Shifts in Public Transit Equity during the COVID-19 Pandemic: A Case Study in Riverside, California

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ABSTRACT

A prime component of any effective public transportation system is equitable access for all riders within the community. Building transportation networks with equity in mind can boost ridership and transit network coverage. The problem of social equity in transportation is further exacerbated by historically auto-dependent cities and the pandemic restrictions from COVID-19. This paper aims to quantify transit equity using a disadvantage index. These results are then applied to different periods of a transit system throughout the COVID-19 pandemic to see how it affected social equity in public transportation as part of a case study in Riverside, California. Heat maps are overlaid on the transit network's lines and stops using geographic information systems (GIS) software to visualize the variables associated with transit equity calculations. Publicly released General Transit Feed Specification (GTFS) data is used to plot the state of the transit network at different points in time. The results show that route changes during the COVID-19 pandemic had a noticeable but minimal effect on social equity in transportation.

1 INTRODUCTION

Social Equity is an increasingly important quality for companies as consumers are concerned about social awareness and practices in each industry. The transportation industry is also increasingly focusing on social equity. Transportation equity aims to ensure that all people have reliable access to transportation. In order to achieve this, The California Transportation Plan includes Transportation Equity in its goals for 2050 (California State Transportation Agency, 2021).

The COVID-19 pandemic provides a rare chance to analyze how a global crisis affects a transit agency. Transit agencies across the country have had to deal with less funding due to a significant decrease in ridership (Southern California Association of Governments, 2020).

In this paper, the authors have split the COVID pandemic into two stages, a pre-pandemic stage using data from January 2020 and a recovery stage using data from July 2021. For this paper, the recovery stage refers to when COVID-19 cases were at a minimum after the COVID-19 pandemic started.

This paper aims to compare transit equity between these two stages. To do this, an index score is created to identify disadvantaged populations accurately. Disadvantaged in this case means populations with less economic opportunity due to factors that include education level, income, and poverty status. This index is used to identify areas of analysis to see how disadvantaged populations were affected by the pandemic restrictions compared to more advantaged populations.

This is the first paper of its kind to analyze the correlation between COVID-19 pandemic restrictions and transit equity within a historically auto-dependent city. More specifically, this paper will be analyzing transit equity regarding the Riverside Transit Agency (RTA) within Riverside County, California.

2 LITERATURE REVIEW

2.1 Transit

A transit network represents complex nodes (stops) and links (routes) with common characteristics serving various origins and destinations. Speed, frequency, and capacity are the most critical terms that define the characteristics of a transit stop or transit route and contribute to conventional transit level-of-service (LOS) evaluation (Bonacich and Lloyd, 2001; Estrada and RodríguezVelázquez, 2005). However, the measures only consider network-level characteristics and ignore the real-world operational conditions.

Newer methods have utilized a graph-theoretic transit connectivity measure that relies on General Transit Feed Specification (GTFS) data coupled with population and employment data to capture the connective power of each stop, line, and traffic analysis zone (TAZ) in a public transit network. Then, the equity of transit connectivity distribution can be analyzed using a Gini index and census data (Sharma et al., 2020).

For several decades now, operations research has successfully solved a wide variety of optimization problems in public transit. Several commercial software systems based on operations research techniques have been designed and used by the transit agencies to help them plan and run their operations. The main goal of most transit agencies is to offer to the population service of good quality that allows passengers to travel effortlessly at a low fare (Desaulniers and Hickman, 2007).

2.2 Transit Equity

The Civil Rights Act of 1964 first mentioned the importance of transit service equity (Welch and Mishra, 2013). Equity means the fairness with which cost and benefits are distributed. Planning for Transportation decisions often has significant equity impacts (Litman, 2018). Evaluating equity needs that people be categorized by their geographic and demographic factors so that they can be evaluated by their capabilities and identify transport disadvantaged (Fan and Huang 2011; Karner and Niemeier 2013; Pereira et al., 2016). For all people, reliable access to essential public and private facilities such as employment centers and medical facilities is vital; for captive riders with few travel choices or high barriers to transportation, public transit may be the only viable means of accessing these services (Banerjee et al., 2012).

2.3 Transit Connectivity

The connectivity of a transit network can be defined as the accessibility that nodes within a transit network can provide to riders (Cheng and Chen, 2015). Transit connectivity is vital to a transit system's overall reliability and utility. It becomes imperative when transit agencies expand on existing networks to meet growing ridership demand (Mishra et al., 2012). Measuring transit connectivity not only requires measuring accessibility but also mobility (Hadas and Ranjitkar, 2012; Kaplan et al., 2014; Welch and Mishra, 2013).

Transit connectivity calculations are usually based on waiting times, access times, egress times, service frequency, service reliability, and transfers for routes in a transit network (Kaplan et al., 2014). The use of connectivity measures in transit services has evolved. Park and Gang (2010) developed a quantitative model for multimodal urban transit network connectivity. The authors identified line length, speed, and capacity as key components of a transit line's utility, then defined its connecting power as the product of those components (Sharma et al., 2020).

2.4 Riverside County

In the last 25 years, the Southern California area invested heavily in public transportation systems (Manville et al., 2018). The study area for this paper is located in Riverside County of California, where the population has dramatically increased recently. It is the fastest growing County in California. From 1980 to 2002, the total population increased by about 200%. By 1992, there were over 1.3 million residents, more than the populations of 13 states (Chen et al., 2010).

One of the sectors most affected by COVID-19 is public transportation. North American cities' ridership dropped by upwards of 90% by the end of March 2020 as governments applied quarantine policies (DeWeese et al., 2020). In the County of Riverside, COVID-19 cases peaked from November 2020 to February 2021, where there was an average of 3,500 cases a week, and it reached a historic high on January 6th, 2022, with 22,415 cases (USAFACTS 2022). With the peak in cases, the transit system in Riverside experienced a significant change. While comparing ridership in Riverside from 2019 to 2020, it remained positive in January (4.5%), and February (9.3%) then dropped significantly in March (-33%) and even further in April (-72.6%) and also negative in May (-66.4%) (Southern California Association of Governments 2020).

As a result of the ridership decline, in April 2020, RTA cut the weekday service by about half by having all the schedules reflect the Sunday service route (Riverside Transit Agency, 2020). This study will look at how these changes may have impacted the community.

While there has been other research done on the impacts of COVID on the transportation system in Riverside County, and some on disadvantage index, this paper is unique in that it combines the two and concentrates specifically on the bus system in a particular smaller area throughout January 2020 – July 2021. One of the relevant studies that have been done is a preliminary study in June 2020 comparing 40 cities over North America. It linked changes in service frequency against average income levels and vulnerability index (DeWeese, 2020). In addition, a study was also done by the Southern California Association of Governments (SCAG), which focused explicitly on change in ridership numbers for all forms of transit comparing the years 2019 and 2020 from January to May (Southern California Association of Governments, 2020). These two studies were not targeted at Riverside County but included them in its analysis.

3 METHODOLOGY

This paper aims to quantify how service changes resulting from the COVID-19 pandemic affected transit equity within Riverside County in California. The quantification of equity is based on data related to job accessibility, population, income, and education. The results of this quantification are analyzed in conjunction with a transit service area analysis.

3.1 Data Collection

The Collection of Data came from a combination of sources from the Environmental Systems Research Institute (ESRI) data repository, U.S. Census Bureau, General Transit Feed Specification (GTFS) data, and the Riverside County Data Website.

The Census data is sourced from ESRI's data repository and the U.S. Census Bureau. From ESRI, the American Community Survey (ACS) Median Household Income Variables, ACS

Poverty Status Variables, ACS Educational Attainment Variables, and ACS Population Variables. This data is formatted to provide relevant information per census tract (ESRI, 2018). In addition to tract-level data, block-level data was also used. The US Census Bureau website provided the Tiger/Line Shapefile for the layout of the blocks (United States Census Bureau, 2021b). It also sourced workplace area characteristics data from the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) data set for jobs available within census blocks.

In the United States, most public agencies' GTFS data is available via open source. The GTFS data provides geographic and schedule information of their transit services. For RTA, the GTFS data for January 2020 and July 2021 was used to map out the transit system and calculate commute times and service frequency using the included transit schedule data.

Street data for the region is sourced from official county data websites (Riverside County Information Technology GIS, 2021). It is used to create a network dataset in ArcGIS, detailed in the Data Processing section.

3.2 Data Processing

ArcGIS Pro v2.9.0 is the primary public transit equity analysis tool. ArcGIS allows for the use of public transit feed data to map out transit lines and stops. In addition, it will assist in the analysis of transit service patterns, such as transit service frequency based on transit schedule data.

A heat map is created using the ACS data collected (ESRI, 2018) based on a disadvantage index calculation that uses relevant data points. The higher the value of a calculated index, the more disadvantaged that area of interest is. The following equation is used for calculating the disadvantage index for a particular census tract.

$$DI = \left(1 - \frac{Ix - \bar{I}}{\bar{I}}\right) + \left(1 - \frac{Ex - \bar{E}}{\bar{E}}\right) + \left(1 - \frac{Px - \bar{P}}{\bar{P}}\right)$$

DI: Disadvantage Index
Ix: The median income for a census tract
$\bar{I}$: The average median income for all census tracts
Ex: Percent of population that has a high school education or above for a census tract
$\bar{E}$: The average percent of the population that has a high school education or above for all census tracts
Px: Percent of the population that is above the poverty line for a census tract
$\bar{P}$: The average percent of the population that is above the poverty line for all census tracts

The disadvantage index scores are split into five groups based on income level to organize the results. Income level cutoff values used for the groupings are based on income data availability. For simplicity, the following ranges will be denoted by an index group number. The disadvantage index value ranges for each group are in the table below:

Finally, a network dataset is created based on GTFS and street data (ESRI, n.d.). After the network dataset is successfully created, a service area analysis is conducted on the network dataset using the transit stops as the facilities.

Table 1: Index Value Range

Index Group	Index Value Range
1	<2.3
2	2.3-2.9
3	2.9-3.2
4	3.2-3.5
5	>3.5

Note. Each value was grouped based on mean income and calculated based on income, poverty, and education factors.

The Service Area Analysis was all run for Wednesday at 12 pm. This timeframe was chosen to capture the activity at mid-day in the middle of the workweek. Future analysis can be done on the effect across different periods.

3.3 Data Analysis

A helpful attribute of GTFS feeds is that historical data about a public transit system is made available. Transit agencies update their GTFS feed every few months with service changes. GTFS data can thus be retrieved from different periods throughout the pandemic and analyzed.

For analysis, GTFS data is used to map out the transit stops and lines for the transit agency of interest. Then, schedule data is used for more in-depth analysis. For this reason, stop, route, trip, stop time, calendar, shape, and frequency files are used.

Two different analyses are performed. The first analysis involves looking at commute times using bus stops in Riverside as the origins. Once bus stops are mapped and the analysis is run, a polygon is formed around each bus stop. This polygon represents the area that can be reached within 30-minutes using the transit system. With this 30-minute service area established, it is then mapped with the disadvantage index and the job availability for that area. The job availability is then compared between the least disadvantaged and most disadvantaged tracts for before and during the COVID-19 pandemic.

The second analysis accesses the service frequency in each of these census tracts. The service frequency is determined by how often buses visit bus stops. The more often an area is serviced, the higher the frequency. From this analysis, the mean runs per hour for both the most disadvantaged and least disadvantaged areas for both time periods is compared.

Overall, the data previously outlined combined with these two analyses provides a snapshot of the state of public transportation equity at different times during the COVID-19 pandemic.

4 RESULTS

4.1 Index

This study is done on the transit system in Southern California, specifically in Riverside County. The main concentration is on the bus systems; Riverside Transit Agency (RTA) services the 2.4 million Population (United States Census Bureau, 2020) of Riverside County. It serves a 2,400 square mile service area in western Riverside and comprises 32 fixed bus routes, 4 CommuterLink express routes, and a 344 vehicle Dial-A-Ride service. They provide service both locally and regionally. The Federal Transit Administration primarily funds the RTA, Transportation Development Act, the South Coast Air Quality Management District, the California Department of Transportation, and Congestion Mitigation and Air Quality (Riverside Transit Agency, 2022).

The transit data is based on the GTFS transit feed data for Riverside Transit Agency for the periods of January 31st, 2020, December 16th, 2020 & July 22nd, 2021 (Open Mobility Data, 2022)

Based on the index calculation and the grouping, the below table shows below the distribution of population and areas based on each index:

Table 2: Population and Geographic Area Based on Index

Index	Index Value Range	Area of Land sq mi	Population	Percent of Total Population	Population Density sq mi
1	1.47-2.3	367.95	407205	17%	1106.68
2	2.3-2.9	963.10	719265	30%	746.82
3	2.9-3.2	627.06	427592	18%	681.90
4	3.2-3.5	784.05	383479	16%	489.10
5	3.5-3.9	4461.94	467698	19%	104.82
Total		7204.11	2405239	100%	

Note. These data were calculated using ArcGIS, which shows the population % for each index value along with area and population density.

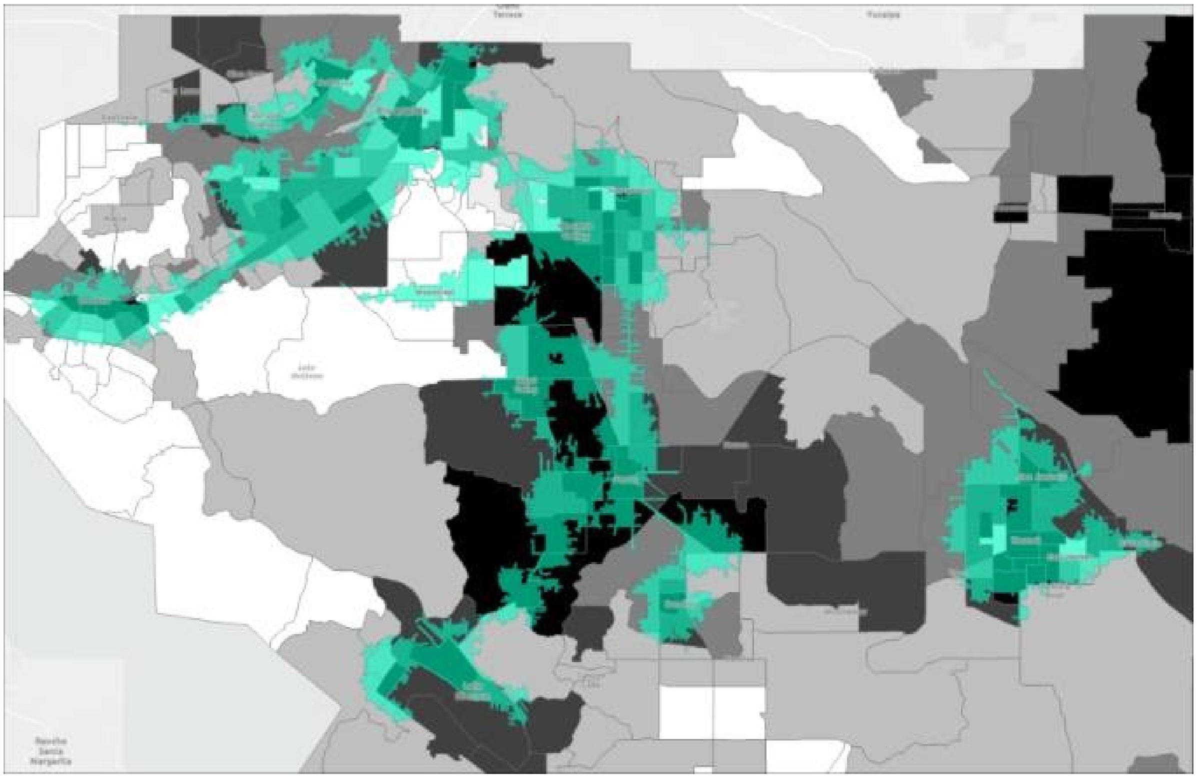
Getting the results for the disadvantage index is only the first step in evaluating transit equity within the transit system before and after the COVID-19 spread. The following section will illustrate how changes in commute times affected transit equity.

4.2 Commute Time

The area accessible to the most disadvantaged areas within a 30-minute commute is shown in Figure 1 below. The green area is a polygon around the most disadvantaged areas of an area that is reachable within 30 minutes by bus from those points. The heat map is divided into census tracts, with the most disadvantaged, the darkest shade, and the least disadvantaged a lighter shade. For example, the figure below shows a thirty-minute commute using public transit from disadvantaged census tracts in the County of Riverside in green with an overlap of the disadvantaged census tracts.

The upcoming table shows job accessibility with the number of jobs and the percentage change within a 30-minute transit commute time before COVID and during COVID.

Using Figure 1, an analysis was done on the number of jobs accessible within a 30-minute commute from both the Most Disadvantaged areas and the Least Disadvantaged areas over both the Pre and During periods. The percentage decrease in jobs available in the same area between Pre and During periods was calculated, and the results are displayed in the table above. The following section will show the relationship between the service frequency and the disadvantage index.



Note: These commute areas were calculated using bus stops in census tracts from the origin of disadvantaged index group 5 (the most disadvantaged group).

Figure 1: 30-minute commute area from the most disadvantaged census tracts in Riverside County

Table 3: Job accessibility within 30-minute transit commutes before and during COVID

	Disadvantaged Level	Index	Dates	# Of Jobs	% Change
Pre COVID	Most Dis.	5	Jan.2020	288,866	
	Least Dis.	1	Jan.2020	196,032	
	Total	All	Jan.2020	464,456	
During COVID	Most Dis.	5	Jul.2021	280,713	-2.82%
	Least Dis.	1	Jul.2021	143,648	-26.72%
	Total	All	Jul.2021	451,841	-2.72%

Note. Percent change in job accessibility for each index group was calculated based on the number of jobs within each respective index group.

4.3 Service Frequency

The change in frequency of service across the transit route and how much change occurred in the most and least advantaged areas is displayed below.

Note. This figure contains two layers. The first layer shows every census tract and its disadvantage index level. The second layer shows bus stops in the most disadvantaged areas and their service frequency.

Figure 2: Service frequency of bus stops overlaid on a heat map of the disadvantage index per census tract

In Figure 2 above, the service frequency of a bus stop is represented by a dot colored according to a scale with the brightest yellow indicating the most frequent stops (>15 runs per hour) and the reddest indicating the least frequent stops (0-1 runs per hour). The second layer of this figure indicates the disadvantage index of each census tract in the immediate region. The darkest colors represent the most disadvantaged areas, and the lightest color represents the least disadvantaged areas.

A comparison of the effect of change of frequency before and during the pandemic between most and least disadvantaged groups is shown in the table below.

Riverside County and the RTA produced a unique set of results as services adapted to meet the needs of people while also dealing with a worldwide pandemic. The raw numbers and figures that illustrate these changes will now be analyzed to extract any conclusions made.

5 ANALYSIS

5.1 Disadvantage Index

Riverside County's population comprises a diverse set of people from different backgrounds and socioeconomic groups. The mean disadvantage index score for census tracts in Riverside County is 3.0, with a standard deviation of 0.58. This implies that the average census tract is neither advantaged nor disadvantaged.

Table 4: Service frequency of bus stops by disadvantage index

	Disadvantage Level	Index	Dates	Mean Runs Per Hour	% Change
Pre COVID	Most Dis.	5	Jan.2020	1.918	
	Least Dis.	1	Jan.2020	1.56	
	Total	All	Jan.2020	1.786	
During COVID	Most Dis.	5	Jul.2021	1.829	-8.90%
	Least Dis.	1	Jul.2021	1.44	-12.00%
	Total	All	Jul.2021	1.687	-9.90%

Note. Calculations were done solely for index groups 1 and 5 to see the disparity between the most disadvantaged groups and the least disadvantaged groups.

In addition, index group 2 has the highest population count with 719,265 people, which makes up 30% of the total population in Riverside County (Table 2). This index range's population density (about 747 people per square mile) is only beaten out by the most advantaged population (1107 people per square mile). However, it should be noted that the population density for more disadvantaged populations is skewed by the large amount of land covered by some of the most disadvantaged census tracts.

For example, Census Tract 469 is one of the most disadvantaged census tracts with a score of 3.59 and has a population density of 0.42 people per square mile. However, this census tract alone covers an area of 3,807 square miles which takes up 52% of Riverside County's total land area.

5.2 Commute Time

Commute time had a minimal but noticeable difference between pre-pandemic and during-the-pandemic periods for the transit system. The total jobs available within 30 minutes of commute time for the service in Riverside County were 464,456 pre-pandemic and 451,841 during the pandemic. This is a decrease of 2.72%. This is an overall decrease in the number of jobs accessible within 30 minutes commute time, making it more challenging for the community to access jobs within 30 minutes. This could also imply that it will take longer for people to get to or from their jobs.

For jobs reachable within 30 minutes of each stop, it decreased 2.82% for the most disadvantaged areas and 26.72% for the least disadvantaged areas. Though the percentage change for the most disadvantaged areas is more minor, these areas tend to rely more on the system for service, so even a tiny change can be substantial. Nevertheless, a decrease of 2.82 % still means 8,153 jobs are not accessible compared to before the pandemic.

On the other hand, in the least disadvantaged areas (areas with average median income >$82,000), there is a more significant difference in the jobs accessible with a decrease of 26.72%. This is 52,384 fewer jobs accessible to these areas during the pandemic compared to before the pandemic. Though this is a significant difference, it aligns with RTA focusing on its service to areas that rely on it more. In addition, as Riverside is a more auto-dependent city, the least disadvantaged have more access to automobiles and are thus more likely to use them versus the transit system.

5.3 Service Frequency

Service Frequency differs from city to city. The volume of transit vehicles and passengers getting on and off are the main factors for transit agencies to determine their service frequency. During COVID, numerous transit agencies throughout the United States have changed their service frequency since the ridership decreased due to the pandemic. Therefore, a service frequency analysis was performed by calculating mean runs per hour for different disadvantage levels before and during the pandemic (See Figure 2).

The data shows a 12% decrease in service frequency for the least disadvantaged areas and an 8.90% drop for the most disadvantaged areas. It shows that transit agencies are focused on providing service to the more disadvantaged areas within the region. Overall, the mean runs per hour range from 1.44 to 1.98 within the study area, which is infrequent regardless of the change in the time period.

It can also be seen that the variance between percent-change values for service frequency is less than the variance in job accessibility. This shows that service frequency did not have a significant difference between disadvantage index groups compared to job accessibility.

6 CONCLUSION

Ever since the COVID-19 pandemic began, RTA has had a unique response. From the results, it can be concluded that though there were changes to the system, the most disadvantaged groups were the least affected. This is because RTA focused on making the necessary service cuts in the least disadvantaged areas where service use might have had less demand.

The disadvantage index provided a means to see how equity was affected in the transit system throughout the COVID-19 pandemic. By using the index against jobs available, it showed that there was a decrease in jobs available within a 30-minute commute time from the bus stops. Though it was a relatively small decrease in percentage for the most disadvantaged, it can still have a considerable effect since over 8,000 jobs were no longer accessible in the same time frame. Note that this group relies heavily on the transit system. In addition, the least disadvantaged groups were significantly more affected by the changes in routes. However, this group is less likely to rely on public transit.

Using the disadvantage index against service frequency, it was also seen that frequency decreased during COVID. However, the variance between the groups was not as noticeable. Therefore, the issue of transit equity is relatively negligible from a service frequency perspective.

Therefore, transit service equity was not an issue that was exacerbated by the COVID-19 pandemic. On the contrary, these results imply that transit equity was a focus of RTA during the pandemic.

Future work might include more in-depth analyses to evaluate transit equity. For example, a walkability area could be computed and cross-referenced with population to calculate the population served in different areas. In addition, analyses could include how transit service changes throughout the day and on different days of the week. Furthermore, data from transit on-board surveys and household travel surveys collected before and during the COVID-19 pandemic can be used to examine the different behaviors of transit users and answer why and how transit equity could be affected.

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