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Access to Out-of-School Resources in Denver

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Introduction

Experiences outside of the school day can be highly enriching to student academic (Augustine et al, 2016; Stein, 2016) and non-academic learning (Bowen, Greene, & Kisida, 2014; Greene, Kisida, & Bowen, 2014; Kisida, Bowen, & Greene, 2016; Kisida, Greene, & Bowen, 2014). For students living in disadvantaged communities, it can be challenging to access organizations or institutions that provide enrichment programs for the arts, sports, and tutoring, or social services such as counseling, meals, or medical care. And while we know that experiences outside of the school day can be beneficial for student academic and non-academic learning, they remain elusive to the students who need them the most (Augustine, 2016; Redford, Burns, & Hall, 2018). Financial, time, accessibility, and safety constraints can all limit the feasibility of a student going from school or home to an enrichment program or service provider.

There is potential for policy solutions that may be able to increase access for disadvantaged students to engage in these out-of-school opportunities. Amidst the barriers to access, there is the need to better understand what the highest impact policy lever might be. In particular, understanding the impact of travel time to programs on student access can be utilized by various transportation providers from public transportation, to school bus service, and even on-demand car services. Various types of scholarships can potentially offset costs, both officially part of programs (tuition and materials) and additional costs (transportation, food, or extra supervision). By reducing both monetary and non-monetary costs to attending out-of-school programs, access to these programs can be increased by these simple levers.

This study specifically analyzes data from ReSchool Colorado's work around summer opportunities through their "Blueprint4Summer" platform. The online platform is designed to give families a simple method of gaining information about summer programs for their students. Programs can be searched by category (academics, arts, nature, sports, etc.), cost, location, and other program specific characteristics. While the platform itself is meant to increase access to summer programs, this research aims to understand the true supply and demand of summer programs for students in Denver.

The first section of this paper explains the background of ReSchool and Blueprint4Summer. We then give an overview of literature on this topic. The third section reviews the data used in the project followed by a discussion of the analytic methods implemented. In the fifth and sixth section, we present the results and then a discussion of the what these results mean, respectively. Finally, we provide recommendations for policy makers to improve access for students to out-of-school opportunities.

Background

ReSchool Colorado, an organization working to reimagine education curated around individual student needs, works to help families design a multi-faceted education that enriches and supports an individual student by leveraging local resources and opportunities that are available. These opportunities include wraparound and community-based services as well as out-of-school learning opportunities. ReSchool utilizes learner advocates, who help families navigate educational options, transportation, and other resources they may need or want. In this way, ReSchool is able to help families overcome the complexity added by engaging in out-of-school opportunities and target the most disadvantaged communities to remedy the inequitable access to opportunities that exists.

Blueprint4Summer is an online platform run by ReSchool to increase access that students and families have to summer programs in the Colorado cities of Denver, Aurora, and Boulder. The Blueprint4Summer website enables parents to search for summer programs using keywords as well as selecting from nine categories of programs, attributes (e.g. special needs students, gifted students, offering before/after care, and scholarship availability), time of day, desired zip code, dates, range of cost, gender restrictions, and student age. Once parents choose their search criteria, they are given a list of available programs with a description of the program, cost, location, and contact information. Individuals can also submit comments on a given program so that other individuals can have additional information.

The theory of action behind the Blueprint4Summer website is around increasing the information available to families around summer programs. Despite targeted advertising for Blueprint4Summer in specific zip codes, it is unclear who actually uses the website and whether it is increasing information for disadvantaged families. The purpose of the current research is to better understand the needs within the city of Denver, Colorado and how the current supply of programs is meeting the needs of students in the city.

Literature Review

Out of School Activities

In a recent article from the popular education news website “Chalkbeat,” authors discuss a “shadow education system,” synthesizing recent literature that finds that wealthier students tend to benefit from out-of-school activities related to art, music, and theater, over the summer, while poorer students miss out (Barnum, 2018). Confirming this, using a nationally representative sample of students, a 2018 U.S Department of Education Report finds that during the summer after kindergarten, only 7 percent of post kindergarten students from poor households attended a summer camp, as compared to 38 percent of students from non-poor households. In addition, a higher percentage of kids from poor households (83 percent vs. 70 percent of non-poor household) did not even have care set up with anyone other than their primary caregiver (Redford & Burns, 2018). This report specifically highlights the disparity in access to experiences outside of the household for students from poor households.

Disadvantaged students may have less access to out-of-school resources (OSR) during the summer, but we know very little about how useful these opportunities are for them during the school year or summer. A 2005 literature review conducted by the RAND Corporation concluded that OSRs tend to, at best, have modest effects on student academic achievement, academic attainment, and social behaviors (such as reduced drug use and pregnancy). The authors concluded that even studies with the most rigorous design found conflicting results based on the age and background of student participants, further complicating how to generalize the limited findings (Bodily S & Beckett M. K. 2005).

In 2000, the Getty Center released a series of meta-analyses on different types of arts education, including theater and visual arts, and its relationship to traditional and non-traditional academic outcomes (Winner & Hetland, 2000). When looking only at studies with an experimental design, there was no causal evidence linking arts exposure to math and verbal test scores (Winner & Hetland, 2000). A similar meta analysis of correlation studies found that students with arts education tend to have higher test scores (Winner & Hetland, 2000). However, the “drive hypothesis” suggests that better test scores are accounted for by self-selection of high achieving students into arts rather than from exposure to arts education (Winner & Hetland, 2000).

In addition, two separate meta-analyses exploring the link between music and spatial reasoning found that for adults, and children 3-12 years old, music improved spatial reasoning, and spatial-temporal abilities. The authors caution it’s exactly unclear how improved spatial temporal tasks translate into test scores (Winner & Hetland, 2000). In another meta-analysis of over 200 experimental studies of in class drama classes, positive associations were found with respect to many verbal reasoning and linguistic skills (Winner & Hetland, 2000). Overall, the initial link between arts education and traditional academic outcomes seems difficult to describe, and this only further complicated with respect to OSRs.

In contrast to previous studies, emerging research focuses on exploring non-traditional academic outcomes associated with arts education and exposure to cultural activities outside of the classroom. Randomized controlled trials found that art field trips increased disadvantage student’s cultural capital and fostered a greater interest in the arts (Kisida, Greene, & Bowen, 2014), particularly in early childhood (Kisida, Bowen, & Greene, 2017). Similar results indicate that field trips to art museums may help improve students’ critical thinking (Kisida, Bowen, & Greene, 2016; Greene, Kisdia, & Bowen, 2014). Similarly, emerging evidences suggests exposure to live theater may also increase social tolerance for difference among students (Greene, Erickson, Watson, & Beck, 2018).

Three recent studies specifically address the effect of summer resources on academic achievement. Alexander et. al. (2007) identifies the ways in which cumulative disadvantage acquired over nine years with reduced access to summer OSRs contributes to learning gaps between wealthy and poor students in ninth grade (Alexander et. al., 2007). A recent five study qualitative RAND report indicates that summer programs of many different types may help to reduce summer learning loss (Augustine et. al., 2017). Finally, a recent evaluation of free academic programs in Baltimore reduced summer learning loss in terms of reading test scores by about 61% (Stein, 2016).

As evidence continues to emerge exploring the value of arts programs and other out-of-school research, the last twenty years have seen consistent growth in the amount of public financing for OSRs (McCombs et al, 2010). In particular, interest groups from school age child-care practitioners, youth-development experts, educators, criminal justice experts, and poverty experts have all argued that OSRs are a part of solution to problems facing youth around the nation (McCombs et al, 2010).

As the recent Department of Education report indicates utilization is greatly shaped by household poverty and demographics (Redford & Burns, 2018). Similarly, previous research indicates that effect of arts programs and by extension arts OSRs may be heavily mediated by the demographics of participants (Winner & Hetland, 2000). Nevertheless, as evidence continues to emerge suggesting OSRs are important to a student's education, understanding what "access" looks like with respect to travel times and cost, and how this may contribute to achievement gaps in education is a valuable piece of understanding OSRs.

Access Index

We elected to create a novel measure of access based on student travel times to OSR session locations, disaggregated by cost and category. To assess access to OSRs in Denver, we utilized literature from a variety of disciplines to inform the design of our model.

Transportation literature provides some insight on how to account for differences in travel times to specific destinations. In particular, we reviewed the Access Across America 2017 methodology which calculated the ten shortest paths between a large number of origin destination pairs, repeated for many departure times. In contrast to our objectives, this methodology measures the number of opportunities, in this case "jobs", in a given destination census block group (Owen & Murphy, 2017). This is for the purposes of creating a more generalizable measure of access to all jobs, while we are specifically interested in access to a number of discrete locations. Authors here used a number of discrete thresholds, for number of locations reachable within 10 minutes to 60 minutes, at ten minute intervals. There is not theoretical justification for these thresholds beyond that they are seemingly intuitive.

Literature related to access to healthy eating options was also reviewed in an attempt to create an applicable access index. In particular, the assumption behind the indices we reviewed on access to healthy food are based on the assumption that travel time to healthy food, the number of places to purchase food, and the quality of the food greatly affect individuals abilities to consume healthy food (United States Department of Agriculture, 2017; Lytle & Sokol, 2017). Similarly, we assume that travel times, and cost of OSR summer programs greatly affect parents ability to enroll their children.

The "index of rural access" produced by Australian researchers McGrail and Humphreys (2009). This index provides a single measure of access, adjusting patient to provider ratios by the "need" based on population health, and decay function of travel times to provider locations over a given time threshold. This index is particularly relevant for our purposes as it provides a unified way of describing which areas have the highest and lowest access, and adjusting these measurements per population needs (McGrail & Humphreys, 2009). While population "need" in our case is not as verifiable as variables which predict population health, the use of the decay function measuring travel times to provider locations is a insightful contribution for how to value opportunities beyond their distance at a somewhat arbitrary threshold.

Critical for our purposes, Talen & Anselin (1998) make a case study by comparing access for given block groups to play grounds, using a minimum distance, travel cost, and gravity model methodologies (Talen & Anselin, 1998). The authors find that the choice of methodology for assessing access in this style drastically changes the results in terms which areas are determined to have the highest and lowest access. They also conclude that the selection of methodology ought to be determined by the understanding of the effect of distance on options (Talen & Anselin, 1998). For example, the minimum distance calculation assumes that individuals will always patronize the resource which is closest to them, and the inequity to be considered with respect to only minimum distances. Alternatively, the travel cost calculations and gravity models consider that individuals may patronize all available options, but consider distance a deterrent when making a selection (Talen & Anselin, 1998). Because we lacked the resources to identify a validated measure of travel cost our study, we elected to begin with the gravity model.

One study in particular utilized a gravity model in assessing access to secondary schools is Glasgow Scotland (Pacione, 1989). Pacione specifically utilizes a model which accounts for travel times from geographic area starting points (comparable to whatever scottish block groups are) to secondary schools in Glasgow, and weights travel time by the proportion of car ownership to account for travel time differences between driving and transit times (Pacione, 1989). This a very important insight, as transit travel times are almost always considerably longer than drive times, which for a gravity model based on travel, this can drastically alter results. While we did not feel confident that proportion of car ownership in a given block group was a useful proxy for mode of transportation to OSRs, we nevertheless felt that recording a separate index for transit times would be valuable to highlight the disadvantage that students with no other means of transportation face.

Overall, it seems clear that that a gravity model must be used to account for the large of number of unique sessions addresses within Denver, and certainly on the borders of Denver and its neighboring cities of Aurora and Boulder. While considering other resources, such as the number of after school activities provided by a local school is likely important, we elected to consider this, along with student demographics, as distinct from the access index, as has been done with previous indices assessing access to health. We additionally consider the difference in transit times and driving times, and provide a breakdown of this information by student demographics.

Internet Search Data

While not a primary focus of the analysis in this report, we were asked to assess the possibility of using Internet search data from ReSchool's BluePrint4Summer website as a measure of demand for summer OSRs in Denver. Presently, there is very little research on the use of this type of data when measuring demand in the context of school OSRs, or education more broadly.

A working paper by Lovenheim and Walsh (2017) makes use of what is likely the largest volume of internet search data for this topic, assessing data for over 100 million searches for unique schools on the largest choice website, greatschools.org (Lovenheim & Walsh, 2017). The authors utilize a difference-in-differences model on areas prior to and after school choice initiatives to assess if introducing school choice increases search volume in that area. They generally find this hypothesis to be true and conclude as a useful tool a useful tool as a proxy for demand of a given school. Unfortunately, the authors were unable to account for search demographics, and assume, *a priori*, that all searches are from a representative sample of parents in the population.

In contrast to the more optimistic findings from Lovenheim and Walsh (2017), Schneider and Buckley (2002) attempt to validate the use of internet search data by comparing the results of a survey of parents targeted for a school choice website campaign to the users of that website, in Washington D.C. (Schneider & Buckley, 2002). Critically, authors find that the population of internet users vs. all parents varied considerably. For example 13% of the users of the website had less than a college degree, compared to 48% of parents surveyed. Furthermore, when researchers compare the first five click throughs parents make on the choice website, they find that the single most common attribute viewed is race. Authors conclude, that this suggests that parents may be primarily using the website to assess the percent of a schools Black student population, rather than reviewing test scores or extracurricular activities, which were rarely observed.

Data Sources

The analyses in this report are based on several datasets, both public and private, which were obtained from multiple partners. All data was retrieved between June 2018 and July 2018.

Denver Public Schools (DPS) Data

Denver Public Schools (DPS) provided data on a variety of student demographics and outcomes for the schools years ranging from 2011-12 to 2017-2018. Student characteristics reported in the data included age, gender, race/ethnicity, disability status, grade in school, primary language spoken in the home, standardized test scores, and disciplinary and attendance outcomes. Students were de-identified in the datasets, with names replaced by randomly generated ID numbers.

We elected to use a subset of the DPS data for which we had approximate student locations, because our spatial analyses on the distances between students and out-of-school summer resources required student location data. This restricted us to work with students who participated in the school choice system, where students apply for a school of their choice instead of going to the school assigned to them according to family location. See Appendix I for a detailed description of comparison between this school choice sample and total student population in the DPS data.

Approximate student locations were obtained by converting student addresses into the centers of census block groups encompassing those addresses. This ensured student privacy while also allowing us to conduct spatial analyses on student locations, and merge this with household demographic information such as median household income based on other data sources (eg. the Census) that report data at this level.

Census Demographic Data

Demographic information at the census block group level for Denver was obtained from the American Community Survey (ACS) five year estimates for the years 2012-2016. The ACS is an ongoing survey, coordinated by the United States Census Bureau, which randomly samples home addresses in every state every year. This is in contrast to the full census, which systematically retrieves a representative sample for every surveyed location once every ten years. The ACS data supplements the more thorough data from the full census, allowing up-to-date estimates of current population demographics more often than once every ten years. The ACS data is openly available on the American FactFinder website.

Census “Block Group” is the second smallest statistical division of census tracts, generally containing between 600 and 3,000 people. We specifically selected block groups for use in this report, as they was smallest statistical division which reported information on median household income. Block groups in Denver all cover contiguous areas, and never cross county or census tract boundaries. We collected the following features for all block groups:

1. Population by age within given ranges (e.g. 5-17 years old)
2. Population by race and ethnicity
3. Population above 25 years by educational attainment
4. Median household income
5. Primary home language
6. Number of households in poverty
7. Number of single parent households

Denver Open Data

In addition to the block group level demographic data, neighborhood level demographic data was obtained from the Denver Open Data catalog, an online catalog of 230 publicly accessible datasets created in a partnership with Open Colorado.[1] The neighborhood level demographic information was also derived from the ACS, but for the years 2011-2015, which was the most recent available from Denver Open Data.

Neighborhoods provide a coarser geographic division of the city than block groups, with block groups being nested within neighborhoods. The boundaries of the statistical neighborhoods were developed in 1970 by the Denver Department of Community Planning and Development, and geographic place names were assigned to each neighborhood to reflect the commonly used names for subdivisions and historical parts of the city. Neighborhoods are less precise than census block groups, but they provide a higher-level, more interpretable breakdown of regions within the city for Denver residents.

From the 230 datasets available on Denver Open Data, we also identified 7 most relevant datasets for use in our analysis to understanding the context for out-of-school summer resources in Denver, including the following:

1. Parks
2. Playgrounds
3. Recreation centers
4. Libraries
5. Athletic Fields
6. Crime
7. Neighborhood Boundaries and Demographics

[1] All Denver Open Data was downloaded in the form of shapefiles, and when necessary the centroids of regions (parks, fields, etc.) were calculated and used to represent point locations of resources.

In addition to these datasets, we also manually collected (via Google searches) the locations of all major museums in Denver. We specifically chose to examine parks, playgrounds, recreation centers, libraries, athletic fields, and museums as they represent non-structured resources which students may utilize during the summer. In addition, these resources represent locations where more structured summer programs can occur.

Blueprint4Summer Program Data

Blueprint4Summer program data are drawn directly from the Blueprint4Summer website. This includes identifying information about available programs at the session level (where one program may have many unique sessions), as well as the program duration, cost, address, size, gender requirements, disability accommodations, scholarship opportunities, and "category" of session. While session size is surely a useful metric for assessing access to out of summer resources, this information was not complete for all sessions, and thus was not a valid sample for comparison. To the best of our knowledge, this is considered the most comprehensive list of out-of-school summer resources in Denver.

Session categories were initially divided into "academic", "arts", "cooking", "dance", "drama", "music", "nature", "sports", and "STEM". These categories are non-mutually exclusive per program session and were determined by Blueprint4Summer. For the sake of simplification in analysis, we aggregate the above categories into the following four:

1. Academic ("academic" or "STEM")
2. Arts ("arts", "cooking", "dance", "drama", or "music")
3. Athletic ("sports")
4. Nature

Google Analytics Data

Data on the Blueprint4Summer Colorado website searches were pulled from Google Analytics[2] for the time period beginning January 1st, 2018 (the approximate start of the BluePrint4Summer Colorado website) and ending July 11th, 2018.

Our goal was to aggregate user locations and search query specifications at the level of unique user searches; however, this information was not available through the use agreement with Google Analytics. Furthermore, the latitude and longitude of user metrics returns, at best, city level locations, which was not helpful for our analysis. Thus we refined our query to "users" who searched a unique "PagePath", subsetted for only searches originating within Colorado. "PagePath" here refers to the html of a given search, which includes all search parameters. The

[2] Data were pulled using the Google Analytics API accessed through the "googleAnalyticsR" package in R.

“PagePath” was then parsed into the categories of a given search, giving us an approximate measure of the different features of user searches.

Access Index Google Distance Matrix API

Distances between approximate student locations and program addresses were geocoded using the Google Distance Matrix API. Distances were computed in terms of driving, transit, and walking travel times. All searches were performed with arrival times of 8:00 AM Mountain Standard Time. Preliminary analysis tested arrival times of 8:00 AM, 12:00 PM, and 5:00 PM for the first 10 blocks groups and first 30 program addresses. However, we found that the mean difference in time traveled, for each mode of transport and across arrival times, was less than five minutes. Thus, for the sake of efficiency, we decided to utilize a 8:00 AM arrival time for all Google Distance Matrix API calls for the remainder of our analysis.

Analytic Methods

Access Index Calculation

We created multiple access indices to measure students’ ease of accessibility to various out-of-school summer resources by their desired mode of transportation (driving or public transit) and program cost (free, low cost[3], or any cost).

Access indices are calculated at the Census block group level, the smallest geographic unit possible, in order to ensure higher accuracy in distance calculations and greater geographic variation in results. Thus, access index scores reflect how easy or difficult it is to reach all available summer program sessions in Denver from the center of a given block group. The access index takes into account the sum of travel times from the block group centers to program locations, mode of transportation, the number of sessions at each location, program types, and program costs as illustrated in the following function:

$$A_{\text{block}}^{\text{type}}(\text{transit mode}) = \frac{1}{n_{\text{programs of type}}} \sum_{\text{programs of type}} f(T_{\text{block to program}}^{\text{transit mode}}) \tag{1}$$

where A denotes the access index score for a given block group for a type of program (eg. art, academic, etc.), by the selected transit mode, n is the number of programs in that type, and T is travel time in minutes by the given transit mode. We pulled travel time data from origins (block

[3] Note that a cost of $50 per day was recommended specifically by ReSchool from this project. In absence of any other literature to inform low cost, we elected to go with this recommendation.

group centers) to destinations (program locations), by driving and by public transit, from the Google Distance Matrix API.[4]

In the access index calculations, we used a decay function, denoted by the function $f(T)$ in the above equation (1), which we adapted from the gravity model widely used in the literature to identify the levels of human interactions between locations based on notions in social physics (Pacione, 1989). The decay function is displayed in detail in the following function.

$$f(T) = \frac{1}{(1 + T/5min)^2} \qquad (2)$$

Note that we adopted an indifference threshold of five minutes to adjust for the extremely short travel times, which otherwise would heavily bias the results in favor of these circumstances. Heavily weighting results in favor of these very small differences would obscure the purpose of this analysis, which is to identify larger trends in terms of access to all programs. We picked the five-minute threshold based on the assumption that parents are likely to be indifferent with respect to travel times of five minutes.[5]

As indicated above, our access index is flexible for both a variety of program types and a variety of cost ranges. Specifically, indices were calculated for “Arts,” “Academic,” “Athletics,” and “Nature” program types. Additionally, indices were calculated for any-cost programs, free programs, and low-cost programs. The “overall” driving and transit access indices refer to the average access index score over all categories of program, at any cost. That is, for a given block group the overall access index is given by:

$$A^{overall} = (\ A^{arts}(driving) + A^{academic}(driving) + A^{athletics}(driving) + A^{nature}(driving)\ )/4 \qquad (3)$$

Given program type(s) and costs ranges, the driving and transit access indices are normalized on the same 0-100 scale; because of this, along with the fact that transit times are always longer than driving times, “access” by transit is categorically lower than driving.

[4] The Google Distance Matrix API is a service that allows users to obtain travel distance and times from a matrix of origins and destinations, using recommended routes and estimated travel times from Google Maps. See https://developers.google.com/maps/documentation/distance-matrix/start

[5] Both the decay function and the threshold of five minutes were tested in a sensitivity analysis using multiple adaptations of decay functions and multiple potential thresholds thresholds. The selected decay function is the least sensitive to changing thresholds. For more information on why the threshold of five minutes and this particular decay function were selected, see the sensitivity analysis in Appendix III.

Cluster Analysis by Local Moran's I

We used Local Moran's I analysis to identify where high and low access indices were clustered on the map of Denver. For each block group, the following statistics were calculated: a local Moran's I value, a z-score, a pseudo p-value, and a code representing the cluster type for each statistically significant feature. A positive value for I indicates that the block group has features with similarly high or low attribute values as their neighboring block group; indicating the block group is part of a cluster. A negative value for I indicates that a feature has features with dissimilar values to the neighboring block group; this block group is an outlier. The z-scores and pseudo p-values represent the statistical significance of the computed I values, indicating whether or not to reject the null hypothesis that the observed spatial clustering is greater than expected given a random distribution.[6] We used the Queen's case continuity[7] to identify neighborhoods. Adjacent areas which share either a border or a corner are counted as neighbors.

Lorenz Curve and Gini Coefficient

The Lorenz Curve was developed by Max Lorenz in 1906 to show the graphical distribution of wealth (Lorenz, 1905).[8] It is also useful for describing inequality in distributions of other resources (see for example, Talen, 2001). It plots the proportion of resources accumulated by a given percentage of the population. The diagonal line at the 45º angle shows a perfectly equal distribution, while the Lorenz curve shows the actual distribution. The Gini coefficient calculates the ratio between (1) the area between the Lorenz curve and the straight diagonal, and (2) the area in the triangle below the diagonal. The further away the Lorenz curve is from the diagonal, the more unequal the distribution of resources is, and the bigger the Gini Coefficient will be as well.

Descriptive Statistics

Understanding Existing Resources in Denver

There are 241 unique locations of out-of-school summer programs representing a total of 3136 "sessions" in Denver for 2018. While the BluePrint4Summer website classifies all programs into eleven categories, we aggregated these into four categories for the analysis purposes. See the section on methods below for a description of this process. With our categories, "Arts", "Athletics", "Academic" and "Nature." These categories are not mutually exclusive, and many programs fall within multiple categories.

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[6] See more details on Local Moran's I here: http://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/h-how-cluster-and-outlier-analysis-anselin-local-m.htm

[7] Lloyd, C. (2010). Spatial data analysis: an introduction for GIS users. Oxford university press.

[8] Lorenz, M. O. (1905). Methods of measuring the concentration of wealth. *Publications of the American statistical association*, *9*(70), 209-219.

Table 1. Description of Blueprint4Summer Sessions

	Number of Sessions	Number of Free Sessions	Median Cost
Total	3136	727	$195
Academic	2094	716	$190
Arts	1815	492	$179
Athletics	1621	56	$195
Nature	1502	196	$195

The majority of sessions are concentrated in the Washington Park Southeast Central area and the commercial business district downtown area of Denver, which have the highest median incomes and White population in the city. This trend is similar for Arts and Academic programs. Sports and Nature programs tend to be more centralized around the Washington Park area, with fewer options available in the northern part of Denver.

In contrast, free programs, in general and each specific type, are primarily concentrated Southwest Central area of Denver where the Hispanic population is the highest. However, given that Academic and Arts programs constitute the sharp majority of all free programs, free Athletics and Nature programs are somewhat more divided between the Southwest Central and Southeast Central Washington Park areas of Denver. These cost thresholds overlay almost directly with census demographics for median household income, where lower income areas are more likely to have free programs, and higher income areas are more likely to have more expensive programs.

Supply and Demand: What Are People Searching for?

With information on the existing programs in mind, we strive to understand the relationship between the supply of summer programs and people's demand for them. Is there a bridge between supply and demand? To answer this question, we explored the Google Analytics data, which contain user information from Blueprint4Summer.

Figure 1 shows the top 20 zip codes that were searched for by the users when looking for summer programs. The majority of searches were for zip codes 80010 and 80202 which are located in the downtown region of Denver. The large presence of certain zip codes in the searches may be attributed to the promotional activities that took place in certain locations. Only 8 of the promotions locations were in the top 20 locations that were searched for.

Figure 2 compares how the number of searches differs from the number of ReSchool program sessions in these zip code areas. When comparing the zip codes people searched for and locations of programs, there is no clear pattern between them, except that the most searched-for zip code areas are the locations with the fewest programs. For example, areas with zip codes 80010 and 80202 have the highest searches yet the lowest number of existing program sessions. An important consideration is that we do not know whether searches are conducted at home or at the workplace.

Figure 1. Number of Searches by Zip Codes and Promotional Activities

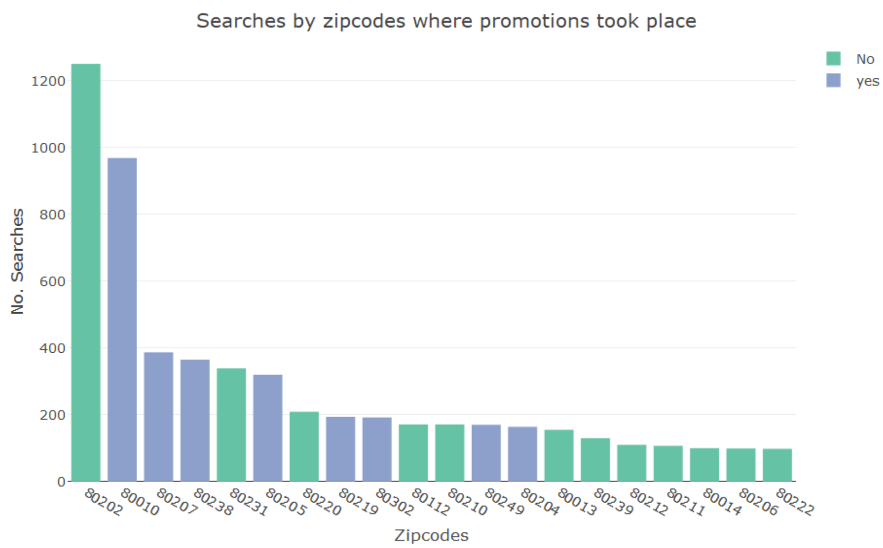
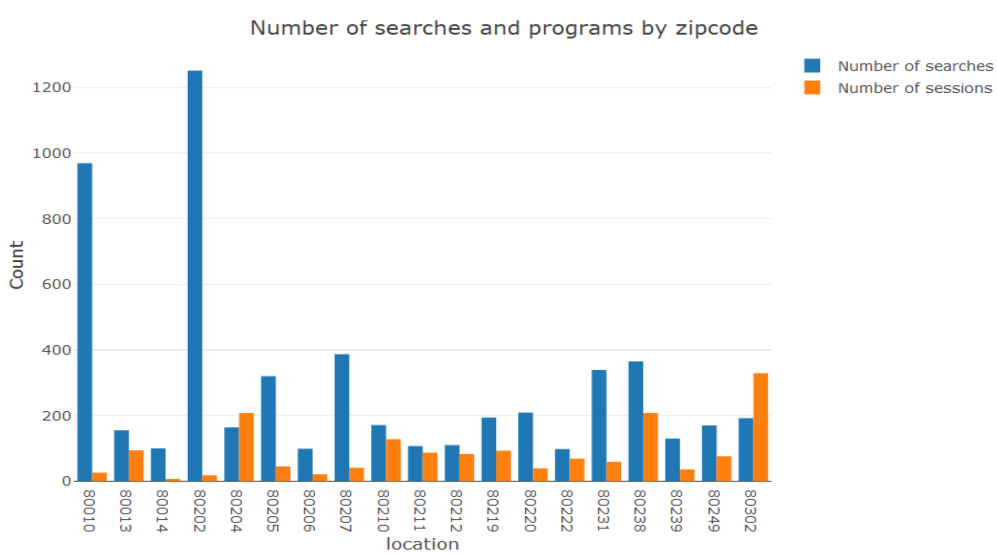


Figure 2. Number of searches and program sessions by zip code

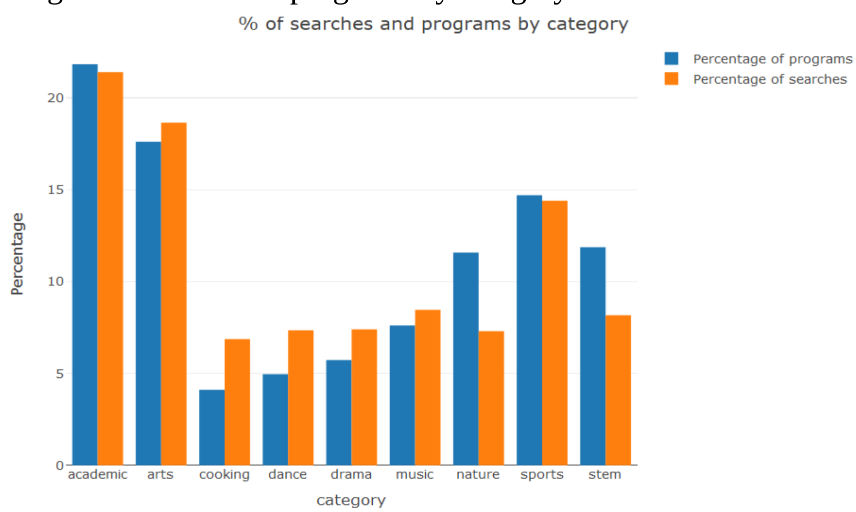


Searches by category

In the previous section, we used Google Analytics search data to understand the geographic distribution of people's demand for summer programs. It is also very helpful the demand by program type and how that corresponds to the reality on the supply side. In other words, are there differences in the demand for various types of programs and existing summer programs offered?

Figure 3 below shows that the demand for academic, arts, and sports programs are higher than cooking, dance, drama, music and STEM. In addition, the percentage of searches for a certain kind of program and its actual existence basically follow the same pattern. A closer look at the graph, however, reveals some differences. The percentage of searches for cooking, dance, and drama programs are higher when compared to the percentage of actual programs. Thus, we recommend adding more programs in these categories. Overall, the supply and demand seem to be even for academic, arts and sports programs while nature and STEM programs have higher a higher supply than demand.

Figure 3. Percentage of searches and programs by category



Denver Demographics

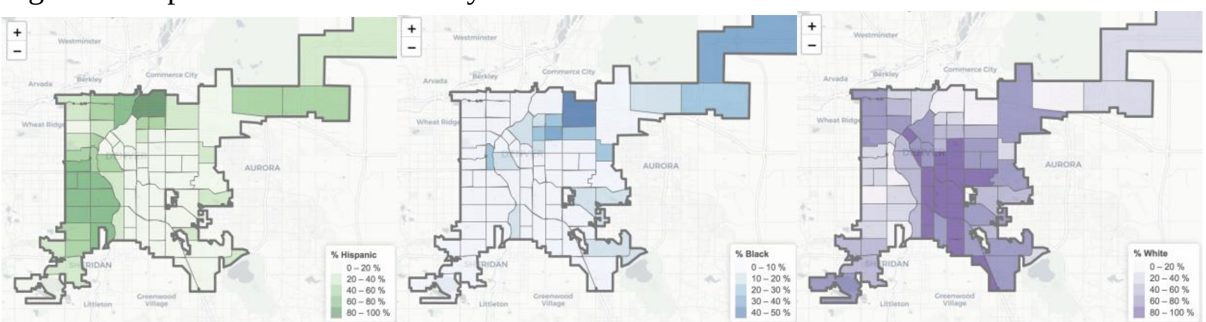
To understand where out-of-school opportunities are distributed in Denver and the equity issues with regard to students' access to them, it is necessary to provide basic demographics on students, their families, and the communities in which they live. This section supplies information on Denver's total population, racial composition, educational attainment of adults, household income, crime, distribution of student-age population by race and ethnicity, as well as other student characteristics.

Total Population

As the most populous city in the State of Colorado, Denver has a total population of 663,303 and 281,072 households, as estimated in 2016 by US Census Bureau[9]. The population is spread across 78 neighborhoods, and is most densely concentrated in the northwest corner near the airport and downtown metropolitan.

Hispanics represented the largest minority in the Denver. In 2016, the Census Bureau estimated about 30 percent, or 204,297, of Denver's population to be Hispanic. This is higher than the State of Colorado and United States overall. Different races and ethnicities tend to concentrate in different regions of the city (See Figure 4). The Hispanic population are clustered in the southwest corner, while the African American population is densely concentrated in the northeast, and the majority of White citizens reside in the center and the southeast.[10]

Figure 4. Maps of Race and Ethnicity in Denver



Estimated in 2016, the median household income for the city was $56,258 dollars and median family income was $71,913. About 12 percent of households with children had income below the poverty line.[11] For educational attainment, 86.4 percent of adult population above 25 years old had a high school or higher degree, and 45.7 percent had obtained a bachelor's degree or higher.[12] Among all households, about 23 percent had one or more children under 18 years old. About 65 percent were married-couple families, 26 percent were single-mom households, and 9 percent were single-dad households.[13]

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[9] U.S. Census Bureau. *2012-2016 American Community Survey 5-Year Estimates: ACS Demographic and Housing Estimates Table DP05.* Retrieved from American FactFinder, August 2018: https://factfinder.census.gov/; U.S. Census Bureau. *2012-2016 American Community Survey 5-Year Estimates: Households and Families Table S1101.* Retrieved from American FactFinder, August 2018: https://factfinder.census.gov/.

[10] See the detailed break down on racial composition in Appendix V.

[11] U.S. Census Bureau. *2012-2016 American Community Survey 5-Year Estimates: Selected Economic Characteristics Table DP03.* Retrieved from American FactFinder, August 2018: https://factfinder.census.gov/.

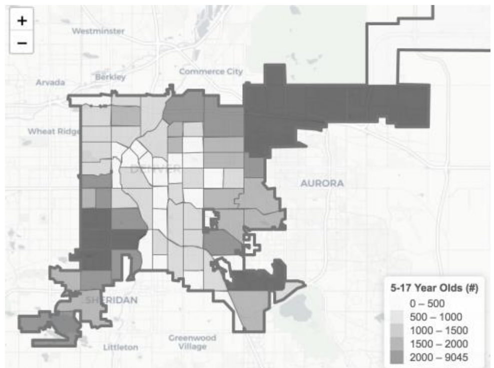
[12] U.S. Census Bureau. *2012-2016 American Community Survey 5-Year Estimates: Educational Attainment Table S1501.* Retrieved from American FactFinder, August 2018: https://factfinder.census.gov/.

[13] U.S. Census Bureau. *2012-2016 American Community Survey 5-Year Estimates: Family Type by Presence and Age of Own Children Under 18 Years Table B11003.* Retrieved from American FactFinder, August 2018: https://factfinder.census.gov/.

Student Population

According to the US Census Bureau 2016 estimates, Denver had a student-age population of 93,132, which is about 14 percent of total population, counting children from 5 to 17 years old. The areas most densely populated by students are generally those farthest away from the city center.

Figure 5. Distribution of student-age population



The racial composition for students is significantly different from that of the overall population. Particularly, in the student population, percentages of minority racial groups are higher than in the overall population of the city.[14] Most prominently, compared with the 31 percent of Hispanics in total population, students with a Hispanic or Latino ethnicity compose 53 percent of the student population. African American students were about 12.4 percent and other races composed 7.6 percent of student population in total. White students are about 27 percent of the student population. This went along with the trends noted by Denver Children's Affairs in their 2018 report *The Status of Denver's Children*[15] that reported that minority populations were undergoing rapid growth in Denver.

About 9 percent of students have a primary disability and 42 percent of students are English-language learners (ELL). Most students speak English as the primary language at home, approximately 73 percent. An additional 26 percent of students speak Spanish at home.

Other Resources in Denver

In addition to analyzing out-of-school summer resources, we also explored the presence of other out-of-school resources in Denver. Specifically, we reviewed the locations of fields, playgrounds, parks, recreation centers, libraries, and museums. It is important to take those into account as the precise role they play in student's access to out-of-school summer resources and how access to certain resources may contribute to a student's overall learning are yet unclear.

[14] Data from DPS Choice.
[15] The Status of Denver's Children: A Community Resource 2018, page 13.

According to Kisida, Bowen, and Greene (2016), students who went on field trips to museums showed improved critical thinking skills as a result. Furthermore, understanding approximately how these other resources are distributed throughout Denver may provide insight for leveraging these resources to improve access to out-of-school summer resources more broadly.
Generally, almost all other resources appear relatively equally distributed throughout Denver, like fields (See Figure 6). The only exception to this is the distribution of museums, which are clustered in the downtown metropolitan areas (See Figure 7). It is not surprising to find museums only located in the central area of the city; however, this may limit the ability of students in certain parts of the city from easily accessing opportunities to visit these resources, which have been found to have positive effects on students.

Figure 6. Distribution of fields in Denver

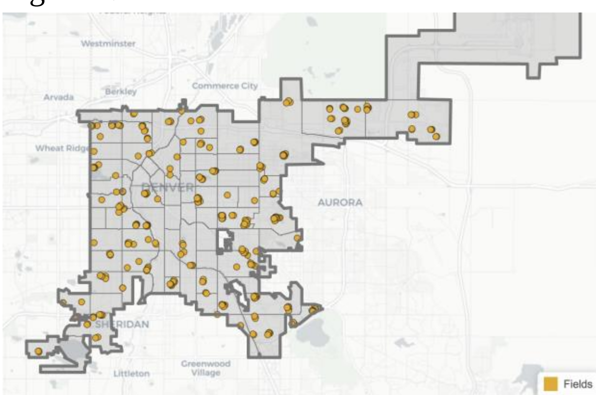
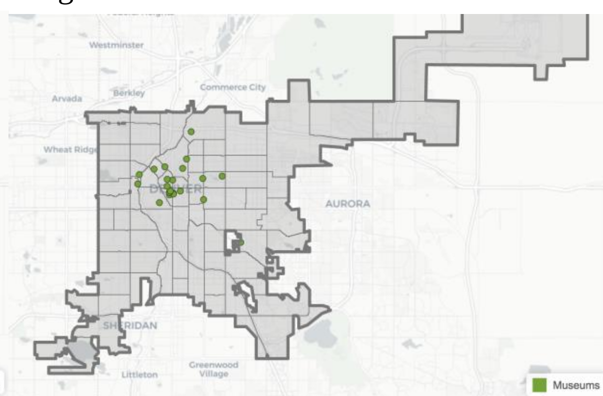


Figure 7. Distribution of museums in Denver



Access Index

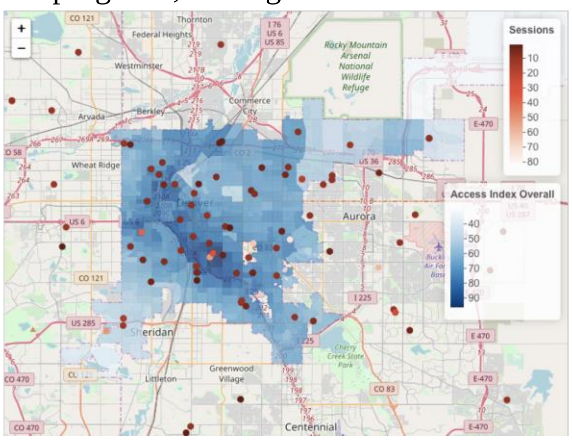
The access indices return a score from 0-100 for each block group, indicating the ease of accessibility from the centerpoint of that block group to all available summer program sessions in Denver. In the index, 0 represents the lowest access in Denver and 100 represents the highest.

As expected, access index scores primarily reflect the concentration of program sessions in Denver, as well as the accessibility to highways and public transportation to these sessions. Figure 8 shows that, for the access index based on driving times, scores are highest in the Southeast Central Washington Park area and in the central business district area of downtown Denver. In contrast, access index scores are the lowest in the outer edges of Denver. In addition, Figure 8 also shows that the transit-based index for all programs renders a similar pattern, but with access being considerably more concentrated.

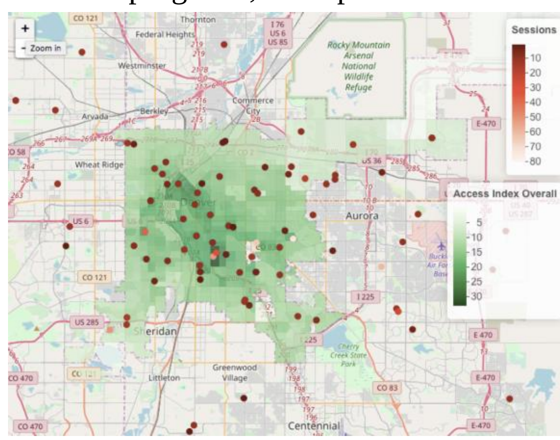
Similar to the access indices for all programs, the access indices for free programs, low cost programs, and programs in a specific category (e.g. academic, arts) reflect the number of easily reachable program sessions of that type, from each block group. Generally, free programs are concentrated in the Southwest Central area of Denver, where access to these programs is highest. This is also the case for programs by category. While overall access is concentrated in the same two regions, the more specific the features we observe (e.g, free nature programs only) the more concentrated access becomes.

Figure 8. Access index maps showing the distribution of programs across Denver

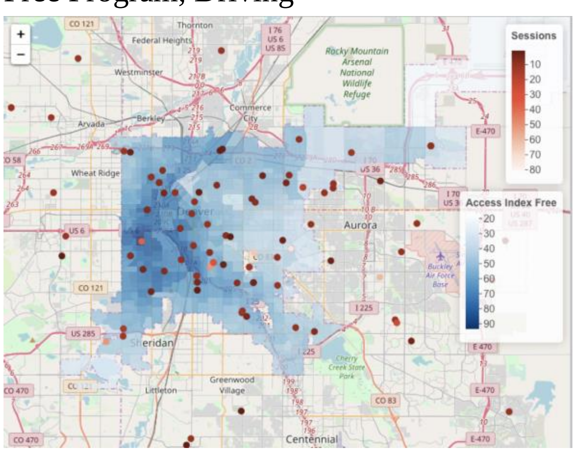
All programs, driving.



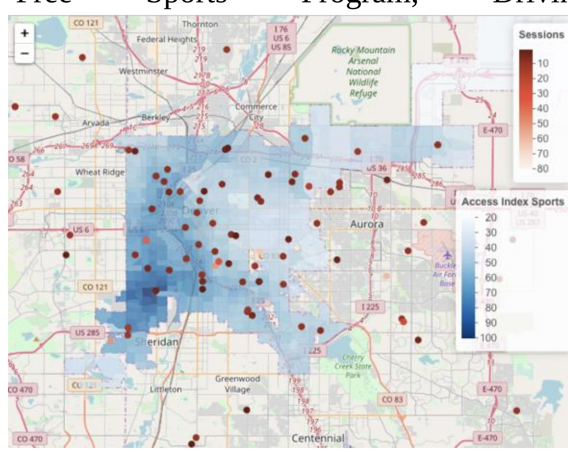
All programs, public transit.



Free Program, Driving



Free Sports Program, Driving



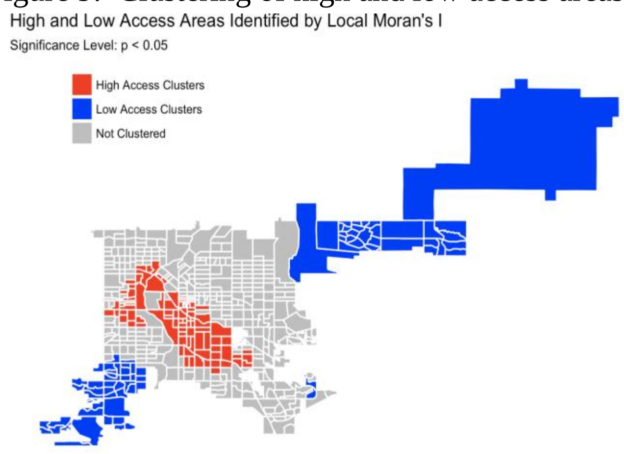
Results: Is Access to Out-of-School Resources Equally Distributed in Denver?

Where Are High and Low Access Areas?

It is fundamental to understand which areas have concentrations of high and low scores on the access index in Denver. Various block groups have low or high scores on the access index based on Local Moran's I, indicating their relative levels of access to out-of-school resources. As illustrated in Figure 9, block groups with high driving access values for programs overall are clustered in the central area while low access block groups are clustered far away from city center, at the northeast, far northeast, and far southwest. Calculations based on the transit access index show a similar pattern[16]. This reflects the fact that more summer programs are distributed in the central, and they are more approachable by both private and public transportation from neighborhoods closer to the city center.

We thus regard the area with clusters of high access scores in Figure 9 (colored in red) as the high access areas, and the two clusters with low access scores (colored in blue) as low access areas for analysis below. The high access area includes 84 block groups, with an average score of 82.5 (*SD* = 4.6), and the low access area includes 75 block groups, with an average score of 50.1 (*SD* = 6.54).

Figure 9. Clustering of high and low access areas in Denver



Is Access Proportional to the Number of Students?

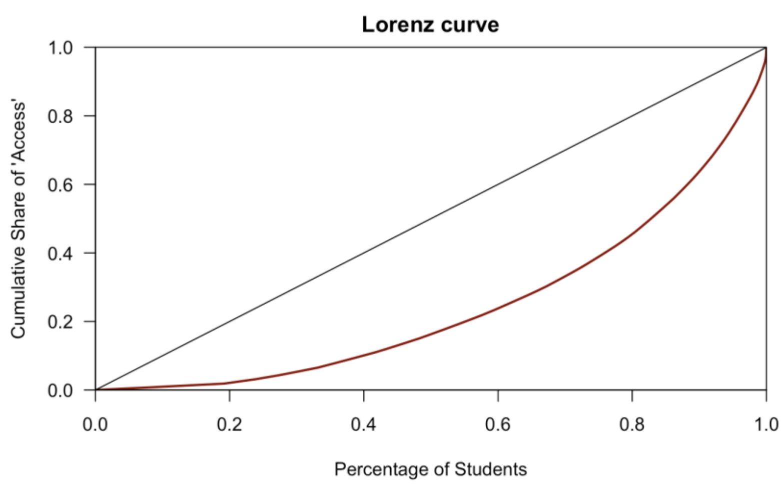
An important factor to examine with respect to whether out-of-school resources are equally distributed for students is the number of students in a given block group. For example, in communities with denser student populations, we would assume that there are more summer

[16] See the map of cluster pattern for transit index in Appendix 4.

programs to accommodate the needs of each student. This section aims to answer the question whether access to overall programs is proportional to the number of students for each neighborhood. Again, as the indices for driving and transit are highly correlated, analysis presented below are solely based on the driving index. Figure 5 shows Denver's students are densely concentrated far away from city center, mainly at the southwest, southeast, and northeast corners, which correspond to low access areas identified by the access index. This has implications for serious inequality for a large number of students who have very low access to out-of-school resources because there are very few summer programs nearby or easily reachable.

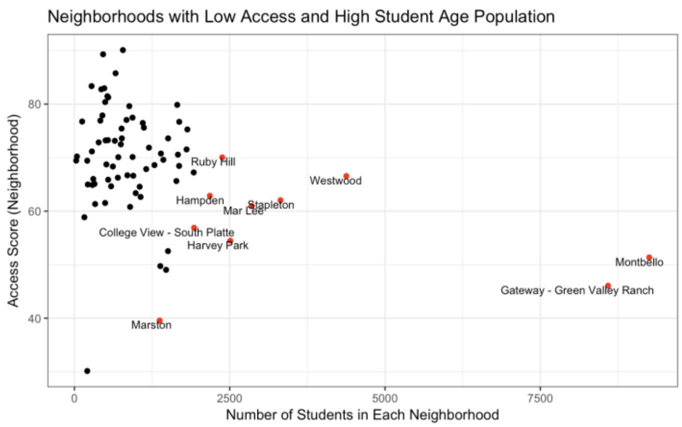
To capture the relationship between the number of students in each neighborhood and access, we calculated student access scores using the ratio of neighborhood access score against the number of students in a given neighborhood. Then we compared the situation with perfect equality in the distribution of student access scores against the actual distribution. In the Lorenz Curve (Figure 10), if there was an even distribution of all access scores, the scores would fall on the diagonal, implying each student had equal access to opportunities. The Gini coefficient quantifies how far the Lorenz curve is from the diagonal by calculating the ratio between the area between the Lorenz curve and the straight diagonal and the area in the triangle below the diagonal. Thus, a high Gini coefficient indicates a large discrepancy between the curve and the diagonal, and high inequality in the distribution. Figure # shows the actual distribution of student access scores is far from equally distributed with a Gini Coefficient of 0.51, implying that a small proportion of students had higher access to out-of-school resources compared with the rest of the students.

Figure 10. Lorenz Curve showing unequal access to summer programs in Denver



The inequality we see is driven by the fact that some neighborhoods with a large quantity of students do not have high access to many, if any, resources. This is well-illustrated by the scatterplot on the in Figure 11, where each dot represents a neighborhood in Denver. The red dots are the ten neighborhoods that ranked the lowest on the ratio of neighborhood access score against the number of students per neighborhood.

Figure 11. Neighborhood access in comparison to total student population



Access Index and Student Characteristics

Students' access to out-of-school resources vary widely based sociodemographic backgrounds like race, family socioeconomic status, family nativity, and student's status of being a second language learner. To inspect if access to opportunities is equitably distributed across diverse social groups, we explore the relationships between student attributes with their levels of access.[17]

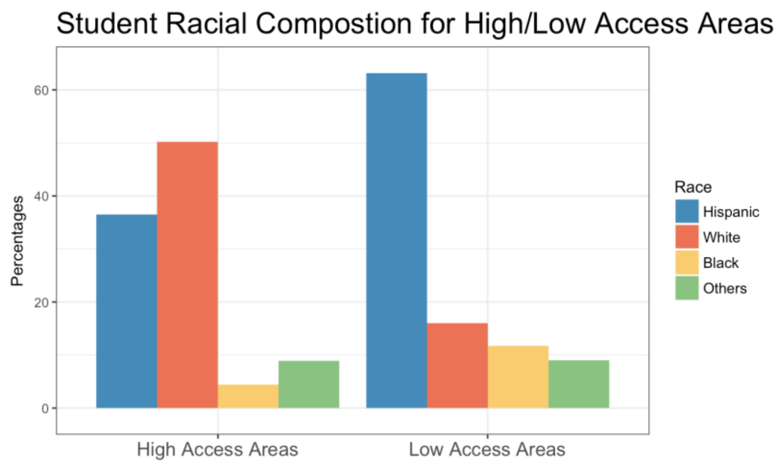
Race

Weighted Pearson's Correlation suggest that, racially, only being White is positively correlated with higher access scores for all programs[18] (r = 0.31, p < 0.001). The correlations are negative between higher access scores and being Black (r = -0.37, p < 0.001), Hispanic (r = -0.12, p < 0.01), and other races (r = -0.187, p < 0.001). For free programs, which comprise 20 percent of sessions in Denver, the association with race changes. Correlations suggest here that only being Hispanic is correlated with higher access to free programs (r = 0.427, p < 0.001). In contrast to all programs, the White students show a weak negative correlation with free programs (r = -0.161, p < 0.001) while Black students show a strong negative correlation with access to free programs (r = -0.506, p < 0.001).

[17] Unit of analysis in this section is block groups.
[18] Driving index for overall programs

A sample comparison between high and low access areas, as previously defined, shows that they have different racial compositions. Figure 12 illustrates the striking differences. There is a highly significant difference in the percentage of White students for high access (M = 50.14, SD = 32) and low access areas (M = 16, SD = 16); t(125) = 8.7, $p < 0.0001$. Similarly, a highly statistically significant difference was found for the percentage of Hispanic students. The average percentage of Hispanic students in high access areas is 36.5 (SD = 32.3), and 63.2 in low access areas (SD = 19.5); t(139) = -6.38, $p < 0.0001$. As for the percentage of black students, there is a smaller black student population (M = 4.4, SD = 6.53) in high access areas than low access areas (M = 11.8, SD = 13.3); t(105) = -3.78, $p < 0.0001$. There is no significant difference for other races (p = 0.95).

Figure 12. Student racial composition in high and low access neighborhoods



Calculating the average access scores for each race and ethnicity shows that White students are the most advantageous with regard of access to a variety of programs, except for free programs, where Hispanic students enjoy the highest access. Black students consistently score the lowest in all scenarios.

Table 2. Access Index Scores by Race and Program Types

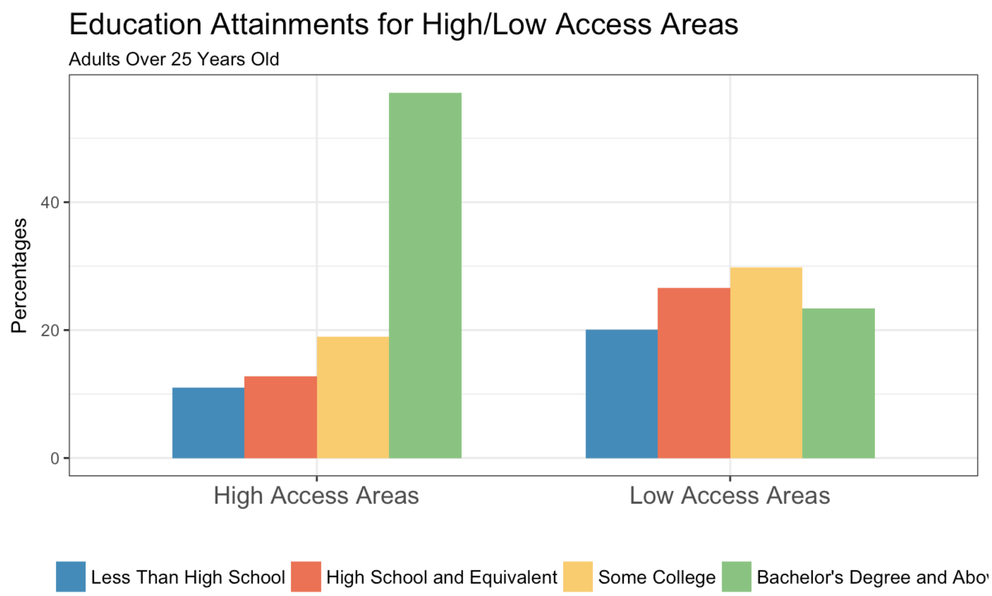
	All	Nature	Sports	Art	Academic	Free
Hispanic	62.93	56.31	63.64	53.67	67.75	66.67
White	67.72	50.24	69.61	63.36	69.92	68.03
Black	58.95	45.34	60.92	54.14	61.04	59.72
Other Races	62.48	49.43	64.12	57.01	65.23	63.56

Socioeconomic Backgrounds

Generally, students from better socioeconomic backgrounds tend to have higher access to out-of-school resources. The correlation between average median household income at the block group level and access index score is 0.13 (p = 0.005), which is maybe weaker than we would have anticipated. Sample comparisons between high and low access areas yielded a significant difference, where high access areas have an average median household income of about $70,000 per year, and $58,500 per year for low access areas, a difference of $11,500 ($p$ = 0.02).

Educational attainment is another important indicator for socioeconomic status and predictor of income (Blau & Duncan, 1967). In high access areas, the percentage of college graduates (M = 57) is significantly higher than low access areas (M = 23, p < 0.0001). In high access areas, the percentage of people having less than a high school diploma, a high school diploma, and some college education are consistently lower than those in low access areas. An independent two sample t-test shows the differences are highly statistically significant.[19]

Figure 13. Educational attainment levels in low and high access neighborhood



Second Language Learners and Nativity

Disparities in access to out-of-school resources exist between students who do not speak English at home and students who are native English speakers. Students who are not English language learners (ELL) are more likely to have higher access to programs. Our sample comparison shows that in high access areas, only 13.6 percent of all students are ELLs, compared with 26.5 percent of students being ELLs in low access areas (p < 0.0001).

[19] Please refer to Appendix VI.

In addition, students from neighborhoods with a higher rate of nativity (individuals born in the United States) tend to be more advantageous in access to summer programs. The percentage of people born in the United States in high access areas is 87.8, slightly higher than 81.2 percent in low access areas (p = 0.0002).

Access and Students with Special Needs

For students with disabilities, we are primarily concerned with access to programs that specify that they serve students with special needs. Programs which offer programs for special needs account for only 648 sessions, or 21 percent of all sessions. Furthermore, it is not clear that the indicator that the session serves students with special needs means the program is appropriate for all disabilities, and ultimately more information is needed here to make more informed comparisons. Shown on the figure below are Census block groups with the highest concentration of students with any disability (purple) and programs with the highest number of sessions for students with special needs. As is clear, the majority of sessions with services for students with disabilities are not concentrated where the majority of students with disabilities are located.

Figure 14. Distribution of students with disabilities and programs serving them

Weighted pearson's correlations show no statistically significant correlations for students with any disability and programs offering special needs services (r = -0.05, p = 0.237). For free programs this pattern changes slightly, where the percent of any students with a disability in a block group shows a moderate positive correlation with higher access (r = 0.227 , p<0.001), students with a developmental delay show a weak positive correlation (r = 0.185, p<0.001), and students with a specific learning disability (SLD) or speech and language disability (SLI) show weak positive correlations (r= 0.138, p=0.002, and r=0.189, p<0.001). This pattern generally holds for all types of programs, where SLD and SLI programs exert weak positive correlations with access to free and low cost programs, while other forms of disabilities are not significant or exhibit weak negative correlations to access.

The only exception to this is access to athletics programs with special needs offerings. Here the percent of students with a developmental delay has a moderate negative correlation with access (r = -0.232, p<0.000) though a weak positive correlation with access to free athletics programs (r = 0.121, p=0.008). The pattern is consistent for all categories of programs, where only the aggregated students with any disability, or SLD and SLI students show weak to moderate positive correlations with free and low cost programs with disability services, while all other disabilities do not show statistically significant correlations.

One might note that the relationship between certain disabilities and access to overall programs and free programs follows a very similar pattern to the difference in correlations between access and percent of Hispanic and percent of White students. While it is outside the scope of this report to assess the relationship between disability status and student race and ethnicity, we can at least explore the correlation between these categories. As an example, the percent of white students has a moderate negative correlation with the percent of students with any disability (r = -0.337, p <0.000). In contrast, the percent of hispanic students has a moderate positive correlation with the percent of students with any disability (r = 0.357, p<0.000). To some extent this may reflect the presence of a large percent of hispanic students in predominantly lower income areas, as median household income is negatively correlated with number of students with disabilities (r = -0.315, p <0.001). Regardless, the takeaway is the same - many students with disabilities are concentrated in the same areas of Denver as the majority of hispanic students, which tend to have higher access to free programs, though lower access to programs overall.

Discussion

An initial takeaway from this study is that fields, playgrounds, recreation centers and parks are relatively evenly distributed throughout Denver, but summer programs are not, especially for sports programs. There are many potential reasons for this, but surely there is some way to leverage these public resources for use in out-of-school summer programs to more evenly distribute them across the city. We also found that Black students consistently have the lowest access to out-of-school summer resources. At nearly every cost threshold for nearly every type of program, or overall, the number of Black students is negatively correlated with access, and the average access index score for Black students is lower than that of Hispanic and White students. Finally, there is little to no relationship between access to programs with services for students with disabilities and the number of those students in a given block group.

In this analysis we specifically sought to explore areas with the highest and lowest access to out-of-school summer resources in Denver and understand the characteristics of students in those areas. With respect to all programs of any type, students with the best access are far more likely to be White, from families with higher median household incomes, and parents with a bachelor's degree or higher. In contrast, students with relatively low access to out-of-school summer resources are much more likely to be Black or Hispanic, have lower median household incomes, and have parents with a high school diploma or less.

With respect to students with disabilities, there appears to be no strong relationship between the number of students with any disability in an area, and access to sessions that indicated they provide services for students with disabilities. There is a moderate relationship in access to free programs provided for students with disabilities, but this may be a function of a collinear relationship between student household income, race, and disability status. More research is needed here to understand these correlations.

Fundamentally, when we assume that access should be measured with respect to student address, than access to out-of-school summer resources in Denver is very unequal, particularly with respect to student race, ethnicity, and household income. It is clear that the majority of students in Denver are concentrated in neighborhoods with relatively low access, while a small minority of students are in neighborhoods with very high access. While to some extent the associations between Hispanic, White, and household income vary with respect to free programs, free programs only account for 20 percent of all sessions, and thus are not likely to be a comparable measure to access to all programs.

Increasingly, literature identifies a gap in utilization of out-of-school summer resources based on student demographics (Redford & Burns, 2018). Furthermore, additional research (Stein, 2016.) indicates that to some extent, utilizing out-of-school summer programs may help decrease summer learning loss, and that the gap in achievement between privileged and disadvantaged students may at least in part, be a function of failure to utilize out-of-school summer programs. While this report points out that access to out-of-school resources is likely to vary between students, it also offers a novel contribution by measuring access to out-of-school resources in Denver for a representative sample of all students, and should assist in the planning of more equitable and just education system in Denver.

Limitations and Directions for Future Research

First, the access index was weighted by sessions not available slots for students in the programs. In addition, the access index utilizes student home address when calculating the access index though parents may prefer locations closer to their place of employment instead. Considering that we lack any information on parents location of employment or their family preference, we cannot be sure that we are truly capturing access.

Moreover, zip codes from the search data indicates that the majority of searches that specified a zip code are located in the central business district downtown area, one of the highest access areas in Denver. While initially we might consider this a threat to our assumption that student home address is critical, the fact is that fewer than 5% of all user searches specified a zip code, so interpreting the “majority” of user searches in this case is a questionable task. Ultimately, more research is necessary to understand how the location of parental employment effects the measurement of access in this case.

Furthermore, we did not consider the quality of out-of-school summer resources in the access index. We did explore use of social media or Yelp reviews to account for quality, however, these reviews did not account for enough specific program sessions to serve as a useful measure of quality. Even if we had a reliable measure of quality, it is not clear how to properly weight the access index equation to account for differences in quality. If the equation identifies individuals as having a high access primarily to programs that are undesirable for any number of reasons, then our measure of access may be incorrect. Therefore, future research should explore measures of quality, and how they would influence the conclusions when assessing access to out-of-school resources.

Although we tried to connect student sociodemographic characteristics with differential access to out-of-school resources, we do not explore other factors associated with systematic inequality for certain group of students. In addition, we saw a high level of spatial autocorrelation in access scores across block groups. It was hard to tell if this was how access was naturally distributed or solely due to the way we calculated the access index. As student attributes like race and family socioeconomic status also tended to cluster at particular regions, future researchers should account for spatial autocorrelation in modeling if they endeavored to address the causal question.

Fundamentally, our access index is only a valid measure of “access” if, in fact, it can be used to predict parents utilization of programs. The limitations described above identify potential ways in which this measure may be limited. Ultimately, future research should focus on validating measures of access against program utilization to more accurately describe the precision and gaps with this measure of access.

Recommendations

Improving Website Search Data

Ask users to share their location using the Google Geolocation API

Currently, user location only returns city, which is at best useful for filtering results only to Denver or Colorado based searches. Requesting users to share their location is a very simple feature, which will return approximate geolocations of user searches in Google Analytics, allowing future analysis to more accurately gauge location. See this for more:
https://developers.google.com/web/fundamentals/native-hardware/user-location/

Explore a mandatory three question survey for website use

This can be a temporary feature, but nevertheless vital for understanding the demographics of who is using the website as compared to overall demographics of parents in Denver. Previous studies (Schneider & Buckley, 2002) have institute three question surveys asking users to identify their role (e.g, “I am a...parent...student” etc), their race and ethnicity, and their neighborhood. This will greatly improve future analysis of the internet search data by decisively identifying if the sample of website users is in fact representative of parents in Denver.

Improve the map of program locations

The current map of search results only shows a very limited number of sessions. Adjusting the map to be more in line with the type of map we provide the RShiny Dashboard.

Improving Program Data Collection

Collect data on program utilization

Currently, the access index is weighted by the number of program sessions. Intuitively, not all sessions are of equal length or interest to parents or students. Likely, a more precise measure of access would be weighted by the utilization of programs, in other words the number of spots filled by students, as this would better account for the real opportunities parents have to enroll their students in a program within a given distance.

Furthermore, understanding which programs are over or underutilized may help to refine our analysis of demand for these programs. In fact, with program utilization data that allowed analysts to match program “users” to block group location, future research will be able to test the validity of the access index by comparing the extent to which our measure of access predicts program utilization.

Collect data on session days

Data recorded for start and end dates and times is valuable for refinding the cost of given sessions. However, the accuracy of this could be greatly improved by understanding the days of the or total days that a session operats for. For example, a week long summer camp where a student is away 24/7 for five days, is currently indistinguishable from a week long summer camp with only one overnight day, that operates only Monday, Wednesday, Friday.

For Policymakers

Utilization of local resources

We can see that public resources, such as parks and libraries, are relatively evenly distributed across the city and should be leveraged to ensure that opportunities are located in every neighborhood. One key challenge is that, even when programs utilize public spaces, they are disproportionately available in the most advantaged neighborhoods. Finding ways to encourage organizations to utilize libraries or other public resources for holding programs to ensure neighborhood needs are met.

Meeting the needs of African American students

African American students have consistently lower access to out-of-school opportunities. New programs should be recruited for neighborhoods with a higher proportion of African American students. In addition, it will be important to collect data to understand what African American families desire for their students so that available programs meet their needs. In the short-term, supporting families in these neighborhoods in traveling to programs through bus subsidies and/or coupons for Hop Skip Drive car service may help students attend programs that are farther away while new programs are recruited.

Targeted scholarships

Hispanic families have higher access to free summer programs, which means that other neighborhoods may benefit from scholarships based on the average cost of programs in their neighborhood. Alternatively, ReSchool or the City of Denver may consider subsidizing higher cost programs in neighborhoods that lack low-cost program options as an alternative to giving individual scholarships, which may be a deterrent to the most disadvantaged families.

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Appendix

Appendix I:

In the report, we used a subset of students data from Denver Public School (DPS), which contains de-identified student home address information. Here we offer a comparison between the selected subset of student data and the rest of the student in the DPS data. From hereafter, we refer to the subset data as “students with address,” and refer the rest of students as “students without address.”

Students with address come from student who participated in school choice system (where students apply for an alternative school instead of the one they are assigned to according to their home addresses). Table 1 shows the percentage of students by year who participated in school choice. The assumption is that students don’t move around, so if we get their address at one point in time then we have their address for all years before and after.

Appendix I, Table 1. Percentage of choice students by year.

	Year				
Grade	**2014**	**2015**	**2016**	**2017**	**2018**
0	66.2%	68.2%	68.6%	67.1%	67.5%
1	24.9%	63%	65.9%	65%	64.7%
2	62.2%	25.1%	61.8%	64.1%	63%
3	65.6%	65.4%	25.2%	60.7%	62.3%
4	69.7%	69%	68.8%	24.7%	59%
5	74.4%	73.3%	73.2%	73.5%	24.5%
6	72%	75%	72.7%	72.7%	71.6%
7	53.6%	71.1%	74.7%	70.8%	70.1%
8	54.3%	57.1%	71.6%	75.7%	68.3%
9	47.4%	51.7%	53.4%	64.6%	69.1%
10	7.4%	47.6%	51.4%	53.9%	64%
11	5%	7.3%	57.1%	51.4%	53.2%
12	1.9%	4.9%	8.3%	46.1%	50.2%

Note that students generally report their address only once in the school choice dataset, which records per unique student for students reporting this information between 2014 - 2018. As final summary numbers, we have addresses for 41.7% of the total students in the DPS enrollment dataset, and 48.3% of the students enrolled somewhere between 2014 and 2018 (school choice began in 2014).

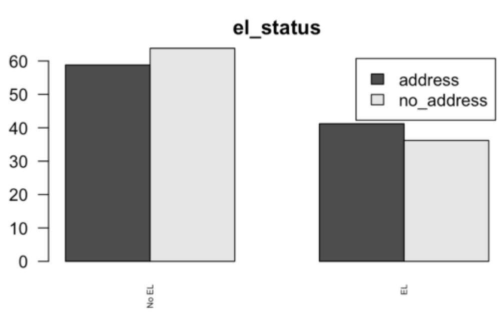
We compared racial of the two samples, i.e. students with and without address information. As a supplement, Table 2 also shows the comparison with racial composition for student age population (from age 5 to 18) from census data.

Appendix I, Table 2. Racial compositions for students with and without address.

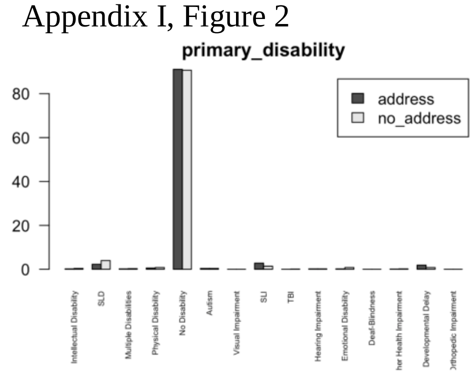
	ACS Student-age Population	DPS Students (2014 - 2018)	DPS Students with address (2014 - 2018)
Total	93,132	84,115	66,718
Hispanic or Latino	48.8%	54.5%	53.1%
White	32.3%	21.3%	26.9%
African American	11.9%	15.7%	12.4%
Asian	3.1%	3.9%	3.2%
American Indian	1.0%	1.0%	0.5%
Pacific Islander	0.1%	0.4%	0.2%
Some Other Race	7.6%	N.A.	N.A.
Two or More Races	6.5%	3.3%	3.7%

We compared other demographics and student disability status of the two samples, i.e. students with and without address information. Figure 1 compares percentage of English Language Learners in the two samples. Figure 2 shows comparison of student disabilities.

Appendix I, Figure 1



Appendix I, Figure 2



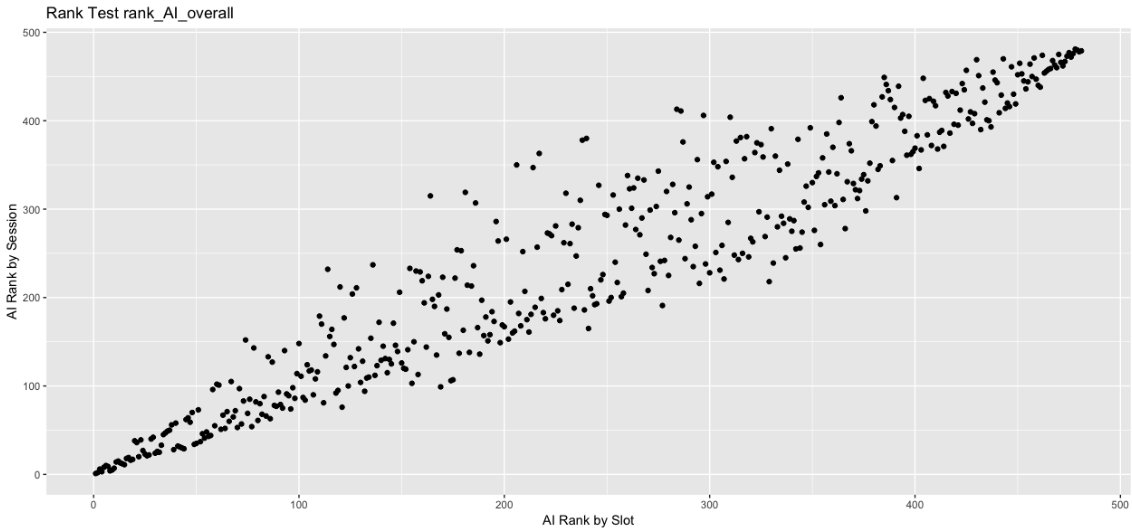
Appendix II: Number of Sessions vs. Session Size

Given that we are interested in examining the access to out-of-school summer activities, it is important that our analysis weights sessions by their appropriate size. Originally, we had hoped to design the access index equation to correctly weight by slots in each available session. However, the original data we received on programs was missing data on the number of slots in available programs for about 48% of all individual sessions. Rather than discard almost half of our original data, we elected to instead weight by number of sessions as a proxy for number of slots.

To test the sensitivity our assumption that number of session is approximately comparable to number of slots per session for the purpose of calculating an access index, we performed additional analysis comparing the block group access index scores of block groups for the subset of data that had the number of slots per session. Because the actual index score is an endogenous variable, we are less concerned with a change in “real” score (i.e, access index = 50 vs access index = 33) than we are with the change in “rank.” That is, our conclusions depend on being able to identify the worst and best off areas of Denver with respect to access. If one block group goes from the top ten best off to top ten worst off, this is serious threat to the validity of our model.

Thus, we compare the ranks of access index scores for each block group, under a model that uses the number of slots per session as compared to the model that uses the number of sessions per program, for the subset of data for which no slots are missing. This requires only a nominal change to the access index equation, where rather than multiplying scores by the number of sessions as we did in the primary analysis, we now perform an additional calculation comparing the equation multiplied by the total number of slots per session. We perform this calculation for every category at every cost threshold, for driving and for transit.

When comparing any cost and free cost programs, there is very little variation for overall programs. The majority of divergence occurs for programs between the “best” and “worst” off block groups, that is for groups in the middle. While overall scores are very similar, the more specific the criteria we observe, the greater the difference in access index ranks between sessions and slots become. In particular sports programs and nature programs, the difference in ranks are much more sensitive to changes in the weight between number of sessions and number of slots.



To our knowledge, it's not clear whether weighting by number of sessions or slots is conceptually more valid. It is easy to speculate justifications for either of these, as one could imagine situations in which both are critical. For example, there are certainly areas with relatively close access to many unique sessions, but the number of available seats in each session is far fewer than the number of eligible students. Similarly, it's equally questionable to assume apriori that if a program with a max number of 30 slots doubles it's max slots, that is has doubled its contribution to access for nearby students.

While the ranks may change for some individual block groups, the majority of block groups do not shift significantly. Thus in this case, while the number of slots is the preferred metric for access, approximating by number of sessions does not appear likely to change the conclusions about who and where has the highest and lowest access in Denver. Because the "best off" and "worst off" locations do not change drastically, we would expect a relatively minor threat to validity of our findings here.

In the end, while our overall conclusions are likely not severely altered by the selection of weights by sessions or slots, for question specifically related to sports or nature programs of a certain cost threshold (below all, or above free) results are more biased by the choice of sessions or slots. Because it is a seemingly arbitrary choice between session or slots we gain some information by electing to use our full sample of the subset for which we have information on slots. Ultimately, future research should consider and test these weights before drawing conclusions about access.

Appendix III: Testing Model Decay Functions

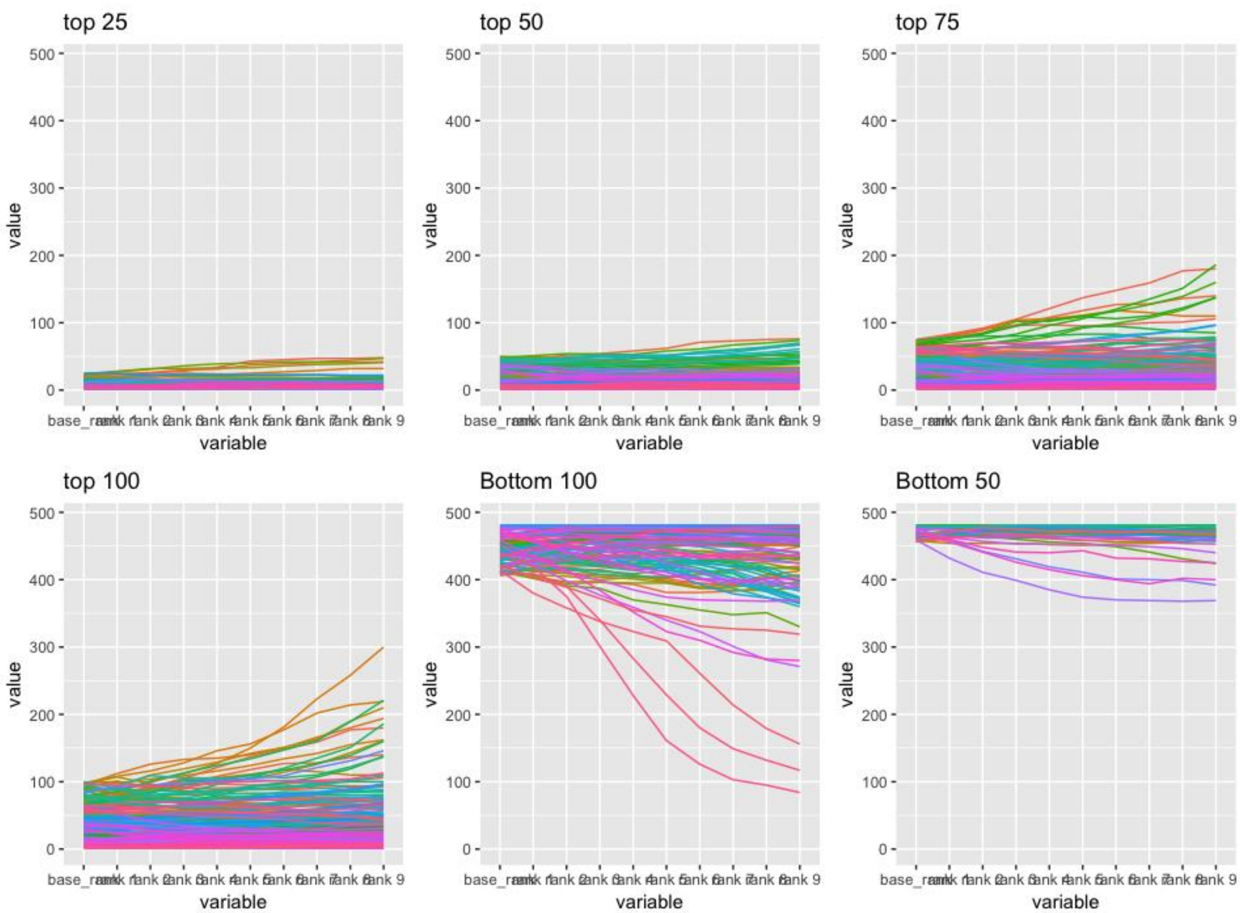
Here we test how sensitive the results of the access are to a change in the soft indifference threshold to help us select a model which is the least sensitive to a somewhat arbitrary assumption of an indifference threshold. To do this, we compare the output of the gravity model with the soft gravity model (i.e used in our base analysis). Specifically, we compare the "ranks" (i.e, order 1 - 481) for block groups access index scores with scale values ranging from 5-15 minutes (i.e, base - rank 9). We compare ranks of block groups rather than scores, as the actual score as a normalized value is difficult to compare between models, while the "rank" of which areas have the highest and lowest access is ultimately what we are concerned with.

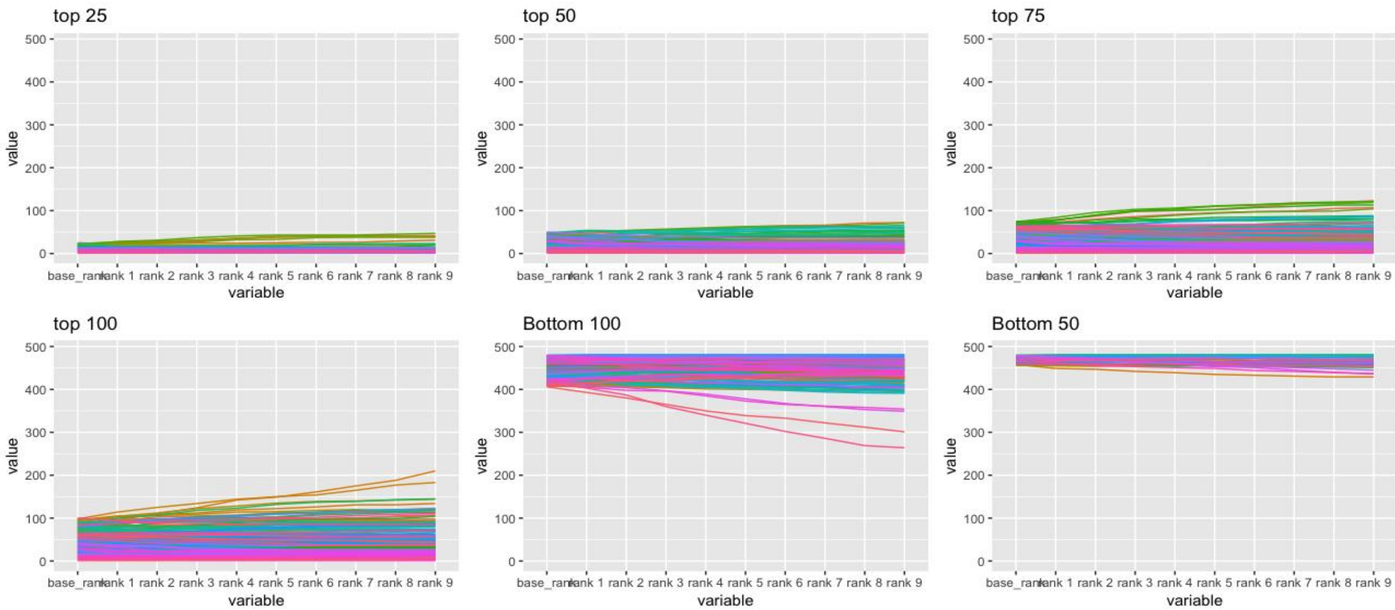
$$f_{\text{soft gravity}}(T) = \frac{1}{(1 + T/5min)^2}$$
$$f_{\text{gravity}}(T) = \frac{1}{(T/5min)^2}$$

We began with the gravity model. This model is naturally the least sensitive to a change in scale as the scale is not relevant for this calculation (it's just a constant out front, and we normalize in the end anyway). However, the model is extremely sensitive to proximity of nearby programs, resulting in a handful of block groups returning AI values between 0.9 and 0.99 and most returning values less 0.2. This is because as T approaches zero, the function approaches infinity. Naturally, this makes results extremely difficult to interpret. More importantly, this a significant threat to construct validity for two reasons: 1.) We use block group centers as our departure points in our analysis, but this is only a proxy for actual student addresses. If we heavily weight programs which are near to the center, but in reality further from a parents addresses this violates the use of a the centroid as a relevant proxy for parental address. 2.) While we do not know what parents actual indifference is with respect to travel time, it is intuitive that very small differences in travel time (for example, less than thirty seconds) should not weight access. It's very likely that the same trip on different days could vary within such small increments of time, and the idea that differences in travel time below a certain threshold should weight results obscures the larger point of looking for patterns of access to all programs.

From here we focus on comparing the results of the Gravity Threshold (i.e base analysis) and the Exponential Model. Shown on the next page are results comparing the order of block groups at different scale iterations for both. Critically, although both models shown deviations in the middle scores (accounted for the vast majority of the block groups), we are most interested in the changes occuring at the heads and tails (around the first and last 100 block groups). We are particularly interested in these, because the entire purpose of creating this index to create a measure which can help select areas of Denver with least and greatest access to OSR summer resources. I.e, if the most/least off block groups changes sharply depending on an arbitrary assumption of indifferent, than not only is our model sensitive to this assumption, but in fact our analysis may return results biased more by our assumption than by the data we have available.

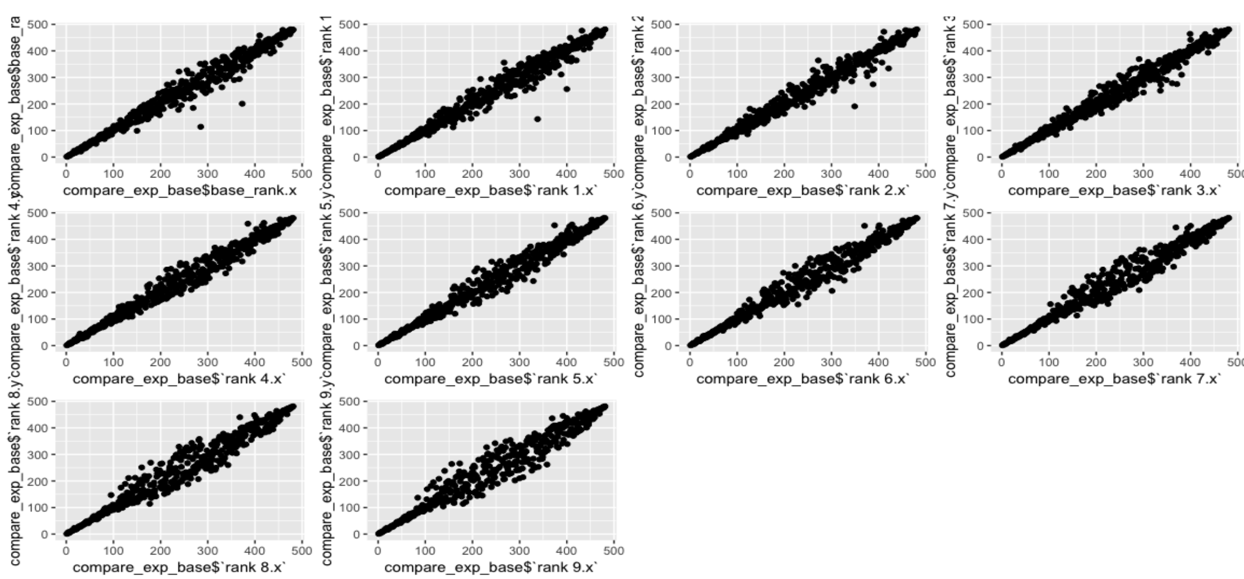
Gravity Threshold


top 25
top 50
top 75
top 100
Bottom 100
Bottom 50
value
variable
0
100
200
300
400
500



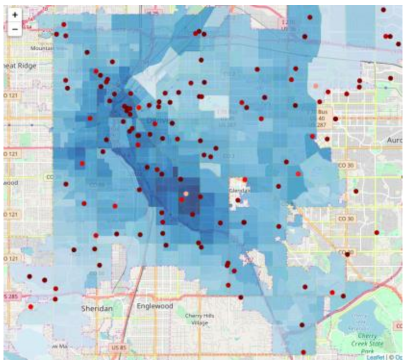
Soft Gravity Threshold

It is clear from the plots that the soft gravity function is somewhat less sensitive to selection of scale. From here, we then test the sensitivity between the models, comparing how ranks of block groups shift at different iterations. As shown in the model below, the majority of deviation between the two models occurs in the middle ranges, very minor deviations in the head and tails, and no extreme deviations (i.e 2nd to 4th quadrant changes). Therefore, we can conclude, the models are not dramatically changing results between them, and we can conclude they are comparable. Therefore, we ought to select the model which is less sensitive to the arbitrary scale cutoff. The soft gravity threshold model.

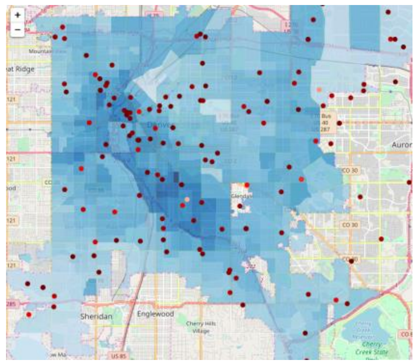


As a final note, we can compare the difference in the block group maps between the soft gravity and the gravity threshold. Shown below, essentially we can see that soft gravity model is more sensitive to the presence of many sessions at a single address, while the gravity threshold model is more sensitive to the arbitrary threshold.

Soft Gravity Threshold

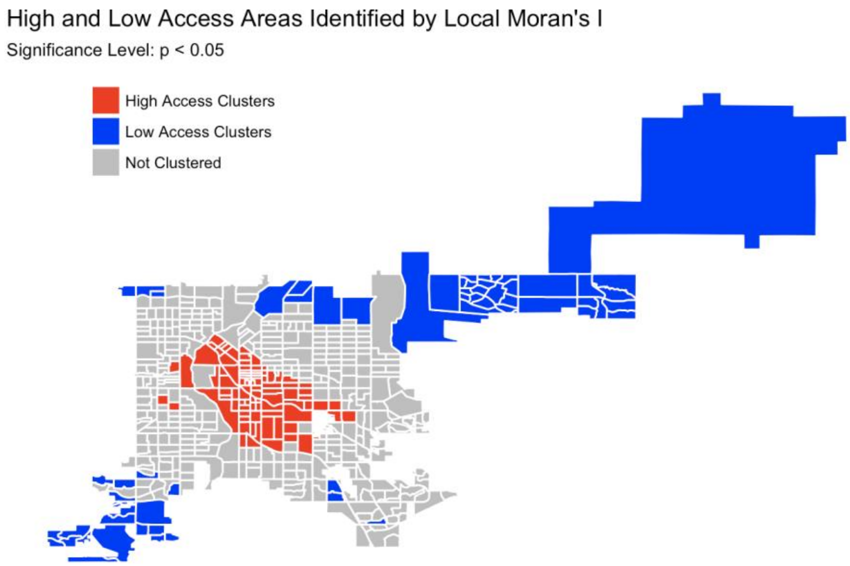


Gravity Threshold



Appendix IV: Moran's I

For Access Index: public transit, all programs.



Appendix V: Descriptives

Table 1. Racial Composition for Denver, Colorado, and the United States, 2016

	Denver	Colorado	United States
Total Population	663,303	5,359,295	318,558,162
Hispanic or Latino	30.8%	21.1%	17.3%
Non-Hispanic White	53.4%	69.0%	62.0%
Non-Hispanic African American	9.4%	3.9%	12.3%
Non-Hispanic Asian	3.4%	2.9%	5.2%
Non-Hispanic American Indian and Alaska Native	0.5%	0.5%	0.7%
Non-Hispanic Pacific Islander	0.0%	0.1%	0.2%
Non-Hispanic Some Other Race	0.2%	0.2%	0.2%
Non-Hispanic Two or More Races	2.3%	2.3%	2.3%

Data Source: U.S. Census Bureau. *2012-2016 American Community Survey 5-Year Estimates: ACS Demographic and Housing Estimates Table DP05*. Retrieved from American FactFinder, July 2018: https://factfinder.census.gov/

Appendix VI: Correlation Tables

American Community Survey Correlates

These tables give the weighted pearson's correlation results for all American Community Census variables tested. For each test, block groups were treated as aggregated samples of students, where the weight is equal to the number of students in the block group based on the denver public schools choice dataset. All times reported here are for the driving access index.

Overall, Any Cost

Correlate	***r***	95% CI Low	High
Less than HS Diploma	-0.105*	-0.194	-0.016
HS Diploma or Equiv	-0.258***	-0.345	-0.172
HS Diploma or Less	-0.189***	-0.277	-0.101
Some College or AA	-0.333***	-0.418	-0.249
Bachelors or Higher	0.309***	0.224	0.394
Median HH Income	-0.016	-0.107	0.075
* sig at 0.05, **, sig at 0.001, ***,sig at 0.0001 or lower			

Overall, Free

Correlate	***r***	95% CI Low	High
Less than HS Diploma	0.354***	0.27	0.438
HS Diploma or Equiv	0.177***	0.089	0.266
HS Diploma or Less	0.317***	0.232	0.402
Some College or AA	-0.261***	-0.348	-0.174
Bachelors or Higher	-0.21***	-0.298	-0.122
Median HH Income	-0.327***	-0.413	-0.241
* sig at 0.05, **, sig at 0.001, ***,sig at 0.0001 or lower			

Nature, Any Cost

Correlate	***r***	**95% CI Low**	**High**
Less than HS Diploma	-0.178***	-0.09	-0.267
HS Diploma or Equiv	-0.305***	-0.22	-0.391
HS Diploma or Less	-0.26***	-0.173	-0.346
Some College or AA	-0.302***	-0.216	-0.387
Bachelors or Higher	0.365***	0.449	0.282
Median HH Income	0.04	0.131	-0.051
* sig at 0.05, **, sig at 0.001, ***,sig at 0.0001 or lower			

Nature, Low Cost

Correlate	***r***	**95% CI Low**	**High**
Less than HS Diploma	0.065	-0.024	0.155
HS Diploma or Equiv	-0.123**	-0.212	-0.034
HS Diploma or Less	-0.013	-0.103	0.076
Some College or AA	-0.308***	-0.394	-0.223
Bachelors or Higher	0.129	0.04	0.218
Median HH Income	-0.108*	-0.199	-0.018
* sig at 0.05, **, sig at 0.001, ***,sig at 0.0001 or lower			

Nature, Free

Correlate	***r***	**95% CI Low**	**High**
Less than HS Diploma	0.352***	0.268	0.436
HS Diploma or Equiv	0.151**	0.062	0.24
HS Diploma or Less	0.303***	0.218	0.389
Some College or AA	-0.263***	-0.349	-0.176
Bachelors or Higher	-0.196***	-0.284	-0.108
Median HH Income	-0.305***	-0.391	-0.218
* sig at 0.05, **, sig at 0.001, ***,sig at 0.0001 or lower			

Athletics, Any Cost

Correlate	***r***	**95% CI Low**	**High**
Less than HS Diploma	-0.372***	-0.456	-0.289
HS Diploma or Equiv	-0.453***	-0.533	-0.373
HS Diploma or Less	-0.456***	-0.536	-0.377
Some College or AA	-0.263***	-0.35	-0.177
Bachelors or Higher	0.542***	0.467	0.618
Median HH Income	0.191***	0.102	0.281
* sig at 0.05, **, sig at 0.001, ***,sig at 0.0001 or lower			

Athletics, Low Cost

Correlate	***r***	**95% CI Low**	**High**
Less than HS Diploma	-0.184***	-0.272	-0.096
HS Diploma or Equiv	-0.308***	-0.393	-0.223
HS Diploma or Less	-0.264***	-0.351	-0.178
Some College or AA	-0.282***	-0.368	-0.196
Bachelors or Higher	0.363***	0.279	0.446
Median HH Income	0.044	-0.047	0.135
* sig at 0.05, **, sig at 0.001, ***,sig at 0.0001 or lower			

Athletics, Free

Correlate	***r***	**95% CI Low**	**High**
Less than HS Diploma	0.351***	0.267	0.435
HS Diploma or Equiv	0.268***	0.182	0.355
HS Diploma or Less	0.357***	0.273	0.441
Some College or AA	-0.131**	-0.22	-0.042
Bachelors or Higher	-0.298***	-0.384	-0.212
Median HH Income	-0.332***	-0.418	-0.247
* sig at 0.05, **, sig at 0.001, ***,sig at 0.0001 or lower			

Art, Any Cost

Correlate	***r***	**95% CI Low**	**High**
Less than HS Diploma	0.04	-0.05	0.129
HS Diploma or Equiv	-0.136*	-0.224	-0.047
HS Diploma or Less	-0.036	-0.126	0.054
Some College or AA	-0.343***	-0.427	-0.259
Bachelors or Higher	0.164***	0.076	0.253
Median HH Income	-0.121*	-0.212	-0.031
* sig at 0.05, **, sig at 0.001, ***,sig at 0.0001 or lower			

Art, Low Cost

Correlate	***r***	**95% CI Low**	**High**
Less than HS Diploma	0.176***	0.087	0.264
HS Diploma or Equiv	-0.013	-0.103	0.077
HS Diploma or Less	0.111	0.021	0.2
Some College or AA	-0.327***	-0.411	-0.242
Bachelors or Higher	0.015	-0.075	0.105
Median HH Income	-0.211***	-0.3	-0.122
* sig at 0.05, **, sig at 0.001, ***,sig at 0.0001 or lower			

Art, Free

Correlate	*r*	95% CI Low	High
Less than HS Diploma	0.319***	0.234	0.404
HS Diploma or Equiv	0.127**	0.038	0.216
HS Diploma or Less	0.27***	0.184	0.357
Some College or AA	-0.302***	-0.387	-0.216
Bachelors or Higher	-0.149**	-0.238	-0.061
Median HH Income	-0.301***	-0.388	-0.214
* sig at 0.05, **, sig at 0.001, ***,sig at 0.0001 or lower			

Academic, Any Cost

Correlate	*r*	95% CI Low	High
Less than HS Diploma	0.076	-0.014	0.165
HS Diploma or Equiv	-0.11*	-0.199	-0.021
HS Diploma or Less	-0.001	-0.09	0.089
Some College or AA	-0.342***	-0.427	-0.258
Bachelors or Higher	0.129**	0.04	0.218
Median HH Income	-0.143**	-0.233	-0.053
* sig at 0.05, **, sig at 0.001, ***,sig at 0.0001 or lower			

Academic, Low Cost

Correlate	***r***	**95% CI Low**	**High**
Less than HS Diploma	0.199***	0.111	0.287
HS Diploma or Equiv	-0.003	-0.093	0.087
HS Diploma or Less	0.131**	0.042	0.22
Some College or AA	-0.328***	-0.413	-0.244
Bachelors or Higher	-0.004	-0.094	0.086
Median HH Income	-0.221***	-0.31	-0.132
* sig at 0.05, **, sig at 0.001, ***,sig at 0.0001 or lower			

Academic, Free

Correlate	***r***	**95% CI Low**	**High**
Less than HS Diploma	0.326***	0.241	0.411
HS Diploma or Equiv	0.126**	0.037	0.215
HS Diploma or Less	0.274***	0.188	0.361
Some College or AA	-0.298***	-0.384	-0.213
Bachelors or Higher	-0.154**	-0.243	-0.066
Median HH Income	-0.303***	-0.39	-0.217
* sig at 0.05, **, sig at 0.001, ***,sig at 0.0001 or lower			

Denver Public Schools Student and Crime Rate Correlates

These tables give the weighted pearson's correlation results for Denver Public Schools variables and crime rates obtained from Denver Open Data. Note that for variables related to percent of students with a disability, correlations are tested **only** for results related to programs offering special needs services. In every case, block groups are treated as aggregated samples of students, and weighted by the number of students in that block group. All times reported here are for the driving access index.

Overall

Correlate	*r*	95% CI Low	High
% of White Students	0.311***	0.226	0.396
% of Black Students	-0.371***	-0.454	-0.288
% of Hispanic Students	-0.12**	-0.209	-0.031
% of Students Other Race	-0.187***	-0.275	-0.099
% of Students who are English Language Learners	-0.174***	-0.262	-0.086
Block Group Total Crime Rate	0.095*	0.006	0.184
Block Group Violent Crime Rate	0.092*	0.003	0.181
Block Group Property Crime Rate	0.085	-0.004	0.175

Overall, Free

Correlate	*r*	95% CI Low	High
% of White Students	-0.161***	-0.072	-0.249
% of Black Students	-0.506***	-0.429	-0.584
% of Hispanic Students	0.427***	0.508	0.345
% of Students Other Race	-0.162***	-0.074	-0.251
% of Students who are English Language Learners	0.267***	0.353	0.18
Block Group Total Crime Rate	0.066	0.155	-0.024
Block Group Violent Crime Rate	0.052	0.142	-0.037

Block Group Property Crime Rate	0.045	0.134	-0.045

Nature, Any Cost

Correlate	***r***	**95% CI Low**	**High**
% of White Students	0.367***	0.283	0.45
% of Black Students	-0.309***	-0.394	-0.223
% of Hispanic Students	-0.209***	-0.297	-0.121
% of Students Other Race	-0.174***	-0.263	-0.086
% of Students who are English Language Learners	0.076***	-0.307	-0.132
Block Group Total Crime Rate	0.076	-0.014	0.165
Block Group Violent Crime Rate	0.071	-0.013	0.166
Block Group Property Crime Rate	0.367	-0.018	0.161

Nature, Low Cost

Correlate	***r***	**95% CI Low**	**High**
% of White Students	-0.135*	-0.224	-0.046
% of Black Students	-0.378***	-0.461	-0.295
% of Hispanic Students	0.352***	0.268	0.436
% of Students Other Race	-0.241***	-0.328	-0.154
% of Students who are English Language Learners	0.254***	0.167	0.341
Block Group Total Crime Rate	0.053	-0.037	0.142
Block Group Violent Crime Rate	0.036	-0.054	0.125
Block Group Property Crime Rate	0.029	-0.061	0.119

Nature, Free

Correlate	***r***	**95% CI Low**	**High**
% of White Students	-0.158**	-0.246	-0.069
% of Black Students	-0.455***	-0.535	-0.375
% of Hispanic Students	0.409***	0.327	0.491
% of Students Other Race	-0.224***	-0.312	-0.137
% of Students who are English Language Learners	0.263***	0.176	0.35
Block Group Total Crime Rate	0.066	-0.023	0.156
Block Group Violent Crime Rate	0.051	-0.039	0.141
Block Group Property Crime Rate	0.043	-0.047	0.133

Athletics, Any Cost

Correlate	***r***	**95% CI Low**	**High**
% of White Students	0.522***	0.445	0.598
% of Black Students	-0.191***	-0.279	-0.103
% of Hispanic Students	-0.432***	-0.513	-0.351
% of Students Other Race	-0.12**	-0.209	-0.03
% of Students who are English Language Learners	-0.404***	-0.486	-0.322
Block Group Total Crime Rate	0.069	-0.021	0.158
Block Group Violent Crime Rate	0.072	-0.017	0.162
Block Group Property Crime Rate	0.069	-0.021	0.158

Athletics, Low Cost

Correlate	*r*	95% CI Low	High
% of White Students	-0.129*	-0.218	-0.04
% of Black Students	-0.262***	-0.349	-0.175
% of Hispanic Students	0.251***	0.164	0.337
% of Students Other Race	0.022	-0.068	0.112
% of Students who are English Language Learners	0.249***	0.162	0.335
Block Group Total Crime Rate	-0.028	-0.118	0.061
Block Group Violent Crime Rate	-0.031	-0.121	0.058
Block Group Property Crime Rate	-0.03	-0.12	0.059

Athletics, Free

Correlate	*r*	95% CI Low	High
% of White Students	-0.248***	-0.334	-0.161
% of Black Students	-0.509***	-0.586	-0.432
% of Hispanic Students	0.492***	0.414	0.57
% of Students Other Race	0.009	-0.08	0.099
% of Students who are English Language Learners	0.324***	0.239	0.409
Block Group Total Crime Rate	0.018	-0.071	0.108
Block Group Violent Crime Rate	0.012	-0.077	0.102
Block Group Property Crime Rate	0.009	-0.081	0.098

Arts, Any Cost

Correlate	***r***	**95% CI Low**	**High**
% of White Students	0.179***	0.091	0.267
% of Black Students	-0.443***	-0.523	-0.362
% of Hispanic Students	0.051	-0.039	0.14
% of Students Other Race	-0.193***	-0.281	-0.105
% of Students who are English Language Learners	-0.046	-0.136	0.044
Block Group Total Crime Rate	0.106	0.016	0.195
Block Group Violent Crime Rate	0.1	0.01	0.189
Block Group Property Crime Rate	0.091	0.002	0.181

Arts, Low Cost

Correlate	***r***	**95% CI Low**	**High**
% of White Students	-0.102*	-0.013	-0.191
% of Black Students	-0.499***	-0.421	-0.576
% of Hispanic Students	0.363***	0.447	0.279
% of Students Other Race	-0.172***	-0.083	-0.26
% of Students who are English Language Learners	0.22***	0.307	0.132
Block Group Total Crime Rate	0.074	0.163	-0.016
Block Group Violent Crime Rate	0.062	0.151	-0.028
Block Group Property Crime Rate	0.053	0.143	-0.036

Arts, Free

Correlate	***r***	**95% CI Low**	**High**
% of White Students	-0.113*	-0.202	-0.024
% of Black Students	-0.496***	-0.574	-0.418
% of Hispanic Students	0.376***	0.293	0.459
% of Students Other Race	-0.183***	-0.271	-0.095
% of Students who are English Language Learners	0.225***	0.137	0.312
Block Group Total Crime Rate	0.078	-0.011	0.168
Block Group Violent Crime Rate	0.065	-0.025	0.154
Block Group Property Crime Rate	0.056	-0.034	0.146

Academic, Any Cost

Correlate	***r***	**95% CI Low**	**High**
% of White Students	0.144**	0.055	0.233
% of Black Students	-0.445***	-0.525	-0.364
% of Hispanic Students	0.091*	0.001	0.18
% of Students Other Race	-0.216***	-0.304	-0.129
% of Students who are English Language Learners	-0.021	-0.111	0.068
Block Group Total Crime Rate	0.107*	0.018	0.196
Block Group Violent Crime Rate	0.099*	0.01	0.188
Block Group Property Crime Rate	0.09*	0.001	0.179

Academic, Low Cost

Correlate	*r*	95% CI Low	High
% of White Students	-0.116*	-0.205	-0.027
% of Black Students	-0.472***	-0.551	-0.393
% of Hispanic Students	0.369***	0.286	0.453
% of Students Other Race	-0.197***	-0.285	-0.109
% of Students who are English Language Learners	0.224***	0.137	0.312
Block Group Total Crime Rate	0.078	-0.011	0.168
Block Group Violent Crime Rate	0.063	-0.026	0.153
Block Group Property Crime Rate	0.055	-0.035	0.145

Academic, Free

Correlate	*r*	95% CI Low	High
% of White Students	-0.121**	-0.21	-0.032
% of Black Students	-0.481***	-0.559	-0.402
% of Hispanic Students	0.378***	0.295	0.461
% of Students Other Race	-0.196***	-0.284	-0.107
% of Students who are English Language Learners	0.227***	0.14	0.315
Block Group Total Crime Rate	0.079	-0.011	0.168
Block Group Violent Crime Rate	0.064	-0.025	0.154
Block Group Property Crime Rate	0.055	-0.034	0.145