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Factors influencing long-term city park visitations for mid-sized US cities: A big data study using smartphone user mobility

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ABSTRACT

City parks provide essential services for the physical activities and the health improvement of residents. Most related literature focuses on the factors affecting park visitations in large cities, but relatively little is known regarding long-term park visitations, especially in mid-sized cities. By using smartphone mobility data tracking the activities of 28 parks in the College Station and Bryan Metropolitan area of Texas, USA, we present the temporal and spatial patterns of park usage within a two-year timeframe. We model the effects of the socioeconomic, built environment, climate, and spatial/accessibility factors on park visitations through a fixed effects regression. Results show variations among park service areas. Water bodies and playgrounds are significant factors enhancing park visitations while walking paths, sports facilities, and pavilions are not. Contrary to previous research, high-income block groups show lower participation in park activities. The study also reveals how smartphone mobility data can be applied to case studies investigating urban design/planning and understanding of the social aspects associated with urban greenspaces. It provides empirical evidence on park visitations as well as what factors future planners, landscape architects, and park managers should consider when deciding on park investment and planning decisions for mid-sized cities.

1. Introduction

1.1. Park usage and health improvement

City parks can be neighborhood gardens, municipal parks, sports fields, playgrounds, and other incorporated places that offer recreation and green spaces to residents; they contribute to human well-being, particularly regarding physical and mental health (Counts & Newman, 2019; Kim & Miller, 2019; Wang & Akbari, 2016). These parks often are managed by city Parks and Recreation Department, with sizes ranging from less than 1 to 500 acres. Studies have found that vegetation in parks can remove particulate matter from the air and have a positive effect on respiratory illness for the local population (Buccolieri et al., 2018). Regular park-based physical activity has been a promising means to fulfill healthy physical activity requirements which can decrease diabetes, high blood pressure, colon cancer, weight, and depression/anxiety (US Department of Health and Human Services, 1996; Wu & Kim, 2021). As processes of urbanization and densification lead to less green spaces, the cost-free and accessible public services by city parks are particularly important (Gardsjord et al., 2014). Many studies have focused on maximizing the benefits of city parks through encouraging more park visitation and usage. Accessibility is one of the most widely accepted factor of park utilization (Xie et al., 2018). Park amenities such as walk paths, shelters, trees, water elements, playgrounds, and sports facilities have also been shown to contribute to more park visitations (La Rosa et al., 2018; Payne et al., 2002; Wendel et al., 2012). Other subjective qualities including openness, naturalness, cleanliness, convenience, safety also draw more people to parks (Fongar et al., 2019; Song et al., 2020). Other than park attributes factors, socioeconomic status also affects park visitations, as parks in high-poverty areas are usually less used when compared to medium- and low-poverty areas (Cohen et al., 2012)

Studies utilizing the aforementioned factors were usually only conducted within a short time frame, and with limited numbers of parks. What is working on a short time basis may not apply to longer time spans. However, quantifying the long-term effects (covering yearly time spans) of factors to city park visitations can be extremely difficult for practitioners and researchers (Donahue et al., 2018). Traditional observational or survey methods record park demand and usage by counting visitors at park entrances or hand out questionnaires from

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random samples of park users (Dallimer et al., 2014; McCormack, et al., 2010). Others have hired field observers to record user activities and their associated park facilities (Evenson et al., 2016; Hamilton et al., 2017). These methods are both time consuming and resource intensive. They also only cover a limited spatial area and a short timeframe (Tenkanen et al., 2017). Risks on potential implicit selection bias during sampling and data collection process exists in these approaches.

1.2. Big data and long-term behavior monitoring

Recently, emerging big data technology has created a transformative potential for monitoring long-term behaviors in urban parks. For example, the amount of social media data grows in volume yearly; such data provides a wealth of knowledge about visitors' behaviors and experiences (Liu et al., 2018; Song et al., 2021; Ye and Andris, 2021). This situation has offered exceptional opportunities for researchers to study topics such as user activities, place perceptions, and landscape design quality and effectiveness within urban parks (Han et al., 2018; Song & Zhang, 2020; Song et al., 2020; Zhang & Zhou, 2018). Although social media studies show promise in better measuring human activities and emotions, they are still subject to limitations and bias from aspects such as the representativeness of social media users, noise from bots, fake accounts, or other related issues (Chen et al., 2020; Park et al., 2022; Wilkins, et al., 2020; Ye et al., 2021). It is also difficult to gain specific locational information (e.g. coordinates) of users through social media platforms (e.g. Instagram, TripAdvisor, FourSquare) due to privacy concerns (Peng and Ye, 2021).

Recently, data from SafeGraph, a company that aggregates cell phone location data through anonymized measures (SafeGraph, 2020), has gained attraction to monitoring urban mobility behaviors. SafeGraph provides compelling data collections, with 6.4 million points of interest (POI) listings and associated mobility patterns of 19 million smartphone users representing 10% of devices in the United States. According to Squire, 2019, SafeGraph's sampling has shown a strong correlation with the true Census populations on several geographic (state, county, census block group) and demographic (race, educational attainment, and household income) dimensions. Many research applications have emerged in multiple disciplines. For example, different machine learning models applying the data have been used to study business locations and parking violations (Gao et al., 2019). Mobility network models using the data have also been developed to explain inequities of COVID-19 transmissions and inform reopening strategies (Chang et al., 2020). Further, Safegraph datasets have been analyzed to examine unhealthy eating patterns to reveal the impact of COVID-19 on populations with obesity (Ashby, 2020). Finally, Van Dijcke & Wright (2020) also used SafeGraph to study political and social mobilization during the George Floyd-related protests.

1.3. Lack of studies in mid-sized cities

Existing studies on park visitations have mainly been conducted only in large cities or high-density urban areas in which park users are recruited from specific neighborhoods (Cohen et al., 2010; Hughey et al., 2018; Zanon et al., 2013). However, cities with different sizes, populations, and densities can vary by social demographics, infrastructure, built environment characteristics and needs, and local economic levels. These factors play an important role in driving park visitation preferences and behaviors (Kaczynski et al., 2014; Zhang & Zhou, 2018). What drives park use in large and highly populated cities may not apply to small or mid-sized cities. Failure to differentiate these differences may lead to prejudiced assumptions on best urban planning and park management practices across different sized cities and users. For example, the 719 mid-sized US cities (between 50k to 250k in population) cover a large amount of population and areas (Statista. (n.d.) 2020), but have been rarely studied.

To address such research disparities, we explore the potential of using smartphone user mobility data (SafeGraph) to overcome the abovementioned challenges with a focus on mid-sized cities and long-term time frames. We ask, how do socio-demographic, environmental, and time based (e.g. weather) factors affect long-term park visitation in mid-sized US cities? Using the College Station and Bryan Metro area in Texas, USA as our focus area, we collect and analyze smartphone data to quantify weekly park visits by establishing origin & destination patterns from park related SafeGraph trajectory data. We then explore the temporal and spatial patterns of park visitations. A longitudinal model is built to identify significant factors that could attract additional park visitations. The results of this study provide important empirical evidence and insights to the future planning, design and management of city parks. Especially regarding mid-sized cities, we aim to promote long-term park visitations for all social groups and thereby improve overall health behaviors and well-beings for future residents.

2. Methodology

2.1. Data collection and processing

As noted, in this study we use "SafeGraph Places." Such data includes three datasets: 1) "Core Point of Interests (POI)" contains basic information of about 6.1 million POIs in the US and Canada such as name, brands, address, category, and other relevant contact information; 2) "Geometry" includes the areas, polygon representation, and other properties for the outline of the POIs are housed in; and 3) "Places Patterns" has visitation patterns that update weekly with information about the number of devices observed to the POIs, total visits, home block groups (BG) of visitors, and total devices tracked of each BGs during the week. The home BGs were detected by tracking user locations during nighttime from 6pm - 7am over a previous 6-week period (SafeGraph, 2020). Regarding privacy concerns, SafeGraph applies several techniques including: 1) a list of home BGs for a POI excludes a home BG having five devices per month for a target POI; 2) statistical adjustments referred to as Laplacian noise for certain variables to protect users; and 3) additional reports for POI data for more than 2 visitors. If there are 2 to 4 users for either a POI (destination) or a BG (origin), SafeGraph will count as 4. To mitigate this overcounting issue, we excluded the SafeGraph data that were recorded as 4 and only records with weekly BG to POI users larger than four were included in the final analysis.

In this study, we focus on the BGs and POIs located in the College Station & Bryan (CSB) metro area. One hundred and eighteen BGs that overlap with CSB boundaries were included, with a median household income of $45,820. Both College Station (113,686) and Bryan (84,096) in CSB area have populations between 50k to 250k among 719 other mid-sized US cities (Statista, n.d.). Texas A&M University is located in the center of the study area with a student population of 68,603. Our data collection constructs a dataset of mobility patterns for this target area related to park visitation and outdoor recreation from 2018/12/31 to 2020/11/30. We first downloaded all available SafeGraph POIs in the "Nature Parks and Other Similar Institutions" sub-category of the SafeGraph 'Core POI' dataset and linked them with "Geometry" and "Places Patterns" dataset. Parent POIs that geographically overlap their 'child' POIs were deleted to avoid double counting. For example, if there is a POI (parent) of a mall that includes many store POIs (child), we did not count this mall POI (parent) into our dataset. For the real visitation estimation, we adjusted the BG-level visitor counts to consider variations from the differences of device sampling ratio for each week through our study period as Eq. (1). Then, the BG-level visitor counts were used to estimate POI-level visitor counts as Eqn 2 which is similar to the approaches adopted by previous studies (Chang et al., 2020; Jay et al., 2020). We also added social-demographic controls using demographic data (e.g. income and age) from the American Community Survey (2016) 5-year estimate and climate controls of CSB such as weekly temperature and average rainfall data from NOAA as for later analysis.

$$VBG_{i,k,t} = \left(SBGV_{i,k,t} * POP_j\right)/SGD_{i,t} \tag{1}$$

$$VP_{k,t} = \sum_{i=1}^{n}\left(VBG_{i,k,t}\right) \tag{2}$$

Where $VBG_{i,k,t}$ refer to the visitor number from BG i to POI k during the t th week of our study period; $SBGV_{i,k,t}$ refer to the SafeGraph visitors from BG i to POI k during the t th week of our study period; POP refers to the total population of the BG i. $SGD_{i,t}$ refers to the total device number sampled for BG i at the t th week of our study.

$VP_{k,t}$ refers to POI k's total visitors during t th week. n refers to the total number of BGs that have traveled to the POI k during t th week.

2.2. Park classification

Although all city parks can serve some form of outdoor recreation purpose, each varies by its functions and capacity. As such, to classify the park POIs in our dataset, we use visual and qualitative examination. We first differentiate community and neighborhood parks based on classification guidelines provided by the National Recreation and Park Association (NRPA). Similar to other local TX Park and Rec agencies (Park Classifications), we assign a park as community park if it has recreational facilities and is larger than 16 acres. All other parks fall into the category of neighborhood parks. Regarding park properties and features, we primarily focus on the amenities within each park Fig. 1. shows a list of park amenities that were important to park use to classify our parks based on the availability of walking paths, water bodies, pavilions and sports facilities (Rivera et al., 2021). These amenities are also included as physical environment components in existing park audit systems (Kaczynski et al., 2012; Saelens et al., 2006) such as the Environmental Assessment of Public Recreation Spaces (EAPRS) and Community Park Audit Tool (CPAT). For walking paths, unpaved paths are counted but need to be at least 500ft long. A water body needs to have a

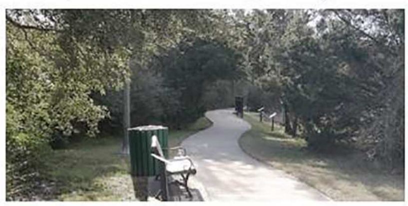
Name	Description and Example	Criteria	Value
Walk Path	A designated trail path for walking and sightseeing purposes. The path usually meanders through the park or as a loop. 	Without walk path	0
		With walk path	1
Water Bodies	The park has natural water bodies such as a lake of creek. 	Without water bodies	0
		With water bodies	1
Pavilions	Structures such as pavilions or seat shelters that provide shade for users to stay. 	Without pavilions	0
		With pavilions	1
Sports Facilities	The level of sports facilities built in the park, including basketball, tennis, baseball, football, etc. 	No Sports Facilities	0
		With 1-3 Sports Facilities	1
		With >3 Sports Facilities	2

Fig. 1. Park categories and classification criteria.

continuous water area of 2000 square feet minimum to be included and pavilions must have at least a 100ft footprint and offer more than four seating capacity to be included. We also specify the level of sports facility numbers. For example, one more basketball court serve 20 more users (4 teams). To consider this difference, we rank sports facilities as: low (value 0, no sports facilities), medium (value 1, 1-3 sports facilities), and high (value 2, >3 sports facilities).

One other key consideration in our study is park design features, specifically, the decorative or aesthetic qualities of each park. As in many rural or mid-sized US cities, not all greenspaces were designed to be visual attractions due to construction and annual maintenance cost considerations. Previous researchers have also studied similar perceived landscape qualities (Fongar et al., 2019; Wartmann et al., 2021), with many only focusing on experiential reactions of parks such as cleanliness, quietness, and comfort. Few studies have addressed the landscape architecture features related to park design. In this study, we refer to the essential design elements included in Booth (1989)'s book, which was widely used to teach many US registered landscape architecture programs. Flower beds (visual plants), pavement patterns, decorative walls, decorative fences, water fountains, and sculptures were selected as elements representing the landscape architecture design efforts of each park (Fig. 2). The decorative walls, fences, and water fountains indicate vertical decorations (often more than 3ft tall) which are often used as visual attractions or spatial separators. Pavement patterns and flower beds are ground-level decorations used to define surface spaces. We then classify our parks by counting how many of these design features were included through site visiting and visual observation. When observing less than 1 design feature within a park, we classify the park as having low design features. Then, 1-3 design features are categorized as medium design features and more than 3 design features is considered as high design features.

2.3. *Fixed effects regression analysis*

The Safegraph data is longitudinal, covers an extensive timespan (during 2018/12/31 to 2020/11/30), and contains observations about different weekly cross sections. We run a fixed effects regression model using Python Stats Model library. The model estimates the effects of our control variables on estimated park visitor amount (Eq. (3)) from one BG across different weeks. Because fixed effects can limit the source of bias to time-varying variables, the heterogeneity of individual parks and different week periods that are unobservable and time-invariant could be controlled. Our basic del can be expressed as follows:

$$VBG_{i,t,k} = \alpha + \beta VP_{k,t} + \gamma_1 D_t + \gamma_2 P_k + \gamma_3 BG_i + \theta_t + \theta_k + \varepsilon_{i,t,k} \tag{3}$$

$VBG_{i,k,t}$ refer to the visitor number from BG i to POI k during the t th

Design Features	Example
Water fountain Manmade water feature that use pumps to force water upwards.	
Flower bed A planting bed with ornamental plants, usually flowers. High maintenance needed.	
Paving pattern Ground paving that uses unit pavers to form certain geometrical shapes.	
Decorative wall Vertical structures using ornamental materials such as stacked stone, stripped wood board, etc.	
Decorative fence Fence made by metal or painted wood. The balusters are wide enough so people can see it through.	
Sculpture Manmade sculptures permanately locate in the park . At least 3 ft tall.	

Fig. 2. Park design features for decorative and aesthetic purposes.

week of our study period. $VP_{k,t}$. refers to POI k's total visitors during t th week to represent the overall popularity; D_t is the time-variant characteristics such as weather; P_k is the time-invariant characteristics of POI k such as area, playgrounds, sports fields, etc. BG_i is the time-invariant characteristics of BG i such as population, median income, etc. θ_t is the time specific fixed-effects. $\theta_k$is the POI (location) specific fixed effects. ε is the error term. α is the intercept of the linear function.

3. Results and findings

3.1. Data description

Our final analysis includes 28 total parks with 9 community parks and 19 neighborhood parks (shown in Fig. 3) as our focus panel dataset for this study. This is only a portion of total parks listed by the city. Several reasons keep us from including all parks: 1) SafeGraph POI datasets are still not complete, many smaller and newer parks are omitted; 2) we excluded park types that do not fit our study such as natural reserve areas, forests, greenway trails, aquatic centers, school parks, and empty lands. 3) We deleted parks with less than 40 weeks of data coverage as we focus on studying long-term visitation patterns. The travel patterns of all park POIs cover an average range of 87 weeks. Each week, SafeGraph re-samples devices residing in each BG. As a result, the sample size of each BG included in the study changes weekly but follows a normal distribution over a long-term timeframe Fig. 4. shows the distribution of SafeGraph sampling percentages of each BG. Overall, an average of 9.57% of all populations in the area were sampled in the weekly panel data utilized.

As Table 1 shows, the parks in the study cover a wide range of

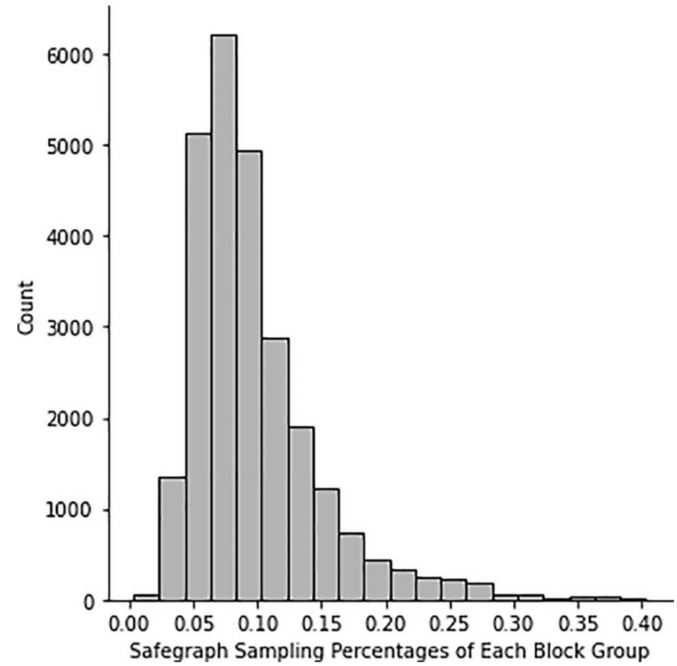


Fig. 4. SafeGraph Sampling Distribution.

features, with each park including at least one targeted facility or amenity. Seven parks have high levels of design features. The average daily visitors vary from 21 (Copperfield Park) to 305 (Southwood

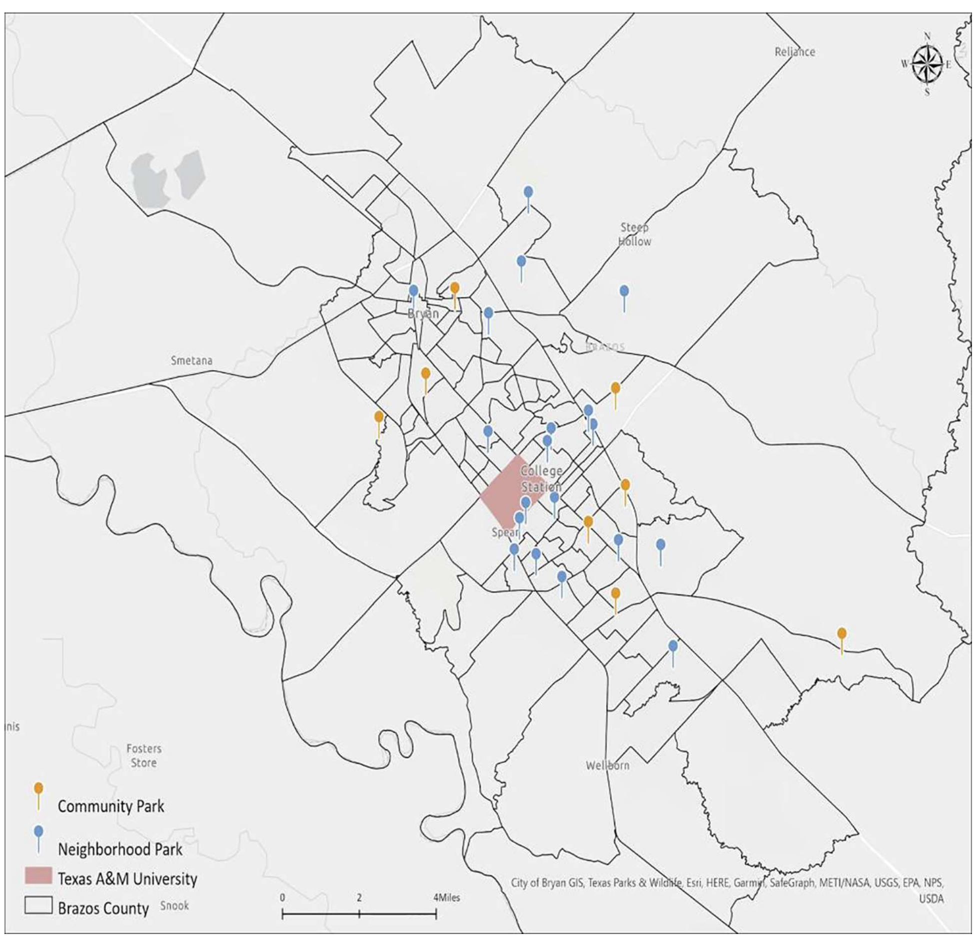


Fig. 3. The study site: College Station and Bryan Metropolitan area.

Table 1
Basic information about participating parks of the study.

Park name	Average daily visitors	Weeks covered	Facilities & amenities	Level of landscape design features
Neighborhood Park Information				
John Crompton	253	101	Trails, sport facilities playgrounds, water body or streams, pavilion/seating areas	High
Southwest Park	132	101	Trails	Low
Anderson Park	129	101	Playgrounds, sport facilities, pavilion/seating area	Low
Southern Oaks Park	69	101	Trails, sport facilities, playgrounds, pavilion/seating areas	Medium
Thomas Pool	66	100	sport facilities	Low
Austin's Colony Park	63	78	Playgrounds, sport facilities, pavilion/seating area	Low
Steeplechase Park	61	101	Trails, sport facilities, playgrounds, water body or streams	Low
Camelot Park	50	78	Trails, waterbody or streams	Low
Gloria Stephen Sale Park	47	78	Pavilion/seating areas	High
Siena Estates Park	43	78	Trails, playgrounds, water body or streams, pavilion/seating areas	Medium
Longmire Park	42	99	Trails, water body or streams	Low
Brison Park	40	99	Trails, water body or streams,	Low
University Dog Park	39	98	Trails, playgrounds, water body or streams, pavilion/seating areas	High
Merry Oaks Park	31	95	sport facilities, playgrounds, water body or streams	Low
Crescent Park	29	80	Trails	Low
Woodcreek Park	29	98	Trails, playgrounds	Low
Richard Carter Park	25	94	Trails, pavilion/seating areas	High
Copperfield Park	21	76	sport facilities, playgrounds, pavilion/seating area	Low
Dr David E Schob Nature Preserve	10	46	Trails, pavilion/seating areas,	High
Community Park Information				
Southwood Athletic Park	305	101	sport facilities, playgrounds	Medium
Stephen C Beachy Central Park	296	101	Trails, sport facilities, playgrounds, water body or streams, pavilion/seating areas	High
Henderson Park	204	78	Trails, sport facilities, playgrounds, pavilion/seating areas	Medium
Sue Haswell Memorial Park	157	78	Trails, sport facilities, playgrounds, water body or streams, pavilion/seating areas	Medium
Travis Athletic Complex	169	78	sport facilities, pavilion/seating areas	Low
Veterans Park	151	82	Trails, sport facilities	Medium
Bee Creek Park	101	90	Playgrounds, sport facilities, pavilion/seating area, trails, water body or streams	Medium
Lick Creek Park	58	60	Trails, playgrounds, water body or streams, pavilion/seating areas	High
Domino Park	48	71	Trails, sport facilities, playgrounds, water body or streams, pavilion/seating areas	Medium

Athletic Park).

3.2. Temporal patterns between neighborhood parks and community parks

We investigate the temporal patterns of park usage by aggregating park visitation data based using two categories: community parks and neighborhood parks Fig. 5. shows the changes of these park categories in median visitors for a weekday vs a weekend day. Overall, the community parks (with a mean of 139.0 for a weekday and 163.0 for a weekend day) have more users than the neighborhood parks (a mean of 45.0 for a weekday and 49.0 for a weekend day). The community parks also have higher visitor variance (77.9 for weekdays and 119.7 for weekends) than neighborhood parks (17.19 for weekdays and 22.28 for weekends). Large visitor spikes of community park usage occur generally in the summer months, from July to late Oct in both 2019 and 2020. Neighborhood park usage does not show extraordinary fluctuations, with a minimum of 24 per day and a maximum of 46 per day. Regarding weekday and weekend differences, the community parks (18%) see more rises in amounts of visitors during the weekends than neighborhood parks (9%). Lastly, significant increases were shown during the late summer and early fall of 2020 (July to Nov) for all parks, for both weekdays and weekends. Overall, COVID looks to have played a significant role in the rise of summer visitations. Many residents in the area are employees for higher education who have family travel plans during the summer. Because of COVID restrictions, more people had to cancel their plans and stay in town instead for this year. Many indoor summer school camps were also canceled due to COVID, which led to more activities being transferred to outdoor locations like parks.

3.3. Distance traveled and factors related with visitations

We use SafeGraph POI travel patterns to calculate the network distances of all available park trips. As the example visualizations show in Fig. 6, we can compare and visualize the weekly median visitors from different BGs to a park Fig. 7. lists the estimated average distances per trip from the user's home BG centroid to each park destination. Although the average distance traveled (7332 m) for all community park users is bigger than the neighborhood park users (5246 m), community parks such as Domino Oaks Park and Henderson Park only attracted users from around three thousand meters. Some neighborhood parks,

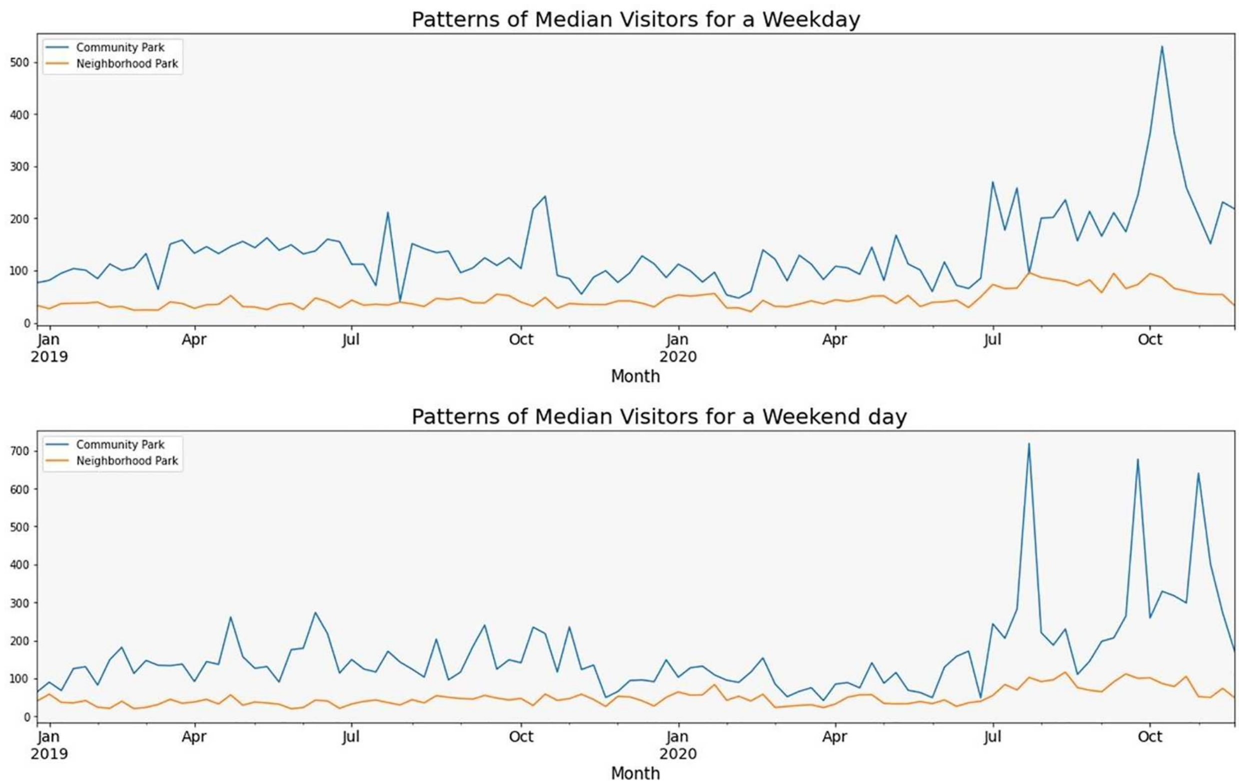


Fig. 5. Weekly median park visitors during a weekend day (upper) and a weekend day (bottom) for community parks and neighborhood parks.

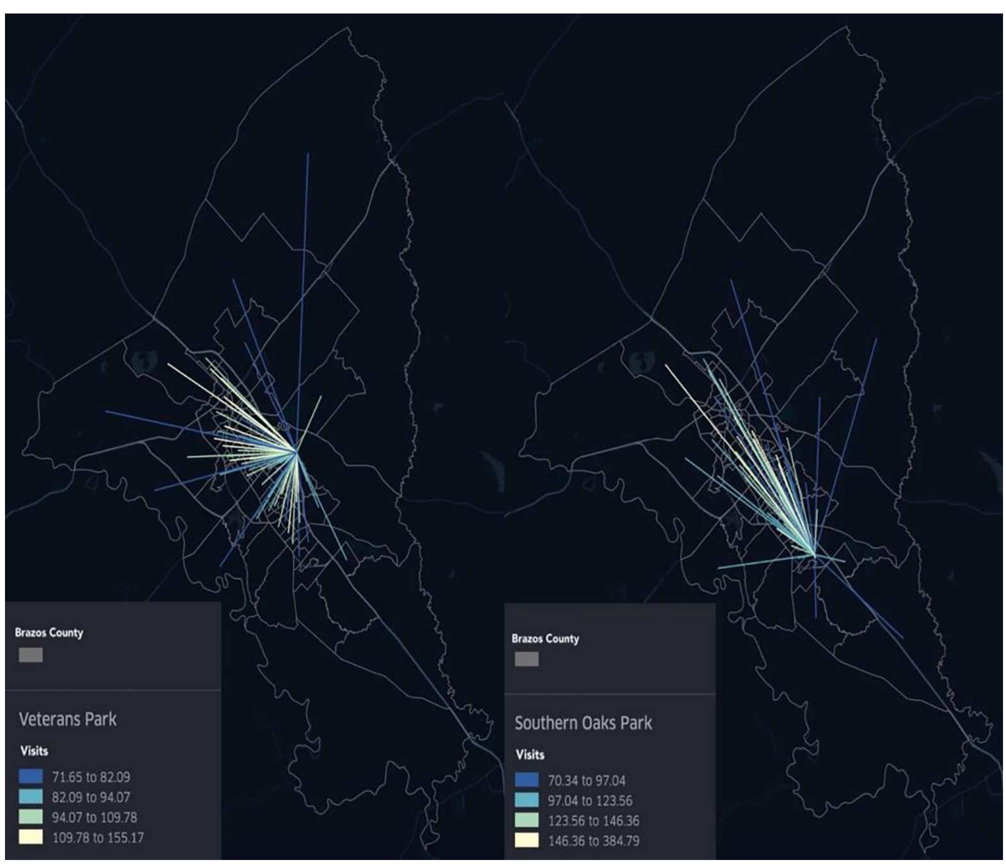


Fig. 6. Weekly median park visitors for two example parks.

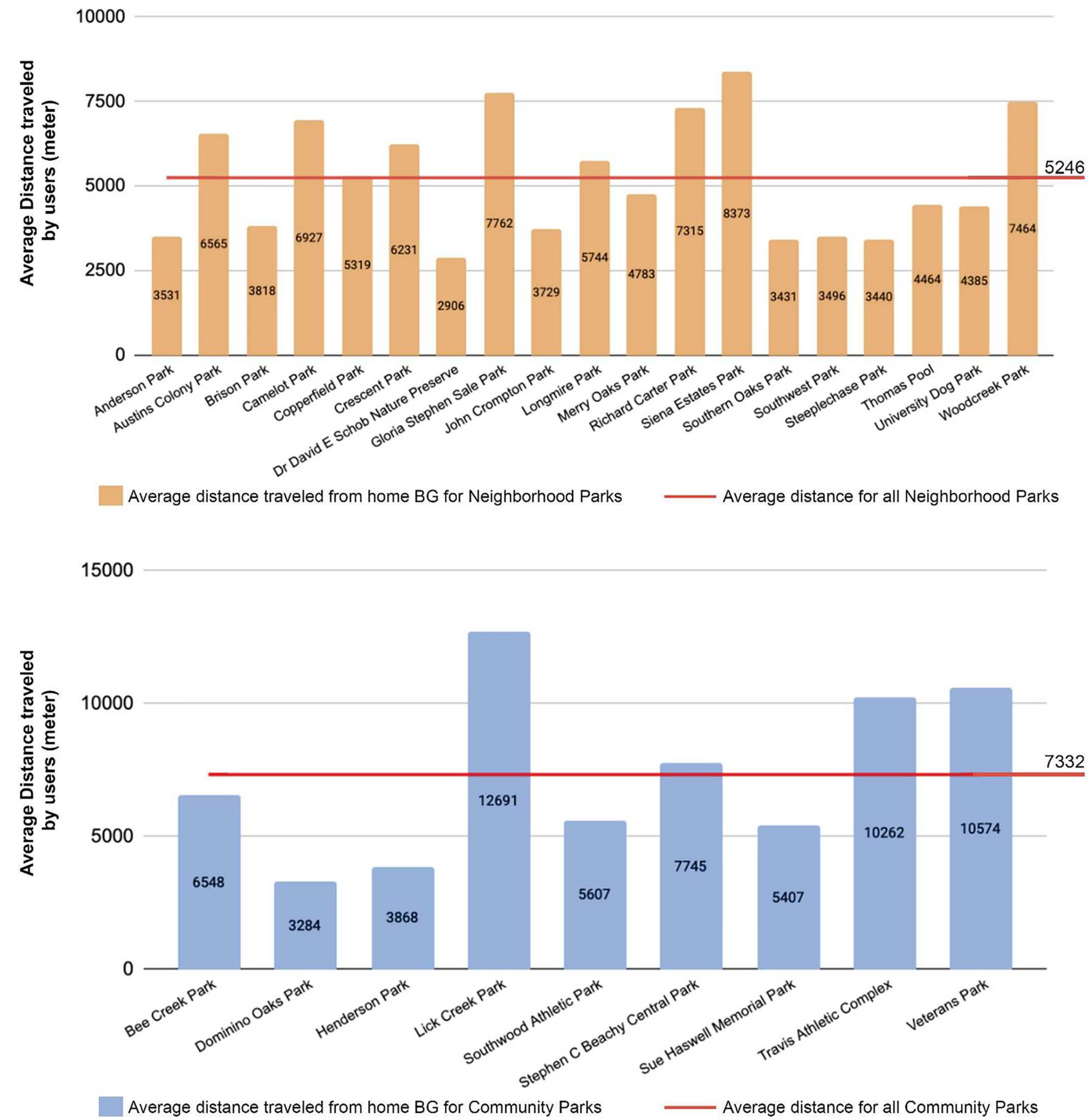


Fig. 7. The average distance the visitors traveled from their home BG to the destination parks.

such as Gloria Stephen Sale Park, Richard Carter Park, Siena Estates Park and Woodcreek Park, attracted users from more than seven thousand meters, which are significantly further than nearby areas.

Our data covered socio-economic factors, built environment factors, climate factors, and spatial/accessibility factors which have all been proven as strong indicators of park visitation (Liu et al., 2017; Zanon et al., 2013). As shown in Table 2, our dependent variable is park visitors from each BG (Visitor from BG). The independent variables include attributes of each BG within the study area (BG Senior, BG Income, BG Population, Distance BG to Park), attributes of all parks (AREA, Path, SPORTS, Playground, Water Bodies, Pavilion, Community Park, Design Features, Total Park Visitors), and time related controls (Precipitation, Temperature, College Holiday, COVID-19). The dependent variable and four block group attributes are right skewed with means larger than the medians which can lead to some data acting as outliers for statistical models. However, the residual errors were normal and we believe the level of skewness is only minimally or moderately skewed, with a skewness less than 1.

With 4104 observations included, we modeled four different specifications (see Table 3). Only key variables related with BGs are included in Model 1, we then add more variables on park attributes and time controls into Model 2 and Model 3. Time and park-specific fixed effects are accounted for in Model 4. The p-value of Playground, Pavilion and Temperature turned from insignificant (at a 0.05 level) to significant

Table 2
Regression model variable descriptive statistics.

Variable	Description	Mean	Std	Min	Median	Max
Dependent Variable						
Visitor from BG	Weekly visitors from a BG to a park	165.34	118.29	12.48	134.76	996
Block Group Attributes						
BG Senior	Total senior population	208.79	169.28	8	178	1073
BG Income	Median Household income ($1000 as unit)	62.72	35.37	8.82	52.03	210.16
BG Population	Total Population	2562.24	1190.75	454	2407	14424
Distance BG to Park	Network Distance between a BG Centroid to the destination Park	5619.95	5446.86	0	4056.77	23824
Park Attributes						
Area	Area Square Foot (1000000 sqft as unit)	1.47	3.19	0.002	0.77	24.17
Path	If a park has designed walking paths	0.54	0.50	0	1	1
Sports	The level of sports facilities in a park	0.86	0.43	0	1	1
Playground	If a park has a playground	0.77	0.42	0	1	1
Water Bodies	If a park has natural water bodies or streams	0.43	0.50	0	0	1
Pavilion	If a park has pavilions or other seating shelters	0.56	0.50	0	1	1
Community Park	If the park is community park	0.57	0.50	0	1	1
Design Features	The level of landscape design features in the park	1.93	0.75	1	2	3
Total Park Visitors	Total weekly Number of Visitors of a park, used as a control for park popularity	1725.78	1277.06	25.73	1396.61	5542.90
Time Related Controls						
Precipitation	Average Precipitation	0.03	0.08	0	0	0.52
Temperature	Average Temperature (F)	82.65	12.39	35	84	101
College Holiday	If the date is during college holiday	0.25	0.43	0	0	1
COVID-19	If the date is during COVID-19 pandemic after National Emergency declaration (Mar 19th, 2020)	0.34	0.47	0	0	1

Table 3
Regression model estimation results.

	Model 1			Model 2			Model 3			Model 4		
	Coefficient Estimate	t stats	P value	Coefficient Estimate	t stats	P value	Coefficient Estimate	t stats	P value	Coefficient Estimate	t stats	P value
BG Senior	-0.016	-1.26	0.207	-0.025	-1.87	0.062	-0.024	-1.83	0.068	-0.003	-0.23	0.816
BG Income	-0.338	-5.28	0	-0.186	-2.80	0.005	-0.207	-3.12	0.002	-0.248	-3.76	0
BG Population	0.007	`	0	0.007	3.84	0	0.006	3.56	0	0.003	1.75	0.081
Distance BG to Park	-0.005	-16.21	0	-0.006	-16.15	0	-0.006	-16.37	0	-0.005	-14.44	0
AREA				-0.733	-1.10	0.273	-1.256	-1.8	0.072	-0.275	-0.41	0.685
Path				4.222	0.58	0.561	2.476	0.34	0.734	7.718	1.10	0.273
Sports				-22.26	-3.56	0	-26.82	-4.19	0	-3.986	-0.73	0.464
Playground				-4.227	-0.66	0.507	-4.8	-0.76	0.449	12.844	2.12	0.034
Water Bodies				5.927	0.79	0.432	4.864	0.65	0.518	20.118	2.76	0.006
Pavilion				1.516	0.32	0.749	4.820	1.01	0.314	1.571	0.33	0.74
Community Park				-30.49	-5.67	0	-26.83	-4.86	0	-22.979	-4.10	0
Design Features				0.878	0.22	0.823	2.001	0.51	0.609	-2.432	-0.45	0.65
Total Park Visitors				0.016	8.84	0	0.016	8.22	0	0.022	9.49	0
Precipitation							-52.98	-2.22	0.027	-36.898	-1.90	0.051
Temperature							0.064	0.41	0.68	1.029	2.67	0.008
College Holiday							22.088	5.07	0	-2.021	-0.15	0.877
COVID-19							13.882	3.34	0.001	24.583	5.50	0
Intercept	202.905	41.746	0	203.18	26.73	0	193.79	13.68	0	73.053	3.12	0.002
Time-fixed	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Park-fixed	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
adj-R2	0.099			0.13			0.139			0.22		

(less than 0.05) in Model 4. BG Population, Sports and College Holiday become insignificant (p-value bigger than 0.05) in Model 4, while they are significant (p-value smaller than 0.05) variables in all previous Models. The overall adjusted R-square raises from 0.099 to 0.13 by adding park attributes variables in Model 2, only 0.009 improvements are shown after adding time-related controls in Model 3. Then, accounting for fixed effects enhanced the adjusted R-square from 0.081 to 0.22. Additional variables such as percentage of racial minorities and number of vacant houses were tested; however, we did not see any significant difference and improvements from these additions in Model 4. Hence, Model 4 is the focus of our interpretation.

From our results, BG Income, Distance BG to Park, Playground, Water Bodies, Community Park, Total Park Visitors, Precipitation (p-value 0.051 but very close to 0.05), Temperature, and COVID-19 are significant variables that highly associated with the dependent variable Visitor from BG. An increase of $1000 of the median income (BG Income) of a BG negatively led to a decrease of 0.248 visitators to a park from that BG. Although previous studies have shown the impact of income disparities on park visitation (Cohen et al., 2016; Mowen et al., 2005), in our case, higher-income community members did not use parks more than lower-income communities (coefficient = -0.248, p-value = 0). Network distances also proved to be a key indicator of accessibility (Sharifi et al., 2021).

Our data shows similar results with a 0.005 negative impact on park visitation for every added meter in Distance BG to Park (coefficient = -0.005, p-value = 0). For environmental factors, rainfall (Precipitation) was apparently a negative factor with a coefficient of -36.898 (p-value = 0.057 while higher Temperature (coefficient = 1.029, p-value = 0.008) led to more visitations. While park amenities such as Playground (coefficient 12.844, p-value = 0.034) and Water Bodies (coefficient

20.118, p-value = 0.006) did positively attract more users, other park feature variables such as Paths, Sports, Pavilions, and Design Features were not significant variables in our model. Park area is also insignificant in all models. This may be because many large parks include greenfields and forests which are managed by the city to offer natural experiences for visitors. If should be noted that these features are often not as attractive to rural residents in the US as dense urban areas since people already have close connections with nearby woods, farms, or prairie fields. College holidays did not significantly associate with park usage since most of the parks included were not in close proximity to the campus (Fig. 3). Finally, COVID (coefficient = 24.583, p-value = 0) shows strong positive effects to park visitation. This indicates that the pandemic encouraged more residents to go to parks as other indoor options related to recreational activities and gatherings were limited.

4. Discussion

In a much-needed approach that differs from previous observations or surveys/interviews (Cohen et al., 2016; McCormack et al., 2010), this study includes a large number of participants with weekly sampling percentages of 9.57%. We also analyze long-term park visitations and visitor home BG locations at weekly levels with the unobserved time-invariant factors controlled through our fixed effects model. Therefore, our findings are more long-term oriented rather than focusing only on certain days or weeks within a year. This approach helps formulate a more holistic view regarding park visitation. Moreover, both College Station and Bryan are midsized US cities. Their sizes, which are similar with the majority of other US cities, make this study more representative of most US cities and, therefore, its findings are more generalizable.

4.1. Park visitations and service areas in mid-sized cities

While 804 m (½ miles) for neighborhood park and 4,848 m (3 miles) for community parks were widely adopted as typical service distances in planning practices (Bonestroo, 2010), the actual service distances are larger. In a recent study (Saxon, 2020) that measured the relationship between park distance and visitation in six largest US cities, the maxim distances that their parks can best serve their users are around 3 km. In our case of mid-sized cities, the actual service area of our community parks (average distance traveled as 7332 m) and neighborhood parks (average distance traveled as 5246 m) are much larger than those. From 3280 m to 12691 m for community parks and 2906 m to 8373 m for neighborhood parks, our results have also shown a wide range of variations of the distances traveled by park visitors (Fig. 7). There are people willing to travel long distances to use parks such as Lick Creek and Veterans Park, but other parks only attract nearby users. Many researchers (Park & Rogers, 2015) and professionals who provide park and green space planning services (Bonestroo, 2010; RDG & HBK, 2017) use conventions of park service radius, such as 400 m (0.25 mile), 800 m (0.5 mile), 1.6 km (1 mile). However, this one-size-fits-all approach may not be applicable in real situations. The relationships between distance and park visitation vary by location, demographics, park attributes, park quality, as well as park management and programing (Rossi et al., 2015). Especially for mid-sized cities, the variations of the distances traveled for different parks served could be relatively large. As such, long term studies that research factors related with distance traveled are much needed in the future. We encourage future urban planners and landscape architects to consider the heterogeneity of park service areas when plan to promote active living and maximize greenspace accessibility and equality/equity.

4.2. Social-economic factors and park attributes

Among the socio-economic variables in our model, income is the only significant factor which shows a negative coefficient. This differs from findings in previous studies, as lower income communities normally have shown less park usage (Cohen et al., 2016). With two mid-sized cities, the CSB metro area is not as densely populated (density of 890 population per km^2) as many major cities in previous park studies (Song et al., 2020). High-income BGs are typically located on the outskirts of the city where our target parks are not very accessible. Most affluent households are homeowners with large front and back yards. Moreover, walking trails, playgrounds, and sports facilities are often well equipped in their neighborhoods which may hinder the demand to use other parks. Therefore, parks in this study were not as attractive for higher-income residents as in other studies.

Although park amenities such as walk Paths, Sports facilities, and Pavilions were found to have positive effects to park uses in previous observational studies, they are not significant variables in our results (McCormack et al., 2010; Cohen et al., 2016). The CSB metro area has built extensive walking path systems and greenways. There are also an abundance of sports facilities such as basketball, soccer, tennis, and baseball which can be found in residential communities and schools. These two amenities may not be meaningful enough to attract additional visitors to a park. Pavilions provide shade and seating which should be important for users in south Texas. Future studies need to specifically focus on microclimate issues with data at hourly levels to better understand why they were not significant. Surprisingly, landscape Design Features have no significant effects on visitor numbers, indicating that local residents value functionality over decorative and aesthetic qualities. Through our observations, many parks with a high level of landscape decorations and detailing were built to memorize local individuals, but lack other amenities such as playgrounds and sports fields, and were not as well known by locals like parks such as Richard Carter Park and Dr David E Schob Nature Preserve. Regarding significant factors, a playground is a key amenity for the local residents of our study, as 50% of the family household with a child under 18 (College Station). Water Bodies attract about 20 additional visitors (coefficient 20.118) in our model. This makes sense, since exposure to Water Bodies is significantly associated with people's mental health, perceived restorativeness, and aesthetic preferences (Pearson et al., 2019). Overall, we found that not all park amenities have helped attract long-term visitators. For CSB metro area, focusing on playgrounds and access areas to water bodies may be more effective on improving park use.

Through smartphone mobility data, we have demonstrated the importance of studying the particularities of each local community regarding park usage for mid-sized cities. Previous findings on income, walk paths, sports facilities and pavilions do not apply to the specific situations for CSB metro area at a long-term timeframe. This indicates that the long-term effects of environmental and social-economic factors on park use may change based on different city context. To make prompt and informed planning decisions for future development, local planners and landscape architects should conduct similar studies like ours to model different social-economic factors and park features. Therefore, they could specify most needed improvements or adjustments of their public assets to maximize the return of investments (ROI) and the health improvement benefits of parks. Considering the large land areas city parks possess, any innovations in park planning could spill over to neighboring areas and enhance overall resilience.

5. Conclusions

This paper presented an empirical study regarding the long-term park visitations of mid-sized US cities. Using smartphone data, we explored the temporal and spatial patterns of park visitations. We found that park service areas vary significantly which indicates the need to consider changing park service distance conventions such as 400 m (0.25 mile), 800 m (0.5 mile), 1.6 km (1 mile) during planning practices. A fixed effects regression model was built to demonstrate how different park attributes, socioeconomic characteristics, and time related factors associate with park visitations. The results showed that waterbodies and playgrounds could enhance long-term park visitations while walk paths, sports facilities and pavilions could not. Contrary to the park use disparity in existing literature, high-income residents were found having less park usage in our case. Long-term park uses for mid-sized cities such as CSB metro area were rarely studied in US. More studies should be conducted in these type of cities since they are the cities within which the majority of US citizens live. Future planners, landscape architects and park managers should consider the particularities of their communities and prioritize most significant factors that could drive park visitations.

This study is subject to several limitations. First, although using fixed effects for our longitudinal data could limit some biases from time-invariant variables, other factors should be considered in our model to improve its robustness such as the quality of the park amenities, the park programs, or the distances to college student housing locations. The overall R-squared of our models are somewhat low, indicating our independent variables are not explaining much variation within our dependent variable. We included a large amount of park visitation data, and they are a complex phenomenon that is difficult to fit using empirical data and linear regression models. Second, we only included the mobility patterns from BGs of CSB metro area, the visitations of parks from people outside CSB metro were not counted. Third, we could not expect the SafeGraph sample to be representative of all population, because smartphone ownership varies across socio-demographic characteristics, particularly age and income (SafeGraph, 2020). Especially, SafeGraph data only represents mobilities from smartphone devices, visitors who don't use smartphone such as kids and youth were not considered in our results. Fourth, our park classification scheme could not differentiate all heterogeneities of their effects to park visitations. For example, different sports facilities such as basketball, volleyball, tennis may attract park users at different levels, but our study only focuses on sports as a general category instead of specific sport types. Fifth, our study is based on the College Station and Bryan Metro area which does not represent all mid-size cities in the US. The influence of Texas A&M University may limit our results to college towns. Regions outside of Texas with different climate and socio-economical contexts may also have different results than ours. Finally, we are not able to include travel records of all parks in our study and our parks are not randomly sampled. It is possible that travel records of our parks could not be generalized to others. Therefore, our results may be subject to limitations of generalizability.

Declaration of Competing Interest

None.

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