If you build it who will come? Equity analysis of park system changes during COVID-19 using passive origin-destination data

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Abstract

During the spring and summer of 2020, cities across the world responded to the global COVID-19 pandemic by converting roadway facilities into open pedestrian spaces. These conversions improved access to public open space, but measuring the variation in that improvement among different populations requires clear definitions of access and methods for measuring it. In this study, we evaluate the change in a utility-based park accessibility measure resulting from street conversions in Alameda County, California. Our utility-based accessibility measure is constructed from a park activity location choice model we estimate using mobile device data — supplied by StreetLight Data, Inc. — representing trips to parks in that county. The estimated model reveals heterogeneity in inferred affinity for park attributes among different sociodemographic groups. We find, for example, that neighborhoods with more lower-income residents and those with more residents of color show a greater preference for park proximty while neighborhods with higher incomes and those with more white residents show a greater preference for park size and amenities. We then apply this model to examine the accessibility benefits resulting from COVID-19 street conversions to create a set of small park-like open spaces; we find that this has been a pro-social policy in that Black, Hispanic, and low-income households receive a disproportionate share of the policy benefits, relative to the population distribution.

Keywords: Accessibility ~~Passive Data Location Choice~~ Passive Data Location Choice Parks

1. Introduction

Parks and other open spaces generate immense value for the public who are able to access them. The City Parks Alliance (2019) categorizes the observed benefits of urban parks as encouraging active lifestyles (Bancroft et al., 2015), contributing to local economies, aiding in stormwater management and flood mitigation, improving local air quality, increasing community engagement (Madzia et al., 2018), and enhancing public equity.

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For many, the value of public parks and open public spaces increased during the widespread lockdowns enacted in 2020 to slow the transmission of COVID-19. With other entertainment venues shuttered and people otherwise confined to their homes, periodic use of public space provided an opportunity for physical and emotional relief unavailable in other forms. Paired with this increased demand for public open space — and the with the epidemiological requirement to leave sufficient space between other users — was the related collapse in demand for vehicular travel. As a result, cities around the world began closing select streets to automobile travel, thereby opening them as pedestrian plazas, open streets, or slow streets (Glaser and Krizek, 2021; Schlossberg et al., 2021; Combs and Pardo, 2021). The effective result of this policy was to create a number of "parks" in urban areas that may have had poor access previously. Understanding the equitable distribution of these benefits is an important land use policy issue. The potential for non-emergency temporary or permanent street conversions also brings up interesting problems for land use and transportation policy; indeed, the possibility for transportation infrastructure to *become* a socially beneficial land use that goes beyond serving mobility needs is a tantalizing proposition.

Unfortunately, quantifying the benefits derived from access to parks in general is a complicated problem. Many previous attempts at quantifying access in terms of isochronal distances or open space concentration have resulted in a frustrating lack of clarity on the relationship between measured access and measures of physical and emotional health (Bancroft et al., 2015). Central to this confusion is the fact that people do not always use the nearest park, especially if it does not have qualities that they find attractive. A better methodology would be to evaluate the park activity location choices of people in a metropolitan area to identify which features of parks — distance, amenities, size, etc. — are valued and which are less valued. The resulting activity location choice model would enable the evaluation of utility benefits via the choice model logsum (Handy and Niemeier, 1997; de Jong et al., 2007).

In this study, we seek to evaluate the socio-spatial distribution of benefits received by residents of Alameda County, California resulting from the temporary conversion of streets to public open spaces during the spring and summer of 2020. We estimate a park activity location choice model using location-based services (LBS) data obtained through StreetLight Data, Inc., a commercial data aggregator. The resulting model illuminates the degree to which simulated individuals living in U.S. Census block groups of varying sociodemographic characteristics value the walking distance between their residence and parks, the size of the parks, and the amenities of parks including sport fields, playgrounds, and walking trails in Alameda county. We then apply this model to examine the inferred monetary benefit resulting from the street conversion policy, and its distribution among different sociodemographic groups.

The paper proceeds in the following manner: A discussion of prior attempts to evaluate park accessibility and preferences is given directly. A Methodology section presents our data gathering and cleaning efforts, the econometric framework for the location choice model, and the approach taken to apply the models to analyze open streets projects. A Results section presents the estimated choice model coefficients alongside a discussion of their implications, including the implied benefits resulting from the street conversions in Alameda County. After presenting limitations and associated avenues for future research, a final Conclusions section outlines the contributions of this study for recreational trip modeling and location choice modeling more generally.

2. Literature

Understanding the equity benefit distribution of park access requires us to consider ~~two integrated but rather distinct~~ multiple literatures. First, we consider the disparity in park utility perception among different populations. We subsequently consider quantitative techniques to evaluate the access that individuals have to park facilities. Finally, we consider recent research documenting and analyzing street conversions instigated by the COVID-19 pandemic.

2.1. Sociodemographic variation in park utility

The idea that different racial, ethnic, or cultural groups have different recreational styles, and might thus have different needs and preferences for parks and open space, has been thoroughly discussed in the leisure studies literature. Husbands and Idahosa (1995) offer a detailed review of that research as of the mid-1990s. In general, explanations for racial and ethnic differences in park use can be classified into two categories: cultural and lifestyle differences on the one hand, and discrimination and marginalization on the other.

Byrne and Wolch (2009) summarize literature in the former category, noting that Black park users have been described as preferring more social, sports-oriented spaces, relative to white park users who prefer secluded natural settings (Washburne, 1978; Hutchison, 1987; Floyd and Shinew, 1999; Gobster, 2002; Payne et al., 2002; Ho et al., 2005); Asian park users are described as valuing aesthetics over recreational spaces (Gobster, 2002; Payne et al., 2002; Ho et al., 2005); and Latino park users are said to value group-oriented amenities like picnic tables and restrooms (Baas et al., 1993; Hutchison, 1987; Irwin et al., 1990).

In an observational and survey-based study of park users in Los Angeles, Loukaitou-Sideris (1995) found a high-level of enthusiasm for park use among Hispanic residents. While she found, consistent with prior research (Baas et al., 1993; Hutchison, 1987; Irwin et al., 1990), that Hispanic park users showed a preference for passive recreation, she found that to be the case for all other user groups as well. She also found that Hispanic park users were the most likely to actively appropriate and modify park space, for example, by bringing items from home. She found that Hispanic park users tended to visit parks as family groups; African American park users tended to visit parks as peer groups; Caucasian park users tended to visit parks alone; and Asian residents were least likely to visit parks, even in a predominantly Asian neighborhood. Interviews with local elderly Asian residents (Chinese immigrants) suggested that a lack of interest in American parks was rooted in perceptions of the ideal park as "an aesthetic element of gorgeous design," leaving them unimpressed with poorly landscaped American parks emphasizing recreational functions.

Byrne and Wolch (2009) criticize such scholarship as having grossly exaggerated ethno-racial differences in park use and preferences, and suggest a model for explaining park use based on four elements: Sociodemographic characteristics; park amenities and surrounding land uses; historical/cultural context of park provision (including development politics and discriminatory land-use policies); and individual perceptions of park space (including safety and sense of welcome).

Byrne (2012) applies a cultural politics theoretical frame to why people of color are underrepresented among visitors to some urban parks. Focus groups of Latino residents of Los Angeles emphasized the importance of parks to children. Participants described visiting parks with their children and the positive and negatives associations that parks evoked of their own childhood memories of parks and wilderness. Participants described barriers to visiting parks including distance, inadequate or poorly maintained facilities, and fear of crime. They cited a lack of Spanish-language signage not only as a barrier to understanding but also as a signal that a park was not intended to serve Spanish speakers. Participants also expressed that they did not feel welcome in parks located in high-income or predominantly white neighborhoods because they expected that other park users would have racist attitudes, that a more boisterous Latino 'recreational style' would not be tolerated, or that there would be other behavioral norms they were not aware of.

2.2. Defining and measuring park accessibility

"Accessibility" is an abstract concept that describes how easily an individual can accomplish an activity at a particular space. Though not strictly quantifiable, the idea of quantifying this access is tempting and has been frequently attempted. Handy and Niemeier (1997) identify three broad types of accessibility measures: cumulative opportunity or isochrone measures, gravity-based measures, and utility-based measures. Dong et al. (2006) follow the same basic classification approach as Handy and Neimeier, illustrating mathematically how the three different types of measures can be collapsed into each other. Geurs and van Wee (2004) group cumulative opportunity and gravity-based measures into a single category that they refer to as location-based measures. In this, Geurs and van Wee (2004) rely on the distinction that utility-based measures incorporate revealed preferences of individuals for particular destinations while location-based measures are entirely geo-spatial in their definition.

2.2.1. Location-based measures of park accessibility

Cumulative opportunity measures are calculated by counting the number of origins or destinations within a threshold travel cost of a location (where "cost" might be some combination of distance, travel time, and/or monetary cost of travel). A strength of cumulative opportunity measures lies in their simplicity and intuitive interpretation. However, they may be too simple, especially with regard to trip costs near the threshold. An example of a cumulative opportunity measure might be the number of parks within a ten-minute walk of a person's home, or the number of households living within ten minutes of a park. This measure would imply that a household living immediately adjacent to a park has the same access to it as one that lives nine minutes away, but that a household living eleven minutes away has no access to it.

ParkScore (Trust for Public Land, 2019), developed by the Trust for Public Land, is a popular measure of park accessibility that starts from a cumulative opportunity measure (the share of the population that resides within a 10-minute walk of a green space) and adjusts this value based on the total city green space, investment, and amenities weighted against the socioeconomic characteristics of the population outside of the 10-minute walk threshold. The resulting score is a convenient quantitative tool in estimating the relative quality of green space access across cities (Rigolon et al., 2018). ParkScore may be less useful at identifying the comparative quality of access within a city, particularly since the vast majority of residents in dense areas like San Francisco (100%) and New York City (99%) may live within the binary 10-minute walk threshold. The Centers for Disease Control and Prevention (CDC) has developed an "Accessibility to Parks Indicator" along similar lines (Ussery et al., 2016), calculating the share of the population living within a half-mile of a park for each county in the U.S.

Gravity-based accessibility measures take a similar approach to cumulative opportunity measures, but theoretically include all possible destinations and weight them according to the travel cost that they impose, based on an impedance function (often a negative exponential calibrated to observed trip distributions). Cumulative opportunity measures may be considered a special case of gravity-based measures, where the impedance function takes the form of a binary step function that equals zero after a cutoff travel cost (which is why Geurs and van Wee (2004) classify them both as location-based).

A major advantage of gravity-based accessibility measures lies in their consistency with travel behavior theory: Gravity-based measures have their roots in the trip distribution step of the traditional four-step travel demand forecasting method, where trips originating in a particular zone are distributed among destination zones, proportionate to each zone's gravity-based accessibility. Urban scholars have used gravity-based measures to explore the spatial distribution of park access across Tainan City, Taiwan (Chang and Liao, 2011) and to estimate the relationship between park access and housing prices in Shenzhen, China (Wu et al., 2017).

Some scholars have used location-based measures of park accessibility to evaluate equity in park access. Chang and Liao (2011) use a gravity-based measure to determine that low-income neighborhoods have less access to parks than higher-income neighborhoods in Tainan City, Taiwan. Bruton and Floyd (2014) conduct a neighborhood-level analysis of park amenities in Greensboro, North Carolina, and find that low-income neighborhoods tend to have parks with more picnic areas, more trash cans, and fewer wooded areas, but they do not address the question of the extent to which different populations might value these different amenities. Kabisch and Haase (2014) find that neighborhoods in Berlin with high immigrant populations and older populations likewise had less access to parks, and they pair these findings with survey results suggesting that these disparities are not consistent with the preferences expressed by those populations.

2.2.2. Utility-based measures of park accessibility

While traditional four-step travel demand models distribute zonal trips based on a gravity-based accessibility model, the travel demand modeling profession has shifted more recently towards a destination choice framework that distributes trips based on discrete-choice regression models. McFadden (1974a) applied discrete choice models to urban travel demand to predict mode choice, and modern disaggregate activity-based models apply them to all travel behavior choices, including to select among alternative routes or alternative destinations (de Dios Ortúzar and Willumsen, 2011). Though the application of random utility models to destination choice is not new (see Anas, 1983), the increasing availability of computing resources makes estimating and applying discrete choice models on large alternative sets in a practical context more feasible.

Destination choice models estimate the probability of selecting a particular destination among a set of alternatives based on the relative attractiveness, or *utility*, of each alternative. Utility may be a function of distance or travel time alone (in which case, a utility-based accessibility measure might be quite similar to a location-based measure), but the function can also incorporate other destination characteristics that lead one destination to be more highly-valued and used than another. For a utility-based measure of park accessibility, these might include park size, cleanliness, or the availability of particular amenities. The degree to which these park and trip attributes influence the destination utility can be estimated statistically using survey data.

Though destination choice utility models have not commonly been used to measure park accessibility, scholars have acknowledged that park accessibility metrics should be linked with park use, since a park that has many visitors must by definition be accessible to those visitors. McCormack et al. (2010) provide a comprehensive review of this literature; it is sufficient here to note that most studies find park use to depend on a complicated interplay between park size, maintenance, facilities, and travel distance. Many of these attributes are incorporated into ParkIndex (Kaczynski et al., 2016), which estimates the resident park use potential within small grid cells by applying utility preference coefficients estimated from a survey in Kansas City.

There are limited examples of researchers using a destination choice model to predict recreation attractions. Kinnell et al. (2006) apply a choice model to a survey of park visitors in New Jersey, and estimate the relative attractiveness of park attributes including playgrounds, picnic areas, and park acreage weighed against the travel disutility and the relative crime rate at the destination. In a similar study, Meyerhoff et al. (2010) model the urban swimming location choice for a surveyed sample. In both studies, the researchers were attempting to ascertain which attributes of a recreation generated the most positive utility, and therefore which attributes should be prioritized for improvement. Though neither was attempting to understand relative park accessibility, Macfarlane et al. (2020) applied the Kinnell et al. (2006) estimates in an exploration of utility-based park accessibility and its relationship to aggregate health outcomes.

One primary obstacle to estimating discrete-choice models on the park destination problem has been the lack of sufficiently detailed, trip-level data on park users. Most destination choice models in practice are estimated from household travel surveys that must focus on all trip purposes, and necessarily group multiple recreation and social trips together (National Academies of Sciences Engineering and Medicine, 2012). However, the advent of large-scale mobile device networks and the perpetual association of unique devices with unique users has given researchers a new opportunity to observe the movements and activity location patterns for large subsets of the population (Naboulsi et al., 2016). Such passively collected location data — sometimes referred to as part of a larger category of "Big Data" — is a by-product of other systems including cellular call data records (e.g., Bolla and Davoli, 2000; Calabrese et al., 2011), probe GPS data (Huang and Levinson, 2015), and more recently Location Based Services (LBS) (Roll, 2019; Komanduri et al., 2017). LBS use a network of mobile applications that obtain the users' physical location at different points in the day. Commercial vendors repackage, clean, and scale these data to population or traffic targets and provide origin-destination flows to researchers and practitioners. Monz et al. (2019), for example, demonstrate that passive device data can accurately estimate trip flows to natural recreation areas.

A number of methods have been proposed to develop destination choice information from these passive data. Bernardin et al. (2018) employs a passive origin-destination matrix as a shadow price reference in an activity-based location choice model, iteratively adjusting the calibration parameters of the choice utilities to minimize the observed error between the passive data and the modeled predictions. Kressner (2017) uses the passive flow data as a probabilistic sampling frame to recreate individual trips through simulation. A similar method developed by Zhu and Ye (2018) uses the passive dataset directly, sampling 10,000 random trips from GPS traces of taxi trips in Shanghai and estimating a destination choice model. Employing the passive data set in this way provides the authors an opportunity to examine the choices of a large sample of a small population (taxi passengers). The Zhu and Ye (2018) methodology could be extended to other situations where collecting a statistically relevant survey sample would be prohibitively difficult, but where passive device location data reveals which destinations people choose among many observable options.

2.3. Street Conversion Equity Analysis

In their analysis of over one thousand reallocations of street space that occurred in response to the global COVID-19 pandemic, Combs and Pardo (2021) find that a plurality created additional space for walking, cycling, and recreation, although some reallocated space to commerce (e.g. outdoor dining and shopping) or converted short-term parking to urban freight or food delivery.

If we define an urban park as a public space that is designated for the purpose of recreation, exercise, and social gathering, then the rapid reallocation of street space to accommodate recreation and active travel could be characterized as a proliferation of small urban parks. Researchers at the Trust for Public Land have explicitly described the reallocation of street space from cars to pedestrians as a strategy to relieve pressure on parks (Hussain, 2020) and have suggested that these actions should (and, in New York, had failed to) prioritize areas that would otherwise have low access to parks (Compton, 2020). Fischer and Winters (2021) have likewise done an equity analysis of street reallocation from vehicles to pedestrians in three mid-sized Canadian cities and found that interventions were generally more common in places with higher proportions of white residents and fewer children. The analyses by both Compton (2020) and Fischer and Winters (2021) were both based on proximity alone rather than on utility-based accessibility measures.

Of course, streets that reallocate space for active travel and recreation do not have the amenities or general character of most parks, and classifying them as equivalent to their greener peers in an accessibility analysis would be erroneous for many reasons. But a utility-based accessibility framework would allow us to discount these street parks for the amenities they lack while also considering the benefits proffered by their availability and proximity. Further, we can model these tradeoffs with statistical weights determinable through observing park trip distribution patterns revealed through passive mobile device data.

3. Methodology

In this section, we describe the methodology we follow for this analysis. We first describe how we created a dataset on which to estimate park activity location choices for a sample of observed trips in Alameda County, California. Then we provide an overview of destination choice modeling and using such models to derive utility-based accessibility.

3.1. Study area

Alameda County is one of nine counties that constitute the San Francisco Bay Area metropolitan region in California. Alameda is the seventh most populous county in California with a population of 1.5 million (U.S. Census Bureau, 2019), and has 14 incorporated cities and several unincorporated communities. It is an economically and ethnically diverse county and hence it was an attractive area to use for this study. The racial makeup of Alameda County was 49.7% White, 11.2% African American, 1.0% Native American, 38.7% Asian, 1.0% Pacific Islander, and 22.4% Hispanic or Latino of any race. Alameda County has a diverse set of parks, ranging from local small community parks, urban and transit-accessible parks like the Lake Merritt Recreational area, coastal access points, and suburban recreational areas like Lake Chabot.

3.2. Data

We constructed an estimation data set from a publicly-available parks polygons layer, a commercially acquired passive device origin-destination table representing visitors to parks and inferred residential block groups for these visitors, and American Community Survey data for the residence block groups. We also constructed a dataset representing open street installations that were implemented in response to the COVID-19 pandemic.

3.2.1. Model estimation data

We obtained a polygons shapefile layer representing open spaces in Alameda County, California from the California Protected Areas Database (GreenInfo Network, 2019). This dataset was selected because it included multiple different types of open space including local and state parks, traditional green spaces as well as wildlife refuges and other facilities that can be used for recreation. We removed facilities that did not allow open access to the public (such as the Oakland Zoo) and facilities whose boundaries conflated with freeway right-of-way – this prevents trips through the park from being conflated with park trips in the passive origin-destination data.

From this initial parks ~~polygons~~ polygon dataset, we obtained park attribute information through OpenStreetMap (OSM) using the `osmdata` package for R (Padgham et al., 2017). Three attribute elements are considered in this analysis. First, we identify playgrounds using OSM facilities given a `leisure = playground` tag. The tagged facilities can be either polygon or point objects; in the former case we use the polygon centroid to determine the point location of the playground.

Second, we consider sport fields of various kinds identified with the OSM `leisure = pitch` tag. This tag has an additional attribute describing the sport the field is designed for, which we retain in a consolidated manner. Soccer and American football fields are considered in a single category, and baseball and softball fields are combined as well. Basketball, tennis, and volleyball courts are kept as distinct categories, with all other sport-specific fields combined into a single "other." Golf courses are discarded. As with playgrounds, polygon field and court objects are converted into points at the polygon centroid.

Finally, we identified trails and footpaths using the `path`, `cycleway`, and `footway` values of the `highway` tag. A visual inspection of the resulting data revealed that the large preponderance of sidewalks and cycling trails within parks in Alameda County are identified properly with these variables. Trails are represented in OSM as polylines, or as polygons if they form a complete circle. In the latter case, we converted the polygon boundary into an explicit polyline object.

It is possible for each of these facilities to exist outside the context of a public park. For example, many private apartment complexes have playgrounds and high schools will have sports facilities that are not necessarily open to the general public. We spatially matched the OSM amenities data and retained only those facilities that intersected with the CPAD open spaces database identified earlier.

We provided the park boundaries layer to a commercial firm, StreetLight Data Inc., which develops and resells origin-destination matrices derived from passive device location data. The provider employs a proprietary data processing engine (called Route Science) to algorithmically transform observed device location data points (the provider uses in-vehicle GPS units and mobile device LBS) over time into contextualized,

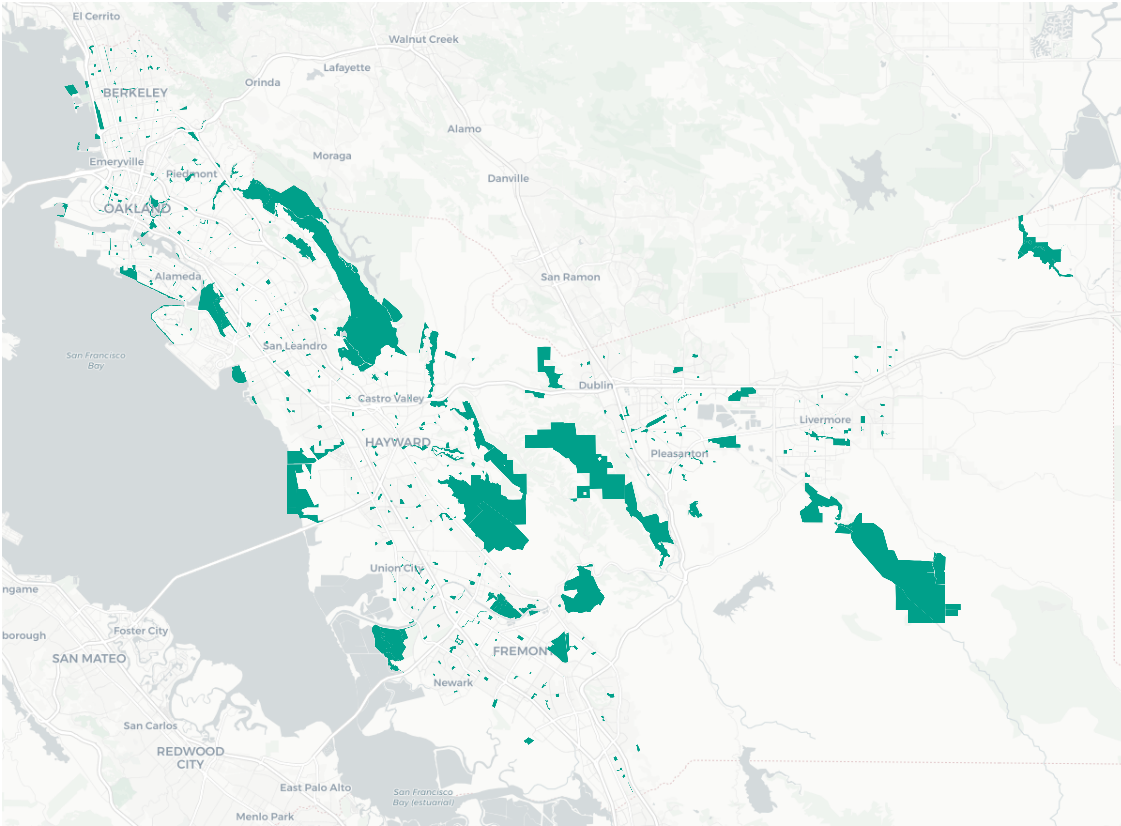

Figure 1: Location of parks in Alameda County.

normalized, and aggregated travel patterns. From these travel patterns, the Route Science processing algorithms infer likely home Census block group locations for composite groups of people and converts raw location data points into trip origin and destination points (Pan et al., 2006; Friedrich et al., 2010).

For each park polygon, the firm returned a population-weighted estimate of how many devices were observed by home location block group over several months in the period between May 2018 and October 2018. We transformed this table such that it represented the weighted unique devices traveling between block groups and parks. We discarded home location block groups outside of Alameda County; the imputed home locations can be far away from the study area for a small amount of trips and are unlikely to represent common or repeated park activities. Table ~~??~~ 1 presents descriptive statistics on the 500 parks assembled for this study, grouped according to the park type as defined on CPAD. A little more than half of the parks have identified paths, while around 40% of the identified parks have playgrounds and sport fields.

In order to understand the demographic makeup of the home block groups and potentially the characteristics of the people who make each trip, we obtained 2013-2017 five-year data aggregations from the American Community Survey using the `tidycensus` (Walker, 2019) interface to the Census API for several key demographic and built environment variables: the share of individuals by race, the share of households by income level, household median income, the share of households with children under 6 years old, and the household density. An important attribute of the choice model is the distance from the home block group to the park boundary. Because we have no information on where in the block group a home is actually located, we use the population-weighted block group centroid published by the Census Bureau as the location for all homes in the block group. We then measured the network-based distance between the park and the home block group centroid using a walk network derived from OpenStreetMap via the `networkx` package for Python (Hagberg et al., 2008),

3.2.2. Model application data

We compiled a list of streets in Berkeley, Oakland, and Alameda that were converted to public open space from each city's respective websites (City of Alameda, 2020; City of Oakland, 2020; City of Berkeley, 2020) and referred to the "Shifting Streets" COVID-19 mobility dataset (Combs et al., 2020) to determine whether other cities and places within Alameda County have similar Open Streets projects (as best as we could determine, they did not). Based on the information we gathered from these sources, 74 individual streets were converted; these streets represent 27.6 total miles across the cities of Berkeley, Oakland, and Alameda. For the purposes of this analysis, we represent each opened street as a single "park" without any sport facilities or playgrounds, but with a trail / walking path. The database provides the opened streets as polyline objects; we assert a 25-foot buffer around the line to represent a polygon with a measurable area. The 25-foot buffer effectively counts one vehicle lane and one shoulder parking lane in each direction as converted to "park" space. Finally, we measure the network-based distance from each population-weighted

Table 1: Park Summary Statistics

		Local Park (N=441)		Recreation Area (N=59)	
		Mean	Std. Dev.	Mean	Std. Dev.
Acres		59.8	370.5	125.6	505.1
Mobile Devices		1450.0	6685.4	2659.0	6161.0
		N	%	N	%
type	Local Park	441	100.0	0	0.0
	Local Recreation Area	0	0.0	57	96.6
	State Recreation Area	0	0.0	2	3.4
Access	Open Access	441	100.0	59	100.0
	No Public Access	0	0.0	0	0.0
	Restricted Access	0	0.0	0	0.0
Playground	FALSE	~~220~~ 213	~~49.9~~ 48.3	~~44~~ 43	~~74.6~~ 72.9
	TRUE	~~221~~ 228	~~50.1~~ 51.7	~~15~~ 16	~~25.4~~ 27.1
Any Sport Field	FALSE	~~274~~ 270	~~62.1~~ 61.2	~~39~~ 38	~~66.1~~ 64.4
	TRUE	~~167~~ 171	~~37.9~~ 38.8	~~20~~ 21	~~33.9~~ 35.6
Football / Soccer	FALSE	414	93.9	51	86.4
	TRUE	27	6.1	8	13.6
Baseball	FALSE	363	82.3	45	76.3
	TRUE	78	17.7	14	23.7
Basketball	FALSE	~~340~~ 337	~~77.1~~ 76.4	52	88.1
	TRUE	~~101~~ 104	~~22.9~~ 23.6	7	11.9
Tennis	FALSE	387	87.8	~~53~~ 52	~~89.8~~ 88.1
	TRUE	54	12.2	~~6~~ 7	~~10.2~~ 11.9
Volleyball	FALSE	433	98.2	57	96.6
	TRUE	8	1.8	2	3.4
Trail	FALSE	~~155~~ 147	~~35.1~~ 33.3	~~22~~ 21	~~37.3~~ 35.6
	TRUE	~~286~~ 294	~~64.9~~ 66.7	~~37~~ 38	~~62.7~~ 64.4

Table 2: Block Group Summary Statistics

	Unique (#)	Missing (%)	Mean	SD	Min	Median	Max
Density: Households per square kilometer	1040	0	1726.3	1576.8	0.0	1373.3	21930.9
Income: Median tract income	978	3	106026.7	48909.9	13472.0	98206.5	250001.0
Low Income: Share of households making less than $35k	977	0	16.2	13.2	0.0	12.9	100.0
High Income: Share of households making more than $125k	1022	0	38.6	20.8	0.0	36.9	89.2
Children: Share of households with children under 6	976	0	14.5	8.7	0.0	13.2	48.7
Black: Share of population who is Black	914	0	11.6	14.0	0.0	6.3	80.8
Asian: Share of population who is Asian	1022	0	26.7	20.6	0.0	20.8	93.9
Hispanic: Share of population who is Hispanic*	1031	0	22.2	18.7	0.0	16.0	88.2
White: Share of population who is White	1030	0	33.5	22.5	0.0	28.8	93.6

* Hispanic indicates Hispanic individuals of all races; non-Hispanic individuals report a single race alone.

block group centroid to the nearest boundary of each new open space facility created by this policy.

3.3. Model estimation

In random utility choice theory, if an individual living in block group n wishes to make a park trip, the probability that the individual will choose park i from the set of all parks J can be described as a ratio of the park's measurable utility V_{ni} to the sum of the utilities for all parks in the set. In the common destination choice framework we apply a multinomial logit model (McFadden, 1974b; Recker and Kostyniuk, 1978),

$$P_{ni} = \frac{\exp(V_{ni})}{\sum_{j \in J} \exp(V_{nj})} \tag{1}$$

where the measurable utility V_{ni} is a linear-in-parameters function of the destination attributes.

$$V_{ni} = X_{ni}\beta \tag{2}$$

where β is a vector of estimable coefficients giving the relative utility (or disutility) of that attribute to the choice maker, all else equal. It is possible to add amenities of the park or the journey to the utility equation. However, as the number of alternatives is large, it is impractical to consider alternative-specific constants or coefficients and therefore not possible to include attributes of the home block group or traveler n directly. We can, however, segment the data and estimate distinct distance and size parameters for different segments to observe heterogeneity in the utility parameters between different socioeconomic groups.

The logarithm of the sum in the denominator of Equation 1 (called the logsum) provides a measure of the consumer surplus of the choice set enjoyed by person n (Williams, 1977),

$$CS_n = \ln \sum_{j \in J} \exp(V_{nj}) + C \tag{3}$$

where C is a constant indicating an unknown absolute value; the difference of logsum values in two different scenarios eliminates C. Additionally, dividing the difference in logsum from choice set J and choice set J' by a cost coefficient β

$$\delta CS_n = (\ln \sum_{j \in J'} \exp(V_{nj}) - \ln \sum_{j \in J} \exp(V_{nj}))/\beta \tag{4}$$

gives an estimate of the benefit received by person n in monetary terms. Thus, such a "utility-based" accessibility term is continuously defined, contains multiple dimensions of the attributes of the choice, and can be evaluated in monetary terms (Handy and Niemeier, 1997; Dong et al., 2006).

In the most typical cases, researchers estimate the utility coefficients for destination choice models from household travel surveys. For example, the California add-on to the 2017 National Household Travel Survey could be used for this purpose for frequent trips like commutes to work and school. However, as a 24-hour trip diary, it is less useful for recreational trips that may take place less frequently. For better data on park access, we need to synthesize a suitable estimation data set. We do this by sampling 20,000 random discrete device origin-destination pairs from the commercial passive data matrix, weighted by the volume of the flows. This corresponds to a 4.3% sample of all the observed device origin-destination pairs.

The sampled origin-destination pair gives the home location as well as the "chosen" alternative for a synthetic person. In principle the individual's choice set contains all the parks in our dataset; in practice it can be difficult to estimate choice models with so many alternatives ($|J| = 500$). For this reason we randomly sample 10 additional parks to serve as the non-chosen alternatives~~for our~~, with a different set of 10 parks for each synthetic choice maker. Such random sampling of alternatives reduces the efficiency of the estimated coefficients but the coefficients remain unbiased (Train, 2009); a more elegant sampling approach might have resulted in smaller estimated standard errors, but the estimation results (presented below) suggest this is not a concern in this application. As the model has no alternative-specific constants, the standard likelihood comparison statistic against the market shares model ρ^2 is not computable. We instead use the likelihood comparison against the equal shares model ρ_0^2.

The resulting analysis dataset therefore contains 20,000 choice makers that select between 11 parks including the park they were observed to choose; the measured distance between the choice maker's block group and all parks in the choice set; and the acreage of each park in the choice set. We use the `mlogit` package for R (Croissant, 2019; R Core Team, 2020) to estimate the multinomial logit models.

3.4. Model application

Using the full set of Alameda County parks — including those added by street conversion — we can apply a destination choice model to calculate the change in park choice utilities and utility-based accessibility values for each block group in Alameda County. As shown with Equation (4), the difference in utility-based accessibility values with and without the opened streets is the additional consumer surplus provided by the policy, converted into a monetary value by a cost-utility coefficient. The purpose of converting the logsum into a monetary value is to scale the benefits in terms that analysts and policy makers can compare more easily than raw utility values. The dataset used for this research does not have any information on travel costs or entrance fees, and such data would likely not be relevant in the context of urban parks. As a result, there is no direct link between the utility and a monetary cost in our estimated models.

As a substitution, we use an estimate of the cost coefficient obtained from the ~~open-source activity-based travel demand model ActivitySim (ActivitySim, 2020), which is itself based on the regional travel model employed by the~~ Metropolitan Transportation Commission (MTC~~), the~~, San Francisco Bay regional MPO~~. ActivitySim uses a cost coefficient of −0.6 divided by the each simulated agent's value of time to determine destination choices for non-work trips .~~[1] ~~In ActivitySim, as in most~~) "Travel Model One" activity-based

[1] ~~To be precise, this is the cost coefficient on the mode choice model for social, recreational, and other trip purposes, which influences destination choice through a logsum-based impedance term.~~

~~travel models, the value of time is considered to vary with an~~ travel demand model (Metropolitan Transportation Commissio . In this model, the utility of destination choice for social and recreational trips uses the mode choice model logsum as an impedance measure. The mode choice model cost coefficient varies with each individual's ~~income, but in this aggregate destination choice model, an aggregate~~ value of time~~will suffice~~. The average value of time in the synthetic population for the ~~Bay Area~~ calibration scenario is \$7.75 per hour~~, resulting in a cost coefficient on the destination choice utility of −0.215. Dividing the difference in accessibility logsums by the negative of this value gives an initial estimate of the monetary value of the policy to each park user~~. Dividing that value of time by the in-vehicle travel time parameter of -0.018 results in an implied mode choice cost coefficient of $(-0.018/min * 60min/hr)/(7.75\$/hr) = -0.139/\$$.

4. Results

We estimated multinomial logit park activity location choice models on the datset described in the previous section. We applied a Yeo-Johnson transformation (Yeo and Johnson, 2000) to both the walk distance (in meters) between the park and the block group centroid, and to the park acreage. The Yeo-Johnson transformation replicates the constant marginal elasticity of a logarithmic transformation while avoiding undefined values (e.g., $YJ(0) = 0$). For simplicity, we call this transformation `log()` in the model results tables. Using a constant marginal elasticity is better reflective of how people perceive distances and sizes; a one-mile increase to a trip distance matters more to a two-mile trip than a ten-mile trip.

Table 3 presents the model estimation results for each estimated model. The "Network Distance" model, which only considers the distance to the park and the size of the park. results in significant estimated coefficients of the expected sign. That is, individuals will travel further distances to reach larger parks. The ratio of the estimated coefficients implies that on average, people will travel ~~3.41~~ 3.47 times further to reach a park twice as large.

Table 3 also shows the results of the "Park Attributes" model, which represents the presence of any sport field with a single dummy variable, and the "Sport Detail" model, which disaggregates this variable into facilities for different sports. The value of the size and distance coefficients change modestly from the "Network Distance" model, with the implied size to distance trade-off rising to ~~4.1~~4.16. Examining the two amenities models — independently and in comparison with each other — reveals a few surprising findings. First, it appears that playgrounds and sport fields in general contribute *negatively* to the choice utility equation. This is both unintuitive and contradictory to previous findings in this space (e.g., Kinnell et al., 2006). Considering different sports separately, there is a wide variety of observed response with tennis and volleyball facilities attracting more trips, and football and basketball facilities attracting fewer, all else equal. Trails and walking paths give substantive positive utility in both models. The difference in likelihood statistics between the three models is significant (likelihood ratio test between Sport Detail and

Park Attributes model has p-value ~~1.19e-31~~2.68e-06), and so in spite of the curious aggregate findings, we move forward with this utility specification.

It is worth investigating the heterogeneity in preferences that exist among populations. Though the income and ethnicity of the synthetic park visitors is not known, we can segment the estimation dataset based on the socioeconomic makeup of the visitors' residence block group. The models presented in Table 4 were estimated on segments developed in this manner. Models under the "Race/Ethnicity" heading include a race- and ethnicity-based segmentation: simulated individuals living in block groups with more than thirty percent Black residents are included in the ">30% Black" model, an analogous segmentation for block groups with high Asian and Hispanic populations are in the ">30% Asian" and ">30% Hispanic" models respectively, and the "Other" model contains all other block groups. Another set of model segmentation relies on the share of the population in each block group with household incomes above or below certain thresholds, and a third relies on the share of households with children under 6 years old. Again, we use the threshold definitions largely informed by the distributions in Table 2.

Table 3: Estimated Model Coefficients

	Network Distance	Park Attributes	Sport Detail
log(Distance)	~~-1.375~~ -1.358 ***	~~-1.418~~ -1.397 ***	~~-1.414~~ -1.389 ***
	(0.010)	(0.010)	(0.010)
log(Acres)	~~0.403~~ 0.391 ***	~~0.348~~ 0.337 ***	~~0.345~~ 0.334 ***
	(0.005)	(0.005)	(0.005)
Playground		~~-0.441~~ -0.448 ***	~~-0.550~~ -0.556 ***
		(0.022)	(0.022)
Trail		~~0.547~~ 0.576 ***	~~0.557~~ 0.592 ***
		(~~0.023~~0.024)	(0.024)
Sport Field		~~-0.352~~ -0.381 ***	
		(~~0.022~~0.023)	
Basketball			~~-0.261~~ -0.293 ***
			~~(0.031~~ (0.030)
Baseball			~~0.056 *~~0.130 ***
			(0.030)
Football / Soccer			~~-0.525~~ -0.467 ***
			(0.042)
Tennis			~~0.244~~ 0.202 ***
			(0.030)
Volleyball			~~0.568 ***~~0.125 *
			(~~0.059~~0.061)
Other Sport			~~-0.241~~ -0.249 ***
			(~~0.040~~0.039)
Num.Obs.	20,000	20,000	20,000
AIC	58,~~368.6~~ 736.3	~~56,793.5~~ 57,014.9	56,~~648.5~~991.2
Log Likelihood	-29,~~182.3~~ 366.1	-28,~~391.7~~ 502.5	-28,~~314.3~~485.6
ρ^2_0	~~0.392~~ 0.388	~~0.408~~ 0.406	~~0.410~~0.406

Standard errors in parentheses.

Table 4: Estimated Model Coefficients with Block Group Segmentations

	Race/Ethnicity				Income			Children		
	> 30% Asian	> 30% Black	> 30% Hispanic	Other Eth.	> 30% Low income	> 50% High income	Other Inc.	> 25% Children	< 5% Children	Other Children
log(Distance)	-1.278 ***	-1.515 ***	-1.268 ***	-1.492 ***	-1.418 ***	-1.392 ***	-1.360 ***	-1.271 ***	-1.561 ***	-1.387 ***
	(0.017)	(0.030)	(0.022)	(0.019)	(0.026)	(0.020)	(0.013)	(0.029)	(0.037)	(0.011)
log(Acres)	0.368 ***	0.262 ***	0.323 ***	0.340 ***	0.310 ***	0.360 ***	0.329 ***	0.339 ***	0.366 ***	0.332 ***
	(0.009)	(0.015)	(0.011)	(0.010)	(0.014)	(0.010)	(0.007)	(0.014)	(0.020)	(0.006)
Playground	-0.458 ***	-0.639 ***	-0.327 ***	-0.780 ***	-0.593 ***	-0.621 ***	-0.520 ***	-0.344 ***	-0.670 ***	-0.579 ***
	(0.038)	(0.060)	(0.047)	(0.042)	(0.055)	(0.045)	(0.029)	(0.062)	(0.078)	(0.025)
Trail	0.533 ***	0.574 ***	0.280 ***	0.970 ***	0.573 ***	0.840 ***	0.527 ***	0.360 ***	0.731 ***	0.610 ***
	(0.041)	(0.062)	(0.049)	(0.049)	(0.058)	(0.054)	(0.031)	(0.064)	(0.087)	(0.027)
Basketball	-0.170 ***	-0.255 **	-0.503 ***	-0.411 ***	-0.230 **	-0.193 ***	-0.390 ***	-0.445 ***	-0.359 **	-0.261 ***
	(0.049)	(0.085)	(0.067)	(0.060)	(0.077)	(0.058)	(0.041)	(0.083)	(0.110)	(0.034)
Baseball	0.097 *	0.200 *	0.148 *	0.163 **	0.226 **	-0.023	0.187 ***	0.162 *	0.153	0.125 ***
	(0.049)	(0.080)	(0.063)	(0.058)	(0.073)	(0.060)	(0.039)	(0.080)	(0.107)	(0.033)
Football / Soccer	-0.282 ***	-0.731 ***	-0.595 ***	-0.630 ***	-0.689 ***	-0.178 *	-0.588 ***	-0.357 **	-0.514 ***	-0.482 ***
	(0.065)	(0.125)	(0.100)	(0.084)	(0.104)	(0.080)	(0.058)	(0.116)	(0.147)	(0.048)
Tennis	0.417 ***	-0.428 ***	-0.067	0.305 ***	-0.211 **	0.560 ***	0.120 **	0.162 +	0.131	0.213 ***
	(0.047)	(0.096)	(0.070)	(0.056)	(0.082)	(0.055)	(0.040)	(0.084)	(0.107)	(0.033)
Volleyball	0.080	-0.222	0.122	0.244 *	-0.184	0.286 **	0.009	-0.116	0.121	0.163 *
	(0.096)	(0.225)	(0.141)	(0.106)	(0.195)	(0.100)	(0.087)	(0.173)	(0.247)	(0.068)
Other Sport	-0.171 **	-0.297 *	-0.418 ***	-0.303 ***	-0.521 ***	-0.170 *	-0.250 ***	-0.220 *	-0.353 *	-0.244 ***
	(0.061)	(0.116)	(0.095)	(0.073)	(0.107)	(0.073)	(0.052)	(0.109)	(0.139)	(0.044)
Num.Obs.	6,861	2,600	3,790	6,749	2,982	5,759	11,259	2,365	1,769	15,866
AIC	20,513.9	7,675.8	12,386.6	15,939.9	9,070.6	14,438.9	33,286.6	7,646.5	4,526.1	44,789.2
Log Likelihood	-10,247	-3,827.9	-6,183.3	-7,960	-4,525.3	-7,209.5	-16,633.3	-3,813.3	-2,253	-22,384.6
ρ^2_0	0.377	0.386	0.320	0.508	0.367	0.478	0.384	0.328	0.469	0.412

Standard errors in parentheses.

[a] Simulated individuals segmented based on the share of households meeting the segmentation threshold in the residence block group.

The model estimates in Table 4 reveal noticeable heterogeneity in the park location choices among visitors from different block group segments. Park visitors living in block groups with a high proportion of Black and low-income residents show less affinity for trails and other walkways, but appear considerably more sensitive to the distance to a park. Park visitors living in high-income neighborhoods are less sensitive to the distance to a park, but receive more utility from certain amenities, in particular trails and tennis courts. Block groups with a high proportion of Hispanic residents and residents with children under 6 show the least negative response to playgrounds of all the segments.

Seeing that there is a difference in the response in the model segmentation, it is also worth considering the role of our segmentation thresholds in these findings. Figure 2 shows the estimated coefficients and confidence intervals for these different amenities at different threshold levels of segmentation. The threshold level means that at least that percent of the block group's population falls in that category. The confidence intervals widen as more observations are excluded from the model. The estimated coefficients for the different segmentations are identical when the share equals zero, and simply represent the "Sport Detail" model from Table 3.

Overall, increasing the segmentation threshold level reveals additional information about user preferences. First, it should be noted that there is some inconsistency: for instance, block groups with at least 30% of low income households show a lower importance of distance than block groups with either 20% or 40% low income households, though all three estimates are within the same confidence intervals. The increasing width of the confidence interval, however, means it is sometimes difficult to make robust statements. Residents of block groups with a higher share of Asian individuals or high income households both show relatively more affinity for tennis courts and trails relative to other groups. Residents of block groups with increasing shares of Hispanic individuals show the highest affinity for playgrounds, and park goers from neighborhoods with a greater share of Black individuals are most sensitive to distance and least sensitive to park size.

4.1. Equity Analysis of COVID-19 Street Openings

In this section, we apply the models estimated above to evaluate the benefits of the street conversion policy in terms of aggregate value determined by the change in accessibility logsum, as well as the equity of the policy with respect to different income and ethnic groups. In this analysis, we apply the "Sport Detail" non-segmented model from Table 3, as it had the best fit of these models.

Figure 3 presents this monetary valuation spatially. Unsurprisingly, the benefits are concentrated in the block groups surrounding the opened streets. Most residents of central Oakland see a benefit of somewhere around $1, while some zones see an equivalent benefit of as much as $30. One property of logsum-based accessibility terms is that there is some benefit given for simply having more options, whether or not those options are attractive in any way. In this application, these benefits are small, on the order of 10 cents for most block groups away from where the street openings occurred.

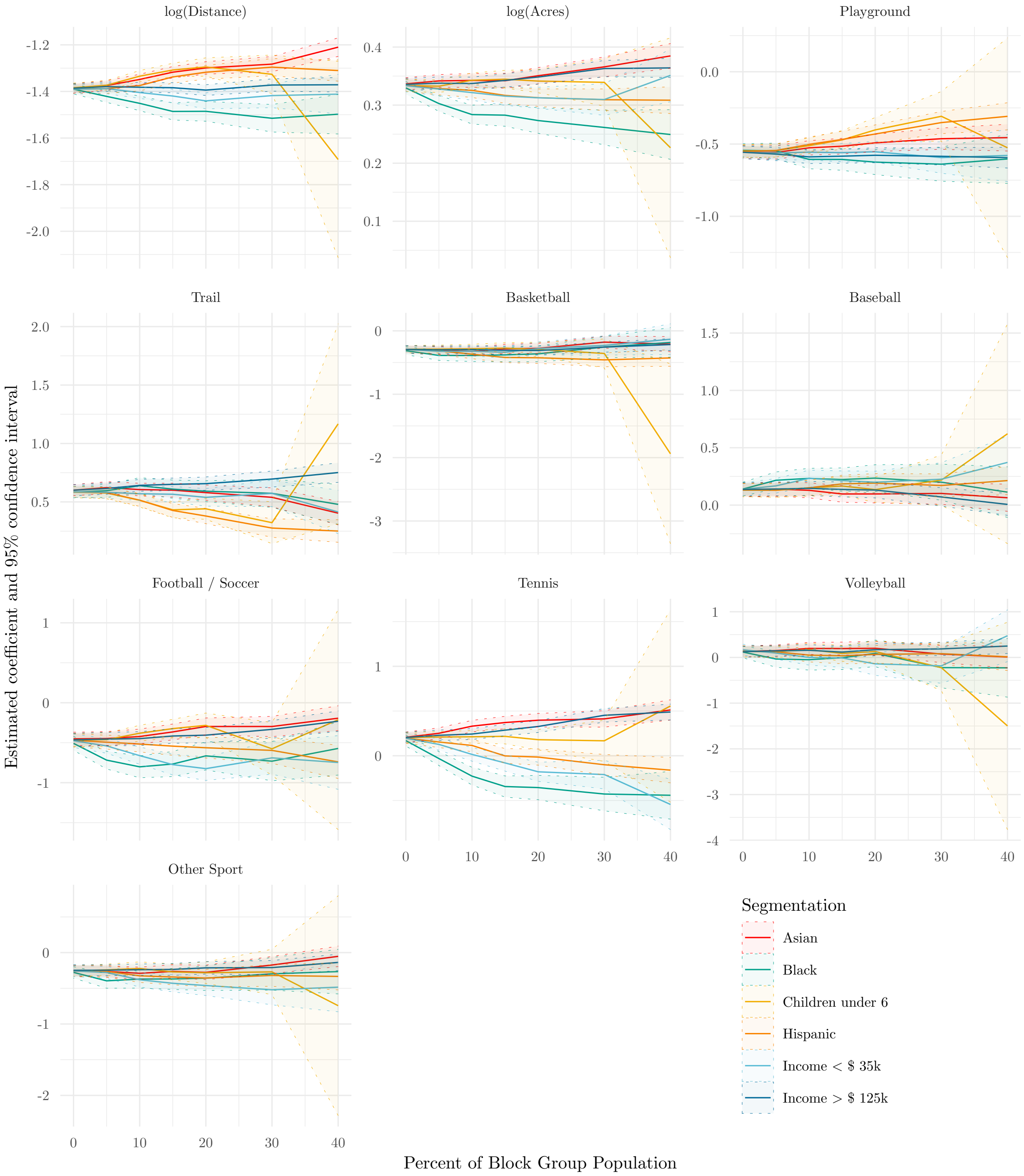

Figure 2: Estimated utility coefficients and 95% confidence intervals for park amenities at different socioeconomic threshold levels.

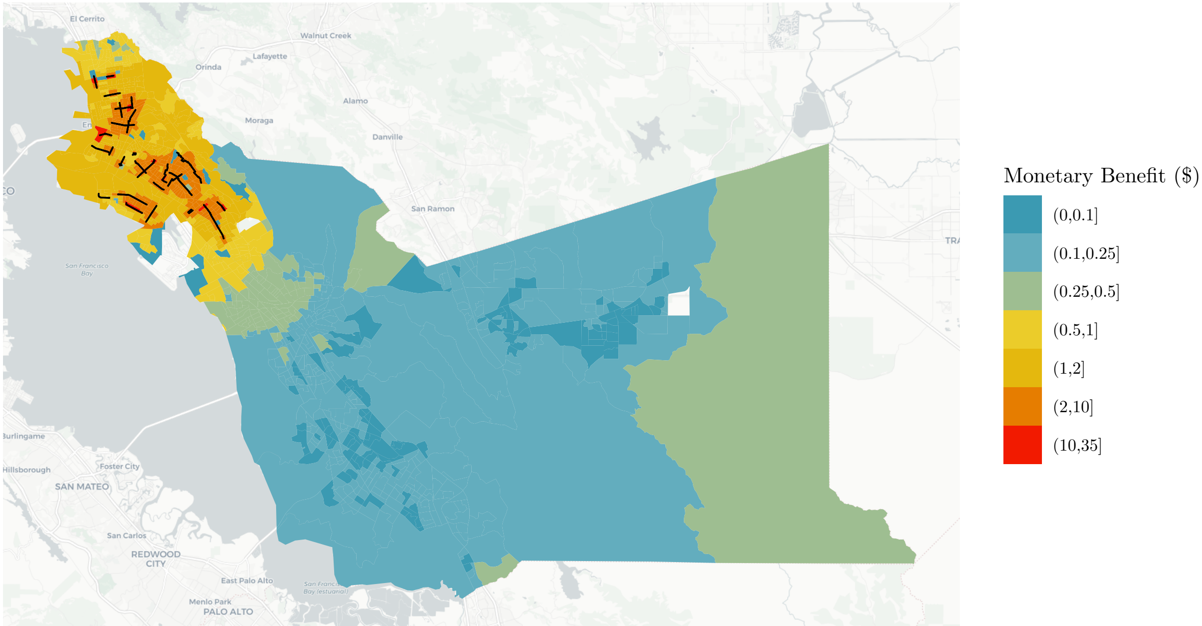

Figure 3: Monetary value of street opening to residents based on utility change. Streets converted to pedestrian plazas are shown in black.

More interesting than the total benefit or even its spatial distribution, however, is the social equity of its distribution among different population segments. If we assign the block-group level monetary benefit to each household in the block group, we can begin to allocate the distribution of benefits proportionally to households of different sociodemographic classifications. Specifically, if a block group with N total households has a measured consumer surplus δCS, then the share of the total benefits going to a particular population segment k is

$$S_k = N * P_k * \delta CS \tag{5}$$

where P_k is the proportion of the block group's population in segment k. There is some opportunity for confusion when some demographic variables we use (share of households with children, household income) are defined at the household level and others (specifically ethnicity) are defined at the person level. It is similarly not clear whether the benefits of improved park access should be assigned at the person level, the household level, or the number of total park trip makers in each block group. For consistency and simplicity, we assert that the benefit is assigned to each household, and that persons receive a proportional share of the household benefit. For example, a block group with 30% Black individuals will receive 30% of the benefits assigned to all the households in the block group.

Table 5 shows the total benefit assigned to households in this way as well as the share of all monetary benefits in the region. In some cases, the policy of opening streets as public spaces had a pro-social benefit,

Table 5: Equity Distribution of Street Opening Benefits

Group	Benefit	Percent* of Benefits	Households**	Percent of Households
Households with Children under 6	$145,604	14.10	83,868	14.53
Income < $35k	$223,853	21.68	90,762	15.73
Income > $125k	$329,431	31.91	229,963	39.84
Black	$187,483	18.16	61,971	10.74
Asian	$199,032	19.28	167,135	28.96
Hispanic	$230,674	22.34	119,013	20.62
White	$351,749	34.07	194,263	33.66
All Households	$1,032,372	100.00	577,177	100.00

[*] As individuals and households will belong in multiple groups, the percents do not sum to 100.

[†] Race and ethnicity are person-level attributes; households are assumed to follow the same distribution.

as 18.7% of benefits went to Black individuals, even though only 11.4% of the population of Alameda County is Black. Similarly, roughly one-quarter of total benefits went to households making less than $35,000 per year even though only one-fifth of the households are in this category. On the other hand, a smaller than expected share of benefits is allocated to Asian individuals and households making more than $125,000 per year.

5. Limitations and Future Directions

The utility-based accessibility metrics we present and apply in this paper are evaluated from a discrete choice model estimated on simulated decision makers constructed from a third-party passive origin-destination matrix. This methodological choice has some strengths: Foremost among these is the ability to readily and affordably construct a large dataset on an infrequent trip purpose. Most destination choice and activity location models are estimated on small-sample household travel surveys. Securing sufficient responses to estimate a rich behavioral model on a trip purpose as infrequent as parks has proven prohibitively expensive outside of extensive research activities (e.g., Kaczynski et al., 2016). Using passive data sets to increase the effective sampling rate possible in a discrete choice model is a potentially powerful strategy, and its application here is an important contribution of our work.

At the same time, passive data sets available from commercial providers do not reveal any details about the specific trip makers beyond what can be learned from their residence block group. In this research we were able to determine whether a device resided in a block group with a high proportion of low-income households, but could not have confidence that a particular device belonged to a member of such a household. Similarly, there is no information on what kind of trip the device-holder actually accomplished at each park. These limitations combined mean that it would likely be infeasible to directly observe devices that traveled to the converted streets during the COVID-19 lockdowns. The ideal dataset for estimating individual park activity location choices generally and in special situations would be a high-quality, large-sample household survey of real individuals.

The individual-level demographic data would also be valuable in understanding more clearly the observed heterogeneity in response among different income or ethnic groups. The trends and correlations revealed in the presented models may reflect situational inequities rather than true preferences. For example, the distinct observed parameters on size and distance for block groups with high minority populations may indicate that areas with large minority populations tend to have smaller parks that are more geographically distributed relative to other areas of the region. This interpretation could also explain some of the non-intuitive response observed in our models, especially in regards to playgrounds.

We limited our analysis to home locations and parks in Alameda County, California. It is possible that some Alameda residents visit parks in neighboring counties, just as it is possible that parks in Alameda County attract trips from outside the county borders. This is most likely for block groups and parks on the north and south borders of the county. The scope of this analysis was determined by the passive data set available for the research, but the county boundaries are not a general requirement for all studies of this kind.

The distance to a park was represented in this study using a walk network retrieved from the OpenStreetMap project. Though perhaps superior to a Euclidean distance, this measure still has many limitations. First, we were unable to verify the integrity of the underlying network information; based on our prior experience, it is likely that some broken or improperly connected links artificially inflated the measured distance for an unknown number of park / block group pairs. A more serious limitation, however, is that experienced travel distances are a function of the transport mode employed by the traveler. Using bare distances does not provide any detail on how access to parks might be increased with improved transit service, for example. Using a mode-choice model logsum as a multi-modal impedance term in the activity location choice model would enable this kind of analysis.

Of course, COVID-19 led to the closure of some park facilities — playgrounds, pavilions, and in some cases entire parks — that were not captured in this analysis. These closures would lead to a decrease in the consumer surplus for park access, which might overwhelm or at least change the distribution of positive benefits we measured here.

6. Conclusions

Converting city roadways into pedestrian-oriented public spaces was in some ways an obvious response to the COVID-19 pandemic: Vehicle traffic demand was down, and there was a also critical need for pedestrian-oriented open spaces in many communities. The research we present here suggests that this policy had measurable and meaningful benefits to neighborhoods in Alameda County, California, and that these benefits were distributed in an equitable or even a pro-social manner. The total benefit to households in the community is estimated at over $660,000, with disproportionately high benefits going to Black, Hispanic and low-income neighborhoods. There is, however, a disproportionately low benefit to neighborhoods with high Asian populations that might be addressed were the policy to continue, be repeated, or made permanent in some way.

In estimating these benefits, we applied an emerging technique to estimate park choice preferences and utility from passive mobile device data. This technique allowed a more nuanced measure of access that allowed us to consider the converted streets as providing quantitatively different access than other city parks. A policy of permanently closing these streets to vehicle traffic may or may not have negative effects on transportation access that would need to be considered against the benefits we measured in this research. But utility-based access measures provide a mechanism to weigh the benefits of access against the costs of travel in a theoretically coherent manner. Adopting such flexible methods of measuring access will help transportation and land use planners better understand the nuances and tradeoffs inherent in a wide range of policy proposals.

Acknowledgments

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