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Christopher K. Wyczalkowski

Visiting Assistant Professor, Department of Public Management and Policy, Andrew Young School of Policy Studies and Affiliated Faculty, Urban Studies Institute, Georgia State University, cwyczalkowski1@student.gsu.edu

Timothy Welch

Senior Lecturer in Architecture and Planning, University of Auckland, t.welch@auckland.ac.nz

Obed Pasha

Assistant Professor of Public Management, School of Government, University of North Carolina – Chapel Hill, pasha@sog.unc.edu

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INEQUITIES OF TRANSIT ACCESS: THE CASE OF ATLANTA, GA

Christopher K. Wyczalkowski,¹ Timothy Welch,² Obed Pasha³

ABSTRACT

Public transportation systems are essential components of urban infrastructure, providing connectivity that contributes to the quality of life for urban dwellers. Particularly important for low-income populations, public transportation systems enhance access to jobs, markets, services, education, healthcare, recreation, and social networks. While low-income populations and minorities make up a disproportionately high share of transit ridership, theories such as spatial mismatch, social construction framework, and Critical Race Theory maintain that public transportation systems may not provide equitable connectivity to all riders. We utilize GIS and regression models to examine the relationship between transit connectivity and poverty, asking whether connectivity is evenly distributed by social class. Atlanta, GA is a city with a significant low-income and minority population that is segregated from affluent, white neighborhoods. We exploit this spatial discontinuity to examine public transit access by socioeconomic status. We utilize ten years of General Transit Feed Specification (GTFS) and census data, and a measure of employment and population connectivity for the period from 2012 and 2017. We find low public transit connectivity in high poverty and minority block groups, relative to other areas in the city. The findings underscore the need to fund public transit investments targeted at low income areas.

KEYWORDS: Public transportation, poverty, connectivity, equity, employment

INTRODUCTION

Public transportation systems are essential components of urban infrastructure, providing connectivity that contributes to the quality of life for urban dwellers. Particularly important for low-income populations, public transit systems contribute to quality of life by enhancing personal autonomy, as well as attending to pragmatic concerns of connection to jobs, markets, social services, education,

¹ Christopher K. Wyczalkowski, Visiting Assistant Professor, Department of Public Management and Policy, Andrew Young School of Policy Studies and Affiliated Faculty, Urban Studies Institute, Georgia State University, Corresponding author - Email: cwyczalkowski1@gsu.edu

² Timothy Welch, Senior Lecturer in Architecture and Planning, University of Auckland, Email: t.welch@auckland.ac.nz

³ Obed Pasha, Assistant Professor of Public Management, School of Government, University of North Carolina – Chapel Hill, Email: pasha@sog.unc.edu

healthcare, and family and recreation (Farrington and Farrington, 2005; Steg and Gifford, 2007; Boschmann and Kwan, 2008; Martens, Golub and Robinson, 2012; Tyndall, 2017). An absence or a weak provision of public transportation is likely to put economically strained residents, who can't afford a car, at an even further disadvantage, limiting opportunity and further fragmenting a region (Pasha, 2018).

The basic tenets of social justice and equity demand a just and equitable distribution of burdens and benefits throughout the society (Salamon, 2002). Transportation planning can help to achieve better social inclusion by redistributing mobility resources toward the communities that need them the most, providing comparable mobility for all citizens (Boschmann and Kwan, 2008; Farber, Bartholomew, Páez and Habib, 2014; Wellman, 2015). However, politically fractured regions and fragmented funding sources have created significant barriers to achieve equity goals (Nelles, 2012), and the legacy of housing discrimination continues to create barriers for minorities (Ihlanfeldt and Sjoquist, 1998).

The spatial mismatch hypothesis calls attention to the concentration of low-income black communities in the inner-city, due to migration of the more affluent white population from city cores to suburban areas, the subsequent out migration of jobs, housing discrimination, such as redlining, and employment discrimination (Kain, 1968; Ihlanfeldt and Sjoquist, 1998; Blumenberg and Manville, 2004; Rothstein, 2017). As a result, inner-city communities are poorer and have higher unemployment rates compared to those who live in suburban areas (Farley, 1982; Howell-Moroney, 2005). Although existing empirical research explores the relationship between the location of low-income or minority populations and access to jobs, overall research focusing on equitable public transportation connectivity is surprisingly scant (Blumenberg, 2004; Altshuler, 2013; Golub and Martens, 2014; Pathak, Wyczalkowski and Huang, 2017; Pasha et al., 2020).

This paper seeks to fill this gap by studying whether communities with higher rates of poverty and Black populations have lower levels of accessibility provided by public transportation, compared to other communities. We exploit the segregated nature of the city of Atlanta, GA, and utilize Graph Theory, General Transit Feed Specification (GTFS), and 5-year American Community Survey (ACS) data to construct a comprehensive measure of transit connectivity (Welch 2013) over the 2012 to 2017 time period. Regression model results show that areas with higher levels of poverty have lower accessibility through public transit.

These findings have three important policy implications for cities. First, our findings contribute to the existing literature on social justice issues related to transportation by drawing attention to the disparities faced by low-income and minority communities. In addition, these results question whether public transit

services are adequately provided to such communities, given that public transit services are disproportionately used by minority and low-income groups.

Second, this is one of the few studies that extends its focus to public bus service in addition to rail systems. Although bus systems outnumber rail systems 20:1, academic research is more focused on rail systems, but effects of these systems on neighborhoods may be heterogenous by mode. Rail systems generally run in their own right of way, but are expensive to build, and this expense is often capitalized in local property values, as developers flock to the ‘beachfront property’ generated by public funding of transit. Bus systems do not require such infrastructure.

Third, these findings suggest support for the isolation and concentration of poverty suggested by the spatial mismatch hypothesis, social construction framework, and Critical Race Theory. These theories argue that minorities and other low-income communities will face discrimination in the distribution of benefits and burdens in the United States (Delgado and Stefancic, 2017). This unequal distribution of public transit is especially relevant for minorities and low-income populations (earning under \$15,000 annually) who makeup over 60% and 21% of transit ridership, respectively (APTA, 2017). Weak accessibility by public transportation in such communities further alienates them from many lower-level jobs that are available in far flung suburban areas (Taylor and Ong, 1995; Blumenberg and Ong, 2001; Ong, 2002;). Taken with literature that finds public transit can affect the housing location of low-income populations (Pathak et al., 2017; Pasha et al. 2020), our findings call attention to the importance of public transit options in high poverty neighborhoods.

LITERATURE REVIEW

The issue of discrimination in transportation policy is not new to the United States. In 1892, Homer Plessy refused to move from the whites-only section of the train car, in defiance of Louisiana’s Withdraw Car Act of 1890. The issue was again brought into the limelight by Rosa Parks refusing to give up her seat on a public bus in 1955, instigating the Montgomery Bus Boycott later that same year. A few years later in 1961, as part of the Freedom Riders Movement, Civil Rights activists rode buses to the Southern States to protest the non-enforcement of the Supreme Court’s decision against segregation of public buses. Scholars such as Alexander (2010) and Eberhardt (2020) argue that discrimination is rooted in history, and is still very much a part of American society, shaping the way resources are distributed among communities.

The spatial mismatch hypothesis (Ihlanfeldt and Sjoquist, 1998), suggests that minority low-income groups are isolated in central cities. In agreement, Critical Race Theory research has shown that these minority communities have lesser access to resources such as employment, education, healthcare, and infrastructure, compared to their white counterparts (Ellwood, 1986; Ihlanfeldt and Sjoquist, 1998; Williams, Neighbors and Jackson, 2003; Alemán Jr., 2007; Gobillon et al., 2007). A recent study by Pasha (2018) showed that such disparities extend to transportation; municipalities in Massachusetts with a higher share of non-white population were found to have less transportation funding available to them compared to other jurisdictions.

Transportation scholars contend that even equity tools such as Title VI of the Civil Rights Act of 1964 and President Bill Clinton's Environmental Justice Executive Order of 1994 have not been successful in removing such disparities. Inequalities remain, primarily due to a lack of mechanisms, guidelines, and clear standards to hold state and local governments responsible for accommodating the needs of minority communities in transportation planning (Wachs and Taylor, 2008; Sanchez, Stolz and Ma, 2003; Lucas, 2006; Thomopoulos, Grant-Muller and Tight, 2009; Martens, Golub and Robinson 2012; Farber, Bartholomew, Páez, and Habib 2014).

In part, such disparities are a direct result of lower comparative participation rates of communities of color in state and federal government, weakening their influence on policy formulation in these areas (Banducci, Donovan and Karp 2004). The policy of emphasizing highway construction, land acquisition by government, and the redirection of transportation funds from public transportation towards highways and suburban living are examples of such policies that have hurt the interest of communities of color and lead to residential segregation (Sanchez, Stolz and Ma 2003). Some of the differences in transportation funding also emerge from the so-called 'white-flight' from city centers toward suburban communities, leaving non-white citizens behind. Coupled with redlining practices, this ensured a concentration of (mostly) low-income communities of color in metropolitan centers, reducing property and other tax collection, further reducing cities' abilities to invest in transportation (Jackson, 1987; Rothstein, 2017). On the other hand, state governments generally remained in the control of the white majority, who felt little political pressure to invest in city cores inhabited by people of color (Sanchez, Stolz and Ma 2003). Atlanta and the State of Georgia are prime examples of these outcomes.

Social networks dictate living and working locations, increasing the likelihood of settlement in areas with lesser infrastructure due to social and economic constraints, and specific job opportunities such as farm work (Sanchez,

Stolz and Ma 2003; Pasha 2018). Pasha (2018) argues that in some cases transportation resource disparities can be incidental, rather than intentional (see the theory of Disparate Impact; Belton 2004; Wellman 2014). Funding and service allocation is based on existing demand, infrastructure availability, and employment rates, but could put segregated inner-city communities in a perpetual stagnation as they are cut off from services. Inadequate transportation infrastructure in such communities restricts mobility and connection to jobs and other services, which in turn, underrepresents them in demand-based calculations that form the basis of public transportation funding (Martens and Hurvitz 2011; Hananel and Berechman 2016). As a result, communities with restricted mobility attract fewer resources compared to communities that are already mobile and can demonstrate need through high mobility figures (Martens, Golub and Robinson 2012; Beyazit 2011).

Individuals belonging to marginalized communities are often seen as ‘deviants’ and ‘dependent’ by the general public and policy-makers (Pasha 2018). The social construction framework suggests that having a negative social construct and weak influence, such groups are more likely to receive burdens and less likely to receive benefits from society, compared to suburban white communities that are viewed as ‘advantaged’ (Ingram, Schneider and DeLeon, 2007; Schneider and Sidney 2009). Not restricted only to the historically marginalized Black communities, immigrants with language barriers, refugees with limited access to public services, formerly incarcerated individuals, and other communities are also negatively impacted by policy bias for falling under the ‘dependent’ or ‘deviant’ category of the social construction typology (Sanchez, Stolz and Ma 2003; Schneider and Sidney 2009).

The literature on the effects of public transit is primarily focused on economic indicators and the majority of that research is only focused on rail transit. Only a few studies include bus transit, despite that bus systems outnumber transit systems. These studies find effects on poverty and employment, but not rent (Pathak et al., 2017; Pasha et al., 2020).

The study area is constituted by the two counties that contain the City of Atlanta, which also is the primary service area of its public transit agency, the Metropolitan Atlanta Public Transit Authority (MARTA). MARTA began operations in 1972 with the purchase of the privately owned and ailing bus system, itself a remnant of the streetcar era that was the highpoint of public transportation in the United States. With much anguish and consternation, MARTA built a heavy rail public transit system in Fulton and DeKalb counties, commencing operations in 1979, and expanding in phases until 2000. However, the distribution of heavy rail transit was disproportionately located in areas with high proportions of white populations (Keating, 2001). The phenomenon of ‘white-flight’ in the 1960s and

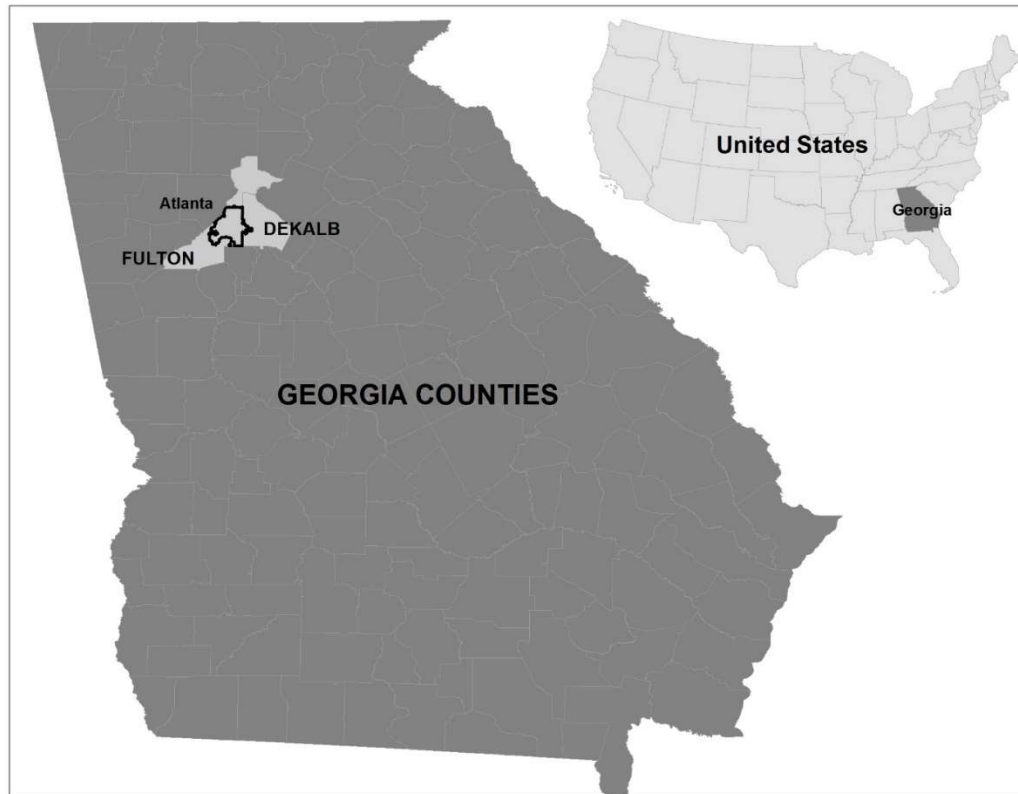
1970s, along with racial housing and job discrimination, resulted in a spatial mismatch between jobs, transit access, and available housing for these groups (Ihlanfeldt and Sjoquist, 1998). We therefore expect that areas in Atlanta, with higher percentage of low-income and African American individuals to have lower connectivity to employment and services using public transportation. Our findings support the expected effects of historic discrimination against minorities, poor implementation of equity tools, white-flight from city centers toward suburbs, faulty transportation funding allocation formulas, and the expectations of theories of social construction, Critical Race, and spatial mismatch.

METHODOLOGY

Our estimation strategy relies on a robust transit connectivity measure, which we utilize in a regression model to predict its effect on poverty. We adopt a two-step framework to construct an index of transit system connectivity in Atlanta. First, a model of the transit system is constructed using publicly available General Transit Feed Specification (GTFS) data files. In the second step, the transit system model is used to compute multiple transit properties (e.g., distance between stops, cumulative distance to each route destination (final stop), the number of routes that use the same stop). Finally, measures of transit system connectivity are computed by combining these transit system properties along with publicly available population and employment census data. The result is a single index value at the bus stop and rail station level (transit stop), indicating connectivity to employment and population centers available at each stop/station.

Study Area

The metropolitan area centered around Atlanta, GA is the ninth largest metropolitan area in the U.S. and MARTA, the local transit authority, is the ninth largest public transit system. It is located in the State of Georgia, United States, and straddles Fulton and DeKalb counties – the study area (Figure 1). Fulton and DeKalb are the first and fourth most populous counties in Georgia, with a combined population of just over 1,750,000, and Atlanta ranks in the top 40 cities in the U.S. by population with a population of just under 500,000 (U.S. Census Bureau, 2018).

FIGURE 1 Study Area**Data**

We utilize two sources of data. Data for the connectivity analysis is obtained from the GTFS, which is a publicly available dataset of the Metropolitan Atlanta Rapid Transit Authority (MARTA) system. Socioeconomic data is obtained from the American Community Survey (ACS) 5-year estimates for years 2012 and 2017 at the block group level. The 5-year ACS represents a spatial and temporal aggregation of data; data is sampled over a rolling 5-year period and aggregated over statistical areas (e.g., county, census tract, block group). Therefore, the 2012 5-year ACS consists of years 2008-2012. Descriptive statistics for both time periods are in Table 1. Pearson correlation coefficients are reported in Table 2. The variables for poverty, percent Black, and housing value are highly correlated.

TABLE 1 Descriptive Statistics

Summary Statistics, 2012							
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Families in Poverty (percent)	644	0.181	0.174	0.000	0.031	0.290	0.882
Connectivity Index	650	75.632	301.635	0.000	5.094	45.822	3,684.944
Less than HS Dress (percent)	648	0.137	0.122	0.000	0.040	0.207	0.877
Median Value	616	216,394.3	151,013.7	14,600.0	113,400.0	272,625.0	1,000,001.0
Population Density (Per Sq. Mile)	649	4,242.360	4,301.915	0.000	2,173.245	4,857.643	65,144.110

Summary Statistics, 2017							
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Families in Poverty (percent)	655	0.164	0.162	0.000	0.033	0.262	1.000
Connectivity Index	661	88.931	574.081	0.000	4.774	37.668	12,870.690
Less than HS Dress (percent)	659	0.117	0.111	0.000	0.032	0.169	0.879
Median Value	591	226,753.1	181,833.5	33,600.0	96,050.0	296,550.0	1,297,300.0
Population Density (Per Sq. Mile)	660	4,561.749	4,478.054	0.000	2,274.411	5,326.728	55,497.810

TABLE 2 Correlation CoefficientsCorrelation of
Coefficients:

	Percent Poverty	Connectivity Index	% Black	Less than HS	Median Home Value
Connectivity Index	-0.04				
Percent Black	-0.79	0.04			
Less than HS Education (percent)	-0.35	0.07	-0.08		
Median Home Value	-0.85	0.06	0.67	0.28	
Population Density	-0.37	-0.23	0.18	-0.05	0.07

Transit System Model Construction

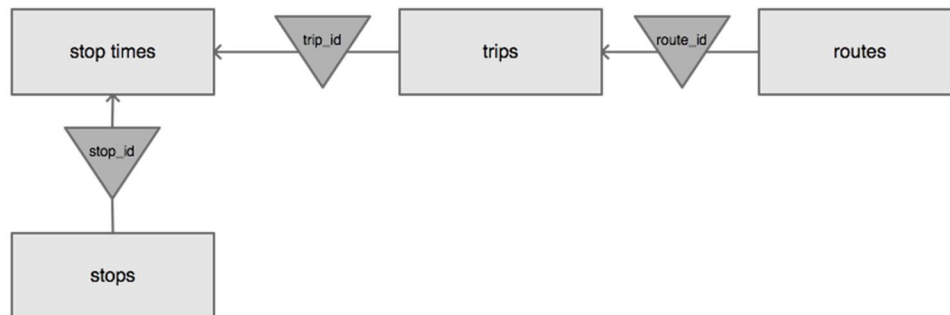
Our analysis uses four required GTFS datasets files, each of which contain segments of information needed to construct a complete digital representation of the transit system and conduct a performance analysis. The files and the variables utilized in this analysis are described in Table 3. Each of these files contains at least one key variable that links it to other files. For example, the ‘stop_times’ file contains records of the arrival and departure times at each stop for every transit trip along a given route and has a key variable called “trip_id” that allows it to be joined to the ‘trips’ table to get information about the sequence of stops that the trip takes. The ‘trips’ file has another key variable called “route_id” that is used to join this file with the ‘route’ file containing information about all the transit routes in the system. Figure 2 provides a schematic diagram of the relationship between these files as they together construct the transit system model in this study.

TABLE 3 GTFS required fields by file

File	Key Variable	Transit Variables	Variable Description
stop_times	trip_id*	--	unique ID for each trip
	stop_id*	--	unique ID for each transit stop
	--	arrival_time*	time the transit vehicle arrived at a stop for a specific trip
	--	departure_time	time the transit vehicle departed a stop for a specific trip
	--	stop_sequence*	the order along a route for a particular stop among all route stops
stops	stop_id*		unique ID for each transit stop
	--	stop_name	the long name of the transit stop
	--	stop_lat*	latitude of the transit stop
	--	stop_lon*	longitude of the transit stop
trips	route_id*	--	unique ID for each route
	service_id	--	unique service ID linked to file for dates of transit operation
	trip_id*	--	unique ID for each trip
		direction_id**	direction of the transit trip, applicable to bi-directional trips
routes	route_id*		
	--	route_short_name	abbreviated name of the route
	--	route_long_name	the full name of the transit route
	--	route_type*	the transit mode

* denotes *required* variables used in this analysis

** denotes *optional* variables used in this analysis

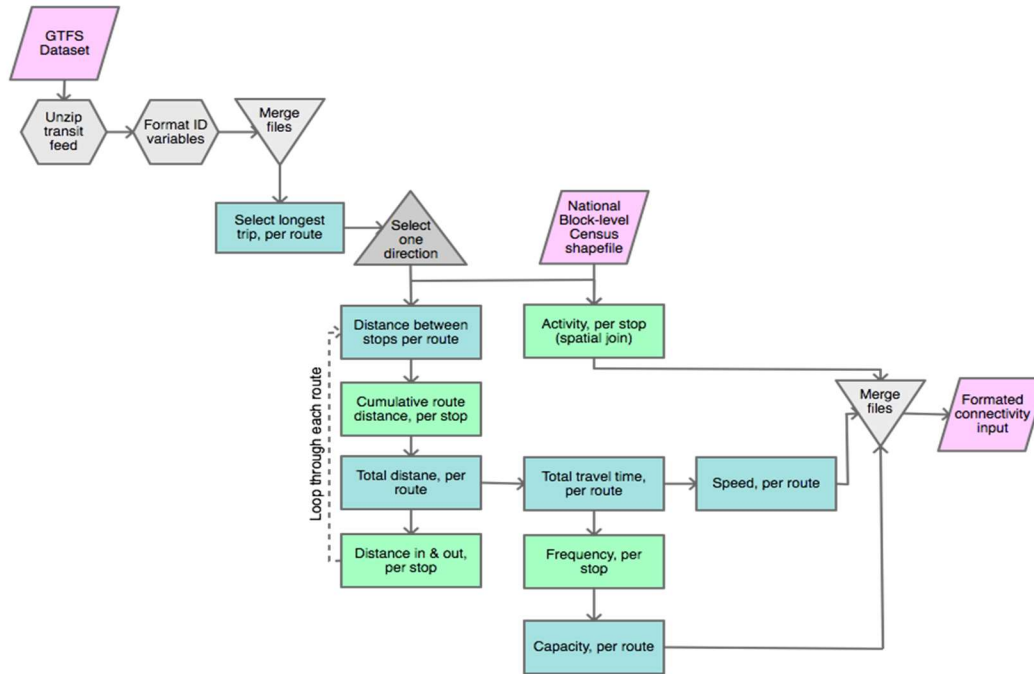
FIGURE 2 Relationship between GTFS files

Using these four files, a complete representation of a transit system is created to compute connectivity (Figure 3). We process the GTFS data to calculate route distance, the distance from the start of the route and distance to end of the route for each stop, speed and capacity of the vehicles on the route. We also exploit census data for computing activity (population and employment) density at each stop.

As explained in Figure 3, this process first links each of the GTFS provided transit files to create a full profile of the transit network. We then select one of the many trips recorded in the data that spans an entire route to get travel times, distance and other route specific data. We then narrow the analysis in the first iteration to a single direction for transit systems that have routes which run in reverse. From these data, we calculate the distance between each stop along a route, then compute the cumulative distance from each stop from the beginning of the route and the total route distance. This allows us to calculate the distance each stop is from the beginning and the end of a route. We repeat the process for the reverse route, if appropriate.

Simultaneously, we calculate the underlying activity density, a factor of population and employment per acre at the census block in which the stop is situated, then merge this with the rest of the route data. The route speeds are calculated based on the arrival time at each stop reported in the GTFS ‘stop_times’ file and the distance between each stop. Finally, the frequency of each stop is determined based on the number of arrivals at a stop along a route per hour, and the capacity of the route is computed by factoring in the vehicle capacity and frequency. The results are merged into a single stop-based file that is used to calculate connectivity.

FIGURE 3 GTFS connectivity model schematic.



Connectivity Measures

The two major elements of a transit network, stops and routes, each require a unique formulation of connectivity. The methodology presented in this paper accounts for the different levels of a transit system. This section explains the mathematical construct of these transit performance measures. The next subsections discuss the concepts, components and formulation of transit stop connectivity and route connectivity. Notations used throughout the paper are provided in Table 3.

TABLE 3 Transit connectivity notation

Notations	Explanation
α_r	Scaling factor for Capacity of a particular bus or rail route r
β_r	Scaling factor for Speed of a particular bus or rail route r
γ_r	Scaling factor for (Origin or Destination) distance of a particular bus or rail route r
φ_r	Scaling factor for Activity of route r
R	$r \in R$; R : Set of transit routes
N	$s \in N$; N : Set of Stops
C_r	Capacity of route r , which is the product of <i>frequency</i> of service on route r and <i>capacity</i> the bus or rail vehicles that serve the route
V_r	Speed of route r
$D_{r,s}^i$	Distance of route r from the origin to stop s
$D_{r,s}^o$	Distance of route r from stop s to the destination
$A_{r,s}$	Activity (population and employment) density at a stop s of route r
A_r	Activity (population and employment) density of route r as a sum of activity at all stops (s) along that route
M	Constant to normalize the connecting power (M=100 is used in this study)
$P_{r,s}^o$	Outbound connecting power of route r at stop s
$P_{r,s}^i$	Inbound connecting power of route r at stop s
$P_{r,s}^t$	The average connecting power of route r at stop s
$CI(s)$	Connectivity index of stop s
$V \sim N(\mu_V, \sigma_V^2)$	V (speed), normally distributed with mean μ_V and variance σ_V^2
μ_V	Mean of given set of Speeds in the data set
σ_V	Standard deviation of a given set of speeds in the data
Θ^s	Number of routes at stop s
S	the set of stops in a transit system
S_r	Set of stops along route r , where $S_r \subset S$
$H_{r,s}^z$	Number of households in the census block z intersected by route r at stop s
$E_{r,s}^z$	Number of employments in the census block z intersected by route r at stop s
$\chi_{r,s}^z$	Area of census block z intersected by route r at stop s

Transit Stop Connectivity

We measure transit stop connectivity at the stop level to: (1) represent how well a stop serves in a multimodal transit network, (2) identify the least, moderate and most connected stops and (3) measure the performance of transit routes at a given stop.

Stop connectivity is defined as a function of the connecting power of transit routes incident upon that stop. As the connecting power may vary depending on the direction of travel, the connecting power of a transit route ($P_{r,s}^t$) is defined as the average of the inbound and outbound connecting powers (provided a stop at a geographical location serves for both inbound and outbound routes). Inbound (Eq. 1) and outbound (Eq. 2) connecting powers of a transit route are a function of capacity, speed, activity density and the distance (transit route length) that it serves.

$$P_{r,s}^i = \left[\left(\frac{\alpha_r \times C_r}{M} \right) \left(\frac{\beta_r \times V_r}{M} \right) (\gamma_r \times D_{r,s}^i) (\varphi_r \times A_r) \right] \quad (1)$$

$$P_{r,s}^o = \left[\left(\frac{\alpha_r \times C_r}{M} \right) \left(\frac{\beta_r \times V_r}{M} \right) (\gamma_r \times D_{r,s}^o) (\varphi_r \times A_r) \right] \quad (2)$$

A transit route with higher scaling coefficient values will indicate higher attractiveness. The scaling coefficients are also responsive in a very intuitive way. If one transit route becomes more attractive, for example, due to an increase in the number of operations during the day, the other transit routes become comparatively less attractive and this change is reflected by the respective scaling coefficient.

Scaling coefficients are calculated assuming that the respective parameter follows a normal distribution (Eq. 3) in order to account for all the values of a parameter in a given data set (However, other distributions could easily be used instead. For example, if past data were available, then a distribution could be tailored to fit these data). Scaling coefficients indicate the probability that the value of that particular parameter is less than or equal to the given value (Eq. 4). For example, in order to calculate β_l , we need to assume $V \sim N(\mu_V, \sigma_V^2)$ where normal distribution is given by:

$$P(V) = \frac{1}{\sigma_V \sqrt{2\pi}} e^{-\frac{(V-\mu_V)^2}{2\sigma_V^2}} \quad (3)$$

And,
therefore

$$\beta_l = P(V < V_l) = \int_0^{V_l} \left(\frac{1}{\sigma_V \sqrt{2\pi}} e^{-\frac{(V-\mu_V)^2}{2\sigma_V^2}} \right) dV \quad (4)$$

The inbound and outbound connecting power considers activity density of a transit route "r" at stop "s", which represents the ambient urban development pattern in which the transit route is situated, based on both land use and transportation characteristics. Development patterns reflect the land use activity in a particular region which can be captured by the number of households, employment and spatial distribution of activities these activities in a given location. Activity density in this analysis is set to the ratio of households and employment in a Census block to the area (Eq. 5). Mathematically, activity density at a stop *s* in route *r* is defined as:

$$A_r = \frac{\sum_{s \in S_r} (H_{r,s}^z + E_{r,s}^z)}{\sum_{s \in S_r} \chi_{r,s}^z} \quad (5)$$

Connectivity index of a stop (Eq. 6) is then calculated as the average of the connecting power of all the transit routes passing through the stop *s*.

$$CI(s) = \frac{\sum_r P_{r,s}^t}{\Theta^s} \quad (6)$$

Route Connectivity

The total connecting power of a route is defined as the sum of the averages of inbound and outbound connecting powers for all transit stops on the route, scaled by the number of stops on each route (Eq. 7). Scaling is used to reduce the connecting score of routes with a large number of stops (e.g. bus routes) so that they can be properly compared to routes with only a few stops (e.g. rail). Route connectivity can be defined as follows:

$$\theta_l = (|S_r| - 1)^{-1} \sum P_{r,s}^t \quad (7)$$

Where, $|S_r|$ represents the cardinality of set S_r .

Estimation strategy

Here, we model route connectivity as a function of poverty. Y_i represents poverty for each block group i and is a function of Ψ_i (connectivity index) and X_i , a vector of control variables: education, home value, population density. Race and housing value are highly correlated and we had to drop one as a control, over concerns of multicollinearity. We chose housing value, excluding race, because it does not directly affect demographics.

$$Y_i = f(\Psi_i, X_i) \quad (8)$$

We employ a linear regression model to estimate the impact of Ψ_i on Y_i . The estimation model is:

$$Y_{i,t} = \alpha + \beta\Psi_{i,t} + \gamma X_{i,t} + \epsilon_i \quad (9)$$

Each block group i in Atlanta, GA is modeled for time period t ($t = 2012$ and 2017). $Y_{i,t}$ is the dependent variable representing families under poverty. β estimates the impact of $\Psi_{i,t}$ on $Y_{i,t}$, controlling for $X_{i,t}$. $\epsilon_{i,t}$ is the error term.

To control for time and space invariant factors, we combine the 2012 and 2017 data into a panel and perform a fixed effects (FE) model.

$$Y_{i,t} = \alpha + \beta\Psi_{i,t} + \gamma X_{i,t} + \lambda_i + \phi_t + \epsilon_i \quad (10)$$

The terms are the same as Equation 9, with λ_i and ϕ_t respectively, representing the spatial and temporal fixed effects.

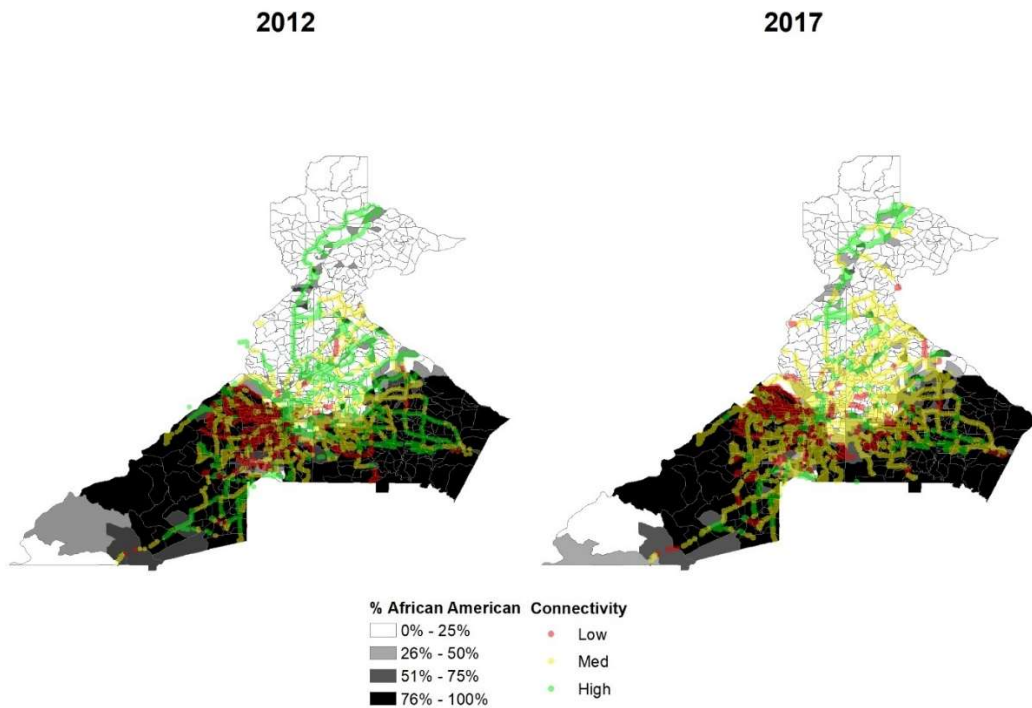
RESULTS AND ANALYSIS

In our analysis, we examined the quality of transit through the lens of connectivity, an index of transit stops that link to areas with a high density of population and employment, with relatively short trips, fast travel times, high capacity, high frequency, and a minimum of transfers. We scaled this connectivity measure and analyzed its relationship with poverty for the 2012 and 2017 ACS statistical periods. We find statistical evidence of lower public transit service levels (connectivity) in areas of Atlanta with the highest percentages of poverty.

As noted, spatial mismatch, social construction framework, and Critical Race Theory suggest that public transportation systems may not provide equitable

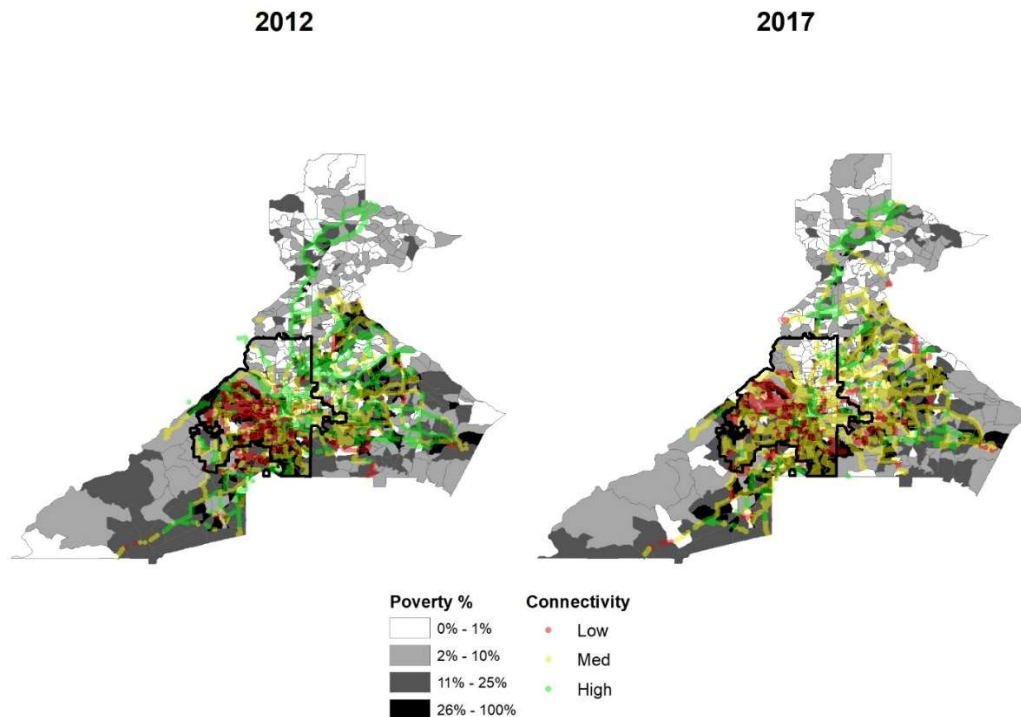
connectivity by race and class. We start with a descriptive analysis of race and connectivity in Atlanta. Figure 4 provides a visualization of these data, showing that census block groups with higher shares of black population also generally have lower levels of public transit service as measured by our connectivity index.

FIGURE 4 Percent black population and transit connectivity, 2012-2017



While there appears to be an uneven distribution of transit connectivity to areas with greater shares of black population, given the high correlation between race and poverty in our data, unsurprisingly there also appears to be a connection to poverty. Figure 5 shows the level of connectivity and percent of families below the poverty line in 2012 and 2017. As shown in the figure, connectivity is typically lower in the southwestern reaches of the city of Atlanta.

FIGURE 5 Poverty and transit connectivity, 2012-2017



The figures illustrate how significantly many Atlanta residents suffer from spatial mismatch, where residents with the highest need for high quality public transportation have access to some of the lowest levels of transit connectivity.

To confirm these initial findings, our analysis modeled the relationship between socioeconomic metrics and transit connectivity across the entire city of Atlanta, an area that spans 134 square miles with a population of 486,290 in 2017. MARTA has over 5,000 bus stops and 38 rail stations. We measured connectivity in 2012 and 2017 at each one of these stops, stations and along every transit route.

To assess significant and often very complex ways in which transit has an impact on the population, we examined how transit quality impacted one important socioeconomic measure, the percent families in poverty. Using ordinary least squares regression, we measure the impact that transit connectivity has on the rate of family poverty in a census block group in both 2012 and 2017. We controlled for education, home value, and population density.

Tables 4 and 5 provide the results of our analysis. Table 4 presents the OLS models for each year (2012 and 2017). The values for Connectivity Index indicate the level of correlation between changes in the quality of transit, as measured by the Connectivity Index on a scale of 0 to 100; where 0 indicates no connectivity and 100 is the best-connected block group in the city. The results indicate that connectivity at the block group level is significant within the 95% confidence interval and for each one-unit increase in the connectivity index, the percent of families in poverty in the block group decreased by 0.1% in 2012 and 0.2% in 2017. While these figures may appear small, the standard deviation of the Connectivity Index is about 8. This indicates that poverty decreases by 0.8% with a change equal to the standard deviation. Transit connectivity in 2012 is correlated with a full 10% difference in family poverty rates between the worst and best transit connected block groups. In 2017, the importance of transit as it relates to incidences of poverty, doubles. A one-unit change in the Connectivity Index is correlated with 0.2% change in poverty. In 2017, transit connectivity is correlated with a 20% difference in family poverty rates between the worst and best transit connected block groups. The FE model results, Table 5, are consistent with the OLS results.

TABLE 4 OLS: Transit connectivity impact on families in poverty

	Connectivity impacts	
	Families in Poverty (percent)	
	2012 (1)	2017 (2)
Connectivity Index	-0.001** (0.001)	-0.002** (0.001)
Less than HS Degree (percent)	0.799*** (0.052)	0.658*** (0.055)
Median Home Value	-0.00000*** (0.00000)	-0.00000*** (0.00000)
Population Density (Per Sq. Mile)	0.00000* (0.00000)	0.00000*** (0.00000)
Constant	0.104*** (0.015)	0.112*** (0.013)
Observations	616	591
R ²	0.418	0.377
Adjusted R ²	0.414	0.373
Residual Std. Error	0.131 (df = 611)	0.116 (df = 586)
F Statistic	109.761*** (df = 4; 611)	88.620*** (df = 4; 586)
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01	

TABLE 5 Fixed Effects: Transit connectivity impact on families in poverty

	Connectivity impacts
	Families in Poverty (percent)
	2012 to 2017
Connectivity Index	-0.002 ^{***} (0.001)
Less than HS Dress (percent)	0.743 ^{***} (0.038)
Median Value	-0.00000 ^{***} (0.00000)
Population Density (Per Sq. Mile)	0.00000 ^{***} (0.00000)
Observations	1,207
R ²	0.399
Adjusted R ²	0.396
F Statistic	199.223 ^{***} (df = 4; 1201)
<i>Note:</i>	* p<0.1; ** p<0.05; *** p<0.01

CONCLUSION

Public transit systems are essential connectors of low-income and minority populations to jobs, education, healthcare, recreation, and other services. However, theories including spatial mismatch, social construction framework, and Critical Race Theory, suggest that these systems may not provide equitable connectivity for all income groups or social classes. This expectation is contrary to the popular belief that vulnerable populations have more access to local transit systems given the assumed high rate of use in such communities.

In this case study of Atlanta, GA, we test the association between poverty and transit connectivity, using data at the block group level, GIS, and linear regression. Atlanta is an interesting case because of its persistent segregation by race, which is a remnant of historical discrimination. The correlation between poverty, minority percentage, and segregation by race is stark in Atlanta, and allows us to examine connectivity differences by socioeconomic status.

Our findings draw attention to the disparities in transit connectivity for low-income and minority populations. We utilize a comprehensive measure of connectivity (Welch 2013), built on Graph Theory and data from the General Transit Feed Specification (GTFS) and American Community Survey, taking advantage of the variation in bus accessibility over two-time periods (2012 and 2017). We utilize regression models and GIS data visualization to examine the relationship between bus connectivity and poverty and race – asking whether connectivity is evenly distributed by economic status.

Despite the fact that public transit primarily serves low-income and minority populations, our findings suggest inequitable public transit connectivity by race and class, using a robust connectivity measure of distance from employment and other population centers. This outcome makes an even stronger case for increasing service levels to low-income/minority neighborhoods, as these groups have to travel further for employment than people in more connected neighborhoods.

Implication for Theory and Practice

This study has implications for both theory and practice. It not only confirms the expectations of the spatial mismatch hypothesis, the Critical Race Theory, and social construction framework, it also raises concerns about the further exclusion of minority communities from employment and economic opportunities. Our connectivity measure utilized the location of employment as a key factor. Therefore, block groups with higher rates of poverty and minority percentage tend to have lower access to employment. This underscores the influence that public transit has on socioeconomic standing, and raises many important social justice and economic concerns. We also find that improvements in the macro economy may exacerbate the problem of uneven distribution. We find a stronger negative correlation between poverty and connectivity in 2017 than 2012. The 2012 ACS data is a sample over the years 2008-2012, capturing a portion of the recovery from the great recession, while the 2017 data captures a period of economic expansion. Finally, the connectivity measure can be utilized in ex-ante analysis to assess equity in transportation system design.

These results highlight the importance of reviewing existing transportation funding modes, and urge policy-makers to include equity as an important factor to drive resources toward areas and people who need them the most. Adding lines and decreasing headways, especially in bus service, in areas with high percentages of low-income populations is key to enhance the cultural and economic activities of urban areas.

As with all quantitative studies, the data have limitations. When choosing a unit of measure using the ACS there is a tradeoff between error and scale. Socioeconomic data from the 5-year ACS is based on sampling and aggregation over time and space. Aggregation over block groups provides the smallest unit of aggregation for which our data is available. This same data is available at larger scales, such as the tract, which also have the advantage of smaller standard errors, but are significantly larger in size. Atlanta is a low-density city, making tracts large, so we chose block groups for this study. However, this increases our measurement error. Additionally, while connectivity is robust measure of transit service quality, it does not reflect the actual demand for destinations reachable via transit. Further research is needed to provide a more detailed analysis of demand based accessibility.

REFERENCES

- Alemán Jr, E. (2007). Situating Texas school finance policy in a CRT framework: How “substantially equal” yields racial inequity. *Educational Administration Quarterly*, 43(5), 525-558.
- Alexander, M. (2010). The war on drugs and the new Jim Crow. *Race, Poverty, and the Environment*, 17, 75-77.
- Altshuler, A. (2013). Equity as a factor in surface transportation politics. *Access: The Magazine of the University of California Transportation Center*, 42, 2-9.
- Banducci, S. A., Donovan, T., & Karp, J. A. (2004). Minority representation, empowerment, and participation. *Journal of Politics*, 66(2), 534-556.
- Belton, R. (2004). Title VII at forty: A brief look at the birth, death, and resurrection of the disparate impact theory of discrimination. *Hofstra Lab. & Emp.LJ*, 22, 431.
- Beyazit, E. (2011). Evaluating social justice in transport: Lessons to be learned from the capability approach. *Transport Reviews*, 31(1), 117-134.
- Blumenberg, E. (2004). En-gendering effective planning: Spatial mismatch, low-income women, and transportation policy. *Journal of the American Planning Association*, 70(3), 269-281.
- Blumenberg, E., & Manville, M. (2004). Beyond the spatial mismatch: Welfare recipients and transportation policy. *Journal of Planning Literature*, 19(2), 182-205.
- Blumenberg, E., & Ong, P. (2001). Cars, buses, and jobs: Welfare participants and employment access in Los Angeles. *Transportation Research Record: Journal of the Transportation Research Board*, (1756), 22-31.
- Boschmann, E. E., & Kwan, M. (2008). Toward socially sustainable urban transportation: Progress and potentials. *International Journal of Sustainable Transportation*, 2(3), 138-157.
- Delgado, R., & Stefancic, J. (2017). *Critical race theory: An introduction*. New York: NYU Press.
- Eberhardt, J. L. (2020). *Biased: Uncovering the hidden prejudice that shapes what we see, think, and do*. Penguin Books.

- Ellwood, D. T. (1986). The spatial mismatch hypothesis: Are there teenage jobs missing in the ghetto?. In *The black youth employment crisis* (pp. 147-190). Chicago: University of Chicago Press.
- Farber, S., Bartholomew, K., Li, X., Páez, A., & Habib, K. M. N. (2014). Assessing social equity in distance based transit fares using a model of travel behavior. *Transportation Research Part A: Policy and Practice*, 67, 291-303.
- Farley, J. E. (1982). Black male unemployment in US metropolitan areas: The role of black central city segregation and job decentralization. *Journal of Urban Affairs*, 4(3), 19-34.
- Farrington, J., & Farrington, C. (2005). Rural accessibility, social inclusion and social justice: Towards conceptualization. *Journal of Transport Geography*, 13(1), 1-12.
- Gobillon, L., Selod, H., & Zenou, Y. (2007). The mechanisms of spatial mismatch. *Urban Studies*, 44(12), 2401-2427.
- Golub, A., & Martens, K. (2014). Using principles of justice to assess the modal equity of regional transportation plans. *Journal of Transport Geography*, 41, 10-20.
- Hananel, R., & Berechman, J. (2016). Justice and transportation decision-making: The capabilities approach. *Transport Policy*, 49, 78-85.
- Howell-Moroney, M. (2005). The geography of opportunity and unemployment: an integrated model of residential segregation and spatial mismatch. *Journal of Urban Affairs*, 27(4), 353-377.
- Ihlanfeldt, K. R., & Sjoquist, D. L. (1998). The spatial mismatch hypothesis: a review of recent studies and their implications for welfare reform. *Housing policy debate*, 9(4), 849-892.
- Ingram, H., Schneider, A. L., & DeLeon, P. (2007). Social construction and policy design. *Theories of the Policy Process*, 2, 93-126.
- Jackson, K. T. (1987). *Crabgrass frontier: The suburbanization of the United States*. Oxford University Press.
- Kain, J. F. (1968). Housing segregation, negro employment, and metropolitan decentralization. *The Quarterly Journal of Economics*, 82(2), 175-197.

- Keating, L. (2001). *Atlanta: Race, class and urban expansion*. Philadelphia, PA: Temple University Press.
- Lucas, K. (2006). Providing transport for social inclusion within a framework for environmental justice in the UK. *Transportation Research Part A: Policy and Practice*, 40(10), 801-809.
- Martens, K., Golub, A., & Robinson, G. (2012). A justice-theoretic approach to the distribution of transportation benefits: Implications for transportation planning practice in the United States. *Transportation Research Part A: Policy and Practice*, 46(4), 684-695.
- Martens, K., & Hurvitz, E. (2011). Distributive impacts of demand-based modelling. *Transportmetrica*, 7(3), 181-200.
- Nelles, J. (2013). Regionalism redux: Exploring the impact of federal grants on mass public transit governance and political capacity in metropolitan Detroit. *Urban Affairs Review*, 49(2), 220-253.
- Ong, P. M. (2002). Car ownership and welfare-to-work. *Journal of Policy Analysis and Management*, 21(2), 239-252.
- Pasha, O. (2018). Social justice implications of municipal transportation apportionments in Massachusetts: A case of disparate impact. *Transport Policy*, 72, 109-115.
- Pasha, O., Wyczalkowski, C., Sohrabian, D., & Lendel, I. (2020). Transit effects on poverty, employment, and rent in Cuyahoga County, Ohio. *Transport Policy*.
- Pathak, R., Wyczalkowski, C. K., & Huang, X. (2017). Public transit access and the changing spatial distribution of poverty. *Regional Science and Urban Economics*, 66, 198-212.
- Rothstein, R. (2017). *The color of law: A forgotten history of how our government segregated America*. Liveright Publishing.
- Salamon, L. M. (2002). The tools approach and the new governance: Conclusion and implications. *The Tools of Government: A Guide to the New Governance*, 600-610.
- Sanchez, T. W., Stolz, R., & Ma, J. S. (2003). Moving to equity: Addressing inequitable effects of transportation policies on minorities.

- Schneider, A., & Sidney, M. (2009). What is next for policy design and social construction theory? *Policy Studies Journal*, 37(1), 103-119.
- Sidney, M. S. (2012). Contested images of race and place: The politics of housing discrimination. *Deserving and Entitled: Social Constructions and Public Policy*, 111.
- Steg, L., & Gifford, R. (2007). Sustainable transport and quality of life. *Building blocks for sustainable transport: Obstacles, trends, solutions* (pp. 183-202) Emerald Group Publishing Limited.
- Taylor, BD, Ong, PM (1995) Spatial mismatch or automobile mismatch? An examination of race, residence and commuting in US metropolitan areas. *Urban Studies* 32(9): 1453–1473.
- Thomopoulos, N., Grant-Muller, S., & Tight, M. (2009). Incorporating equity considerations in transport infrastructure evaluation: Current practice and a proposed methodology. *Evaluation and Program Planning*, 32(4), 351-359.
- Tyndall, J. (2017). Waiting for the R train: Public transportation and employment. *Urban Studies*, 54(2), 520-537.
- U.S. Census Bureau. (2018). *2014-2018 American Community Survey 5-year estimates*. Retrieved from: data.census.gov
- Wachs, M., & Taylor, B. D. (1998). Can transportation strategies help meet the welfare challenge? *Journal of the American Planning Association*, 64(1), 15-19.
- Welch, T. F. (2013). Equity in transport: The distribution of transit access and connectivity among affordable housing units. *Transport policy*, 30, 283-293.
- Wellman, G. C. (2014). Transportation apartheid: The role of transportation policy in societal inequality. *Public Works Management & Policy*, 19(4), 334-339.
- Wellman, G. C. (2015). The social justice (of) movement: How public transportation administrators define social justice. *Public Administration Quarterly*, 117-146.
- Williams, D. R., Neighbors, H. W., & Jackson, J. S. (2003). Racial/ethnic discrimination and health: Findings from community studies. *American journal of public health*, 93(2), 200-208.

