DISCLAIMER

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LIST OF AUTHORS

Lead PI:

Kari E. Watkins, Ph.D.
Georgia Institute of Technology
kari.watkins@ce.gatech.edu
0000-0002-3824-2027

Co-PI:

Noreen McDonald, Ph.D.
University of North Carolina, Chapel Hill
noreen@unc.edu
0000-0002-4854-7035

Eleni Bardaka, Ph.D.
North Carolina State University
ebardak@ncsu.edu
0000-0001-8306-4939

Ruth Steiner, Ph.D.
University of Florida
rsteiner@dcp.ufl.edu
0000-0001-7276-3742

Additional Researchers:

Ilir Bejleri, Ph.D.
University of Florida
ilir@ufl.edu
0000-0002-6498-7292

Simon Berrebi, Ph.D.
Georgia Institute of Technology
sberrebi3@gatech.edu
0000-0003-4338-6137

Abhinav Alakshendra, Ph.D.
University of Florida
alakshendra@dcp.ufl.edu
0000-0003-0153-0233

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ABSTRACT

With nationwide declines in public transportation ridership, transit may be falling behind in its ability to help cities deal with congestion. Increasing real-estate values are causing the economic displacement of low-income populations, those most closely associated with transit ridership. A plethora of new mobility options are providing alternatives for transit riders *who can afford them* and even for those who require subsidy. But how will access to transit, ridership, and congestion be impacted by these shifts in demographics and the introduction of new mobility services?

In thrust 1, the team assessed the impacts of low-income individuals and families moving to the periphery of communities, i.e., the suburbanization of poverty, on public transit. In addition, this thrust provided a detailed analysis of sociodemographic and accessibility changes over time. In thrust 2, the study team developed a novel approach to understand how levels of transit service and demographics impact transit ridership on a highly specific spatial and temporal scale. In thrust 3, the study team developed a better understanding of the interactions between public transit and transportation network company (TNC) providers. In thrust 4, the study team documented the rapid evolution of paratransit services available to access healthcare. Although the research in all four thrusts focused on specific areas of the southeast US, the results are applicable nationally to aid transit and regional planning agencies.

EXECUTIVE SUMMARY

This project includes researchers from four universities in the STRIDE partnership that together will address access to public transportation issues with specific contributions in suburbanization of poverty, Transportation Network Companies (TNC), healthcare access, and vulnerable populations. The research took place in four thrusts, each led by one of the primary researchers. It is of note that although this report is being published in its final form in 2021, all of the research took place prior to the COVID-19 global pandemic. Despite this, we feel the lessons take on even more importance as we seek a sustainable long-term future for public transportation.

In thrust 1, the research team investigated how changes in transit service and urban migration impacted job accessibility for low-income populations. The research team found that between 1990 and 2013, job accessibility in the Triangle region declined despite transit expansions. The authors conclude that the suburbanization of low-income population is the likely cause of declining job accessibility. This research informs how service expansion plans could maximize job accessibility in the future. Researchers shared their findings with GoTriangle, the regional transit agency, in order to help plan for future transit improvements.

In thrust 2, the research team investigated bus ridership trends in four cities between 2012 and 2018 on a hyper-local level. The research explored the impact of service frequency and demographic trends. The authors found that bus ridership is inelastic to changes in service frequency, i.e., each marginal bus added to a route will generate less than the average bus on the route. The authors also found that the bus ridership decline on a local level is correlated with the proportion of white residents. This research can help inform how service provision and demographic trends may affect bus ridership in the future. Researchers shared route-level ridership data in all four cities.

In thrust 3, the authors explored the partnership between transit agencies and ride-hailing company. The research evaluates the challenges and opportunities for transit agencies to leverage demand-responsive services. A geospatial model was developed to identify specific service gaps facing the transportation disadvantaged and opportunities for how improved TNC partnerships could potentially fill these gaps in metro Orlando. While these services are popular among transit riders, the authors raise their high operating costs as an important barrier to scaling up the relationship. These results may help determine how local government can facilitate mobility as a service.

In thrust 4, the research team focused on access to healthcare for paratransit users. Transportation is found to be a significant barrier to receiving health services. The authors conducted a national review of these emerging services and developed a typology of innovations including three strategies in which medical transportation could be provided by TNCs. The typology has been shared with practitioners nationwide. New mobility solutions promise cost saving potential for insurers and more reliable access for patients; however, it is unclear whether these services could be financially viable in low-density, non-urban areas.

jobs. The following model was established to account for the spatial difference in job demand and different travel modes:

$$A_i^G = \alpha_i A_i^{auto} + (1-\alpha_i) A_i^{tran} \tag{13}$$

where A_i^G is the general accessibility for people living in zone i to opportunities in all zones J; α_i is the proportion of the workers in zone i with at least one auto; A_i^{auto} and A_i^{tran} are the accessibility by car and transit, respectively, and are defined as:

$$A_i^{auto} = \sum_{j=1}^{J} \frac{E_j f\left(C_{ij}^{auto}\right)}{\sum_{k=1}^{J}\left[\alpha_k P_k f\left(C_{kj}^{auto}\right) + (1-\alpha_k) P_k f\left(C_{kj}^{tran}\right)\right]} \tag{14}$$

$$A_i^{tran} = \sum_{j=1}^{J} \frac{E_j f\left(C_{ij}^{tran}\right)}{\sum_{k=1}^{J}\left[\alpha_k P_k f\left(C_{kj}^{auto}\right) + (1-\alpha_k) P_k f\left(C_{kj}^{tran}\right)\right]} \tag{15}$$

where E_j is the number of employment opportunities in zone j; P_k is the number of jobseekers living in zone k; α_k is the proportion of workers in zone k with at least one auto; $f\left(C_{ij}^{auto\ or\ tran}\right)$ and $f\left(C_{kj}^{auto\ or\ tran}\right)$ are the impedance functions that determined by the travel cost of auto or transit between zone i/k and zone j.

In general, all the gravity-based measures in previous paragraph are well-accepted and widely used in current studies, since they reflect a joint effect of transportation systems ($f\left(C_{ij}\right)$) and land-use patterns (α_j) on accessibility (Dong et al., 2006). However, the gravity-based measure cannot capture the variations across individuals, since it assumes everyone has the same interests in all activities.

2.2.3.2 Infrastructure-based measures

Infrastructure-based measures mainly assess the performance of transport infrastructure as an indicator of the accessibility (Geurs and van Wee, 2004). In other words, this measure helps to find how a road, transport mode or other infrastructure connects an origin and a destination based on its characteristics. For example, in order to visualize how the light rail served the public in the San Francisco Bay Area, Cervero (1995) first developed a method to measure the areas with accessibility to light rail by all travel modes, which he named “catchment areas”. The catchment areas were defined as the contiguous census tracts that encompassed the origins of 90% of all access or egress trips to stations (Cervero, 1995). Similarly, Zuo et al. (2018) presented a practical approach for estimating the transit service catchment area by non-motorized modes (i.e., walking and bicycling) in the Cincinnati metropolitan area. The non-motorized accessibility to transit was determined by the connectivity and facilities of non-motorized transportation network. The estimation of transit service coverage involved two steps: (1) identifying the service coverage area that was accessible by pedestrians and bicyclists, and (2) estimating the population and jobs within the service area. Unlike the previous studies, Lei and Church (2010) defined the catchment areas by transit from the University of California, Santa Barbara (UCSB) as the areas that can be reached within a travel time threshold (0-15 min, 15-30 min, 30-45 min, 45-60 min, 60-75 min, 75-90 min, 95-105 min, and 105-

120 min). In addition, some studies have focused on assessing the importance of road facilities on accessibility. For example, Chandra et al. (2017) conducted a study measuring the accessibility of low-income workers from employment centers to transit stops by walking or biking at night, and they found that the street light poles played an important role. The following relationship was assumed:

$$A_i = \sum_k \frac{\Theta_k E_{i,k}}{T^{\alpha}_{i,k}}, \forall k \in 1,2,3,\dots,K \tag{16}$$

where A_i is the accessibility by walking or biking from all employment centers K to a transit stop i; Θ_k is a dummy variable indicating that the path between the employment center k and the transit stop i has continuous streetlight poles; $E_{i,k}$ is the number of jobs at the employment center k; α is a decay factor for walking or biking; $T^{\alpha}_{i,k}$ is the travel time between the employment center k and the transit stop i; K is the total number of employment centers around stop i within a threshold of walking or biking (0.25 mile and 0.5 mile, respectively).

Lin et al. (2014) proposed a more complex measure to estimate the elderly's accessibility to train stations by walking, personal vehicles, and bus. This study assumed that the accessibility was the sum of several weighted factors including distance, walking or driving route directness, land-use diversity, service and facility quality, parking location, and bus connection.

Furthermore, an infrastructure measure can also be an index that assesses the accessibility to several types of activities by any travel mode. As an example, Pyrialakou et al. (2016) established accessibility-level criteria by measuring the accessibility to each type of activity destination, including hospital, schools, recreational facilities, museums, and public libraries. Each destination had its own travel buffer based on travel time by a destination-specified travel mode to estimate accessibility (e.g., for large hospital, the radius of buffer is 9 miles, and the travel mode is auto). For each area, low accessibility indicated this area could not reach activity destinations within the given travel time by the given mode; medium accessibility indicated this area could not reach school and recreational facilities within the given travel time by walking but could reach other places by auto; high accessibility indicated this area could reach any activity destination within the given travel time by the given mode.

2.2.3.3 Person-based measures

Person-based accessibility measures analyze accessibility based on the individuals' characteristics (Geurs and van Wee, 2004) such as "the activities that an individual can participate within a given a constraint of time". More specifically, the possible spatial opportunities (e.g., supermarket, health center, school) that an individual might access could be identified based on the residential and work locations, the travel time constraints, and the travel mode. A main method that captures the individual-level accessibility is the space-time geography, which was first introduced by Hägerstraand (1970) to assess the influence of spatial, temporal, and personal constraints on people's movement patterns. The person-based measure usually requires abundant data of trips to estimate the spatial choices and impacts of constraints on choices. A main application of the person-based measure is assessing the accessibility to healthy food. As an example, Widener et al. (2013) conducted a study in Cincinnati, Ohio to measure the accessibility under time-space constraints to the supermarkets by a single-occupancy automobile from households residing in a food desert area. The supermarket interaction potential (SMIP) score, which quantifies the available time for shopping at a supermarket, was adopted as an index of accessibility. The study assumed that the higher the score was, the higher accessibility an individual had to the supermarket. The SMIP score for an individual who lives in TAZ i that works in TAZ j and shops at a supermarket in TAZ k is estimated as:

$$SMIP_{ijk} = max\left(0, B - \left(t_{jk} + t_{ki}\right)\right) \tag{17}$$

where B is the available time an individual has before he/she has to go home after work; t_{jk} is the travel time in minutes from work to the supermarket; t_{ki} is the travel time in minutes from the supermarket to home; Then, the possible time spent on shopping in the supermarket in the trips between home and general commuting destinations is quantified as:

$$SMIP_i = \sum_j P_j^i \sum_{k \in K} SMIP_{ijk} / n \tag{18}$$

where P_j^i is the proportion of commuters in TAZ i that works in TAZ j; K is the set of n supermarkets that have the largest $SMIP_{ijk}$ scores. After that, the study further analyzes the trips between home TAZ i and a set of supermarkets K using the home-to-supermarket interaction potential (HIP) score:

$$HIP_i = \sum_{k \in K} HIP_{ik} / n \tag{19}$$

where HIP_{ik} is the home-to-supermarket interaction potential score between a pair of TAZ i and a supermarket k and is estimated as:

$$HIP_{ik} = max\left(0, B - (t_{ik} + t_{ki})\right) \tag{20}$$

where t_{ik} and t_{ki} are the travel time to and from the supermarket k; B is the time budget for grocery shopping. Widener et al. (2015) conducted a follow-up study on the measure of accessibility by bus to the supermarkets from households residing in a food desert area. This study also adopted the interaction potential score to quantify the available time at supermarket. Considering the characteristic of walking, the study only includes the TAZs that are within two- miles from a bus stop.

A person-based measure can also capture the possible travel path of an individual by finding the probability of an individual being at an exact location. Horner and Downs (2014) established a density-based accessibility measure for assessing an individual's accessibility to potential opportunity locations based on time-geographic density estimation (TGDE). TGDE is a technique that can estimate the probable location of an object in space within a time slot (Downs, 2010). Horner and Downs (2014) first estimated the probabilities $f_t\left(x_{qk}\right)'$ that one individual q is at kth location between a pair of origin i and destination j:

$$f_t(x)' = PPT^*\left(\frac{t_p(i,x) + t_p(x,j)}{t(i,j) - t_a(i,j)}\right) \tag{21}$$

where PPT^* is the distance weighting function of the potential path tree; $t(i,j)$ is the time elapsed between origin i and destination j; $t_a(i,j)$ is the time spent at kth location; $t_p(,)$ is the minimum travel time between two locations. Then, an attractiveness factor O_k of each location k is introduced to estimate the accessibility level value to location k from location x, which was $f_t(x_{qk})' O_k$. The attractiveness factor O_k is bounded from zero to one. Finally, the accessibility value at location x is estimated by summing the accessibility level for each i − j pair:

$$A_{qk} = (N-1)^{-1} \sum_{i=1}^{N-1} f_t(x_{qk})' s_{ij}^{-1} O_k \tag{22}$$

where A_{qk}, which was bounded from zero to one, was the accessibility score for individual q to location k; N is the number of control points on dataset; s_{ij}^{-1} is the dimension of potential path tree for origin i and destination j. Higher score meant greater accessibility. Thus, the total accessibility of all individuals to an activity was:

$$S_k = \sum_q A_{qk} \tag{23}$$

Recently, Lee et al. (2018) suggested that previous studies have not fully considered the spatiotemporal changes of the population by using the census data. Thus, in their study of accessibility to bus system, Lee et al. (2018) used the phone-based hourly floating population that is defined as the population who transmit mobile signals in a grid-cell unit over a one-hour period instead of the population data in census. This study used mobile phone-based GPS information in Gu-district, Seoul, Korea to obtain the floating population. Also, the impacts by the frequency of bus on accessibility is captured by comparing the accessibility at different times of day, including morning rush hour, evening rush hour, and late night.

Furthermore, Järv et al. (2018) measured dynamic accessibility to food by public transportation in Tallinn, Estonia, while included both the spatial-temporal information of the individual, and the temporal of the public transportation and grocery stores (transit schedule and store opening hour).

2.2.3.4 Utility-based measures

Utility-based measures are based on random utility theory: individuals choose the alternative with the highest utility. Random utility models can measure the amount of "benefits" individuals derive from access to the spatially distributed activities by using the expected maximum utility as the measure of accessibility (Geurs and van Wee, 2004; Dong et al., 2006; Lei and Church, 2010). The accessibility using the utility-based measure is defined as:

$$E\left(max_{i \in C_n} U_{in}\right) = ln \sum_{i \in C_n} exp(\mu V_{in})/\mu \tag{24}$$

where V_{in} is the systematic component of utility U_{in} for individual n choosing destination i from the choice set C_n. Usually, a multinomial logit model of destination choice or a nested logit model of the destination and mode choice is used to measure the accessibility. The utility-based measure is individual-based and captures the impact of all modes on accessibility.

A case study of morning commuter accessibility to work in King County, Washington adopted the utility-based measure (Handy and Niemeier,1997). The choice set c in this study was defined as a combination of travel mode and destination. Then, the utility function $V_{n(c)}$ included the cost of travel ($e_{n(c)}$), household income (Y_n), socioeconomic characteristics of the individual n (Z_n), transportation choice attribute for choice c ($T_{n(c)}$), destination choice attribute ($D_{n(c)}$), and unobserved part (ε_n):

$$V_{n(c)} = f\left(\frac{e_{n(c)}}{Y_n}, Z_n, T_{n(c)}, D_{n(c)}, \varepsilon_n\right) \tag{25}$$

The accessibility contribution of a specific variable is the logsums difference between before and after removing that variable from Equation 25; for example, to compare the accessibility contribution of walking mode, the walking mode was removed from the transport mode and then compared the logsums difference. The difference in logsums can be estimated as:

$$\delta v_n = -\frac{1}{\lambda}\left[ln \sum exp\, V_n n(c)\right]_{V_{n(c)}^{B}}^{V_{n(c)}^{A}} \tag{26}$$

Derived from random utility theory, Dong et al. (2006) established a new measure of accessibility of an individual, called the activity-based accessibility (ABA) measure, and adopted it in a case study in Portland, Oregon. Different from the other random utility measures, the choice set in ABA measure was a set of activity schedules, describing all possible schedule of activities through a day, given individuals' residential location. Thus, accessibility was assumed to be the activity schedule with the maximum utility. By using the day activity schedule (DAS) model system, ABA measured an individual's accessibility to all involved activities by taking the trip characteristics (e.g., scheduling and trip chaining) into consideration in addition to the basic variables in the other measures (e.g., travel time, distance and etc).

2.3 METHODOLOGY

Although there are different ways to measure accessibility, the gravity-based measure has been widely used (Shen, 1998; Hu, 2015), because it reflects the joint effect of transportation systems and land-use patterns on accessibility (Dong et al., 2006). Gravity measures are adopted in this study to estimate the accessibility to transit and qualified jobs by transit for low-income and higher-income populations at the census block group level over time in different geographical regions in the Triangle region. We hypothesize that longer travel time to opportunities, including bus stops and qualified jobs, is equivalent to lower accessibility.

2.3.1 Accessibility to transit

We assume that accessibility to transit A_{it} for the individuals in zone i at year t is the sum of products of number of transit stops a_{jt} and friction function $f\left(C_{ijt}\right)$ in all zones J, as suggested by the gravity model (Hansen,1959):

$$A_{it} = \sum_{j=1}^{J} a_{jt}\, f\left(C_{ijt}\right),\ i,j = 1,\ldots,J \tag{27}$$

where t includes 1995, 2006, and 2015; a_{jt} is the number of bus stops in zone j at year t; $f\left(C_{ijt}\right)$ is an impedance function of walking time at year t from zone i to zone j. We assume travelers are not sensitive to the travel cost within a certain threshold (e.g. distance and travel time), which results in relatively higher accessibility compared to the trips beyond that threshold.

Based on previous studies, travelers accessing transit have varies maximum walking distances according to several studies that investigated the walking distances to transit in North American cities (Lam and Morrall, 1982; Canadian Urban Transit Association, 1993). However, most transit users (over 75%) walked 0.25 mile or less to a bus stop (Brinckerhoff, 2013). Assuming that travelers walk at an average speed of 3 miles per hour, a 0.25-mile distance is equivalent to a walking time of 5 minutes. Thus, we assume that if a bus stop is within a 5-minute walk of an individual's residence location, this individual experiences low friction when accessing this stop, which makes $f\left(C_{ijt}\right)$ equal to 1. If walking time is more than 5 minutes, we use a distance decay function to capture impedance. As suggested by previous studies (Skov-Petersen, 2001; Geurs and van Wee, 2004; Foth et al., 2013), the decay function is estimated as a negative exponential function of the inverse relative cumulative trip frequency and travel time. Data on walking time to bus stops are available from the Greater Triangle Travel Study conducted in 2006. The same friction function is used for all analysis years due to limited data availability for other years:

$$f\left(C_{ij}\right) = \begin{cases} 1 & if\ travel\ time \leq 5\ min \\ \alpha e^{-\beta C_{\{ij\}}} & if\ travel\ time > 5\ min \end{cases} \tag{28}$$

where α equals 2.3142 and β equals -1.199.

2.3.2 Accessibility to employment by transit

As for measuring the accessibility by transit to qualified jobs, we adopt the measure developed by Shen (1998) to capture the spatial distribution of both demand and supply of qualified jobs:

$$A_{it} = \sum_{j=1}^{J} \frac{a_{jt} f\left(C_{ij}\right)}{D_{jt}},\ i,j = 1,\ldots,J \tag{29}$$

where A_{it} is the accessibility to qualified jobs in all zones J for job seekers living in zone i at year t; a_{jt} is the number of qualified jobs in zone j at year t; D_{jt} is the demand for jobs in zone j at year t:

$$D_{jt} = \sum_{k=1}^{J} P_{kt} f\left(C_{kj}\right),\ k,j = 1,\ldots,J \tag{30}$$

P_{kt} is the number of job seekers living in zone k seeking the same type of jobs in zone j at year t; C_{ij} and C_{kj} are the travel time by transit between zone i/k and zone j at year t.

We use the average travel time to work by bus from the Greater Triangle Travel Study in 2006 as our cut-off threshold in the friction function, which is 35-minute for the low-income population and 25-minute for the higher-income population. It is worth noting that in order to capture the difference of the travel behavior between the low-income and higher-income population, we estimate different friction function for each group of population based on the survey data in 2006.

$$f(C_{ij}) = \begin{cases} 1 & if\ travel\ time \leq t_m\ min \\ \alpha e^{-\beta C_{\{ij\}/kj}} & if\ travel\ time > t_m\ min \end{cases}$$

where m is the low-income status indicator that equals to 1 when the individual is low-income; and 0, otherwise; when m = 0, α = 0.436901 and β = 0.047551; when m = 1, α = 0.57359 and β = 0.03988; tm = 35 when m = 1, and tm = 25 when m = 0.

The travel time in all friction functions refers to center-to-center network travel time between the census block group of residential and bus stop/job, which is estimated in ArcGIS. The travel time by public transit is estimated using the “Add GTFS to a network dataset” toolbox. The General Transit Feed Specification (GTFS) data in 2015 is obtained from TransitFeeds, which is a public GTFS source website (TransitFeeds, 2015). We rebuilt the 2006 GTFS based on historic hard-copy maps provided by local transit agencies in the RTP area.

2.4 DATA AND DESCRIPTIVE ANALYSIS

The study is conducted for the Triangle region of North Carolina. As shown in Figure 1, the area includes ten counties: Chatham, Durham, Franklin, Granville, Harnett, Johnston, Nash, Orange, Person, and Wake. The Triangle region is well-known for the Research Triangle, anchored by the three universities: North Carolina State University, Duke University, and the University of North Carolina at Chapel Hill. Multiple public transportation agencies, working as a partner system, currently serve the Triangle region under the joint GoTransit branding. Triangle Transit, known as the Triangle Transit Authority (TTA), works in cooperation with all transit systems mentioned above by offering transfers between its routes and those of the other systems. With high population migration because of numerous opportunities (i.e., jobs, educational institutions), transit agencies have been striving to expand the transit network to provide access and reduce the burden on the road network.

Figure 2-1: County Boundary in Study Area

In this section, we first introduce the geographical area definitions used in our study to classify the city center, suburban and rural areas[3]. Then, we present the distribution of poverty rate in different geographical areas in 1990, 2000 and 2013 to reveal any changes in the spatial distribution of poverty. We also plot the difference of poverty rate between 1990 and 2000 and between 2000 and 2013. Last, we present the distribution of both low-income workers/jobs and higher-income workers/jobs to find the areas with the most unbalanced job/worker rate. The term "low-income" in this study includes two types, "low-wage" and "low-skilled"; these definitions will be introduced in the following section.

2.4.1 Geographical Area Definitions

Our study uses a combined definition by Cooke and Marchant (2006) and United States Census Bureau (2015) to define the city center, urban/suburban and rural areas: the city center is defined as the census block groups located in the center with greater than 400 pre-1940 housing units per square mile; and any adjacent block groups that have more than 200 pre-1940 housing units per square mile and at least 1,000 people per square mile (Cooke and Marchant, 2006). The urban/suburban areas are defined as the rest of the block groups within the census urban boundary except the city center. The rest of the block groups in our study area are categorized as rural based on the Census definition. Based on these definitions, the changes in the geographical areas and transit networks are identified between 1990 and 2010. The built year of housing, population density, and boundary data are retrieved from the Census and American Community Survey (ACS). Due to the lack of housing structure year data, we use the 2013 ACS data set as an approximation of 2010 data. The changes in geographical areas along with the transit network in each decade is shown in Figure 2 and presented in Table 2. It should be noted that historical transit network data are available only for the years 1995, 2005, 2010 and after 2015. Thus, we use the transit data in 1995 and 2005 as approximated transit networks in 1990 and 2000, respectively. The transit network data are provided by the Institute for Transportation Research and Education (ITRE).

[3] We put the selection process of geographical area definitions in the Appendix

Table 2-2 - Changes in size and transit network length of different area types over time

Total	Area(Sq. Mile)			Transit Lenth (Mile)				
	City Center	Urban/Suburban	Rural		City Center	Urban/Suburban	Rural	Total
1990	23.71	289.2	5328.57	1995	253.2	587.06	143.22	966.17
2000	23.88	537.77	5079.83	2005	360.28	1087.24	492.72	1913.33
2010	24.17	863.52	4753.78	2010	396.5	1191.31	604.65	2164.48
90/00	0.72%	85.95%	-4.67%	95/05	42.29%	85.20%	244.03%	98.03%
00/10	1.21%	60.57%	-6.42%	05/10	10.05%	9.57%	22.72%	13.13%

According to Figure 2 and Table 2, the size of urban/suburban areas increases significantly in our study area between 1990 and 2010. As we can see in Figure 2, the development of the transit network seems to follow the expansion of the suburban areas. The areas within Wake, Durham, and Orange County experienced a remarkable increase in the size of both suburban areas and transit networks. The development of the transit network in these areas mainly improved express routes and local routes for certain destinations. Express routes connect major cities in Wake County, including Raleigh and Cary, and major cities in Durham/Orange County, including the cities of Chapel Hill and Durham, directly. The local routes offer local transit services that connect with activity centers, such as the airport and shopping malls. However, the extension of the transit system slows down between 2005 and 2010; the average increase rate per year of this period is only 26.79% of the period between 1995 and 2005, while the major extension happened in the rural area.

2.4.2 Spatial distribution of the low-income population

In this study, due to lack of migration data, we assume that any substantial net increase in the low-income population rate in the suburban areas represents “suburbanization of poverty.” Similar to previous studies, we investigate the changes in average low-income population rate in each geographical area during each study year. The low-income population is the population below the federal poverty limit as defined by the US Census in 1990, 2000, and 2013. Since the geographical definition of city center, urban/suburban, and rural is changing over time, we use the 1990 geographical definition for the whole study period to compare the status of low-income and higher-income population in each geographical area at the same scale. Figure 3 shows the percentage of low-income population in each census block group in each study year. Additionally, we use the local Moran’s I statistic to identify local spatial autocorrelation for changes in poverty rate in our study area. The local Moran’s I analysis presents the statistically significant clusters of similar values of poverty rate, providing additional insights in the spatial distribution of poverty.

Table 2-3 - Changes in the Proportion, Population, and Density of Low-income and Higher-income Population Over Time by Geographical Area

	Rate		Total Population		Population Density	
	Low-	Higher-	Low-	Higher-	Low-	Higher-
City Center						
1990	0.228	0.703	20732	58462	1662.8	3822.2
2000	0.217	0.759	20906	60360	1098.14	2990.7
2013	0.328	0.672	27186	54495	1360.4	2643

90/00	-5%	8%	1%	3%	-34%	-22%
00/13	51%	-11%	30%	-10%	24%	-12%
Urban/Suburban						
1990	0.079	0.878	33469	354824	220.32	1804.6
2000	0.097	0.8875	51433	443788	344.43	2158
2013	0.165	0.835	92630	513486	568.54	2387
90/00	23%	1%	54%	25%	56%	20%
00/13	70%	-6%	80%	16%	65%	11%
Rural						
1990	0.101	0.875	62881	494579	34.18	250.28
2000	0.095	0.903	78971	742395	45.03	410.24
2013	0.14	0.86	148851	1055310	96.71	683.5
90/00	-6%	3%	26%	50%	32%	64%
00/13	47%	-5%	88%	42%	115%	67%

The local Moran's I analysis identifies five clusters: (i) a statistically significant cluster of high values (HH), (ii) a statistically significant cluster of low values (LL), (iii) statistically significant outliers in which a high value is surrounded primarily by low values (HL), (iv) statistically significant outliers in which a low value is surrounded primarily by high values (LH), and (v) not statistically significant neighbors. Table 3 presents the average rate, total population and population density of low- income / higher-income population in different geographical areas.

Overall, the city center in our study area has the highest average rate and density of the low- income population since 1990. We find a clear trend of suburbanization of poverty between 1990 and 2000, since the average rate of low-income population increases in the urban/suburban area, while it decreases in the other geographical areas during this decade (Table 3). In addition, the increase in the low-income population and the density of the low-income population are also the greatest in urban/suburban areas during this period. Between 2000 and 2013, all geographical areas experience a significant increase in the average rate of the low-income population, while the increase in urban/suburban remains the highest. Moreover, according to Figure 3 and 4, we find that the edges of the city center in both Wake and Durham County have substantial increase in the low-income population and always have high-high clusters of low-income population. The rural areas have the highest increase in the low-income population and density of the low-income population between 2000 and 2013. The rate of the higher-income population does not have a significant change compared to the low-income population in the Triangle region between 1990 and 2013. Interestingly, the density of higher-income population decreases in the city center for both time periods, while we see a substantial increase in the rural areas.

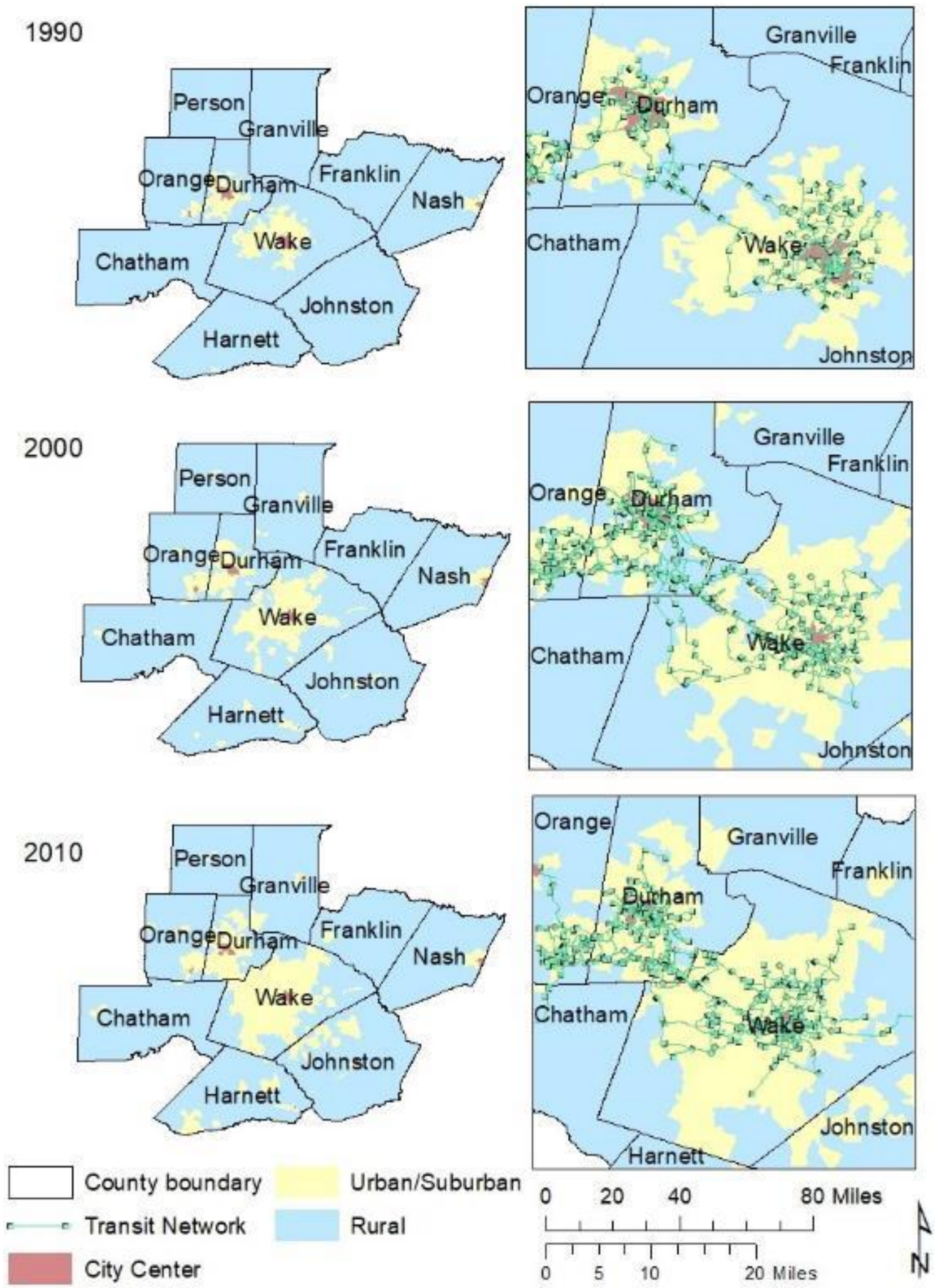


Figure 2-2: Change in Each Type of Geographical Area and Transit Network Between 1990 and 2010 in the Triangle region, NC

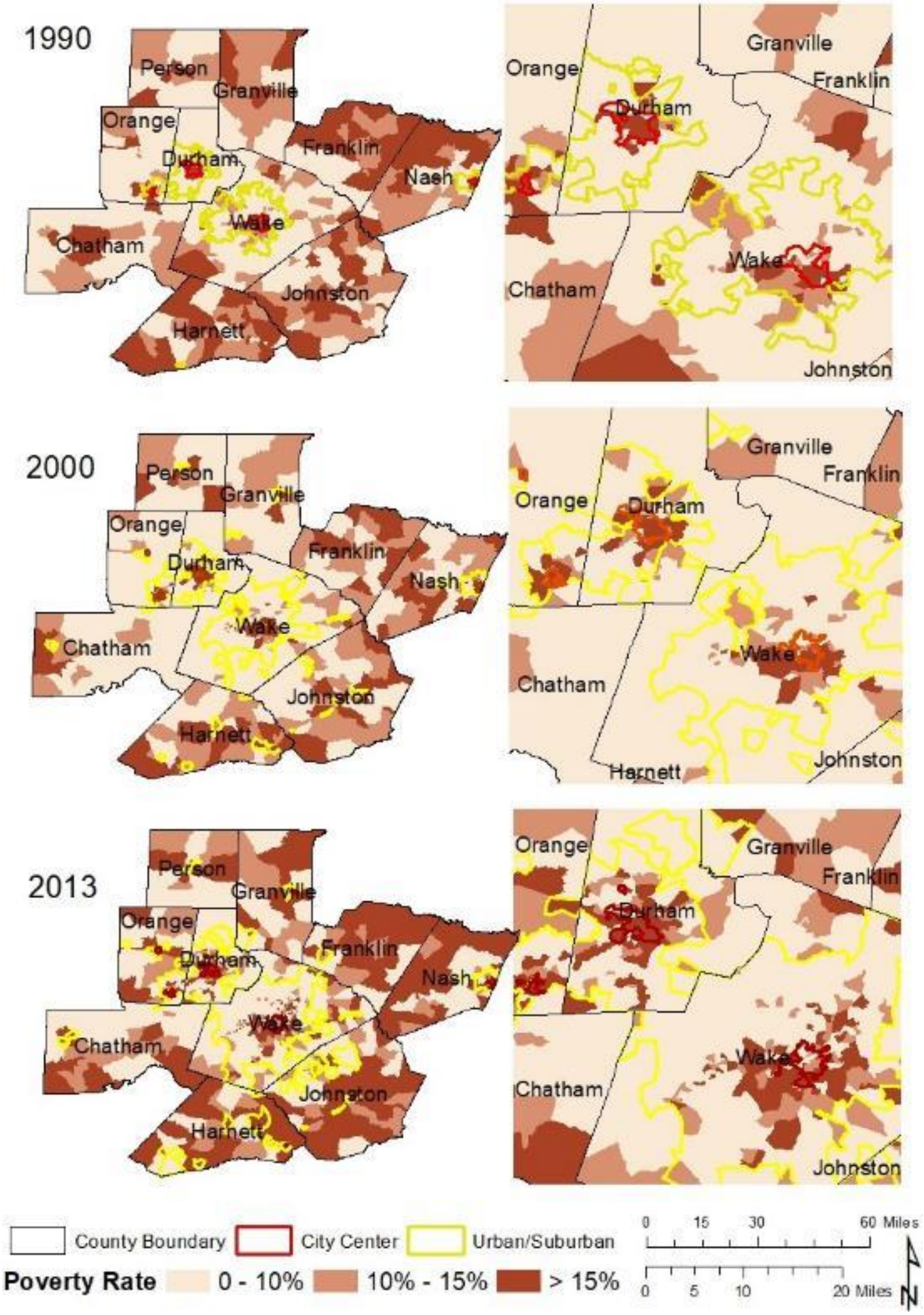


Figure 2-3: Percentage of Low-income Population in Different Types of Geographical Areas from 1990 to 2013

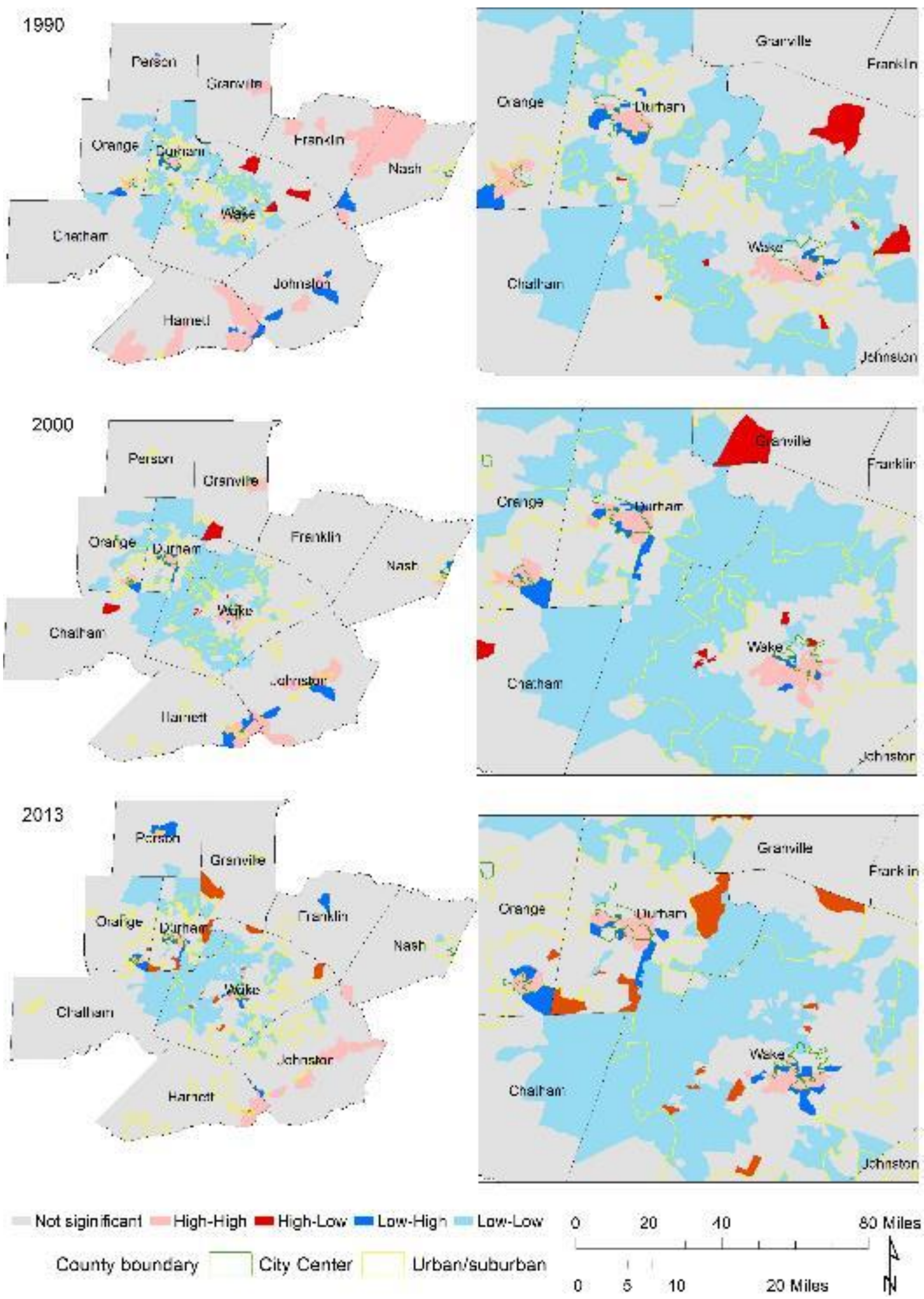


Figure 2-4: Cluster of Rate of Low-income Population in Different Types of Geographical Areas from 1990 to 2013

2.4.3 Low-income workers and jobs

In this study, the low-income population is assumed to be associated with accessing two types of jobs, the low-wage and low-skilled jobs. Thus, we mainly focus on the accessibility of the low-wage and low-skilled workers to their corresponding type of jobs. In addition, the accessibility results between the low-income and the higher-income workers are compared in order to understand the relative changes. A combined definition based on Longitudinal Employer-Household Dynamics (LEHD) and Foth et al. (2013) is used to identify the low-wage and low-skilled jobs. A low- wage job is defined as a job offering a monthly wage lower than $ 1,250. The jobs with higher wages are referred to as high-wage jobs. Following the study by Foth et al. (2013), a low-skilled job is defined as a job in the sectors of utilities (NAICS 22), manufacturing (NAICS31-33), wholesale trade (NAICS 42), retail trade (NAICS 45-55), and transportation and warehouse (NAICS 48-49). The population working in each type of job are defined as the low-wage workers and low-skilled workers, respectively. The employment data are retrieved from the Longitudinal Employer-Household Dynamics (LEHD) database. This data includes individual original-destination data, individual residence area characteristics data, and individual workplace area characteristics data between 2002 and 2015. In our study, the analysis uses individual residence area characteristics data and individual workplace area characteristics data in 2006 and 2015. Figure 5 and 6 present the spatial distribution of the low-wage/skilled workers and results of a local Moran's I analysis in 2006 and 2015, respectively, while Figure 7 and 8 present these results for the low-wage/skilled jobs. The majority of low-wage/skilled workers are clustered in the rural areas in both years. Some of low-wage workers are also clustered around the city center. Both types of jobs are randomly distributed and do not have significant clusters compared to that of workers. We further present the low-income job/worker ratio of each census block group in Figure 9. We assume that a census block group with more than three jobs per worker has a high opportunity to find a satisfying job, while a census block group with less than one job per worker has a low opportunity. The rest of census block groups have a fair opportunity to find a satisfying job for the job seekers. As shown in Figure 9, the majority of rural areas lack the opportunity to find a satisfying number of jobs for both low-wage and low-skilled workers, while no obvious improvements are observed in 2015. Census block groups with a fair or high opportunity to qualified low-income jobs are found to cluster in the city center and urban/suburban areas. The areas between Wake and Durham County have a high opportunity to find satisfying jobs for low-income workers. These results suggest that there is an unbalanced relationship between demand and supply of qualified jobs within census block groups in the study area. Additional analysis of the numerical data in each geographical area is presented in Table 4 and Table 5.

Table 4 and Table 5 summarize the average rate of workers/jobs, population/number of jobs, and population/job density, respectively. Both low-income and higher-income worker and job rates in each geographical area do not substantially change between 2006 and 2015. Overall, the city center still has the highest density of both types of jobs compared to the other areas from 2006 to 2015. Moreover, the density of each type of worker is much smaller than their qualified jobs, which means job seekers can have more chances to find satisfying jobs. However, the job density for both types of jobs is decreasing over time in the city center. Interestingly, the number of high-wage and high-skilled workers increases by 15% and 13%, respectively, while the low-wage and low-skilled workers decreases by 5% and 4%, respectively, in the city center from 2006 to 2015. It is worth mentioning that the rural areas have the highest increase in the density of all types of workers. There are small differences between the rates of workers and jobs, but unbalanced demand and supply still exists between qualified workers and jobs. Rural areas experience lower increase in qualified jobs than actual demand, especially for the high-wage and high-skilled workers. In summary, the density of both low-income and higher-income workers in urban/suburban and rural areas is higher than their corresponding qualified jobs, which in turn results in commuting across different geographical areas by job seekers looking for more job opportunities.

Table 2-4 - Changes in Workers and Jobs with Different Income Over Time in Different Geographical

	Rate				Total Population				Population Density			
	Low-wage		Non-low-wage		Low-wage		Non-low-wage		Low-wage		Non-low-wage	
	Worker	Job	Worker	Job	Worker	Job	Worker	Job	Worker	Job	Worker	Job
City Center												
2006	0.31	0.31	0.69	0.69	10754	23669	24858	84766	626	943	1433	3195
2015	0.28	0.29	0.72	0.71	10011	25226	28214	72065	592	924	1652	2274
06/15	-10%	-6%	5%	3%	-7%	7%	14%	-15%	-5%	-2%	15%	-29%
Urban/Suburban												
2006	0.25	0.33	0.75	0.67	101036	123131	315355	333619	363	338	1376	927
2015	0.23	0.30	0.77	0.70	103149	128914	357550	463229	362	337	1168	1086
06/15	-8%	-10%	3%	5%	2%	5%	13%	39%	0%	0%	-15%	17%
Rural												
2006	0.25	0.31	0.75	0.69	74134	60184	223824	188153	35	34	112	93
2015	0.23	0.27	0.77	0.73	92445	68379	334731	255865	53	38	210	132
06/15	-9%	-10%	3%	5%	25%	14%	50%	36%	49%	13%	88%	42%

Table 2-5 - Changes in Workers and Jobs with Different Skills Over Time by Geographical Area

	Rate				Total Population				Population Density			
	Low-skill		Non-low-skill		Low-skill		Non-low-skill		Low-skill		Non-low-skill	
	Worker	Job	Worker	Job	Worker	Job	Worker	Job	Worker	Job	Worker	Job
City Center												
2006	0.26	0.23	0.74	0.77	9103	19531	26509	88904	513	588	1546	3550
2015	0.23	0.21	0.77	0.79	8446	11477	29779	85814	492	395	1752	2803
06/15	-11%	-6%	4%	2%	-7%	-41%	12%	-3%	-4%	-33%	13%	-21%
Urban/Suburban												
2006	0.28	0.24	0.72	0.76	116984	107268	299407	349482	401	251	1040	1014
2015	0.25	0.24	0.75	0.76	111399	110579	349300	481564	367	259	1163	1164
06/15	-13%	-1%	5%	0%	-5%	3%	17%	38%	-8%	3%	12%	15%
Rural												
2006	0.34	0.30	0.66	0.71	98521	102551	199437	145786	46	51	101	76
2015	0.29	0.30	0.71	0.70	122477	126224	304699	198020	70	63	192	107
06/15	-13%	3%	6%	-1%	24%	23%	53%	36%	54%	24%	90%	41%

2.5 ACCESSIBILITY ANALYSIS

In this section, we first present the relationship between accessibility to transit and poverty rate. Second, we present and compare the results of accessibility by transit to qualified employment by people with different income (low and high-wage) and with different skilled jobs (low and high- skill) in 2006 and 2015, respectively. Third, we summarize the results and discuss conclusions.

2.5.1 Accessibility to transit and suburbanization of poverty

This section presents the relationship between accessibility to transit and poverty status in each geographical area. Figure 10 shows the spatial distribution of the poverty rate deciles in 1990, 2010, and 2015. Each decile contains 10% of the census block groups included in our study area in a specific year. The darkest color represents the census block decile with the highest poverty rate. About 55% of the block groups in the 10th decile in 1990 no longer have the highest poverty rate in 2000. The proportion of shifted block groups of the 10th decile is 20 percentage points higher between 2000 and 2015 compared to the previous decade. An increase in the block groups with the higher poverty rate can be observed in urban/suburban areas, while the city centers experience a decrease. This result represents a suburbanization trend of the areas with the highest poverty rate from 1990 to 2015. Such results may indicate that the low-income population is more attracted to reside in the urban/suburban areas compared to all the other areas.

In order to visualize the change in poverty rate in each geographical area, the percentage point differences of poverty rate between 1990/2000 and 2000/2015 are displayed in Figure 11. Overall, the poverty rate is decreasing in most areas, while it increases in some urban/suburban areas between 1990 and 2000. Between 2000 and 2015, the majority of the study area has an increase in poverty rate. Especially, the urban/suburban area experiences a higher increase in poverty rate compared to the previous decade. Moreover, the poverty rate in the city center in Wake and Durham County is always decreasing between 1990 and 2015.

Figure 12 displays the spatial distribution of accessibility to transit deciles in 1990, 2000, and 2015. The darkest red represents the census block groups with the highest accessibility to transit. In general, the closer the census block group to a bus stop, the higher accessibility it has. As indicated in the descriptive analysis section, the transit development seems to follow the expansion of the urban/suburban areas. Thus, accessibility to transit also increased across the urban/suburban areas in addition to the city center over time. According to the percentage change of accessibility to transit between 1995/2006 and 2006/2015 presented in Figure 13, the boundaries of the urban/suburban areas are found to have a substantial increase in accessibility to transit over time. Specifically, in addition to the development in Raleigh–Durham–Chapel Hill, Hillsborough in Orange County seems to become as a new center with good accessibility to transit.

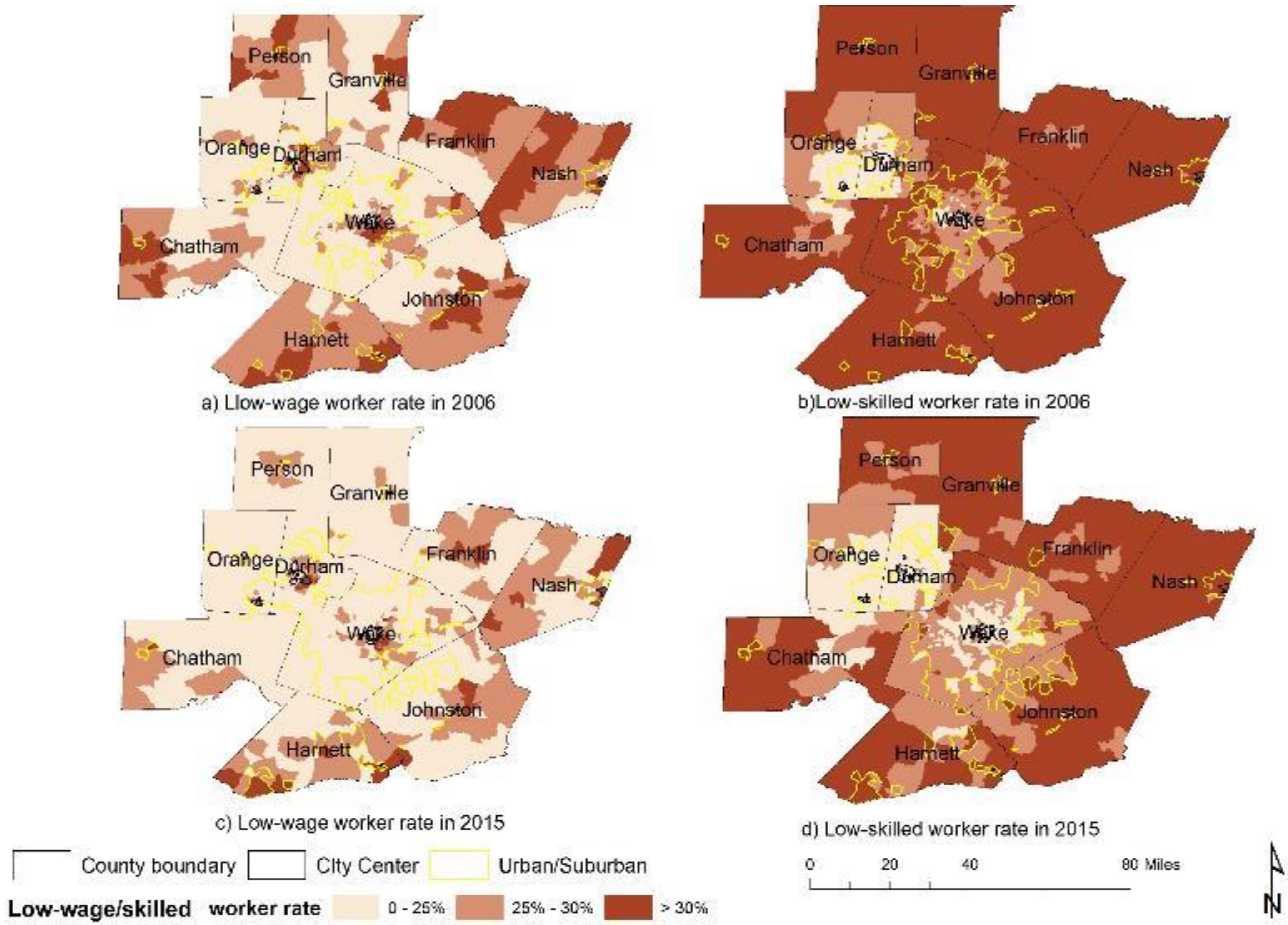


Figure 2-5: Rate of Low-wage/skilled Worker in Different Types of Geographical Areas in 2006 and 2015

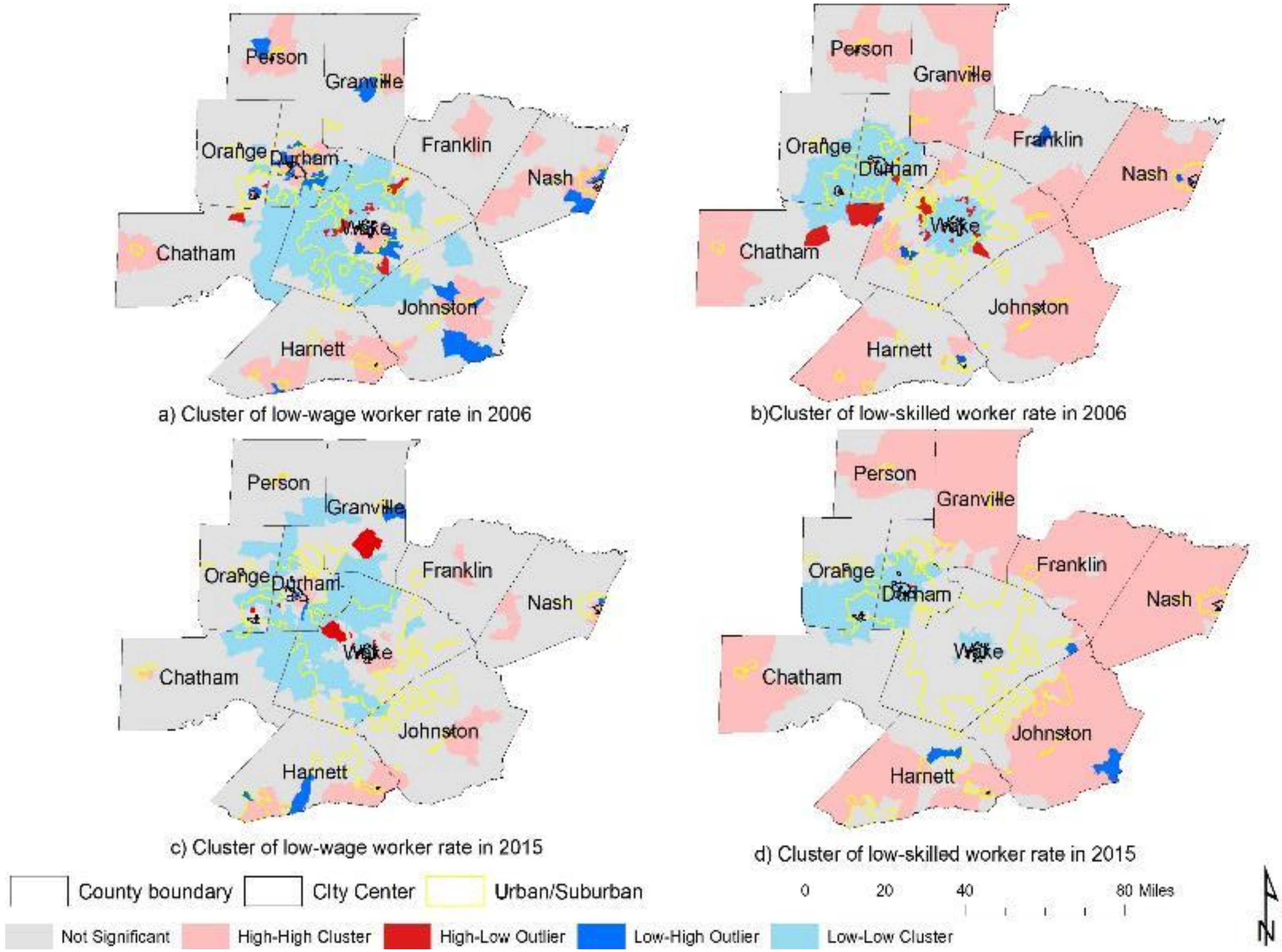


Figure 2-6: Cluster of Rate of Low-wage/skilled Worker in Different Types of Geographical Areas in 2006 and 2015

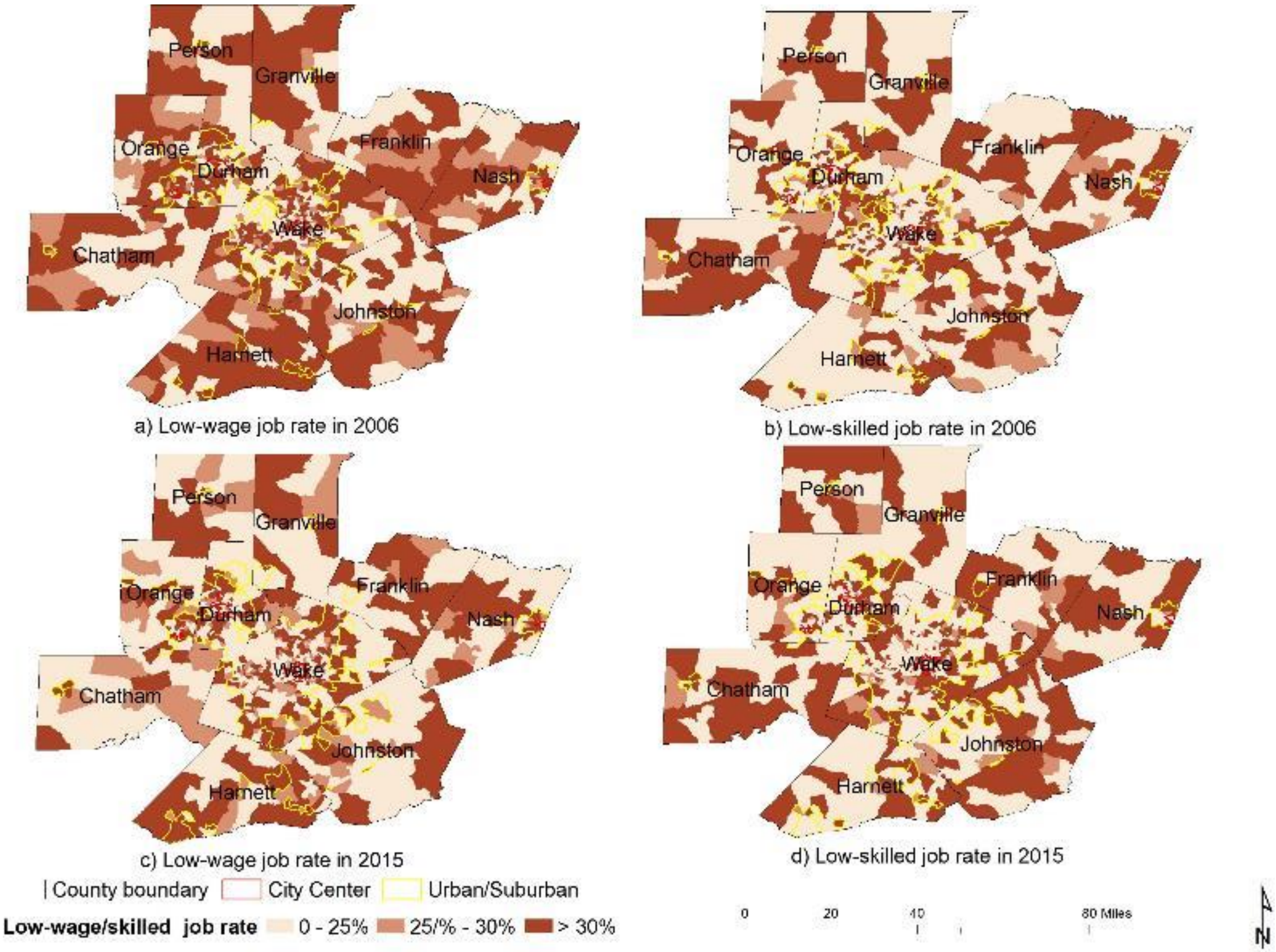


Figure 2-7: Rate of Low-wage/skilled Job in Different Types of Geographical Areas in 2006 and 2015

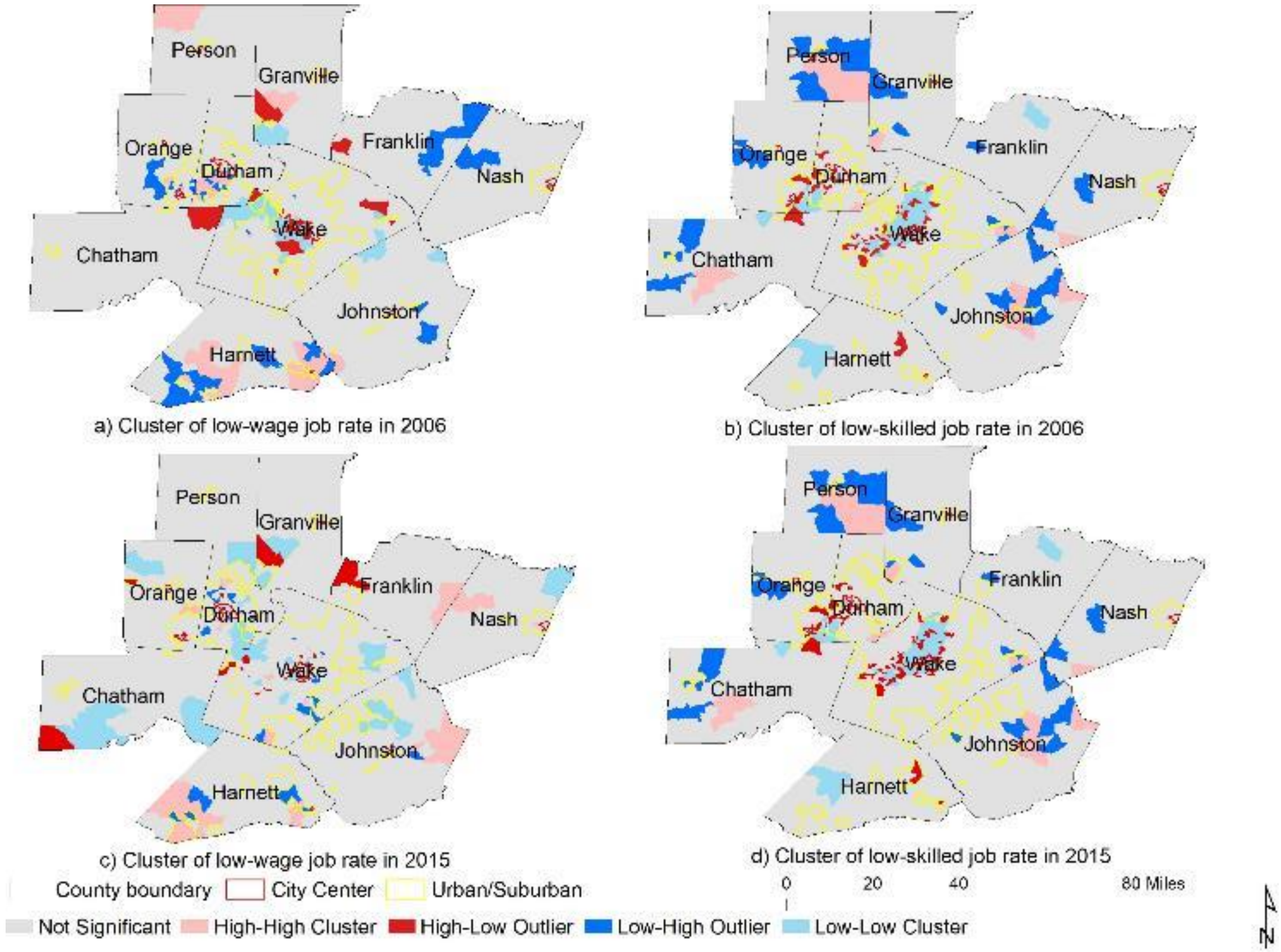


Figure 2-8: Cluster of Rate of Low-wage/skilled Job in Different Types of Geographical Areas in 2006 and 2015

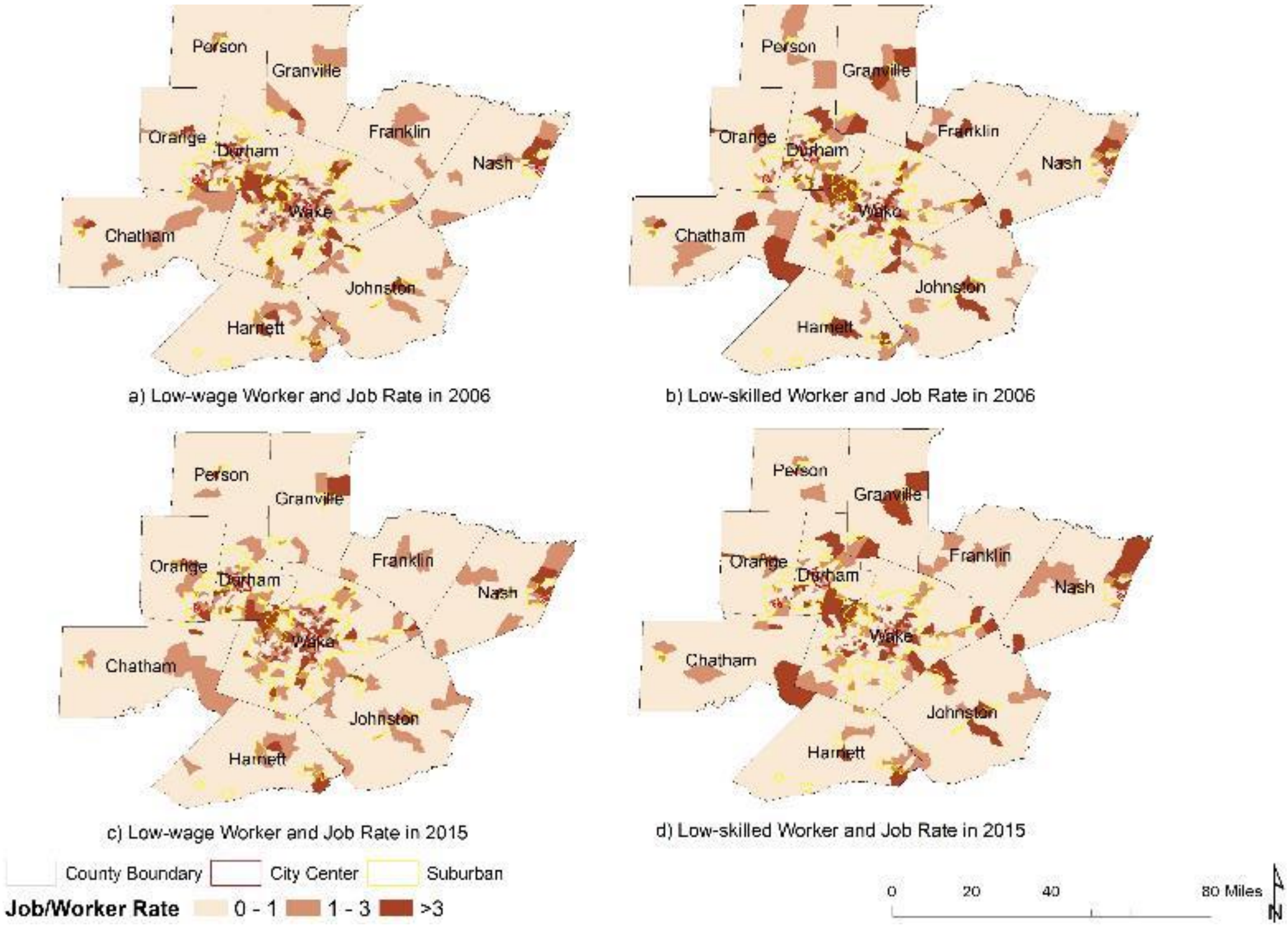


Figure 2-9: Job/Worker Ratio in Different Geographical Areas in Different Year

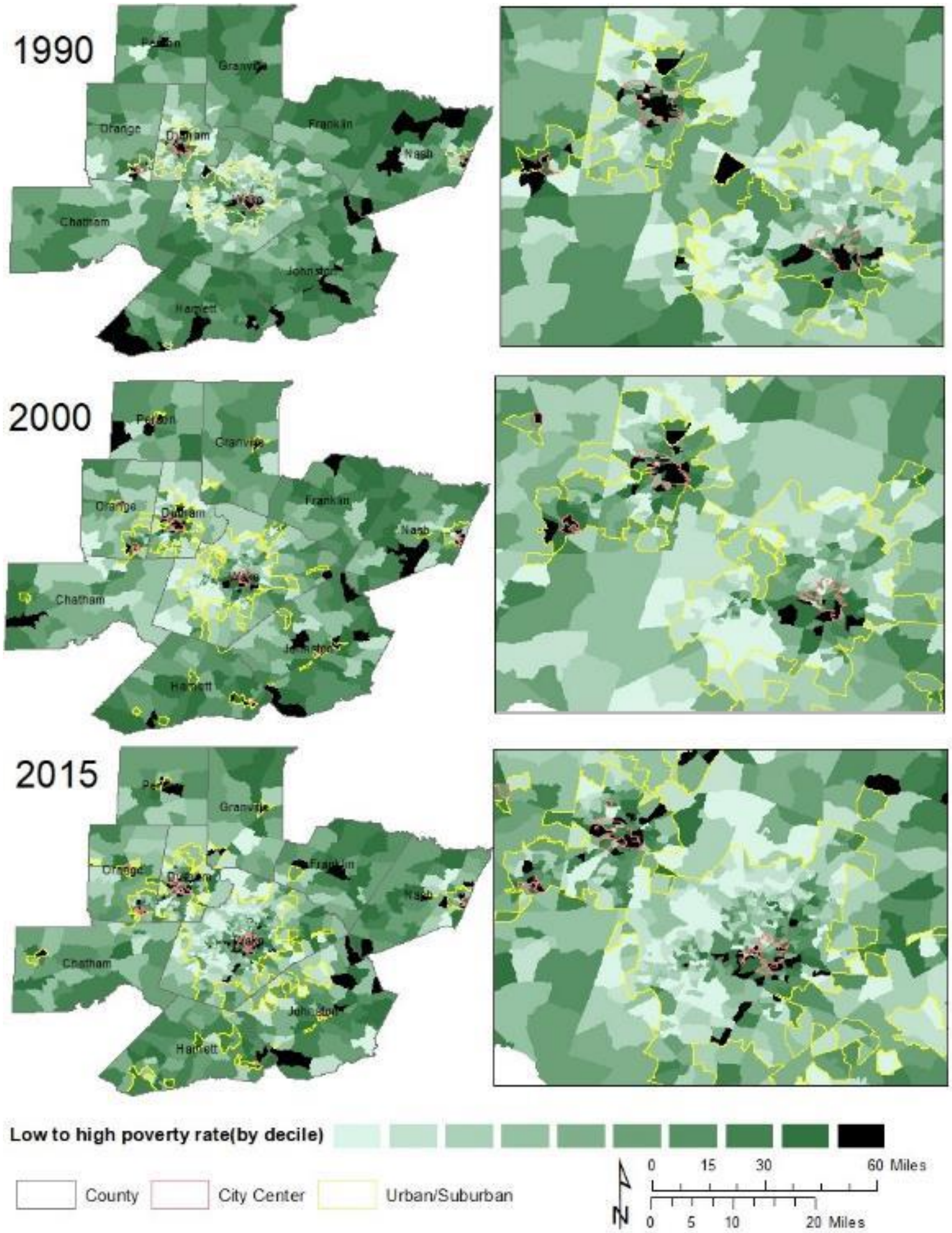


Figure 2-10: Poverty rate deciles in 1990, 2010, and 2015

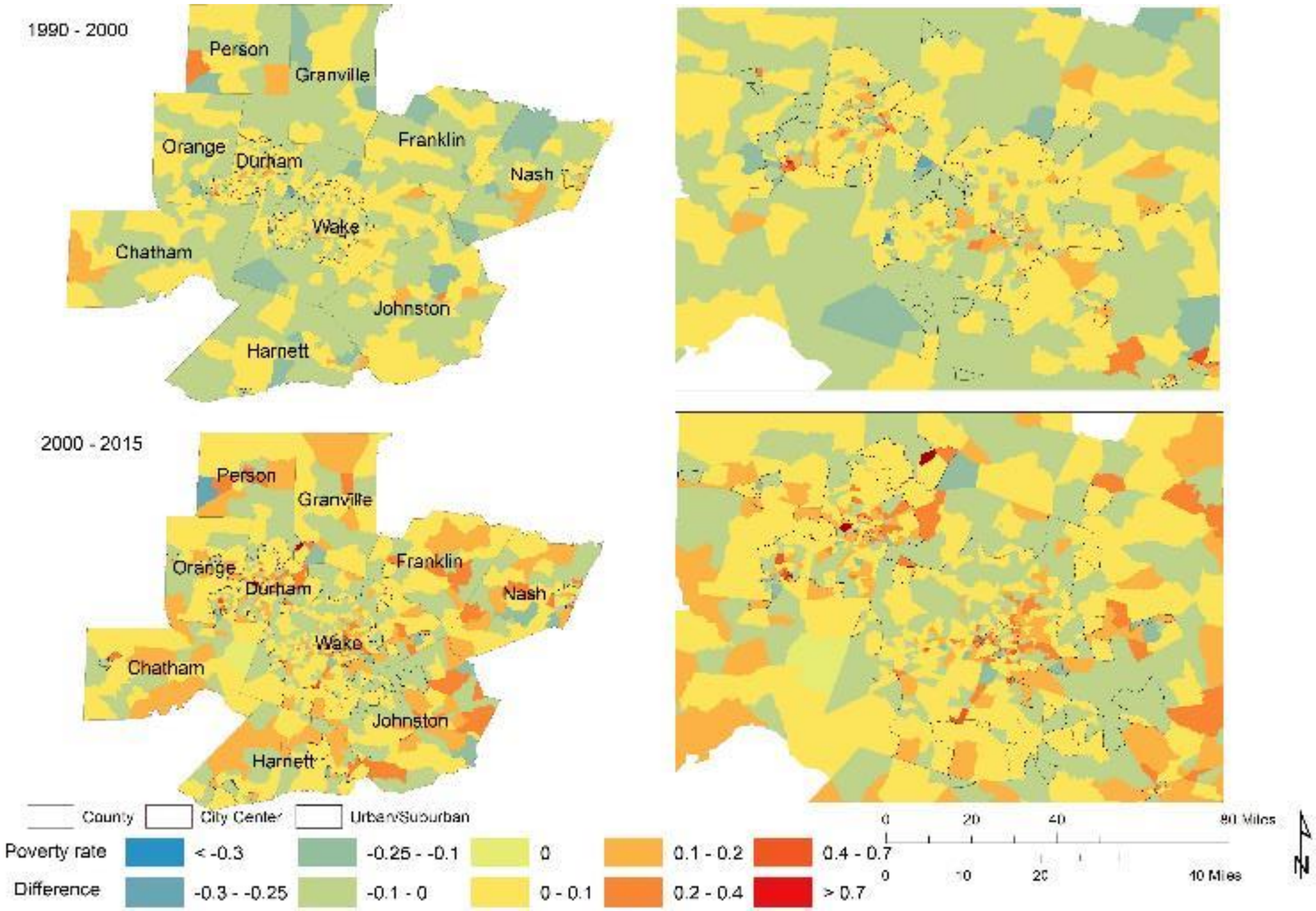


Figure 2-11: Percentage point differences of the low-income population between 1990/2000 and 2000/2015

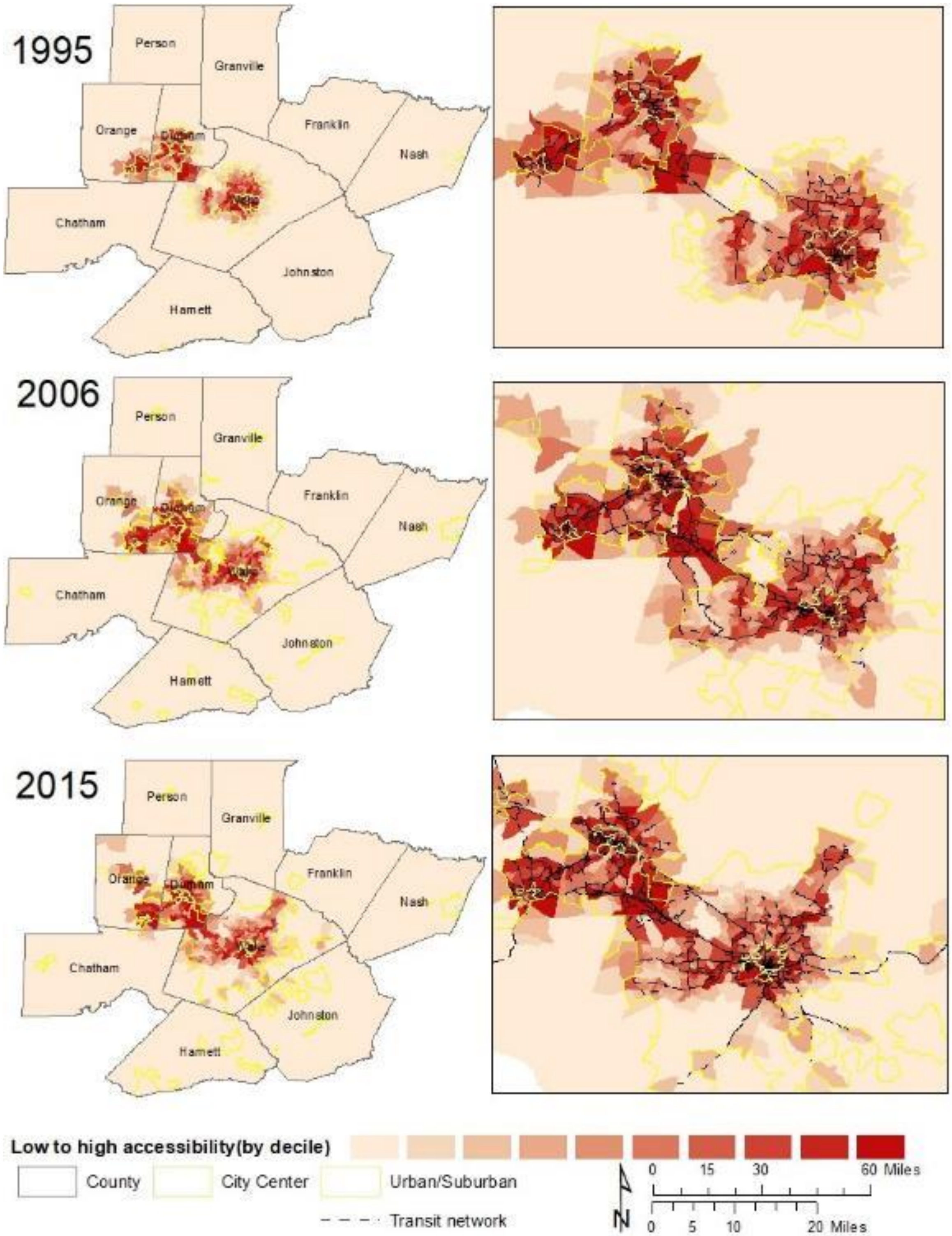


Figure 2-12: Accessibility to transit deciles in 1995, 2006, and 2015

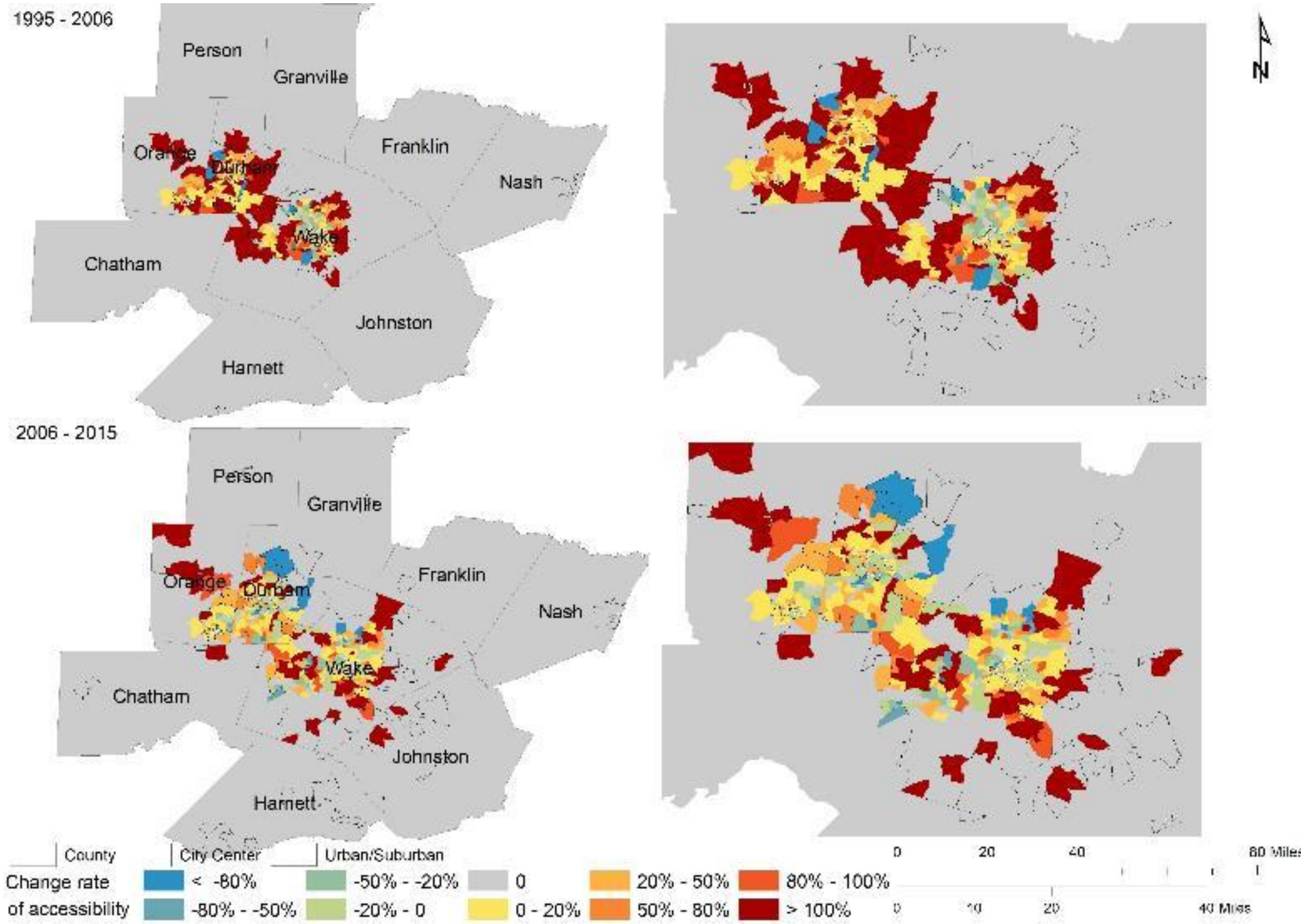


Figure 2-13: Percentage change of accessibility to transit between 1995/2006 and 2006/2015

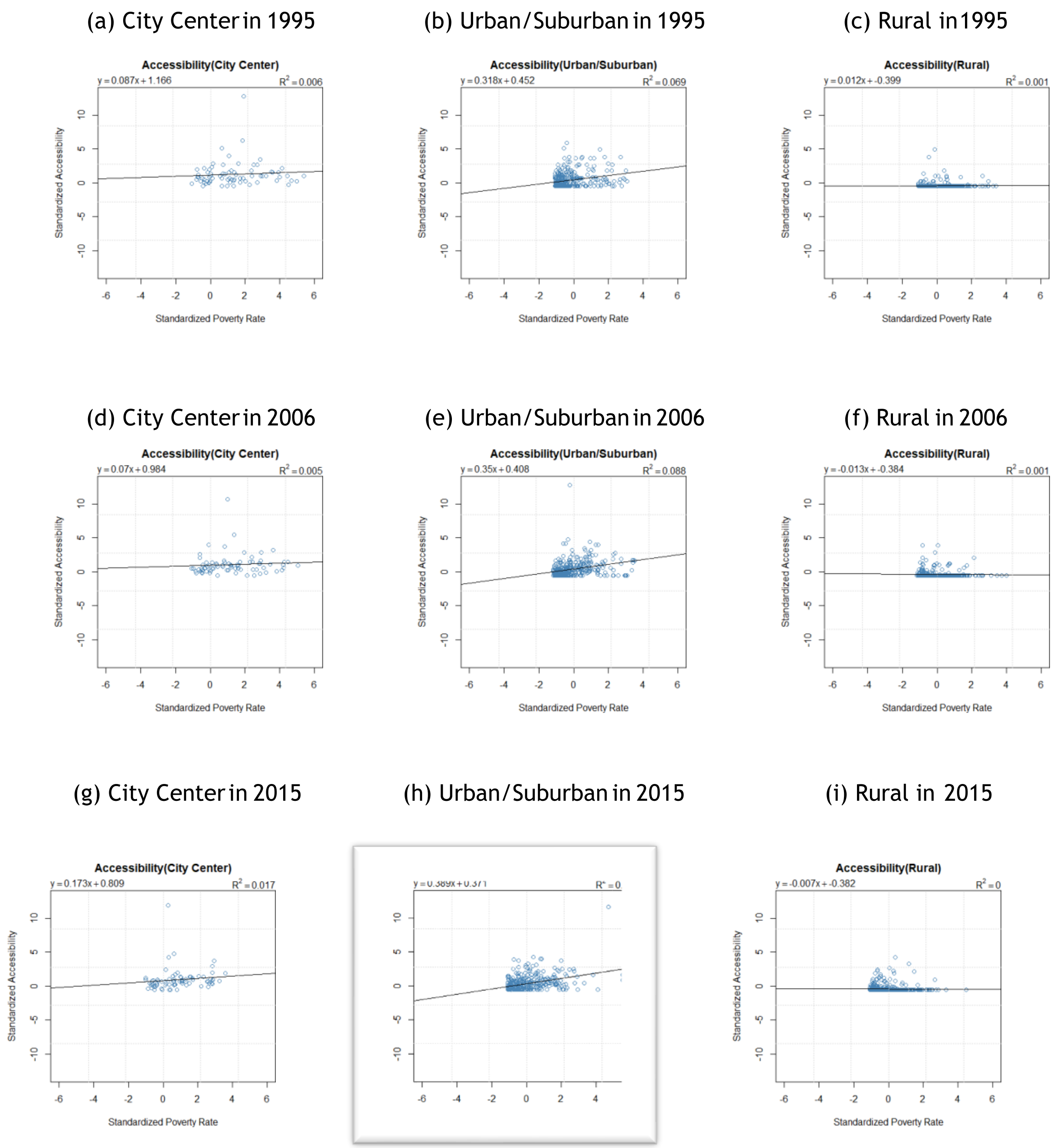


Figure 2-14: Comparing standardized accessibility to standardized poverty rate in different geo- graphical areas (the standardized poverty rate is statistically significant only in (b), (e), and (h)

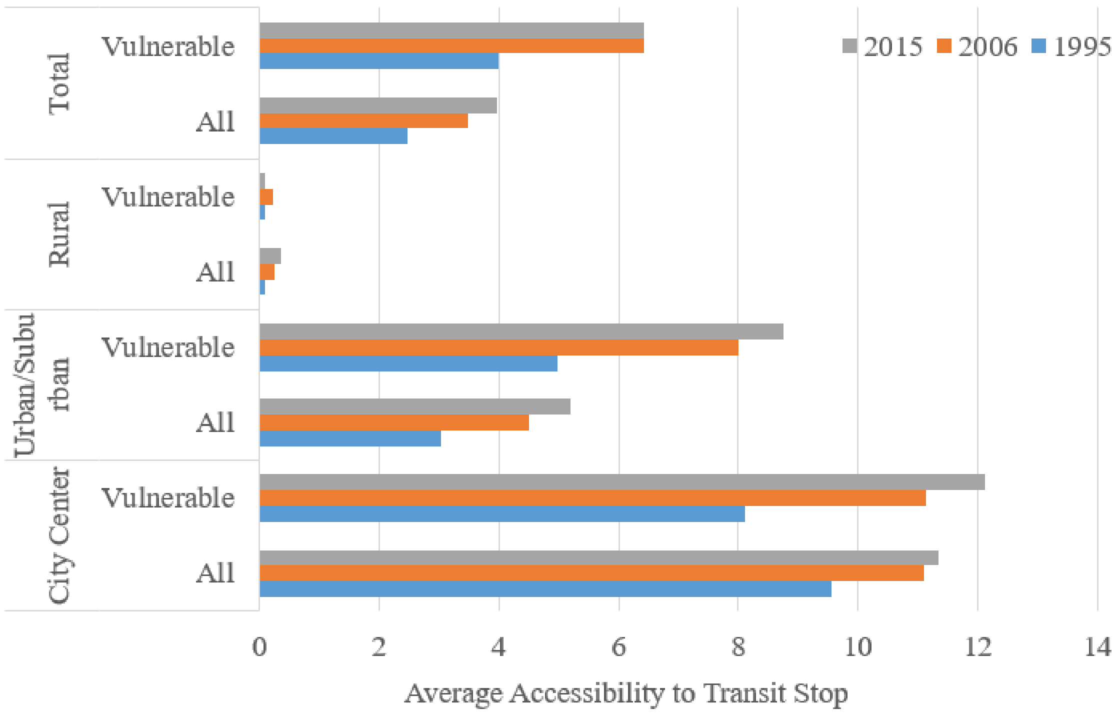


Figure 2-15: Comparison of average accessibility in vulnerable census block groups and others in different geographical areas

Figure 14 presents the relationship between standardized accessibility and standardized poverty rate in different geographical areas over time. The standardized poverty rate is significantly associated with the standardized accessibility in the urban/suburban areas only at a 99% significance level. In the urban/suburban areas, the block groups with higher poverty rate are found to have higher accessibility to transit compared to the rest of the region. Figure 15 further compares accessibility in the areas with higher poverty rate to the total respective geographical region. The block groups with the highest quarter of poverty rates are defined as "vulnerable zones". Looking at the entire study area, the vulnerable zones have higher accessibility compared to all block groups over time across our study area. Compared to all block groups, the vulnerable zones in the urban/suburban areas have higher accessibility over time. The vulnerable zones in the city center gradually surpass all block groups with regard to the average accessibility, although they have lower accessibility in 1995. Overall, the results in the urban/suburban areas are consistent with the studies by Foth et al. (2013) and Deboosere and El-Geneidy (2018).

2.5.2 Accessibility by transit to qualified jobs

Table 6 presents the results of accessibility to qualified jobs by low-wage/high-wage and low- skilled/high-skilled populations in 2006 and 2015. Accessibility less than one is defined as low accessibility since it means job seekers have very few opportunities to access qualified jobs. At the same time, accessibility more than three is defined as high accessibility since the possibility that individuals can find satisfying jobs for themselves increases. Figure 16 and 17 present the results of accessibility to qualified jobs by low-wage/high-wage and low-skilled/high-skilled population, respectively.

The results show a decreasing trend of accessibility to employment by transit for all populations between 2006 and 2015. The accessibility to low-skilled jobs by low-skilled workers decreases faster than that of low-wage workers, while the accessibility to high-wage jobs by high-wage workers decreases faster than that of high-skilled workers. The accessibility is distributed unevenly across our study area with no apparent differences between income-classified and skill-classified population groups. For both of these groups, we see large clusters with high accessibility in the city center and its adjacency block groups in both Figure 16 and 17. Also, the results in Table 6 indicate that the population

Table 2-6 - Average Accessibility to Qualified Jobs by Transit in Different Geographical Areas for Different Groups of Population

Accessibility to transit	City Center		Urban/Suburban		Rural	
	Low-wage	Non-low-wage	Low-wage	Non-low-wage	Low-wage	Non-low-wage
2006	2.321	3.387	1.393	1.340	0.840	1.159
2015	2.166	2.507	1.325	1.321	0.715	0.918
Change rate	-6.7%	-26.0%	-4.9%	-1.4%	-14.9%	-20.8%
	Low-skill	Non-low-skill	Low-skill	Non-low-skill	Low-skill	Non-low-skill
2006	2.100	3.403	1.226	1.380	1.286	0.913
2015	1.540	2.676	1.103	1.384	1.056	0.754
Change rate	-26.7%	-21.4%	-10.0%	0.4%	-17.9%	-17.5%

in the city center has higher accessibility compared to the population in other geographical areas. Consistent with our assumption, the low-wage and low-skilled populations in the city center have lower accessibility to qualified jobs by transit on average compared to their counterparts. However, the accessibility decreases faster for the high-wage population than the low-wage population in such areas. The differences in average accessibility between these groups are negligible in other geographical areas. As for the populations in urban/suburban areas, the average accessibility to jobs by transit is quite steady over time compared to the other geographical types. It is worth mentioning that some rural areas without transit network show relatively high accessibility in both Figure 16 and 17. Also, the areas between Wake and Durham County show high accessibility to all job types by transit. However, the results in the previous section show that the accessibility to transit in such areas is low since express routes connect two counties directly without setting stops in the middle of the routes. The reason of these results is that workers have relatively high accessibility to the jobs in their residential census block groups, which means if a census block group has more qualified jobs than job seekers, it will show high or fair accessibility although there is no transit available.

2.6 CONCLUSIONS

By using a comparative descriptive and accessibility analysis of Census data and transit network data from one US metropolitan area, this study attempts to improve our understanding with respect to the changes over time and space in accessibility to transit and employment by transit for low-income populations residing in central, suburban, and rural areas. We primarily focus on the suburbanization of poverty and how this phenomenon impacts accessibility to and by public transportation. This study categorizes our study area, the Triangle region, NC, into three regions: city center, urban/suburban, and rural areas. The descriptive analysis provides information on the changes in the transit network, low and higher-income populations, low-wage/high-wage, and low-skilled/high-skilled jobs and workers in each geographical area. Our results suggest that the urban/suburban areas experience a significant increase in its size between 1990 and 2010 compared to the other geographical types. We also see a substantial increase in transit length between 1995 and 2005, while the transit expansion between 2005 and 2010 is relatively slow. With respect to poverty rate, population, and population density changes in each geographical area, we observe a substantial increase in poverty rate in urban/suburban areas, while the poverty rates in other geographical areas decrease between 1990 and 2000, which indicates potential poverty suburbanization. Poverty rates increase in all three geographical areas between 2000 and 2013, which indicates that low-income households are attracted to the Triangle region or that households' income decrease over time.

In our analysis of accessibility, we use gravity-based measures that account for travel time between home and bus stop and the number of bus stops to quantify the accessibility to transit, while a more advanced gravity measure that accounts for travel time, and demand and supply of jobs is used for quantifying the accessibility to qualified jobs by transit. We first estimate the accessibility to transit in combination of the distribution of the low-income population. Then, we estimate the accessibility to qualified jobs by transit for the low-wage/high-wage, and low- skilled/high-skill populations. The results show that the areas in the city center have the highest average accessibility to transit and jobs over time compared to the other geographical areas. We also find that the accessibility to transit increased over time for everyone, while the accessibility to qualified jobs by transit decreased across the study area for all population groups between 2006 and 2015. This result indicates that the expansion of the transit network in the recent years has not improved the accessibility between residential locations and employment centers.

Future research can overcome some of the limitations of the current study, including data analysis for multiple metropolitan areas, and estimating accessibility changes over time and space to various facilities by transportation disadvantaged groups.

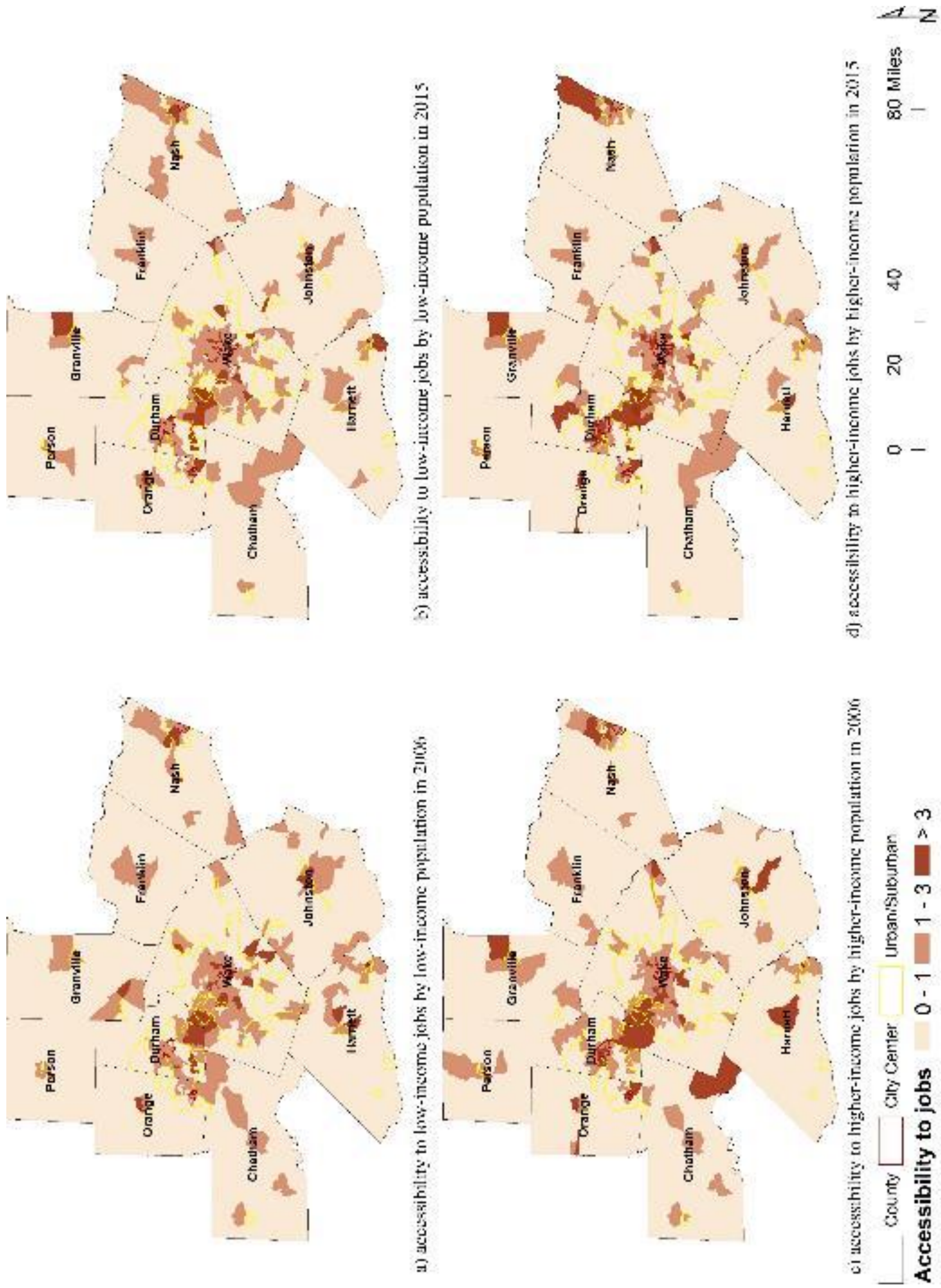


Figure 2-16: Accessibility to Qualified Jobs by Transit for low-wage and high-wage Population in Different Geographical Areas

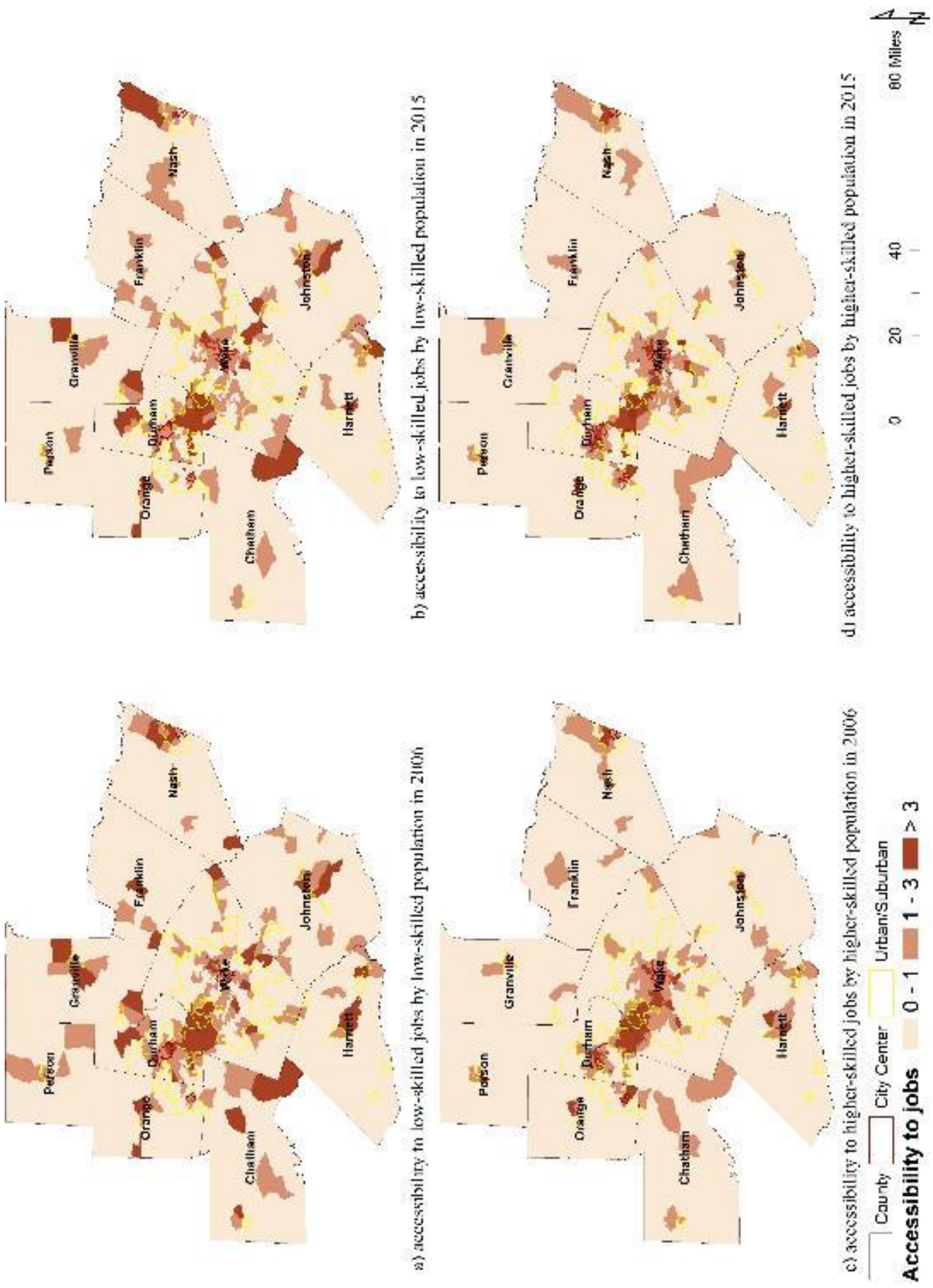
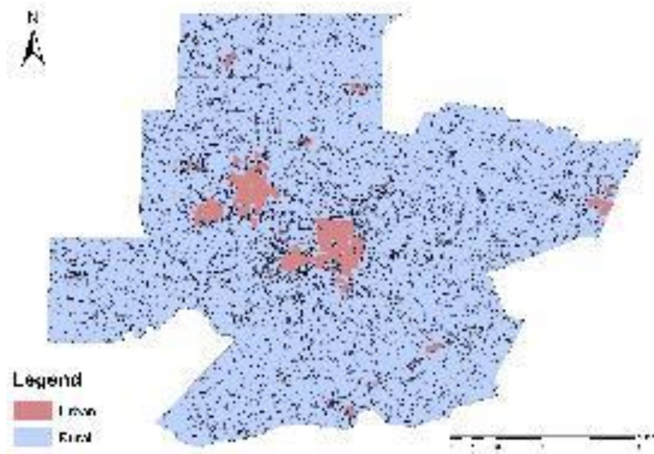


Figure 2-17: Accessibility to Qualified Jobs by Transit for Low-skilled and High-skilled Population in Different Geographical Areas

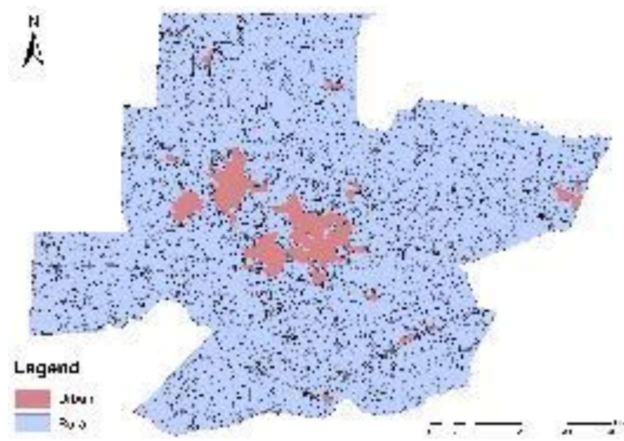
2.7 APPENDIX: SELECTION OF GEOGRAPHICAL AREA DEFINITION

In this section, we compare different urban/suburban definitions to look for the most suitable definition for our study area. Our study area has multi-city centers, and it is not easy to identify a nature boundary, such as a highway circle. Thus, we only choose from the population, housing structure year, and census urban definition of urban/suburban. We first adopt the population density definition by Ratcliffe et al. (2016), which the urban area is defined as the census block with more than 1,000 people per square mile. Figure 18 shows the urban areas change over time by population definition. We find that the urban areas in 2010 appear to be separated with each other, which is not reasonable since the urban areas are supposed to cluster together.

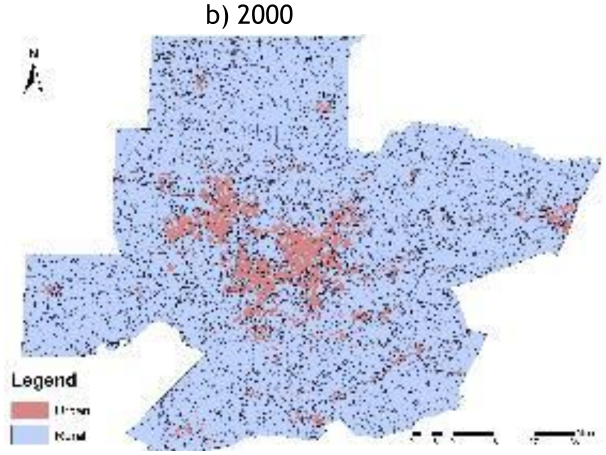
Then we present the urban boundary maps from the Census bureau which are available for each decade since 1990. The Census Bureau identifies two types of urban areas, which we name as the boundary definition in the following sections: (i) Urbanized Areas (UAs) of 50,000 or more people; and (ii) Urban Clusters (UCs) of at least 2,500 and less than 50,000 people. “Rural” encompasses all population, housing, and territory not included within an urban area. Figure 19 shows the geographical areas change by the boundary definition. We can see that the urban areas increase over time and cluster together, which enables our comparison on the accessibility in different geographical areas. But the boundary definition does not identify the suburban areas, thus we need to further split the urban areas into the city center and suburbs. We adopt the house structure year definition to determine the city center - located in the center with greater than 400 pre-1940 housing units per square mile; and any adjacent census tract that has more than 200 pre-1940 housing units per square mile and at least 1,000 people per square mile (Cooke and Marchant, 2006). Figure 20 shows the house structure year and boundary definitions in 1990. According to the comparison, we find that the housing structure year identifies a clear boundary of city center within the urban areas in the boundary definition. Thus, our study uses a combined definition by Cooke and Marchant (2006) and United States Census Bureau (2015) to define the city center, urban/suburban and rural areas: the city center is defined as the census block groups located in the center with greater than 400 pre-1940 housing units per square mile; and any adjacent block groups that have more than 200 pre-1940 housing units per square mile and at least 1,000 people per square mile (Cooke and Marchant, 2006). The urban/suburban areas are defined as the rest of the block groups within the census urban boundary except the city center. The rest of the block groups in our study area are rural areas.



(a) 1990

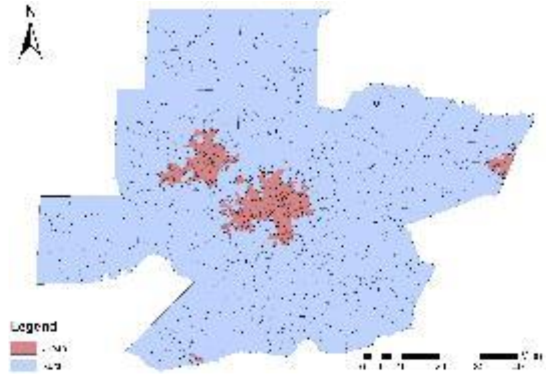


b) 2000

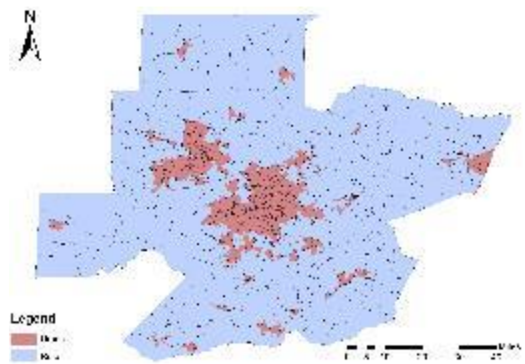


(c) 2010

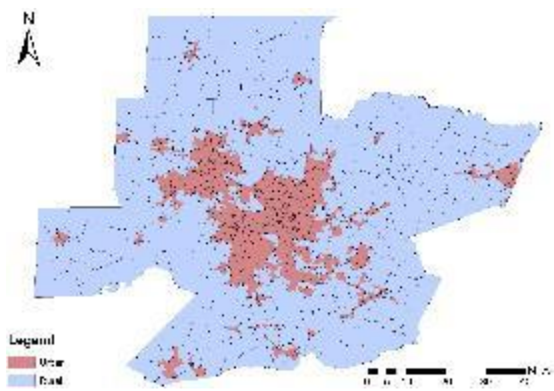
Figure 2-18: Comparison urban/rural by population definition over time (census block)



(a) 1990

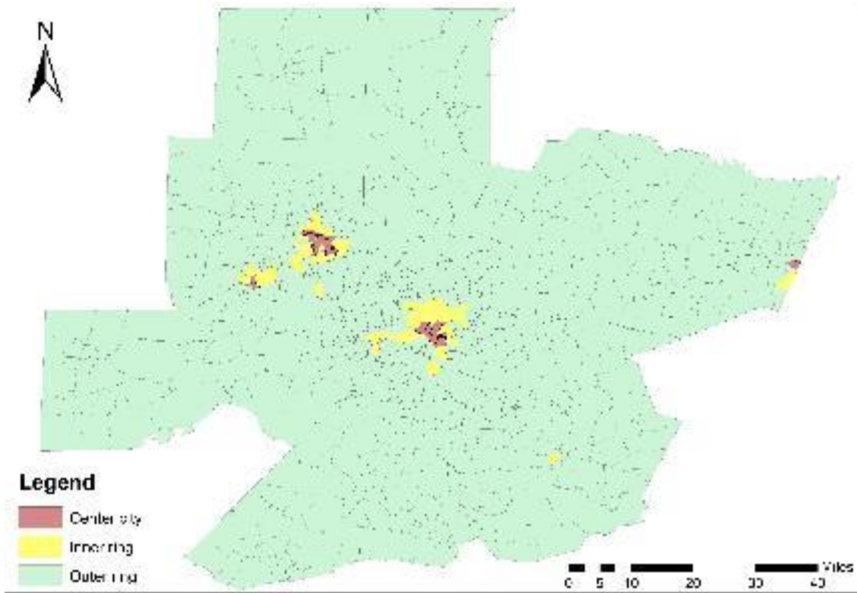


(b) 2000

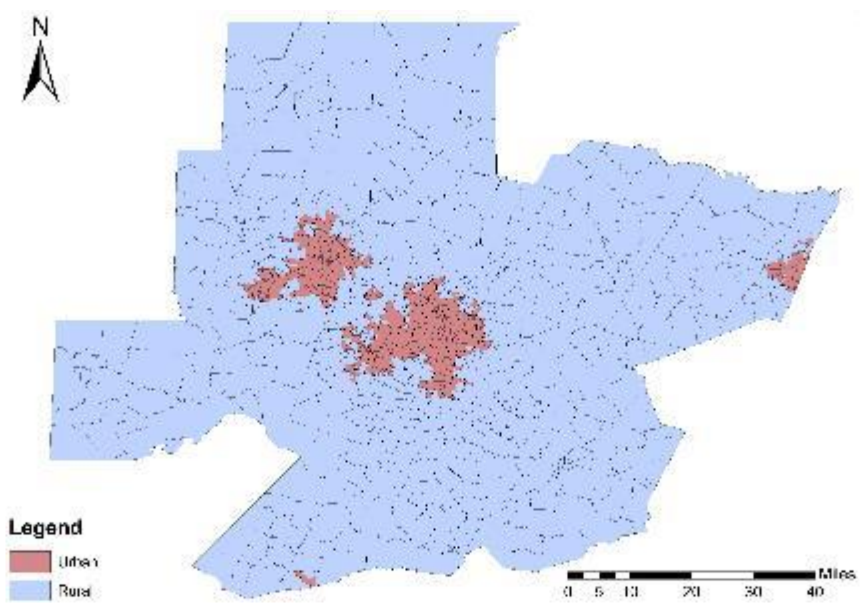


(c) 2010

Figure 2-19: Comparing geographical areas by the boundary definition over time (census block group)



(a) Defined by house structure year



(b) Defined by urban boundary

Figure 2-20: Comparison between house structure year definition and census boundary definition

2.8 REFERENCES

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3.0 ON RIDERSHIP AND FREQUENCY

Research conducted by Dr. Kari Watkins, Dr. Simon Berrebi, Taylor Gibbs, and Sanskruti Joshi, Georgia Institute of Technology. The full paper has been published in Transportation Research Part A: Policy and Practice:

Simon J. Berrebi, Sanskruti Joshi, and Kari E. Watkins. "On bus ridership and frequency," Transportation Research Part A: Policy and Practice, Volume 148, 2021, Pages 140-154, ISSN 0965 8564, Link: [On bus ridership and frequency](#).

3.1 INTRODUCTION

In 2018, following six years of consecutive decline, bus ridership in the United States attained its lowest level in recorded history, which started in 1965 (Cihak and Pham, 1990; Dickens, 2018). Each transit trip lost to private cars contributes to traffic congestion, pollution, and road fatalities. The revenue lost from declining ridership also impedes the ability of transit agencies to provide service, which hurts ridership further in a downward cycle. Transit agencies therefore need to understand how this trend can be reversed and at what cost.

The main tools transit agencies have available to influence ridership are service allocation policies. Transit planners are tasked with setting frequencies throughout the network under constrained resources. They must balance ridership with other, sometimes conflicting, objectives including equitable access, connection to places of strategic importance, and reliability. In particular, agencies must decide whether to spread service to reach the few or concentrate it to attract the many. In order to allocate service in a transparent manner that maximizes total welfare, the effect of frequency on ridership should be quantified. This effect may not be linear; each vehicle-trip added to a route may not produce as much (or as little) ridership as the current route productivity, measured in passengers per vehicle-trip. Elasticity measures the percentage change in ridership resulting from a 1% increase in frequency. When elasticity is greater than one, adding more service increases the route productivity. Because elasticity measures the sensitivity of demand, it varies across routes based on frequency and across stops based on local characteristics.

Automated Passenger Count data (APC) can be used to model ridership at the stop level over time. Although transit agencies started deploying APCs in the mid-1970's (Attanucci and Vozzolo, 1983), the technology has not yet been used to conclusively explain disaggregated ridership change. The first reason is that passenger count data are rife with errors and inconsistencies, which can quickly overwhelm sensitive ridership models. The second reason is that complex models are required to capture the variation happening on different spatial and temporal scales.

This chapter presents a new method to scrub, process, and model ridership data over time and space. Passenger counts are cross-checked with the General Transit Feed Specification (GTFS), a schedule meta-data standard. Passenger counts are then aggregated by route-segments (groups of seven stops on the same route and direction) and combined with data sources on population and jobs. The *change* in ridership is modeled over time through panel regression. Fixed-effects models avoid unobserved heterogeneity and endogeneity biases that plague cross-sectional models by using each individual as its own control over time. Fixed-effects models therefore control for variation **between** individual locations to capture the variation **within** each. In this chapter, ridership is modeled using Poisson fixed-effects, which was developed by Hausman et al. (1984) for count data such as passenger boardings and alightings.

The chapter proceeds as follows: Section 2 organizes the main studies from the literature by level of aggregation and identifies panel models of hyper-local ridership trends as the gap in research. Section 3 presents the four case studies. Section 4 describes the process of cleaning, aggregating, and combining multiple relevant datasets. Section 5 presents the modeling results. Section 6 discusses their implications and identifies future research questions.

3.2 LITERATURE REVIEW

Ridership elasticity to frequency remains largely unaddressed in the literature. Table 1 classifies the main studies on transit ridership by level of spatial aggregation (rows) and whether the sample is observed once or at multiple time periods (columns). All the references in the top row evaluate ridership at the transit agency or metropolitan area level. These studies can help compare the impact of aggregated factors across regions, and for studies in the top-right quadrant, across time. Many factors that explain ridership can vary widely between regions (Taylor et al., 2009) and explain why ridership is greater in New York City than in Mobile, AL. However, the variation in the aggregated explanatory variables over time, within each region, can drown the local dynamics that cause overall ridership change. Just shifting resources from one route to another can impact overall ridership without even affecting the total service provided. Likewise, aggregated effects of population, jobs, and demographic factors are diluted in a system-level study.

Table 3-1 - Main studies on transit ridership by level of spatial aggregation (rows) and whether the sample is observed once or at multiple time periods (columns)

	Cross-Section	**Multiple Time Periods**
System-Level	Taylor et al. (2009); Ingvardson and Nielsen (2018)	Kain and Liu (1999); Kohn et al. (2000); Brown and Thompson (2008); Lane (2010); Chen et al. (2011); Iseki and Ali (2015); Boisjoly et al. (2018); Driscoll et al. (2018); Hall et al. (2018); Graehler Jr et al. (2019); Taylor et al. (2019); Ederer et al. (2019); Berrebi et al. (2019); Ko et al. (2019)

Local-Level	Peng et al. (1997); Kimpel et al. (2007); Estupiñán and Rodríguez (2008); Ryan and Frank (2009); Gutiérrez et al. (2011); Dill et al. (2013); Pulugurtha and Agurla (2012); Chakrabarti and Giuliano (2015); Hu et al. (2016); Chakour and Eluru (2016); Ma et al. (2018); Mucci and Erhardt (2018); Taylor etal. (2019)	Maloney et al. (1964); Kyte et al. (1988); Tang and Thakuriah (2012); Frei and Mahmas- sani (2013); Kerkman et al. (2015); Brakewood et al. (2015)

The bottom left quadrant of Table 1 contains studies modeling bus ridership at a local level at a single point in time. These studies capture the local variation **between** individual stops, routes, or route-segments. These models are formulated as if each individual location was similar in every aspect except for the variation captured by explanatory variables. In reality, individual locations are different from each other in ways that cannot be measured and that may affect ridership. Travel demand is derived from the desire or need to access destinations. The destinations served by a bus route are likely to affect both frequency and ridership, causing a potential unobserved heterogeneity bias. Ridership itself is likely to affect frequency directly. When allocating service throughout the network, transit planners strive to maximize ridership. Therefore, elasticities are likely inflated by the two-way causality. This problem is referred to as the endogeneity bias.

The bottom right quadrant contains studies modeling bus ridership on a local level over time. Results from Maloney et al. (1964) and Kyte et al. (1988) still serve as the main reference on ridership elasticity to frequency (Evans et al., 2004; Litman, 2017). Following service changes in Boston, MA, and Portland, OR, these studies computed separate ridership elasticities for each route. With values ranging from zero to 3.77 (Kyte et al., 1988), route-specific elastiticites are not overly meaningful. Fixed-effects models harness the combined explanatory powers of all individual locations in the panel to explain the change in ridership. Tang and Thakuriah (2012) and Brakewood et al. (2015) use fixed-effects models at the route level to evaluate the impact of real-time passenger information on ridership. The regression structure in both papers is linear, which can be suitable for route-level ridership, where counts are approximately normal.

In more disaggregated analysis, however, ridership data is heavily skewed. Frei and Mamassani (2013) and Kerkman et al. (2015) apply a log-transform to model ridership data at the stop-level at two time periods. The log-linear regression, however, can lead to inconsistent (and inefficient) parameter estimates for count data (Silva and Tenreyro, 2006). While the log-transform allows the mean to be strictly positive, linear regression still assumes normally distributed errors around the mean. This is particularly problematic for low-ridership stops where almost half of observations would be expected to be negative. In addition, zero-values in the original data must be either truncated or a constant must be added to each observation, which can also introduce a bias.

Modeling ridership change at a disaggregated level is complicated by the missing data, endogeneity, and multiple levels of interaction. The models are highly sensitive to even slight misspecification. This chapter presents a unifying framework to analyze the causes of ridership change on a disaggregated level. A step-by-step methodology to clean, process, and model APC data over multiple periods is described in detail to facilitate the development of this field of research by future studies. The effects of service changes on ridership are estimated. Retrospectively, this analysis can be used to control for frequency, and identify underlying trends based on a host of other factors. More broadly, this study opens the door to a wide range of research topics on the sensitivity of transit ridership.

3.3 CASE STUDIES

To evaluate the relationship between transit ridership and frequency, four transit agencies were selected based on the quality of their APC data. The research team initially contacted 14 mid-sized transit agencies. Of these agencies, eight were able to provide stop-level data. Three of these data sets did not pass our initial screening. One agency had undergone a network redesign, which created disruptions of a greater magnitude than the phenomena we are looking to capture. The analysis presented in this chapter is therefore based on four agencies, which are at the leading edge of best practices:

- Tri-County Metropolitan Transportation District of Oregon (TriMet) in Portland OR, from Spring 2012 to Spring 2017
- Miami-Dade Transit in Miami, FL, from Dall/Winter 2013 to Fall/Winter 2018
- Metro Transit in Minneapolis/St-Paul, MN, from Fall/Winter 2012 to Fall/Winter 2017
- Metropolitan Atlanta Rapid Transit Authority (MARTA) in Atlanta, GA, from Summer 2014 to Summer 2018

When the study team approached each transit agency, we asked for historical APC data going back as far as possible. Agencies provided data averaged by markup (see §4). Transit agencies typically have three markups per year, Spring, Summer and Fall/Winter. Because ridership is subject to seasonality, only one markup was used for each year. Since agencies started implementing APC technology at different times, the range of available data varies. Our objective was to make the study period as long as possible. We therefore decided to pick the season that maximized the number of markups in the analysis instead of using the same season for each agency. With only 5-6 years of data available, losing an entire year would have substantially affected the sample size.

Table 2 shows characteristics of the transit agencies and their metro areas. Data in the first two rows, 2018 bus ridership and hours of directly operated service, come from the National Transit Database (NTD, 2019). The last two rows of Table 2 show Metropolitan Statistical Area (MSA) population, and percent of population living in dense Census Tracts according to the 2016 single-year American Community Survey (ACS, 2016). Percent living in density is calculated as the share of metro area population living in Census Tracts with more than three housing units per gross acre, which is the "transit-supportive density" according to Kittelson Assoc (2013).

Table 3-2 - Ridership and service provided by agency in 2018 according to NTD (2019)

	Tri-met	Miami-Dade	Metro-Transit	MARTA
Unlinked Passenger Trips (000's)	56,727	49,716	54,910	49,788

	Tri-met	Miami-Dade	Metro-Transit	MARTA
Vehicle Revenue Hours (000's)	1,988	1,961	2,050	2,249
MSA population (000's)	2,425	6,066	3,551	5,790
% living in transit-supportive density	43.1	58.7	22.9	10.8

The transit agencies in this study are similar in size but they vary widely in other aspects. Ridership and revenue hours in each of the four agencies are all within 15% of each other. Dividing passenger trips by revenue hours gives operational efficiencies. TriMet is the most efficient agency with 28.5 passengers per revenue hour and MARTA is the least efficient with 21.9 passengers per revenue hour. While TriMet serves more passenger trips than Miami-Dade, the Miami region has 2.5 times more population than the Portland area. The Miami region is the densest, followed by Portland, Minneapolis/St-Paul, and Atlanta, where only 11% of the population lives at transit-supportive densities. The case-studies therefore represent a wide cross-section of mid-sized transit agencies. Coming from different parts of the United States, these agencies form a basis of comparison that can be useful to their peers.

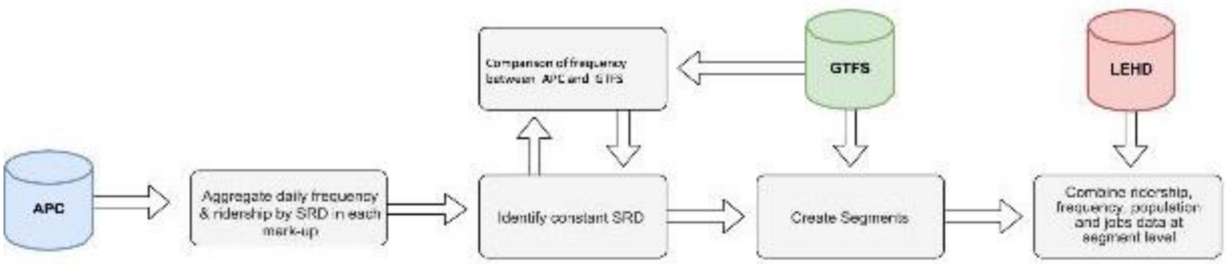

Figure 3-1: Flow chart describing the data scrubbing and aggregation process

3.4 DATA PROCESSING

Transit agencies in this study provided the research team with ridership data at the stop-route-direction-trip level. Passenger count data were then scrubbed, aggregated, and combined with other data-sets through a process illustrated in Figure 1. Each step of this process is described in this section. The outcome is a dataset that serves as input to our models. For a detailed outlook, see Joshi (2019).

3.4.1 Aggregate Daily Frequency and Ridership

To provide a basis of comparison between all possible combinations of stop-route-direction (SRD), total daily frequency and ridership were aggregated by day. Total daily frequency was obtained by counting the number of trips. Aggregated ridership was obtained by summing boardings and alightings across trips. Summing both boardings and alightings is necessary to avoid the asymmetry problem: some stops, typically located near the end of the line, are only ever used to alight buses. For example, 18% of stops in Minneapolis/St-Paul have zero recorded boardings in Fall 2012. In addition, all weekdays are pooled together, their averages are based on sample sizes five times greater than Saturdays and Sundays. In order to consider the most comprehensive dataset possible, we chose to focus on weekday ridership.

3.4.2 Identify Constant Stop-Route-Directions

In order to understand the relationship between the *change* in ridership and the *change* in frequency, only stop-route-directions that remained constant over the entire study period were considered. Any stop that was either added or removed between the first and the last year was disregarded. In Portland, Miami, and Minneapolis/St-Paul, more than 85% of stop-route-directions were already there in the first year. In Atlanta, however, almost half of all stop-route-directions in the last year had been added since the first year. The agency underwent a comprehensive operational analysis in which many routes were altered. A number of routes and stops remained the same but were simply renamed, causing them to be discounted from constant stop-route-directions. In any case, the purpose of this analysis is to evaluate the sensitivity of ridership to frequency, not to explain overall ridership change.

3.4.3 Comparison between APC and GTFS

The completeness of passenger count data is subject to the proper functioning of hardware aboard vehicles. The concentration of deficient passenger counters in particular geographic areas or time periods may introduce a bias. To avoid this issue, the number of observed daily trips in APC were compared with the number of scheduled trips for each stop-route direction. Historical schedule data published by transit agencies in GTFS format were obtained from third-party websites. The number of daily trips in APC and GTFS were then compared. All segments with more than one missing trip in the first year were filtered out of the analysis entirely. Route-segments with more than one missing trip in subsequent years are removed from the analysis only for the offending years.

3.4.4 Route Segments

While the main objective of this chapter is to understand the relationship between frequency and ridership, population and jobs also affect transit ridership on a local level. To extract meaningful results, these variables should be measured on the scale of their variation. While the service coverage area (i.e. accessible walking distance) for a bus stop is defined by the Transit Capacity and Quality of Service with a ¼ mi radius (Kittelson Assoc, 2013, §5-10), typical stop spacing in urban areas is only 1/8 mi according to the TCRP Report 19 - Location and Design of Bus Stops (Fitzpatrick et al., 1996). Hyper-local variations in ridership are more likely to be explained by walkability, which is determined by connectivity, land-use patterns, quality of path, and context, on which no data is available (Southworth, 2005). Therefore, what accounts for differences in ridership between adjacent stops on the same route-direction is unlikely to be captured by our explanatory variables. Modeling ridership at the stop-route-direction level would reduce explanatory power. Furthermore, the passenger's choice to use one stop over the next one introduces serial correlation, which may affect estimated variances.

To address these issues, we define route segments, clusters of seven adjacent stops on the same route-direction, as the spatial unit of analysis. To create route segments, the stop sequence (i.e., order on the route) of constant stop-route-directions was obtained from GTFS. Since a stop can have different sequences on the same route-direction across different trips, the stops, stop_times, trips, and routes tables were joined and the sequence index common to the most trips was recorded. Spatial coordinates for each stop were also obtained from the GTFS stops table. Each route-direction was then divided in segments of seven stops in sequential order. The last remaining stops at the end of each route were merged with the upstream segment. Ridership and frequency were then averaged by segment across stops.

3.4.5 Population and Jobs

Population and job data were obtained from Longitudinal Employer Household Dynamics (LEHD). The LEHD are data products compiled by states using Unemployment Insurance earnings and published by the US Census Bureau. The number of jobs is provided at the Census Block level, by year. These data, however, are only available between 2011 and 2015. We therefore included a lag to match the LEHD time-fame with APC. The underlying assumption is that population and job trends between 2011 and 2015 continued their course until 2018 in Atlanta and until 2017 everywhere else. In other words, a Census Block that gained five residents per year until 2015 was assumed to keep growing at the same rate.

The LEHD data were first cleaned and prepared for import into ArcMap. Block Group shapefiles were joined using a common GEOID field. A dissolved ¼ mi buffer was applied to the stops based on the common route segment field. This buffer was overlaid with LEHD data using a pairwise intersection tool, which compares the input features of overlapping layers. Features common to both input layers were sent to the output feature class. The output mirrors the geometric intersections of the two layers while considering which layers they are derived from. Therefore, the overlapping service coverage areas of bus stops within the same segment were only counted once. Under the assumption that people and jobs are uniformly distributed within their geographic unit, LEHD data were weighted by the proportion of each Census Block in the segment buffer.

Figure 2 shows a map illustrating LEHD workplace locations by route segment buffers, which are differentiated by color. Overlapping segment buffers hide each other and are therefore not visible on the map. The length of each buffer varies considerably depending on the stop density. Block Group boundaries are shown as thick dashed lines and Census Block boundaries are shown as light gray lines. The small gaps in segment buffers represent the Census Blocks without any job locations.

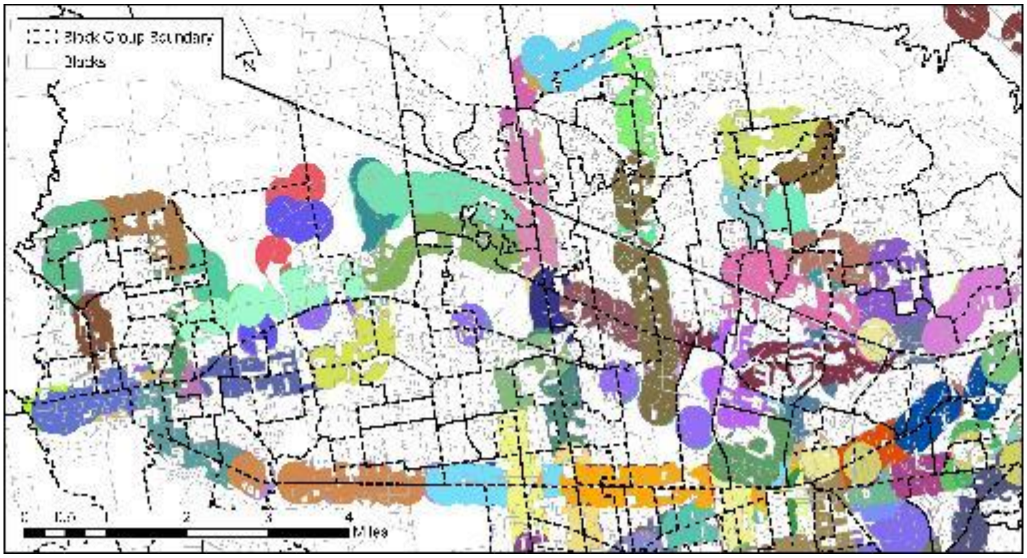

Figure 3-2: Map illustrating LEHD workplace locations by route segment buffers along with Census Blocks and Block Groups lines

3.5 RESULTS

This section presents the results from the Poisson cross-section and fixed-effects models. For derivation of the model forms, please see the published paper. These models were run in the software program R Studio using the stats and pglm packages, respectively (R Core Team, 2017; Croissant, 2017).

3.5.1 Cross-Section

Table 3 shows the results of the cross-sectional model in 2012 presented in Equation (2). McFadden's pseudo-R^2 is shown for each agency at the bottom of Table 3. Just like the OLS R^2, the pseudo-R^2 for MLE represents the proportion of variation in the response variable explained by the model. In Portland, Miami, and Minneapolis/St-Paul, pseudo-R^2 values close to one indicate an excellent fit. In Atlanta, however, the model explains 39.3% of the variation. The first row, log(Freq) is the elasticity of ridership to frequency. For all four agencies, elasticity is significantly greater than one, and hence elastic. In other words, for two route-segments with the same population and jobs, the one with the greater frequency is likely to have more passenger per trip. The second row shows the sensitivity of ridership to the total of population and jobs. In all four agencies, the parameter estimate is significantly below one. For the same level of frequency, a segment surrounded by more development than another is expected to have less ridership per capita.

Table 3-3 - Cross Section Models

	Response Variable: Rid			
	Portland	Miami	Minn. / St Paul	Atlanta
log (Freq)	1.36 (0.03)***	1.21 (0.03)***	1.50 (0.04)***	1.33 (0.08)***
log (Pop + Job)	0.52 (0.02)***	0.53 (0.02)***	0.52 (0.02)***	0.33 (0.04)***
(Intercept)	-4.87 (0.19)***	-4.45 (0.17)***	-5.86 (0.19)***	-3.57 (0.40)***

Pseudo R2	0.82	0.72	0.81	0.39
Deviance	9447.14	13138.63	10732.59	14363.80
Num. obs.	874	1165	959	718

** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; $^{\cdot}$ $p < 0.1$

In order to verify the model results of Table 3, we need to represent the relationship between ridership and frequency in 2012/2013 graphically. Figure 3 shows route productivity in weekday passenger boardings per trip against frequency in daily trips. Productivity allows us to compare the ridership contribution of each vehicle trip on routes with different frequencies. The size of each dot corresponds to the number of stops on the route. One would expect routes with more stops to connect more places, and therefore yield more passengers per trip. Express routes in all agencies are excluded because their stop densities are so much lower than the rest. A trend line is shown in red. The gray band represents its standard error.

Figure 3 provide a different lens to observe the same phenomenon identified in the cross-sectional regression model. There is a clear positive relationship between productivity (in passenger boardings per trip) and frequency (in number of daily trips) at one point in time. This trend is strongest in Portland and Miami and weakest in Minneapolis. In all four agencies, frequent routes carry more passengers per trip than lower frequency routes. Since these routes concentrate the most service, slight changes in productivity can have a disproportionate impact on overall ridership. At the same time, increasing service on these routes could greatly benefit overall ridership if their high productivity can be maintained.

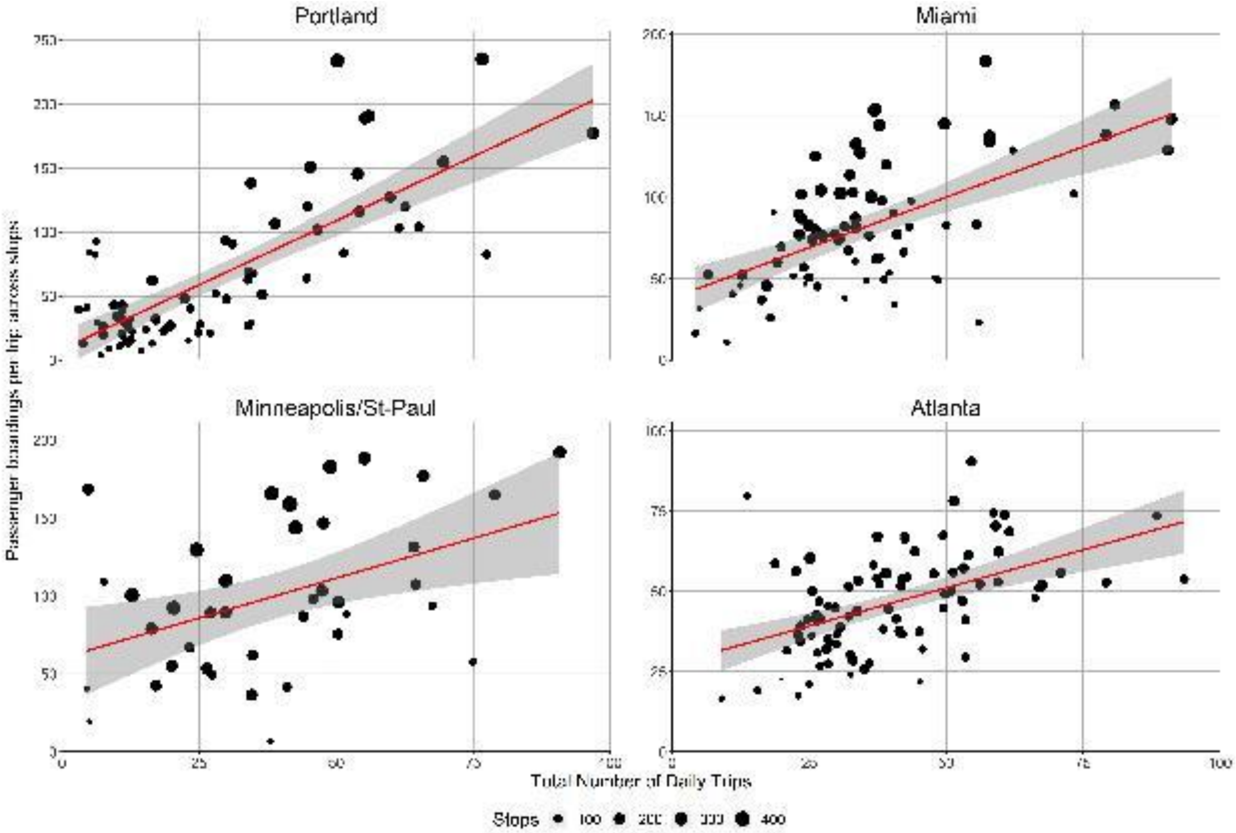

Figure 3-3: Route level productivity in passenger boardings per stop per trip as a function of weekday frequency over time in four metro areas in 2012 and 2013.

Both the cross-sectional model and the graphical representation show that, when comparing the variation **between** route-segments or routes, productivity is positively correlated with frequency. As discussed in the literature review, this does not necessarily mean that increasing frequency on a route-segment will produce increasing returns. High-frequency segments may be more productive due to unobserved heterogeneity or endogeneity. The effect of frequency change on ridership can, therefore, only be tested by comparing the variation **within** each route-segment *over time*. The next subsection does just that.

3.5.2 Fixed Effects

Table 4 shows the results of the Poisson fixed-effects model. For each agency, the elasticity of ridership to frequency and to population and jobs is presented. In this model, the interaction between frequency and prior frequency are omitted to enable a comparison with the cross-sectional results. The log-likelihood, total number of observations, individual segments, and time periods are shown at the bottom of the table. Unfortunately, there is no equivalent to the pseudo-R^2 for the fixed-effects Poisson model. However, the good fit of the cross-sectional models indicate that the fixed-effects model is also well specified. Finally, note that μ_t is significantly negative for all agencies. This indicates that, even when controlling for frequency, population, and jobs, ridership is still declining over time.

The elasticity of ridership to frequency is far weaker in the fixed-effects model than in the cross-section. While the **between** elasticity in the previous model ranged from 1.21 to 1.50, the **within** elasticity shown in Table 4 ranges from 0.67 to 0.80. For all agencies studied, ridership is inelastic to frequency. In other words, each vehicle-trip added to a route-segments generates diminishing productivity returns.

Table 3-4 - Fixed Effects Model Without Prior Frequency

	Response Variable: Rid_{it}			
	Portland	Miami	Minn. / St Paul	Atlanta
log ($Freq_{it}$)	0.71 (0.04)***	0.80 (0.04)***	0.75 (0.03)***	0.67 (0.01)***
log (Pop_{it} + Job_{it})	-0.00 (0.04)	0.02 (0.03)	0.11 (0.04)**	0.06 (0.01)***
μ_t	-0.01 (0.00)***	-0.04 (0.00)***	-0.03 (0.00)***	-0.05 (0.00)***
Log-likelihood	-10135.99	-10341.42	-10891.49	-19433.92
Num. obs.	4884	5264	5647	3453
n	874	1165	959	718
T	6	5	6	5

** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; · $p < 0.1$

In order to represent the **within** elasticity of ridership to frequency graphically, we must add the time dimension to our scatter plots. Figure 4 shows route-level productivity as a function of frequency in the first year (2012/2013/2014) in red and the last year (2017/2018) in blue. The slopes of the arrows linking the first year and the last year data points are marginal productivity. There is clearly a trend pulling productivity down in all agencies, which is not dependent on frequency change. However, if frequency had no impact on productivity (i.e. elasticity = 1), then all routes would lose the same relative productivity. In all agencies, routes in which frequency increased seemed to experience more relative decline in productivity than expected and *vice versa*. This is particularly true in Portland, where long arrows pointing towards the bottom-right contrast with short arrows spread in every direction.

The trends in Figure 4 also show the connection between frequency change and prior frequency. For example, in Portland, frequent routes gained frequency, perhaps in an attempt to combat overcrowding, while in Miami, frequent routes lost the most frequency, perhaps in an attempt to maintain coverage. Adding the interaction term between frequency and prior frequency can help determine whether the elasticity differs between previously frequent and infrequent routes.

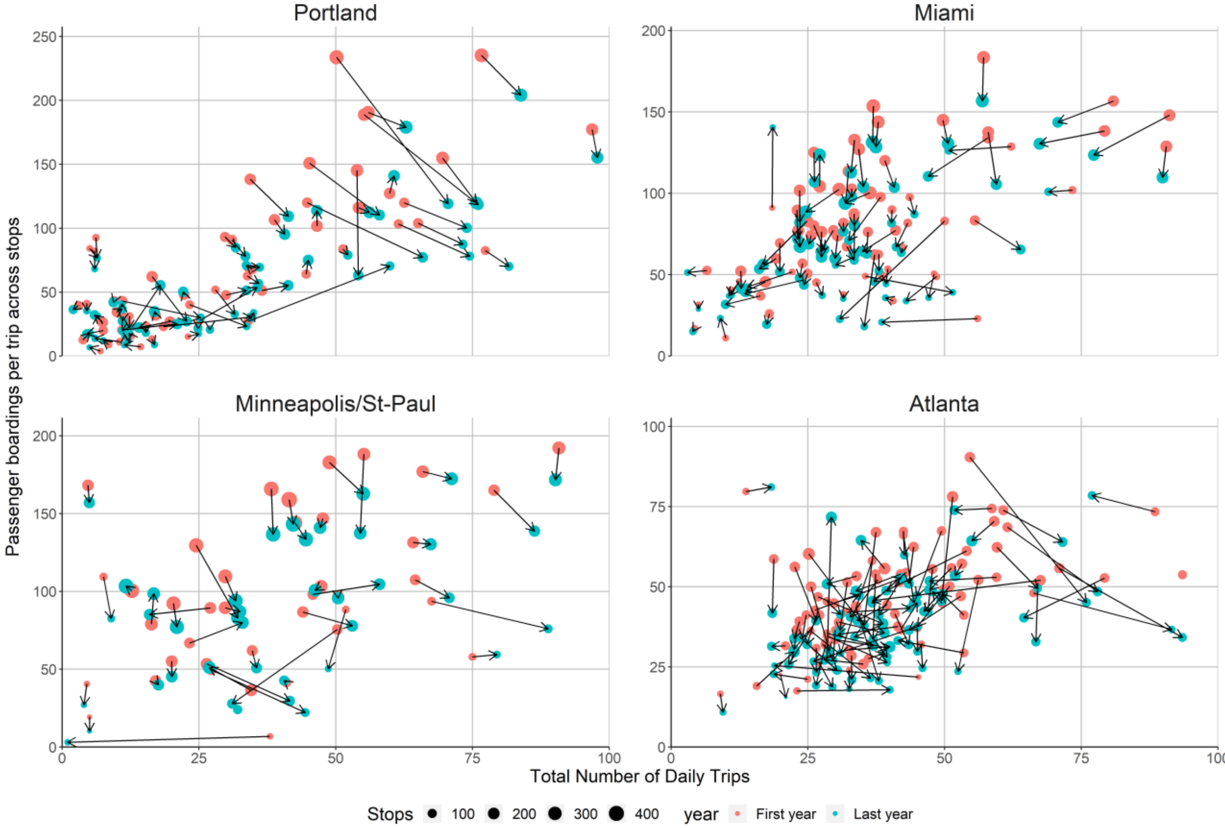

Figure 3-4: Route level productivity in passenger boardings per stop per trip as a function of weekday frequency over time in four metro areas.

3.5.3 Sensitivity to Prior-Frequency

Table 5 shows the fixed-effects model results where frequency is interacted with prior frequency. The $\log(Pop_{it} + Job_{it})$ and μ_t are almost identical to the previous model. The elasticity is the sum of its two first terms, $\beta_1 + \beta_2\log(Freq_{it0})$. The estimate of β_1 is far off from the estimate in Table 4 because the term is not centered. Its interpretation should assume that $\log(Freq_{it0}) = 0$, which is difficult to represent intuitively.

Figure 5 shows the elasticity of ridership to frequency as a function of prior frequency. Confidence bands of one standard deviation surround the estimated elasticity. Since the elasticity term includes two components, one fixed, β_1, and one based on frequency in the first year, $\beta_2\log(Freq_{it0})$, the combined standard deviation was obtained using the Delta Method (Oehlert, 1992). In Portland, Miami, and Atlanta, elasticity is greatest on low-frequency routes, while in Minneapolis/St-Paul elasticity is greatest on high-frequency routes. These results indicate that in all agencies besides Minneapolis, each percentage increase in frequency will produce greater percentage increase in ridership on routes that were previously infrequent than on routes that already had high-frequency.

Table 3-5 - Fixed Effects Model with Prior Frequency

	Response Variable: Rid_{it}			
	Portland	Miami	Minn. / St Paul	Atlanta
log ($Freq_{it}$)	1.39 (0.20)***	1.64 (0.28)***	-0.08 (0.22)	1.66 (0.09)***
log ($Freq_{it0}$) * log ($Freq_{it}$)	-0.20 (0.06)***	-0.22 (0.08)**	0.22 (0.06)***	-0.25 (0.02)***
log (Pop_{it} + Job_{it})	-0.01 (0.04)	0.02 (0.03)	0.10 (0.04)*	0.07 (0.01)***
μ_t	-0.01 (0.00)***	-0.04 (0.00)***	-0.03 (0.00)***	-0.05 (0.00)***
Log-likelihood	-10129.75	-10336.89	-10883.90	-19370.27
Num. obs.	4884	5264	5647	3453
n	874	1165	959	718
T	6	5	6	5

** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; · $p < 0.1$

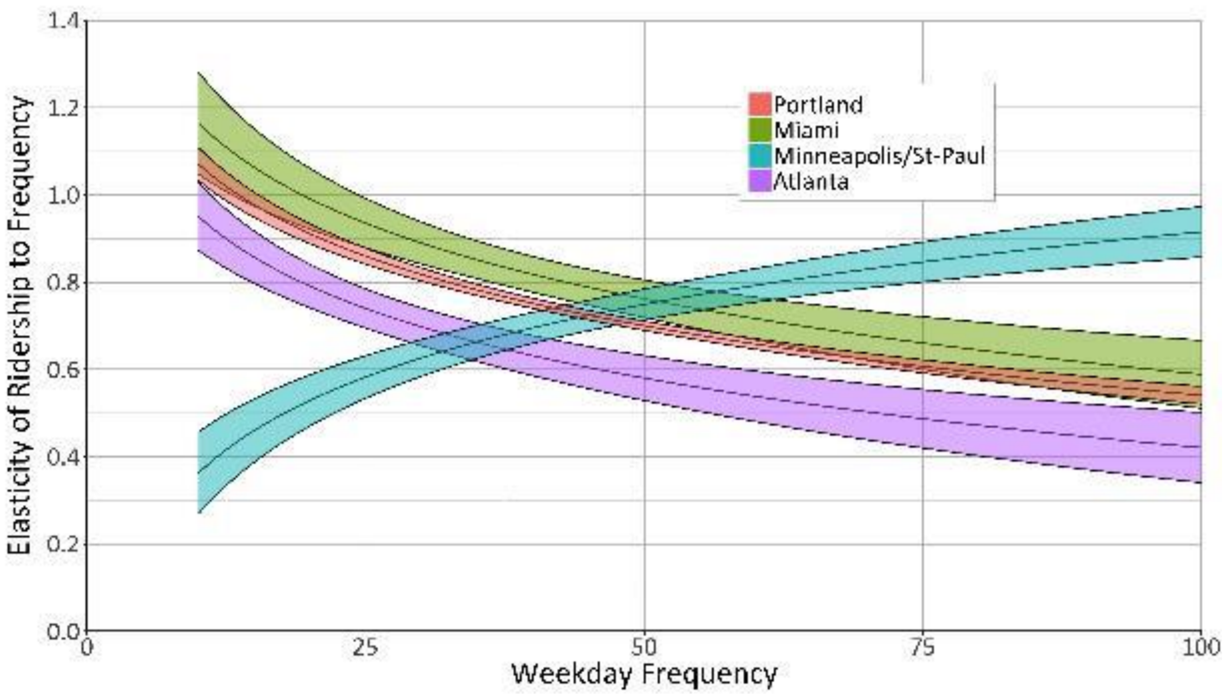

Figure 3-5: Elasticity of ridership to frequency as a function of frequency

3.6 DISCUSSION AND CONCLUSION

Through this study, we have shown how ridership can be modeled on a highly disaggregated level, while capturing the effects of frequency. A Poisson fixed-effects model was proposed to control for endogeneity and unobserved heterogeneity in ridership, which is count data. With the development of a new data standard for historical APC data, GTFS-ride (Porter et al., 2018), passenger count data are expected to become increasingly available. The methodology applied to this problem for the first time can guide future research to address some of the most pressing contemporary problems facing public transportation.

The large difference in elasticities between the cross-sectional and fixed-effects models imply the presence of unobserved heterogeneity at the segment or route level. Controlling for variation in frequency **within** each segment or route is therefore necessary to evaluate the effect of other factors outside of transit agencies' control. Therefore, stops, segments, or routes should be used as the spatial unit to analyze transit ridership. Evaluating ridership data on geographic units that are not related to transit service (e.g. Census Blocks, Block Groups, neighborhood) involves blending the unobserved heterogeneities of several routes together. For example, a 10% increase in service in an area will have a very different effect depending on which route increased in frequency.

Transit agencies are tasked with making decisions with the tools available. Basing these decisions on a snapshot of ridership at one point in time is tempting because it provides an intuitive framework of comparison. Simply looking at a cross-section of ridership, one may conclude than increasing frequency leads to greater productivity. After all, frequent routes serve more passengers per trip than lower-frequency routes as shown in Figure 4 and in the cross-sectional analysis of Subsection 6.1. In reality, however, no agency has an overall elasticity greater than one, as shown in Subsection 6.2. Therefore, each marginal trip added to a route will, on average, produce less ridership than the current route productivity. For all agencies studied, the expected ridership returns from frequency are diminishing.

The relationship between elasticity and prior frequency is a product of both the potential demand and the existing transit system. In the pursuit of ridership, transit planners set frequencies to the point of diminishing returns. In Portland, Miami, and Atlanta, the potential demand on high-frequency corridors is already matched by the current service levels. In these cities, more potential demand remains untapped on lower-frequency routes, as shown in Subsection 6.3. This is particularly true in Atlanta, where the productivity advantage of frequent routes is minor and where elasticity decays with prior frequency at a fast rate. In Portland and Miami, the elasticity decay with prior frequency **within** route-segments over time is offset by the productivity advantage of prior frequency **between** route-segments at a point in time. In Minneapolis, on the other hand, frequency is positively associated with productivity when comparing both **between** and **within** route-segments. Minneapolis/St-Paul, therefore, has more untapped demand on corridors that already have high frequency than on the coverage network.

The expected ridership change from cutting service on a low-frequency route to prioritize a high-frequency route (or *vice versa*) can be estimated solely based on prior frequency and productivity of both routes, as shown in Section 5.3. Therefore, the decision to prioritize service coverage or concentration should be made on a case-by-case basis to attain the best possible compromise. This chapter gives transit agencies the tools to predict the effects of service changes.

These results bring nuance to one of the most ingrained assumptions in service allocation policy-making: the binary choice between ridership and coverage. Walker popularized this postulate, encouraging transit agencies to split operating budgets between the two categories of service (Walker, 2012). This study found that operating dollars can contribute to both objectives simultaneously to different degrees. In particular, a transit agency exclusively focused on ridership would not want to concentrate all its service on the single most productive route. As theorized by Furth and Wilson (1981) the optimal ridership would be attained when the marginal productivity is the same on all routes. This idea is confirmed by this research, which shows that frequent routes are, on average, more productive than lower-frequency routes, but that increasing frequency on a route leads to a decline in productivity.

The service allocation problem consists in setting frequencies throughout the bus network with the objective of minimizing a combination of waiting costs for passengers and operating costs for the agency (Mohring, 1972). The method was extended by Furth and Wilson (1981) to consider the societal benefit of transit ridership in the objective function based on elasticitiesfrom Mayworm et al. (1980). More recent research has used ridership elasticity to frequency as an input parameter (Verbas and Mahmassani, 2013). The optimal service allocation policy was found to be sensitive to the assumed elasticity. The elasticities modeled in this chapter can support these types of service allocation optimization tools. Future research could take the relationship between elasticity and prior frequency into account to attain even greater efficiency.

This chapter provides the keys to understanding where ridership is declining and its relationship with frequency. While frequency is not the only factor affecting ridership, it determines the feasibility, travel time, and reliability of transit trips. Frequency changes every three to four months, bringing sudden jolts to the transit service, which must be considered in any ridership model. Changes in service level may even affect ridership on adjacent lines. The model presented in this chapter could be extended in future research to consider the ridership impact of nearby service changes, from slight bus schedule adjustment to heavy rail station opening.

Several research questions remain unaddressed. In particular, service changes do not explain the current nation-wide ridership crisis. Other factors such as changing travel behaviors, demographics shifts, and competition from dynamic mobility companies may also affect the demand for buses on a local level. They may ultimately explain the ridership change at the regional and national level. But their effects are necessarily lower order as they tend to drift slowly over time. Therefore, the elasticity to frequency is necessary to understand the underlying causes of ridership change. The approach presented in this chapter will allow future research to understand the causes of ridership decline and identify strategies to reverse the trend.

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4.0 WHO'S DITCHING THE BUS?

Research conducted by Dr. Kari Watkins and Dr. Simon Berrebi. The full paper is published in Transportation Research Part A.

Simon J. Berrebi, and Kari E. Watkins, "Who's ditching the bus?", Transportation Research Part A: Policy and Practice, Volume 136, 2020, Pages 21-34, ISSN 0965-8564, Link: [Who's ditching the bus?]()

4.1 INTRODUCTION

Public Transportation in the United States attained an unprecedented level of crisis in 2018, when, following six consecutive years of decline, bus ridership fell to its lowest level ever recorded (Cihak and Pham (1999); Dickens (2019). Bus ridership, which represents almost half of all transit trips, is driving down overall transit usage. While rail ridership started declining in 2015, it is still higher than in 2012. The 12.9% drop in bus unlinked passenger trips during the same period has caused overall transit ridership to fall by 6.1%. The lost fare revenue makes it more difficult for transit agencies to deliver service, which reduces access for parts of the population that have no other means of transportation.

There still lacks a consensus on the root causes of the current ridership crisis. Recent studies have pointed to a number of possible explanations, including urban migration, demographic shifts, service levels, and competing ride-hailing services (Manville et al., 2018; Driscoll et al., 2018; Boisjoly et al., 2018; Hall et al., 2018; Graehler Jr et al., 2019; Ederer, 2019). Studies have reached diverging conclusions on the role of each of these factors. To-date, virtually all the research investigating ridership trends over time have used the metropolitan area or transit agency as the spatial unit of analysis. However, the dynamics affecting ridership are likely to be taking place at a far more disaggregated scale.

In order to understand **why** ridership is declining, we must first ask **who**. Transit agencies serve diverse constituencies, which have different travel behaviors. On an individual level, the demand for buses changes over time in reaction to personal circumstances and competition from alternative modes. The external factors driving travel demand and the reaction they elicit are not homogeneously spread across socio-demographic groups. For example, the rise of telecommuting almost only applies to white-collar jobs. Another example is dropping car ownership costs, which apply to all but have more impact on the travel behavior of low-income people. Therefore, whatever is causing the ridership decline on a national level may have different effects on individual patrons.

Understanding which passenger characteristics are most closely associated with the decline is a necessary step towards identifying the causes of behavior change. If the ridership loss is particularly prevalent among certain socio-demographic groups, then the factor leading to this shift in travel behavior may be identified. If, on the other hand, the ridership decline is evenly distributed, then the underlying cause could be a blanket factor affecting all in the same way. Based on this determination, transit agencies would then be able to anticipate future changes in ridership and implement treatments to reverse the trend. They could then decide whether to lure back these lost riders with more service or concentrate on more promising market segments.

While we are seeking to identify the neighborhood demographics associated with ridership and change thereof, higher order effects must be controlled for: population, jobs and service frequency. To analyze ridership at a fixed point in time, we develop a model that represents the interaction between travel demand and supply. To identify the demographic characteristics associated with ridership change between 2012 and 2018, a fixed-effects model captures the impact of changing population, jobs, and frequency over time. This analysis is based on the same four transit agencies as Chapter 3:

- Tri-County Metropolitan Transportation District of Oregon (TriMet) in Portland OR
- Miami-Dade Transit in Miami, FL
- Metro Transit in Minneapolis/St-Paul, MN
- Metropolitan Atlanta Rapid Transit Authority (MARTA) in Atlanta, GA

This chapter proceeds as follow: the next section describes the research done thus far on who is ditching the bus. The Data section introduces the model variables and their sources. The Case Study section introduces the four transit agencies featured in this research. The Results section shows the cross-section and fixed-effects regression model results, which are verified with scatter plots. Finally, the broader implications of this research are discussed in the Conclusion Section.

4.2 LITERATURE REVIEW

Recent studies have included demographics variables in their analysis of ridership change over time to shed light on the effects of urban migration and demographic shifts. Driscoll et al. (2018) estimate the effects of aging population on ridership. Assuming that travel demand and mode share by age bracket have remained constant since 1980, they simulate how ridership would have changed under different age distribution scenario. They find that 3% of the 20% decline could be due to aging population. In a longitudinal study of Utah Transit Authority ridership over 10 years, Lyons et al. (2017) find that the change in proportion of white residents correlates negatively with the change in ridership. Boisjoly et al. (2018) model the factors affecting ridership change in 25 North American transit agencies over 14 years. They find that the change in proportion of carless households is positively correlated with ridership change. These results help understand how transit agencies serving customers with different needs evolve over time, but they lack the granularity to explain behavioral changes happening on a local level.

To capture the relationship between local demographics and ridership, studies cross APC data with neighborhood-level data sources. Dill et al. (2013) model stop-level ridership in Portland, Eugene, and Medford, OR. They find that across the three cities, the proportion of local residents who are white, college-educated, and have access to a car correlate negatively with ridership. Frei and Mahmassani (2013) evaluate how static demographics explain stop-level ridership. They find that the proportion of residents who are employed and under 17 years old correlates with higher ridership. Mucci and

Erhardt (2018) model factors affecting ridership at one point in time and measure whether these factors changed between 2009 and 2016. Assuming that the effect of income on ridership has not changed, they find that the 6% increase in high-income households could be responsible for 4% of the decrease in ridership. While these studies help understand who rides the bus at one point in time, they don't explain changes in travel behavior overtime.

A host of research has evaluated the connection between demographics and ridership on an individual level using surveys. Based on the Canadian Census, Pasha et al. (2016) model the influence of demographics and transportation-related variables on transit mode-share in Calgary. They find that income is negatively correlated to transit mode share. Based on the 1995 National Household Transportation Survey, Giuliano (2005) find that low-income earners and African-Americans are more likely to have less access to private vehicles and to use public transportation more often.

Based on travel surveys from 1998, 2003, and 2008, Grimsrud and El-Geneidy (2013) and Grimsrud and El-Geneidy (2014) find that transit mode share declines over the course of one's life due to longer commutes, parental responsibilities, etc. However, when controlling for these variables, recent younger generations exhibit greater transit mode shares than previous cohorts. It is telling that demographic factors are significant and consistent when approached from three levels of aggregation: regional, local, and individual. While some of the studies in the literature seek to understand how changes in demographics explain changes in ridership, they are all based on the assumption that travel behavior by age, race, and social status remains constant over time. In reality, changes in behaviors from transit patrons may explain the current ridership crisis.

This research seeks to evaluate how the propensity to use transit among different demographic groups have changed over time. We use panel regression to control for changes in frequency, population, and jobs. The next sections describes the data, case studies, and modeling techniques employed in this study.

4.3 DATA

In this chapter, the spatial unit of analysis is again the route-segment. See Chapter 3 for more information about how these route-segments were created. All the terms and variables used in this chapter are defined in Table 1. The data sources (ridership, frequency, population and jobs, demographics) were also similar to those in Chapter 3.

Table 4-1 - Summary of Variable Definitions

Variable	Definition
Rid	Total weekday passenger boardings and alightings
Freq	Total weekday vehicle-trips
Pop+Job	Total population and jobs within ¼ mi of segment
$Dem_{ZeroVehHH}$	Proportion of households with zero vehicles
Dem_{White}	Proportion of residents who are white
$Dem_{HighSch}$	Proportion of residents who completed high-school or less

$Dem_{Millenial}$	Proportion of residents aged 22 to 34 at time of Censussurvey
Dem_{Senior}	Proportion of residents over 62 at time of Census survey
Dem_{Jobs}	Proportion of Pop+Job that are jobs
x	Vector of explanatory variables
t	Year $\in (0, \dots, T)$
i	Route-segment $\in (0, \dots, n)$

The same four transit agencies were selected to explain the nation-wide ridership decline. These transit agencies are similar in key ways that make their comparison possible. They are also different enough to be representative of the broader trend. The four agencies are all mid-sized to large from different regions of the United States. They were early adopters of APC technology and attained full or almost full coverage several years ago. Table 2 shows the years of data availability and summary statistics of the regression variables. None of the transit agencies had data available for 2012 through 2018. The analysis starts in 2013 in Miami, in 2014 in Atlanta and ends in 2017 in Portland, Miami, and Minneapolis.

The transit agencies in this case study vary widely with respect to the model variables. The average stop serves 50.9 passengers per weekday in Portland, but only 36.4 in Atlanta. Average frequency is more homogeneous across agencies, ranging between 37.5 trips per day and Atlanta with 43.6 trips per day. Atlanta also has the least average population and jobs surrounding bus stops with less than half of any other city. Portland is by far the whitest city with, on average, 80% of white resident surrounding bus stops. Miami is the least educated city with almost half of resident surrounding bus stops having no secondary education. The proportion of millennials and seniors is similar across the four cities. Jobs represent between 31%, in Miami, and 39%, in Portland, of trip generators close to bus stops.

Table 4-2 - Years of Data Availability and Summary Statistics of the Regression Variables

	Portland		Miami		Minn. / St. Paul		Atlanta	
Variables	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
First Year	2012		2013		2012		2014	
Last Year	2017		2017		2017		2018	
Rid	50.9	62.0	45.3	49.6	39.6	63.2	36.4	41.7
Freq	40.4	28.1	37.5	20.6	40.8	26.1	43.6	18.2
Pop+Job	1,451	2,004	1,439	1,573	1,681	2,435	710	915
$Dem_{ZeroVehHH}$	0.13	0.11	0.13	0.10	0.15	0.10	0.16	0.11
Dem_{White}	0.80	0.09	0.66	0.29	0.66	0.18	0.35	0.29
$Dem_{HighSch}$	0.22	0.13	0.47	0.16	0.27	0.13	0.33	0.16
$Dem_{Millennial}$	0.23	0.08	0.19	0.04	0.26	0.09	0.23	0.08
Dem_{Senior}	0.17	0.05	0.19	0.06	0.15	0.05	0.15	0.06
Dem_{Jobs}	0.39	0.25	0.31	0.24	0.38	0.25	0.35	0.25

4.4 RESULTS

This section presents the results from the Poisson cross-section and fixed-effects models. For derivation of the model forms, please see the published paper.

4.4.1 Cross-Section

We begin by modeling ridership at a fixed point in time as a function of static frequency, population, jobs, and demographics. Table 3 shows the cross-section model results. Ridership in the first year (2012 for Portland and Minneapolis/St-Paul, 2013 for Miami, and 2014 for Atlanta) is explained with the change in frequency, population, and jobs, and with static demographics. We use the McFadden pseudo-R^2 to evaluate the fit. The high pseudo-R^2 in Portland, Miami, and Minneapolis/St-Paul indicates that the model explains the vast majority of the variation. Although the pseudo-R^2 in Atlanta is lower, it still explains almost half of thevariation.

While the concentration of millennial residents can be positively or negatively correlated, the presence of seniors is associated with lower bus ridership in all four cities. In Miami, the parameter estimate for millennials is significantly negative, whereas in Minneapolis/St-Paul it is significantly positive. This result may be a reflection of the different types of places where millennials live in both cities. Regarding seniors, the parameter estimates are consistent in sign and significance in all four cities. Neighborhoods with high concentrations of residents above 62 have lower ridership when controlling for frequency, population, and jobs.

Table 4-3 - Cross-Section Models

	Response Variable: Rid			
	Portland	Miami	Minn. / St Paul	Atlanta
log (Freq)	1.35 (0.04)***	1.21 (0.03)***	1.50 (0.04)***	1.33 (0.08)***
log (Pop + Job)	0.41 (0.06)***	0.53 (0.02)***	0.52 (0.02)***	0.33 (0.04)***
$Dem_{ZeroVehHH}$	0.32 (0.31)	0.34 (0.18)	0.46 (0.34)	1.36 (0.40)***
Dem_{White}	-0.44 (0.26)	-0.24 (0.08)**	-0.20 (0.24)	-0.05 (0.17)
$Dem_{HighSch}$	0.58 (0.19)**	0.41 (0.12)***	0.96 (0.34)**	0.59 (0.30)*
$Dem_{Millennial}$	-0.15 (0.35)	-3.18 (0.48)***	1.61 (0.29)***	0.92 (0.48)
Dem_{Senior}	-1.34 (0.50)**	-1.60 (0.39)***	-1.88 (0.55)***	-1.67 (0.65)*
Dem_{Jobs}	0.46 (0.12)***	0.16 (0.09)	0.28 (0.15)	0.61 (0.17)***
(Intercept)	-3.87 (0.49)***	-4.44 (0.24)***	-4.92 (0.46)***	-2.87 (0.49)***
Pseudo R2	0.83	0.75	0.83	0.45
Deviance	8829.85	11730.70	9246.77	12979.48
Num. obs.	874	1165	959	718

$^{**}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

In all four cities, the share of jobs in total trip generators (populations + jobs) is positive, which indicates that each job contributes more to ridership than each individual resident. This may be because areas with high job to total trip generator ratio tend to be highly concentrated, and therefore transit-supportive. This effect explains the low coefficient of log(Pop+Job).

Finally, race, education, and vehicle ownership all correlate with transit usage. In all four cities, the proportion of white residents and zero vehicle households are negatively and positively correlated with ridership, respectively, albeit not significantly so in every city. The proportion of residents whose maximum level of education is high-school correlates significantly and positively with ridership in all four agencies. These results are consistent with the literature (Giuliano, 2005), particularly with Dill et al. (2013), who modeled ridership at the stop-level in Portland as a cross-section analysis.

4.4.2 Fixed-Effects with Static Demographics

We now model the change in ridership over time as a function of frequency, population, and job change, and of static demographics. Table 4 shows the fixed-effects model results. Unfortunately, the Poisson fixed-effects model does not have an equivalent to R^2. The variable Year represents the ridership change across route-segments, which is otherwise unaccounted for in the model. It is only significant in Atlanta, where it can be interpreted as a systematic effect pulling ridership downwards. In the other three agencies, the time-intercept is not significant, indicating that the model explains the overall ridership decline.

The effects of population and job change over time is only significant in Atlanta, and to a lesser extent in Minneapolis/St-Paul. Even in these cities, the coefficient is unrealistically low. The population change captured between 2011 and 2015 may not be sufficient to explain the ridership change in subsequent years. The variation from changing population and jobs may already be captured by the frequency and demographic variables in the model. In particular, the proportion of jobs in total trip generators is significant in every city except for Portland. The advantage of jobs versus residents in generating ridership was strengthened in Miami and Atlanta, and diminished in Minneapolis/St-Paul.

Table 4-4 - Fixed-Effects Models

	Response Variable: Rid_{it}			
	Portland	Miami	Minn. / St Paul	Atlanta
log ($Freq_{it}$)	0.71 (0.04)***	0.82 (0.04)***	0.74 (0.03)***	0.69 (0.01)***
log (Pop_{it} + Job_{it})	-0.02 (0.04)	-0.02 (0.03)	0.08 (0.04)	0.05 (0.01)***
Dem$ZeroVehHH_{it0} * t$	0.01 (0.06)	-0.26 (0.07)***	-0.13 (0.08)	-0.39 (0.04)***
Dem$White_{it0} * t$	-0.18 (0.07)*	-0.12 (0.03)***	-0.17 (0.07)**	-0.12 (0.02)***
Dem$HighSch_{it0} * t$	0.02 (0.05)	0.22 (0.05)***	-0.13 (0.09)	0.27 (0.03)***
Dem$Millennial_{it0} * t$	0.38 (0.10)***	-0.55 (0.20)**	-0.05 (0.08)	0.25 (0.05)***
Dem$Senior_{it0} * t$	0.37 (0.14)**	-0.42 (0.17)*	0.55 (0.14)***	-0.08 (0.06)
Dem$Jobs_{it0} * t$	-0.02 (0.03)	0.13 (0.03)***	-0.17 (0.03)***	0.06 (0.01)***
Year	-0.02 (0.02)	-0.01 (0.02)	0.03 (0.02)	-0.06 (0.01)***
Log-likelihood	-10117.52	-10303.07	-10825.20	-19333.60
Num. obs.	4884	5264	5647	3453
N	874	1165	959	718
T	6	5	6	5

** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; · $p < 0.1$

There is no consistent change in age-related transit ridership across cities. The presence of both seniors and millennials correlate with ridership gain in Atlanta but with ridership loss in Miami. Neighborhoods were more likely to increase in ridership if they had high concentrations of millennials in Minneapolis/St-Paul and seniors in Atlanta.

The proportion of white residents is the only demographic factor that consistently and significantly affects ridership across all four agencies. In every case study, white neighborhoods were more likely to decline in ridership when controlling for frequency, population, and job change. In Miami and Atlanta, the proportion of residents without secondary education is associated with ridership gains and the proportion of residents without access to a car is associated with ridership loss. These results indicate that the recent decline in ridership is happening in white, educated, and carless neighborhoods.

In order to investigate the main trend found in Table 4, Figure 1 shows the log-relative change in ridership versus proportion of white residents within a ¼ mile radius surrounding route-segments. The vertical axis shows the log of ridership in the last year divided by the first year, which is how the Poisson model considers change in the response variable. The opacity of each point is weighted by its first-year productivity in ridership per trip. The red line shows a simple regression trend with every route-segment weighted the same.

There is a consistent negative relationship between the proportion of white residents and the change in ridership, but it does not entirely explain the overall ridership decline. In all four agencies, whiter neighborhoods lost more productivity even when not controlling for population, jobs, and all other demographic variables. This trend is strongest in Portland and Atlanta; less so in Miami and Minneapolis/St-Paul.

The trend, however, does not account for all of the ridership decline. Route-segments surrounded by low proportions of white residents also lost ridership, just not as much as homogeneously white neighborhoods. In Miami, Minneapolis/St-Paul, and Atlanta, places with just 50% of white residents were still expected to drop in productivity. Portland is the exception but almost all route-segments are majority-white.

In all four agencies, the trend is strongest among the most productive route segments. Lighter points, which represent low-productivity route-segments have considerably more variation. Since these route-segments have fewer boardings and alightings per trip to begin with, a few more or less passenger can overwhelm the log-relative change in ridership. Productive route-segments, on the other hand, exhibit a stable trend wherein ridership declines across the board but more so in white neighborhoods.

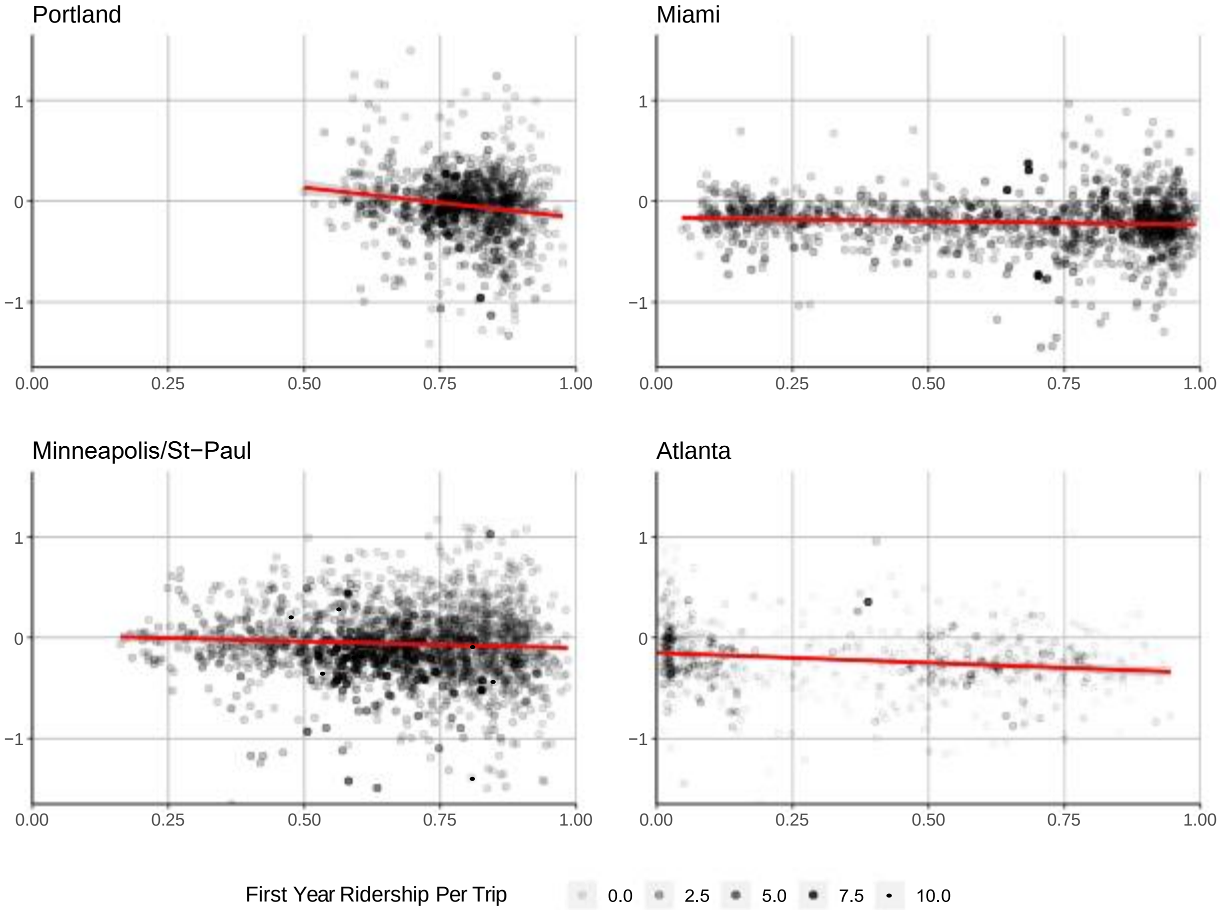

Figure 4-1: Log-Relative Change in Ridership Versus Proportion of White Residents

4.5 CONCLUSION

In all four cities, the demographic groups associated with high ridership at a point in time are also associated with the least ridership decline over time. This study confirms that the factors associated with transit-dependence in the literature correlate with cross-sectional ridership at the route-segment level. While ridership declined across neighborhood demographics between 2012 and 2018, it happened at a faster rate in places with few transit-dependent residents. When controlling for the change in frequency, population, and jobs, ridership declined the most in white neighborhoods. In addition, ridership change correlates positively with the proportion of high school educated residents and negatively with the carelessness rate in Miami and Atlanta.

While these findings do not explain why ridership is declining, they provide an important clue: the underlying cause of ridership decline affects travel behaviors in all types of neighborhoods, but especially in places where white, educated, and carless people live. One trend that has affected travel behaviors of white employees is the upsurge of telecommuting (Walls et al., 2007). Between 2012 and 2016, US employees working remotely rose from 39% to 43% and they spent more time doing so

(Gallup, 2017). Another possible explanation is the rise of ride-hailing. Several studies report that people who are white, college educated, and have low-vehicle access are more likely to use ride-hailing (Rayle et al., 2016; Clewlow and Mishra, 2017; Dias et al., 2017; Circella et al., 2018; Sikder, 2019). Ride-hailing more than doubled the size of the overall for hire services sector between 2012 and 2017, when they were expected to surpass overall bus ridership in the United States (Schaller, 2018). Trends in telecommuting and ride-hailing therefore correspond with the ridership decline across time and neighborhood demographics.

The results also suggest that factors primarily affecting non-white neighborhoods are most likely not responsible for the ridership decline. Manville et al. (2018) assign the ridership decline in Southern California to a growth in vehicle ownership among low-income earners. This trend is likely to reach beyond Southern California; between 2012 and 2016, average gas prices in the United States declined every year and new car loan interest rates never rose above 5% (EIA, 2019; Butters, 2018). Meanwhile, real median income increased by 10.8% for African American households and by 20.5 % for Hispanic households. However, the fact that ridership is declining the most in white, and in the case of Miami and Atlanta highly educated, neighborhoods indicates that vehicle affordability is unlikely to be the root cause of the nation-wide ridership decline (Wilson, 2018). It is possible that the effects of rising car ownership among people who previously depended on transit was offset by the decline in African-American and Hispanic unemployment every year between 2012 and 2016 (BLS, 2018).

One of the key missing pieces of this analysis is the rail network. Since the early 1990's transit agencies started prioritizing rail service over buses in an effort to capture potential riders who have access to private cars. This effort culminated in 2017 when rail ridership surpassed bus ridership for the first time since the dismantlement of the American streetcar system (Dickens, 2019). Future research should verify whether rail stations located in mostly white and educated neighborhoods have increased in ridership as a result of mode substitution. Or if, on the contrary, the same trends exhibited in the bus network apply to rail. In either case, the findings may have profound policy ramifications.

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5.0 PARTNERSHIPS WITH TNCS TO BETTER SERVE THE TRANSPORTATION DISADVANTAGED POPULATIONS

Research conducted by Dr. Ruth Steiner, Dr. Ilir Bejleri, Xueyin Bai, Mengjie Han, and Soowoong Noh, University of Florida. The paper has been accepted for publication by the Transportation Research Record:

Steiner, R. L., Bai, X., Bejleri, I., Han, M., and Yan, X. (2021; forthcoming). Partnerships between Agencies and Transportation Network Companies for Transportation Disadvantaged Populations: Benefits, Problems and Challenges. Transportation Research Record; The Journal of the Transportation Research Board.

5.1 INTRODUCTION

The emergence and rapid growth of Transportation Network Companies (TNCs) such as Uber and Lyft have gained considerable prominence in offering a new mode of transportation to consumers. An increasing number of public agencies are partnering with TNCs in order to reduce operation cost, increase transit ridership, and improve service levels and customer experiences (Westervelt, Schank and Huang, 2017; Schwieterman, Livingston and Van Der Slot, 2018). These partnerships include using TNCs to serve first- and last-mile rides to and from transit stations, to complement regular transit services during off-peak periods and in underserved areas, and even to substitute for underperforming transit routes (Westervelt et al., 2017; Schwieterman et al., 2018).

Transit agencies are often charged with equity goals of providing services to the Transportation Disadvantaged (TD) populations. TD populations, defined by Florida Statutes Section 411.202, are those who, because of physical or mental disability, income status, or age, are unable to transport themselves or purchase transportation and are dependent on others to obtain access to life-sustaining and social activities. In the state of Florida, they have been provided transportation services by public transit agencies, private for-profit and non-profit organizations, and other human service agencies. However, sustaining these transportation services has long been under great pressure due to the high cost and continuously increasing demand. As a new service model, partnerships between public transit and TNCs create opportunities to improve transportation services for TD populations. The 2019 Florida State Legislature Bill (CS/HB 411) makes these partnerships more promising by allocating designated funds and authorizing TNCs to provide nonemergency medical transportation services for TD populations. To make these partnerships work for TD populations, however, many challenges such as financial constraints and regulatory restrictions need to be addressed. The issue of how to work with TNCs to better serve the TD populations is an understudied research topic.

This research explores the current state and future opportunities of the TNCs partnership programs for TD populations especially, through literature review and semi-structured interviews with related

(Collier et al., 2017). Although TNCs' employment strategy have enabled their competitive pricing for customers and the potential to benefit the transportation disadvantaged, the rights of TNC drivers is still a crucial aspect that is closely related to how TNCs could benefit all populations in the long run.

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6.0 HEALTHCARE ACCESS & HOW TECHNOLOGY IS RESHAPING PARATRANSIT

Research conducted by Dr. Noreen McDonald and Mary Wolfe, University of North Carolina at Chapel Hill.

Transport barriers to healthcare lead to adverse health outcomes and increased healthcare costs. Technological advances are reshaping strategies to overcome transport barriers and have potential to change the current usage of paratransit and dial-a-ride services in the U.S. These changes affect level of service provided to riders as well as the cost to users and transportation providers. While these advances are occurring swiftly and across the country, it is unclear how these changes might shift access to care for certain populations. Our research is multi-pronged and aims at 1) identifying the scale of transport barriers to care in the US, 2) assesses current patterns of paratransit usage to reach healthcare services in NC, 3) analyzes perspectives from healthcare providers on transport barriers and strategies t overcome, and 4) investigates the evolution of paratransit in light of innovation in mobility services. The findings of our research shed light on the rapid evolution of paratransit services and provide decision-makers with an understanding of how technology is changing this service. While this research was conducted prior to COVID, the pandemic emphasizes the need for further attention to innovative solutions for overcoming transport barriers to care.

Taken together these strands of research show the large and unmet need for transport to healthcare in the United States. They document the strong actions taken by current providers attempting to meet this gap including transit operators and medical providers as well as innovative solutions being tried to transit agencies, medical providers, and insurers to utilize shared mobility services. The results highlight the complexity of the issue – there is no simple technology-based solution – but do show the potential for integrated solutions that meet the needs of transport and healthcare providers. Our research findings are provided in this report, have been published in journal articles, and presented at conferences and through STRIDE webinars and meetings with transport and healthcare practitioners working on these issues. The resulting journal articles are:

Wolfe, M.K., McDonald, N.C. Innovative health care mobility services in the US. BMC Public Health ***20,*** *906 (2020).* *Innovative health care mobility services in the US*

Mary K. Wolfe, Noreen C. McDonald, and G. Mark Holmes, 2020. Transportation Barriers to Health Care in the United States: Findings from the National Health Interview Survey, 1997–2017. American Journal of Public Health ***110***, *815_822*. ***Transportation Barriers to Health Care in the United States: Findings from the National Health Interview Survey, 1997–2017***

The following sections summarize our research in each of these areas:

6.1 Document the prevalence of transportation barriers nationally and for specific patient populations,

6.2 Inventory traditional and new paratransit services providing access to health destinations,

6.3 Assess the motivation for new providers of paratransit to offer the service, and

6.4 Inventory traditional and new paratransit services providing access to health destinations.

6.1 DOCUMENT THE PREVALENCE OF TRANSPORTATION BARRIERS NATIONALLY AND FOR SPECIFIC PATIENT POPULATIONS

Given the lack of access to information regarding operating costs of new paratransit services (as was originally proposed), we instead documented the prevalence of transportation barriers to care nationally, as this is an important figure to understand and the most recent estimate available is from 2005. A full paper titled 'Transportation Barriers to Healthcare in the U.S.' has been published in the *American Journal of Public Health* based on this research. A summary is presented below. We have also disseminated this research to practitioners through a STRIDE webinar on September 18, 2019, which is available through the STRIDE website. The full citation for the article is:

Mary K. Wolfe, Noreen C. McDonald, and G. Mark Holmes, 2020. Transportation Barriers to Health Care in the United States: Findings from the National Health Interview Survey, 1997–2017. American Journal of Public Health ***110****, 815_822* ***. Transportation Barriers to Health Care in the United States: Findings from the National Health Interview Survey, 1997–2017***

Introduction

While there are many demonstrated barriers to health care access including socioeconomic constraints and health literacy limitations, a lack of viable transportation inhibits a patient's ability to travel to health-promoting institutions like doctors' offices and pharmacies. Transportation barriers interrupt adherence with medical appointments and can prevent people from seeking care at all, which can exacerbate chronic disease and worsen health status over time (CDC, 2012). Patients who miss medical appointments experience adverse health outcomes, including increased hospital readmissions, medication noncompliance, and disrupted continuity of care (Mehrotra, 2008; Salameh, Olsen, and Howard, 2012; Syed, Gerber, and Sharp, 2013). Research shows that missing follow-up appointments to primary care providers leads to health risks for patients who miss diagnostic testing (Karter et al., 2004). Missed appointments also undermine early detection of disease (Weingarten, Meyer, and Schneid, 1997).

An oft-cited study from 2005 estimates that approximately 3.6 million Americans miss or delay non-emergency medical treatment every year despite having health care coverage due to lack of transportation to care facilities (Wallace, Hughes-Cromwick, Mull, and Khasnabis, 2005). In order to update this estimate, we use data from the National Health Interview Survey to conduct a descriptive cross-sectional and longitudinal analysis of the prevalence of transportation barriers to care in the US. Uncovering patterns of transportation barriers to care will inform healthcare providers and insurers who have a vested interest in promoting patients' kept appointments.

Methodology

We used data from the National Health Interview Survey (NHIS) to investigate the prevalence of transportation barriers to care in the US. We leverage a particular question in the NHIS that asks: "*There are many reasons people delay getting medical care. Have you delayed getting care for any of the following reasons in the past 12 months? . . . you didn't have transportation?"*

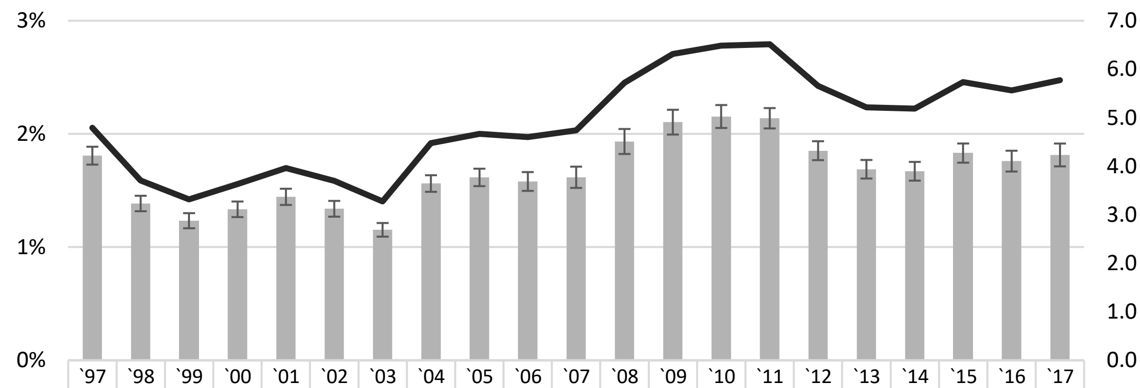
We examine responses to this question in three ways. First, we look longitudinally from 1997 to 2019 at the proportion of people who delay medical care due to lack of transportation over time. From each wave of data, we excluded only those respondents who were not asked about transport barriers to care because they were not part of the adult or child samples (n= 1,090,240) or who did not provide a valid answer to this question (n= 6,674) leaving a total pooled sample of 892,235 children and adults across 21 years.

Next, we take an in-depth look at patterns of transportation barriers to care for adults in the year 2017. We evaluate transport-delayed care across various sociodemographic subgroups and for people with various health conditions. Finally, we examine what factors might make someone more likely to report a transportation barrier to care. For the same 2017 sample, we specify a binary logistic regression model to look at correlates of this outcome adjusting for age, sex, race, ethnicity, educational attainment, poverty status, insurance status, employment status, and geographic region.

Findings

The number of Americans who delay medical care because they did not have transportation has grown over time, from 4.8 million in 1997 to 5.8 million in 2017. The proportion of Americans with this transportation barrier has fluctuated over time, spiking significantly during the Great Recession with a peak of 2.2% in 2010. While the proportion of Americans reporting this barrier is 1.8% in both 1997 and 2017, there is evidence of linear growth in the rate of delayed care due to a transportation barrier over time at a pace of .03 percentage points per year ($P<0.001$). These longitudinal trends can be seen in **Figure 8,** which reflects the weighted frequency of this transportation barrier for all ages at the population level.

In 2017, 1.9% (95% CI [1.7, 2.1]) of American adults aged 18 years and older delayed medical care because of a transportation barrier. Overall, 2.2% of women and 1.5% of men report delaying care because of transportation and this difference is statistically significant ($P<0.001$). There is variation across age groups, however the difference between groups is borderline significant ($F= 2.37$, $P=0.076$). Rates of transport-delayed care vary significantly across race and ethnicity groups ($F=10.31$, $P<0.001$) with non-Hispanic black respondents reporting the highest rates. Transport barriers to care vary significantly by educational attainment of respondents, with nearly 3% of those with a high school diploma or less reporting a transport barrier and only 0.6% of those with a bachelor's degree or higher reporting the same barrier. Poorer people are more likely to report transport-delayed care, with 7% of those living below the federal poverty threshold and 5.6% of those receiving Medicaid doing so in 2017



	`97	`98	`99	`00	`01	`02	`03	`04	`05	`06	`07	`08	`09	`10	`11	`12	`13	`14	`15	`16	`17
proportion	1.8%	1.4%	1.2%	1.3%	1.4%	1.3%	1.2%	1.6%	1.6%	1.6%	1.6%	1.9%	2.1%	2.2%	2.1%	1.9%	1.7%	1.7%	1.8%	1.8%	1.8%
millions	4.8	3.7	3.3	3.6	4.0	3.7	3.3	4.5	4.7	4.6	4.7	5.7	6.3	6.5	6.5	5.7	5.2	5.2	5.7	5.6	5.8

Figure 6-1: Frequency of transportation barriers to care in the US, 1997-2017 (all ages)

Conclusions

Lack of transportation delays medical care for millions of Americans every year, with this number nearing 6 million in 2017. There is a separate and robust literature that describes how increased patient access to routine and preventative care leads to improved overall health outcomes as well as avoidance of costly ambulance bills and emergency department visits. Our estimate of the number of Americans who delay medical care because of lack of transportation is likely conservative because there is often non-response bias in NHIS among those who are poor, homeless, and in very poor health.

Trips to medical facilities can be provided via Medicaid NEMT; mileage reimbursement through the Veteran's Administration; several offerings by Accountable Care Organizations; and rides through community organizations and volunteers. Even with these various current strategies, however, our finding that nearly 2% of the population reports transport-delayed care is evidence that current transportation options do not work for a large number of people.

6.2 DOCUMENT USAGE PATTERNS FOR TRADITIONAL PARATRANSIT SERVICES IN THE TRIANGLE REGION OF NORTH CAROLINA FOR ACCESS TO HEALTH SERVICES

There is not yet a presence of health-focused TNC services in the Triangle region of North Carolina. For Task 4.2, we therefore document usage patterns of existing paratransit provision in this region.

First, we assessed Medicaid non-emergency medical transportation (NEMT) trip counts at the county-level in 2018. NEMT is a Medicaid benefit that facilitates access to and from medical services for beneficiaries who have no means of transportation, or who need accommodations for physical or mental disabilities. Since its inception in 1966, Medicaid pays for NEMT services using the most appropriate and least costly form of transportation. Through this required benefit, states purchase hundreds of millions of rides from taxis, livery vehicles, vans, ambulettes, and public transit every year. Medicaid NEMT provision in the Triangle region for fiscal year 2018 is displayed in **Table 2.**

Table 6-1 - Regional NEMT utilization in the Triangle, NC (FY 2018)

County	Medicaid Trips	% of total trips
Orange	4,761	13%
Wake	145,175	81%
Chatham	8,708	11%
Johnston	48,398	52%
Lee	18,309	29%
Person	6,163	13%

Data reflects directly-operated demand response provision. Counties displayed are members of the Research Triangle Regional Partnership with exceptions: no directly-operated demand response in Warren, Granville, and Franklin Counties. Data for Durham County unavailable as it is owned and managed by contract agency Frist Transit.

Next, we use the city of Durham, NC as a case study to closely examine characteristics of paratransit provision in order to understand the demand that would need to be served by innovative services entering this region. Over an eleven-month period from July 2018 to May 2019, we analyze the overall distribution of trip destinations as well as the origins and destinations of all paratransit trips carried by the GoDurham transit agency. These trips include ADA trips as well as Medicaid NEMT trips.

Between July 1, 2018 and May 31, 2019, the number of total weekday paratransit trips was 127,359. Across these trips, the distribution to “medical,” “work,” and “recreational” destinations are shown in **Table 3.**

Table 6-2 - Distribution of paratransit trip destinations

Medical (not including Dialysis)	7.27%	9,254
Medical (including Dialysis)	14.02%	17,857
Work	1.15%	1,468
Recreational	2.38%	3,028
Other/unknown	75.18%	95,752

The most frequent ADA paratransit client took a total of 590 trips in this 11-month period. The following heatmaps **(Figures 1 & 2)** show ADA, Medicaid NEMT, and County Trip origins and destinations (note: Highest intensity areas in red; Heatmap radius [i.e. How close trips must be to each other to make colors intensify] = 1 mile).

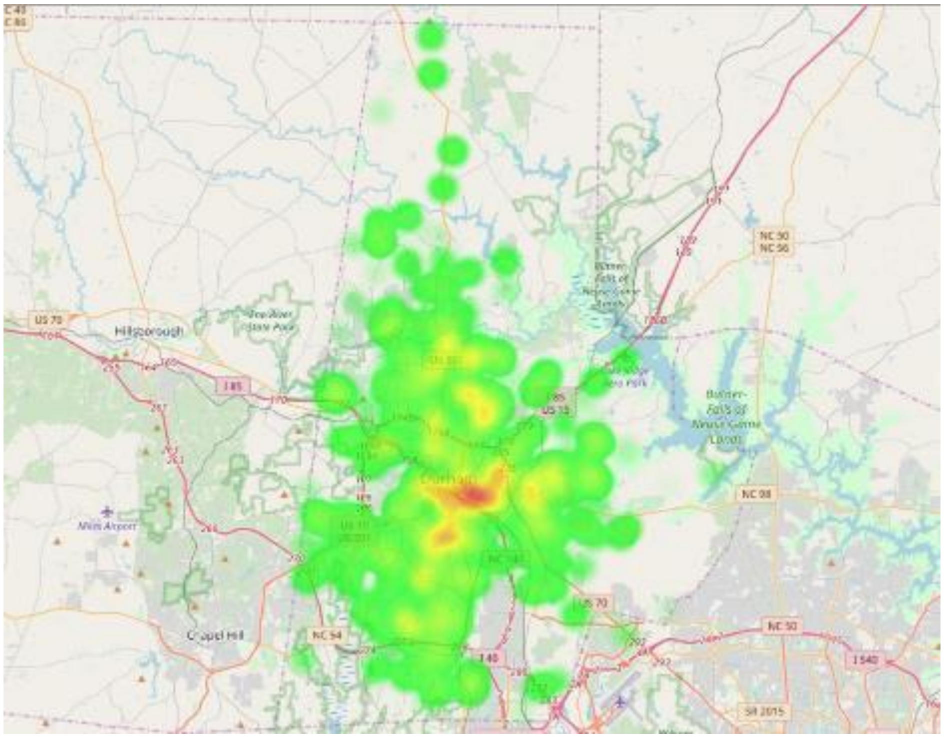


Figure 6-2: Paratransit Trip Destinations (trips carried by GoDurham; 7/1/18-5/31/19)

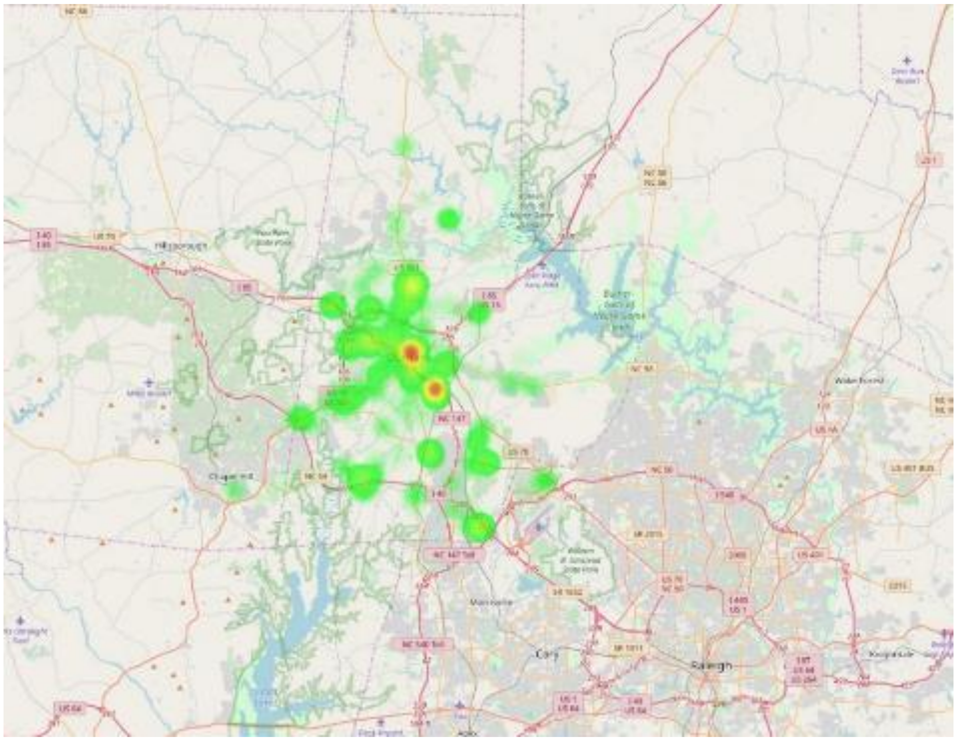


Figure 6-3: Paratransit Trip Destinations (trips carried by GoDurham; 7/1/18-5/31/19)

6.3 ASSESS THE MOTIVATION FOR NEW PROVIDERS OF PARATRANSIT TO OFFER THE SERVICE

We addressed this task by working with a group of health care providers in Durham, NC to assess motivation for innovation in the provision of paratransit. Specifically, we targeted care coordinators, social workers, and case managers who work with behavioral health patients to understand the unique challenges in acquiring transportation to medical appointments for this patient population.

Care coordinators are people who are trained in a health-related field, most often social work or nursing, who support groups of low-income or chronically ill patients, helping them to understand their care plans, and schedule primary-care visits, and plan transportation to medical appointments.

In addition to transportation barriers, individuals who live with a behavioral health condition often face other significant barriers to accessing care, such as time conflicts, limited availability of appointments with community-based providers, and the social stigma associated with seeking treatment for a mental illness or substance use disorder. It is especially important for these patients to keep scheduled behavioral health treatment appointments and to keep up with prescribed medications in order to avoid increased risk of experiencing a relapse or crisis that can lead to hospitalization.

We conducted a survey of care coordinators, social workers, and case managers who attended a travel training session hosted by GoTriangle (the regional transit agency). The half-day session was organized to teach attendees about the various transportation options available to their behavioral health clients. Importantly, the training covered eligibility criteria and approval processes for all travel options. Volunteers and GoTriangle employees taught sessions about bus service, van service, and the various online resources available to help in the trip making process (see **Figure 3**).

Forty-one people attended the training in Durham, NC. We conducted a pre- and post-survey to ascertain specific aspects about the transportation booking process for behavioral health clinicians and case managers. Of all attendees, 33 people responded to the voluntary survey; 2 respondents were dropped due to incomplete surveys leaving a final sample size of 31. Our findings from the pre- and post-survey follow.

<u>Findings from Travel Training pre-/post-survey of behavioral health care providers:</u>

About the respondents: The career breakdown of the respondents was as follows: there were 14 mental health care providers with a clinical focus; this included Intake clinicians, Community Support Team specialists, behavioral health urgent care clinicians, and outpatient therapists. There were 17 respondents with a case management focus, which included care managers, care coordinators, case managers, and Registered Nurse care coordinators.

Figure 6-4: Family nurse practitioner Julia Gamble shares various transportation

Costs of arranging transportation: On average, respondents said that 70% of their clients have unmet transportation needs. When their clients travel to a medical appointment, they estimate that 45% take the bus, 28% travel by van, 24% travel by car, and 6% by taxi. In a typical week, respondents serve about 20 clients (this ranges from 0 to 55 depending on their job description. On average, our respondents with a case management focus see more clients (n=24) compared to those with a clinical focus (n=17). Respondents were also asked to estimate how much time they personally spend each week arranging transportation for their clients: respondents with a case management focus estimated spending 3.6 hours a week while those with a clinical focus estimated 2.3 hours a week. Over 70% of all respondents said that the average time spent booking transportation for a single client is less than one hour, while a quarter of respondents said they spend between 1-3 hours booking transportation for a single client.

Pre-training sentiments: Before the training, respondents were asked about their level of comfort booking transportation with a range of available services in the area **(Figure 4).** They were also asked about the reasons for choosing which transportation mode to arrange for their clients **(Figure 5).**

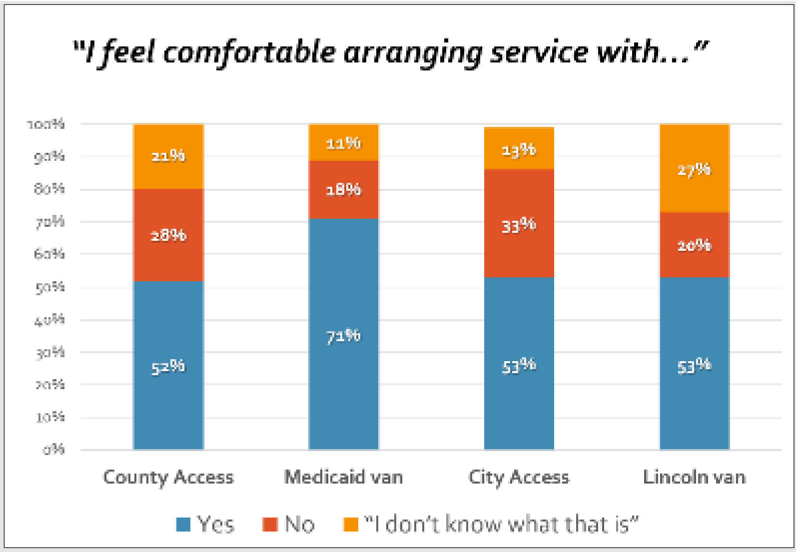


Figure 6-5: Determining factors for arranging various transportation options

Figure 6-6: Influence scale

Post-training findings: Respondents were asked to react to various statements both before and after the training to assess the effectiveness of the travel training. Responses followed a Likert-scale ranging from *strongly disagree* to *strongly agree.* In response to the prompt: *"I feel comfortable helping my clients plan a trip using the bus system,"* there was a major shift among respondents after the training from those who disagreed or felt neutral about their level of preparation to agreeing or strongly agreeing **(Figure 6).** A similar shift was observed in response to the prompt: *"I feel prepared to use online resources to plan a trip using the bus system"* **(Figure 7).**

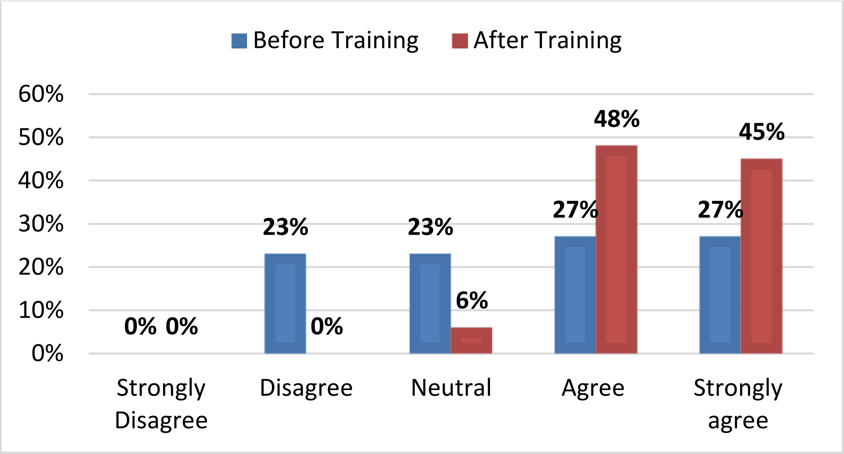


Figure 6-7: Likert Scale responses to the prompt: "I feel comfortable helping my clients plan a trip using the bus system"

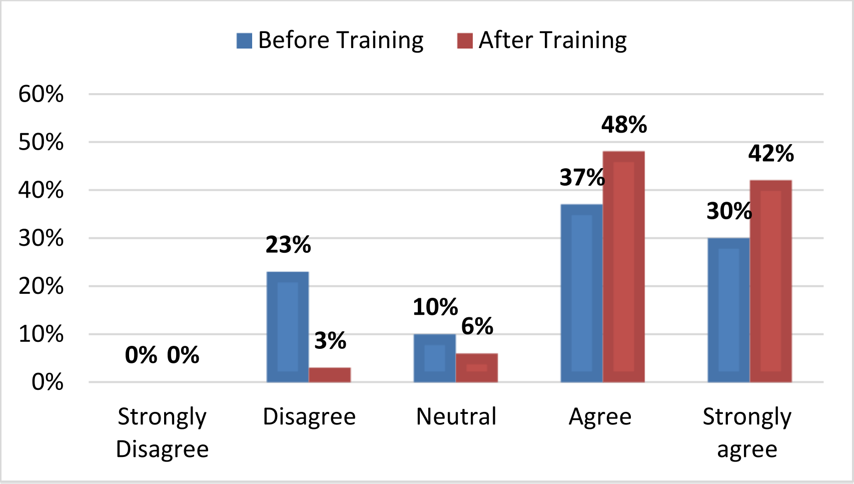


Figure 6-8: Likert Scale responses to the prompt: "I feel prepared to use online resources to plan a trip using the bus system"

Before the training, when asked about available van services, 13 respondents reported that they were uncomfortable booking with the service or didn't know what the service was. After the training, when asked whether they "feel more informed about possible van services," 94% of respondents reported 'yes'.

6.4 INVENTORY TRADITIONAL AND NEW PARATRANSIT SERVICES PROVIDING ACCESS TO HEALTH DESTINATIONS

Technology and policy innovations are reshaping medical transportation options. As the healthcare market moves towards value-based arrangements, treatment adherence is critical. At the same time, the U.S. has seen a proliferation and normalization of shared mobility technology in recent years. Ridehailing companies like Uber and Lyft have entered the market to capture a significant share of current spending on non-emergency healthcare transportation. Across the country, care providers are partnering with shared mobility services to establish new ways for patients to access on-demand rides to and from medical appointments.

In this task, we build on our Year 1 STRIDE research to develop a final inventory and catalog of innovative healthcare mobility strategies. We identified three core types of innovation or collaboration in this space and our final typology can be seen in **Table 1.** The first and most common type of innovation is when a healthcare provider leverages ridesourcing technology to book patient trips. This involves both established and nascent transportation companies tailoring the ridesourcing experience to the healthcare industry by adding HIPPA-compliance to the booking process. The second type of innovation involves an insurer, health plan, or care delivery system partnering with a ridesourcing company to expand transportation offerings to beneficiaries or offer these services for the first time. The third type of innovation is when a paratransit provider partners with a ridesourcing company to carry trips for riders who qualify for traditional paratransit services.

We are disseminating this research through multiple channels and aim to reach academic and practice audiences. We have developed a journal manuscript, *'Innovative healthcare mobility services in the U.S.'* which has been published by *BMC Public Health.* We have conducted a STRIDE webinar on September 18, 2019, which was attended by approximately 30 practitioners and is available for viewing through the STRIDE website. The full citation for the journal article is:

Wolfe, M.K., McDonald, N.C. Innovative health care mobility services in the US. BMC Public Health ***20,*** *906 (2020). Innovative health care mobility services in the US*

Table 6-3 - Typology of innovative healthcare mobility services

	Type I **Healthcare provider leverages ridesourcing tech.**	*Type II* **Insurer partners with TNC**	*Type III* **Paratransit provider partners with TNC**
Who books the ride?	Clinician (on patient's behalf); patient (sometimes)	Patient or clinician	Usually the riders/patients
Who pays?	Healthcare providers; brokers; patient	Insurance companies; health plans	Transit agency; patient pays 'fare' with substantial subsidy from transit agency

Eligible for Medicaid reimbursement?	Varies by TNC; in many cases, yes, given patient eligibility	n/a	Yes, given patient eligibility
Patient Benefits:	Shorter wait times & less uncertainty; Reminders and tracking through smartphone, flip phone, or analog phone	Financial support for patients; Addresses social determinant of health Greater patient engagement	Dynamic booking circumvents need for advance booking; Increased trip reliability; Patients who otherwise can't afford TNC service have access
Healthcare Provider Benefits:	Can track patients' trips as well as own spending; Dynamic booking (instant or in advance)	Greater patient engagement; reduced costs in long-term	Reduced appt. no-shows

Source: authors' own analysis of findings of nationwide scan

6.5 CONCLUSIONS: HEALTHCARE ACCESS & HOW TECHNOLOGY IS RESHAPING PARATRANSIT

This work documents various avenues through which innovation in shared mobility is driving the evolution of healthcare transportation. Ridesourcing options are appearing in electronic medical record workflows of clinicians, and they are becoming a part of the choice set for patients through formal partnerships with care providers, insurance companies, and transit agencies. The growth in popularity of these options will have important implications for transit agencies who currently provide trips to medical destinations as a significant share of their paratransit trips, as demonstrated in GoDurham trip data from 2018. New mobility solutions promise cost saving potential for insurers and more reliable access for patients; however, it is unclear whether these services could be financially viable in low-density, non-urban areas.

Through our qualitative work with health care providers in Durham, NC, it is clear that there is a need for improved transportation to medical services—especially for populations with acute medical needs such as behavioral health patients. An important consideration of implementation of any healthcare transportation innovation is the lived experience of target users. Patient level of comfort with ridehailing technology is likely a very important determinant of uptake.

Our work also documents a significant problem in transportation access to health care nationally. We found that transportation barriers to care disproportionately impact individuals who are poor and who have chronic conditions, yet there is a need for further research on transportation barriers to care that is even more nuanced in relation to health conditions and patient populations, and that incorporates greater place-based information. With additional research, innovative transportation solutions can be tailored to target patients by geographic region or by diagnosis.

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7.0 APPENDIX A – SUMMARY OF ACCOMPLISHMENTS

Date	**Type of Accomplishment** *(select from drop down list)*	**Detailed Description** *Provide name of person, name of event, name of award, title of presentation, location and any links to announcements if available* *Please attach any abstracts, summaries, high quality photos, or additional details as an appendix.*
Nov 2018	Conference Presentation	Berrebi, S., Gibbs, T., Joshi, S., Watkins, K., "Understanding Ridership Change at a Disaggregated Spatial and Temporal Level: A Comparison of Portland, Minneapolis, and Miami" Rail~Volution, Pittsburgh, PA
Jan 2019	Conference Presentation	Berrebi, S., T. Gibbs, S. Joshi, K. Watkins, "Understanding Ridership Change at the Route Level: A Comparison of Portland and Minneapolis St-Paul", *Transportation Research Board 2019 Annual Meeting*
Jan 2019	Conference Presentation	Wolfe, M & N. McDonald. "Healthcare transportation services: Policy shifts and the influence of shared mobility," *Transportation Research Board 2019 Annual Meeting,* Washington, DC.
Jan 2019	Student Accomplishment or Award	1st place, STRIDE poster competition at the *Transportation Research Board 2019 Annual Meeting,* Washington, DC.
Mar 2019	Other	K. Watkins, *What do we know about maintaining and increasing transit ridership?* Invited Seminar, TU Delft, March 2019
Apr 2019	Conference Presentation	Liu, C., Bardaka, E., and Karlson, T. Suburbanization of poverty and changes in transportation access, Presentation at NCAMPO Annual Meeting, Charlotte, April 2019.
April 2019	Conference Presentation	Wolfe, M. and McDonald, N. "Transportation Barriers to Healthcare in the US," Presentation at the *13th Association of European Schools of Planning (AESOP) Young Academics Conference,* Darmstadt, Germany.
April 2019	Conference Presentation	Wolfe, M. "Innovative healthcare transportation services for older Americans," Poster at the *Safe Systems Summit,* Durham, NC.
June 2019	Paper submitted	Wolfe, M., McDonald, N., Holmes, M. "Transportation Barriers to Healthcare in the U.S" submitted to Amer Jour Public Health

July 2019	Paper submitted	Berrebi, S., Joshi, S., Gibbs, T. and Watkins, K. "On Ridership and Frequency" submitted to Transportation Research Part C.
July 2019	Conference Presentation	Berrebi, S., Gibbs, T., Joshi, S., Watkins, K., "On Ridership and Frequency: Modeling elasticity on a hyper-local scale between 2012 and 2017." Transit Data Conference, Paris, France
August 2019	Paper submitted	Steiner, R., Bejleri, I., Bae, X., Han, M. & Noh, S. "Requirements and Challenges for Partnerships between Transportation Disadvantaged Service Providers and TNCs. Submitted to *Transportation Research Record, Journal of the Transportation Research Board.*
August 2019	Paper submitted	Berrebi, S. and Watkins, K. "Who's Ditching the Bus?" submitted to Transportation Research Part A.
August 2019	Paper submitted	Berrebi, S., Joshi, S., and Watkins, K. A Method to Cross-Check Automated Passenger Counts for Ridership Analysis" Submitted to *Transportation Research Record, Journal of the Transportation Research Board*
August 2019	Paper submitted	Berrebi, S. and Watkins, K. "Who's Ditching the Bus?" Submitted to *Transportation Research Record, Journal of the Transportation Research Board (presentation only)*
August 2019	Paper submitted	Berrebi, S., Joshi, S., Gibbs, T. and Watkins, K. "On Ridership and Frequency" Submitted to *Transportation Research Record, Journal of the Transportation Research Board (presentation only)*
Sept 2019	Conference Presentation	Berrebi, S., Watkins, K., "Modeling Bus Ridership Trends on a Hyper-Local Scale" TRB Conference on Performance and Data in Decision Making, Atlanta, GA.
Sept 2019	Conference Presentation	Berrebi, S. "How Would Ride-Hailing Fit in a Transit Utopia?" Rail~Volution, Vancouver, BC.
October 2019	Conference Presentation	Steiner, R., Bejleri, I., Bai, X., & Han, M. Improving Transportation Accessibility for the Transportation Disadvantaged: Collaboration Between Transit Agencies and TNCs Accepted for Presentation to the Association of Collegiate Schools of Planning conference
October 2019	Invited Seminar	Watkins, K. "Understanding recent transit ridership decline in the US" University of North Carolina