like COVID-19. That is, the differential impact across communities of the disaster and policy efforts can widen already existing health disparities and green space inequalities between these groups (Millett et al., 2020; Smith et al., 2020).

Interestingly, we did not find heterogeneous effects across communities by other socioeconomic status variables such as race, ethnicity, and children population, in terms of park visitation at the early stage of the pandemic. While the evidence is mixed, green

space access inequalities across different communities in the U.S. are well-documented (Rigolon, 2016, 2017; Rigolon et al., 2018). These previous studies typically rely on proximity measures for access inequalities instead of visitation (or use) variables. Our findings suggest that the effects of COVID-19 on park visitation did not vary by different social groups (with income being the one socio-economic status exception here). We used census block group fixed effects, controlling unobserved, time-invariant factors that might affect park visitation, such as proximity to or quality of parks. We plan to explore the role of these park access characteristics under the COVID-19 in our future research.

Moreover, the lack of heterogeneous effects across other socioeconomic variables such as race, ethnicity, and the percentage of children may be explained by previous findings that, in the Phoenix metro area, the total area of parks within walking distance is positively correlated only with per capita income (Y. Kim et al., 2023). In contrast, variables like %Non-White, %Hispanic, and %Children Under 18 did not show statistically significant correlations with park area (Y. Kim et al., 2023). This suggests that income-based inequalities in park area existed prior to COVID-19, which could have been exacerbated during the pandemic when the size of parks became especially crucial for safe outdoor activities (Honey-Rosés et al., 2021). Larger parks provided more space for social distancing, making them more attractive and accessible for residents seeking outdoor recreation while adhering to health guidelines. Therefore, the pre-existing disparities in park size could have contributed to the observed income-based heterogeneity in park visitation during the pandemic.

There are some limitations for this study. First, we used the smartphone mobility dataset that was released for the public during COVID-19 to capture park visits. Because approximately 19% of American adults do not own a smartphone (Pew Research Center, 2019), our dataset may not be representative of the entire population (Haraguchi et al., 2022). This means that our findings only apply to smartphone owners and the movements of non-smartphone owners are not captured in the data. Also, park visitation patterns from the mobility data could be compared and validated with data from traditional data sources, such as visitor surveys and vehicle count. For example, a recent study showed that monthly and weekly visit counts from SafeGraph data are strongly correlated with those from trails/gates count data in Yellowstone National Park (Liang et al., 2022). Similar data validation efforts for other types of parks, such as local and state parks, can be undertaken in future studies. Second, we explored only one dimension of heterogeneity: the socio-economic status of communities in an urban city. Another crucial dimension that could reveal heterogeneity is the variable of park size. The risk of getting COVID-19 virus is higher in small parks (Johnson et al., 2021), suggesting that smaller parks may witness a greater reduction in visitation than larger parks (c.f., Venter et al., 2020). Future research could look into heterogenous effects in terms of park size. Additionally, there is inherently the generalizability issue of our findings in other cities in the U.S. We plan to expand our research to other cities in the U.S. that might represent distinct policy landscapes.

In conclusion, our results further explain environmental inequities that might be experienced by different socio-economic groups within the context of a pandemic (or another emergency that would require severe government policies that restrict people's mobility). Lower income communities significantly reduced their park visits during the pandemic, whereas park visit reduction by higher income communities was minimal. Therefore, social groups that might already experience lower levels of health (i.e., lower income communities) did not receive the same level of mental and physical benefits of urban green spaces during the pandemic as more affluent communities. These findings can help local governments reevaluate environmental equity from the use-based perspective, while also preparing for future extreme events that may again call for restrictions on social mobility and interactions.

CHAPTER 3

DISCONNECTION FROM GREEN SPACES: BARRIER EFFECT OF HIGHWAYS THROUGH MOBILE PHONE DATA

3.1 Introduction

Transport infrastructures can create a "barrier effect," also known as community severance, which separates people from facilities, services, and one another (P. R. Anciaes, Jones, et al., 2016; Lara & Rodrigues da Silva, 2019; Ribeiro et al., 2022; van Eldijk et al., 2020). These barriers include static elements like fences, noise screens, elevation differences, and wide roads, as well as dynamic factors such as high traffic flow, a large proportion of heavy vehicles, and long waiting times at controlled crossings (Guo et al., 2001). Even when individuals can physically cross these barriers, psychological factors—such as concerns about traffic accidents and exposure to air and noise pollution—can still deter them (Brugge et al., 2007; Clark et al., 1991). The barrier effect impacts not only residents living near these infrastructures but also commuters and visitors passing through the area. Non-motorized modes of transportation, especially walking and cycling, are particularly affected (Emond & Handy, 2012; Fonseca et al., 2022; Greenberg & Renne, 2005).

This phenomenon has garnered considerable attention because its adverse impacts extend beyond mobility inconveniences to broader issues like health, well-being, and social cohesion (Appleyard & Lintell, 1972; Boniface et al., 2015; Clark et al., 1991;

Mindell & Karlsen, 2012). Transportation barriers impose additional travel effort, resulting in delays, extra travel time, and discomfort (P. R. Anciaes et al., 2019; P. R. Anciaes & Jones, 2018; Sisiopiku & Akin, 2003). These increased efforts discourage active transportation modes such as walking and cycling, which are known to provide significant physical and mental health benefits (Saunders et al., 2013). Consequently, the barrier effect negatively impacts people's health and well-being (Higgsmith et al., 2022; Mindell & Karlsen, 2012) and disrupts social connections between communities (Geurs et al., 2008). It also raises social justice concerns, disproportionately affecting disadvantaged populations—including low-income individuals and people of color—who often reside along highway corridors where land and housing are more affordable (Rowangould, 2013).

The increasing attention to the barrier effect is evident in recent policy initiatives. Notably, the U.S. Department of Transportation launched the Reconnecting Communities Pilot Program (RCPP) in 2022, a five-year initiative aimed at restoring community connectivity by removing or retrofitting transport infrastructures. This federal program builds upon previous city and state-level projects, such as highway-to-boulevard conversions where elevated highways are replaced with at-grade roads (Khalaj et al., 2020). These efforts reflect a paradigm shift in transport policies, moving away from car-centered approaches toward fostering healthy, equitable, and sustainable transport systems to enhance overall livability (P. Anciaes & Jones, 2020; Jones, 2014).

Despite growing interest, most studies on the barrier effect have focused on quantifying additional travel effort, with relatively few examining changes in people's

travel behavior (van Eldijk et al., 2022b). This research gap limits the understanding of the chain effects of barriers, where increased travel effort leads to behavioral changes that, in turn, impact social outcomes. This issue is particularly significant when the destinations offer substantial benefits to visitors. To address this gap, this study examines the impact of highways on people's visitation behavior to local parks (i.e., parks within walking distance of a neighborhood), which are known to foster health, well-being, and social cohesion

3.2 Measurement of Barrier Effects

As the measurement of barrier effects becomes increasingly important in transportation infrastructure projects and policies, researchers have proposed various assessment methods (Anciaes et al., 2014, 2016; van Eldijk et al., 2022). Recognizing the multifaceted nature of the barrier effect—which ranges from extra trip efforts to broader individual and community-level outcomes (Anciaes et al., 2016)—researchers have categorized it into three types: direct barrier effects, indirect barrier effects, and wider barrier effects (van Eldijk et al., 2022).

Direct barrier effects refer to the additional trip effort imposed on individuals by transportation infrastructure or motorized traffic. The term "direct" implies a straightforward causal link from the infrastructure or traffic to the extra effort experienced (Anciaes et al., 2016a). This extra effort represents the inconvenience people face when trying to maintain their usual travel behavior despite the presence of barriers. Studies on direct barrier effects have measured pedestrians' perceived difficulty in

crossing roads based on factors like traffic volume, speed, and the availability of crosswalks (Anciaes et al., 2019; Baltes and Chu, 2002; Hine, 1996; Sisiopiku and Akin, 2003). Surveys have also been conducted to understand intangible and psychological barriers—such as noise, air pollution, and the risk of traffic accidents—that negatively affect activities near roads (Hine and Russell, 1993).

Indirect barrier effects occur when the additional trip effort caused by transport features exceeds what individuals are willing to accept, thereby hindering their local travel behavior. This may lead people to choose alternative routes that avoid crossing barriers, reduce the frequency of local trips on foot, or switch from walking or cycling to using motorized vehicles (Mindell et al., 2017; Winters et al., 2010, 2011). Wider barrier effects encompass the broader impacts resulting from changes in travel behavior. These include alterations in social contacts, mental and physical health, and land use patterns (Appleyard and Lintell, 1972; Gbban et al., 2023; Mindell and Karlsen, 2012).

Among these three types, indirect barrier effects serve as a crucial link between direct and wider effects, helping us understand how the additional trip effort leads to broader social impacts. However, studies examining indirect barrier effects are less common than those focusing on direct effects. This is partly due to the challenge of measuring suppressed trips or trips not made (Anciaes et al., 2016a; van Eldijk et al., 2022). For example, if one observes that a person visits a park across the highway five times a year, it's difficult to determine whether they would have visited ten times annually if the highway weren't there—a potential 50% reduction—or whether the highway has no effect on their visitation frequency. While comparing hindered trips with

unhindered ones could address this challenge, such comparisons are rare due to the lack of data on trips unaffected by barriers.

Another limitation in studying indirect barrier effects is the lack of specificity regarding trip destinations. For instance, Mindell and colleagues (2017) analyzed video recordings from cameras placed along roads to calculate the "crossing ratio"—the proportion of pedestrians crossing the road compared to those walking along adjacent sidewalks. However, their focus was solely on the act of walking, without identifying pedestrians' intended destinations when crossing. While hindering active transportation modes like walking and cycling—which have well-known health benefits (Mueller et al., 2015; Sallis et al., 2004)—is problematic in itself, the severity of the impact can vary significantly depending on the destination. This is especially relevant for trips to green spaces. Visits to green spaces, as a form of nature exposure, are known to positively affect health and well-being by providing opportunities for physical activity, psychological restoration, and social cohesion (Bratman et al., 2019; Hartig et al., 2014; Markevych et al., 2017). If transportation barriers hinder visits to these spaces, it not only reduces physical activity but also severely limits contact with nature, potentially leading to widespread negative consequences.

This study addresses the limitations of previous research by investigating the influence of highways on visits to local parks. I measure the barrier effect by comparing visitor flows of two types of local trips: those to parks located on the opposite side of a highway (treatment group, interrupted by barriers) and those to parks on the same side (comparison group, uninterrupted by barriers). This approach helps tackle the challenge

of measuring suppressed trips. This research also provides empirical evidence of behavioral barrier effect by using novel mobile phone location data to track people's visits to local parks—a data gaining recognition for its applicability in travel behavior and human mobility research (Chen et al., 2016; Wang et al., 2018).

3.3 Data and Methods

3.3.1 Study Area

The study area, the Phoenix-Mesa Urbanized Area (hereafter Phoenix), comprises 17 cities and 2,102 block groups. Phoenix experienced the fastest population growth among major U.S. cities from 2010 to 2020 (City of Phoenix, 2021), resulting in a population of approximately 4.2 million and 11th largest urbanized area in the country (U.S. Census Bureau, 2020). Phoenix presents a particularly intriguing setting for testing the barrier effect of highways on local park visitation for several reasons. First, Phoenix is known for its auto-dependency and extensive freeway system comprising three major freeways (Interstate 10, Interstate 17, U.S. Route 60) as the backbone, along with three beltways (State Routes 101, 202, 303) encircling cities in the region. Secondly, due to its arid climate, Phoenix faces a scarcity of naturally occurring vegetation, making artificially created and managed parks a critical resource. The already scarce park resources may become even more limited if the accessibility to parks is hindered by transport infrastructure. The combination of auto-dependency, a developed freeway system, and the scarcity of green spaces renders Phoenix a suitable location for assessing the barrier effect. Figure 3.1 illustrates the map of the area, highways, and parks in Phoenix.

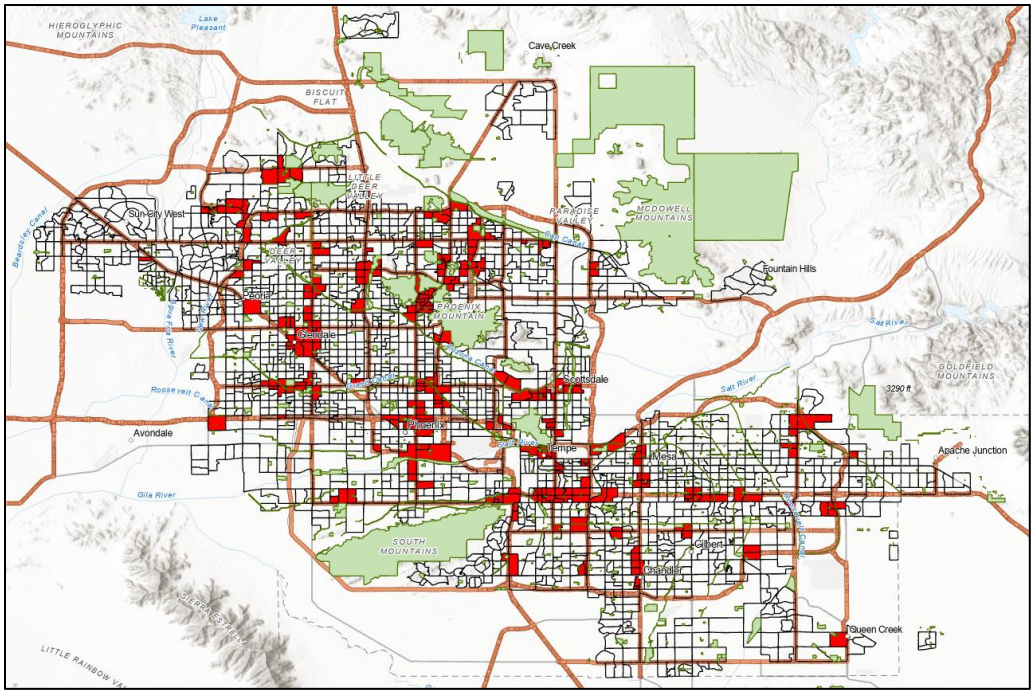


Figure 3.1. Phoenix-Mesa Urbanized Area

Notes: The thick orange lines represent principal arterials in the Phoenix-Mesa Urbanized Area, while the green polygons represent parks. The black-bordered polygons indicate all Census Block Groups (CBGs) in this area. The red-filled polygons are located near highways, and they contain local parks on both sides of the highway, enabling the measurement of barrier effects. These 234 CBGs were ultimately used in the analysis (as described in Section 3.5).

3.3.2 Data

Park visitation data for the Phoenix area were obtained from SafeGraph, a dataset that aggregates visit information to places of interest (POIs) such as parks, using GPS signals collected from approximately 10% of mobile phones across the United States (SafeGraph, 2022b). Specifically, I computed the annual park visitation for 2019 by summing the monthly park visits using SafeGraph's monthly patterns dataset. SafeGraph employs spatial clustering algorithms to convert GPS pings into visits and matches them with specific POIs (SafeGraph, 2022a). In cases where multiple POIs are in close

proximity to a GPS ping, making it ambiguous which POI was visited, SafeGraph utilizes a machine learning algorithm that considers various factors such as distance to the GPS ping location, POI type, and opening hours to determine the most likely matching POI. Only GPS signals that remained at a POI for a minimum of 4 minutes were considered visits. SafeGraph identifies the residential locations of mobile device owners based on their common nighttime locations (between 6 pm and 7 am, local time) over the past 6 weeks. To protect individual privacy, SafeGraph aggregates locations at CBG level instead of precise point locations. Moreover, data are provided only for POIs with a minimum of two visitors observed (SafeGraph, 2022b).

The representativeness and validity of the SafeGraph dataset have been acknowledged in the literature. Squire (2021) compared the number of sampled devices in the SafeGraph dataset to the U.S. Census population across multiple geographic and demographic dimensions and concluded that it was well-sampled in most dimensions. In a study that validated the accuracy of SafeGraph data by analyzing POIs in Yellowstone National Park found a strong correlation between the visitation frequencies derived from SafeGraph's mobile phone location data and those collected from traditional sources, such as visitor surveys and trail/gate vehicle counts (Liang et al., 2022).

The locations and polygon data for parks in the Phoenix area were obtained from the Trust for Public Land (TPL) (Trust for Public Land, 2019). For this study, I focused solely on parks within Phoenix that were present in both the SafeGraph POI dataset and the TPL park dataset. During data processing, I found that not all parks in the TPL dataset had visit counts available. Among the 958 parks in Phoenix within the TPL dataset, 702

parks (73%) had visit counts, while the remaining 256 parks (27%) did not. As park visitation data are essential for measuring barrier effects, I included the 702 parks with visit counts as the final set of parks for analysis.

Transport infrastructure data were obtained from the Highway Performance Monitoring System (HPMS), a nationwide highway dataset maintained by the Federal Highway Administration of the U.S. Department of Transportation. Specifically, I used 2018 HPMS Public Release dataset, containing geospatial information on highways along with operational characteristics such as annual average daily traffic, functional classification, and posted speed limits (Federal Highway Administration, 2018). Information concerning park visitors was derived from the U.S. Census American Community Survey (ACS) 2015-2019 (U.S. Census Bureau, 2020). By utilizing the CBG IDs of park visitors, I linked the SafeGraph dataset with the ACS 2015-2019 dataset to ascertain their demographic and socioeconomic characteristics. I calculated the network distance from each CBG to the parks using Google's Distance Matrix API (Google, 2024).

I merged these datasets to construct an *Origin-Destination (OD) matrix*, where the origins are CBGs and the destinations are parks. OD matrix constructed using SafeGraph data has been widely used in urban and environmental literature (Gu et al., 2023; Kang et al., 2020; Prestby et al., 2020). The dependent and independent variables, which will be explained in the following section, are computed for each row (*Origin-Destination link or OD link*) of this OD matrix.

3.3.3 Dependent Variable

The dependent variable in this study is the yearly CBG-to-park visitor flow, representing the per-capita visits to parks within 1km of a CBG centroid (i.e., local parks) in 2019. This variable is computed at the level of each OD link, indicating the number of visits made by individuals residing in CBGs within the Phoenix-Mesa urbanized area to local parks, divided by the total population of the origin CBG. For the purpose of this analysis, local parks are defined as those intersecting with 1km circular buffer centered on the CBG centroid. I have set the threshold for local parks at 1km based on previous literature (Y. Kim et al., 2023; Nesbitt et al., 2019). This decision is primarily motivated by the fact that the concept of barrier effects is predominantly applicable to pedestrian activities (P. R. Anciaes, Jones, et al., 2016).

3.3.4 Independent Variables

The primary independent variable in this study, *HighwayInterruption*, is a binary variable indicating whether the path from a CBG to a local park is severed by principal arterials. When the straight-line path from the CBG's centroid to the nearest park boundary intersects with principal arterials, I coded the variable as 1, representing an interrupted OD link. Conversely, when there is no intersection with principal arterials, the variable is coded as 0, representing an uninterrupted OD link. Principal arterials refer to high-speed, high-traffic roads such as interstates, freeways, and expressways. I focus solely on principal arterials and exclude minor arterials and collectors because it is expected that higher traffic volume and faster speeds of principal arterials can create larger barrier

effects[4]. Furthermore, principal arterials have become a primary target of recent U.S. policies, such as the Reconnecting Communities Pilot Program, due to their anticipated barrier effects. While previous studies have reported on railway-based barrier effects, I excluded them from the analysis due to structural differences between railways and roads, requiring distinct analytical approaches (P. R. Anciaes, Jones, et al., 2016).

I also included the variables *NetworkDistance* and *ParkSize*, which are independent variables that could confound the difference in park visitation between interrupted and uninterrupted OD links. Network distance measures the shortest route along the street network between a CBG and parks, providing a more realistic representation of travel distance compared to straight-line Euclidean distance. Since differences in park size between parks on the same side of the highway and those across the highway may also explain variations in visitation, I included the ParkSize variable as well.

Figure 3.2 provides a visual representation of how the highway crossing variable is coded for OD links. Within a distance of 1 km from the centroid of CBG with ID 040133194032, two parks are situated. Daumler Park is located at a distance of 930m from the CBG centroid. However, the straight-line path to this park is obstructed by State Route 101, resulting in an interrupted OD link (a dashed line). Conversely, Selleh Park is

[4] According to the Highway Functional Classification System, all roads in the United States are broadly categorized into arterials, local roads, and collectors (Federal Highway Administration, 2013). Arterials are designed primarily to facilitate high-speed, long-distance travel within the road network, and they typically have fewer access and egress points. In contrast, local roads prioritize short-distance travel and provide direct access to and from residential and commercial areas, emphasizing ease of access over speed. Collectors serve as connectors between arterials and local roads, offering intermediate levels of speed and ease of access.

also located within 1 km of the CBG, but the straight-line path to it remains uninterrupted by State Route 101, indicating an uninterrupted OD link (a solid line). The difference in the yearly visit counts between these two types of OD links corresponds to the barrier effect.

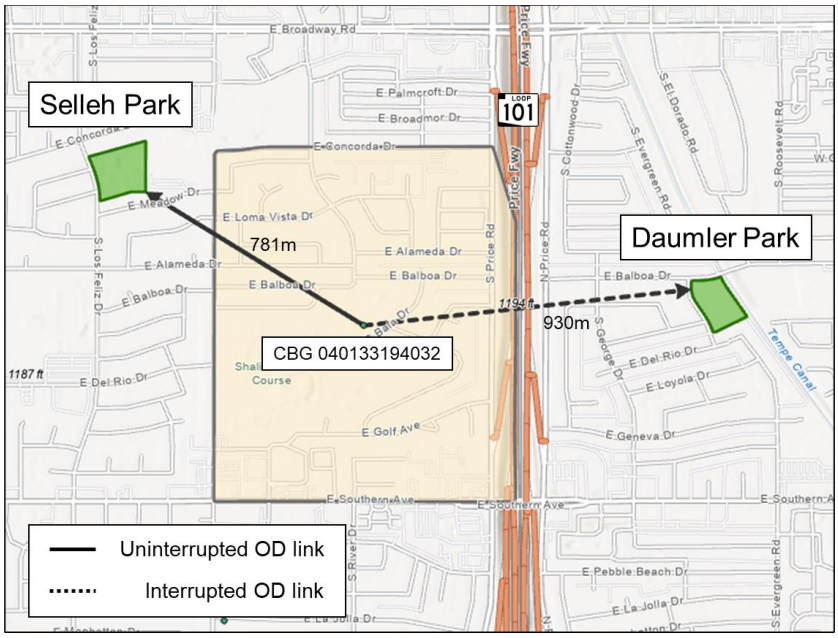


Figure 3.2. Interrupted and Uninterrupted Origin-Destination (OD) Links
Notes: This figure displays two types of OD links, namely interrupted and uninterrupted links. Each OD link represents the visitor flow from the Community Block Group (CBG) ID 040133194032 to two local parks. The solid line connecting the CBG centroid to Daumler Park indicates an interrupted OD link, as it is interrupted by State Route 101. In contrast, the line connecting the same CBG to Selleh Park represents an uninterrupted OD link, as it is not interrupted by a highway.

3.3.5 CBG Selection Criteria

Based on the research design, I identified CBGs in Phoenix that meet the following conditions: each CBG must have a principal arterial in its vicinity, and on both sides of this principal arterial, there must be at least one local park. Out of a total of 2,102 CBGs

in Phoenix, I excluded 381 CBGs that either lacked local parks or had no visit records for any local parks, leaving us with 1,638 CBGs that met the specified criteria. To compare park visits affected and unaffected by highways, I further narrowed down the selection to 258 CBGs that satisfied the condition of having a principal arterial nearby and at least one local park on each side of the principal arterial.

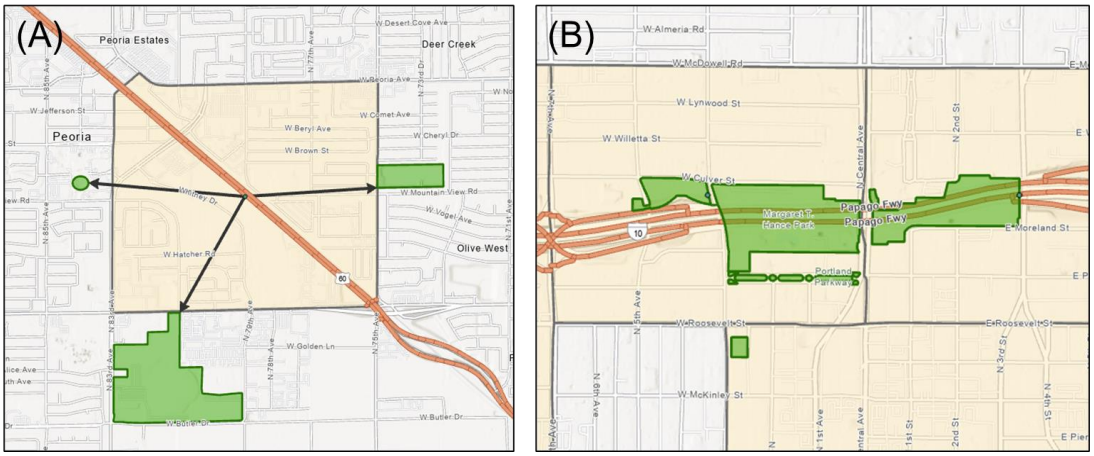


Figure 3.3. Excluded Cases from Barrier Effect Analysis
Notes: This figure illustrates two challenging scenarios that were excluded from the barrier effect analysis. Case A shows a situation where a highway divides a single CBG into two parts, making it difficult to define interrupted OD links and uninterrupted OD links. Case B demonstrates a scenario where a freeway cap park covers the area above a below-grade highway, resulting in visits to the park being uninterrupted by the presence of the highway barrier.

Moreover, during the visual inspection of the 258 CBGs, I identified instances where measuring the barrier effect is unfeasible. While the majority of CBGs (Figure 3.2) were clearly positioned on one side of the highway, with their boundaries directly adjacent to it, there were cases where the highway passed through the middle of a CBG, creating ambiguity about the community's location with respect to the highway (Figure

3.3A). Consequently, defining interrupted OD links and uninterrupted OD links for such instances became challenging. Additionally, I encountered other challenging scenarios, like freeway cap parks constructed to cover below-grade highways. One example is the Margaret T. Hance Park in Phoenix, located right above Interstate 10 and connecting communities on both sides that were previously divided by the highway (Figure 3.3B). As visitors from nearby communities accessed these Freeway cap parks, they remained unaffected by the barrier effect of the highway. Consequently, I excluded these freeway cap parks and their neighboring CBGs from the analysis. Following this visual inspection process, the final sample for analysis included 234 CBGs and 707 OD links, connecting them to local parks.

3.3.6 Poisson Fixed Effects Model

I employ a fixed effects model to address the omitted variable bias. Simply comparing visitation frequencies of local parks on opposite sides of the highway may lead to biased estimation by omitting important factors such as park characteristics and visitor community attributes. Without controlling for community characteristics, I might calculate the barrier effect by comparing the interrupted visitor flow from CBG c_1 to Park p_1 with the uninterrupted visitor flow from CBG c_2 to Park p_2. In other words, a simple OLS model without fixed effects may calculate across CBG barrier effects. However, CBG c_1 and c_2 may have different population compositions, and their respective community members may exhibit variations in socio-economic characteristics and park preferences. Comparing different CBGs does not account for the bias introduced by

omitted community characteristics variables. This study employs CBG fixed effects, enabling a comparison of interrupted and uninterrupted visitor flow from the same CBG (within CBG difference), thus mitigating the bias arising from omitted community variables.

Similarly, omitted variable bias may arise due to the differences in park characteristics between parks p_1 and p_2. However, instead of adding park fixed effects to the model, we controlled for these characteristic differences by including the park size variable due to huge loss of observations when using park fixed effects. To measure within-park barrier effects, both interrupted OD links and uninterrupted OD links should exist for each park. This allows us to calculate the difference in visit frequency between the two different OD links to the same park (within-park difference). However, out of the 277 local parks in the final dataset, only 93 (34%) have both types of OD links, resulting in a loss of too many observations. To prevent such a huge observation loss, I instead control for park characteristics by incorporating the size variable, which has a well-established strong correlation with park quality variables (Engelberg et al., 2016). Equation 1 represents the fixed effects model described above.

$$y_{ij} = \beta_1 HighwayInterruption_{ij} + \beta_2 NetworkDistance_{ij} + \beta_3 ParkSize_j + \alpha_i + \varepsilon_{ij} \quad (1)$$

The dependent variable, y_{ij}, represents the visitor flow between CBG i and Park j, indicating the number of times CBG i residents visited Park j in 2019. The dummy

variable $HighwayInterruption_{ij}$ is assigned a value of 1 when principal arterials intersect the straight-line path of the OD link, and 0 otherwise. The subscript of $HighwayInterruption_{ij}$ indicates that this variable is determined jointly by the locations of CBG i and park j. To account for the potential negative influence of distance on park visitation, I control for the network distance between the CBG i centroid and park j, referred to as $NetworkDistance_{ij}$. α_i represents the CBG fixed effect and allows for the measurement of the within-CBG barrier effect. The parameter of interest is β_1 which quantifies the barrier effect of highways on local park visits.

To assess the presence of overdispersion in the dependent variable, I performed a dispersion parameter test. The results revealed a dispersion ratio of 0.98 ($\chi^2(df = 705) = 691.59$, $p = 0.63$), indicating that overdispersion was not detected. Consequently, a Poisson regression model was deemed appropriate for analyzing the per capita visit count.

3.4 Results

3.4.1 Descriptive Statistics

Table 3.1 presents descriptive statistics for the final dataset. Panel A shows that there is a total of 707 OD links (all theoretically possible links) connecting 234 CBGs with 277 local parks. On average, each CBG is connected to approximately 3 local parks (707/234). The average visits per OD link are 0.92, suggesting that, on average, each individual visited a local park slightly less than once in 2019. Panels B and C display the descriptive statistics for the dataset divided into two groups based on the OD link type.

Comparing the two panels, the interrupted links have a lower visitation frequency of 0.5 compared to 1.26 for the uninterrupted links, indicating the presence of a barrier effect.

Table 3.1. Descriptive statistics

	Obs.	Mean	St. Dev.	Min	Max
A. Both OD Links					
Park visits per capita	707	0.94	1.08	0.01	7.37
Network distance (meter)	707	1059.75	607.34	0.00	5349.00
CBG Population	234	1525.16	622.24	357.00	4147.00
Park Size (acre)	277	127.99	1051.97	0.26	16620.51
B. Interrupted OD Links					
Park visits per capita	311	0.54	0.57	0.01	3.48
Network distance (meter)	311	1317.83	602.39	237.00	5349.00
Park Size (acre)	154	205.82	1404.01	0.27	16620.51
C. Uninterrupted OD Links					
Park visits per capita	396	1.26	1.27	0.02	7.37
Network distance (meter)	396	857.07	529.98	0.00	4596.00
Park Size (acre)	216	72.80	378.24	0.26	4859.20

However, this difference could partially be attributed to differences in travel distance and park characteristics (e.g., park size) between the two link types. The travel distance for interrupted links is approximately 200 meters shorter (735 meters) than for uninterrupted links (527 meters), likely due to the space occupied by the highway and 'border vacuums' created by transport corridors (Jacobs, 1961). Not accounting for this difference may lead to an overestimation of the barrier effect as individuals may have to travel longer distances to visit parks located across the highway. Additionally, the average park size for interrupted links is 205.8 acres, smaller than the average size of 72.8 acres for uninterrupted links. This suggests that, on average, parks located across the

highway tend to be larger. Failing to consider this difference may result in an underestimation of the barrier effect, as larger parks across the highway may attract more visitors.

3.4.2 Poisson Fixed Effect Regression Results

The results of the Poisson regressions are presented in Table 3.2. In all models, the dependent variable is "local park visits per capita". Both Model 1 and Model 2 include CBG fixed effects. In Model 1, the regression coefficient of the "Highway Interruption" variable is -0.879, significant at the 0.1% level. This implies that parks interrupted by principal arterials experienced 58.5% fewer visits in 2019 compared to parks not interrupted by highways (=1-$e^{-0.879}$). In other words, the barrier effect of principal arterials is estimated to be -58.5%.

Table 3.2. Poisson Regression Analysis of Highway Barrier Effects

	(1)			(2)		
DV: Local park visits per capita	Coef.	S.E.	Stat. Sig.	Coef.	S.E.	Stat. Sig.
Highway Interruption	-0.879	0.079	***	-0.723	0.085	***
ln(Network Distance)	-	-		-0.269	0.057	***
ln(Park Size)	-	-		0.173	0.024	***
CBG Fixed Effects	Yes			Yes		
S.E. type	Clustered by CBG			Clustered by CBG		
Observations	707			707		
Pseudo R2	0.186			0.234		
BIC	3009.8			2936.2		

Notes: *p<0.05; **p<0.01; ***p<0.001

However, Model 1 may be biased as it does not account for differences in characteristics between parks interrupted by principal arterials and those that are not, nor does it consider the actual travel distance to these parks. To address this, I introduced network distance and park size as control variables in Model 2. As expected, network distance is negatively correlated with park visits; a 1% increase in travel distance results in a 0.269% decrease in park visitation. Additionally, park size is positively correlated with park visits, with a 1% increase in park size leading to a 0.173% increase in visitation. Importantly, in Model 2, the regression coefficient for highway crossing decreases in magnitude to -0.723 (a 51.5% reduction in park visitation) from -0.879 (a 58.5% reduction) in Model 1. This suggests that without accounting for network distance and park size, the barrier effect may be overestimated.

3.5 Discussion

This paper examines the barrier effect of highways on local park visitation in the Phoenix-Mesa Urbanized Area using mobile phone location data. The results demonstrate a substantial impact: trips to local parks that are interrupted by highways experience a significant 51.5% reduction in visitation compared to uninterrupted trips. This significant decrease highlights the adverse effects of transportation barriers on people's access to green spaces. These findings underscore the importance of addressing barrier effects in transportation infrastructure projects and policies to create healthier and more equitable urban environments.

The primary contribution of this paper to the barrier effect literature is providing empirical evidence of behavioral barrier effects by measuring them based on human mobility patterns. Given the conceptual complexity of barrier effects, scholars have proposed various comprehensive and multidisciplinary methods, including participatory mapping, spatial analysis, video surveys, street audits, and travel surveys (Mindell et al., 2017). However, empirical evidence capturing actual human movement patterns across barriers is scarce (van Eldijk et al., 2022a). Complementing existing studies, this study leverages SafeGraph mobile phone data to analyze people's movements to destinations across highways. By utilizing this novel dataset, which offers detailed spatial and temporal resolution, the study provides new insights into how barriers like highways impact human mobility—insights that were previously unattainable with traditional data sources.

While this research provides valuable insights, one limitation is its exclusive focus on analyzing trip suppression due to severance, overlooking the possibility of diverse behavioral adaptations. Besides reducing trips, individuals may choose to alter their travel mode or modify their routes to bypass highways (van Eldijk et al., 2022a). The mobile phone data used in this study does not provide information about specific travel routes and modes; it only captures the visitation frequency to particular locations. As a result, I could not fully account for the nuanced behavioral changes resulting from highway severance.

While the Poisson regression models controlled for park size, it is important to recognize that factors influencing the use of green spaces extend beyond size alone.

Differences in park characteristics between those located on the same side of the highway and those on the opposite side could explain variations in visitation rates. These characteristics encompass a range of aspects such as availability, accessibility, attractiveness, and overall quality of the green spaces (Biernacka & Kronenberg, 2018; Corley et al., 2018; J. Zhang & Tan, 2019). Additionally, factors like park safety, the presence of amenities, maintenance levels, and aesthetic appeal may significantly affect visitation patterns (Cohen et al., 2009; Lapham et al., 2016; McCormack et al., 2010) and were not accounted for in this study. Therefore, the potential influence of unobserved heterogeneity in park attributes suggests that the estimated barrier effects may be partially confounded by omitted variables. Future research should consider incorporating a broader set of park characteristics to more accurately isolate the impact of infrastructural barriers on park visitation.

Moreover, this study contributes to the discourse on environmental justice by highlighting how transportation barriers can exacerbate inequities in access to walkable green spaces from current residences. Traditionally, research on green space accessibility has focused on spatial proximity, assuming that parks within a certain distance are equally accessible to all residents. However, this approach may overlook the impact of transportation infrastructures that hinder pedestrian movement, particularly in marginalized communities disproportionately affected by such barriers. By considering transportation barriers, these findings suggest that assessments of green space equity should not only account for distance but also the quality and safety of the routes available to residents. This perspective complements existing studies on inequities in green space

accessibility and underscores the need for holistic planning approaches that address both spatial and infrastructural obstacles to promote environmental justice.

CHAPTER 4

DOES PUBLIC TRANSIT PROMOTE URBAN NATURE VISITS IN UNDERSERVED NEIGHBORHOODS?

4.1 Introduction

Exposure to nature is widely recognized for its positive impacts on human well-being, offering psychological, physical, and social benefits (Hartig, Mitchell, Vries, et al., 2014; Jimenez et al., 2021). Mountain preserves, in particular, offer unique natural settings where city residents can escape urban environments and immerse themselves in nature through activities such as hiking, camping, trail running, and mountain biking (Wolf & Wohlfart, 2014). These areas provide restorative experiences that reduce stress, enhance mood, and encourage physical activity (Abraham et al., 2010; Korpela et al., 2001). However, since mountain preserves are often located on the periphery of cities, they can be difficult to access for many urban residents—especially those without private transportation or those living in central urban areas. This peripheral placement can limit certain populations' ability to benefit from these natural landscapes.

In recent years, the idea of linking neighborhoods—particularly those lacking adequate or any park space ("underserved neighborhoods")—to mountain, forests, parkland, monuments, or recreational opportunities through public transportation has gained significant policy interest (O'Connell, 2024; Phair, 2024; Rigolon et al., 2024). As of 2022, 74 Transit to Parks (T2P) initiatives—including pilot programs in Los Angeles and King County—have been established across the United States, highlighting a

considerable emphasis on improving equitable access to natural amenities (Wang et al., 2024). Additionally, at the federal level, the Transit to Trails Act was recently introduced, proposing funding to provide transportation connectors linking neighborhoods and green spaces, particularly for underserved neighborhoods (S.1440 - 118th Congress (2023-2024), 2023). This growing interest indicates that connecting people to green spaces via public transportation is a promising idea that has garnered substantial attention from policymakers.

Despite the potential and policy interest in public transportation, little research has examined whether transit connections actually lead to increased use of green spaces, particularly among residents of underserved neighborhoods. In this study, I aim to fill this gap by investigating the impact of public transportation on visits to South Mountain Preserve in the Phoenix metropolitan area in 2019. Using large-scale human mobility data collected from mobile phone location tracking, I examine whether transit connections result in more frequent use of South Mountain and how the effect varies depending on neighborhood access to parks within walking distance (i.e., 1km), which I refer to as “local parks” of a neighborhood throughout the paper.

4.2 Addressing Green Space Inequity through Public Transportation

The equitable distribution of green space has been a significant focus in urban planning and environmental justice literature (Corley, 2024; Rigolon, 2016; J. R. Wolch et al., 2014). Studies have highlighted substantial inequities in the availability and accessibility of green spaces within walking distance among different neighborhoods (Dai, 2011;

Sister et al., 2010; Wen et al., 2013). Low-income and minority communities often have less access to parks and green spaces within a reasonable walking distance compared to affluent neighborhoods (Boone et al., 2009; Cutts et al., 2009). These disparities contribute to environmental injustices, limiting opportunities for physical activity, recreation, and associated health benefits (Jennings et al., 2017; Kaczynski et al., 2014).

To address these inequities in walkable green space access, the most straight forward solution is to develop new parks in underserved neighborhoods. While this solution can directly improve local access, it faces significant challenges. Urban centers often have limited land availability and high property values, making land acquisition difficult and costly (Rigolon & Flohr, 2014; J. Wolch et al., 2005). Moreover, the introduction of new parks can lead to unintended consequences like green gentrification—where new green spaces increase property values and living costs, potentially displacing low-income residents (Campbell et al., 2024; Gould & Lewis, 2016; J. Kim et al., 2024; Stuhlmacher et al., 2022). Municipalities may also prioritize developments that generate tax revenue, such as commercial or residential projects, over non-tax-generating open spaces (Haaland & van den Bosch, 2015).

Improving access to existing green spaces through public transportation is a more feasible and cost-effective alternative, posing fewer challenges than installing new parks (Park et al., 2021; Y. Wang et al., 2024). By extending the reach of residents beyond their immediate walking distance, public transportation can mitigate spatial inequities without the need for new park development. Utilizing existing infrastructure, this approach offers a scalable solution without significant land use changes or substantial financial

investment. Buses, in particular, are cost-effective due to lower infrastructure requirements and operational flexibility, making them a viable choice for expanding access. Furthermore, improving public transit aligns with broader urban sustainability goals by reducing reliance on private vehicles and lowering greenhouse gas emissions (Cervero, 1998; Kennedy, 2002).

Recent research has begun to consider the role of public transportation in enhancing green space accessibility by evaluating how transit systems can extend access for neighborhood with limited nearby green space. These studies often assess the accessibility and connectivity of green spaces through public transportation across various neighborhoods. For example, Park and colleagues (2021) utilized the gravity model to measure neighborhood accessibility by considering factors such as transit time to green spaces, the attractiveness of these spaces, and the number of reachable green spaces within a specified transit travel time threshold. Dony and colleagues (2015) employed Floating Catchment Area (FCA) methods, defining catchment areas around each green space based on public transit speed. Additionally, researchers have used social network analysis to identify green spaces that remain poorly connected via public transportation (Chen & Chang, 2015; Xu et al., 2024). These studies provide insights into how public transportation can improve green space accessibility and highlight areas where transit improvements are most needed.

While these studies employ various methods to assess transit-based accessibility to green spaces, they primarily focus on the potential exposure provided by public transportation rather than actual usage. However, simply having transit access does not

ensure that the benefits of green spaces are fully realized. With the exception of Zhang & Zhou (2018), who explored the correlation between the number of nearby bus stops and park visit counts, there is a paucity of research examining whether transit connectivity translates into higher utilization of green spaces by residents. The assumption that public transportation automatically leads to increased green space use remains underexplored in the literature. Addressing this gap, this study investigates whether existing transit connections result in greater utilization of green spaces, particularly among neighborhoods with limited walking access to green space.

To address this gap, recent advancements in mobile technology, specifically smartphone location tracking, provide new opportunities to observe human mobility patterns, including green space visitation (Pappalardo et al., 2023; R. Wang et al., 2022). Traditionally, studies relied on surveys, observational studies, interviews, and diary-based approaches, which were limited by small sample sizes, high resource demands, potential respondent biases, and challenges in collecting large-scale movement data. In contrast, mobility data from companies like SafeGraph offer comprehensive, anonymized human mobility information that tracks visits between places of interest (POIs), such as green spaces, and neighborhoods. By leveraging such large-scale mobility data, researchers can gain a deeper and more nuanced understanding of utilization patterns (e.g., Kim et al., 2023). This study utilizes SafeGraph's human mobility dataset to conduct quasi-experiments, comparing visit frequencies between neighborhoods connected to green spaces via public transportation and those without such connections.

By leveraging large-scale mobility data, this study evaluates whether public transportation increases green space utilization. Furthermore, it assesses whether transit access can alleviate inequities based on walkable green space access by examining how the effect of public transportation varies depending on local parks. Through this analysis, I aim to provide evidence on whether providing public transit connections is a viable and effective strategy for promoting equitable green space use.

4.3 Data and Methods

4.3.1 Study Context

South Mountain Preserve in Phoenix, Arizona encompasses over 16,000 acres of desert landscape and consists of three mountain ranges: Ma Ha Tauk, Gila, and Guadalupe. The mountain offers a wide range of recreational activities, including over 100 miles of trails for hiking, mountain biking, and horseback riding, as well as popular roadways for bicyclists. I selected South Mountain as the focal point of this study because its substantial size and popularity make it a popular tourist destination in the Phoenix metropolitan area. Additionally, its location on the southern edge of the urban core presents unique challenges and opportunities for public transportation connectivity. By examining South Mountain, I aim to understand how public transit routes influence access to large natural spaces within an urban setting and to assess the role of public transportation in promoting equitable access to recreational resources.

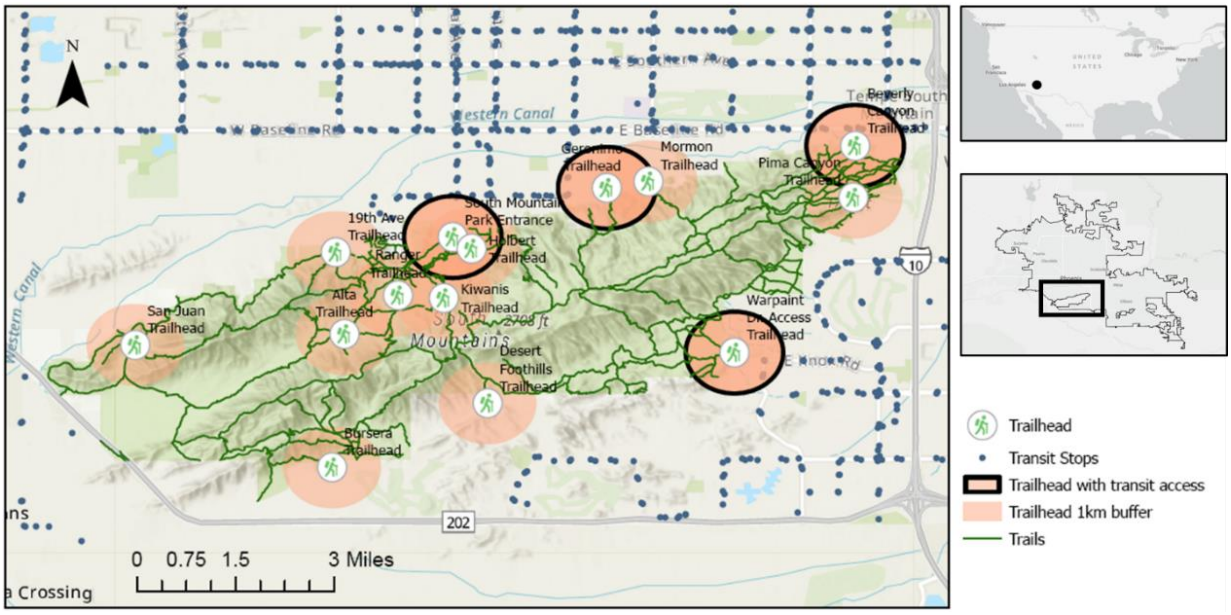


Figure 4.1. Trailheads of South Mountain and their Transit Connectivity
Notes: The two insets on the right display the location of South Mountain within the continental United States and the Phoenix-Mesa urbanized area.

Figure 4.1 shows the 14 trailheads that serve as entrance points to South Mountain. Out of these, only four—South Mountain Park Entrance, Geronimo Trailhead, Beverly Canyon Trailhead, and Warpaint Dr. Access Trailhead—are within walking distance (i.e., within 1 km) of a bus stop. The other 10 trailheads are far from bus stops, making them less accessible by public transportation. To construct treatment neighborhoods, this paper analyzes the transit stops connected to the four trailheads, and the routes that serve these stops. More details are provided in the next section. Figure 4.1 also illustrates that South Mountain is located at the southern edge of the Phoenix-Mesa urbanized area, which had a population of 4.95 million in 2019—accounting for 68% of Arizona's total population (Census Reporter, 2019). Public transportation in this area is managed by Valley Metro, a regional authority that operates 124 routes across 8,803

stops, primarily using buses and a single light rail line. The analysis focuses on the year 2019. During that year, total ridership in the area was 64.4 million, with buses accounting for 76.6% and light rail for 23.4% of boardings (Valley Metro, 2019). A 2014 survey indicated that 9.4% of both light rail and bus trips were made for park visits (Center for Urban Innovation, 2014).

4.3.2 Treatment and Comparison CBGs

I conducted geospatial analyses to identify neighborhoods—specifically, Census Block Groups (CBGs)—that are connected to South Mountain's trailheads via public transit routes, referred to as "treatment CBGs." This process involved two main steps. First, I identified transit stops located within 1 km of South Mountain's four trailheads (as shown in Figure 4.1) and the bus routes that serve these stops. This resulted in 30 bus stops and 5 bus routes serving the area. Second, I identified CBGs that overlap with a quarter-mile radius of the stops along these five bus routes. The quarter-mile buffer follows guidance from the U.S. Federal Transit Administration (Federal Transit Administration, 2012), which considers a quarter-mile as a typical walking distance to access public transportation. Additionally, I limited the treatment CBGs to those located within 15 km of South Mountain. This 15 km threshold was chosen because it represents a practical maximum distance that residents might be willing to travel via public transit for recreational purposes, ensuring that South Mountain is a feasible destination for them.

Through this process, I ultimately classified 164 CBGs into the treatment group (highlighted in yellow in Figure 4.2). Defining neighborhoods within the transit corridor

as the treatment group is a widely accepted method for measuring the effects of public transportation (Song et al., 2023; Stewart et al., 2017). By setting the 15 km limit, I focused on neighborhoods close enough for residents to realistically consider visiting South Mountain, thereby enhancing the relevance and accuracy of the analysis.

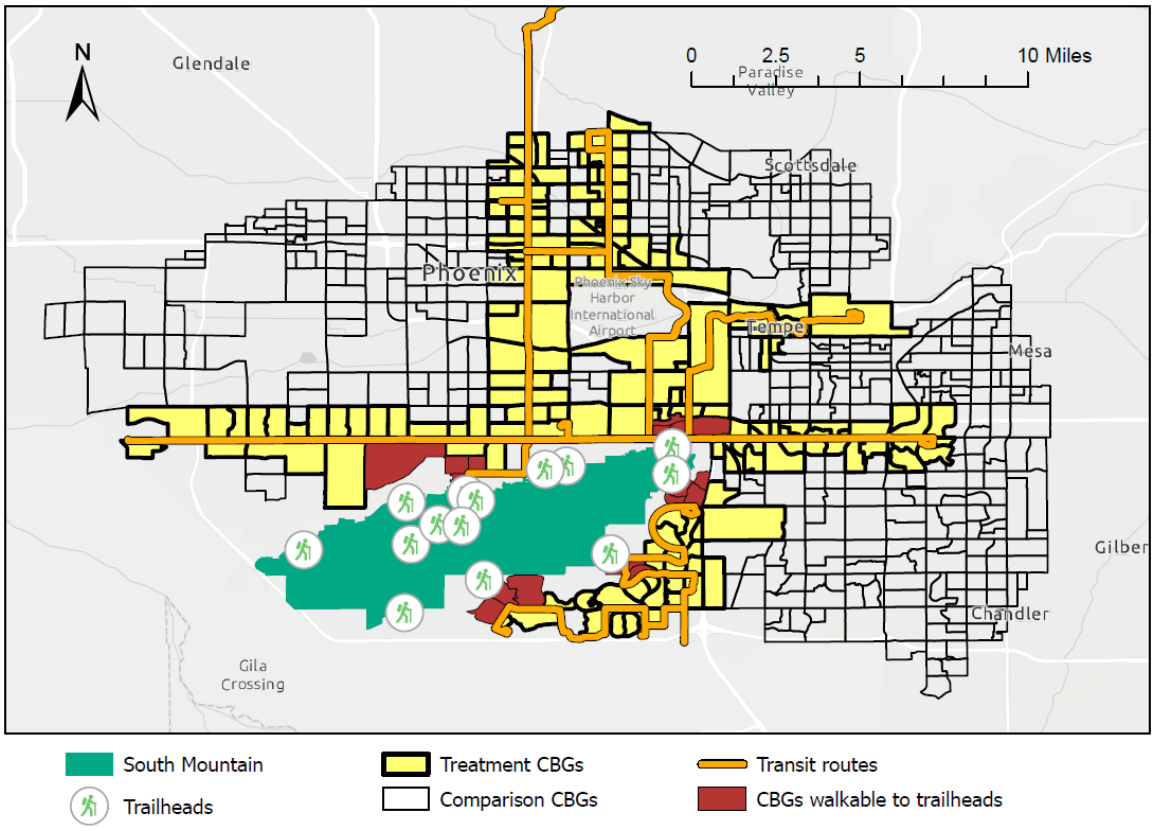


Figure 4.2. Treatment and Comparison CBGs

Based on the treatment CBGs, I constructed comparison CBGs as the remaining CBGs within 15 km from South Mountain, excluding the treatment CBGs themselves. I excluded 18 CBGs that have any area within 1 km of South Mountain trailheads from further analysis, even if they are connected to the trailheads through public transportation

(these are shown in dark red color in Figure 4.2). This is because residents in these areas are likely to walk to the trailheads rather than use public transit and including them could skew the estimation of public transit's impact. Ultimately, regression analysis was conducted using a dataset that included 164 treatment CBGs and 415 comparison CBGs.

Transit route and stop data were obtained from the General Transit Feed Specification (GTFS) reported by Valley Metro (Open Mobility Data, 2024). The South Mountain shapefiles and trail data were sourced from the Trust for Public Land's 2019 ParkServe dataset (Trust for Public Land, 2019).

4.3.3 Dependent Variable

The dependent variable is the per capita visitor flow from CBGs to South Mountain. Visit count data was obtained from SafeGraph, a company that provides human mobility data (https://www.safegraph.com). SafeGraph identifies visits to points of interest (POIs) based on GPS pings from mobile phones detected within POI boundaries. Since SafeGraph provides the number of mobile devices detected in a park rather than the actual number of visits, I normalized the device count to visit count following the normalization procedures developed by the SafeGraph team (Ouyang, 2020). The normalized visit count was further divided by the population to obtain per capita visit rates, which served as the dependent variable in the analysis. I focused only on the total visit counts during the five months of January to March and November to December of 2019. These months were selected because they represent periods of pleasant weather in Phoenix, making them ideal for outdoor activities. The mild temperatures and favorable

conditions during these months encourage higher levels of green space visitation, providing a more accurate assessment of the effect of public transportation on South Mountain.

4.3.5 Independent Variables

The treatment variable, transit connection, is the key independent variable. Additionally, to examine how the regression coefficient of transit connection varies based on local park access, I operationalized local park access into three variables. A local park is defined as any park that overlaps with a 1 km radius buffer from the centroid of a CBG. For each CBG, I calculated both the number of local parks and their average size. Furthermore, I included the Euclidean distance from the CBG centroid to the nearest park as an independent variable.

I also included the Euclidean distance from each block group to South Mountain as a control variable, since distance influences visitation. Seven key demographic characteristics of the CBGs were included as control variables: population density (number of people per acre), income (median household income), car ownership (percentage of housing units without a vehicle), race (percentage of White residents), ethnicity (percentage of Hispanic residents), age (percentage of children under 18, percentage of senior over 65), education (percentage of people with a bachelor's degree or higher). I obtained CBG's sociodemographic information from the 2015–2019 5-year American Community Survey (U.S. Census Bureau, 2020).

4.3.6. OLS Regression Model

$$Y_i = \beta_0 + \beta_1 TransitConnection_i + \beta_2 DistToSouthMountain_i$$

$$+\boldsymbol{\beta_L L_i} + \boldsymbol{\beta_X X_i} + \varepsilon_i$$

In the above regression equation, Y_i represents the per capita visitor flow from CBG i to South Mountain. β_1 is the coefficient of the key independent variable *TransitConnection*$_i$. It measures the effect of transit connectivity on South Mountain visitation. β_2 is the coefficient of *DistToSouthMountain*$_i$, showing for the influence of distance to South Mountain. $\boldsymbol{L_i}$ represents the vector of coefficients corresponding to the three local park access variables (i.e., distance to nearest park, number and average size of local parks). Similarly, $\boldsymbol{X_i}$ denotes the vector of sociodemographic control variables. This model is estimated using Ordinary Least Squares (OLS) regression.

4.4. Results

4.4.1 Impact of Public Transit on South Mountain Visitation

Table 4.1 shows how access to public transportation influences visits to South Mountain. It presents the average marginal effects (AMEs) of having a transit connection—a binary variable where 1 indicates presence and 0 indicates absence—alongside other control variables. The results show that CBGs with transit connections had a 3.1% more per capita visits to South Mountain during January to March and November to December 2019, compared to comparison CBGs without such connections. This difference is statistically significant at the 99% confidence level. Since the dependent variable is the logarithm of per capita visits, these results are interpreted in terms of percentage.

Table 4.1. Average Marginal Effects of Public Transit on South Mountain Visitation

	AME	S.E.	P-value	Stat. Sig.
Transit connection (1: connected; 0: unconnected)	0.031	0.012	0.009	**
Distance to the closest park (km)	-0.063	0.207	0.761	
Number of parks within walking distance	-0.018	0.010	0.071	
Average size of parks within walking distance (100 acres)	0.088	0.082	0.282	
CBG-to-South Mountain distance (km)	-0.027	0.003	<0.001	***
% White	0.121	0.113	0.059	
% Hispanic	0.012	0.067	0.860	
Per capita income (1,000$)	0.009	0.002	<0.001	***
% Bachelor's or higher	0.044	0.092	0.632	
% Children under 18	0.723	0.113	<0.001	***
% Senior over 65	0.099	0.106	0.348	
% Housing units without a vehicle	0.107	0.106	0.315	
Population density (1000 people per sq. mile)	-0.000	0.002	0.770	
Observations	579			
R2	0.471			
Adj. R2	0.447			
Residual Std. Error	0.104			
F Statistic	19.680***			

Notes: The dependent variable is the logarithm of per capita visits to South Mountain during January–March and November–December 2019. Significance levels: *p < 0.05, **p < 0.01, ***p < 0.001.

An analysis of the control variables identified three factors with statistically significant associations to visitation frequency at South Mountain. Firstly, for every additional kilometer of distance from South Mountain, visitation frequency decreased by 2.7%, emphasizing the pivotal role of proximity in park visitation. Secondly, per capita income exhibited a positive relationship with visitation frequency; specifically, each $1,000 increase in income corresponded to a 0.9% rise in visits, suggesting that higher-income individuals may have greater means or motivation to access the park. Lastly, neighborhoods with a higher percentage of children under 18 years old showed increased

visitation frequencies, with a 1% uptick in the proportion of children linked to a 0.7% increase in park visits.

Table 4.2. Regression Results with Interaction Terms between Transit Connection and Local Park Access Variables

	Coefficient	S.E.	P-value	Stat. Sig.
Transit connection (1: connected; 0: unconnected)	0.092	0.072	0.199	
Distance to the closest park[a]	0.006	0.004	0.158	
Number of parks within walking distance	0.004	0.003	0.210	
Average size of parks within walking distance[a]	-0.007	0.003	0.018	*
CBG-to-South Mountain distance[a]	-0.138	0.014	<0.001	***
% White	0.065	0.040	0.108	
% Hispanic	0.009	0.036	0.793	
Per capita income[a]	0.075	0.020	<0.001	***
% Bachelor's or higher	0.023	0.044	0.603	
% Children under 18	0.286	0.060	<0.001	***
% Senior over 65	0.039	0.118	0.743	
% Housing units without a vehicle	-0.032	0.053	0.550	
Population density (people per sq. mile)	-0.000	0.000	0.098	
Transit connection X Distance to the closest park[a]	-0.010	0.009	0.262	
Transit connection X Number of parks within walking distance	-0.038	0.012	0.002	**
Transit connection X Average size of parks within walking distance[a]	0.010	0.006	0.121	
Intercept	0.487	0.220	0.027	*
Observations	579			
R2	0.429			
Adj. R2	0.413			
Residual Std. Error	0.108			
F Statistic	26.372***			

Notes: Variables are marked with an "a" to indicate log transformation. Significance levels: *p < 0.05, **p < 0.01, ***p < 0.001.

4.4.2 Variation in Treatment Effects by Local Park Access

Table 4.2 presents the results of interacting the transit connection variable with local park access variables. Among the three interaction terms tested, only the number of parks within 1 km was statistically significant. The negative regression coefficient for the interaction between transit connection and the number of nearby parks indicates that the treatment effect decreases as the number of parks within 1 km increases. This suggests that the presence of more local parks diminishes the positive impact of transit connections on visitation frequency.

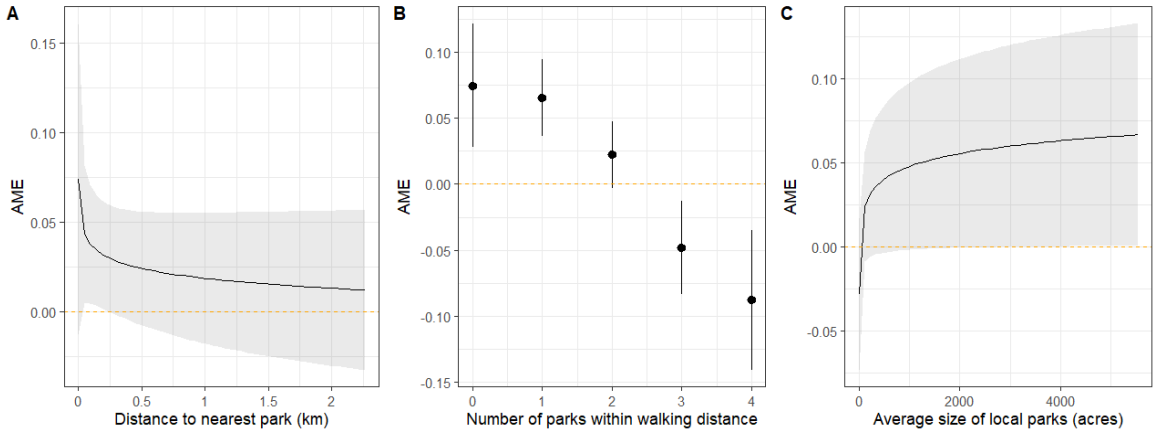


Figure 4.3. Conditional Marginal Effects by Local Park Access
Notes: The vertical bars and bands represent the 95% confidence intervals.

To visualize how the treatment effect varies with the number of local parks, I created conditional marginal effect plots in Figure 4.3. Figure 4.3B shows that the AME decreases as the number of parks within walking distance increases. Specifically, in CBGs with zero or one nearby park, the AME is positive and statistically significant, indicating that transit connections have a stronger effect on visitation frequency in areas

with fewer local parks. Figures 4.3A and 4.3C illustrate that the AME tends to decrease as the distance to the nearest park increases (Figure 4.3A) and tends to increase as the average size of local parks increases (Figure 4.3C). However, neither of these relationships were statistically significant.

4.5 Discussion

This paper examined the effectiveness of public transportation in increasing visits to South Mountain by integrating public transit feeds and mobile phone location data. Two findings are worth mentioning.

First, public transportation was effective in increasing visits to South Mountain, supporting the assumption that transit access enhances visitation to green spaces. This finding aligns with Zhang and Zhou's (2018) study, which observed a positive correlation between the number of bus stops near parks and visitor numbers. While their research simply compared bus stop proximity to park visitation rates, this study provides more robust empirical evidence by comparing visitation frequencies from neighborhoods connected to South Mountain via bus routes with those that are not connected. This approach offers stronger support for the role of public transportation in promoting access to green spaces.

To understand why public transportation was effective in increasing visits to South Mountain, I note that five bus routes—16, 32, 48, 77, and ALEX—had stops within 1 km of the mountain's trailheads, all operating on weekends. Since visits to green spaces are more frequent on weekends than on weekdays (Banda et al., 2014; Shores &

West, 2010), the availability of weekend service likely contributed to the increased visitation. Moreover, except for the ALEX route, which had a 60-minute headway, routes 16, 32, 48, and 77 had headways of 30 minutes. A 30-minute headway is recommended as the minimum service frequency by government agencies such as Los Angeles Metro and King County (Los Angeles Metro, 2019; The Wilderness Society, 2019). By meeting this minimum service frequency standard, public transportation to South Mountain was likely effective in promoting increased visitation.

Second, public transportation had the most significant impact in underserved neighborhoods lacking nearby parks. The greatest increase in visitation to South Mountain was observed in areas without any local parks, followed by those with only one park. According to the green space compensation hypothesis, individuals who lack access to green spaces in their immediate dwelling environment are more likely to seek out distant natural areas to fulfill their recreational needs (Bopp et al., 2024; Haaland & van den Bosch, 2015; Maat & de Vries, 2006). This suggests that residents in neighborhoods without accessible parks have a higher demand for visiting distant green spaces, and public transportation enables them to do so.

The effect of transit access diminished as the number of local parks increased, further supporting this notion. This finding has important policy implications. When designing initiatives like "Transit to Parks" and "Transit to Trails (Los Angeles Metro, 2019; The Wilderness Society, 2019), a key consideration is determining which areas should receive enhanced public transportation routes. The results suggest that prioritizing underserved neighborhoods can maximize the effectiveness of such policies.

Moreover, these areas often face not only a lack of parks but also qualitative disparities, such as smaller park sizes and fewer amenities (Rigolon, 2016). By providing residents of these neighborhoods with access to high-quality natural environments like South Mountain—renowned for its excellent hiking trails—public transportation can help address both quantitative and qualitative disparities in green space access. Enhancing accessibility to such premium green spaces promotes environmental equity and improves the well-being of communities that have been historically underserved.

This study has limitations. First, I focused on a single site, South Mountain, where all connected bus routes operated on weekends. Public transportation systems are primarily developed to address the spatial mismatch problem—the geographic separation between low-income communities and job opportunities in the United States (Bastiaanssen et al., 2020; Brandtner et al., 2019). As a result, in other cases, public transportation services may not be suitable for visiting green spaces. Scruggs (2021) highlighted a related issue: the absence of dedicated transit services for green space trips often forces people to use "transit hacks"—creative use of regular transit services to get as close as possible to trailheads or park entrances. This requires visitors to piece together multiple segments of public transit to bridge the gap between urban transit stops and remote park entrances or hiking paths. Therefore, the findings may not generalize to other green spaces where transit services are less accommodating. Future research should evaluate the effectiveness of public transportation for various green spaces to better understand where and under what conditions transit promotes park visitation.

Another limitation is the reliance on cross-sectional data, which restricts the ability to perform a before-and-after analysis of public transportation's impact on park visitation. The public transportation system in the Phoenix metro area has been established for several decades, with Valley Metro's bus service beginning in the 1980s and the light rail system commencing operations in 2008. Due to the lack of mobility data on park visits from before the implementation of these transit services, I was unable to conduct a longitudinal analysis to directly assess changes in park visitation attributable to the introduction of the transit system. Although I controlled for the distance between CBGs and South Mountain, as well as neighborhood-level sociodemographic characteristics, there may still be unaccounted differences between treatment and comparison CBGs—such as their connectivity to other green spaces within the Phoenix metro area.

Despite these limitations, I took deliberate steps to enhance the validity of the research design. I concentrated my analysis on periods ideal for outdoor activities in the Phoenix area—specifically, the months of January to March and November to December—when park visitation is typically higher. This focus ensured that the data reflected peak usage periods, thereby strengthening the relevance of the findings. Additionally, I utilized trailhead data that serve as entrance points to South Mountain to intensify the treatment effect under study. By concentrating on these specific access points, I aimed to more accurately capture the influence of public transportation on visits to South Mountain. These methodological choices were intended to bolster the robustness of the findings and mitigate some of the study's limitations.

CHAPTER 5

CONCLUSION

This dissertation advances environmental justice literature by addressing the limitations of static methods in assessing exposure to green spaces. Traditional research often estimates green space exposure based on fixed locations like residences or workplaces, assuming individuals utilize nearby green spaces. This static approach overlooks the dynamic nature of daily human movement, potentially misrepresenting true exposure levels and skewing health-related findings. It also hinders the measurement of behavioral changes in green space visitation resulting from government interventions and their equity impacts. By incorporating human mobility data and measuring exposure through actual visits to green spaces, this study provides a more accurate and nuanced understanding of green space equity.

The findings in dissertation essays pose important policy design challenges that arise when policies in one domain inadvertently negatively impact another—particularly concerning environmental justice on green spaces. For example, the first essay found that during periods of strict mobility restrictions in the COVID-19 pandemic, park visits among Phoenix residents decreased, a burden disproportionately fell on lower-income communities. This illustrates how social distancing policies can unintentionally worsen environmental injustice. This raises the question of whether vital public health measures should be avoided due to their unintended environmental justice implications—which is

neither practical nor ethical. Similarly, the second essay revealed that highways act as barriers, negatively impacting community visitation to nearby parks. Transportation infrastructure intended to enhance regional mobility can unintentionally create local barriers that impede residents' access to green spaces, exacerbating environmental injustice for communities along highway corridors. Avoiding the construction of highways is impractical given their importance for economic growth and connectivity. Rather than pursuing such unrealistic goals, governments have implemented creative ways to uphold environmental justice while maintaining public health guidelines. For instance, Philadelphia opened certain golf courses and private green areas to the public during the pandemic (Philadelphia Inquirer, 2020). Parks Canada temporarily waived entrance fees to national parks in 2020, encouraging safe outdoor activities while adhering to social distancing measures (Parks Canada, 2020). In Sydney, Australia, the local government extended park hours and added amenities to promote the safe use of green spaces (City of Sydney News, 2020). Regarding the barrier effect, the Biden administration's Reconnecting Communities Pilot Program aims to mitigate the negative impacts of previous highway expansions that resulted in community severance and reduced access to local amenities, including green spaces (U.S. Department of Transportation, 2021). This initiative exemplifies policy layering by adding new elements to existing transportation policies to address past shortcomings. These initiatives represent efforts to mitigate the unintended negative impacts of stay-at-home orders on environmental justice. They highlight the importance of developing strategies that

consider the interconnectedness of different policy domains to effectively address unintended consequences.

These initiatives exemplify concepts in policy design literature known as policy patching and policy layering (Howlett, 2019). Policy layering involves adding new policy elements to existing frameworks without completely replacing them, thereby introducing measures to mitigate unintended consequences. In contrast, policy patching focuses on correcting flaws within the existing policy structure or adjusting it to new circumstances. While patching aims to resolve issues internally, layering seeks to complement or enhance policies by incorporating additional provisions. Policy patching and layering are particularly effective approaches for addressing unintended consequences that cross policy domains. Unintended consequences often arise because policies impact phenomena beyond their initial scope due to the interconnected nature of societal systems. By employing these approaches, policymakers can introduce targeted solutions that address cross-domain impacts without overhauling the original policy or compromising its primary objectives. This flexibility allows for adaptive responses to complex challenges, effectively mitigating negative effects that were not anticipated during the initial policy design.

By adopting policy patching and layering, governments can effectively address unintended consequences that transcend policy domains. Recognizing that policies do not operate in isolation, these approaches allow for the strategic addition and adjustment of policy elements to mitigate negative cross-domain impacts, promote equity, and enhance overall effectiveness without undermining initial objectives. This holistic approach is

essential for developing resilient policies capable of navigating the complexities of interconnected societal systems (Maroulis, 2016; Maroulis et al., 2010).

Future research should focus on evaluating the effectiveness of policy patching and layering in mitigating unintended consequences across policy domains. Empirical studies assessing the long-term impacts of such interventions on environmental justice outcomes would provide valuable insights. Additionally, developing methodological frameworks for systematically identifying unintended consequences and designing appropriate patching or layering strategies could enhance policy responsiveness and equity (Campbell et al., 2024).

The findings from this dissertation underscore the importance of anticipating and addressing the unintended consequences of policies across different domains. While abandoning critical public health measures or essential infrastructure projects is neither feasible nor desirable, policymakers can employ strategies like policy patching and layering to mitigate negative impacts on environmental justice. By integrating additional measures that enhance equitable access to green spaces and consider community impacts, it is possible to promote sustainable development that is both effective and equitable. This research not only contributes to a more accurate assessment of green space equity but also offers a framework for policymakers to design more holistic and adaptive policies. Ultimately, embracing dynamic methodologies and integrative policy approaches is crucial for advancing environmental justice and fostering healthier, more equitable urban environments.

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APPENDIX A

SUPPLEMENTARY MATERIALS FOR CHAPTER 2

Table A1. Monthly Estimates from the Event Study Analysis

DV: Ln (Visit Count)	(1)
Year2020 * Week 1 to 4 (January)	0.074
	(0.074)
Year2020 * Week 5 to 9 (February–1st Week of March)	0.011
	(0.071)
Year2020 * Week 10 (2nd Week of March)	Reference (Omitted)
Year2020 * Week 11 to 12 (3rd – 4th Week of March)	-0.418***
	(0.079)
Year2020 * Week 13 to 16 (April)	-0.826***
	(0.073)
Year2020 * Week 17 to 21 (May)	-0.748***
	(0.070)
Year2020 * Week 22 to 25 (June)	-0.526***
	(0.073)
Year2020 * Week 26 to 29 (July)	-0.483***
	(0.073)
Year2020 * Week 30 to 34 (August)	-0.705***
	(0.071)
Year2020 * Week 35 to 38 (September)	-0.500***
	(0.075)
Year2020 * Week 39 to 43 (October)	-0.518***
	(0.070)
Year2020 * Week 44 to 47 (November)	-0.527***
	(0.076)
Year2020 * Week 48 to 52 (December)	-0.577***
	(0.072)
Block Group FE	Yes
Weather Controls	Yes
Observations	101,296
R^2	0.032
F Statistic	119.847***

Notes: *p<0.05; **p<0.01; ***p<0.001