

Evaluating the connection between transit and TNCs (Transportation Network Companies) in Pinellas County for statewide application

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16. Abstract This report proposes to conduct a comprehensive investigation of active and inactive partnerships between transit agencies and TNCs in Pinellas County to enhance understanding of project development and how the partnership can be cost-effectively achieved. This report used a spatiotemporal analysis and on the Direct Connect rides over the past three years (2018 to 2020), which tells the spatiotemporal characteristics of the ride demand. The results of panel data analysis manifest how much the Uber contributes to the transit ridership. Cost-efficiency analysis, and scenario analysis examines the whether the Direct Connect program are cost-efficient and proposes two potential scenarios to increase the cost-efficiency of program. The geographically weighted regression model is also applied to both the Direct Connect and TD-Late Shift ridership. Several variables are identified to have significant impacts on the ridership of the programs. Finally, the two satisfaction surveys are conducted to the users of Direct Connect and TD-Late Shift services. Important findings are found to help to further improve the Direct Connect and TD-Late Shift services.				13. Type of Report and Period Covered Draft Final	
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Executive summary

Pinellas Suncoast Transit Authority (PSTA) has launched Direct Connect (DC) and TD-Late Shift service in 2016, and both involve transportation network companies (TNCs) as a part of the service. Although research has been conducted to understand the potential connections between transit and TNC service, the result is still unclear that different relationships happen at various locations. This report proposes to conduct a comprehensive investigation of active and inactive partnerships between transit agencies and TNCs in Pinellas County to enhance understanding of project development and how the partnership can be cost-effectively achieved. This report used a spatiotemporal analysis and the geographically weighted regression model on the Direct Connect rides over the past three years (2018 to 2020), cost-efficiency analysis, and scenario analysis to answer the following research questions:

1. What are the spatiotemporal characteristics of users who participated in the Transit-TNC partnership program?
 - a. Uber's quarterly travel volume rose significantly between the second quarter of 2018 and the third quarter of 2019;
 - b. Public transit ridership showed an overall trend of growth between February 2018 and January 2020, with a total increase of about 22,000 trips;
 - c. In line with Uber's trips, Monday to Thursday is the peak period for public transit;
 - d. The peak hours of Uber trips in a day are the periods from 6 am to 10 am and 3 pm to 7 pm;
 - e. As for the day of week pattern, trips that occurred from Monday to Thursday hold the main share of the overall trips that happened in a week.
2. What are the determining factors that impact the trips of the Direct Connect program?

- a. Female percentage, Hispanics percentage, Black percentage, education level, median income, median age, and access to the job have significant impacts on weekday Uber ride demand;
 - b. Education Level and Median Household Income have significant but geographically limited impacts on weekend Uber ride demand.
3. What are the determining factors that impact the trips of the TD-Late shift service?
- a. Education level, percentage of black, household density, population to employment, access to job, and household with 0 vehicle have strongly significant impacts on the ridership of TD-Late shift service.
 - b. Percentage of people with a disability and road density have less significant impacts on the ridership of TD-Late shift service.
4. Is the current funding strategy cost-efficient and have the original goals been achieved? What are the alternative funding strategies to make the program sustainable?
- a. The transit-TNCs partnership had a significant positive impact on transit ridership, with every increase of one unit in the Uber trip, the transit ridership would increase by seven units;
 - b. The cost-effectiveness of the entire Pinellas County transit system kept declining from FY 2011 to FY 2019. However, we can't prove that the transit-TNCs partnership was the cause of the cost effectiveness decline;
 - c. Replacing the five least-utilized fixed routes of the Pinellas transit system with Uber service had significant cost-saving potential for the transit agency. However, the alternative that using the transit agency's own vehicles to replace the transit-TNCs partnership could not achieve the cost-saving goal and even resulted in more cost to the transit agency.

In addition, we conducted a Customer Satisfaction Survey (the questionnaires were collected from February 1st to March 31st in 2021, and were distributed via email) to evaluate the performance of

Direct Connect and TD-Late Shift service Before & During the COVID-19. The main findings from the results questionnaires are as follows:

Direct Connect User:

- a. Most of Direct Connect service users are satisfied with the service;
- b. Before COVID, most of users (78.43%) used the service 1 to 6 times per week, however, 72.55% of users used the service 0 to 3 times per week during COVID;
- c. In terms of users' service origin and destination, Home and Workplace are the most frequent origin and destination before and during COVID;
- d. The service shortcomings suggested by 49.02% of users include: Difficulty using service, App related issues, Fares and Bonus related issues, Limited Direct Connect service, and Lack of TD-late Shift availability.

Direct Connect Non-user:

- a. For the reasons why not using Direct Connect service, 41.18% of Direct Connect service non-users indicate that they Don't know how to use the App, 23.53% of non-users indicate that they Drive their own car;
- b. In terms of non-users' main travel mode, 47.06% of Direct Connect service non-users choose transit as their primary travel mode, 35.29% of non-users choose drive, and 11.76% and 5.88% of non-users choose Uber/Lyft and Walk respectively.

TD-Late Shift:

- a. Before COVID, 50% of users think the “Service Time” should be extended, and 30% of users think the “Service Area” should be extended as well. During the COVID, both “COVID Sanitary Concern” and “More Trips per Month” are the first concerns of users;
- b. The satisfaction level has decreased during COVID (60% users are “Very Satisfied” compared to 73.33% before the COVID);
- c. The suggestions for the service are related to “More Trips per Month”, “Longer Service Time” and “Larger Service Area”. Needs of persons with disabilities and safety are also mentioned.

In Panel data model analysis, the study find that:

- a. The increase of 1 percentage of Direct Connect trip ended at the surrounding area will lead to the 0.116 percentage increase of onboarding people for bus stops on weekdays.
- b. The access to jobs has a positive influence on the bus ridership, while household median income has a negative impact on the bus ridership.

For Direct Connect Program, we suggest:

- a. increasing service accessibility (i.e., more eligible stops) at the middle-west and southeast parts of Pinellas County since the Direct Connect trips were mainly generated and distributed in those areas.
- b. increasing service accessibility in the neighborhood with lower income and education levels because people living in there are more likely to use this program.
- c. replacing the least cost-effective fixed routes (i.e., route 300, 812, 813, and 814) with the Transit-TNC partnership.

- d. providing more detailed mobile phone application instruction since the many non-users indicate that they do not know how to use the App.
- e. achieving data-sharing agreement with TNCs to track users' transfer process.

For TD-Late Shift Program, we suggest:

- a. Promote the TD-Late Shift service according to the spatial ride demand characteristics revealed by the GWR results.
- b. Consider extending the monthly cap, service hour or service area.
- c. During the COVID-19, more preventive measure should be conducted to solve the sanitary concerns of users.
- d. Other improvements should include more disability care, better service Apps.

Table of Contents

1.	Introduction	1
1.1	Emerging TNCs and Transit-TNC partnership	1
1.2	Transit-TNC partnership program in Pinellas County	2
1.3	Research Questions	4
2.	Literature Review	7
2.1	Relationship between TNCs and transit.....	7
2.2	Competition and complement between TNC and transit.....	11
2.2.1	Complement.....	11
2.2.2	Competition	12
2.3	Private-public Partnership Programs across the United States.....	13
2.4	Approaches to Procurement and Contracting.....	18
2.5	Funding mechanism and payment strategies.....	19
2.6	Spatiotemporal Pattern of TNC and Transit Usage.....	21
2.7	Economic analysis for evaluating transit services.....	25
2.7.1	Definition of Benefit-Cost Analysis	25
2.7.2	Cost and benefit indicators	26
2.7.3	Applications of Benefit-Cost Analysis	29
3.	Comparative Case Study	31
3.1	Exposition Area Innovation Zone Pilot – Austin, TX.....	31
3.2	Partnership Details.....	32
3.3	Key Takeaways	34
3.4	Challenges	35
4.	Overall Temporal Pattern of Uber rides	37
4.1	Quarterly pattern	37
4.2	Monthly pattern.....	38
4.3	Day of week pattern.....	40
4.4	Time of day pattern	41
5.	Overall Temporal Pattern of Transit Ridership	42
5.1	Every Four-month pattern	42
5.2	Day of Week pattern.....	43
5.3	Total Ridership by Route.....	44

6.	Time of Day Pattern	48
6.1	Origin Pattern.....	48
6.1.1	Census block group	48
6.1.2	Stop level analysis	49
6.2	Destination Pattern.....	54
6.2.1	Census block group	54
6.2.2	Trip Patterns at the Stop Level.....	54
6.3	Origin-Destination (OD) Pattern	59
7.	Day of Week Pattern.....	61
7.1	Origin Pattern.....	61
7.1.1	Census block group level analysis	61
7.1.2	Stop level analysis	61
7.2	Destination Pattern.....	67
7.2.1	Census Block Group	67
7.2.2	Stop Level Analysis	67
7.3	Origin-Destination (OD) Pattern	73
8.	Geographically Weighted Regression Analysis	76
8.1	Data Source.....	76
8.1.1	Direct Connect Program.....	76
8.1.2	TD-Late Shift Program	77
8.2	Weekday Model.....	82
8.2.1	Socio-Demographics	82
8.2.2	Population Density.....	88
8.2.3	Land Use.....	90
8.2.4	Road Network Design.....	91
8.2.5	Accessibility to Jobs.....	93
8.3	Weekend Model.....	94
8.3.1	Socio-demographics.....	94
8.3.2	Population Density.....	100
8.3.3	Land Use.....	102
8.3.4	Road Network Design.....	103
8.3.5	Accessibility to Jobs.....	105
8.4	TD-Late Shift Model	106

8.4.1	Education Level	106
8.4.2	Percentage of Black.....	107
8.4.3	Percentage of Male.....	108
8.4.4	Percentage of People with a Disability	109
8.4.5	Household Density	110
8.4.6	Population to Employment	111
8.4.7	Access to Jobs	112
8.4.8	Household with 0 Vehicle	113
8.4.9	Road Density	114
9.	Cost-Efficiency Analysis (CEA)	115
9.1	The Cost-Efficiency of the Entire Transit System in Pinellas County	115
9.2	The Cost-Efficiency for Each Route in Pinellas County	118
9.3	Summary.....	122
10.	Scenario Evaluation.....	123
10.1	Evaluation of Scenario 1.....	123
10.2	Evaluation of Scenario 2.....	127
11.	Result of Customer Satisfaction Survey	136
11.1	Direct Connect Users	138
11.1.1	Background of the Users.....	138
11.1.2	How did the users know the Direct Connect Service?.....	141
11.1.3	Travel Behavior and Direct Connect Service Reflection.....	142
11.1.4	Suggestions of Direct Connect Users	145
11.2	Direct Connect Non-Users	150
11.2.1	Background of the Direct Connect Non-users	150
11.2.2	Travel behavior – Taxi/Lyft/Uber Users.....	154
11.2.3	Travel Behavior – Car Drivers.....	156
11.2.4	Travel Behavior – Transit Users	158
11.2.5	Non-user's Attitudes	162
11.3	TD-Late Shift Users.....	165
11.3.1	Background of the TD-late Shift Users.....	165
11.3.2	How do users found out about the TD-late Shift Service	169
11.3.3	Travel Behavior	169
11.3.4	The Value of the Service	174

11.3.5	Users' Concerns and Advice	176
12.	Panel Data Model Analysis.....	180
12.1	Data source	180
12.2	Methodology.....	181
12.3	Results.....	183
13.	Summary	185
13.1	Spatiotemporal Pattern	185
13.2	GWR Regressions for the Determining Factors	188
13.2.1	GWR for Direct Connect Program.....	188
13.2.2	GWR for TD-Late Shift Program	190
13.3	Cost Efficiency	193
13.4	Customer Satisfaction Survey	194
13.4.1	Direct Connect User	194
13.4.2	Non-Direct Connect User	195
13.4.3	TD Late Shift users.....	196
13.5	Panel Data Model Results	196
13.6	Recommendation.....	197
13.6.1	Direct Connect Program.....	197
13.6.2	TD-Late Shift Program	198

List of Figures

Figure 1.3.1 Research Framework	6
Figure 2.3.1 Partnership cases across the US (Curtis et al., 2018)	14
Figure 3.2.1 Exposition Area Innovation Zone Service Area	33
Figure 4.1.1 Quarterly Uber Ridership	37
Figure 4.2.1 Monthly Uber Ridership	38
Figure 4.3.1 Daily Uber Ridership	40
Figure 4.4.1 Hourly Uber Trips from April 2018 – March 2020	41
Figure 5.1.1 Every Four-month transit ridership (in 1,000 ridership) from February 2018 to January 2020	42
Figure 5.2.1 Day of Week Pattern of Transit Ridership	43
Figure 6.1.1 Trip Patterns based on Origin Census Blocks in Time of Day	50
Figure 6.1.2 Fares of Trips based on Origin Census Blocks in Time of Day	51
Figure 6.1.3 Trip Patterns Based on Origin Pilot Stops in Time of Day	52
Figure 6.1.4 Fares of Trips based on Origin Pilot Stops in Time of Day	53
Figure 6.2.1 Trip Patterns based on Destination Census Blocks in Time of Day	55
Figure 6.2.2 Fares of Trips based on Destination Census Blocks in Time of Day	56
Figure 6.2.3 Trip Patterns based on Destination Pilot Stops in Time of Day	57
Figure 6.2.4 Fares of Trips based on Destination Pilot Stops in Time of Day	58
Figure 6.3.1 Origin-Destination Pattern in Time of Day	60
Figure 7.1.1 Trip Patterns based on Origin Census Blocks in Day of Week	63
Figure 7.1.2 Fares of Trips based on Origin Census Blocks in Day of Week	64
Figure 7.1.3 Trip Patterns based on Origin Pilot Stops in Day of Week	65
Figure 7.1.4 Fares of Trips based on Origin Pilot Stops in Day of Week	66
Figure 7.2.1 Trip Patterns based on Destination Census Blocks in Day of Week	69
Figure 7.2.2 Fares of Trips based on Destination Census Blocks in Day of Week	70
Figure 7.2.3 Trip Patterns based on Destination Pilot Stops in Day of Week	71
Figure 7.2.4 Fares of Trips based on Destination Pilot Stops in Day of Week	72
Figure 7.3.1 Origin-Destination Pattern in Day of Week	74
Figure 7.3.2 Origin-Destination Pattern from 2018 to 2020	75
Figure 8.1.1 Spatial distribution of TD-Late Shift ridership	79
Figure 8.1.2 Spatial distribution of socio-demographic variables	80
Figure 8.1.3 Spatial distribution of built environment variables	80
Figure 8.1.4 Spatial distribution of poverty rate	81
Figure 8.2.1 Black Percentage GWR Analysis	82
Figure 8.2.2 Female Percentage GWR Analysis	83
Figure 8.2.3 Hispanic Percentage GWR Analysis	84
Figure 8.2.4 Education Level GWR Analysis	85
Figure 8.2.5 Median Income GWR Analysis	86
Figure 8.2.6 Median Age GWR Analysis	87
Figure 8.2.7. Employment Density GWR Analysis	88
Figure 8.2.8 Population Density GWR Analysis	89
Figure 8.2.9 Land Use Mix GWR Analysis	90
Figure 8.2.10 Road Network Density GWR Analysis	91
Figure 8.2.11 Sidewalk Density GWR Analysis	92

Figure 8.2.12 Access to Job GWR Analysis	93
Figure 8.3.1 Education Level GWR Analysis.....	94
Figure 8.3.2 Median Household Income GWR Analysis	95
Figure 8.3.3 Median Age GWR Analysis	96
Figure 8.3.4 Percentage of Female GWR Analysis	97
Figure 8.3.5 Percentage of Black GWR Analysis.....	98
Figure 8.3.6 Percentage of Hispanic GWR Analysis.....	99
Figure 8.3.7 Population Density GWR Analysis	100
Figure 8.3.8 Employment Density GWR Analysis.....	101
Figure 8.3.9 Land Use Mix GWR Analysis.....	102
Figure 8.3.10 Road Network Density GWR Analysis	103
Figure 8.3.11 Sidewalk Density GWR Analysis.....	104
Figure 8.3.12 Access to Job GWR Analysis.....	105
Figure 8.4.1 Education level GWR result	106
Figure 8.4.2 Percentage of black GWR result	107
Figure 8.4.3 Percentage of male GWR result	108
Figure 8.4.4 Percentage of people with a disability GWR result.....	109
Figure 8.4.5 Household density GWR result	110
Figure 8.4.6 Population to employment entropy GWR result.	111
Figure 8.4.7 Access to job GWR result.	112
Figure 8.4.8 Percentage of household with 0 vehicle GWR result.	113
Figure 8.4.9 Road density GWR result.....	114
Figure 9.3.1 Distribution of Cost-Effectiveness Ratio for Each Route.....	121
Figure 10.1.1 The Routes with the Least Cost-Efficiency in Pinellas County.....	123
Figure 10.1.2 The Distance from Transit Stops to Designated Direct Connect Stops.....	126
Figure 10.2.1 O-D Pattern of Downtowner Rides in 2019	130

List of Table

Table 2.3.1 Summary of implemented programs based on Curtis et al. (2018).....	15
Table 2.7.1 Summary of benefits and costs in different stakeholders of TNC service	28
Table 3.3.1 The pilot details compared to The Direct Connect service	34
Table 4.1.1 Quarterly Uber Ridership Basic Statistics	37
Table 4.2.1 Monthly Uber Ridership descriptive statistics	39
Table 5.3.1 Four-month Transit Ridership by Route from February 2018 to January 2020.....	45
Table 8.1.1 Summary of data source.....	76
Table 8.1.2 Dependent variable and socio-demographic and built environment independent variables	77
Table 9.1.1 Expenses and Revenue of Transit System in Pinellas County from FY 2011 to FY 2019....	116
Table 9.1.2 Cost-Effectiveness Ratio of Transit System in Pinellas County from FY 2011 to FY 2019 .	117
Table 9.2.1 Cost-Effectiveness Ratio for Each Route in Pinellas County in FY 2019.....	119
Table 10.1.1 Costs and Benefit of Scenario 1 From PSTA’s Perspective	124
Table 10.1.2 Uber Price Structure.....	125
Table 10.1.3 Users’ Costs of Scenario 1	126
Table 10.2.1 Annual Budget of the Downtowner Operation	128
Table 10.2.2 Information about the Downtowner and the Direct Connect Program	131
Table 10.2.3 Travel Time Demand of the Peak Time Period of One Day in the Pinellas County Based on Two Wait Time Assumptions	133
Table 11.1.1 Direct Connect Service Users’ Residence Status.....	139
Table 11.1.2 Direct Connect Service Users’ Age-group Status.....	139
Table 11.1.3 Direct Connect Service Users’ Gender Status	139
Table 11.1.4 Direct Connect Service Users’ Ethnicity Status	139
Table 11.1.5 Direct Connect Service Users’ Income Status	140
Table 11.1.6 Direct Connect Service Users’ Employment Status	140
Table 11.1.7 The Information Source to know Direct Connect Service	141
Table 11.1.8 Direct Connect Service Users’ Attitude to the Ease of Using Transit Service	142
Table 11.1.9 Direct Connect Service Users’ Service Usage Frequency	143
Table 11.1.10 Direct Connect Service Users’ Last Time Usage.....	143
Table 11.1.11 Direct Connect Service Users’ Last Time Usage (specific time)	143
Table 11.1.12 Direct Connect Service Users’ Service Origin and Destination (Option to select more than one answer).....	144
Table 11.1.13 Direct Connect Service Users’ advice about Service Shortcomings (Option to select more than one answer)	146
Table 11.1.14 Current Shortcomings of the Direct Connect Service – Other suggestion.....	147
Table 11.1.15 Whether the users need to transfer to transit service after using Direct Connect service ..	147
Table 11.1.16 Direct Connect Service Users’ Satisfaction Level about Service	148
Table 11.1.17 Direct Connect service Users’ Alternative Travel Modes (Option to select more than one answer).....	148
Table 11.1.18 Direct Connect Service Users’ Reason(s) to use this Service (Option to select more than one answer).....	149
Table 11.2.1 Direct Connect Service Non-users’ residence Status.....	151
Table 11.2.2 Direct Connect Service Non-users’ Age-group Status	151
Table 11.2.3 Direct Connect Service Non-users’ Gender Status	151
Table 11.2.4 Direct Connect Service Non-users’ Ethnicity Status	151

Table 11.2.5 Direct Connect Service Non-users’ Income Status.....	152
Table 11.2.6 Direct Connect Service Non-users’ Employment Status	152
Table 11.2.7 Direct Connect Service Non-users’ Main Travel Mode	152
Table 11.2.8 Do Non-users know about the Direct Connect Service in the Pinellas County	153
Table 11.2.9 Taxi/Lyft/Uber Users’ Travel Frequency	154
Table 11.2.10 Taxi/Lyft/Uber Users’ Travel Cost.....	155
Table 11.2.11 Car Drivers’ Travel Frequency per Week.....	156
Table 11.2.12 Car Drivers’ Parking Cost per Week	157
Table 11.2.13 Transit Users’ Attitude to the Ease of Using Transit Service	159
Table 11.2.14 Transit Users’ Travel Methods to Transit Stops	159
Table 11.2.15 Transit Users’ Travel Time from Home to Transit Stops	160
Table 11.2.16 Transit Users’ Travel Time from Workplace to Transit Stops	160
Table 11.2.17 Transit Users’ Travel Frequency per Week	161
Table 11.2.18 Direct Connect Service Non-users’ Suggestions about Public Transportation (Option to select more than one answer).....	163
Table 11.2.19 Direct Connect Service Non-users’ Reason(s) for Not Using this Service (Option to select more than one answer).....	163
Table 11.2.20 Direct Connect Service Non-users’ Interest about this Service.....	164
Table 11.3.1 TD-late Shift Users’ Residence Status.....	165
Table 11.3.2 TD-late Shift Users’ Age Group Distribution.....	165
Table 11.3.3 TD-late Shift Users’ Gender Distribution.....	166
Table 11.3.4 TD-late Shift Users’ Ethnicity Distribution	166
Table 11.3.5 TD-late Shift users’ Employment Status Distribution	167
Table 11.3.6 TD-late Shift Users’ Income Distribution.....	167
Table 11.3.7 TD-late Shift Users’ Car Ownership Distribution	168
Table 11.3.8 TD-late Shift Users’ Special Transportation Need Distribution.....	168
Table 11.3.9 TD-late Shift Users’ Wheelchair Use Distribution	168
Table 11.3.10 The Way that the Users Know the Service	169
Table 11.3.11 Last 12 Months Usage Distribution	169
Table 11.3.12 Time of Last Service Use.....	170
Table 11.3.13 Usage per Month.....	170
Table 11.3.14 Time Spent Distribution (Before the Service was Provided).....	171
Table 11.3.15 Time Spent Distribution (After the Service was Provided)	171
Table 11.3.16 Frequent Destination Distribution.....	172
Table 11.3.17 Waiting Time Distribution.....	173
Table 11.3.18 Alternative Travel Modes Distribution (If the Service is not Provided).....	174
Table 11.3.19 Values Brought to Users Distribution.....	175
Table 11.3.20 Concerns Before COVID-19 Distribution (With 1 Being the Most Important and 6 Being the Least Important).....	176
Table 11.3.21 Concerns during COVID-19 Distribution (With 1 Being the Most Important and 7 Being the Least Important).....	176
Table 11.3.22 Shortcomings of the Service (Users’ Opinion).....	177
Table 11.3.23 Satisfaction Level.....	178
Table 11.3.24 Other Opinions from Users.....	179
Table 12.1.1 Variable description and data source in Panel data model.....	180
Table 12.3.1 Estimation Results for Panel Models (Weekdays).....	183

Table 12.3.2 Estimation Results for Panel Models (Weekends).....	184
Table 13.2.1 Summary of GWR regressions result.....	188

1. Introduction

We will first introduce the fast growth of transportation network companies (TNC) in the ridesharing age, which provides backgrounds and evidence for the emerging Transit-TNC partnership. Then, we will introduce three Transit-TNC partnership programs operated by Pinellas Suncoast Transit Authority (PSTA) since 2016. Given the challenges in the Transit-TNC partnership in Pinellas County, we will accordingly identify research questions and the framework to conduct the research.

1.1 Emerging TNCs and Transit-TNC partnership

On-demand dynamic ridesharing, or ridesharing, has emerged as an important urban travel mode. The on-demand service is operated by transportation network companies (TNC), such as Uber and Lyft. Ridesharing is a service based on smartphone applications, through which TNCs dynamically match the ride requests from travelers anywhere in real-time with nearby drivers. Compared with traditional taxi services, the major service advantages of ridesharing are less waiting time, larger service coverage, and convenient in-App payment (Alemi et al., 2018). Recently, ridesharing use is experiencing rapid growth. For example, operating in 600 cities globally, the total number of Uber trips is 6.9 billion in 2019. Another TNC giant, Lyft, globally reached to 5.1 billion trips in 2019 (Iqbal, 2019). However, growth does not come without creating controversies. It has sparked a heated debate on the potential impacts of ridesharing on cities (McCoy et al., 2018; Rayle et al., 2016). Supporters of ridesharing service found it a sustainable travel mode, which could reduce auto dependence and increase travel mobility options. Critics weighed in and suggested that the significant growth of ridesharing led to more congested cities. For example, a report suggested that in major U.S. cities, ridesharing has increased billions of vehicle miles traveled (VMT) (Rodier et

al., 2016). A report from McCoy et al. (2018) conducted a nationwide survey on MPOs, DOTs, and agencies, indicating the negative impacts of ridesharing on congestion and transit use. In addition, concerns on other related issues such as how the security should be improved or whether it is only for certain age cohorts or socioeconomic levels, have also been raised. One of the major concerns is how to integrate transit with TNC service. Research has been conducted to understand the potential connections between these two modes but found different results. For example, Wang and Ross (2017) found TNC could complement, compete, and substitute for rail transit. These different relationships happen at different locations. Even though the relationship between TNC and transit is still unclear, some TNCs like Uber are seeking to incorporate ridesharing into existing transit systems by partnering with local transit agencies. To this end, a comprehensive investigation of active and inactive partnerships between transit agencies and TNCs, should be developed to enhance understanding of project development and how the partnership can be cost-effectively achieved, which will be examined in this project.

1.2 Transit-TNC partnership program in Pinellas County

In Florida, Pinellas Suncoast Transit Authority (PSTA) became the first transit agency in the United States to partner with TNCs since 2016. More specifically, three programs have been implemented.

(1) Direct Connect: To meet the demand of first-mile and last-mile trips to transit stations, the Direct Connect program was approved in December 2015 and launched in February 2016. Between 6 a.m. and 11 p.m., passengers are offered \$3 compensation to commute to bus stops within Pinellas Park and the East Lake area. However, according to the report of the Shared-use Mobility Center (2019), the first phase of the project carried a small number of passengers,

generating 202 trips in six months. Then, in 2017, PSTA expanded the service area to the entire county and the subsidy reached \$5 per trip.

(2) TD Late Shift: Following the Direct Connect project, PSTA launched the TD Late Shift program in August 2016 (Zipper, 2019). Since public bus services usually stop at night, the project is intended to address the problem of insufficient bus service on fixed routes at late night. TD Late Shift participants must pre-enroll with PSTA to become eligible for the program. Participants pay \$11 per month for a discounted PSTA transit pass (regular value \$70) and an additional \$9 per month for up to 25 Uber, United Taxi or Care Ride rides per month. Late Shift riders must earn no more than 150 percent of the federal poverty level, and discounted rides are only valid from 10 p.m. to 6 a.m., when PSTA fixed-route transit is not in service (Zipper, 2019). Riders can only use the service to go between registered home and work addresses.

(3) P4-MOD: In its Public-Private-Partnership for Paratransit Mobility on Demand (P4-MOD) project, PSTA aims to improve mobility of paratransit customers and operate paratransit trips more cost-effectively than its current Demand-Response Transportation (DART) program. According to the transit agency's MOD grant application, PSTA currently spends \$22.50 per ride on its current DART service, which utilizes nearly 10% of the transit agency's operating budget. PSTA seeks to achieve these goals through centralized dispatch technology that matches riders with TNCs, taxis, or wheelchair vans depending on the rider's needs, estimated arrival time, and cost.

Other cities in the United States are also exploring cooperation between transit and ridesharing service by different funding strategies by directly subsidizing TNC trips from the TNC platform (e.g., Denton Region, TX; New York City, NY) or marketing TNC services as a complement to fixed-route transit service (e.g., Livermore, CA). However, there is a lack of economic analysis of

the performance of the partnership. Such limitation does not guide the development of new partnerships. In addition, policymakers and urban planners have little evidence to understand whether the programs have been successful and have achieved the expected goals. Specifically, departments of transportation and Metropolitan Planning Organizations (MPOs) in the nation are interested in knowing how to avoid the negative impacts of TNCs (e.g., increased congestion and mode shift from transit to TNCs) on public transportation and to take advantage of TNCs to enhance transit services by integrating transit with ridesharing services.

However, to the best of our knowledge, there is no study that explores such connection in depth besides the TCRP report on Partnerships Between Transit Agencies and Transportation Network Companies (Curtis et al., 2018). Even though the TCRP report summarized the programs across the United States, how to evaluate these programs from the perspective of cost-effectiveness have not been thoroughly answered, which is expected to be explored in this project.

1.3 Research Questions

The objective of this project is to provide a systematic approach to evaluate the partnership between TNC and the public transit agency. It intends to answer the following questions:

1. What are the spatiotemporal characteristics of users who participated in the Transit-TNC partnership program?
2. What are the determining factors that impact the trips of the Direct Connect program?
3. Is the current funding strategy cost-efficient and have the original goals been achieved?
What are the alternative funding strategies to make the program sustainable?

To achieve these goals, we developed a research framework as illustrated in Figure 1.3.1. The researchers will first conduct a literature review of the current practice in the United States to understand the partnerships between transit and TNCs beyond the PSTA case. Specifically, to understand how the partnership would change people's mobility, the literature review will focus on understanding the spatiotemporal pattern of users and transit usage and the competition and complement relationships between transit and TNCs. To understand whether the program is cost-effective, we seek to summarize funding, marketing and contracting strategies in existing programs, and identify appropriate methods and indicators to evaluate the economic performance.

A Cost-benefit analysis for these scenarios has been conducted. In specific, the research team used the transit network to understand the transit operating costs. Under different partnership scenarios as well as the base scenarios, the research team also compared the costs and benefits. Therefore, based on the scenario analysis, the research presented findings, provided an evaluation framework, and assessed the best payment strategy.

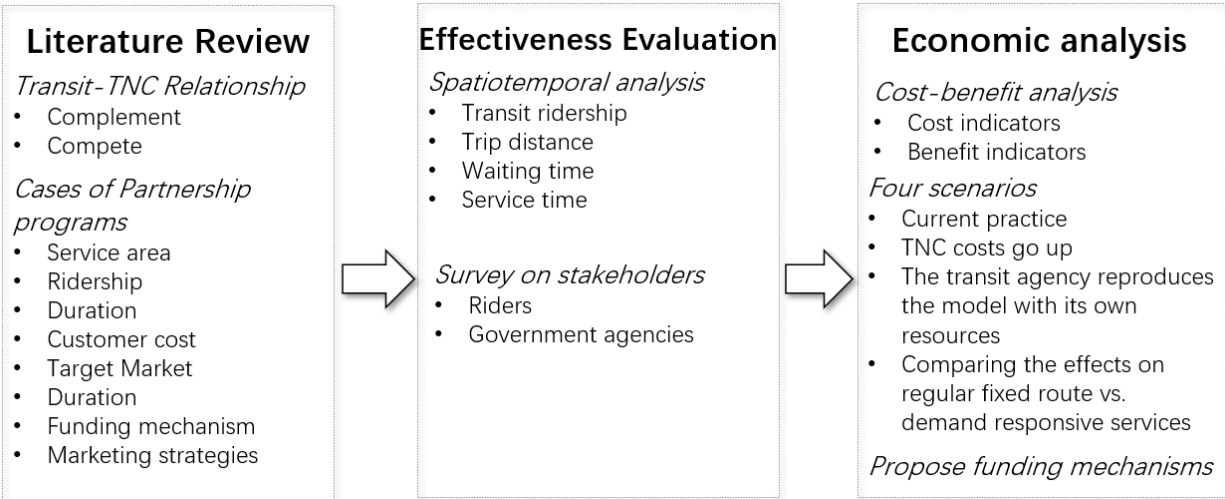


Figure 1.3.1 Research Framework

2. Literature Review

We conducted a literature review of private-public partnership projects in the United States. Specifically, to help us answer the research questions proposed in Section 1, the literature review will focus on understanding the relationship, funding mechanisms, operation practice, and assessing the pros and cons in each case. The literature review will also summarize the spatiotemporal patterns of TNC and transit usage and economic analysis for evaluating the benefits of transit services.

2.1 Relationship between TNCs and transit

New mobility services such as Uber and Lyft are becoming the alternative modes of travel and increasing the flexibility of public transit. How these new services affect public transit is important for decision-makers. Understanding why customers choose these mobility options can help provide firsthand information about the advantages and disadvantages of these services. Gathering information about the kind of trips these individuals make can further provide insight into the relationship between these services and traditional transit.

Two recent papers have studied the relationship between TNCs and transit to offer policy recommendations. A large study on transit ridership by Boisjoly et al. (2018) used data from the 25 largest transit agencies in North America. The study measured the presence of Uber as a binary variable using the opening dates from a review of press releases. This study found that the presence of Uber is associated with high levels of transit ridership and suggested that investments in bus services are an effective way to mitigate the decline in transit ridership.

A study by Hall et al. (2018) employed differences in regression to evaluate the relationship between Uber's presence and transit ridership. In addition to the binary presence of Uber in a

metropolitan statistical area, the study measured the intensity of search engine keywords using Google Trends. The study found that the ridership positively correlated with the population sizes in MSAs.

In a Center for Urban Transportation Research report (2016), Steve Polzin outlines policies for public transportation regarding TNCs (and automated vehicles). He advises that agencies monitor and assess the impact of new technology on travel behavior, redefine the role of the transit system in changing modes of travel, and locate transit systems to the emerging problems. He specifically addresses the possibility of evolving paratransit and affordable mobility.

A Transit Center report published in early 2016 suggested that transit agencies partner with TNCs to create efficiencies in how service is provided by replacing inefficient markets and reallocating services (Transit Center, 2016). They also suggested that transit agencies prompt TNCs to exchange data to understand rider needs better and many agencies have been following this advice. The result of this agency push to exchange data resulted in Uber sharing a portion of their usage data for analysts to dissect.

In a chapter of Meyer and Shaheen's *Disrupting Mobility*, Henao and Marshall (2017) explain the complexities of understanding the impact of TNCs on the transportation system. First, the amount of open data to understand how TNCs are used is limited. Second, it is difficult to assess if a TNC trip is a replacement of a transit trip or not. Even if a particular trip takes place with a TNC, it may enable a household to own one less car and encourage more usage of transit in general. They employed modality styles (car, multimodal with car, non-car, and bi-style which means the subset are a mix of the previous three classes) to classify travelers and found the evolving transportation services significantly impact transportation.

Another study by Clewlow and Mishra (2017) used an internet survey to target a wider range of neighborhoods and suburban areas in some metropolises, like Boston, Los Angeles, Chicago, San Francisco, Washington DC, Seattle, and New York. The survey collected information on attitudes towards travel, neighborhood, technology, and environment, as well as vehicle ownership and housing choice. Nearly 4,100 people responded from a wide variety of urban and suburban populations. They found that adopters of TNCs reduced their bus usage by 6% but increased their commuter rail usage by 3% on average, and 22% of respondents reported making a trip with a TNC that they would not have made without it, indicating a rise in overall trips due to TNCs.

The most comprehensive work to date on the subject is the Transit Cooperative Research Project (TCRP) Report 188 (Feigon and Murphy, 2016). The study draws on interviews with transportation agencies and shared mobility users. There are five key findings:

- (1) Among respondents, greater use of shared modes is associated with more frequent use of transportation, fewer cars and reduced transportation costs.
- (2) Shared modes are an effective way to supplement public transportation.
- (3) As the importance of shared modes is expected to grow, public entities should engage with them to ensure that benefits are equitably shared.
- (4) The public sector and private mobility operators are willing to work together to improve paratransit.
- (5) The new business model of public-private partnership is emerging to provide mobile and related information services.

Agencies interviewed for the study expressed a strong desire to form partnerships with ridesharing companies to bring down the cost of paratransit trips. Several hurdles were identified, however, including drug and alcohol testing of drivers, liability associated with transferring of non-ambulatory passengers, wheelchair and service animal accommodations, vehicle safety and insurance requirements.

A FiveThirtyEight article investigated the cost factors for households with varying levels of transit service (Silver and Fischer-Baum, 2015). Uber usage appeared to correspond well to transit usage in New York City, and neighborhoods with no subway access had significantly fewer Uber trips than those with even one line, suggesting a link between the two. The authors examined the cost of vehicle ownership and determined that middle-income groups with at least moderate transit access would save money by relying on a transit-TNC combination. The article did not discuss its methodology or sample size, limiting its authority.

Overall, research in the area of transit partnerships with TNCs and the impacts of TNCs on transit ridership are limited due to the recent emergence of the services. Survey studies such as Clewlow (2017) help understand the attitudes of transit riders through stated preference surveys. Regression studies such as Hall et al. (2018) and Boisjoly et al. (2018) help establish the connection between the presence of TNCs and transit ridership. However, neither approach has managed to establish clear trends. There needs to be a study of revealed preference data on a wide and representative scale in order to observe the full effects of TNCs on transit ridership. However, there is a consensus: understanding the competition and complement between transit and TNCs is among the most pressing research needs.

2.2 Competition and complement between TNC and transit

In recent years, more and more studies on the Transit-TNC partnership as well as TNC's impact on public transportation have been published. In this section, we reviewed articles about the impact of TNC on public transportation, divided it into two parts, complement and competition.

2.2.1 Complement

Feigon & Murphy (2016) made a general conclusion about ridesharing, which can supplement public transportation. Especially during off-peak hours, TNCs play a more important role in replacing the use of taxis and private cars rather than transit trips. Nevertheless, Malalgoda & Lim (2019) pointed out that although TNC had an insignificant negative impact on bus ridership in their model, there was still no clear evidence that TNC competes directly with transit. They believed that the decline in the effectiveness (measured by demand-related factors) of public transport was an important factor in the changes of passenger volume. Other means of transport such as dockless bikes and e-scooters also provide affordable, flexible and convenient services, thus affecting public transport traffic. In large cities with limited public transportation options and parking, TNCs serve as an additional travel option for young people without private cars, reducing the waiting time and travel time of users. After collecting a large amount of ridesharing and taxi customer survey data, Rayle et al. (2016) argued that TNCs bring a different way of travel from public transportation and taxis. Therefore, the service of TNC can be developed as a supplement to public transportation.

The ridesharing is also seen as beneficial to users because of the extra cost paid by TNCs to improve the user's experience, such as discounts and free rides for the first time. In addition, in the research study, Luo & Nie (2019) claim that although the combination of TNCs with fixed-line

transportation services did not significantly improve the economy scale of the public transportation system, it did improve the cost-based operating efficiency of the whole fix-route transit system to some extent.

Furthermore, in 2018, the Shared-Use Mobility Center (Feigon & Murphy, 2018) conducted a broader analysis of the influence of TNCs on Transit. After the analysis of TNCs trip data and passenger survey, the study shows that TNCs trips are generally short and mainly concentrated in the core areas of cities, with relatively fewer roundtrips between residential areas, central business districts, and other major work areas. In addition, the survey noted that public transit is unlikely to provide late-night trips and trips to and from the airport. Therefore, the study argues that the competition between TNCs and public transportation is not significant and transit agencies should actively participate in the services provided by TNCs.

2.2.2 Competition

The conclusion of TNCs competition with public transportation is mostly based on the decline of public transportation passengers. Gehrke, Felix & Reardon (2018) concluded in a report that TNCs compete with public transit. In a study of nearly 1,000 TNCs service users in the Boston area, the researchers found that TNCs increased the number of total trips in the area by 15% due to people using ridesharing instead of public transportation. Similarly, the vast majority of trips offered by TNCs cost more than \$10, and one in five trips cost more than \$20. This price is much higher than the cost of people taking public transport. Furthermore, the study provides a startling number, showing that 42 percent of customers who used TNCs service would otherwise have taken public transport. The study concluded that TNC's service did bear some responsibility for congestion as well as the ridership decline in the use of public transport.

In a separate study, seven major metropolitan areas have been surveyed by Clewlow & Mishra (2017) in the United States to determine the impact of TNCs on individuals and public transportation. According to the survey, one in five adults use services provide by TNCs, and most are college-educated and affluent people. The study also confirmed TNCs affected public transportation in major U.S. cities, which reduced the total ridership on buses by 3 percent and on the light rail by 6 percent, while supplementing commuter rail services, resulting in 3 percent net increase. In addition, the study also found that TNCs increased vehicle miles traveled.

Even as a first/last mile service provider of public transit, TNCs are not necessarily a supplement to public transport. According to Jin, Kong & Sui (2019), in areas with well-developed public transport services, TNCs compete with public transport most of the time and plays a role in supplementing public transport services in late night. Similarly, the survey of Transportation Research Board Research Report, made by Feigon & Murphy (2016) indicates that in large cities with the developed transit system, TNCs have a competitive relationship with the public transport system in the period when public transport runs infrequently. In addition, this kind of competition also exists in certain fixed routes and time periods with special events that some public transit runs.

More and more Transit-TNC partnerships has been implemented throughout the country as the research goes on. These pilot projects attempt to supplement public transit with the technical and service advantages of TNC. Therefore, the study of these cases will provide useful experience for the further development of Transit-TNC partnerships.

2.3 Private-public Partnership Programs across the United States

Based on the summary of 20 private-public partnership projects in the United States (Figure 2.3.1), the main goal is to effectively attract private capital in the transportation infrastructure. The first

project is MARTA in July 2015. There are six projects in 2016, seven projects in 2017, and four projects in 2018. The target market is for the public, especially the disabled and seniors. For example, Omnitrans, a public transit agency in the San Bernardino Valley, operates local and express bus routes, OmniGo hometown shuttle service, and paratransit service for the disabled persons.

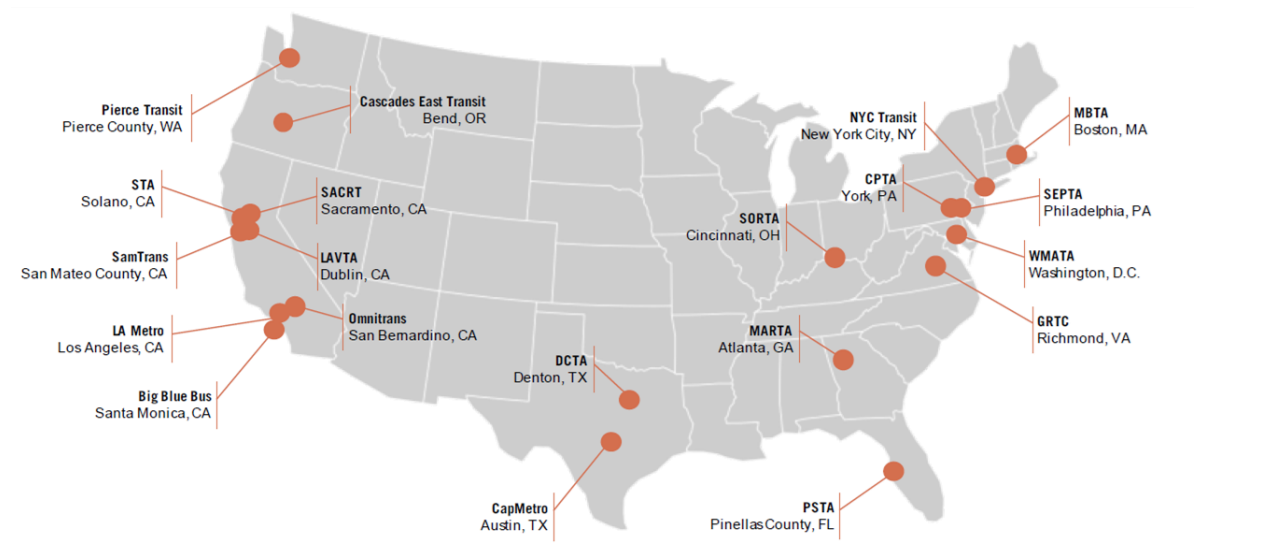


Figure 2.3.1 Partnership cases across the US (Curtis et al., 2018)

For the type of arrangement, most of them in private-public partnership projects are formal, except for CET (Central Oregon, OR), MARTA (Atlanta Region, GA), and SEPTA (Philadelphia, PA). Unlike the PSTA service in Tampa that only serves Pinellas County, private-public partnership projects in Table 2.3.1 all cover a larger service area within the city. Each one operated a various number of service zones. To encourage the development of private-public partnership projects, the state and local governments provide substantial financial support. For the budget, the largest allocated fund is about \$1.35 million in LA Metro, \$600,000 for Metro, \$350,000 for Puget Sound, and \$400,000 for research.

Table 2.3.1 Summary of implemented programs based on Curtis et al. (2018)

Transit Agency	Partnership Name	Location	Types of arrangement	Target Market	Subsidy/Discount	Duration	Funding Source(s)	Budget
BBB	Mobility on Demand Everyday (MODE)	Santa Monica, CA	Formal	Senior and disabled persons	Unlimited subsidized rides, customer copays \$0.50	2018/07-Now	Local return state dollars	<ul style="list-style-type: none"> ◆ Allocated: \$600,000 ◆ Expended: \$100,000
CapMetro	Exposition Area Innovation Zone Pilot	Austin, TX	Formal	Transit customers with limited transit access	Unlimited, fully subsidized rides to and from two bus stops	2018/06-2018/12	CapMetro General Fund	<ul style="list-style-type: none"> ◆ Allocated: \$24,900 ◆ Expended: \$99
CET	None	Central Oregon, OR	Informal	Transit customers	Initially provided free rides up to \$15, then transitioned to a 50% discount (up to \$30 off)	2017/06-2017/09	N/A; no exchange of funds	N/A
CPTA dba RabbitTransit	Paratransit for Seniors and People with Disabilities	Central Pennsylvania, PA	Formal	Senior and disabled persons	Fully subsidized rides when more cost-effective for CPTA than other options	Mid-2017-Now	Pennsylvania's Lottery-Supported Shared Ride Program funds	<ul style="list-style-type: none"> ◆ Allocated: Part of funds allocated for subcontracted paratransit service. ◆ Used: \$11,032
DCTA	Highland Village Lyft Discount Program	Denton Region, TX	Formal	Suburban people in Highland Village with limited transit access	\$2 subsidy for all trips within Highland Village and to/from the nearby hospital and A-train regional train	2016/10 - Now	DCTA's General Fund (local sales tax revenue from member cities)	<ul style="list-style-type: none"> ◆ Uber Partnership Allocated: \$20,000 Expended: \$1,500 ◆ Lyft Partnership Allocated: \$20,000 Expended: \$120
GRTC	Care On-Demand	Richmond, VA	Formal	ADA paratransit eligible customers	Customers initially copays \$6, GRTC subsidized up to the next \$15, and customers pay any excess over \$21	2017/08-2018/08 (option to extend for an additional year)	State and local funds	<ul style="list-style-type: none"> ◆ Allocated: \$224,00 ◆ Expended: \$187,503
LA Metro	Mobility on Demand Pilot	Los Angeles County, CA	Formal	Transit customers, vulnerable persons	TBD	2018/01 - 2019/01	FTA MOD Sandbox grant	<ul style="list-style-type: none"> ◆ Allocated: \$1.35 million (\$600,000 for Metro, \$350,000 for Puget Sound, and \$400,000 for research) ◆ Expended: \$20,000 on research

Transit Agency	Partnership Name	Location	Types of arrangement	Target Market	Subsidy/Discount	Duration	Funding Source(s)	Budget
LAVTA	GoDublin!	Livermore, CA	Formal	Transit customers	50% subsidy (up to \$5) for shared trips that start and end in Dublin	2017/01–2019/06	Grant from the Alameda County Transportation Commission and LAVTA marketing funds – both stemmed from Measure BB funds (local sales tax)	<ul style="list-style-type: none"> ◆ Allocated: \$200,000 ◆ Expended: \$60,000
MARTA	None	Atlanta Region, GA	Informal	Transit customers	TNCs offered discounts ranging from 20-50%	2015/07–Now	N/A; no exchange of funds	N/A
MBTA	The RIDE	Boston Region, MA	Formal	The disabled persons (customers of ADA Paratransit)	Rider copays \$2 and MBTA subsidizes the next \$13 (later increased to \$40).	2016/09–Now	MBTA Operating Budget	<ul style="list-style-type: none"> ◆ Allocated: Unknown ◆ Expended: \$2.2 million
NYCT	Access-a- Ride E-Hail	New York City Region, MA	Formal (under negotiation)	The disabled persons (customers of ADA Paratransit)	TBD	TBD	Access-a-Ride (AAR) program	TBD
Omnitrana	RIDE Taxi & Lyft Program	San Bernardino, CA	Formal	Senior and disabled persons	50% subsidy in the form of a \$40 purchase for \$80 worth of rides per month	2016/07 – Now	Local, state and federal funding, JARC grants (federal)	<ul style="list-style-type: none"> ◆ Allocated: Unknown ◆ Expended: \$11,000
Pierce Transit	Limited Access Connections	Seattle Region, WA	Formal	Transit customers, college students, and residents with limited transit access	Fully subsidized, limited to 48 rides per month	2018/05 – 2019/05	MOD grant (80%) and local match (20%)	<ul style="list-style-type: none"> ◆ Allocated: \$206,000 (MOD); \$51,500 (local) ◆ Used: ~\$12,500
PSTA	Direct Connect, TD Late Shift, P4- MOD	Pinellas County, FL	Formal	Transit customers, paratransit customers, late night workers	(1)Direct Connect: \$5 subsidy, \$25 for Wheelchair Transport rides (2)TD Late Shift: \$20/month for a transit pass and 25 rides P4-MOD: fully subsidized	Direct Connect: 2016/02 - Now TD Late Shift: 2016/08 - Now	(1)Direct Connect: PSTA operating cost savings from previous circulators (\$40,000 per year; varies by year) (2)TD Late Shift: Florida Commission for the Transportation Disadvantaged (\$507,000; varies by year) (3)P4-MOD: FTA MOD (\$625,000)	<ul style="list-style-type: none"> ◆ Allocated: The funding for Direct Connect and TD Late Shift vary each fiscal year. ◆ Expended: Unknown

Transit Agency	Partnership Name	Location	Types of arrangement	Target Market	Subsidy/Discount	Duration	Funding Source(s)	Budget
SacRT	RT Station Link	Sacramento, CA	Formal	Transit customers	\$5 subsidy, limited to ten rides per customer	2016/10–2017/03	Grant from the Sacramento Metropolitan Air Quality Management District and Sacramento Area Council of Governments	<ul style="list-style-type: none"> ◆ Allocated: \$50,000 ◆ Expended: \$4,554
SamTrans	TNC Partnership Pilot (in planning)	San Mateo County, CA	Formal	Transit customers, commuters	TBD	TBD	SamTrans operating budget	<ul style="list-style-type: none"> ◆ Allocated: None to date. ◆ Expended: N/A
SEPTA	None	Philadelphia, PA	Informal	Persons driving and parking at SEPTA rail stations	40% discount, up to \$10	2016/05/27 – 2016/09/05	N/A; no exchange of funds	N/A
SORTA	None	Cincinnati, OH	Formal	Transit customers	20% discount for first-time users	2016/03–2017/03	CMAQ (for GRH trips only)	N/A, no exchange of funds outside of GRH
STA	First Mile/Last Mile Pilot	Solano County, CA	Formal	Workers at selected worksites within 2 to 5 miles of a rail station	User copays \$2 and STA subsidizes the remainder	2017/05 - Now	California's Transportation Fund for Clean Air (TFCA)	<ul style="list-style-type: none"> ◆ Allocated: \$100,000 ◆ Expended: \$7,000
WMATA	Abilities-Ride – An Alternative to MetroAccess	Washington, D.C. Region	Formal	ADA paratransit customers	User copays \$5 and WMATA subsidizes the next \$15, user pays any amount over \$20	2017/09 - Now	WMATA's ADA paratransit budget.	<ul style="list-style-type: none"> ◆ Allocated: No funds specifically allocated for pilot. ◆ Expended: Unknown

2.4 Approaches to Procurement and Contracting

There are several procurement methods as shown below when transit agencies consider and join the TNC partnerships.

- (1) A formal Request for Proposals (RFP) with a pilot or partnership scope;
- (2) A Request for Information (RFI) from TNCs, taxi companies or other transport providers, or emerging mobile providers;
- (3) Contact with a TNC directly, initiated either by transit agency staff or, less frequently, by a representative from a TNC, taxi company, or other transportation or software providers;
- (4) Partnerships between transit agencies and TNCs usually involve multiple suppliers. A number of transit agencies have established relationships with multiple TNCs, including the signing of contracts and the exchange of funds, and many transit agencies have established relationships with TNCs and taxi companies or other transport service providers; and
- (5) The most common motivation for providing services for customers who are disabled, do not own cell phones, or do not have credit or debit cards is to bring taxi companies or other transportation providers into the partnership.

Most formal partnerships are initiated through an RFP or RFI. Informal partnerships generally begin through directly contacting with TNCs and do not involve a formal procurement process.

2.5 Marketing and Customer Outreach

Marketing plays a critical role in the partnership between transit agencies and TNCs, in which co-marketing attracts the attention of many partnerships. Two general forms of marketing partnerships (Curtis et al., 2018) are as follows:

- Co-marketing on the service, which means TNC creates the marketing materials, representing or working together with transit agencies. Generally, marketing materials are disseminated by both transit agencies and TNCs. The advertising space such as stations, vehicles, and transit agency's website are provided by the transit agency without any payment of TNCs.
- Co-marketing by using the TNC discount codes to provide customers with information about how to take advantage of TNCs to travel or as a supplement to transfer to the transit system. The detail of the partnership is that TNCs receive free advertising space from transit agencies and provide discount codes to potential customers without any payment from transit agency.

In order to emphasize that customers can treat TNCs as a supplement service to transit service, TNCs sometimes will purchase advertising space independently, which is not a specific partnership effort, although this action looks like the partnership effort between the transit agency and TNCs.

2.5 Funding mechanism and payment strategies

Three models have been developed in partnerships between transit agencies and TNCs (Curtis et al., 2018):

- Direct subsidies: Local transit agencies subsidize the resulting trips, normally directly through the TNC platform.
- Indirect subsidy: Local transit agencies do not subsidize TNC trips directly but promote or publicize TNC services as an extension or supplement to existing fixed-route transit service.
- Adopt TNC technology: Local transit agencies have their fleets and operators that provide transportation services to customers by using TNC software platforms such as TriMet's RideTap. This is a new model of collaboration between transit agencies and TNCs, and no studies have been found.

Transit agencies have developed a variety of designs and service combinations to meet customer travel needs. Some of the more common methods (Curtis et al., 2018; Schwieterman et al., 2018; National Academies of Sciences, Engineering, and Medicine., 2019) include:

(1) First Mile/Last Mile Connections to Transit stops with subsidized TNC trips.

The transit agency is responsible for TNC service subsidies, usually provided by:

- ✓ The local transit agency pays the TNC trip a fixed amount of fare, with the rest paid by passengers.
- ✓ Passengers pay TNC trip a fixed amount of fare, with the rest paid by the local transit agency.
- ✓ Passengers pay TNC trip a fixed amount of fare, with the next fixed amount of fare paid by the local transit agency, and the customer pays any excess costs.

- ✓ The local transit agency pays full expenses for the TNC trip.

(2) First Mile/Last Mile Connections to Transit stops with marketing strategy:

- ✓ Partnerships exist based on agency marketing. Transit agencies encourage people to use TNC services to access transit, and TNC provides code to passengers, who receive discounts subsidized from TNC by using this code.

The code can be used in a variety of ways (Curtis et al., 2018), including:

- ✓ A discount offered to customers who use the service for the first time (similar to the discount TNC usually offers for new customers).
- ✓ A discount offered to TNC customers who start and/or end at the specific transit stops.
- ✓ A discount for TNC customers who travel to specific destinations or areas, such as pilot zones.
- ✓ A discount for all TNC customers regardless of whether they plan to use transit services on their trip.

2.6 Spatiotemporal Pattern of TNC and Transit Usage

The spatial and temporal pattern is an important part of understanding travel behavior and travel demand. However, the spatiotemporal pattern is rare in previous studies on TNCs' user flow. These studies are of great significance not only for the evaluation of current PSTA partnership programs, but also for the comparison of trip changes before/after program implementation.

According to Feigon & Murphy (2016), ridesharing is mainly used during off-peak hours. Demand for the use of ridesharing reached a noticeable peak between 10 p.m. and 4 a.m. The reason for this is the unavailability of public transport. In addition, the peak use of ridesharing also occurs during the morning rush hours on weekdays. In another report from the Shared Use Mobility Center (Feigon & Murphy, 2018), the impact of TNCs on transit was analyzed more broadly. After analyzing TNCs trip data and passenger survey, the authors found that Saturday is the most concentrated day of TNCs travel, and trips on this day account for 20%-32% of total trips. The study also found that the TNCs service was the busiest between 7 pm and midnight.

From the perspective of geographical distribution, TNCs trips typically have short-distance and concentrated in the urban core. It also provides a late-night to/from the airport service. Lavieri et al. (2018) analyzed ridesharing demand in Austin, Texas, and found that during the weekend, ridesharing was mostly used for outdoor activities. On weekdays, however, TNC travels are generated from areas with high activities and more likely happened after outdoor activities.

A study that analyzed the spatial and temporal patterns of Uber and taxi pickup information in New York City (Correa et al., 2017) found that the duration of PM peak for taxi demand was shorter than that of Uber because taxi drivers needed to change shifts in the afternoon. In addition, the taxi and uber demands were significantly correlated spatially. In the report, they identified key variables that affect ridesharing demand, including the transit access time (TAT), road length, vehicle ownership, education level, employment, and income. Also, there was a consistent trend; compared to taxis, the pick-up orders for Uber were more concentrated in central areas and drop-offs were evenly distributed throughout the city.

Furthermore, ridesharing has also been used to go to areas with poor transportation. In a study on the relationship between taxi use and public transport services in New York City (Yang and Gonzales, 2014), regions with inconvenient transportation were found to have a higher demand for taxis, and the demand for taxis from 7 am to 6 PM was more affected by the total number of employees. Thus, as a different travel option for public transport, it can be used as a last-mile connection, potentially changing the way passengers use public transport.

Chen et al. (2017) analyzed two different relative spatial systems of ridesharing. The study found that operating TNC vehicles on fixed routes is better in terms of agency and user costs than zone-based TNC service systems. This is because the line-based system (operates ridesharing services along a fixed-route transit line) makes the route/headway structure of ridesharing more standardized and efficient, while in the zone-based (operates ridesharing service within a zone) system, ridesharing will experience relatively long detour time for each passenger.

In research conducted by Yu & Peng (2020), a wide range of environment factors and their impact on the demand for ridesharing was evaluated. They found that a higher density of population, employment, and service employment in communities lead to higher demand for TNCs services. Moreover, employment had a significant impact on travel demand only during weekday working hours. The land-use type has a significant effect during the noon and evening periods. Similarly, in Austin, Texas, one study found that variables such as building density, land use diversity, distance to the city center as well as intersections had apparent effects on transit riders (Zhang, 2016). They argue that due to their negative, indirect effects through crime increase, very intensive residential and commercial developments could lead to a decline in TNCs' ridership. Moreover, compact residential and commercial developments have a positive direct impact on bus ridership. This conclusion is consistent with recent research that pointed out a positive correlation between

regional accessibility by car and people's use of ridesharing, and that people from neighborhoods with mixed-use land use were more likely to use TNC service (Alemi et al., 2018).

In San Francisco, ease of payment and short wait time are the top two reasons for people to use ridesharing. Through a survey of ride-sharing users (Rayle et al., 2014), researchers found that a large part of the sampled TNC trips was not well served by public transportation in terms of space and time. In addition, compared with public transportation, the response time of TNCs trips was much shorter, and the demand was more consistent in terms of the time of day and place.

In Ann Arbor, Michigan, Merlin (2017) analyzed hypothetical traffic scenarios, comparing the service level, ride cost, emissions, and traffic-congestion impact performance of taxi and ridesharing with fixed-line buses. The study concluded that ridesharing and taxis provided a high level of transport service at a higher cost, but that taxis had higher carbon emissions than the fixed-route transit system. In addition, ridesharing offers shorter travel times and waiting times, which will increase the number of passengers when it coordinates with large vehicle transit and may mitigate the problem of rush-hour congestion.

Stillwater et al. (2009), pointed out in their study that neither density nor population had an obvious effect on the demand for ridesharing. Moreover, ridesharing served as a complement to high-density auto travel. On the other hand, the proportion of commuters that drive alone as well as street width significantly and negatively affected ridesharing. The impact of public transportation is different from place to place. Celsor & Millard-Ball (2007), however, provide conflicting results on the importance of residential density to ridesharing which has a significant impact on the ridesharing demand. They said the correlation between low vehicle ownership and the number of

ridesharing services was the strongest and most consistent. The vehicle ownership rates and the proportion of single-person households are the two main factors influencing ridesharing demand.

2.7 Economic analysis for evaluating transit services

One of the research questions of the project is to determine whether the partnership is successful and whether the primary goal of the partnership is achieved or not. Generally, to answer this question, in the three kinds of partnerships, namely Direct Connect Program, TD Late Shift, and P4-MOD in Pinellas County, costs and benefits should be evaluated first to see whether the application of the partnership benefits local transportation, the economy, or other aspects, and if the benefits outweigh the costs. Based on the results of the evaluation, the question about how to improve the partnership mechanism to make the program sustainable should be considered. Therefore, the main task of economic analysis for evaluating transit services is to examine the performance of the partnership in terms of economy, in which Benefit Cost Analysis (BCA) is the method that is commonly used.

2.7.1 Definition of Benefit-Cost Analysis

Benefit-Cost analysis is widely used to evaluate the performance of a project according to the total costs and benefits, which is also a systematic technique to provide the best scenario to achieve maximum benefits while maximizing savings (David et al., 2013). The basic principle of BCA is to propose several scenarios to achieve a certain goal. Every cost and benefit of each scenario should be identified and placed with dollar values. Costs include any negative influences of the program, and every positive impact should be treated as a benefit (Newcomer et al., 2015). Based on the results, the dollar value of costs should be compared with that of benefits and then, the optimal decision plan can be selected (Newcomer et al., 2015). BCA is always used to identify,

measure and compare the benefits and costs of an investment project or program, and can be used to analyze the effects of changes in public policies like the subsidy (Campbell and Brown, 2003).

Boardman et al. (2017) mentioned the major steps in BCA. First, a framework for the analysis should be set up, and the potential objects whose costs and benefits are needed to be considered should be decided. The next step is to decide the objects that will be included in the research. After that, Impact categories should be identified, and indicators of measurement need to be decided. The next step is to predict the impacts over the whole period of the program and monetize them. Since the dollar value always changes over time, costs and benefits should be discounted by using a social discount rate, which is a kind of discount rate used on social projects to get the present values. Then compute a net present value, perform sensitivity analysis and make a recommendation. Net present value is important for BCA, which can clearly indicate if the project improves social welfare (Newcomer et al., 2015). The results of BCA usually can be expressed by benefit-cost ratio, which is the portion of the net present value of the benefits to that of the costs. If the ratio is better than 1, the project can be considered successful (Newcomer et al., 2015).

2.7.2 Cost and benefit indicators

According to the evaluation of transit benefit in the previous research, although there were various classification methods, there were many common indicators utilized in the evaluation. The benefit tree was mentioned in Beimborn et al. (1993)'s article, which was used to display the influence of transit service. The influences mainly come from four aspects, namely alternative means of travel, trip generation, land-use, and supply. The existence of transit will provide people options available for travel and positively affect the value of properties. Also, transit is an enterprise that provides employment. Southworth et al. (2002) divided the transit benefits into two principal types, namely public transit benefit: the direct benefits from traveler's use of the transit, and transit supply, which

refer to the potential benefit to local areas. The transit use benefit includes mobility accessibility, environmental, and safety benefits, and the transit supply includes economic benefits to society and the community. HLB Decision Economics Inc. (2006) analyzed the transit benefit from three aspects, namely affordable mobility benefits due to the accessibility to low-cost mobility, congestion management benefits which are the benefits from less congestion, and economic development benefits.

In the Direct Connect Program in Pinellas County, PSTA sought partnership with TNCs to provide a subsidy of \$5 to travelers who take the ridership of Uber, United Taxi, or Wheelchair Transport from or to the area within 800 feet of the 24 selected transit stops. The main effect of this project is to promote the transit accessibility in the area where there is a lack of transit services and increase the transit ridership. Inspired by the research of Southworth et al. (2002), the benefits and costs can be considered towards the different stakeholders, including transit agencies, TNCs, and users. Typical benefits and costs are listed in the Table 2.7.1.

Table 2.7.1 Summary of benefits and costs in different stakeholders of TNC service

	Benefit	Cost
Users	<ul style="list-style-type: none"> • Trip cost saving (especially for the customers whose daily travel mainly depended on TNC services previously.) (Southworth et al., 2002) • Travel time saving (especially for the customers who lack the connection service to transit.) (Beimborn et al., 1993) 	
Transit	<ul style="list-style-type: none"> • Revenue from the increasing ridership of public transit. (Southworth et al., 2002) 	<ul style="list-style-type: none"> • The subsidy from the transit agency. • Administration costs. • Environment costs of the increased ridership of TNC in the pilot area (air quality, noise).
TNCs	<ul style="list-style-type: none"> • The income of TNCs from the increasing short-distance ridership of TNC services. • Increasing the income of TNC drivers because of increasing short distance travel of TNC services. 	

2.7.3 Applications of Benefit-Cost Analysis

Benefit-Cost analysis has been used in the field of evaluating public transportation for a long time. In 1993, Beimborn et al. (1993) conducted comprehensive research on the benefits of transit, which is mainly focused on the urban area to figure out the impacts on society. Cambridge Systematics Inc. (1996) used cost-benefit analysis to estimate the benefits and disbenefits of transit in ten areas and ~~fund~~ found (?) ~~that~~ the economic benefits are related to the distance from the transit. Since then, more studies have emerged to focus on estimating the benefits of public transit, and the study area has expanded to small urban and rural areas. Previous studies can be divided into several types: simple evaluation of the program cost and benefit, cross-program or cross-scenario comparison, and identification of improvement strategies. The researches and reports of these types are demonstrated as follows.

For the simple evaluation of program cost and benefit, Solnik and Schreiner (1998) examined the economic impacts of transit service in a small urban area in Connecticut by calculating the costs and benefits of the local transit service, the results of which indicating that the public transit service benefits the local communities significantly. Burkhardt (1999) noticed that compared to the effects of transit service in a large urban area, the benefits of rural transit were neglected. He estimated the benefits of rural transit systems in 22 case studies and found out it had significant benefits to rural communities. Southworth et al. (2002, 2005) developed a process to evaluate the benefits generated by the operation of the state-supported public transit services in metropolitan areas in Tennessee, including both urban and rural transit systems. In the base year (1998), the total benefits in both urban and rural transit systems were estimated from six aspects, namely user mobility, congestion reduction, safety, air quality, expenditure multiplier benefits, and transportation efficiency. The total benefits of the urban transit system were \$170,317,576, while the costs were

\$47,178,387. The total benefits of the rural transit system were \$16,766,535, while the costs were \$10,414,224. The benefits were greater than the costs in both urban and rural scenarios, while the net benefits were higher in an urban transit system.

For the cross-program or cross-scenario comparison research, Burkhardt et al. (1998) evaluated the economic impacts of several transit programs, including both benefits and costs. In the Blacksburg Transit case in Virginia, the benefits were divided into four parts, namely direct benefit (\$2,819,350), congestion reduction (\$323,400), accident reduction (\$269,550), and parking need reduction (\$1,076,800). The total benefits were \$2,819,350, which outweighed the annual operating costs which were \$1,677,975. In the County Commuter program in Hagerstown, Maryland, the total benefits were \$3,462,717, which were consisted by \$2,376,000 from employment, \$250,588 from shopping, \$225,478 from medical benefit, \$333,096 from training, and \$240,547 from parking, while the annual operating costs were \$1,089,201. HLB Decision Economics Inc. (2003, 2006) constructed three scenarios, including the base case scenario, an optimistic scenario, and a pessimistic scenario to estimate the costs and benefits of a transit system based on the current investment in Wisconsin. Even under the pessimistic scenario, the benefit-cost ratio was 3.32, and the return on investment was 6.03%, indicating that the transit always improves the welfare no matter under which scenarios. HDR Decision Economics (2011) made the same research in South Dakota and received the finding that public transit is a sound investment.

For the research of identification of improvement strategies, Crain and Associates (1999) focused on the costs and benefits of public transportation from the aspect of personal immobility and developed public transit system to reduce the costs. One of the conclusions was that the practices in public transportation which aimed at reducing personal immobility were economically

beneficial. For example, the benefit-cost ratio of PDRTA, Myrtle Beach was 27.4, and the net annual benefits were \$2,097,140. Apart from that, the benefit-cost ratio of SEPTA Horsham Breeze, MDTA Metro Pass, MTA Immediate Needs, OATS, and Fremont travel training were all greater than 1, indicating that the benefits outweighed the total costs. ECO Northwest and Parsons Brinckerhoff Quade & Douglas, Inc. (2002) also addressed the same issue that analyzing the costs and benefits of public transit service to help decision-makers.

Previous studies have shown that in both urban and rural areas, the benefits to communities and society from public transport are significant and outweigh the costs. However, with the generation of new public transportation services modes like the partnership between TNCs and transit agencies, there is no study to evaluate the performance of the partnership. Whether they can bring benefits like public transportation or whether they can bring other or even greater benefits still needs to be studied by researchers.

3. Comparative Case Study

3.1 Exposition Area Innovation Zone Pilot – Austin, TX

Between June 2018 and December 2018, the Capital Metropolitan Transportation Authority (Capital Metro) established a pilot Transit-TNCs partnership in Austin, Texas, called the Innovation Zone. After the local transit authority eliminated several poorly performing fixed transit lines, the project tried to make up for the lack of public transport by providing additional TNC services to Austin's customers. The agreement, signed in 2016 by Capital Metro and Ride Austin, provides the public transport services to solve the first/last mile issue in areas lacking public transport. Specifically, customers can take completely free trips that start and end within a certain distance of bus stop in the pilot area, which is funded by the Capital Metro General Fund.

3.2 Partnership Details

The Capital Metro canceled several underperforming traditional public transit routes in June 2015 and reorganized them. In a subsequent transport study, the areas where fixed bus lines were eliminated were replaced by six "Transport Innovation Areas". The center of The Exposition Area, which was the first transportation pilot, was a mile-long exposition avenue with no public transportation (Figure 3.2.1).

Based on two fixed bus stations, The Capital Metro set up a pilot area to provide residents with flexible short-distance travel services in the absence of fixed public transport services. The project reduces the impact of the lack of public transport services on residents, decreases the operating costs of the transit agency, and improves the level of transport services while increasing the mobility of residents.

The Capital Metro procurement process began in May 2018 to seek work opportunities with TNCs. Three TNC providers have submitted proposals for the project. Eventually, Ride Austin, a local non-profit company, met the data-sharing requirements of the Capital Metro agreement and signed the agreement.

Ride Austin offered unlimited free rides in the pilot area between June 2018 and December 2018, with the Capital Metro fully subsidizing the fees. They ran Monday through Friday between 7 AM and 7 PM; the trip must begin and end within a quarter of a mile of two specific bus stops (i.e., Enfield & Exposition, Westover & Exposition).



Figure 3.2.1 Exposition Area Innovation Zone Service Area

Source: Existing Transportation Network Companies Used as a Part of Basic Mobility: White Paper, Texas A&M Transportation Institute.

3.3 Key Takeaways

The local transportation agency conducted major marketing and internal promotion tests. In the two months prior to the implementation of the project, the Capital Metro promoted Ride Austin's free shuttle service through its website and social media outlets. Moreover, handouts were distributed at major bus stations, and public meetings were held in local schools and libraries in the pilot area.

During the project implementation, The Capital Metro regularly updated the cooperation progress to the transit agency's Board of Directors. Ride Austin also provides periodic reports and data to The Capital Metro under contract. This data includes the start and destination of trips, the distance traveled, trip costs, the time of day (TOD), day of week (DOW), the driver's name for each vehicle, the response time, and the customer's name. However, The Capital Metro has limited the content of its data to the public, publishing only the number and duration of trips.

Table 3.3.1 The pilot details compared to The Direct Connect service

	Exposition Area Innovation Zone Pilot-Austin, TX	The Direct Connect-Pinellas County, FL
Partners	Ride Austin	Uber, United Taxi, Wheelchair Transport
Duration	June 2018-December 2018	February 2016-Present
Subsidy	Free	5 dollars per trip
Geographic Constraints	Trips must begin or end within a quarter mile of 2 potential transit stops within the Innovation Zone	Trips must begin or end within 800 feet of 26 potential transit stops spread throughout the county
Service Time	Monday to Friday from 7 AM to 7 PM	7 days a week from 5 AM to 12 AM
Funding	CapMetro General Fund	PSTA
Issue Addressed	First/Last mile	First/Last mile

3.4 Challenges

The main challenge of the pilot project is attracting customers. Despite the Capital Metro's promotional efforts, only one customer has used the service in its first two months (Hampshire, 2017). They had hoped that schools in the pilot area would encourage students to use the service, but unfamiliarity with the rules limited the use of the program. In addition to the public's hesitancy, the process was also slowed down by federal law requirements that had transit operators take drug and alcohol test, as well as background checks which took time to process and also affected worker availability. During the implementation of the project, laws and regulations related to the Transit-TNC partnership in Austin city were lacking, leading to potential safety concerns. Moreover, while passengers use mobile Apps, the project faces challenges from traditional payment methods. Cash payments are not used as a supplemental payment. These social, legal and monetary challenges posed to be substantial obstacles to the intended project.

Attraction to the target customer is especially important in Transit-TNCs partnership projects. Generally speaking, transit disadvantaged groups such as low-income people and the elderly are the main users of public transport. However, the experience these key customers have with on-demand dynamic ridesharing services based on smartphones is limited. Therefore, teaching users to effectively use the services provided by TNCs is an important way to improve ridership. Furthermore, limited publicity time may be the other reason for the low passenger flow in the early stage of the project. The Capital Metro used only two months of publicity before the project was implemented, resulting in limited exposure.

In addition, it is very important to establish a sound evaluation system during the operation of the project, which can not only allow for timely adjustments to the ongoing project, but also benefit similar cooperations in other areas in the future. Capital Metro has developed the following points as indicators for project evaluation (Curtis et al., 2018):

- Ridership changes for both bus stations and Ride Austin
- Ridership per hour
- Response time
- Cost (per passenger, per mile, per hour, per trip)
- Customer satisfaction (from the questionnaire)
- Changes in TNC service costs
- Project cost versus the money saved by eliminating the fixed bus route

Finally, evaluating project effectiveness requires valid data. Although the contract states that Ride Austin is responsible for providing most of the operational data, this is not the common case around the nation. Private TNCs often keep their data strictly confidential, which requires local transport authorities and research institutes to communicate effectively with TNCs to obtain more valid data.

Therefore, given the case study in Austin, we need to effectively evaluate the performance of given essential metrics. In this task, we will first use ridership to evaluate the operation of the partnership program in Pinellas County from a spatiotemporal perspective.

4. Overall Temporal Pattern of Uber rides

4.1 Quarterly pattern

Figure 4.1.1 shows the quarterly ridership of Uber rides from the second quarter of 2018 to the first quarter of 2020. The number of trips ranges from 3,636 rides per quarter to 9,932 rides per quarter, which first increased significantly from the second quarter of 2018 to the second quarter in 2019 and then decreased dramatically from third quarter to fourth quarter in 2019. This sharp growth of the trips should be the result of the launch of the third phase of the Direct Connect program, which generated a significant change in the service design.

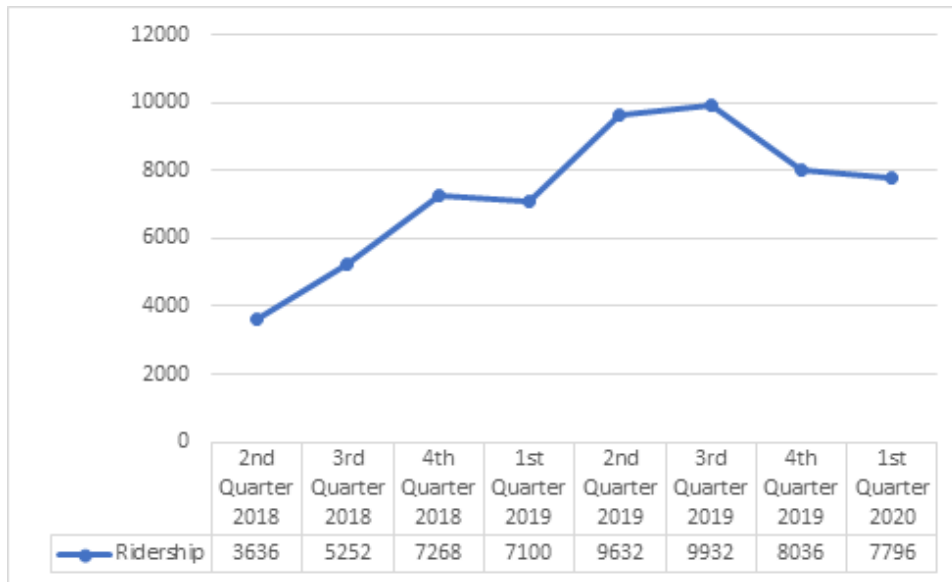


Figure 4.1.1 Quarterly Uber Ridership

Table 4.1.1 Quarterly Uber Ridership Basic Statistics

Season	Mean	Minimum	Maximum
Spring	7448	7100	7796
Summer	6634	3636	9632
Fall	7592	5252	9932
Winter	7652	7268	8036

4.2 Monthly pattern

Figure 4.2.1 represents the monthly ridership of Uber rides, which was similar to the trend of quarterly trips. The number of monthly ridership experienced a dramatical growth from 864 trips in April 2018 to 3,856 trips in October 2019. This dramatical growth should also be the results of the implementation of third phase of Direct Connect Program. However, between October 2019 and May 2020, the number of trips experienced sharp decline from the highest point, 3,856 trips per month to 1,320 trips per month. This sharp decline should be the results of the spread of COVID-19. Stay-at-home rules constrained people's mobility and led to the dramatical drop of the Uber rides.

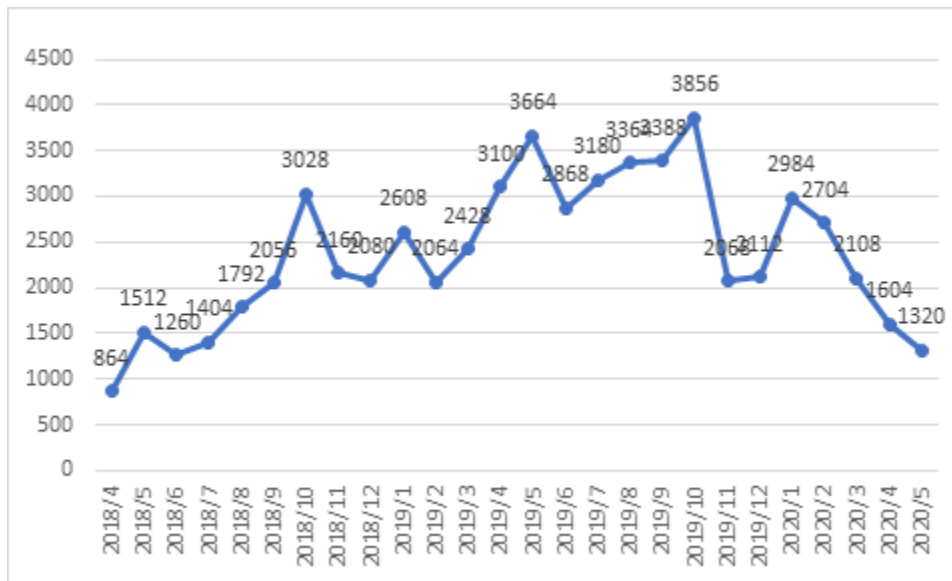


Figure 4.2.1 Monthly Uber Ridership

Table 4.2.1 Monthly Uber Ridership descriptive statistics

Month	Mean	Minimum	Maximum
January	2796	2608	2984
February	2384	2064	2704
March	2268	2108	2428
April	1856	864	3100
May	2165	1320	3664
June	2064	1260	2868
July	2292	1404	3180
August	2578	1792	3364
September	2722	2056	3388
October	3442	3028	3856
November	2114	2068	2160
December	2096	2080	2112

4.3 Day of week pattern

Figure 4.3.1 shows the daily pattern of Uber trips. From the original dataset, Uber trip data was provided in three time periods, namely Monday to Thursday, Friday, and Saturday to Sunday. Figure 4.3.1 were produced by averaging the aggregated trip data into each day based on the assumption that the Uber ridership of Monday, Tuesday, Wednesday, and Thursday is similar, and the Uber ridership of Saturday and Sunday is similar. As Figure 4.3.1 shows, the average daily Uber ridership of Monday to Thursday is the highest among the whole week, which is about 126 trips per day. Friday has the lowest daily Uber ridership, which is only 11.34 trips per day. The daily ridership on Saturday and Sunday is a relatively higher than that on Friday, which is 33.04 trips per day.

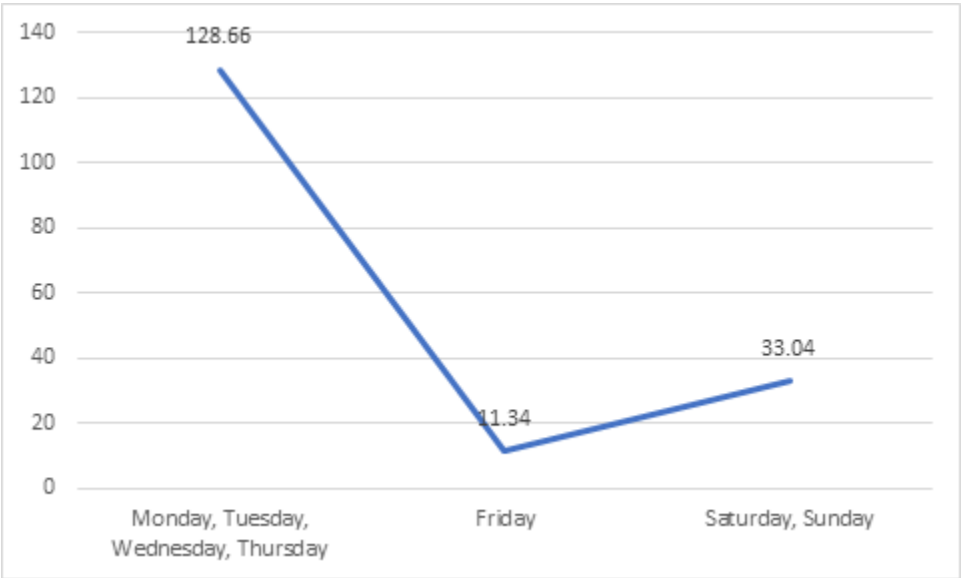


Figure 4.3.1 Daily Uber Ridership

4.4 Time of day pattern

Figure 4.4.1 represents the average number of hourly trips of Uber rides. In terms of the average number of trips of each time period, 6 am-10 pm and 3 pm-7 pm had a higher number of trips than other time periods, which was 33.79 and 23.79 trips. 6 am-10 pm and 3 pm-7 pm are the peak hours, which coincide with users' commuting time. However, the average number of Uber trips generated during other time periods was much smaller, especially 3.43 trips from 10 pm-2 am.

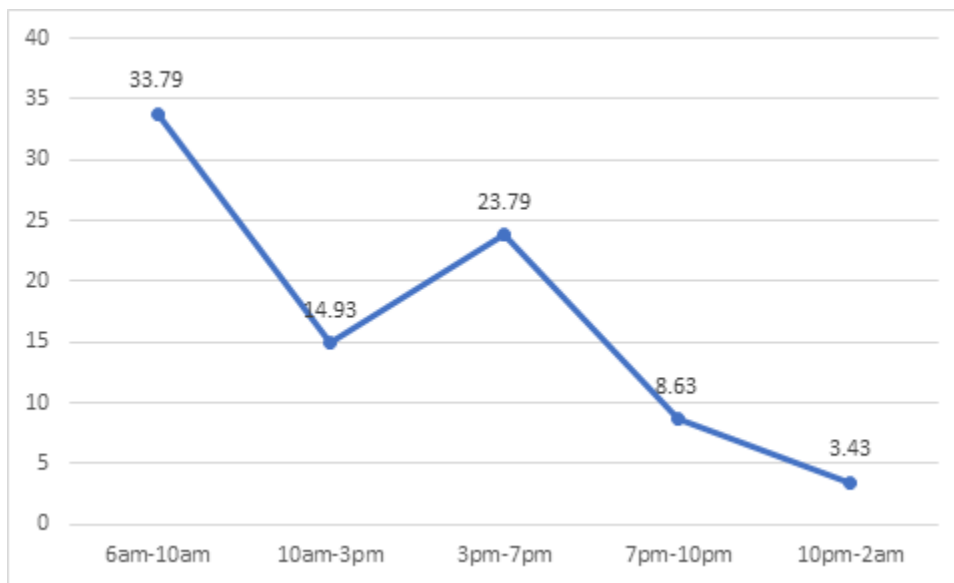


Figure 4.4.1 Hourly Uber Trips from April 2018 – March 2020

5. Overall Temporal Pattern of Transit Ridership

5.1 Every Four-month pattern

Figure 5.1.1 shows every four-month transit ridership from February 2018 to January 2020, which ranges from about 4,102,562 trips per four months to approximately 5,087,594 trips per four months. Transit ridership shows an overall growth trend. The ridership rose slowly from February 2018 and reached a peak in February 2019 with 5,087,596 trips, and then steadily declined.

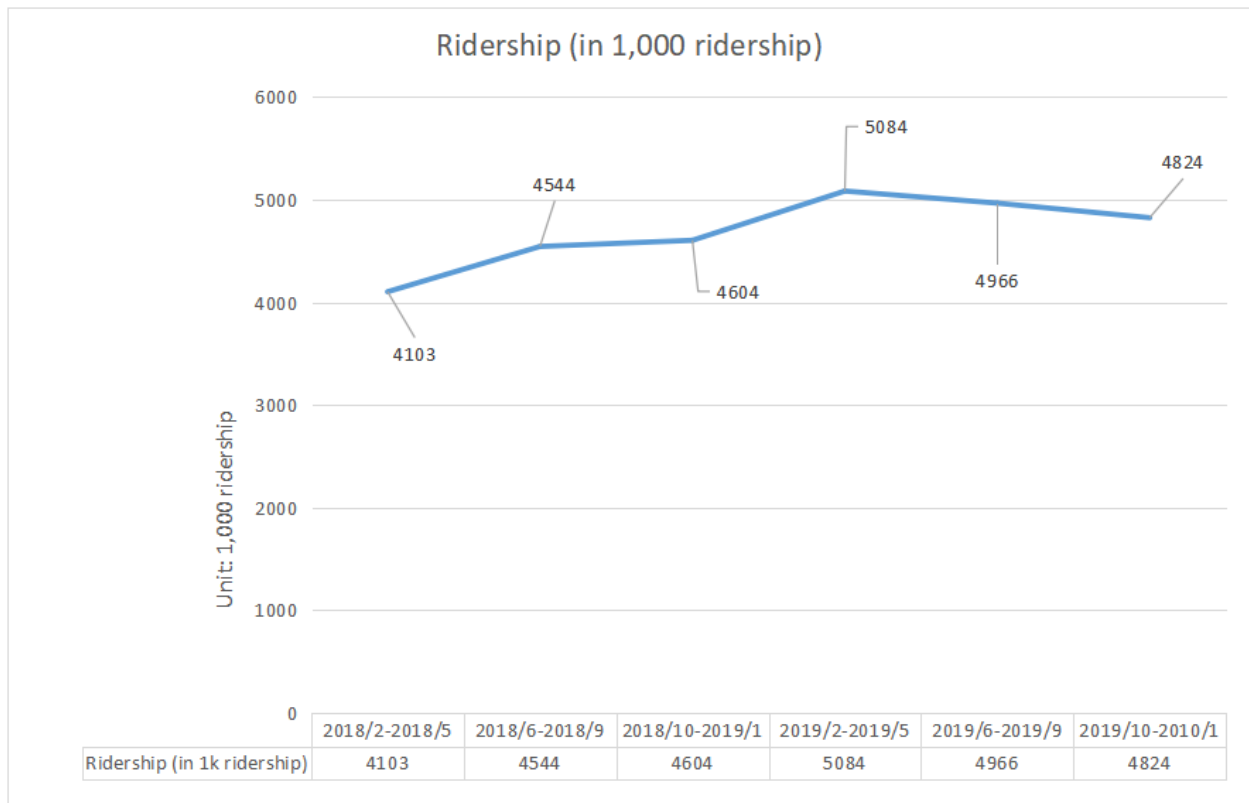


Figure 5.1.1 Every Four-month transit ridership (in 1,000 ridership) from February 2018 to January 2020

5.2 Day of Week pattern

Figure 5.2.1 represents the day of week pattern of daily transit ridership. Like the Uber data, the original daily transit data is divided into three time periods, namely Monday to Thursday, Friday, and Saturday to Sunday. Figure 5.2.1 was made by averaging the aggregated data into each day. As the picture shows, the transit ridership of all seven days shows an overall upward trend, although there are some fluctuations. Monday to Thursday is the time period with the highest transit ridership, which ranges from 46,130 trips to 57,097 trips. It is higher than the transit ridership on Friday and during the weekend by approximately 10,000 trips. What's more, the transit ridership during the weekend is relatively higher than that on Friday. These patterns of transit ridership are similar to the day of week pattern of Uber rides.

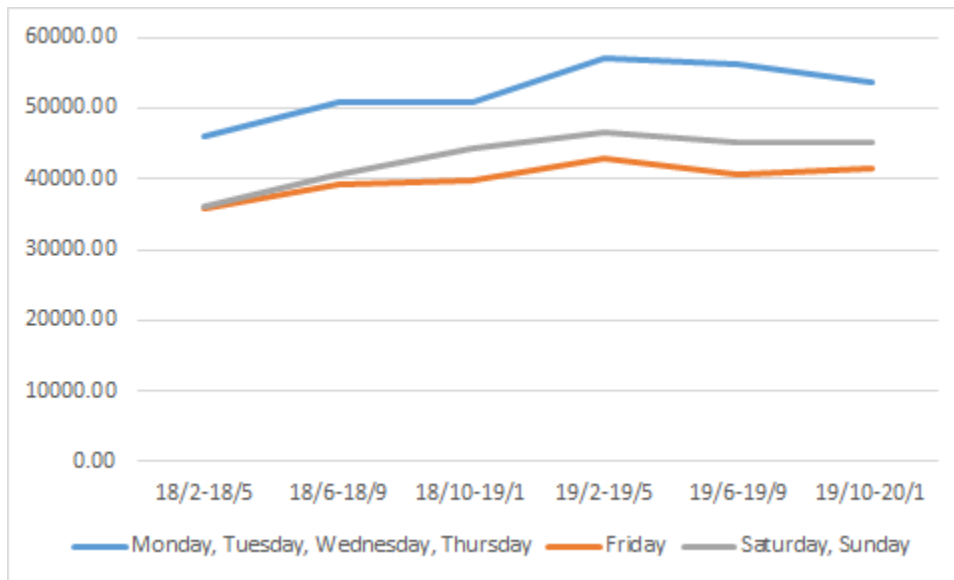


Figure 5.2.1 Day of Week Pattern of Transit Ridership

5.3 Total Ridership by Route

Table 5.3.1 shows the transit ridership by routes. From February 2018 to January 2020, the transit routes have been redesigned four times before stabilized in 2019, including adding and canceling some routes. Routes 101, 521, 701, 702, 703, 711, and 814 are the newly added routes, while Routes 97, 98, 101, and 3001 are canceled. The ridership of each route varies widely, which ranges from around 10 trips to about 13,280 trips. There are ten core routes with the highest performance among all the routes, namely Route 52, 18, 34, 4, 35, 19, and 59, the ridership of which are all above 200,000 trips. The ridership of routes 52 is the highest, which is above 400,000 trips. However, Routes 0, 813, and 812 are the lowest performed routes, the ridership of which are less than 10,000 trips per time period (four months).

Table 5.3.1 Four-month Transit Ridership by Route from February 2018 to January 2020

Route	Ridership					
	18/2-18/5	18/6-18/9	18/10-19/1	19/2-19/5	19/6-19/9	19/10-20/1
0	1,333	1,647	1,444	1,390	3,391	1,242
4	335,764	342,639	365,736	371,452	354,112	335,320
5	66,528	71,032	83,852	93,703	29,419	26,122
7	53,703	66,172	78,811	74,748	85,796	84,232
9	103,090	127,855	113,703	136,857	182,645	187,698
11	107,890	112,953	112,924	113,438	109,915	110,341
14	189,813	188,261	181,772	163,908	177,963	179,473
15	49,612	57,879	81,938	81,380	79,956	83,546
16	20,659	27,175	27,912	29,539	26,123	25,717
18	382,526	426,521	410,792	414,500	430,818	409,427
19	187,478	198,658	211,424	178,425	194,309	193,263
20	45,216	66,285	51,904	63,849	65,613	62,281
22	12,567	13,705	13,514	13,715	12,724	12,746
23	66,725	72,870	69,943	77,422	72,255	74,490
32	12,253	16,482	14,111	15,787	14,289	12,608
34	333,686	343,177	379,088	387,721	392,672	372,129
35	286,366	273,996	268,413	336,504	294,535	250,422
38	50,080	50,540	45,192	51,349	48,932	49,265
52	446,105	452,459	410,512	470,623	455,790	445,297
58	16,697	19,449	19,187	17,888	20,137	19,141
59	200,037	205,437	200,696	223,414	212,654	193,652
60	151,583	207,396	195,846	227,928	214,617	202,869
61	52,644	59,780	64,395	76,788	70,667	73,770
62	52,250	60,013	55,405	57,920	54,492	56,474

65	35,393	41,694	39,977	33,964	40,749	41,611
66	13,285	13,145	19,043	16,638	10,981	20,812
67	33,056	32,917	38,606	40,185	43,337	40,763
68	23,368	23,622	30,758	24,153	30,892	27,214
73	37,405	38,472	37,869	36,056	36,556	38,156
74	131,122	131,594	129,828	135,991	131,773	134,537
75	73,013	74,298	68,118	75,824	72,106	69,494
76	34,418	37,756	36,372	35,638	36,300	36,320
78	72,140	94,941	101,231	132,066	120,440	119,033
79	176,141	183,158	170,836	187,751	174,646	174,755
90	12,582	12,827	12,318	15,135	12,323	12,634
100	18,518	17,889	19,528	20,763	20,668	20,682
101	-	-	6,383	7,086	5,683	5,664
300	14,000	-	15,203	14,127	14,166	14,295
355	97,476	89,511	89,882	137,061	111,590	70,558
521	-	-	33,121	45,503	45,974	47,704
701	-	-	-	37,198	35,998	41,560
702	-	-	-	29,223	25,598	28,492
703	-	-	-	43,843	48,480	56,024
711	-	-	8,991	13,224	15,854	13,733
777	57,925	165,898	182,602	223,537	220,777	235,829
812	2,260	480	10,117	7,886	7,511	7,067
813	1,542	160	6,206	3,869	3,898	3,532
814	-	-	5,832	6,526	5,067	5,261
888	20,771	77,263	82,191	84,099	91,307	96,390
97	14,459	13,153	-	-	-	-
98	9,084	8,528	-	-	-	-
1001	-	5,481	-	-	-	-

3001	-	18,448	-	-	-	-
Grand Total	4,102,563	4,543,619	4,603,526	5,087,594	4,966,497	4,823,642

6. Time of Day Pattern

6.1 Origin Pattern

6.1.1 Census block group

Figure 6.1.1. (A) (B) (C) (D) (E) represents trip patterns based on origin blocks in different periods of a day. It shows the visualization of transit demand change within a day. The blocks with trips of 6am-10am (A), 10am-3pm (B), and 3pm-7pm (C) are significantly more than that of 7pm-10pm (D) and 10pm-2am (E). The periods between 6 am-10am (A) and 3pm-7pm (C) are peak hours, and the trips mainly concentrate in the southeast part of the county. At 6am-10am (A), the blocks close to the southeastern side of Ulmerton Rd, Park Blvd N and 22nd Ave S have more trips. At 3pm-7pm (C), the trips are highly clustered at the area shaped by the southeastern side of Ulmerton Rd, U.S. 19, and Grandy Blvd. The period from 10am-3pm (B) indicates less trips compared with peak time, and the trips concentrate at the blocks near Grandy Blvd. In the off-peak time, 7pm-10pm (D) and 10pm-2am (E), the blocks located at the northeastern part and the western part show more trips.

Figure 6.1.2. (A) (B) (C) (D) (E) indicates the mean fare of trips based on origin blocks in different time periods of a day. Similar to Figure 4.1, the blocks with trips of 6am-10am (A), 10am-3pm (B), and 3pm-7pm (C) are significantly more than that of 7pm-10pm (D) and 10pm-2am (E). In terms of fares, the average fare of five periods is similar. At 6am-10am (A) and 10am-3pm (B), the blocks along Missouri Ave N and the south part of U.S. 19 have a higher fare. However, at 3pm-7pm (C), the blocks with relatively higher fare are clustered at the southeast part of the county. In the off-pick time, 7pm-10pm (D) and 10pm-2am (E), the blocks with trips are significantly reduced, whereas, these blocks have a relatively high fare.

6.1.2 Stop level analysis

Figure 6.1.3. (A) (B) (C) (D) (E) illustrates trips based on origin pilot stops in different time periods of a day. By comparing the five figures, the number of operating pilot stops are similar in each period. However, at the peak periods of 6am-10am (A) & (B) 3pm-7pm, the average number of trips range from 7.6 to 8.5. At 6am-10am (A), the pilot stops with more trips are distributed along U.S. 19 and Ulmerton Rd. Whereas, in other periods, trips concentrate in the area south of E Bay Dr (B) (C) (D) (E).

Figure 6.1.4. (A) (B) (C) (D) (E) shows the mean fare of trips based on origin pilot stops in different periods of a day. Although the number of operating pilot stops are similar among the five time periods, the mean fare of 10am-3pm (B) is relatively lower than others. In general, Tarpon Ave & Huey Ave, the Largo Transit Center, and Belcher Rd & Park Blvd N are the pilot stops with a relatively higher mean fare.

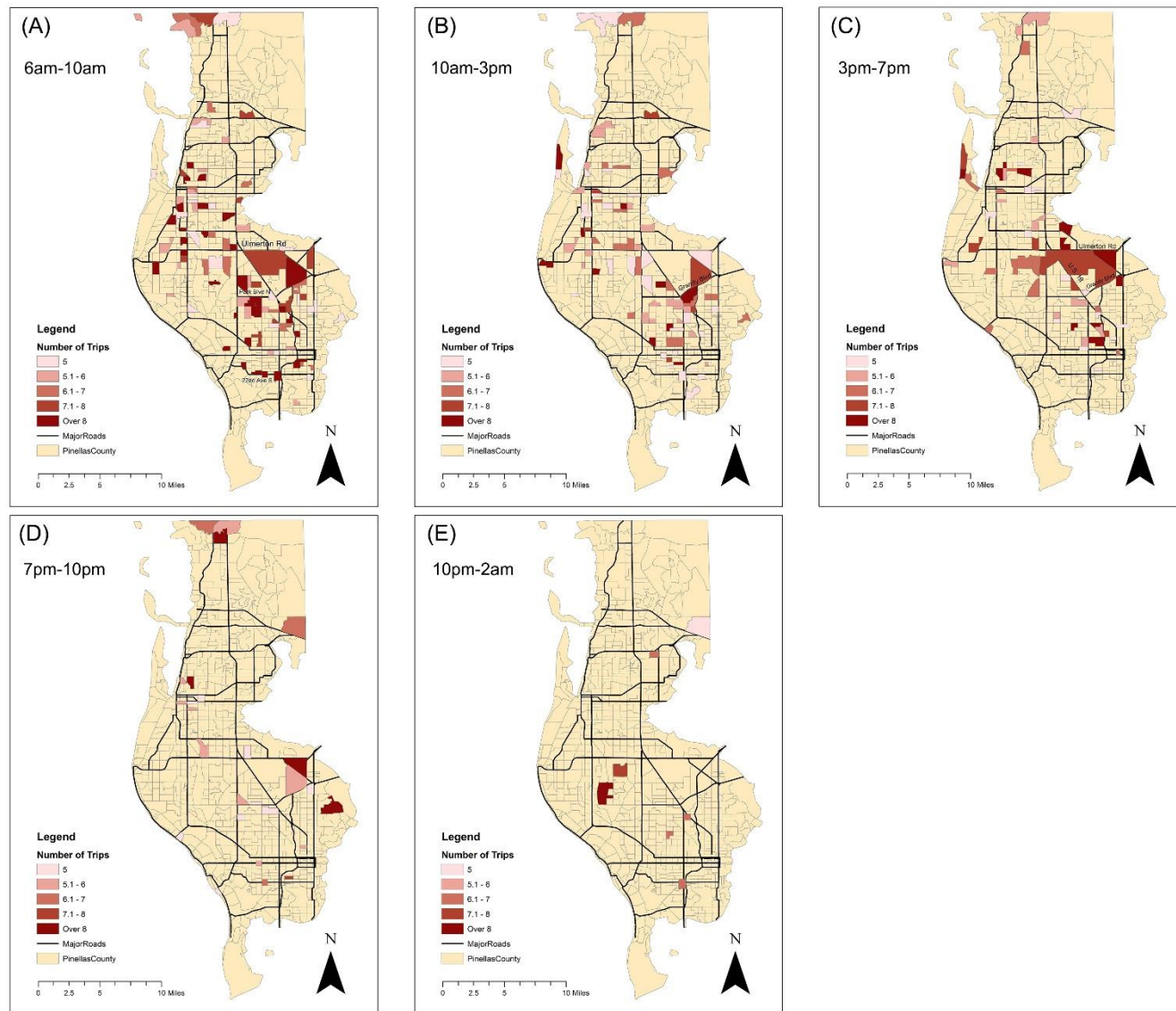


Figure 6.1.1 Trip Patterns based on Origin Census Blocks in Time of Day.

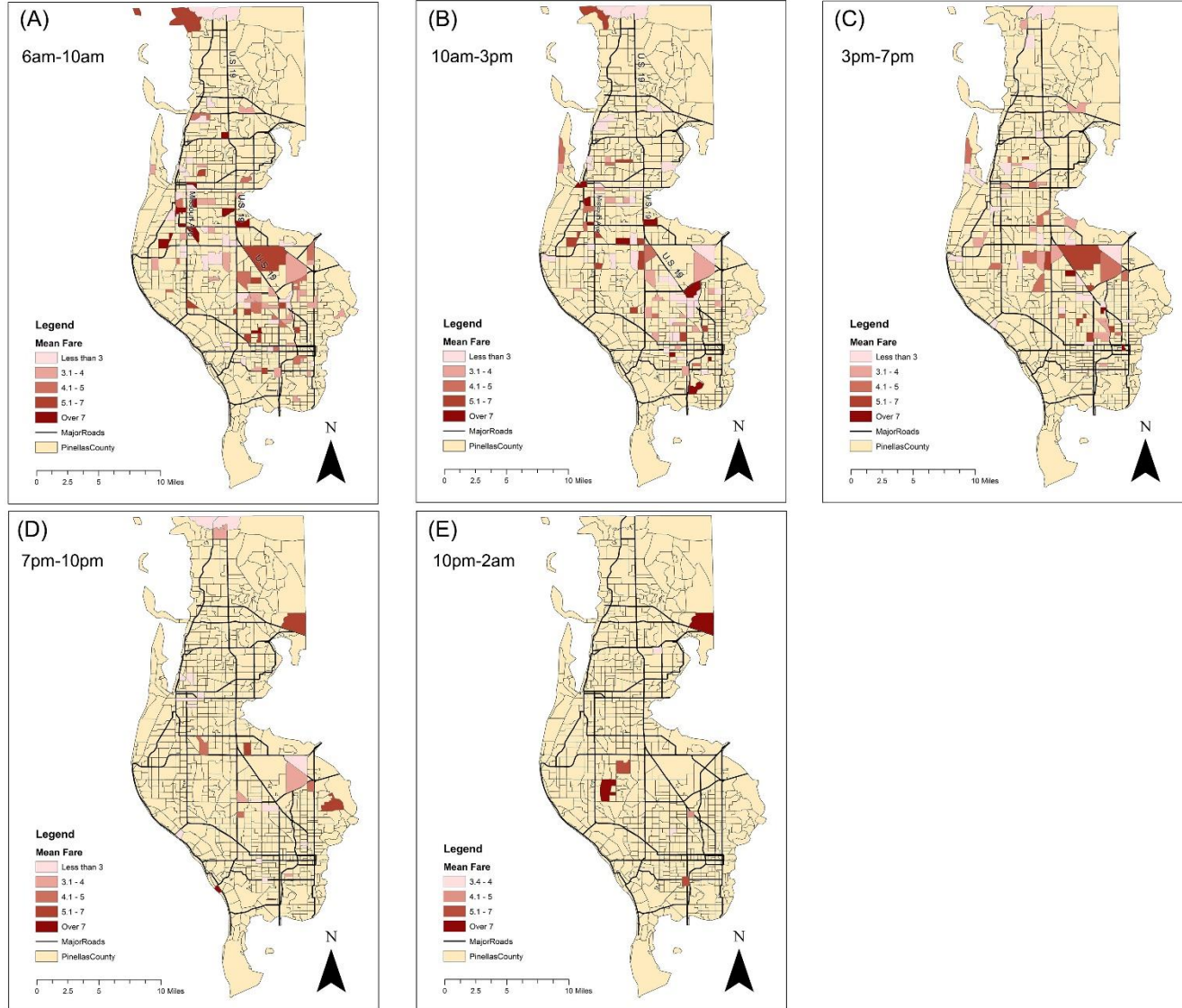


Figure 6.1.2 Fares of Trips based on Origin Census Blocks in Time of Day

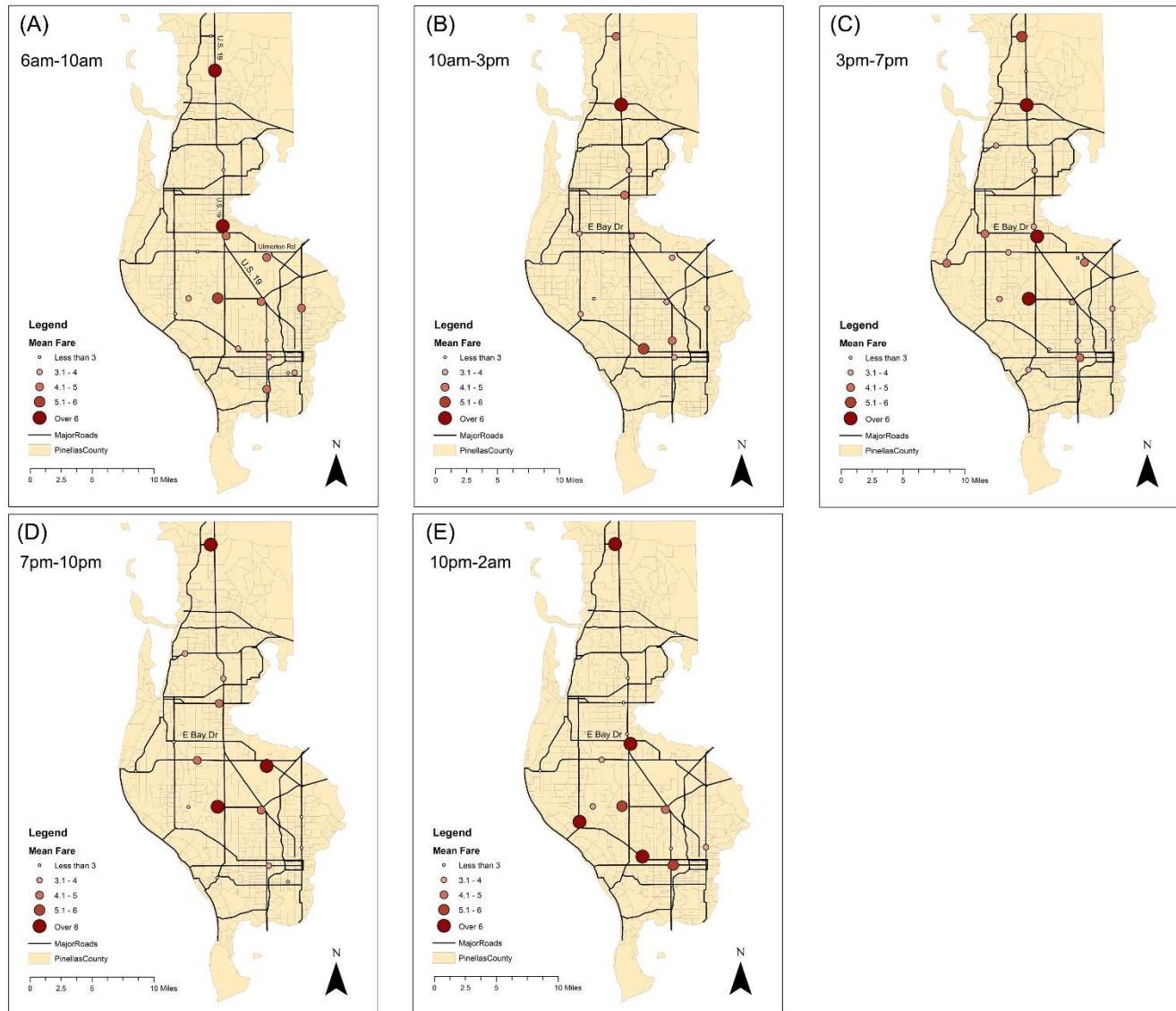


Figure 6.1.3 Trip Patterns Based on Origin Pilot Stops in Time of Day

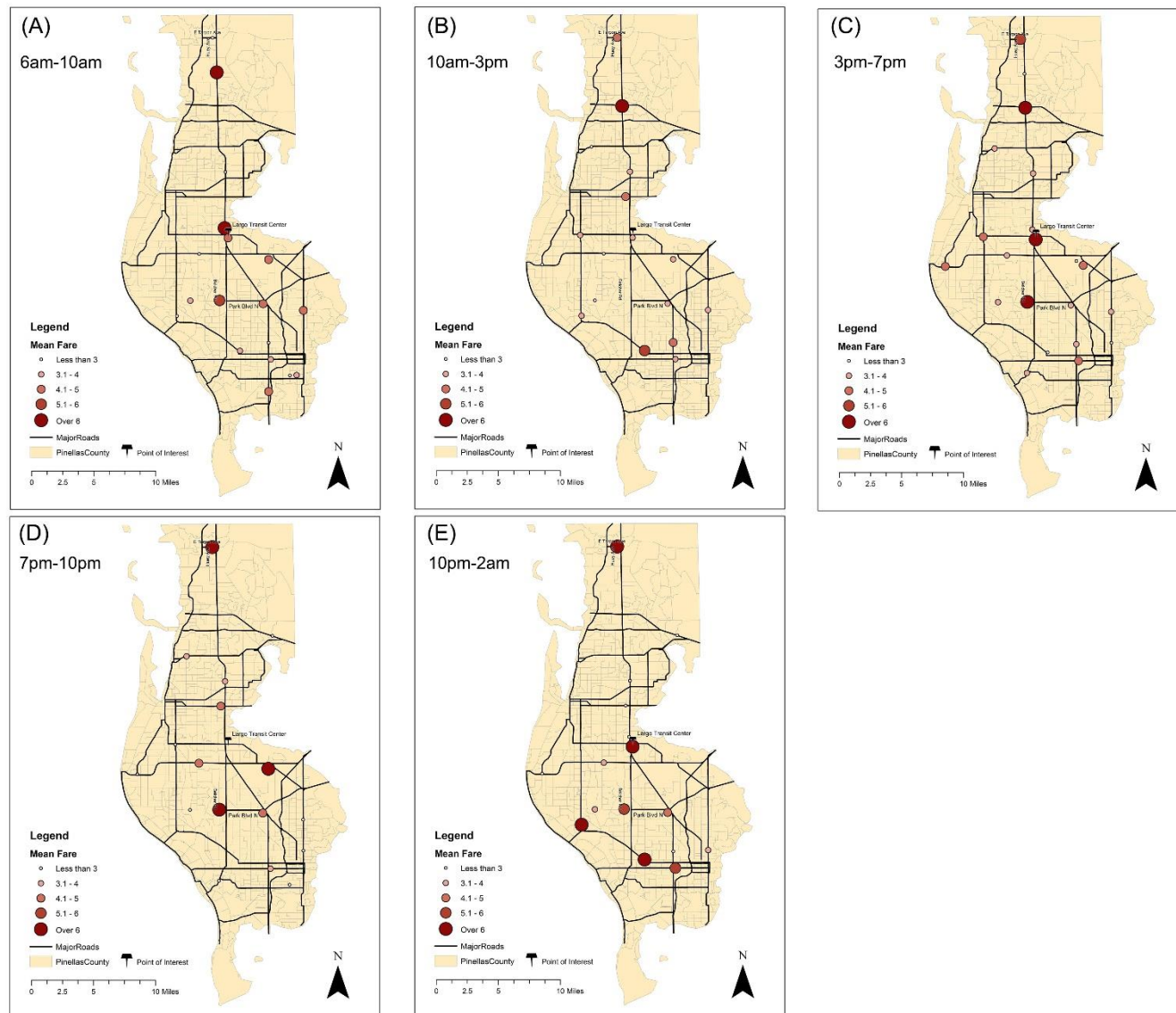


Figure 6.1.4 Fares of Trips based on Origin Pilot Stops in Time of Day

6.2 Destination Pattern

6.2.1 Census block group

Figure 6.2.1. (A) (B) (C) (D) (E) indicates trip patterns based on destination blocks in different time periods of a day. It visualizes the number of trips to destination blocks in different time periods. In peak hours, 6am-10am (A) and 3pm-7m (C), there are more blocks with trips than in off-peak hours, 10am-3pm (B), 7pm-10pm (D) and 10pm-2am (E). In general, the blocks at the east part of the county show more trips, and the block located at the south side of eastern Ulmerton Rd and north side of Roosevelt Blvd has the most trips.

Figure 6.2.2. (A) (B) (C) (D) (E) illustrates the mean fare of trips based on destination blocks in different time periods of a day. In the morning peak hour, 6am-10am (A), fares of trips at the east and south part of the county are significantly higher than the rest of the blocks. However, in other periods (B) (C) (D) (E), although the blocks with more trips concentrate in the east part of the county, these blocks do not show relatively high fare.

6.2.2 Trip Patterns at the Stop Level

Figure 6.2.3. (A) (B) (C) (D) (E) shows the number of trips based on destination pilot stops in different time periods of a day. As the figure illustrates, 6am-10am (A) & 3pm-7m (C) are peak time. When reviewing the five time periods, it shows that 9th Ave N & 58th St N, Gulf to Bay Blvd & Coachman Rd, and Layby station are the main termini.

Figure 6.2.4. (A) (B) (C) (D) (E) represents the mean fare of trips based on destination pilot stops in different time periods of a day. In the periods from 6am to 10pm (A) (B) (C) (D), the cost of getting to Belcher Rd & Park Blvd N and Layby station is higher than that of other places.

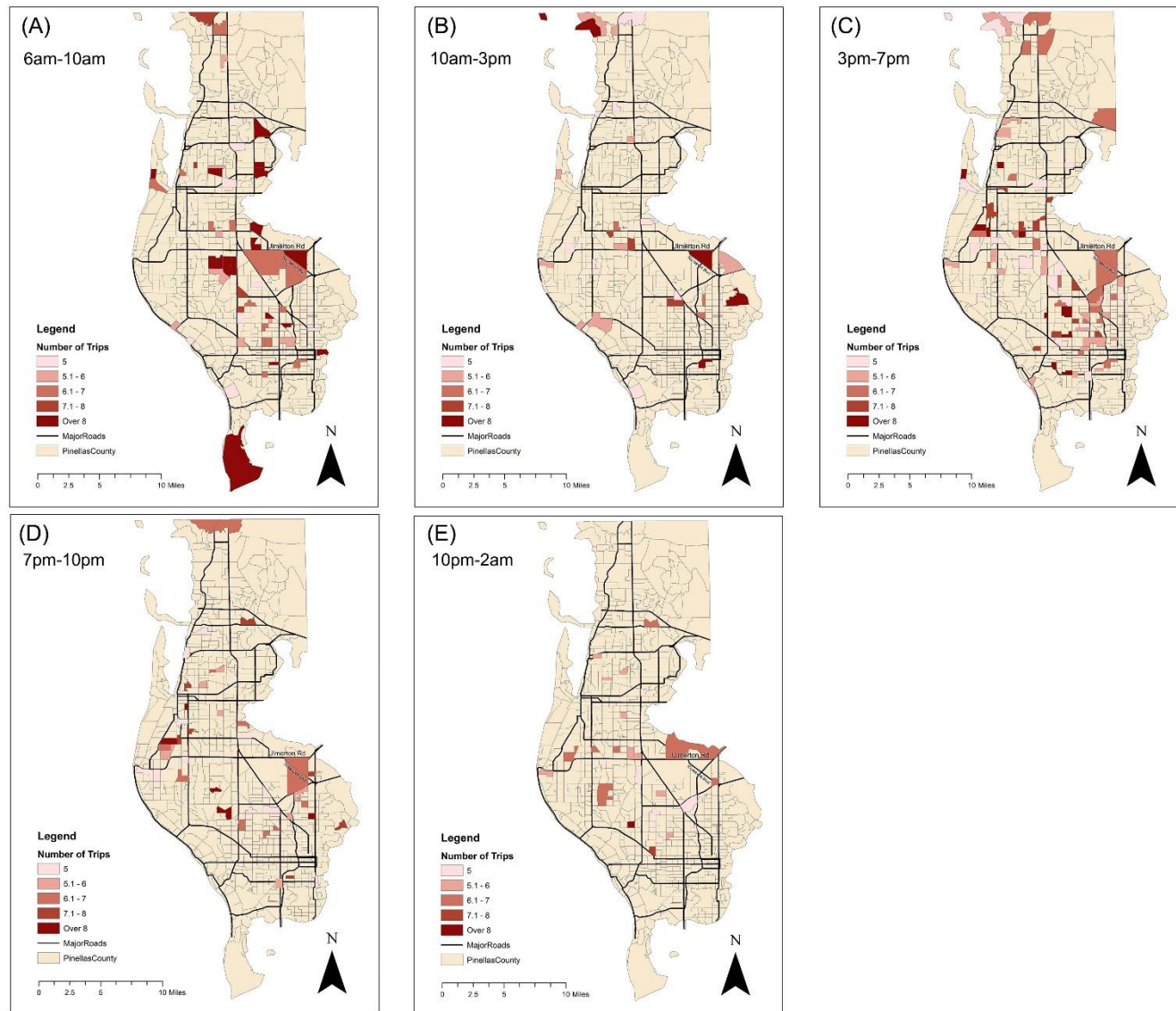


Figure 6.2.1 Trip Patterns based on Destination Census Blocks in Time of Day.

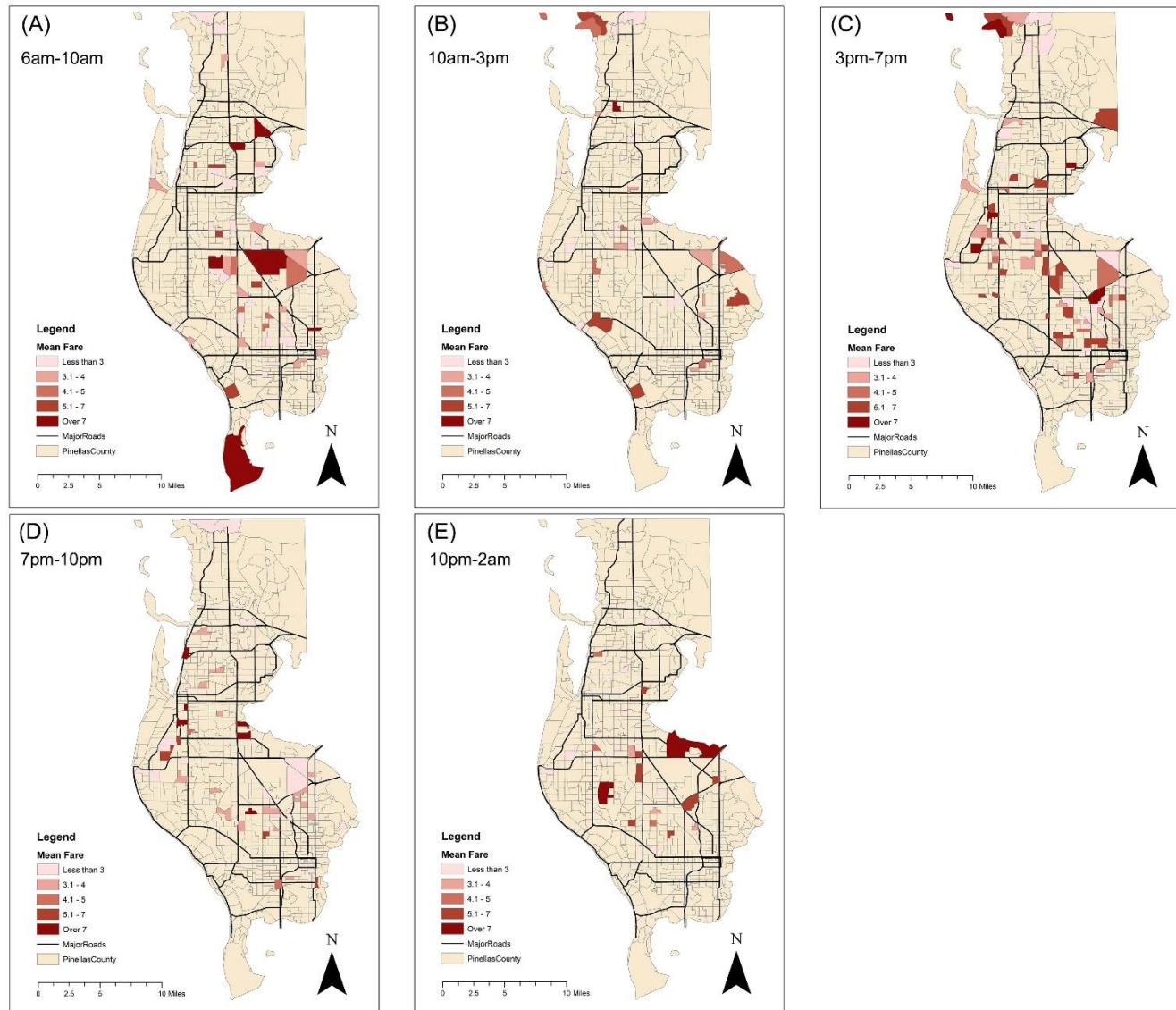


Figure 6.2.2 Fares of Trips based on Destination Census Blocks in Time of Day.

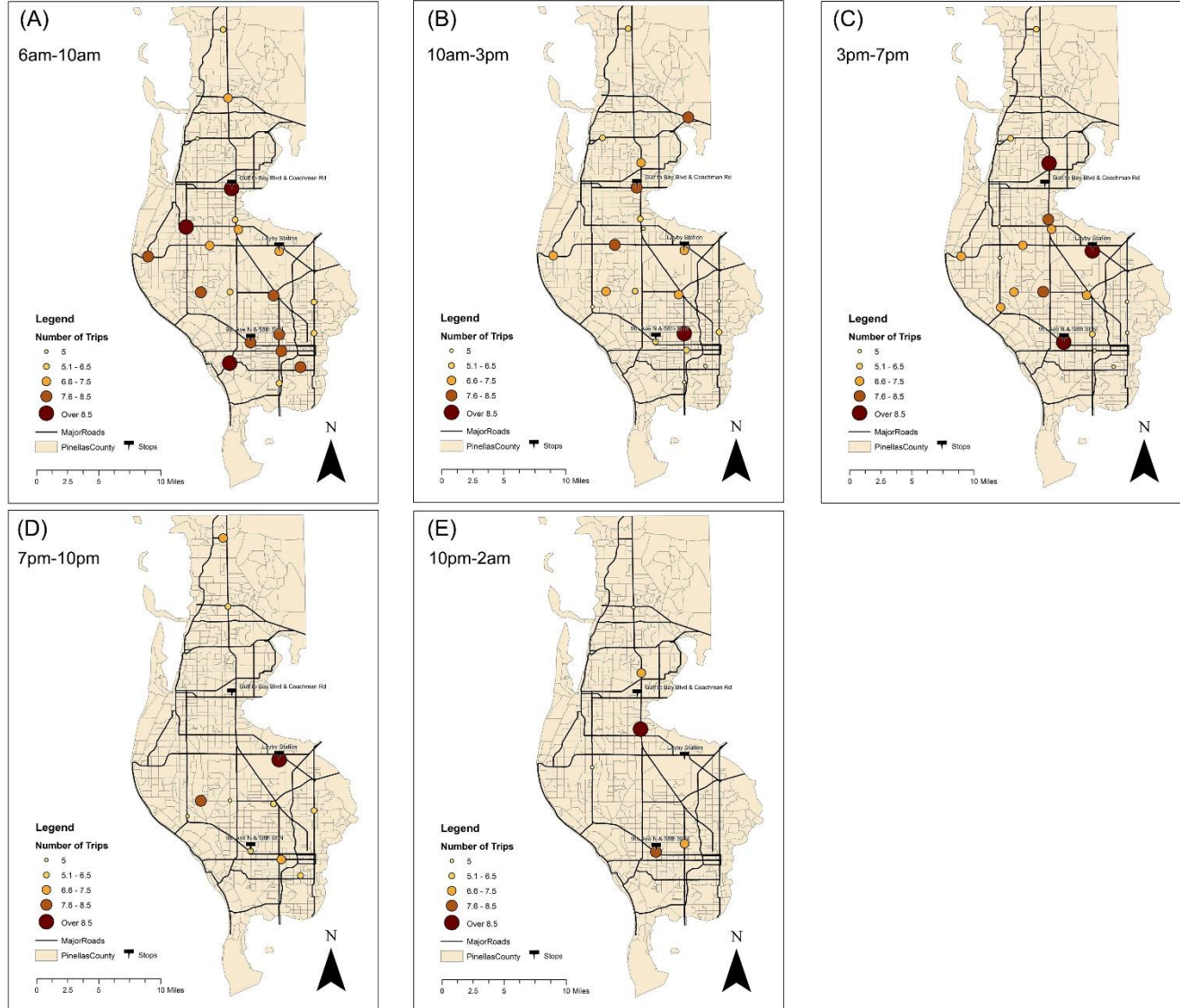


Figure 6.2.3 Trip Patterns based on Destination Pilot Stops in Time of Day

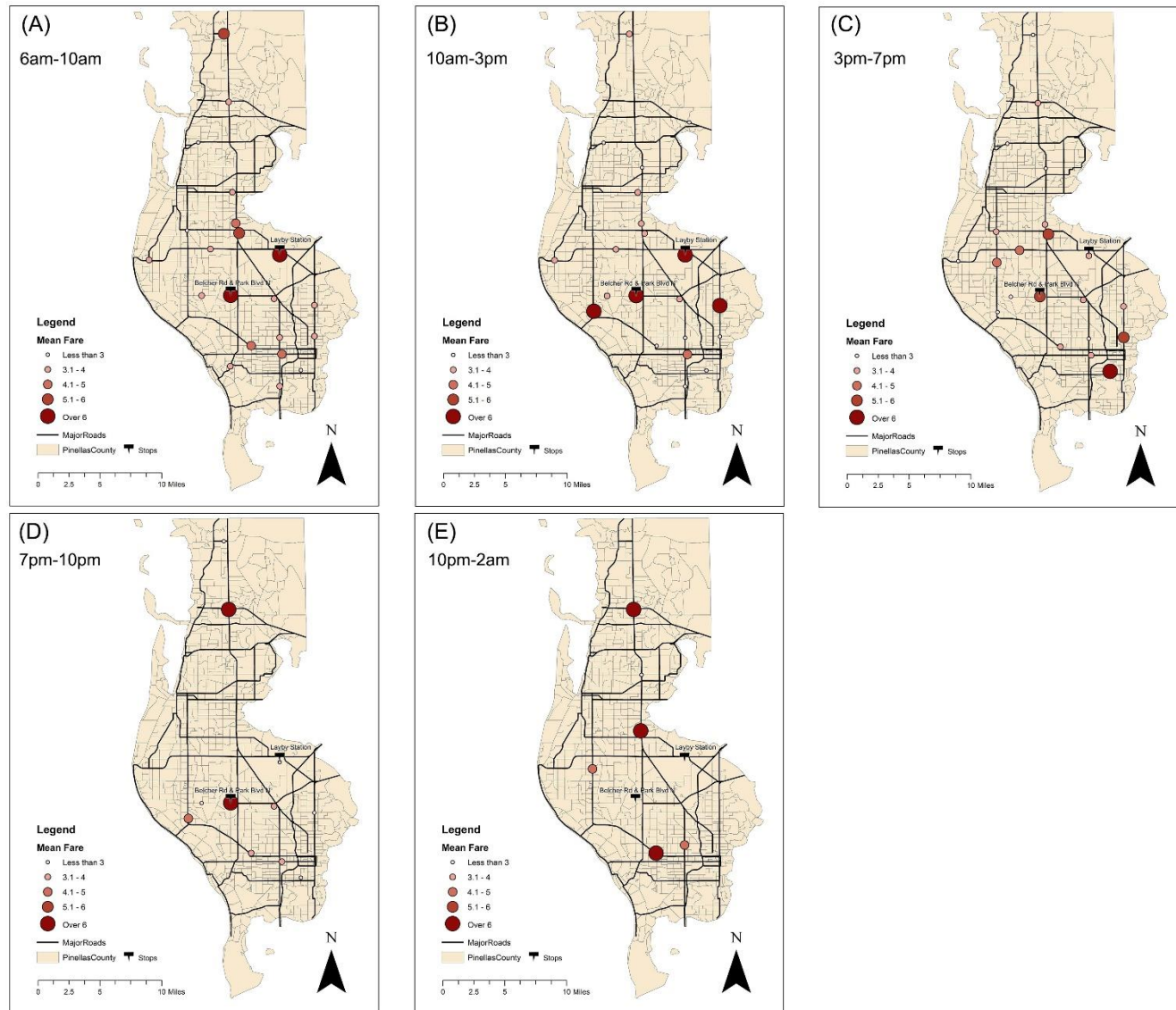


Figure 6.2.4 Fares of Trips based on Destination Pilot Stops in Time of Day

6.3 Origin-Destination (OD) Pattern

As for the different time periods of a day, Figure 6.3.1 (A) (B) (C) (D) (E) shows that most connections happen during peak hours (6AM – 10AM and 3PM – 7PM). Park St & S Garden Ave, Pinellas Park Transit Station, and Pasadena Ave & Sun Island Dr S have the most connections.

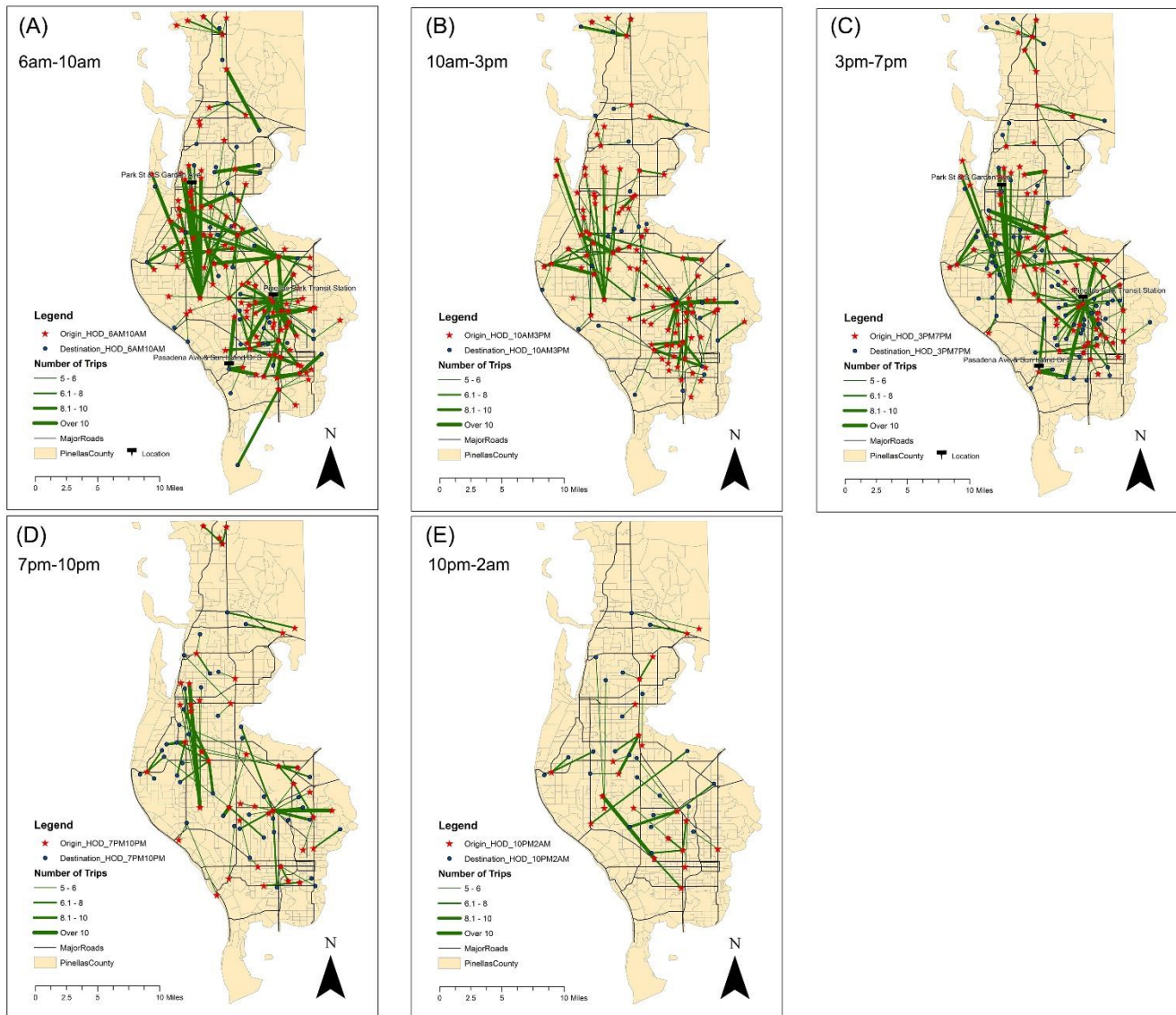


Figure 6.3.1 Origin-Destination Pattern in Time of Day

7. Day of Week Pattern

7.1 Origin Pattern

7.1.1 Census block group level analysis

Figure 7.1.1 (A) (B) (C) shows the average demand on different days of the week. It reveals that the number of blocks with daily trips from Monday to Thursday is significantly higher than that on Friday and the weekend. However, some specific locations like the triangle census block above the Grandy Blvd have a similar demand on either weekends or weekdays. The average number of trips from Monday to Thursday is from 6.5 to 10, which is higher than that on the weekend (5 to 6.5) and Friday (5).

Figure 7.1.2 (A) (B) (C) reveals the average fare on different days of one week. Like the scenario of demand on different days of week, generally, the average fare from Monday to Thursday is higher than that on Friday and weekend. However, some blocks near E Bay Dr have the same fare from Monday to Thursday and the weekend. And the triangle census block above Grandy Blvd has a similar demand on either weekends or weekdays. The mean fare from Monday to Thursday ranges from \$4.6 to \$6.5, which is higher than that on the weekend (\$3.1 to \$4.5) and Friday (less than \$3).

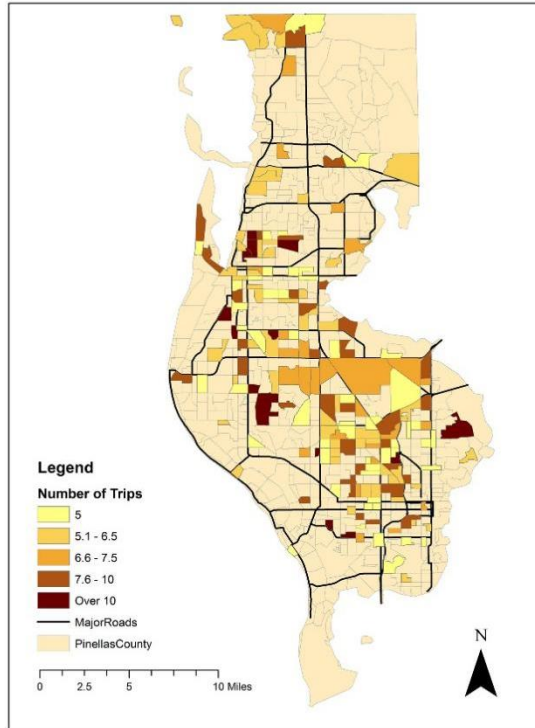
7.1.2 Stop level analysis

The average number of origin trips based on the bus stop in different days of one week is shown by Figure 7.1.3 (A) (B) (C). On average, the operating pilot stops during Monday to Thursday are significantly more than that on Friday and the weekend, most of which have more than six trips. The number of trips on Friday is the least, with three stops having around only five trips. On the weekend, most of the stops have more than five trips on average; the four stops at

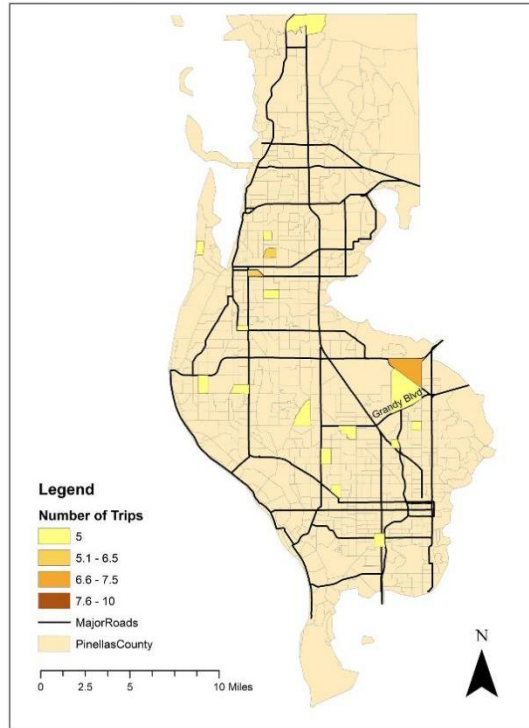
Ulmerton Rd, Seminole Blvd, 5th Ave N, and 22nd Ave S and the one stop within the area enclosed by Ulmerton Rd, the Seminole Blvd, Troy Blvd N, and 66 St N have more than six trips on average. The top three bus stops with the highest number of trips are Pasadena Ave & Sun Island Drive (12.33, Monday to Thursday), Layby (11.87, Monday to Thursday), and US 19 & Sunset Point Rd. (11.34, Monday to Thursday).

Figure 7.1.4 (A) (B) (C) reveals the mean fare of origin trips based on the bus stop on different days of one week. It shows that the numbers of the operating pilot stops from Monday to Thursday and on weekend are relatively higher than that on Friday. The mean fare of most stops from Monday to Thursday range from \$3.1 to \$5. The number of stops with a mean fare over \$5 during the weekend (6) is more than that on Friday (4) and Monday to Thursday (3), and these bus stops are mainly located on U.S. 19 and 66 St. N. The top three bus stops with the highest mean fare are 54th Ave N & Seminole Blvd (\$9.77, weekend), US19 & Tampa Rd (\$9.08, Monday to Thursday), and Largo Transit Center (\$8.1, Friday).

(A) Monday - Thursday



(B) Friday



(C) Weekend

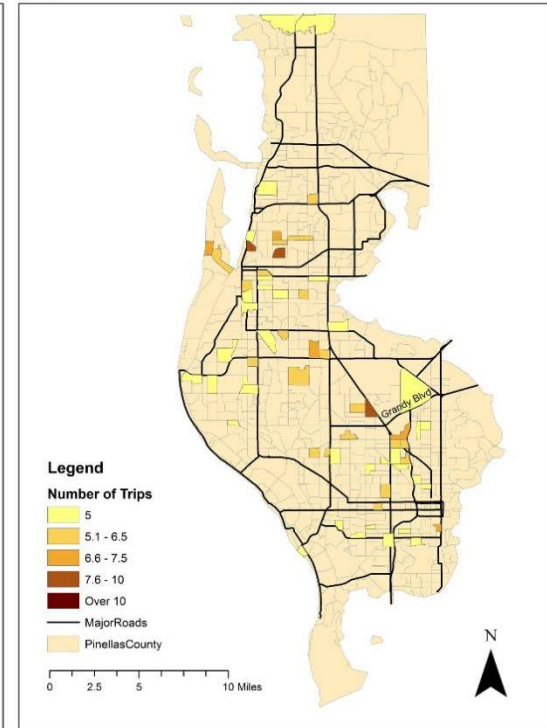
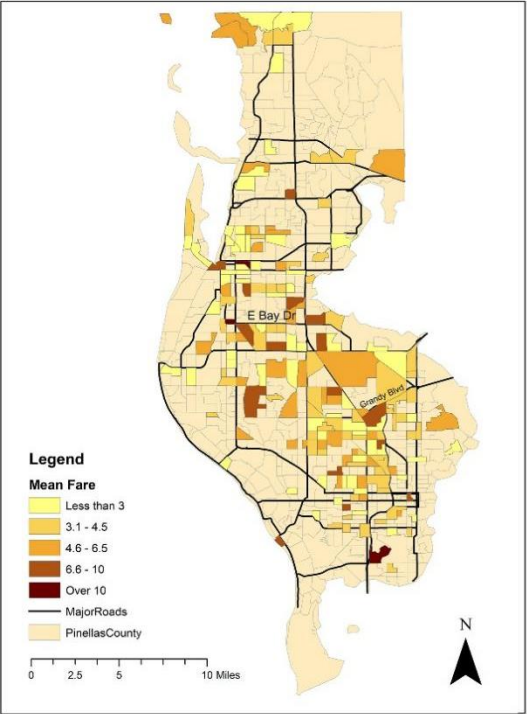
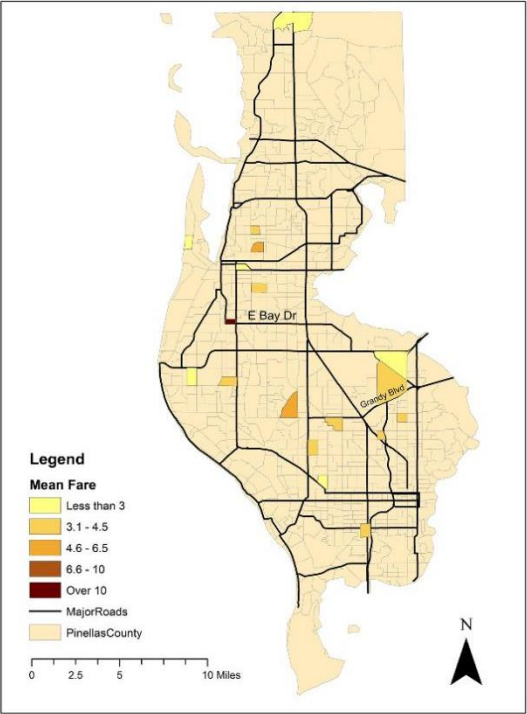


Figure 7.1.1 Trip Patterns based on Origin Census Blocks in Day of Week

(A) Monday - Thursday



(B) Friday



(C) Weekend

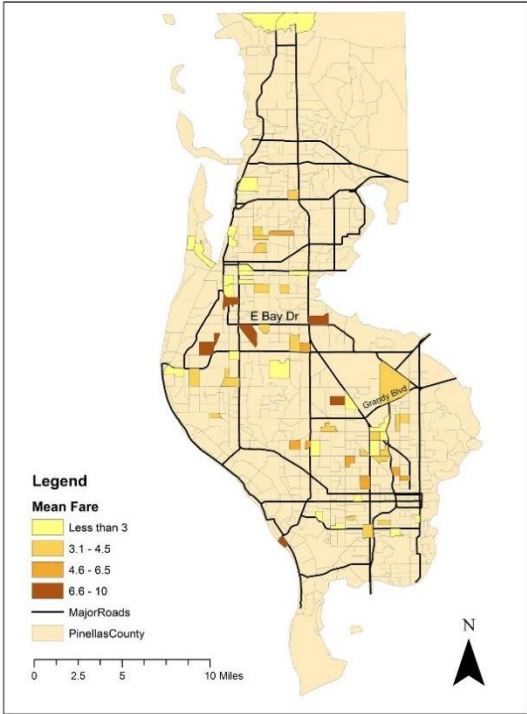
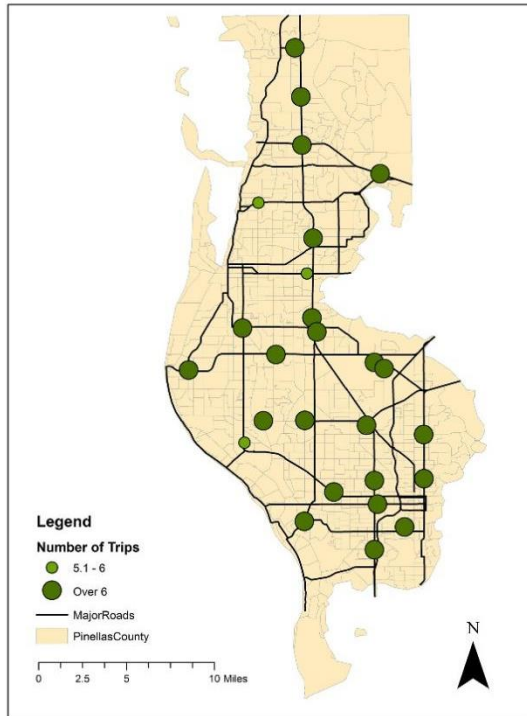
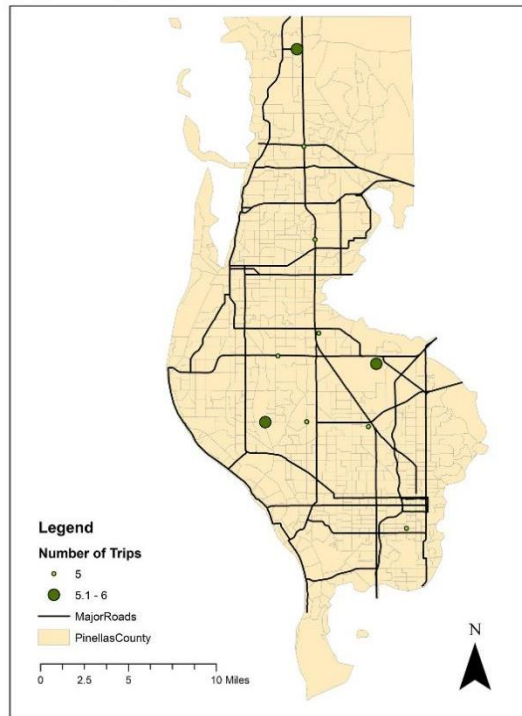


Figure 7.1.2 Fares of Trips based on Origin Census Blocks in Day of Week

(A) Monday - Thursday



(B) Friday



(C) Weekend

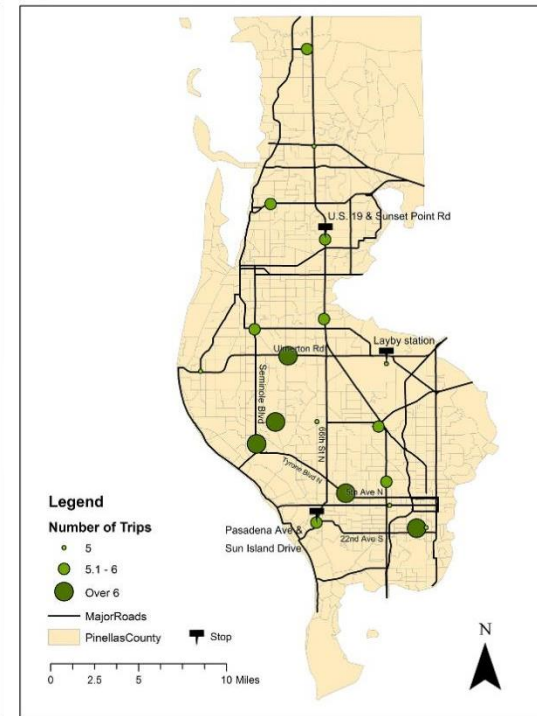
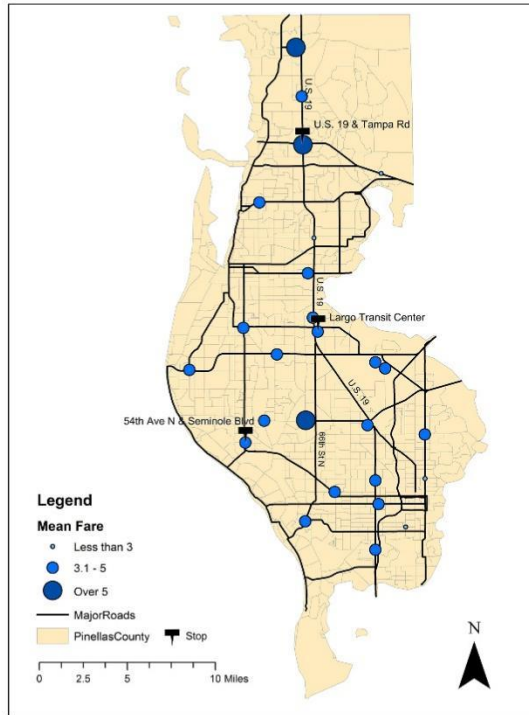
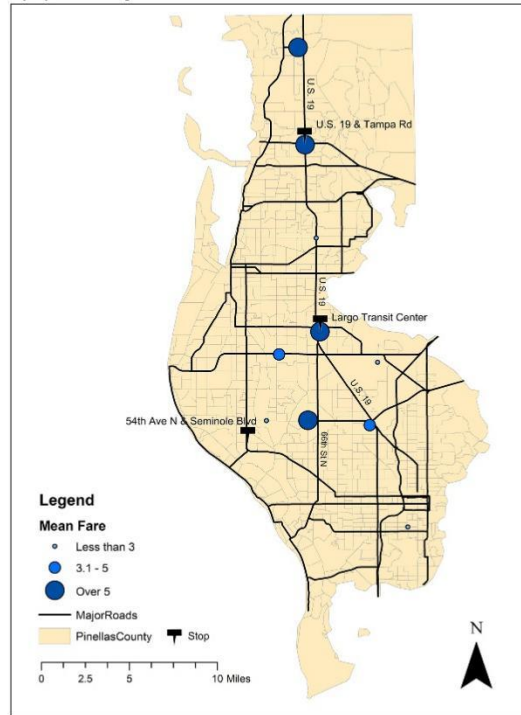


Figure 7.1.3 Trip Patterns based on Origin Pilot Stops in Day of Week

(A) Monday - Thursday



(B) Friday



(C) Weekend

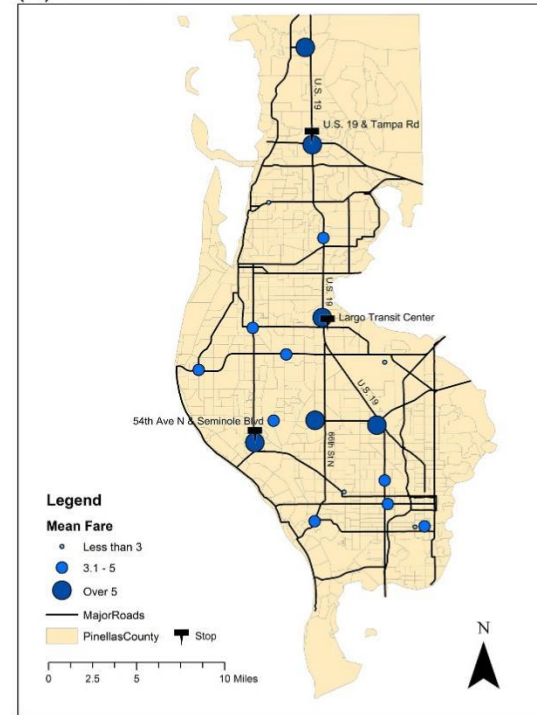


Figure 7.1.4 Fares of Trips based on Origin Pilot Stops in Day of Week

7.2 Destination Pattern

7.2.1 Census Block Group

By observing the destination trips based on census blocks on different days of the week (Figure 7.2.1 (A) (B) (C)), we can learn that the number of blocks whose average destination trip exceeds ten occurred on Monday to Thursday, as opposed to Friday or the weekend. The most popular destinations from Monday to Thursday are located near the west part of Ulmerton Rd., north part of 66th St. N, Roosevelt Blvd, Philippe Rkwy, and the east part of Main St.

Figure 7.2.2 (A) (B) (C) shows the destination trips based on census blocks in different days of one week. The average fare from Monday to Thursday has an obvious difference when compared to that of Friday and the weekend. More than ten blocks had fares that exceeded \$6.6 on average from Monday to Thursday compared to two on Friday and four on the weekend. Most of the higher fare cost blocks are located at Ulmerton Rd, 66th St N, and Main St.

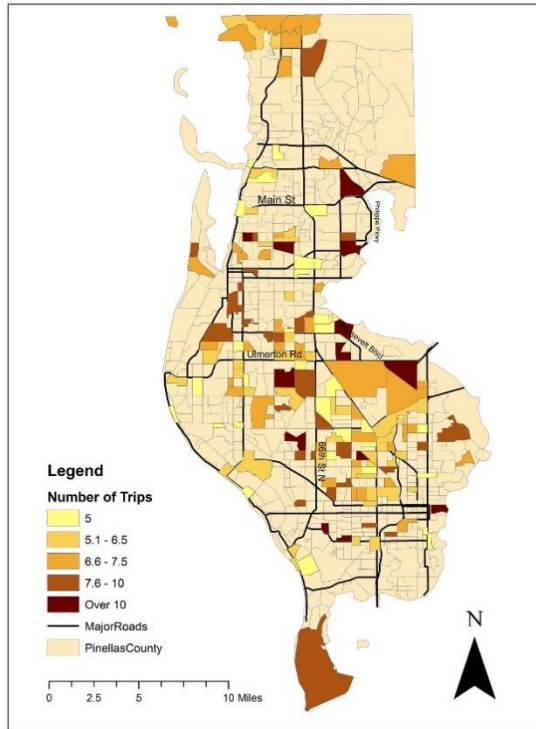
7.2.2 Stop Level Analysis

Figure 7.2.3 (A) (B) (C) illustrates destination trips based on bus stops in different days of one week. Still, just like the scenario in the map based on census block, most of the bus stops have more than six trips on average from Monday to Thursday. On the other hand, 1 stop and 3 stops have more than 6 trips on average on Friday and the weekend respectively. Pasadena Ave S & Majestic Way, Gulf Bay Blvd & Coachman Rd, and Missouri Ave & W Bay Dr received the top three highest number of trips from Monday to Thursday.

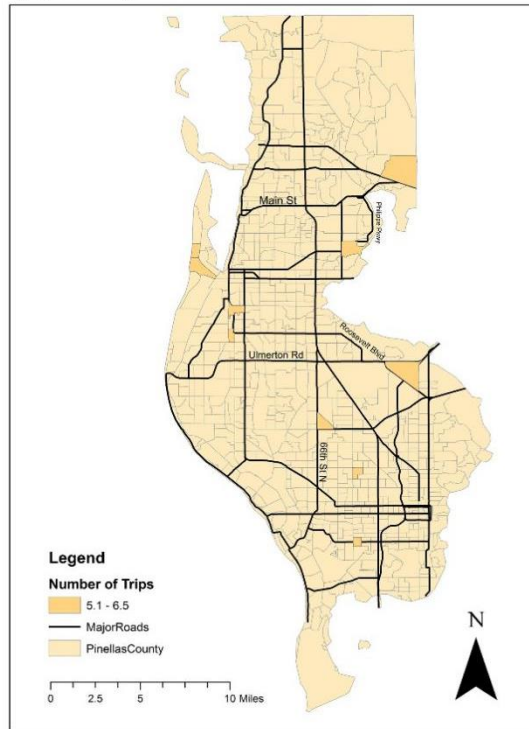
In terms of the destination fare based on bus stops on different days of one week, as shown by Figure 7.2.4 (A) (B) (C), fewer differences are observed when we compare the three maps with

each other. 54th Ave N & Seminole Blvd, Belcher Rd & Park Blvd N, and Largo Transit Center are the stops with higher mean fare.

(A) Monday - Thursday



(B) Friday



(C) Weekend

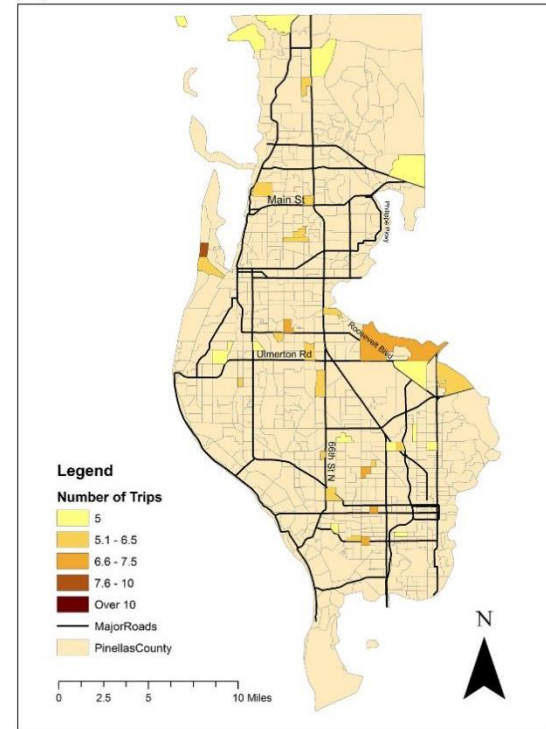
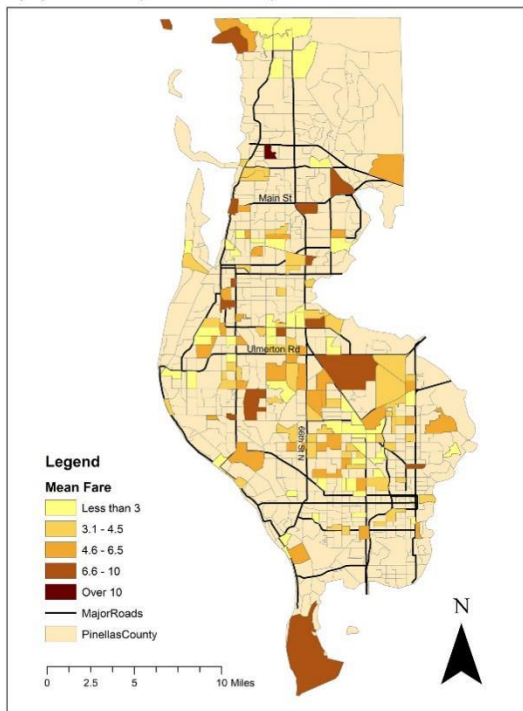
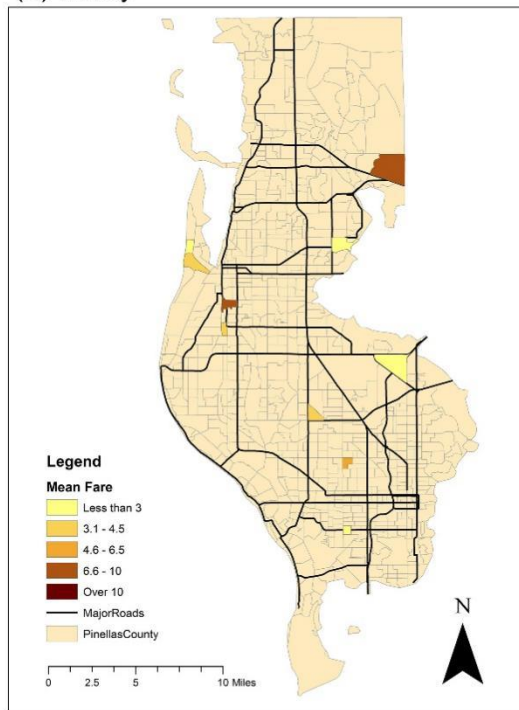


Figure 7.2.1 Trip Patterns based on Destination Census Blocks in Day of Week

(A) Monday - Thursday



(B) Friday



(C) Weekend

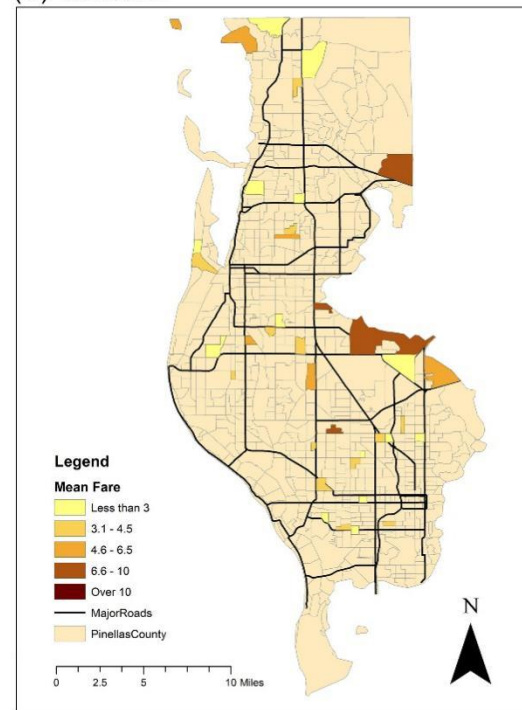
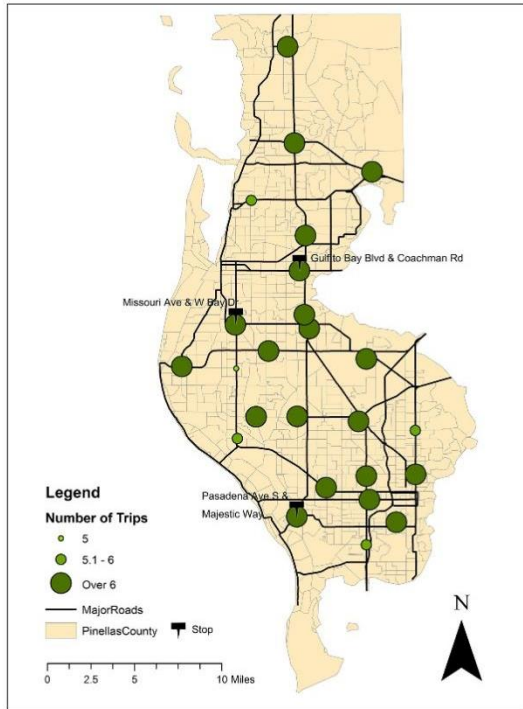
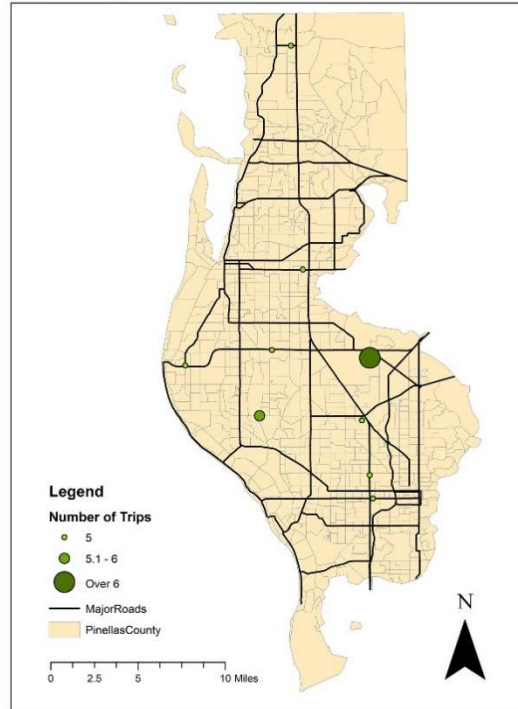


Figure 7.2.2 Fares of Trips based on Destination Census Blocks in Day of Week

(A) Monday - Thursday



(B) Friday



(C) Weekend

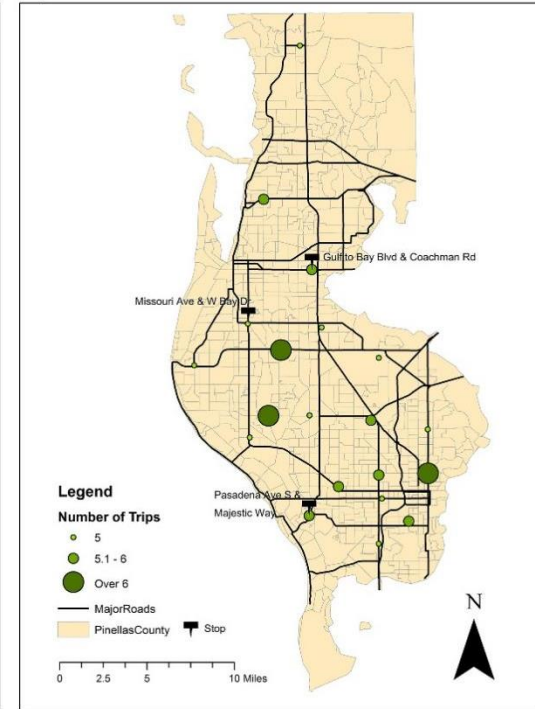
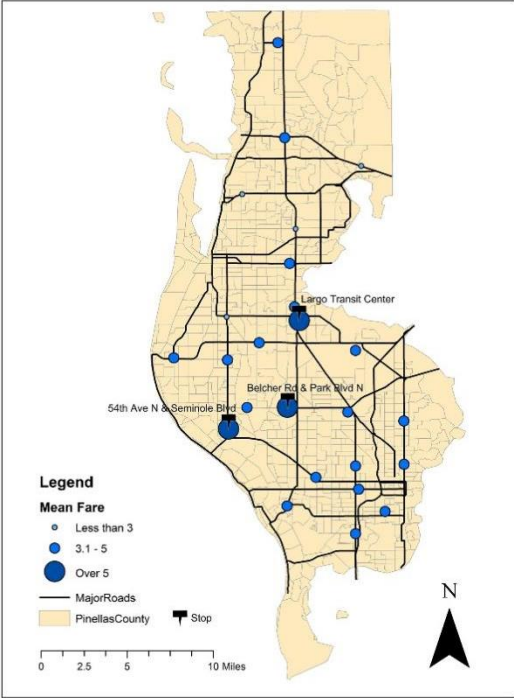
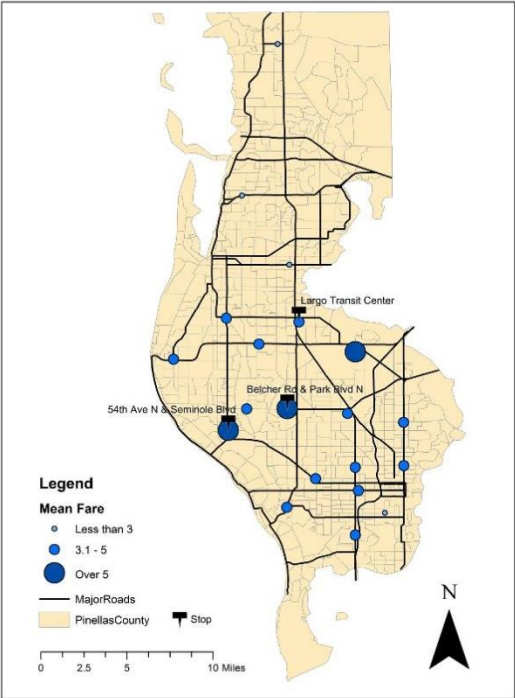


Figure 7.2.3 Trip Patterns based on Destination Pilot Stops in Day of Week

(A) Monday - Thursday



(B) Friday



(C) Weekend

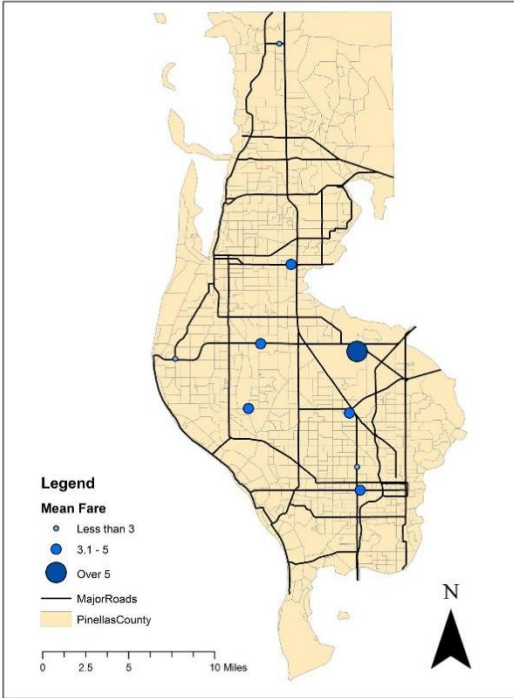


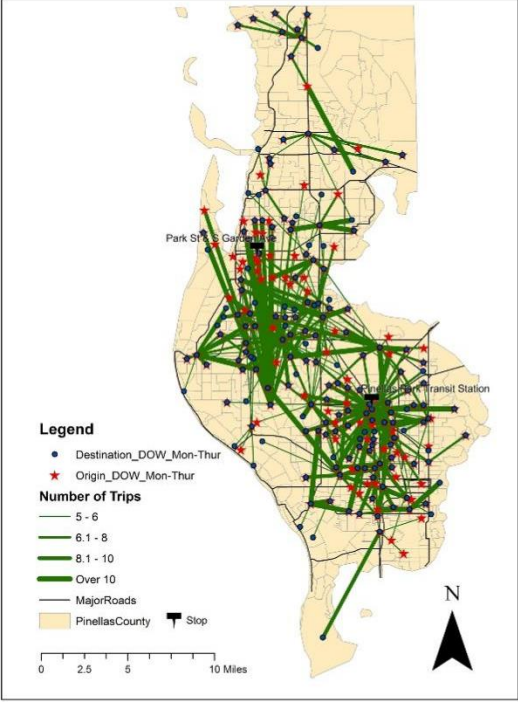
Figure 7.2.4 Fares of Trips based on Destination Pilot Stops in Day of Week

7.3 Origin-Destination (OD) Pattern

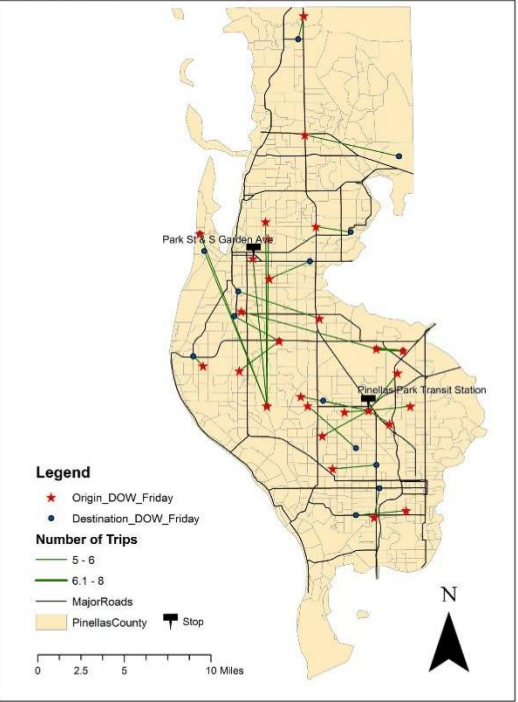
OD patterns of different days of the week are shown in Figure 7.3.1 (A) (B) (C). The connections with Pinellas Park Transit Station (pilot) and Park St & S Garden Ave are the strongest from Monday to Thursday, and the connections are also obvious on weekends.

Figure 7.3.2 (A) (B) (C) reveals the yearly Origin-Destination (OD) pattern. The width of the trip line highlights the most frequent transit routes. Among these OD combinations, many rides originate near Drew St to the area enclosed by Ulmerton Rd, Seminole Blvd, Tyrone Blvd N, and 66th St N; and they commute within the area enclosed by Ulmerton Rd, 66th St N, 22 Ave S and 4th St N. There are two typical centers where the structure remained the same from 2018 to 2020. The two OD connections with the most trips are Pinellas Park Transit Station (pilot stop) and Park St & S Garden Ave.

(A) Monday - Thursday



(B) Friday



(C) Weekend

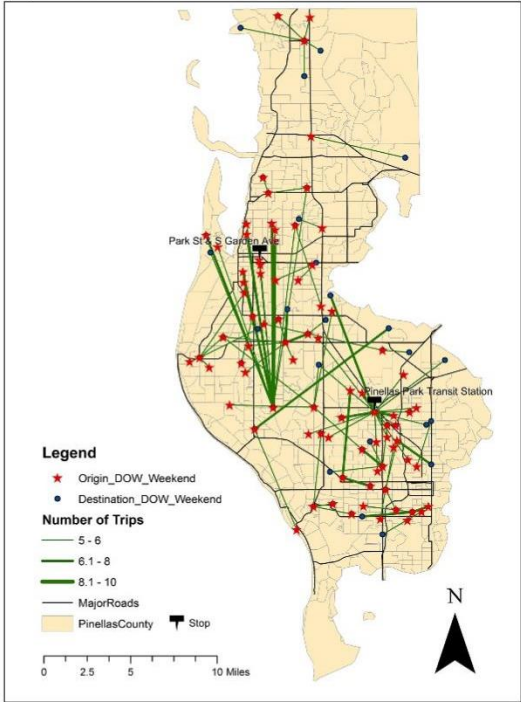
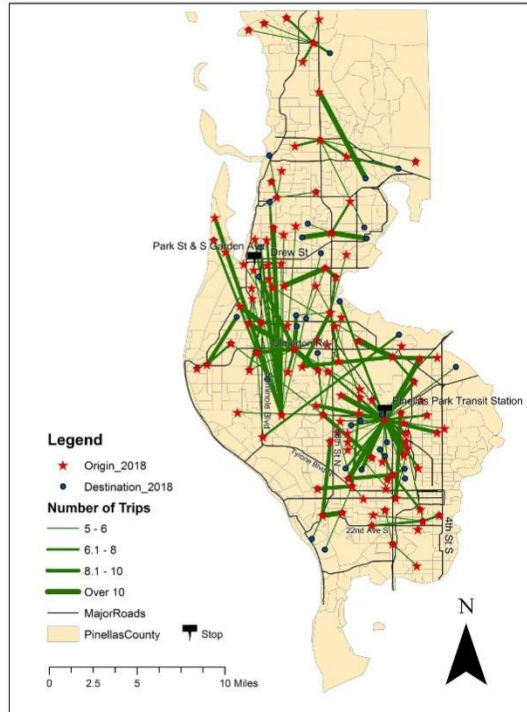
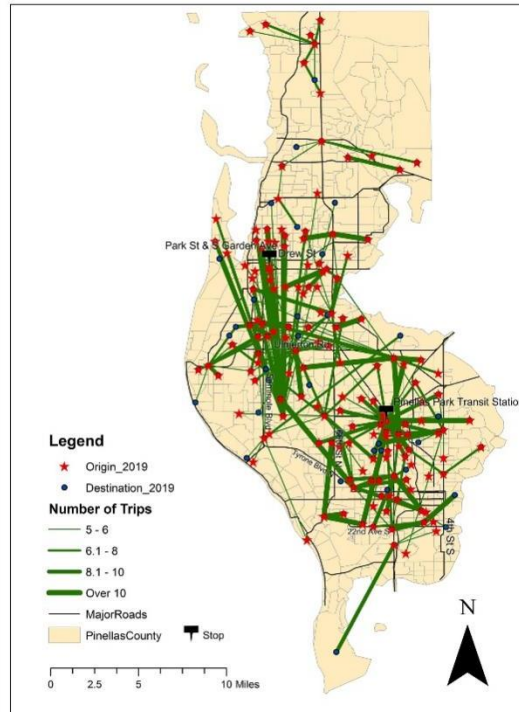


Figure 7.3.1 Origin-Destination Pattern in Day of Week

(A) 2018



(B) 2019



(C) 2020

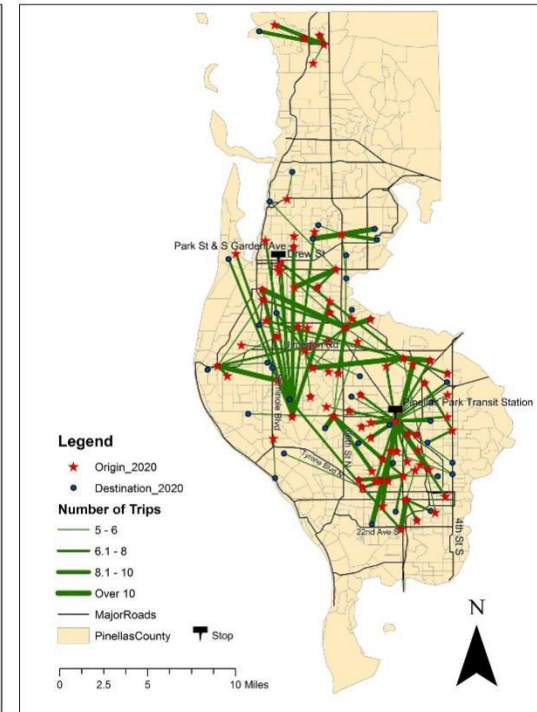


Figure 7.3.2 Origin-Destination Pattern from 2018 to 2020

8. Geographically Weighted Regression Analysis

8.1 Data Source

8.1.1 Direct Connect Program

To understand the driving factors for daily trips of the Direct Connect program, we aim to conduct the geographically weighted regression model (GWR). Therefore, we collected the data at the census block group level from the following sources (Table 8.1.1).

Table 8.1.1 Summary of data source

Variables	Description	Data sources
<i>Dependent variables</i>		
Weekday	Average daily Uber ride demand for weekdays	Uber Technologies, Inc.,
Weekend	Average daily Uber ride demand for weekend days	Uber Technologies, Inc.,
<i>Independent variables</i>		
Socio-demographics		
Education level	% of population with Bachelor degree or above	ACS ^a
Median income	Median household income in \$1000	ACS
Median age	Median age	ACS
Built environment		
Density		
Population density	Population density by 1 people per acre.	ACS
Employment density	Employment density by 1 people per acre.	ACS
Design		
Road network density	Road network density in mi. per acre.	TIGER ^b
Sidewalk density	Sidewalk network density in mi. per acre.	County of Pinellas ^c
Diversity		
Land use mix	0 (single land use) to 1 (most diverse land mix)	Calculated by the team ^d
Accessibility		
Access to jobs	Total jobs by cumulative accessibility within 30 mins transit in 1000 weighted by employment	Access Across America: Transit 2017
<p>a. American Community Survey (ACS) Source: U.S. Census Bureau, 2015. Selected demographic characteristics, 2014–2018, American Community Survey 5-year estimates. Retrieved on 9.2020, from https://www.fgdl.org/metadataexplorer/explorer.jsp</p>		

- b. TIGER database Source: U.S. Census Bureau, 2018, TIGER/Line Shapefiles, county, Pinellas County, FL, Retrieved on 9.2020, from <https://catalog.data.gov/dataset/tiger-line-shapefile-2018-county-pinellas-county-fl-all-roads-county-based-shapefile>
- c. County of Pinellas Source: County of Pinellas, 2019, Sidewalks, Retrieved on 9.2020, from https://new-pinellas-egis.opendata.arcgis.com/datasets/c6897116c081444091fdf1adfc66e019_22
- d. Parcel land use data was obtained from the University of Florida GeoPlan Center and entropy measures were calculated in ArcGIS 10.5.

8.1.2 TD-Late Shift Program

To understand the driving factors for daily trips of the TD-Late Shift program, we also conduct the geographically weighted regression model (GWR). We collected the data at the census block group level from the following sources.

Table 8.1.2 Dependent variable and socio-demographic and built environment independent variables

Variables	Description	Data sources
<i>Dependent variables</i>		
TD Late Shift Ridership	The count of service ridership at census block level.	PSTA
<i>Independent variables</i>		
Socio-Demographic		
Education Level	% of population with bachelor degree or above.	ACS ^a
Percentage of Black	% of African American population.	ACS
Percentage of Male	% of Male population.	ACS
Percentage of People with a Disability	% of Population 20 to 64 years old with a disability.	ACS
Built Environment		
Household Density	Numbers of households per acre.	ACS
Population to Employment Entropy	0 (single land use) to 1 (balanced population and employment)	Calculated by author

Access to Jobs	Total jobs by cumulative accessibility within 30 mins transit in 1000 weighted by employment.	Access Across America: Transit 2017 ^b
Percentage of Household with 0 Vehicle	% of Household with 0 Vehicle.	ACS
Road Density	Road network density in meters per acre.	Calculated by author ^c
<p>a. U.S. Census Bureau. (2021). 2015 Census Block Groups in Florida (With Selected Fields From The 2015-2019 American Community Survey) [Data file]. Available from: https://www.fgdl.org/metadataexplorer/full_metadata.jsp?docId=%7BFC504933-3FCB-4321-B26A-C809CBC379F6%7D&loggedIn=false (Accessed 21 April 2021). Florida Geographic Data Library, University of Florida, Gainesville, FL.</p> <p>b. Owen, A., & Murphy, B. (2018, June 01). Access Across America: Transit 2017 Data. Retrieved on January 28, 2021, from https://conservancy.umn.edu/handle/11299/200508</p> <p>c. Road data for Florida state is obtained from U.S. Department of Commerce, U.S. Census Bureau, Geography Division. (2018). ROADS (US CENSUS BUREAU'S TIGER/LINE) IN FLORIDA - 2018 (FGDC) / tiger_roads_2018 (ISO) [Data file]. Available from: https://www.fgdl.org/metadataexplorer/full_metadata.jsp?docId=%7B1B90755C-D48B-49ED-A498-55FBE7976BEB%7D&loggedIn=false (Accessed 21 April 2021). Florida Geographic Data Library, University of Florida, Gainesville, FL.</p>		

The following figures (from Figure 8.1.1 to 8.1.4) show the spatial distribution of TD-Late Shift ridership, socio-demographic variables, built environment variables, and poverty rate in Pinellas County respectively.

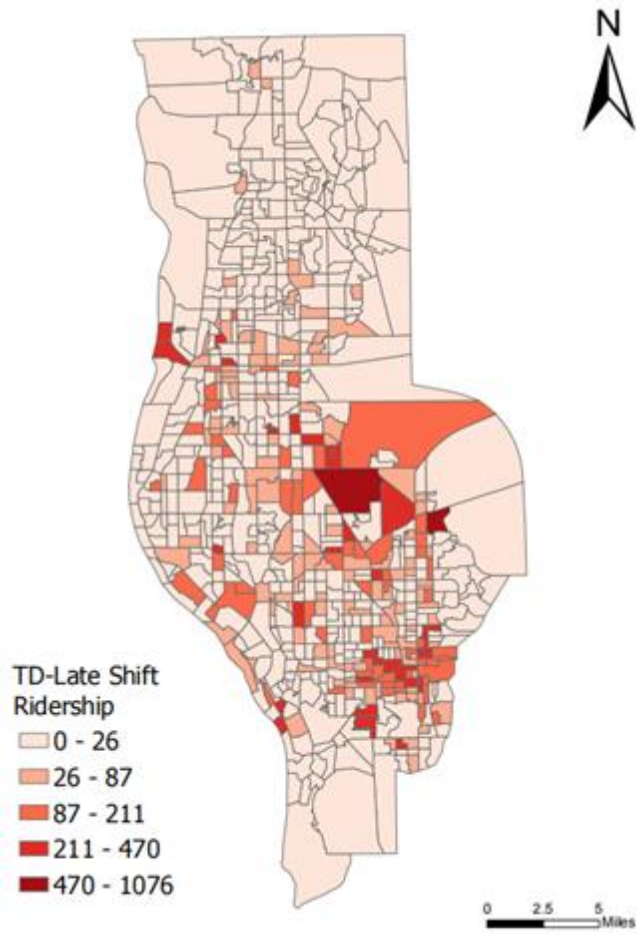


Figure 8.1.1 Spatial distribution of TD-Late Shift ridership

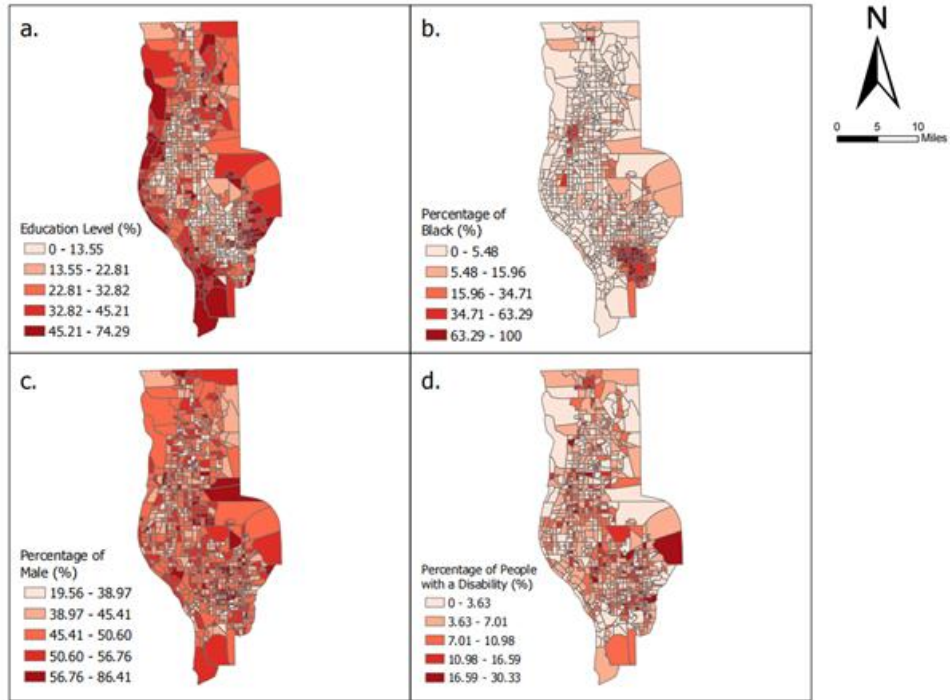


Figure 8.1.2 Spatial distribution of socio-demographic variables

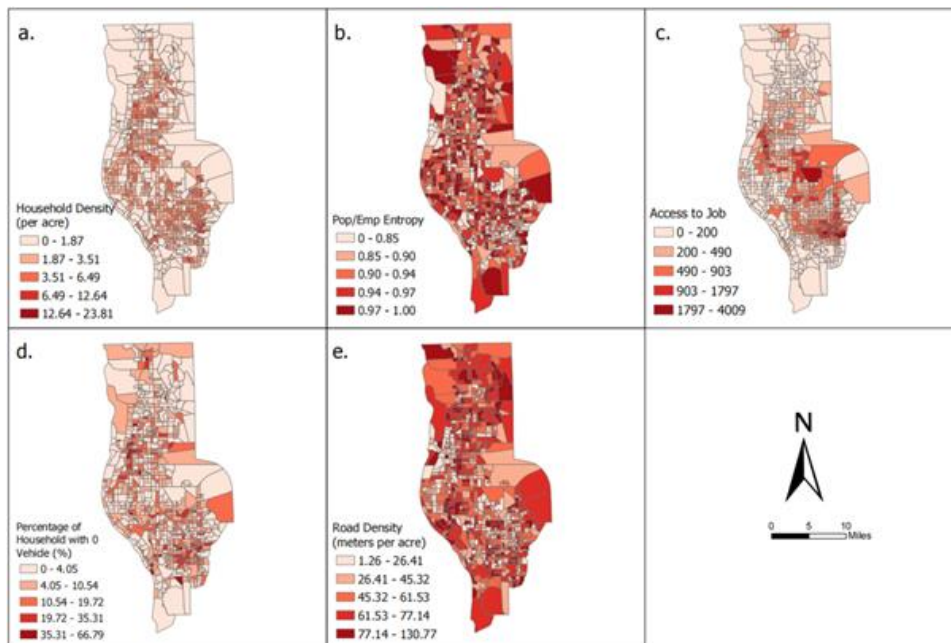


Figure 8.1.3 Spatial distribution of built environment variables

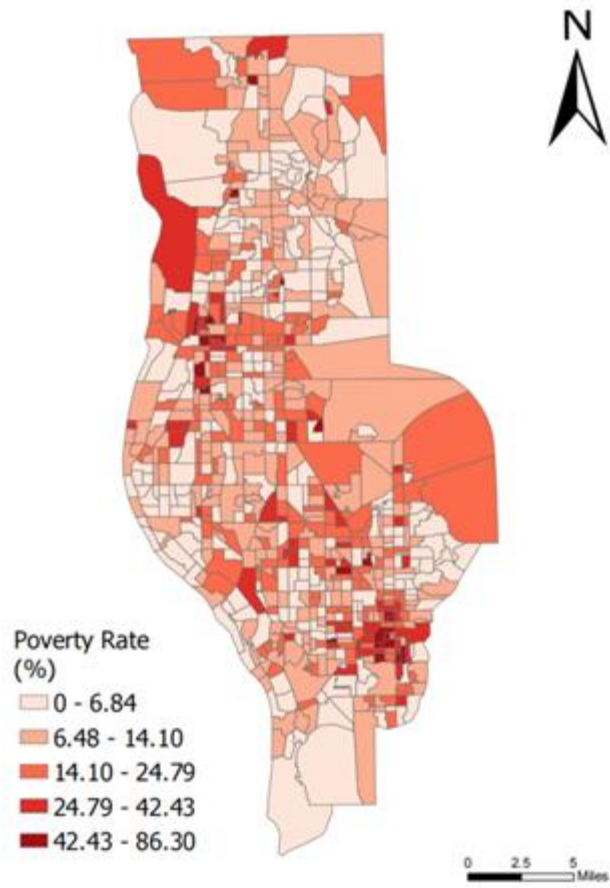


Figure 8.1.4 Spatial distribution of poverty rate

8.2 Weekday Model

8.2.1 Socio-Demographics

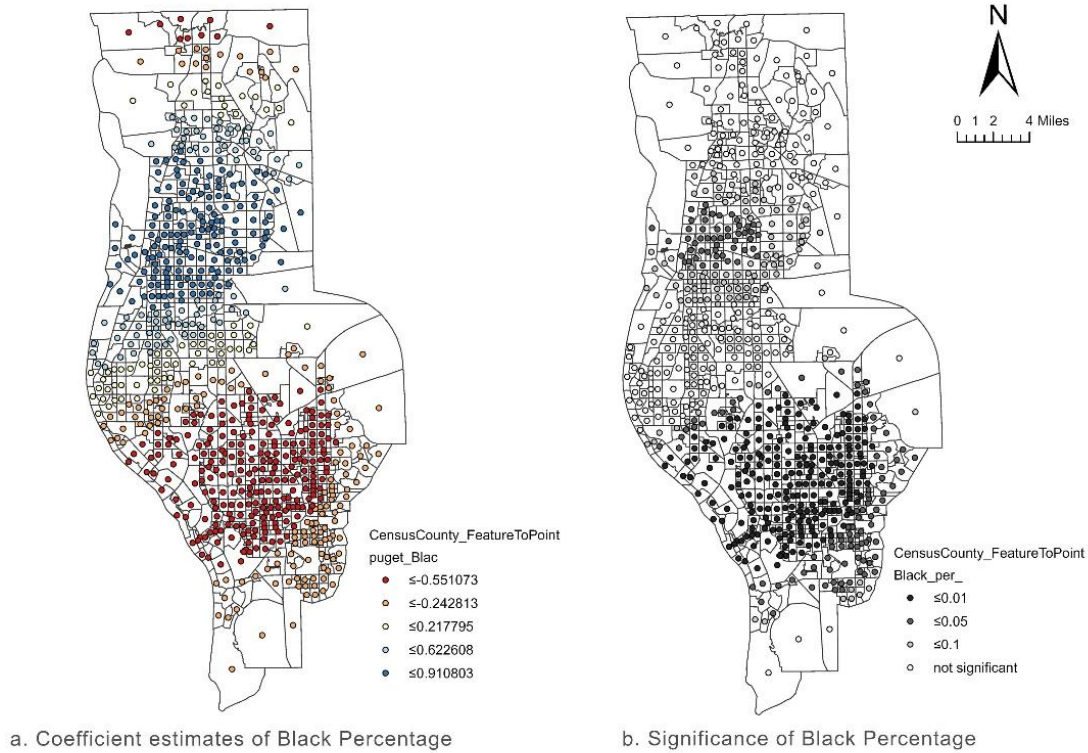


Figure 8.2.1 Black Percentage GWR Analysis

The north and south part of the county show distinctive impacts of Black percentage on the Uber ridership during weekdays. The percentage of the Black population in the south part of the county has significant and negative impacts on the Uber ridership (Figure 8.2.1.a). However, the Uber ridership in the north part of the county shows significant and positive impacts of the Black percentage (Figure 8.2.1.b).

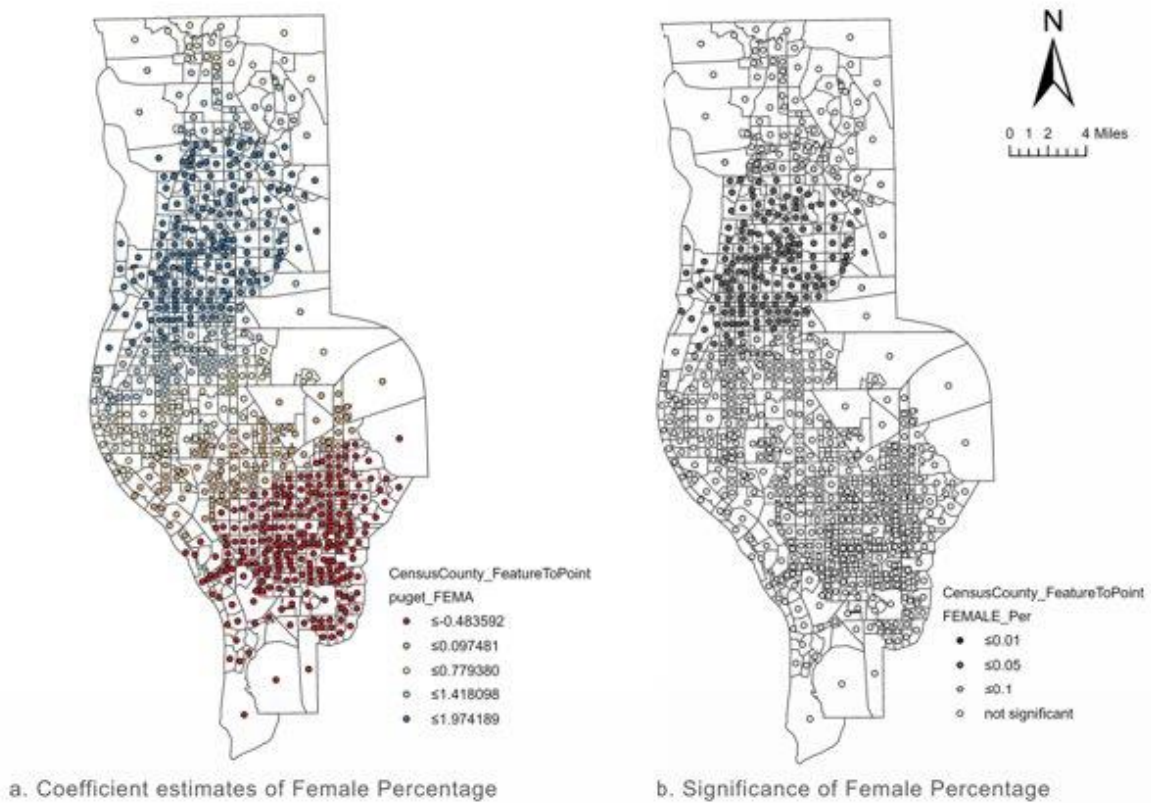


Figure 8.2.2 Female Percentage GWR Analysis

The percentage of Females has significant and positive impacts on the Uber trips in the north part of the county. In the north part of the county, there is a confidence level over 95 percent (Figure 8.2.2.b) indicating that the Uber ridership would increase about 1.97 trips with the rise of 1 percentage Females population (Figure 8.2.2.a).

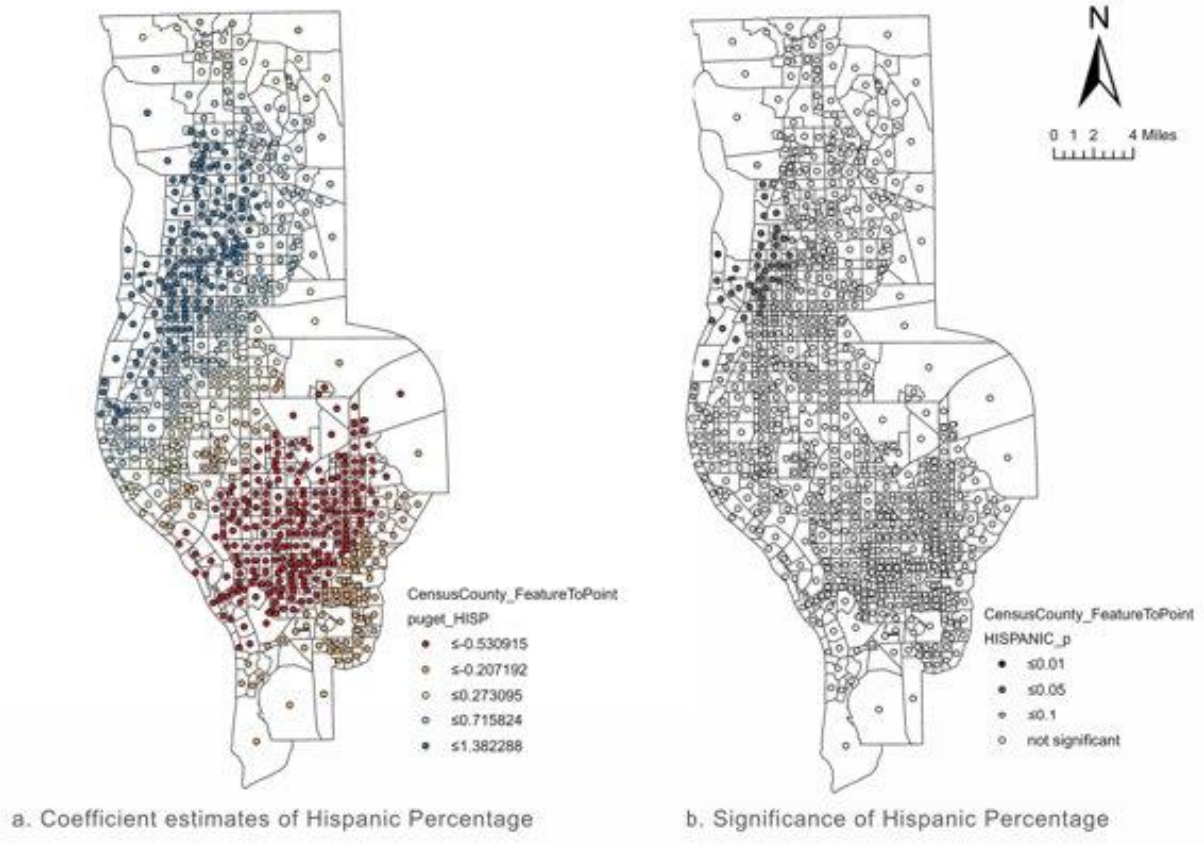


Figure 8.2.3 Hispanic Percentage GWR Analysis

The percentage of Hispanics shows significant and positive impacts on the Uber trips in the northwestern part of the county. In the northwestern part of the county, there is also an over 95 percent confidence level (Figure 8.2.3.b) representing that the Uber ridership would rise about 1.38 trips with the 1 percentage increase of the Hispanics (Figure 8.2.3.a).

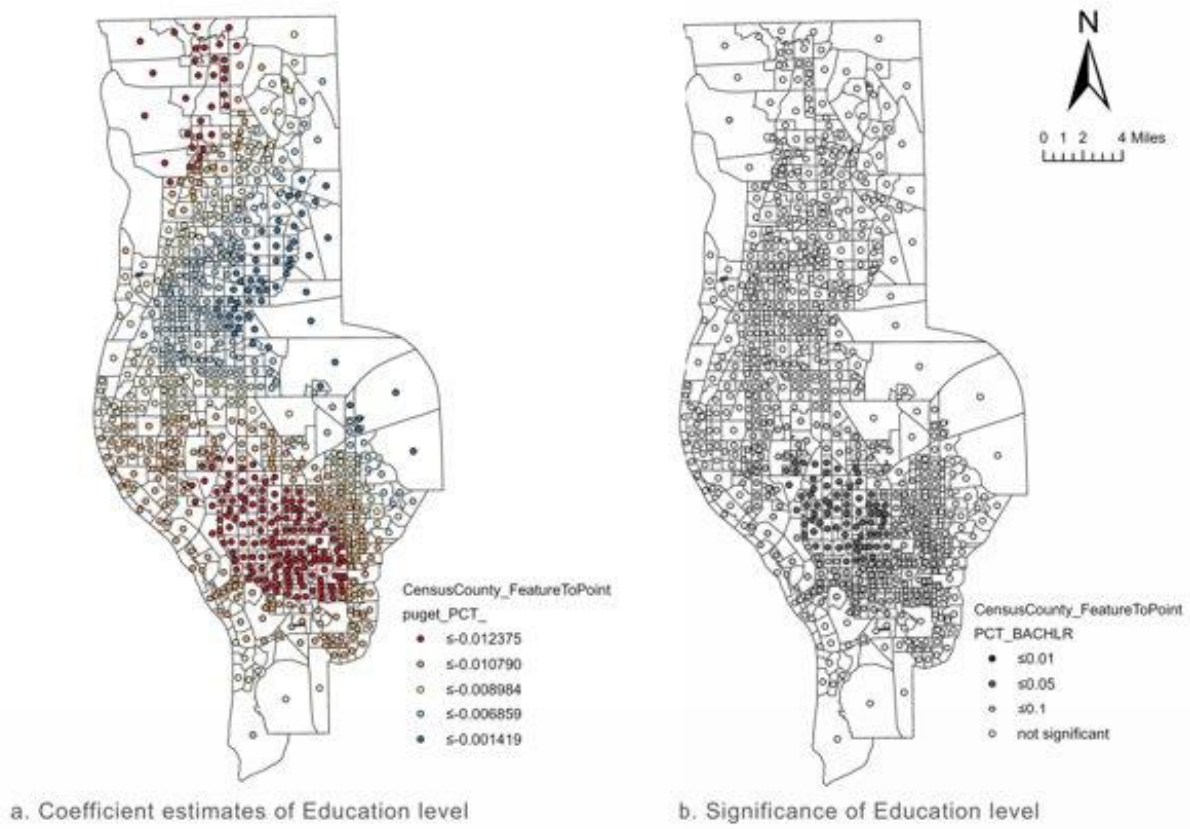


Figure 8.2.4 Education Level GWR Analysis

Education Level has a significant negative relationship with the total Uber demand in the south part of the county. In the south part of the county, there is a confidence level over 95 percent (Figure 8.2.4.b) revealing that the Uber ridership would decrease about 0.012 trips with the 1 percentage increase of population with a bachelor or higher degree (Figure 8.2.4.a).

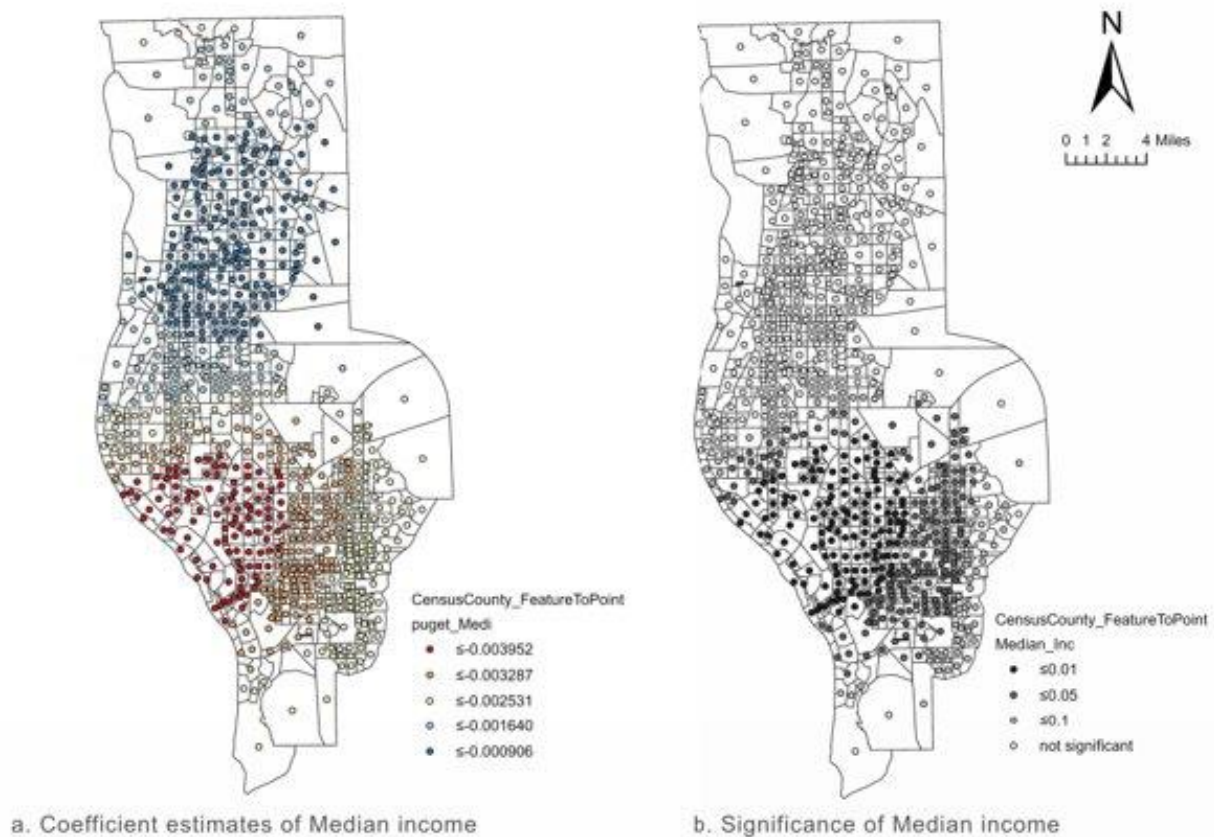


Figure 8.2.5 Median Income GWR Analysis

The Median income represents significant and negative impacts on the Uber trips in the south part of the county. In the south part of the county, there is a confidence level over 95 percent (Figure 8.2.5.b) indicating that the Uber ridership would decrease around 0.0032 to 0.0039 trips with 1,000 dollars increase of median family income (Figure 8.2.5.a).

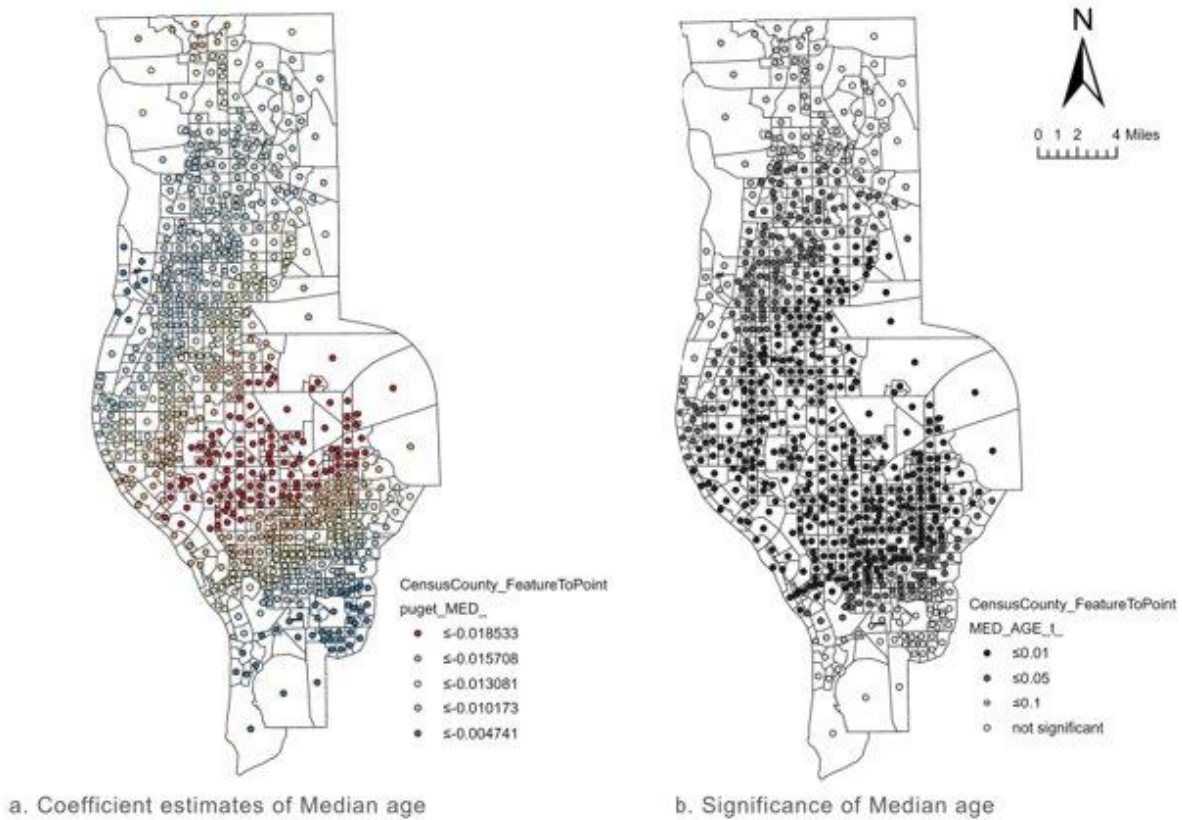


Figure 8.2.6 Median Age GWR Analysis

The median age has significant and negative impacts on the Uber demand in the whole county. In the almost whole county, there is an over 95 percent confidence level (Figure 8.2.6.b) showing that the Uber ridership decrease with the increase of median age. In the middle part of the county, it shows the most obvious trend that Uber ridership decrease about 0.0185 trips with the 1-year increase of median age (Figure 8.2.6.a).

8.2.2 Population Density

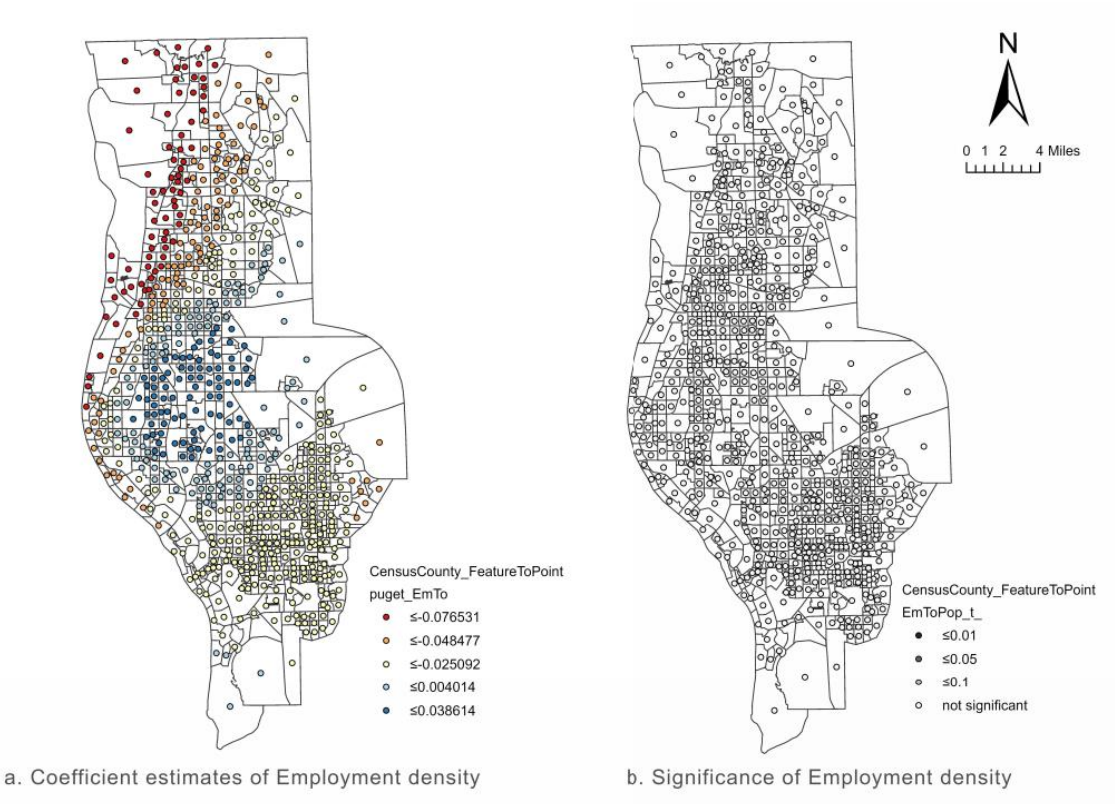


Figure 8.2.7. Employment Density GWR Analysis

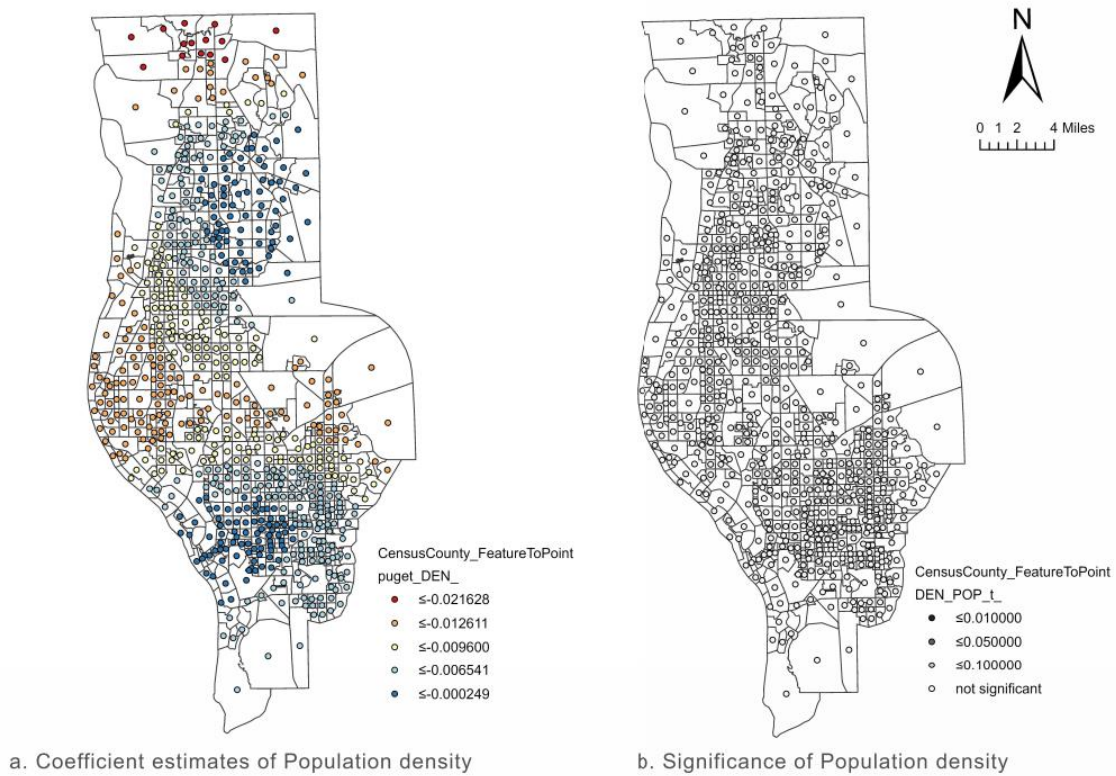


Figure 8.2.8 Population Density GWR Analysis

The confidence levels for employment density and population density GWR analysis are not significant (Figure 8.2.7.b & 8.2.8.b). It indicates the increase and decrease of Uber ridership are not correlated with the increase of employment or population density.

8.2.3 Land Use

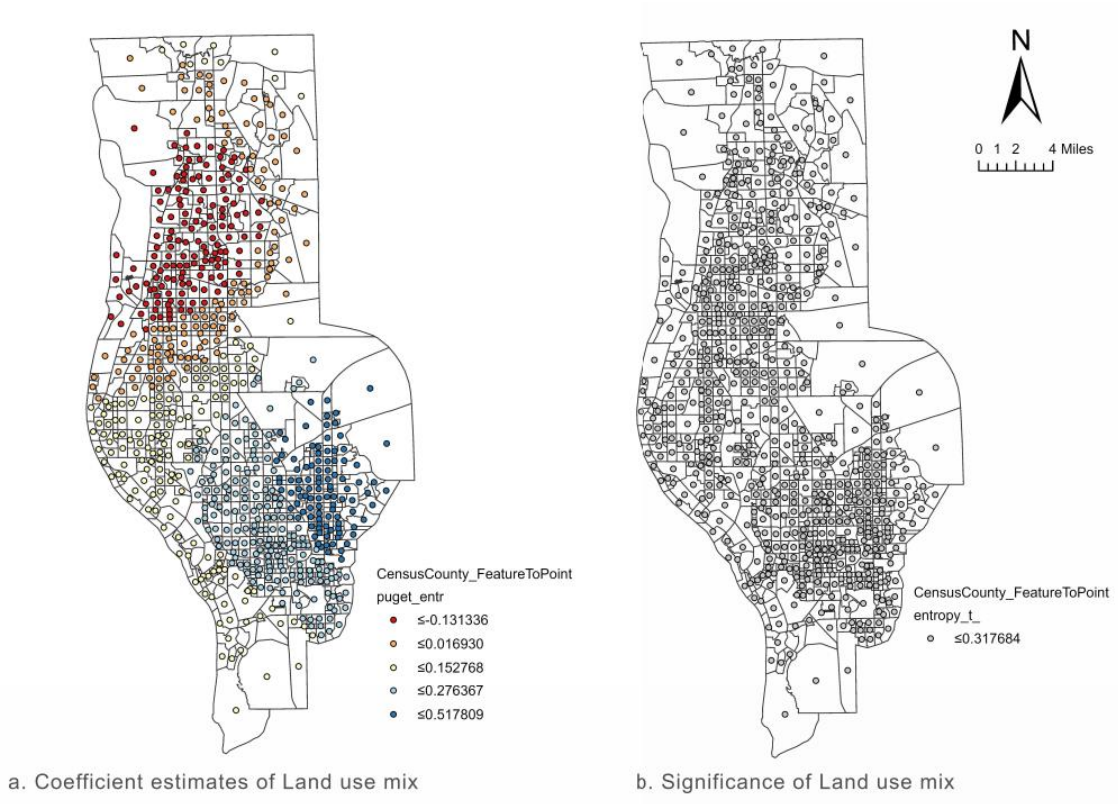


Figure 8.2.9 Land Use Mix GWR Analysis

The confidence level for land use mix GWR analysis is about 68.2 percent, which is not significant (Figure 8.2.9.b). It shows that the increase and decrease of Uber ridership are not correlated with the increase of land use mix degree.

8.2.4 Road Network Design

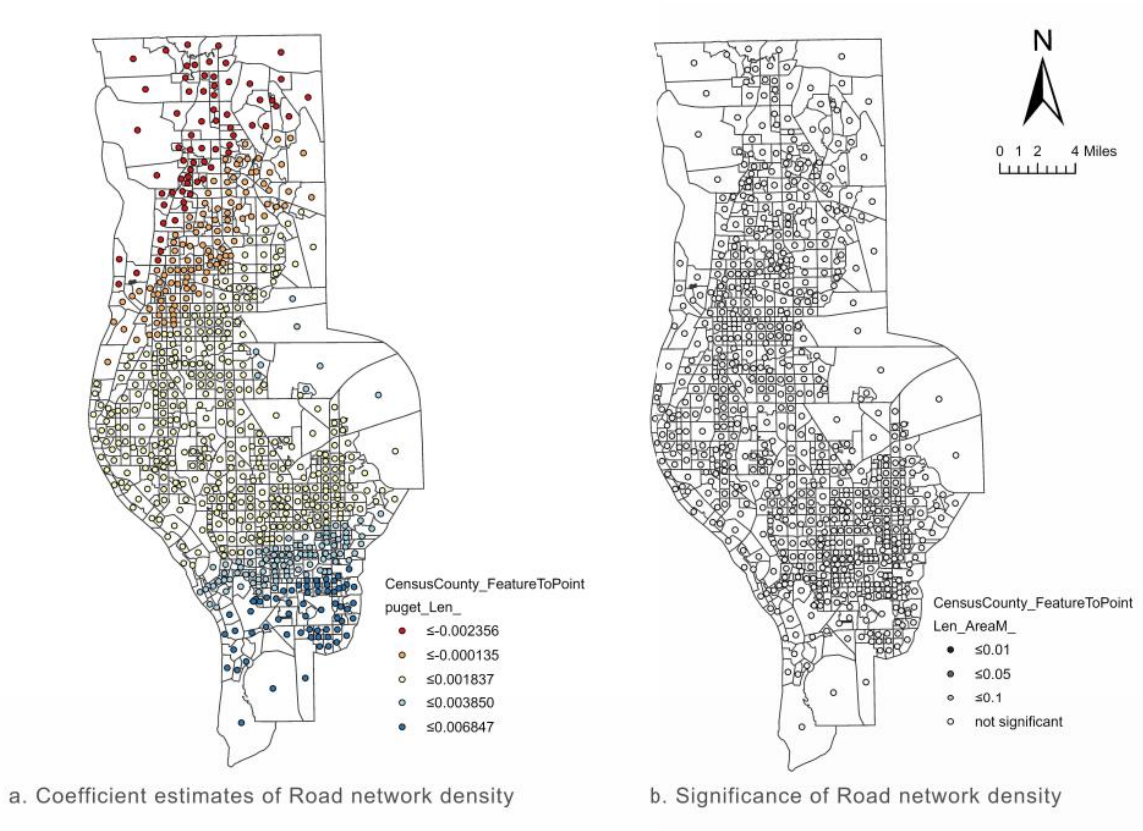
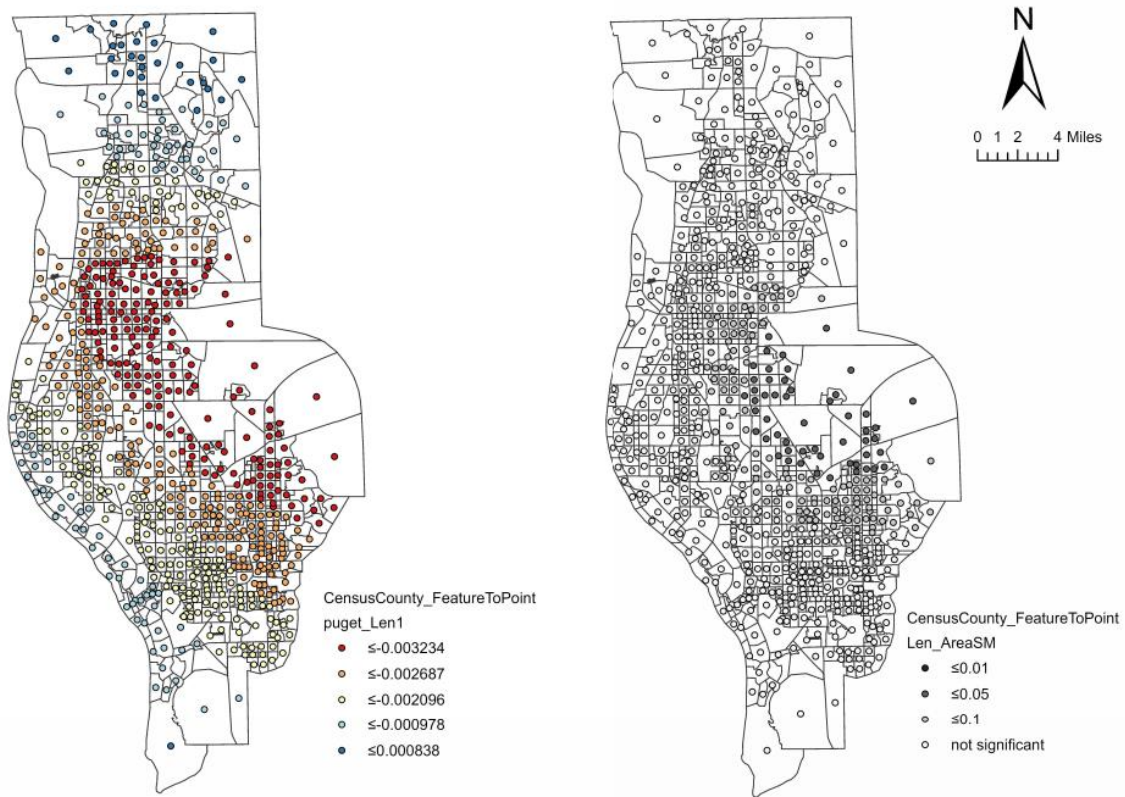


Figure 8.2.10 Road Network Density GWR Analysis



a. Coefficient estimates of Sidewalk density

b. Significance of Sidewalk density

Figure 8.2.11 Sidewalk Density GWR Analysis

The confidence levels for road network density and sidewalk density GWR analysis are not significant (Figure 8.2.10.b & 8.2.11.b). It means the increase and decrease of Uber ridership are not correlated with the increase of road network density or sidewalk density.

8.2.5 Accessibility to Jobs

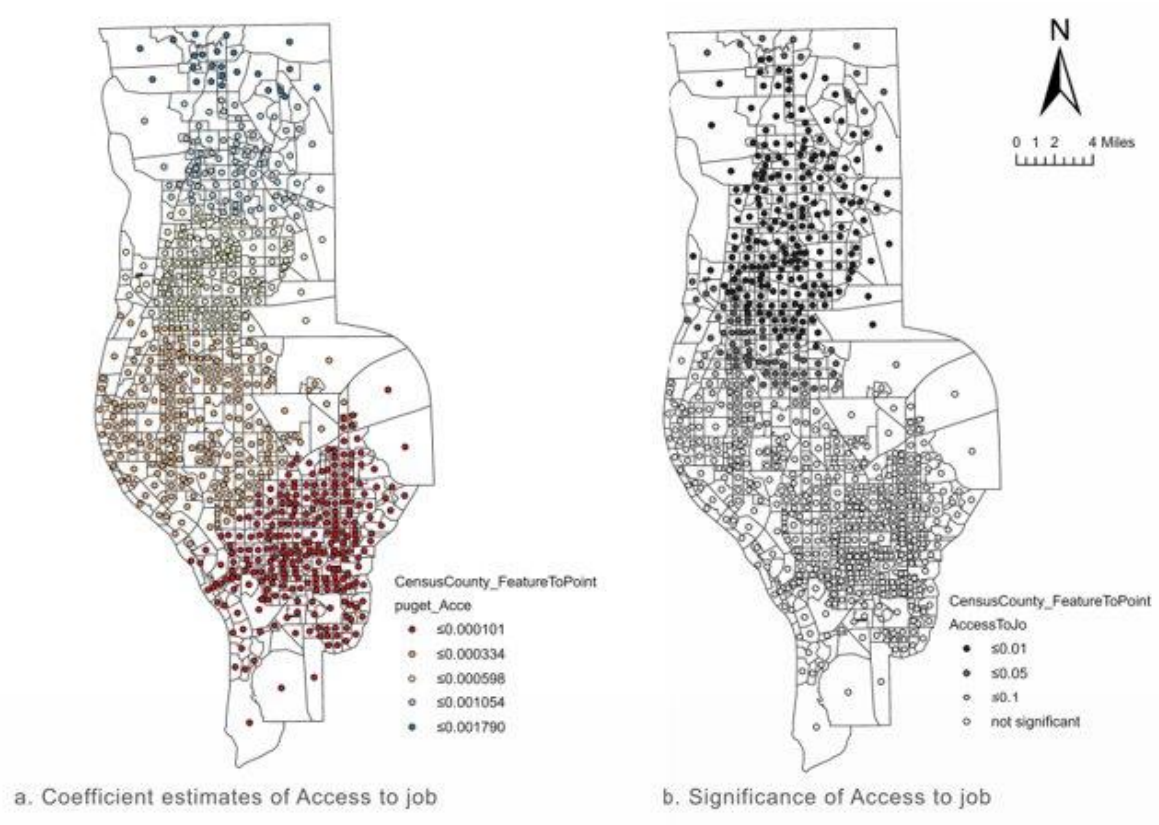


Figure 8.2.12 Access to Job GWR Analysis

Access to the job has significant and positive impacts on the Uber demand in the north part of the county. In the north part of the county, it has a confidence level of over 95 percent (Figure 8.2.12.b) representing that the Uber ridership would increase around 0.00059 to 0.00179 trips with the increase of 1 job within 30 mins transit (Figure 8.2.12.a).

8.3 Weekend Model

8.3.1 Socio-demographics

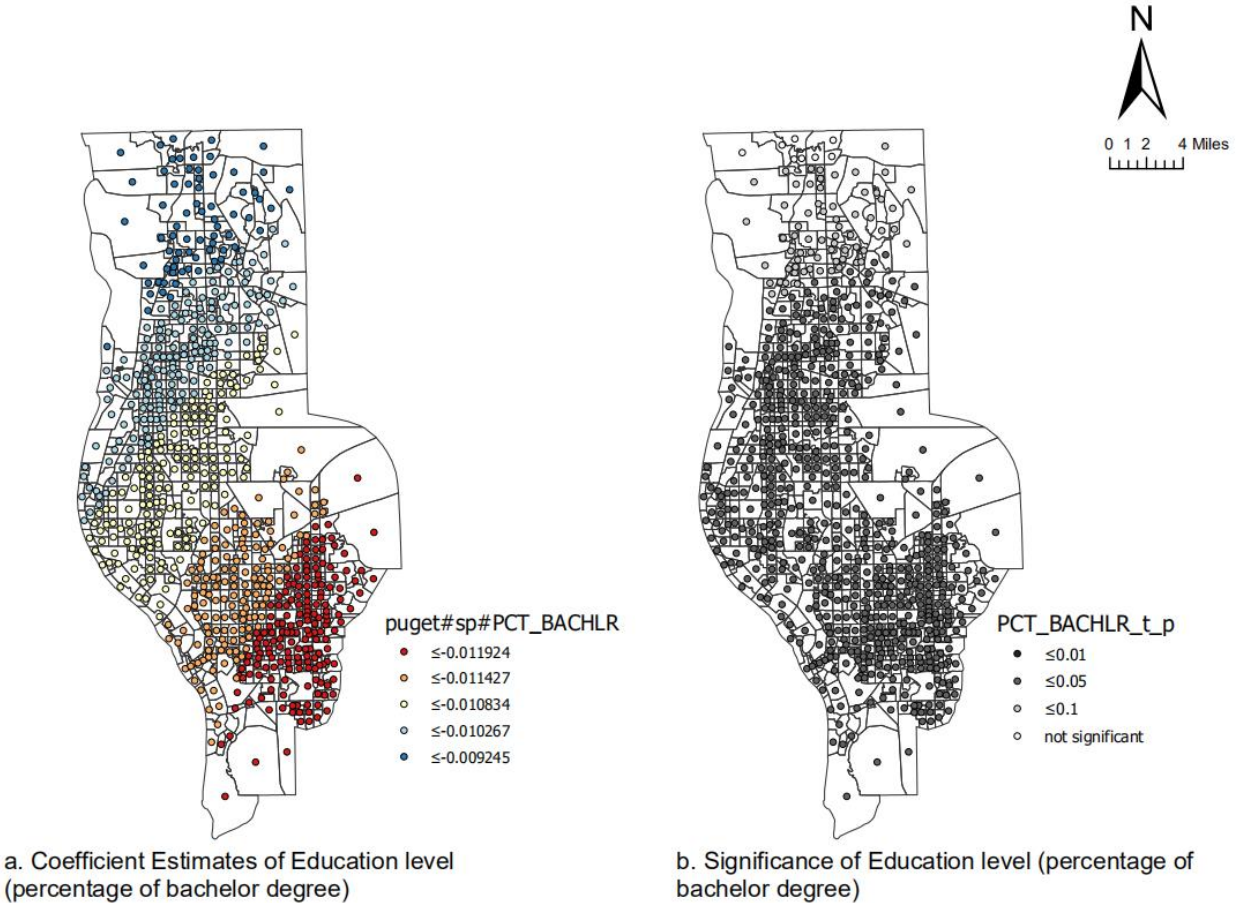


Figure 8.3.1 Education Level GWR Analysis

Education Level is a significant independent variable for most parts of the city during the weekend. From the (a) of Figure 8.3.1, we can see that the education level has a negative relationship with the total travel demand during the weekend. This is probably because people with a higher education level tend to have a high income and their own cars, thus they will use their private cars instead of Uber. This negative relationship is less obvious for the travel demand in the north part of the city, and this relationship is most obvious in the southeast part of the city (the coefficient here is about -0.012 which means when the percentage of people who have a bachelor's degree or

above increases 1%, the average daily Uber trip demand happened during the weekend will decrease 0.012).

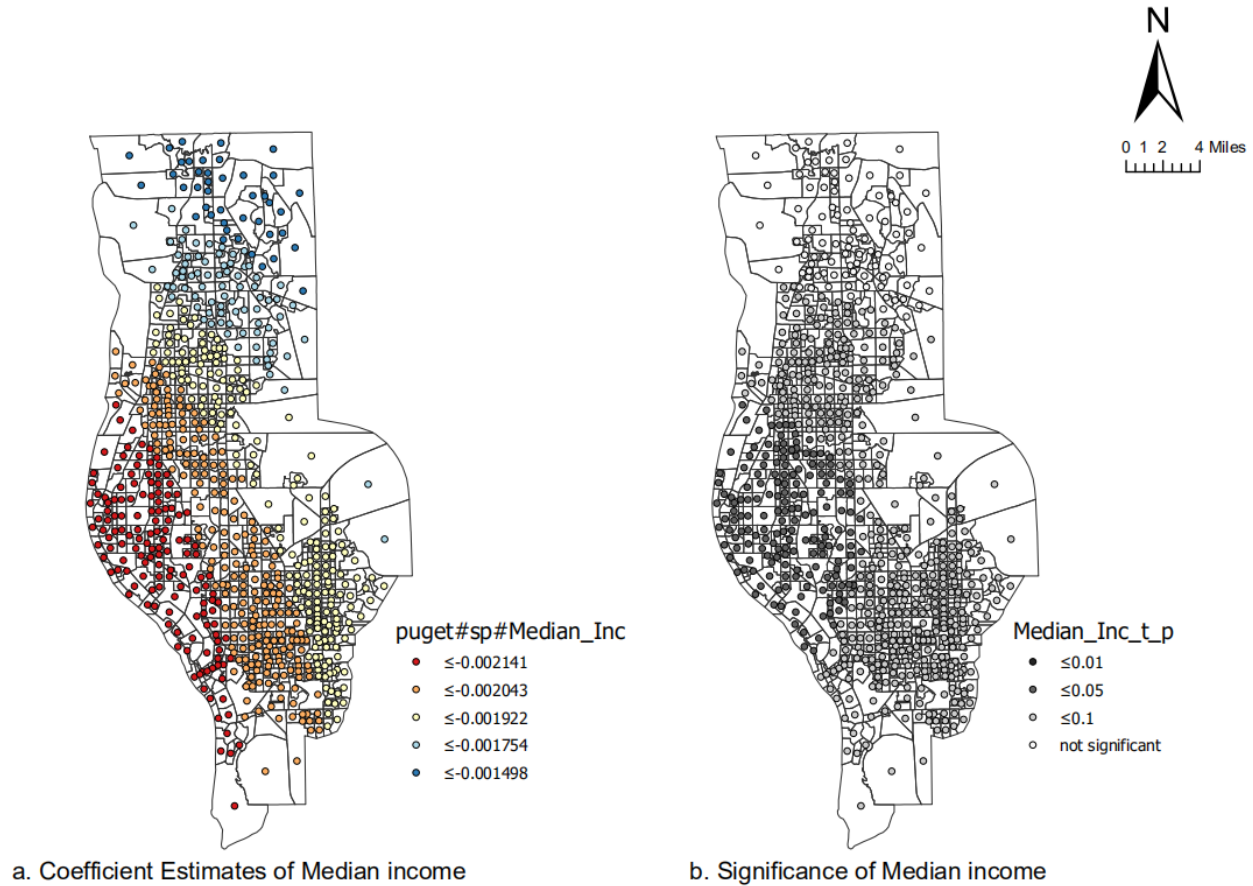


Figure 8.3.2 Median Household Income GWR Analysis

Median household income is a significant independent variable except for the upper-north part of the city. Figure 8.3.2 (a) reveals that median household income has a negative relationship with the total travel demand during the weekend. There is no doubt that people with a higher median household income will have private cars and thus decreasing the frequency of using Uber. And this negative relationship becomes relatively more obvious when the trip demand generates from the southwest part of the city. For the southwest part, Median household income has the most obvious negative relationship with the travel demand during the weekend (the coefficient here is

about -0.002 which means when the median household income increases \$1,000, the average daily Uber trip demand happened during the weekend will decrease 0.002).

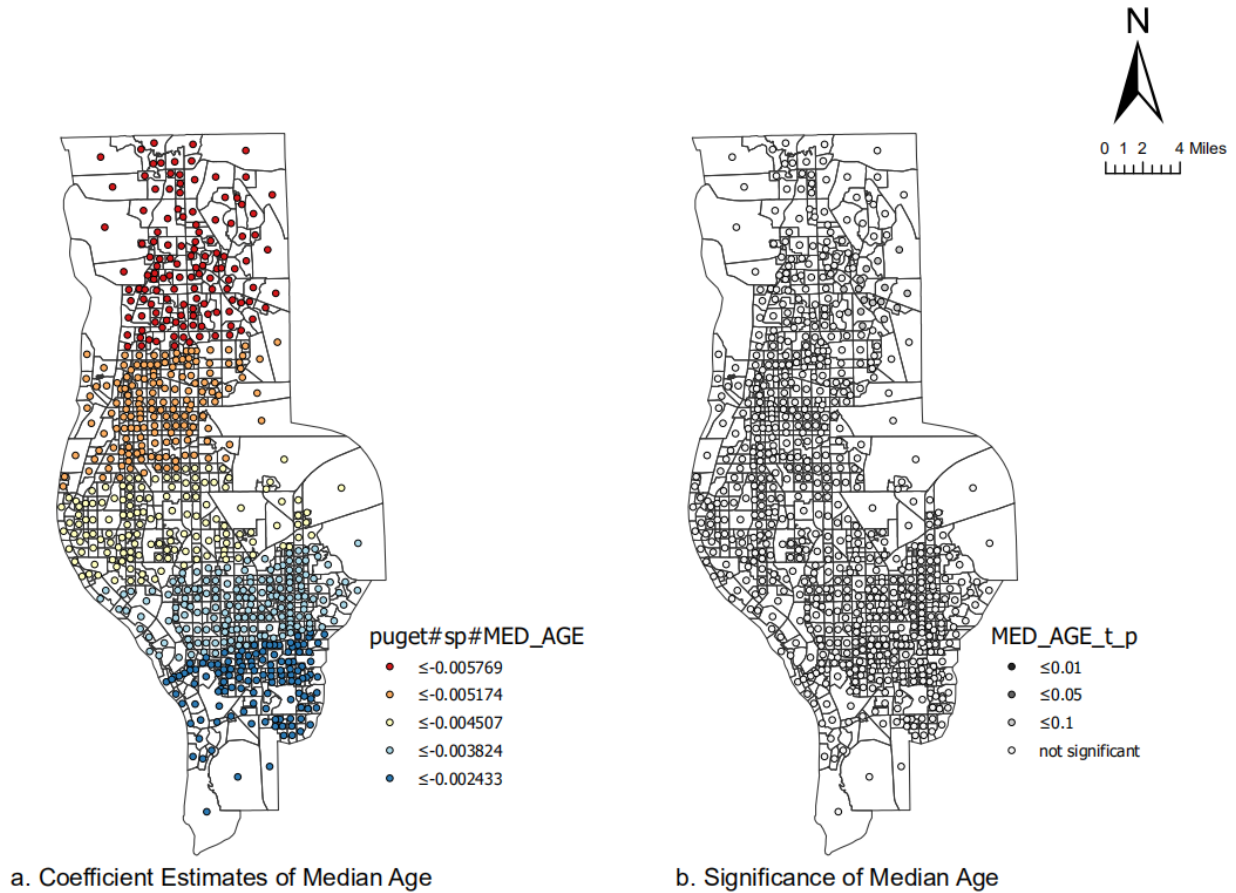


Figure 8.3.3 Median Age GWR Analysis

Median age is a significant independent variable only in the northeast part of the city (90% confidence level). And Figure 8.3.3 (b) shows that the median age is an insignificant variable for most parts of the city. For this northeast part, the median age has a most obvious negative relationship with the travel demand during the weekend (the coefficient here is about -0.006 which means when the median age increases one year, the average daily Uber trip demand will decrease -0.006). The reason for this relationship might be because elder people are more likely to stay at home or own private cars.

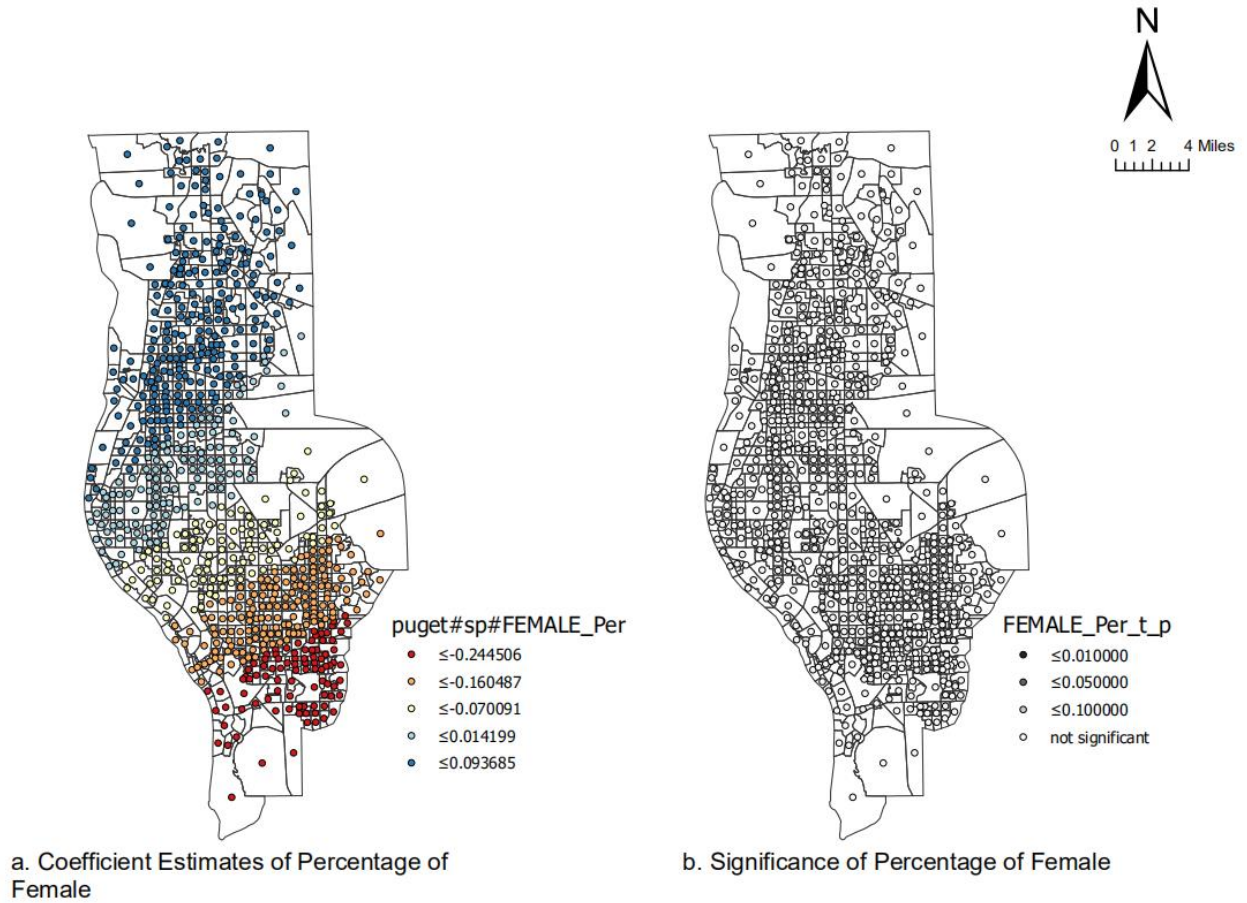


Figure 8.3.4 Percentage of Female GWR Analysis

Figure 8.3.4 (b) shows that percentage of the female is an insignificant variable for the Uber trip demand during the weekend.

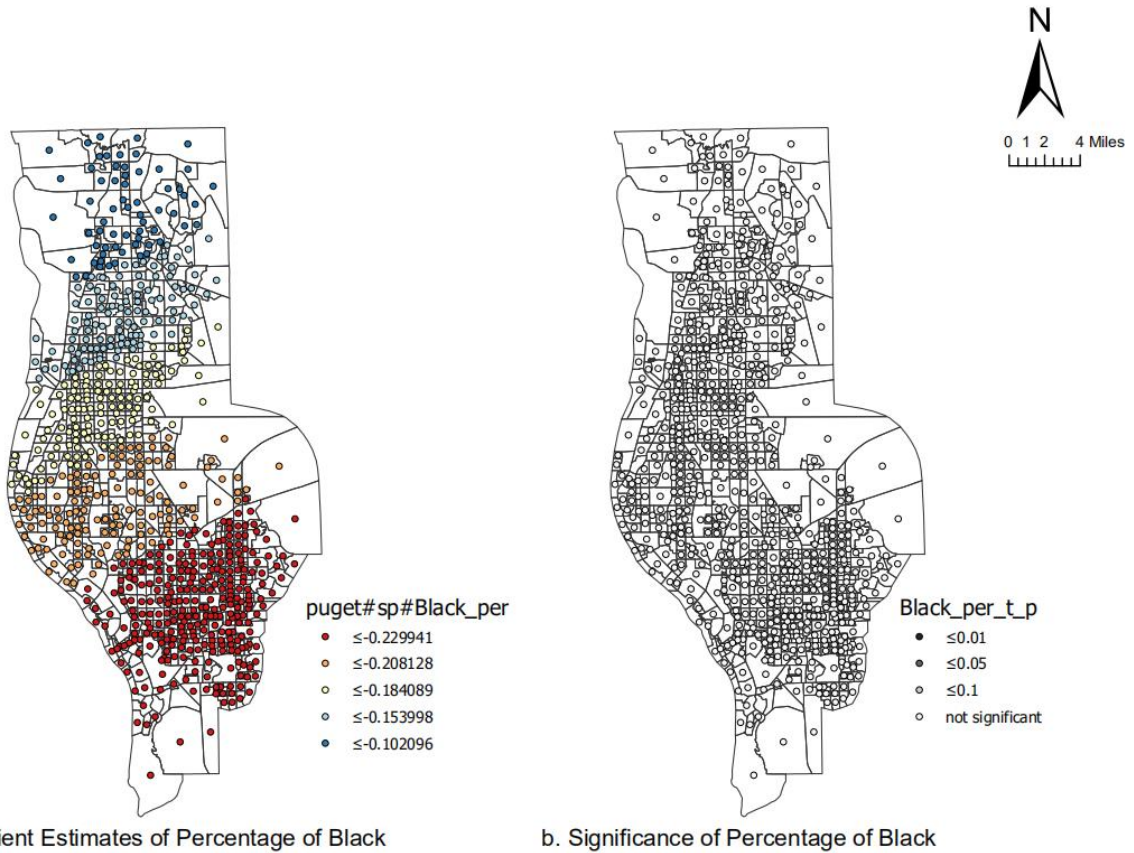


Figure 8.3.5 Percentage of Black GWR Analysis

Figure 8.3.5 (b) shows that percentage of Black people is an insignificant variable for the Uber trip demand during the weekend.

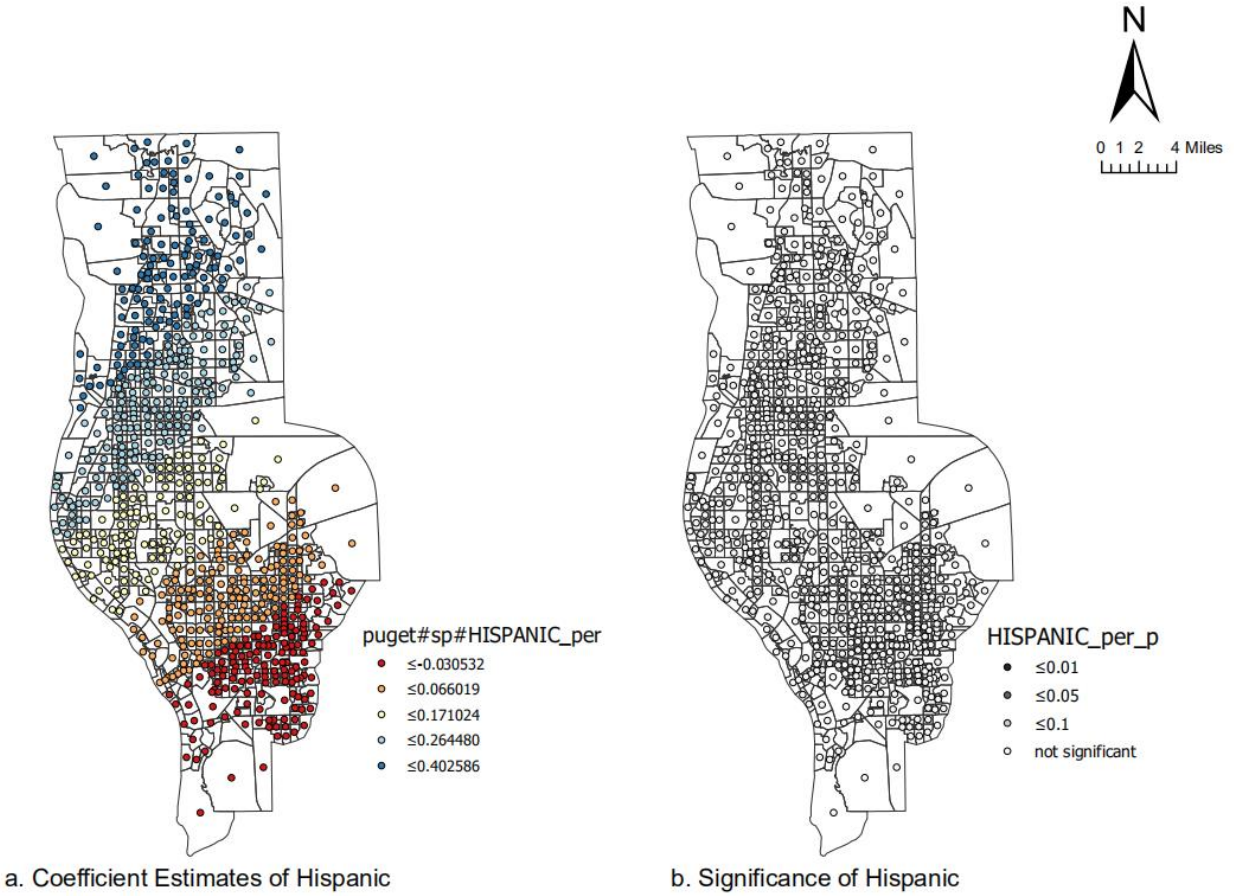


Figure 8.3.6 Percentage of Hispanic GWR Analysis

Figure 8.3.6 (b) indicates that the percentage of Hispanic people is an insignificant variable for the Uber trip demand during the weekend.

8.3.2 Population Density

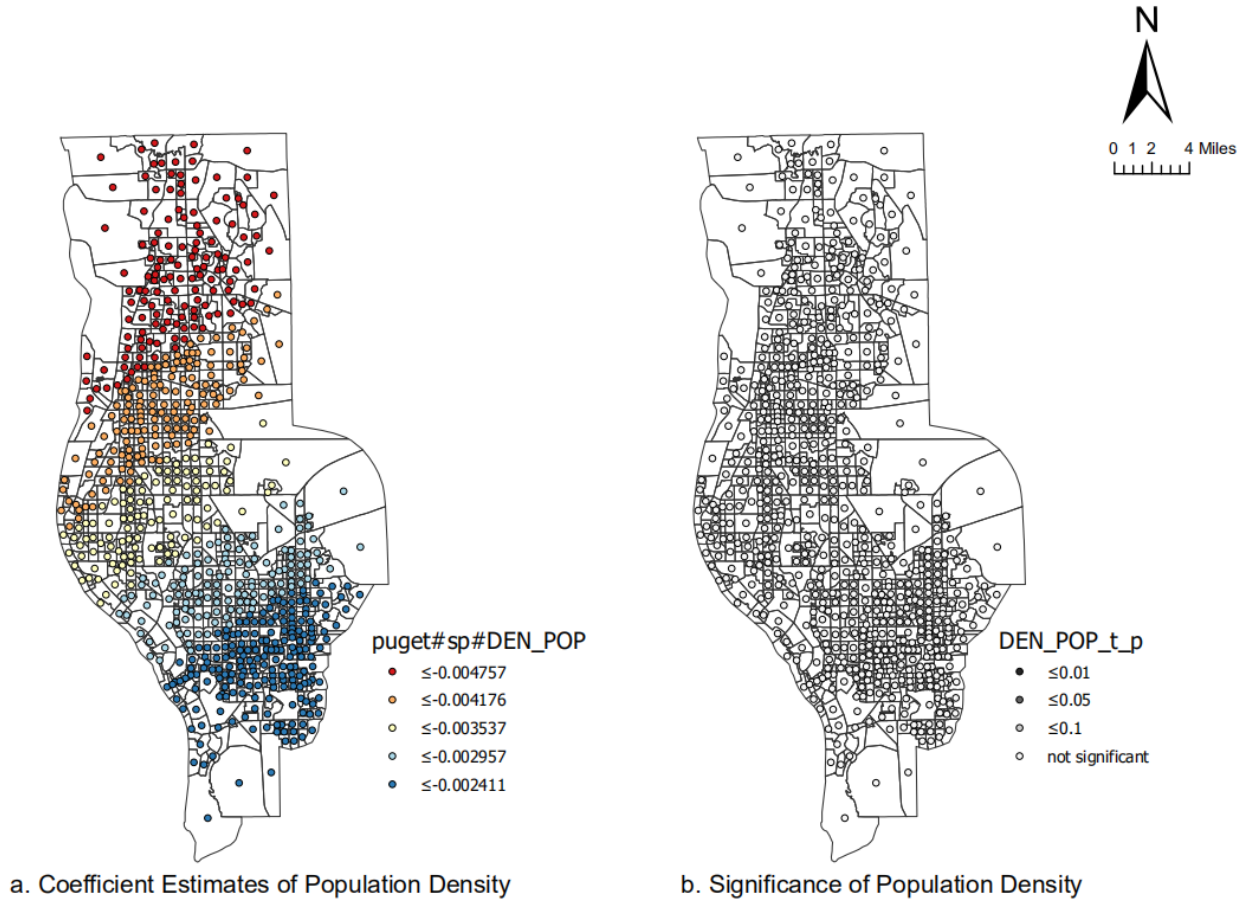


Figure 8.3.7 Population Density GWR Analysis

Figure 8.3.7 (b) reveals that population density is an insignificant variable for the Uber trip demand during the weekend.

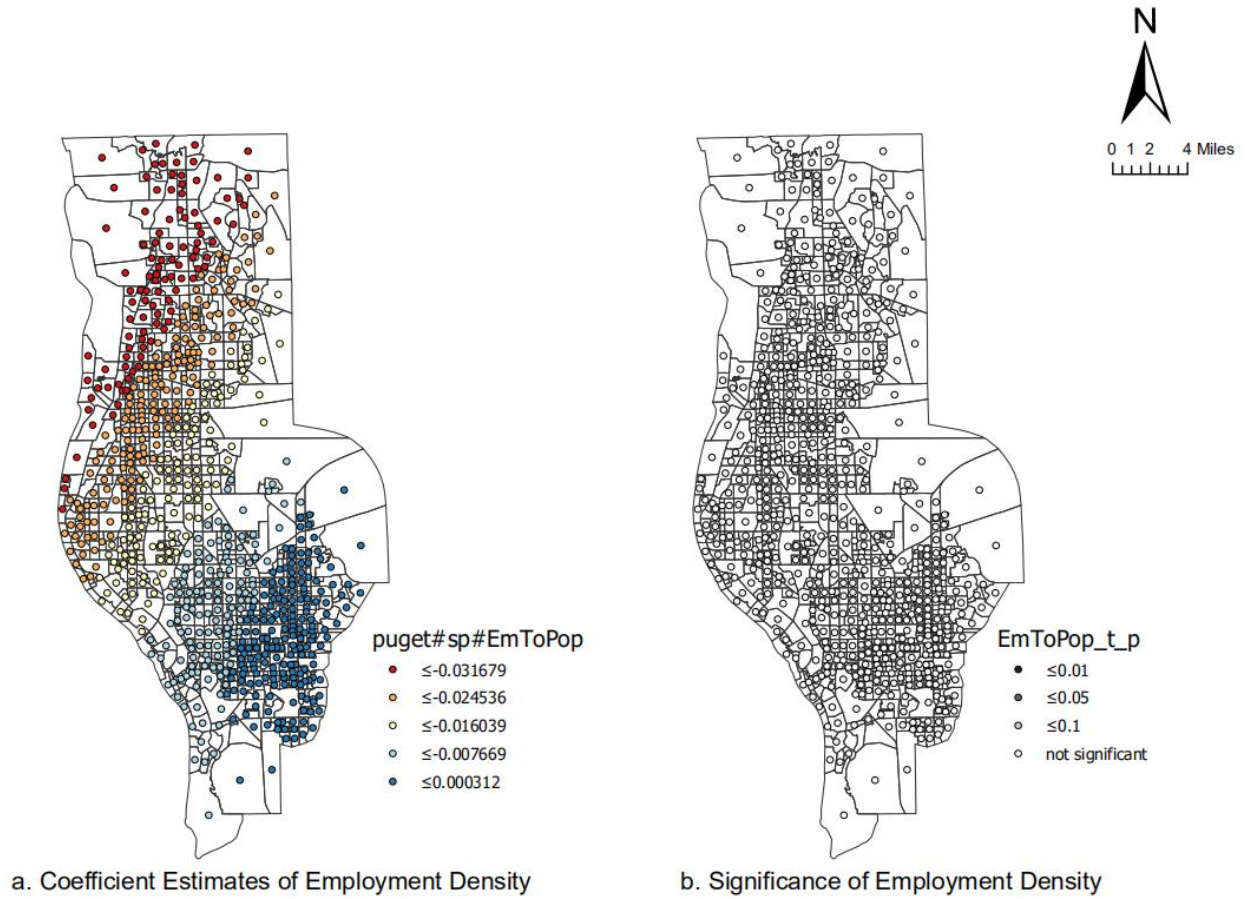


Figure 8.3.8 Employment Density GWR Analysis

As shown by Figure 8.3.8 (b), employment density is an insignificant variable for the Uber trip demand during the weekend.

8.3.3 Land Use

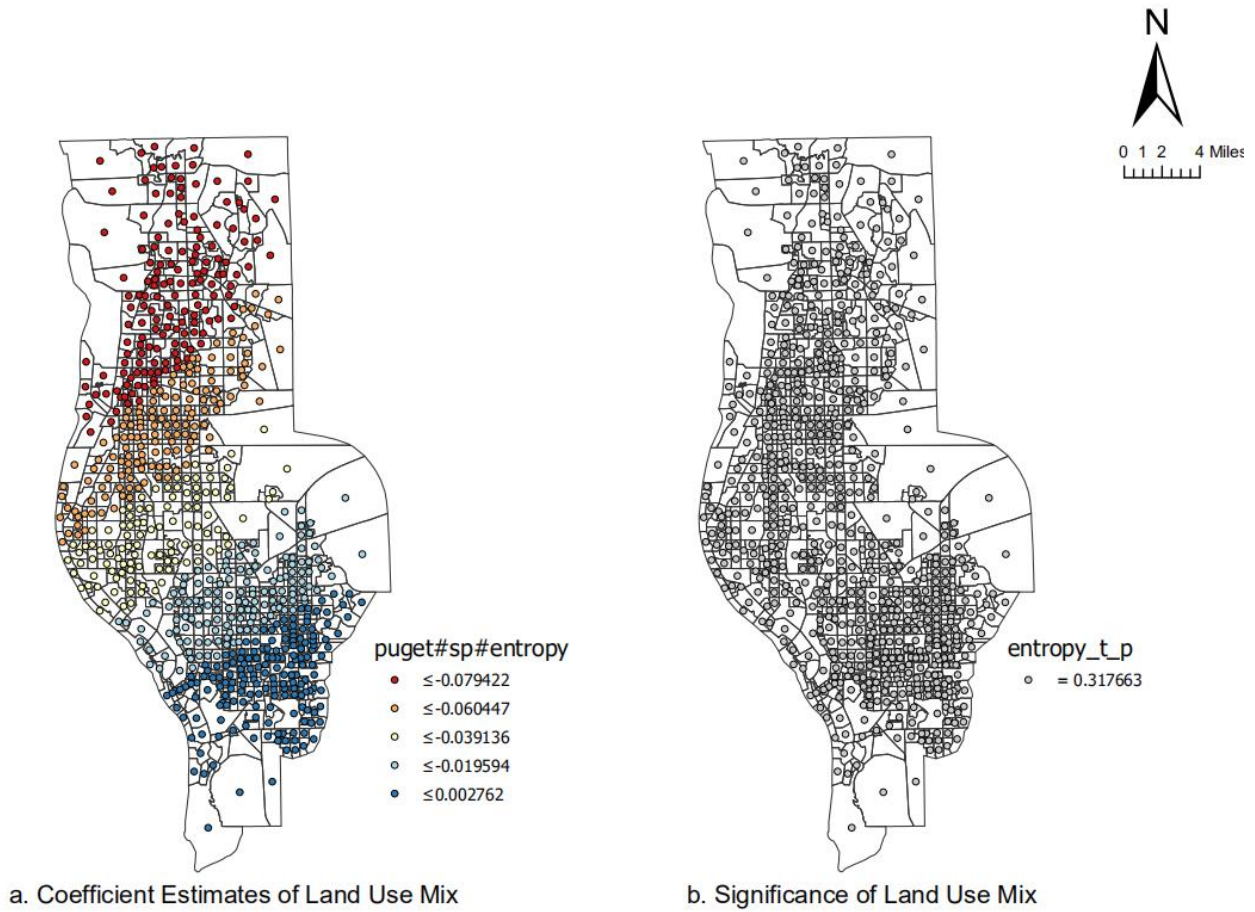


Figure 8.3.9 Land Use Mix GWR Analysis

Figure 8.3.9 (b) shows that the land use mix is an insignificant variable for the Uber trip demand during the weekend.

8.3.4 Road Network Design

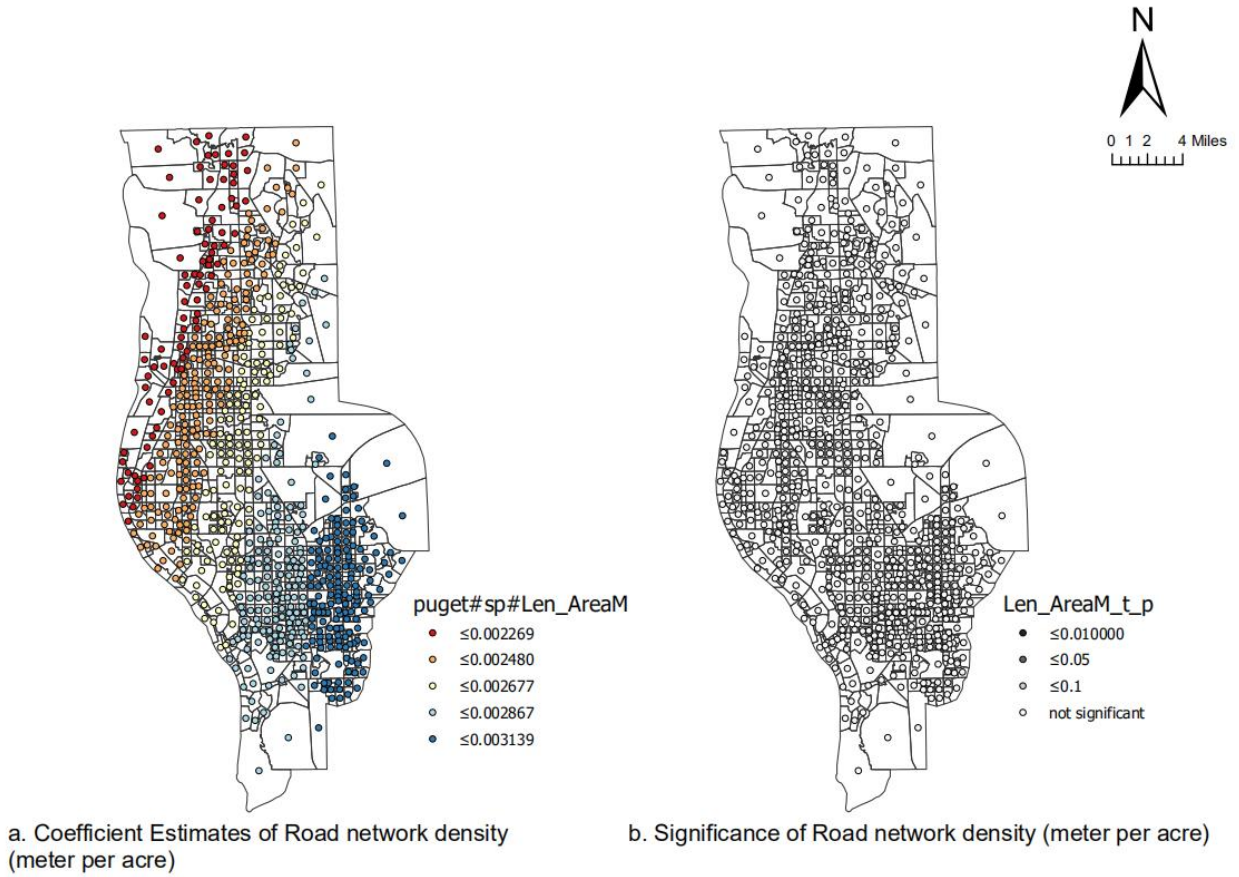


Figure 8.3.10 Road Network Density GWR Analysis

Figure 8.3.10 (b) indicates road network density is an insignificant variable for the Uber trip demand during the weekend.

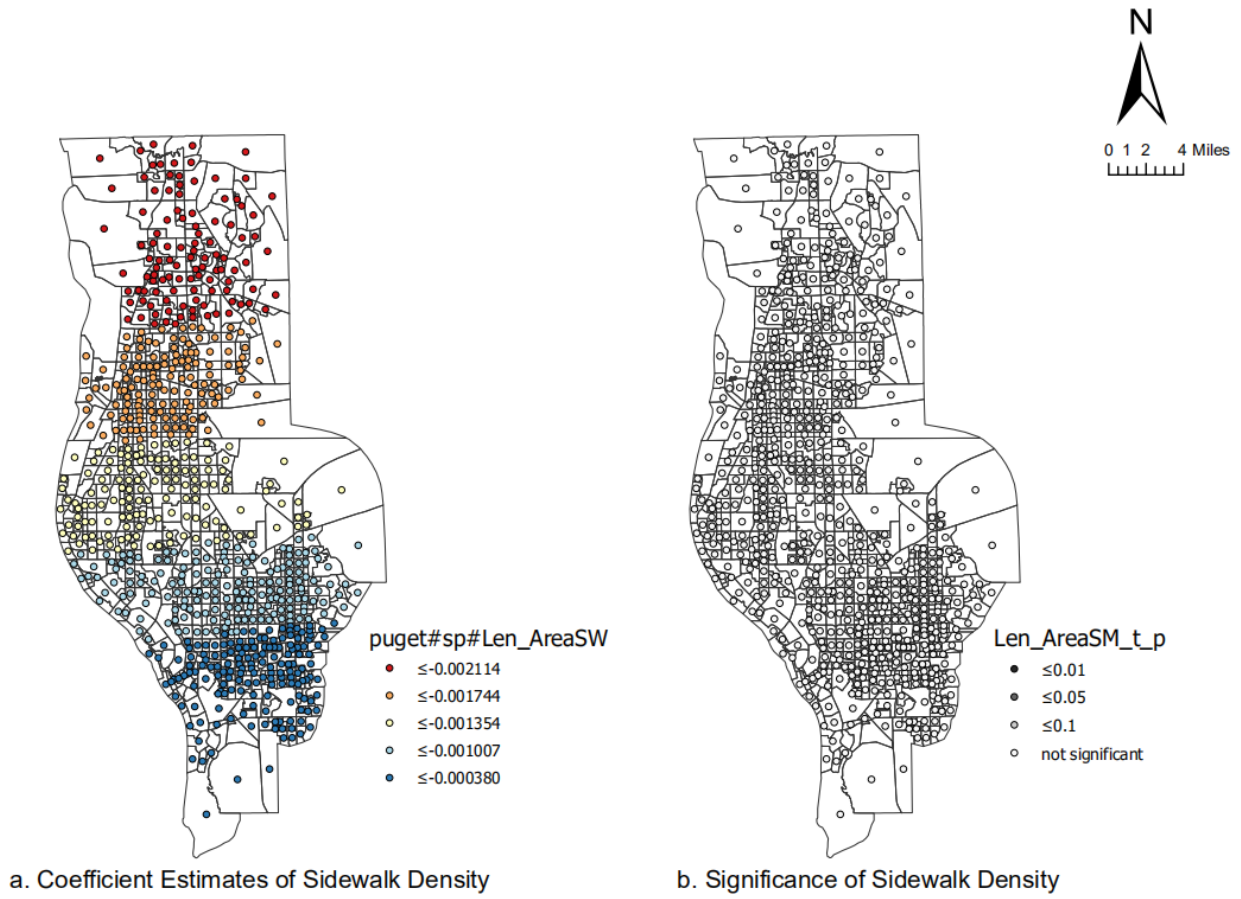


Figure 8.3.11 Sidewalk Density GWR Analysis

As shown by Figure 8.3.11 (b) sidewalk density is an insignificant variable for the Uber trip demand during the weekend.

8.3.5 Accessibility to Jobs

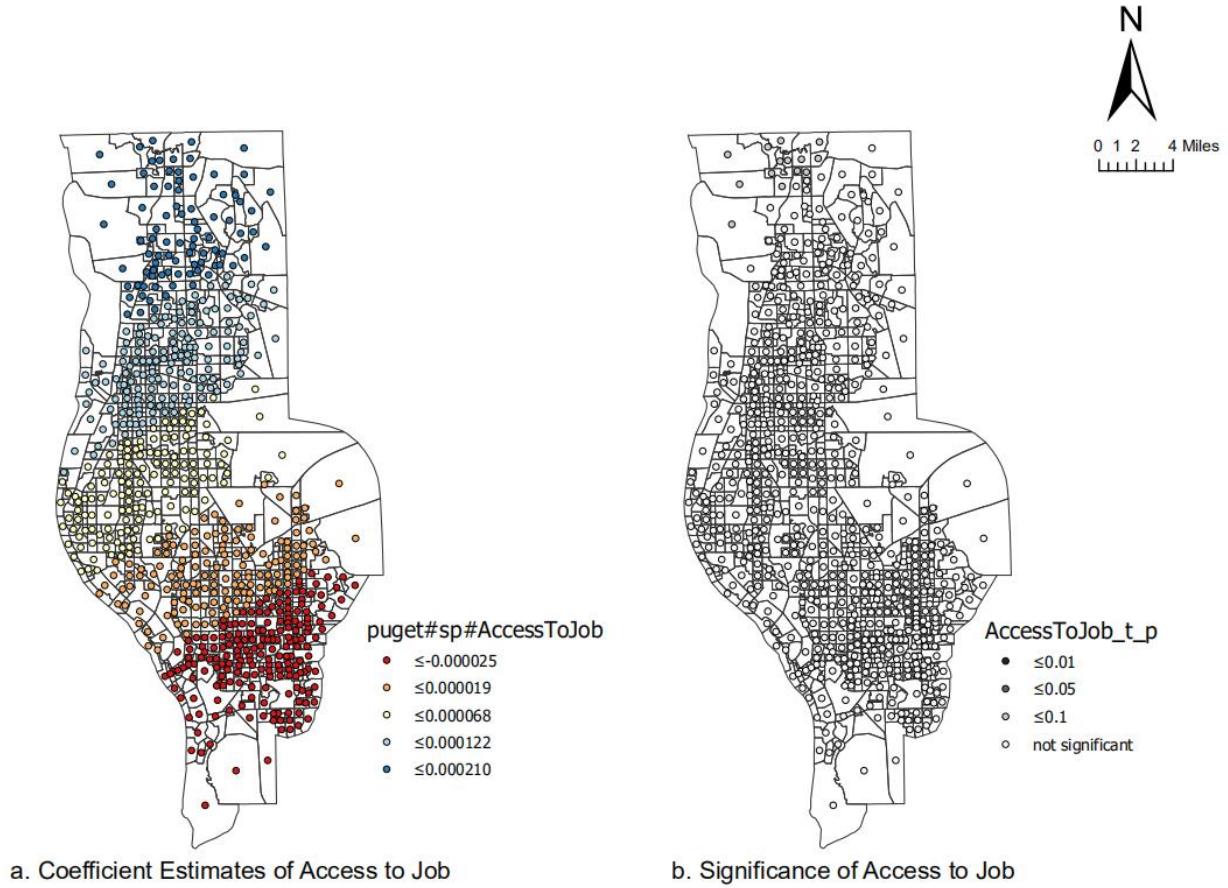


Figure 8.3.12 Access to Job GWR Analysis

Access to the job is a significant independent variable only in the most north part of the city (90% confidence level). And Figure 8.3.12 (b) shows that access to the job is an insignificant variable for most parts of the county. Figure 8.3.12 (a) reveals that, for the most north part, the access to jobs has a positive relationship with the travel demand during the weekend (the coefficient here is about 0.0002 which means when the number of job accessible within a 30-minute commuting time increase one, the average daily Uber trip demand will increase 0.0002). This probably because when there are jobs accessible and more people need to commute, the demand for Uber trip will increase accordingly.

8.4 TD-Late Shift Model

8.4.1 Education Level

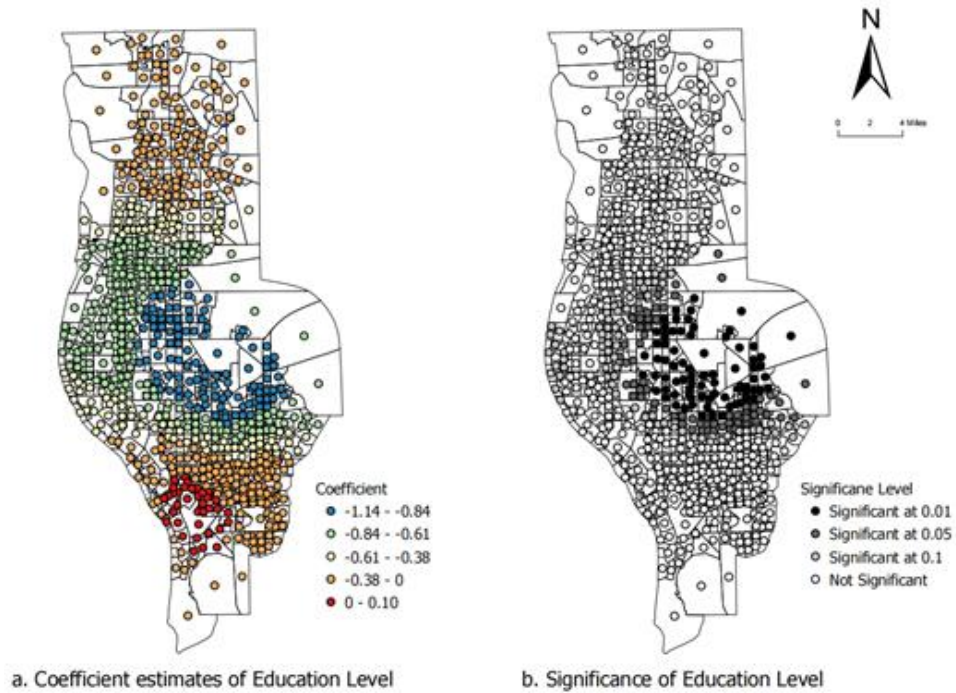


Figure 8.4.1 Education level GWR result

For GWR model result, in the socio-demographic variables, Figure 8.4.1 shows education level is significant at county center at 99% confidence level and has a negative on the ridership (with 1 percent increase results in 0.8 to 1.1 decrease in monthly ridership of the census block).

8.4.2 Percentage of Black

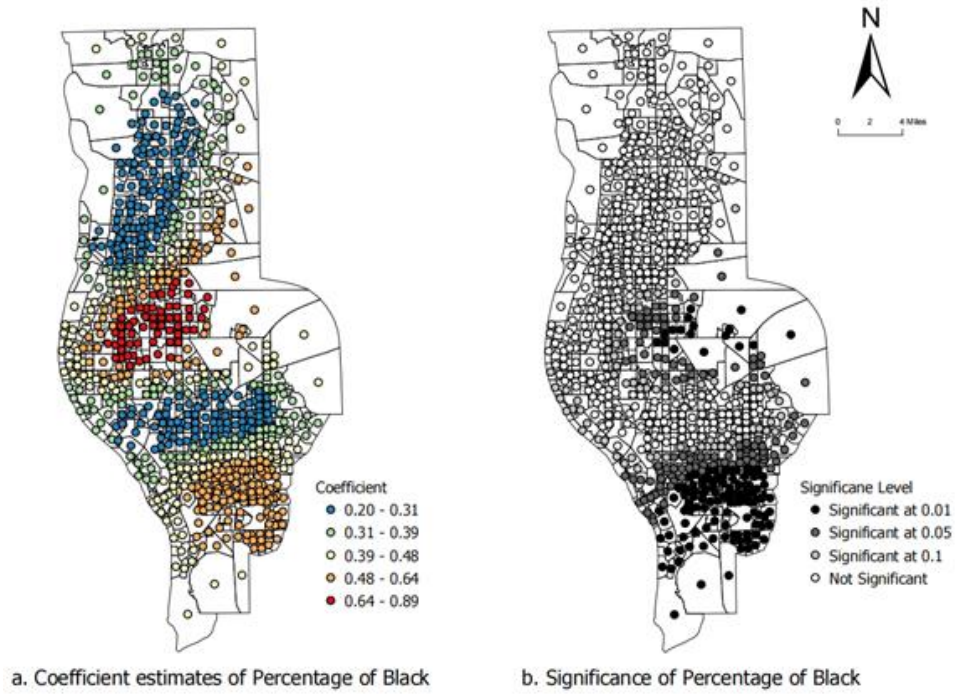


Figure 8.4.2 Percentage of black GWR result

Figure 8.4.2 indicates that percentage of black has a positive influence not only at county center (with 1 percent increase results in 0.5 to 0.9 increase in monthly ridership of the census block) but also at the south part of the county (with 1 percent increase results in 0.4 to 0.6 increase in monthly ridership of the census block) at 99% confidence level. This positive influence is stronger at county center.

8.4.3 Percentage of Male

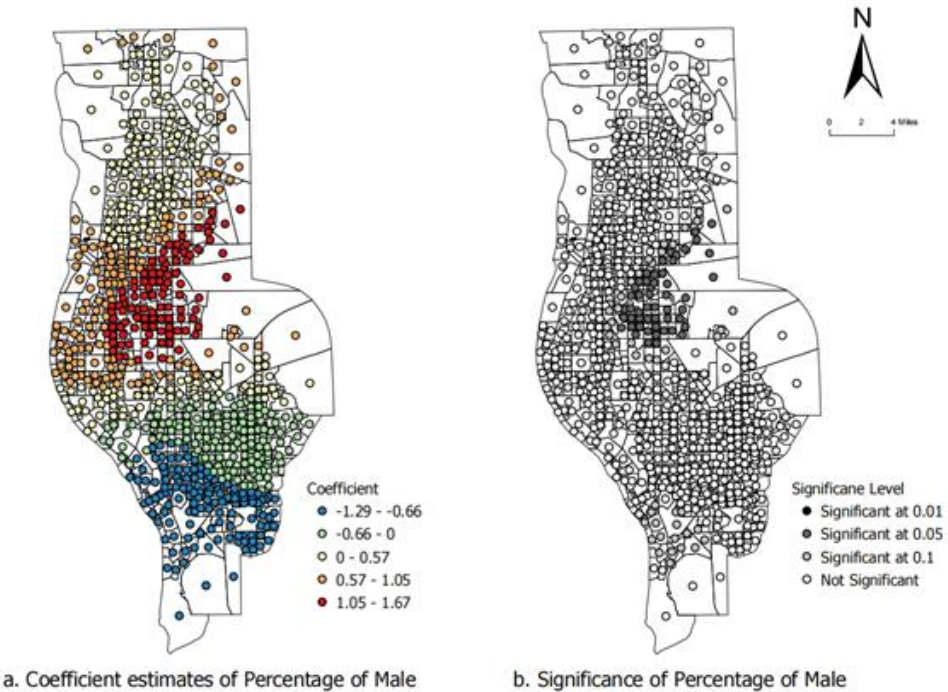


Figure 8.4.3 Percentage of male GWR result

Figure 8.4.3 shows percentage of male has a positive impact on ridership at the center part of the county, but the confidence level is only at 95%.

8.4.4 Percentage of People with a Disability

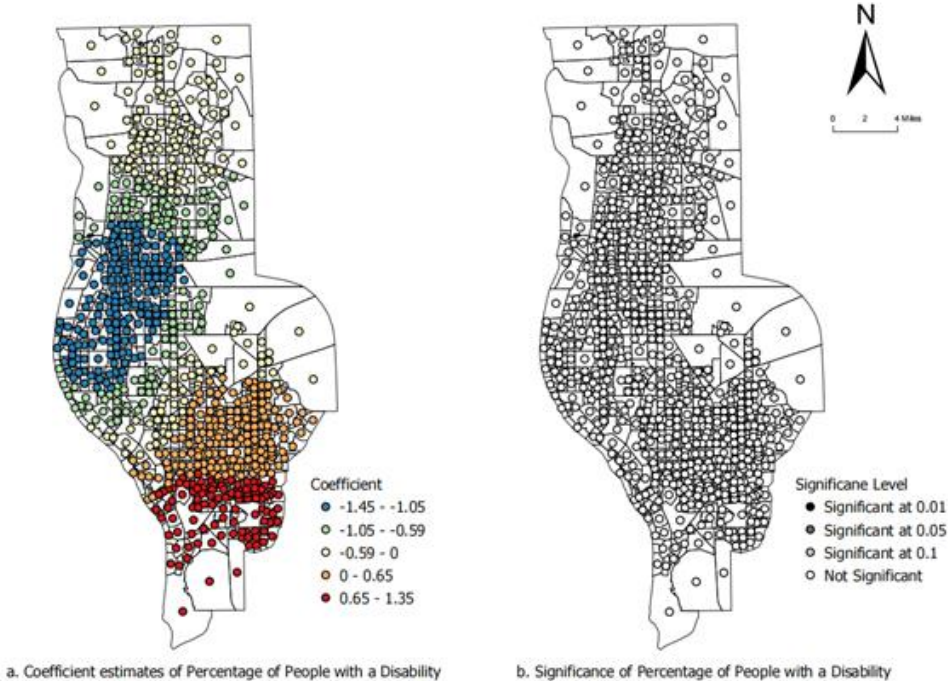


Figure 8.4.4 Percentage of people with a disability GWR result

Percentage of people with a disability is not significant in our analysis (shown in Figure 8.4.4).

8.4.5 Household Density

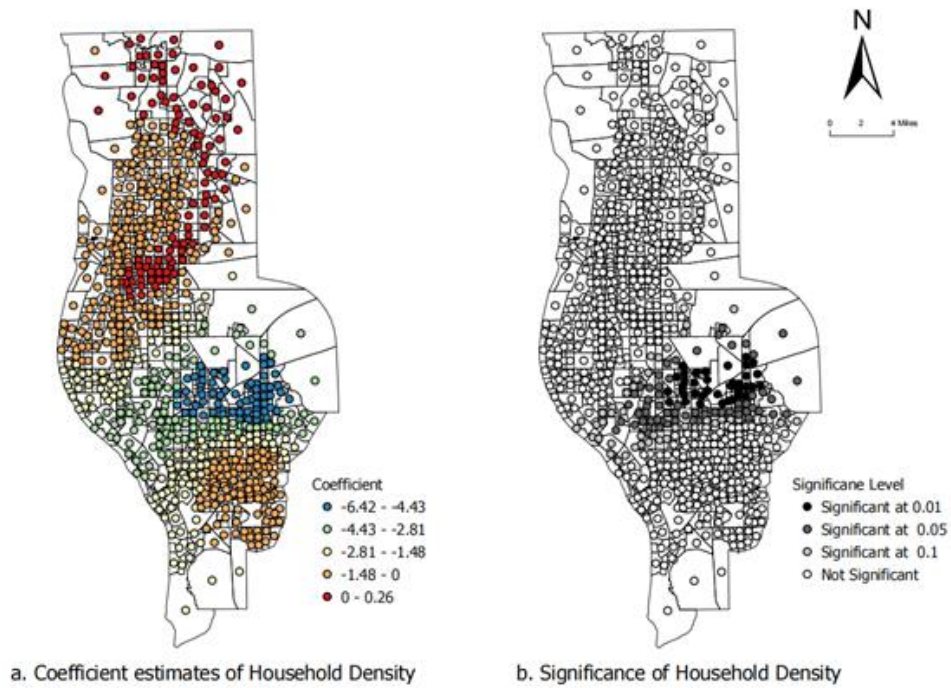


Figure 8.4.5 Household density GWR result

In the built environment variables, Figure 8.4.5 shows household density has a negative impact at the center part of the county at 99% confidence level (with 1 household per acre increase results in 4.4 to 6.4 decrease in monthly ridership of the census block).

8.4.6 Population to Employment

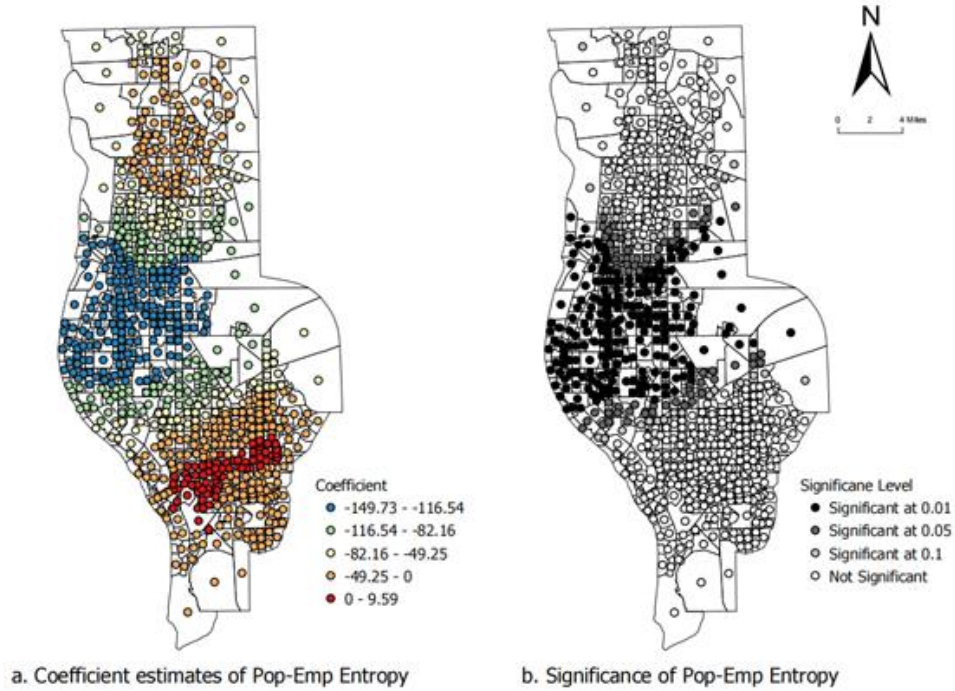


Figure 8.4.6 Population to employment entropy GWR result.

As shown in Figure 8.4.6, population to employment entropy has a negative impact on the ridership at the middle part of the county at 99% confidence level (with 1 unit increase results in 49.3 to 149.7 decrease in monthly ridership of the census block). This negative influence becomes more obvious as it goes north.

8.4.7 Access to Jobs

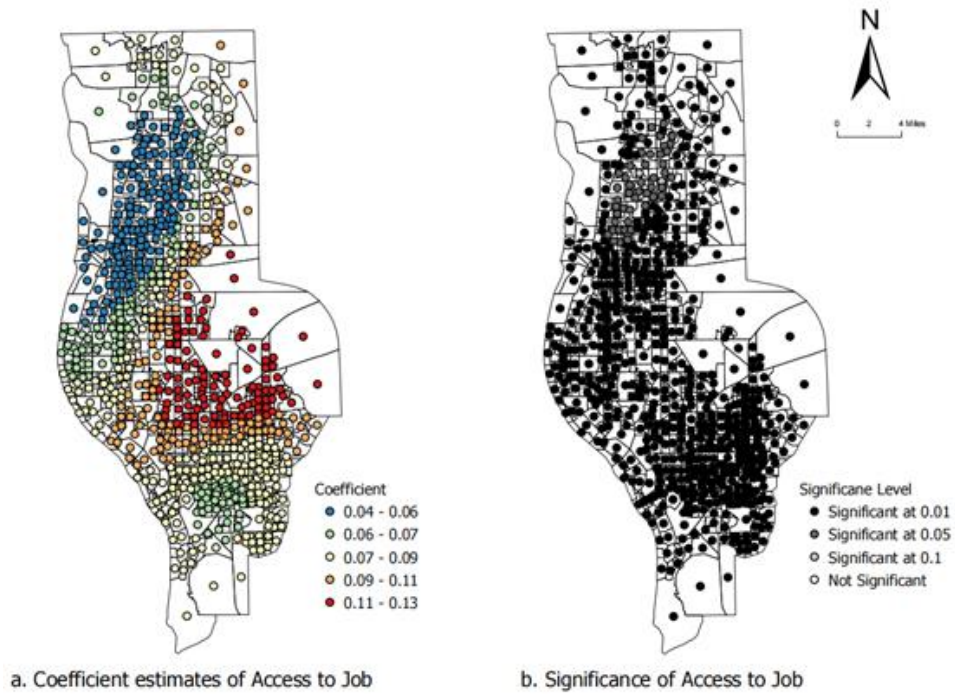


Figure 8.4.7 Access to job GWR result.

Figure 8.4.7 indicates that access to job has a positive impact at most part of the county at 99% confidence level except for the upper-center part (with 1 unit increase results in 0.04 to 0.13 increase in monthly ridership of the census block). This positive impact becomes more obvious when it goes to the center part of the county.

8.4.8 Household with 0 Vehicle

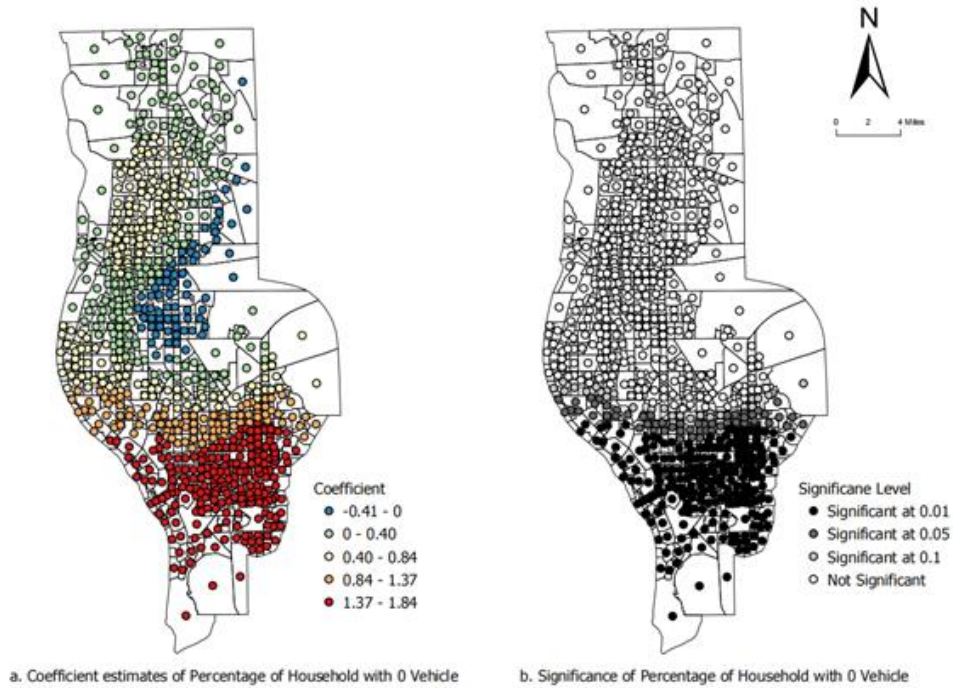


Figure 8.4.8 Percentage of household with 0 vehicle GWR result.

Figure 8.4.8 shows percentage of household with 0 vehicle has a positive impact at the south part of the county at 99% confidence level (with 1 percent increase results in 1.4 to 1.8 increase in monthly ridership of the census block).

8.4.9 Road Density

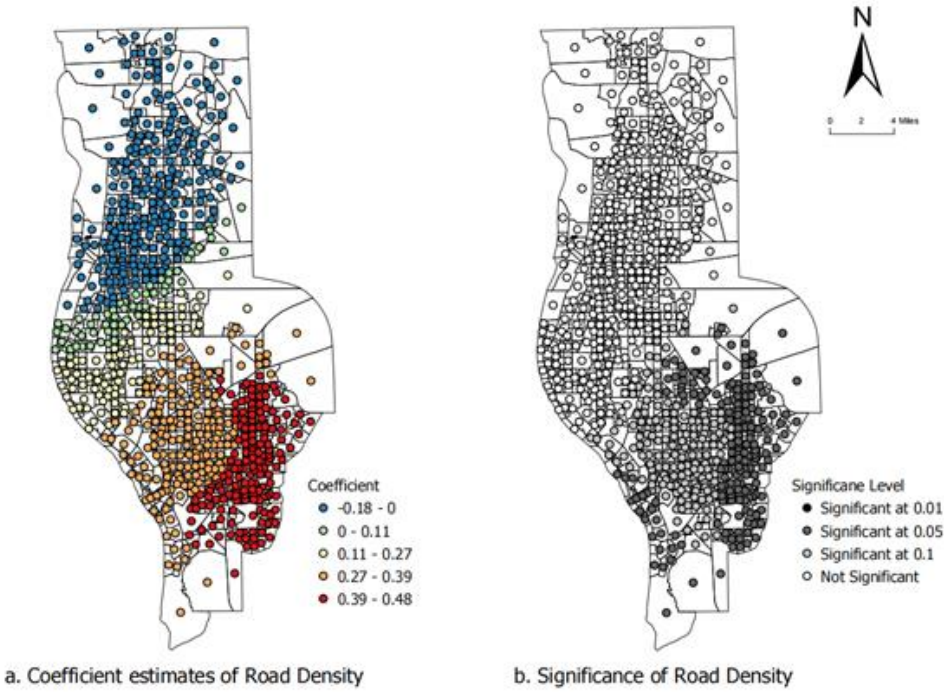


Figure 8.4.9 Road density GWR result

Figure 8.4.9 shows road density also has a positive impact at the south part of the county but are significant only at 95% and 90% confidence level. This positive impact gets stronger when it goes westward.

9. Cost-Efficiency Analysis (CEA)

9.1 The Cost-Efficiency of the Entire Transit System in Pinellas County

Table 9.1.1 shows the expenses and revenue of the transit system in Pinellas County. The operating expenses include operations, purchased transportation, maintenance, administration and finance, and marketing, while the operating revenue is the sum of passenger fares and advertising revenue. From FY 2011 to FY 2019, the operating expenses of the transit system increased by about thirty million dollars. The amount of passenger fares collected declined during these nine years along with the overall decline of transit ridership. Although there was a growth in advertising revenue, the operating revenue still decreased by about four million dollars.

The cost-effectiveness ratio is the result of the CEA, which is calculated according to the total cost and the key outcomes of the Direct Connect program. In this research, the key outcome was selected as the transit ridership because rising transit ridership was one of the goals of the Direct Connect program. The total cost of the Direct Connect program was taken as the net operating cost, which was the difference between operating expenses and operating revenue. Table 9.1.2 shows the results of the CEA of the whole transit system. The cost-effectiveness ratio remained stable at around four from FY 2011 to FY 2014, indicating the cost for each transit ridership was around four dollars. However, since 2015, the ratio has been growing rapidly, rising from 4.38 in 2015 to 7.20 in 2019. This result means that the cost-effectiveness of the whole transit system in Pinellas County was declining.

Table 9.1.1 Expenses and Revenue of Transit System in Pinellas County from FY 2011 to FY 2019

Fiscal Year	Operating Expenses	Passenger Fares	Advertising Revenue	Operating Revenue
2011	\$64,603,621	\$12,788,411	\$395,847	\$13,184,258
2012	\$64,266,635	\$14,279,728	\$439,557	\$14,719,285
2013	\$69,087,863	\$14,098,511	\$417,851	\$14,516,362
2014	\$71,966,673	\$13,585,399	\$248,224	\$13,833,623
2015	\$73,838,187	\$12,194,799	\$485,359	\$12,680,158
2016	\$74,832,127	\$10,791,925	\$577,046	\$11,368,971
2017	\$81,158,913	\$9,535,246	\$582,761	\$10,118,007
2018	\$84,923,787	\$9,473,561	\$615,234	\$10,088,795
2019	\$93,719,169	\$9,129,892	\$660,371	\$9,790,263

Source: Comprehensive Annual Financial Report For Fiscal Years Ended September 30, 2019, and 2018, Pinellas Suncoast Transit Authority St. Petersburg, Florida.

Table 9.1.2 Cost-Effectiveness Ratio of Transit System in Pinellas County from FY 2011 to FY 2019

Fiscal Year	Net Operating Cost	Fixed Ridership	Route	Cost-Effectiveness Ratio
2011	\$51,419,363	12,380,638		4.15
2012	\$49,647,350	13,713,646		3.62
2013	\$54,571,501	13,491,328		4.04
2014	\$58,133,050	13,614,858		4.27
2015	\$61,158,029	13,950,951		4.38
2016	\$63,463,156	12,682,856		5.00
2017	\$71,040,906	11,894,513		5.97
2018	\$74,834,992	11,566,002		6.47
2019	\$83,928,906	11,663,314		7.20

9.2 The Cost-Efficiency for Each Route in Pinellas County

Table 9.2.1 shows the cost-effectiveness ratio for each route in Pinellas County in FY 2019, which was also calculated according to the net cost and ridership of each route. The cost-effectiveness ratio for each route was calculated based on the fixed-route performance data in FY 2019 provided by PSTA. The cost for each route was estimated according to the cost per revenue hour (\$97.55) and the total revenue hours for each route. The revenue for each route was estimated according to the passengers per revenue hour, revenue per passenger, and total revenue hours for each route.

$$\text{Route Cost} = \text{Cost/RevHour} * \text{RevHours} \quad (3-1)$$

$$\text{Route Revenue} = \text{Pax/RevHour} * \text{Revenue/Pax} * \text{RevHours} \quad (3-2)$$

Where,

Cost/RevHour is the cost per revenue hour for each route;

RevHours is the revenue hours for each route;

Pax/RevHour is the number of passengers per revenue hour for each route;

Revenue/Pax is the revenue per passenger for each route.

Figure 9.3.1 shows the distribution of the cost-effectiveness ratio for each route in Pinellas County. The Y-axis indicates the value of the cost-effectiveness ratio, and the X-axis indicates the fixed routes' names. The cost-effectiveness ratio for each route varies widely from 2.30 to 49.54. Most of the cost-effectiveness ratios are concentrated within the range of 2.30 to 15.00, five of which are extremely high (larger than 20.00), indicating that these five routes are relatively less cost-effective than others. These five routes with a cost-effectiveness ratio larger than 20.00 are Route

101, 300, 812, 813, and 814, among which Route 813 has the highest cost-effectiveness ratio which indicates that Route 813 is the least cost-effective route.

Table 9.2.1 Cost-Effectiveness Ratio for Each Route in Pinellas County in FY 2019

Route	Cost	Revenue	Net Cost	Ridership	Cost-Effectiveness Ratio
4	4,426,905	821,843	3,605,062	847,125	4.26
5	989,732	116,337	873,395	132,188	6.61
7	954,139	132,132	822,008	146,797	5.60
9	1,623,650	277,232	1,346,417	298,103	4.52
11	1,367,151	221,850	1,145,301	235,950	4.85
14	2,161,235	360,110	1,801,125	400,221	4.50
15	881,317	145,296	736,022	163,286	4.51
16	542,553	65,764	476,788	67,772	7.04
18	5,343,675	1,021,253	4,322,422	1,064,035	4.06
19	2,609,486	566,549	2,042,937	505,714	4.04
20	1,001,408	141,560	859,848	150,588	5.71
22	446,381	36,361	410,020	33,347	12.30
23	1,673,994	153,373	1,520,622	159,784	9.52
32	242,412	28,133	214,279	33,893	6.32
34	3,657,657	904,249	2,753,408	913,299	3.01
35	2,713,247	615,945	2,097,302	800,010	2.62
38	929,143	119,692	809,451	117,321	6.90
52	4,598,706	1,085,210	3,513,496	1,085,151	3.24
58	619,547	48,212	571,335	46,820	12.20
59	3,063,100	492,275	2,570,825	482,489	5.33
60	1,384,389	408,036	976,352	424,978	2.30
61	1,730,171	174,354	1,555,817	181,583	8.57
62	1,179,039	170,969	1,008,071	159,814	6.31
65	862,920	83,912	779,007	82,245	9.47
66	340,356	57,206	283,150	61,524	4.60
67	744,342	107,124	637,217	98,251	6.49

68	548,053	67,781	480,273	64,580	7.44
73	776,133	105,175	670,958	103,119	6.51
74	2,389,451	315,902	2,073,549	322,327	6.43
75	994,222	135,738	858,484	138,536	6.20
76	732,376	87,908	644,468	97,656	6.60
78	1,132,477	240,871	891,606	248,272	3.59
79	2,894,694	448,884	2,445,810	453,288	5.40
90	163,192	21,027	142,166	26,614	5.34
100	559,911	67,334	492,577	35,050	14.05
101	325,107	26,722	298,385	14,053	21.23
300	626,441	54,827	571,614	28,674	19.93
355	1,237,216	195,281	1,041,935	207,769	5.01
521	698,208	114,304	583,904	114,309	5.11
711	698,208	114,304	583,904	36,664	5.11
777	2,241,959	403,325	1,838,634	433,782	4.24
812	795,410	28,630	766,780	21,698	35.34
813	604,962	11,131	593,831	11,988	49.54
814	317,470	14,191	303,279	14,928	20.32
888	1,084,199	151,377	932,822	151,401	6.16

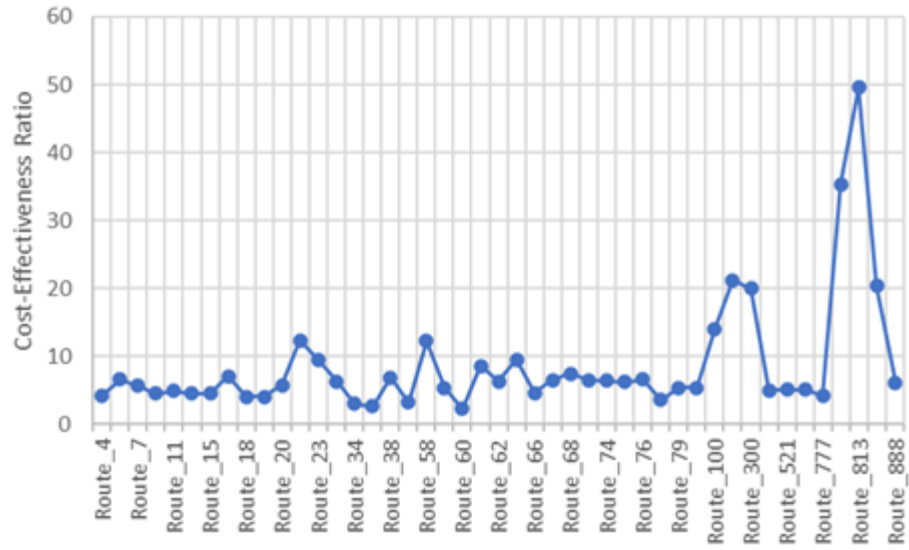


Figure 9.2.1 Distribution of Cost-Effectiveness Ratio for Each Route

9.3 Summary

From the results of the CEA of the entire transit system in Pinellas County, it can be seen that the cost-effectiveness of the entire transit system has been declining from 4.15 in FY 2011 to 7.20 in FY 2019. Although the implementation of the Direct Connect program has alleviated the drop in transit ridership in Pinellas County to a certain extent, which is not as severe as the transit ridership drop in Florida, the rapidly rising operating costs and continuously decreasing operating revenue still led to the reduction in the cost-effectiveness of the public transportation system from FY 2011 to FY 2019.

10. Scenario Evaluation

10.1 Evaluation of Scenario 1

According to the results of the cost-effectiveness analysis for each route, it can be distinguished that Route 101, 300, 812, 813, and 814 are the routes with the least cost-effectiveness, which is shown in Figure 10.1.1. Therefore, in this scenario, we proposed to cancel these five least cost-effective routes and replace them with the Uber service to see whether this measure can reduce costs when compared to the current case.

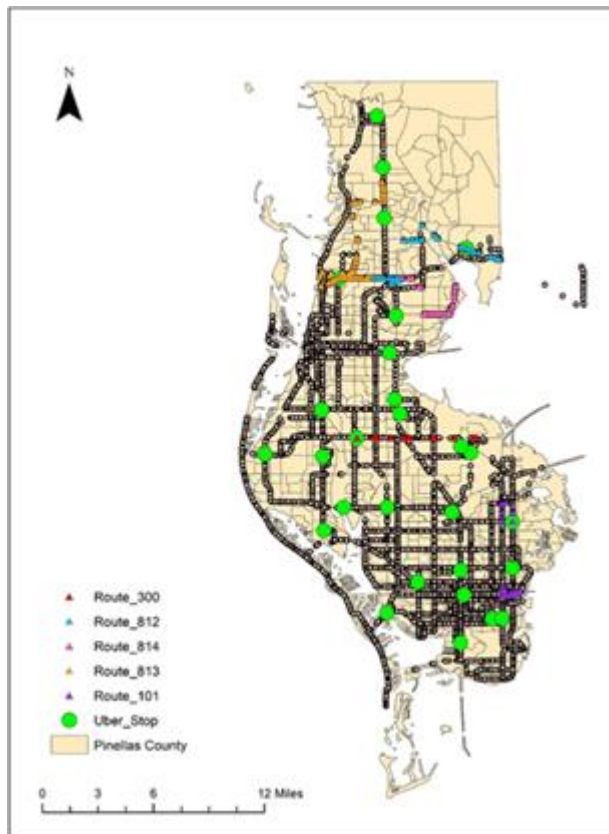


Figure 10.1.1 The Routes with the Least Cost-Efficiency in Pinellas County

Based on the assumption that all of the original transit passengers of these five canceled routes would adopt Uber services and continue to use transit service to complete their travels, a cost-benefit analysis (CBA) was conducted from the perspective of the transit agency (PSTA) and users. From the perspective of PSTA, there were two kinds of costs for this measure. The first one was the additional subsidies provided to the passengers of five canceled routes to access the transit service by using Uber services. The second one was the loss of revenue, including the fare revenue. In the Direct Connect program, if the passenger uses the service of the Direct Connect program to access public transportation service, then the bus fee can be waived with the Direct Connect service receipt. Therefore, if these passengers use the Direct Connect service to connect to the bus service due to the cancellation of the original bus lines, they do not need to pay for the bus ticket. However, the benefit of this measure for PSTA was the saving of operating these five routes. Table 10.1.1 presents PSTA's costs and benefit from the measure proposed in Scenario 1. The costs to run each route which has the least cost-effectiveness far outweighed the revenues they could generate. The proposed measure in this scenario has great potential for cost savings for the public transport agency.

Table 10.1.1 Costs and Benefit of Scenario 1 From PSTA's Perspective

Route	Ridership	TNC Subsidy	Original Revenue	Operating Expense	Net Benefit
101	14,053	\$70,265	\$26,721	\$325,106	\$228,120
300	28,674	\$143,370	\$54,826	\$626,440	\$428,244
812	21,698	\$108,490	\$28,629	\$795,410	\$658,291
813	11,988	\$59,940	\$11,131	\$604,962	\$533,891
814	14,928	\$74,640	\$14,190	\$317,469	\$228,639
Total	91,341	\$456,705	\$135,497	\$2,669,387	\$2,077,185

However, from the user’s point of view, what this measure mainly generated was the cost. Passengers needed to use the Direct Connect program service to the nearest designated transit stations in the Direct Connect program to access the transit service, which would increase their travel fare. Table 10.1.2 shows the Uber price structure, including booking fees, additional cost per mile, cost per-minute wait time, and minimum fare. There is total five kinds of Uber service, namely UberPool, UberX, UberXL, Select, and Uber Black. UberPool provides shared rides service, which is the door-to-door service or only needs passengers to have a short walk. UberX provides the private ride service, which can contain up to four people per ride. UberXL is a promotion choice of the UberX, which fits six riders or extra luggage. Uber select provides the comfortable rides with top-rated drivers. Uber Black provides the top service with top-rated drivers and luxury vehicles. For each Uber service type, the minimum fare includes three miles of service mileage. After three miles, the total fare will exceed the minimum fare.

Table 10.1.2 Uber Price Structure

	UberPool	UberX	UberXL	Select	Uber Black
Booking Fee	\$2.20	\$2.20	\$2.45	\$2.45	N/A
Additional cost per mile	\$1.29	\$1.60	\$2.47	\$2.81	\$3.81
Per-minute wait time	N/A	\$0.42	\$0.43	\$0.50	\$0.65
Minimum fare	\$7.65	\$7.20	\$9.45	\$11.45	\$15.00

Source: How much does a ride with the Uber App cost? Uber, 2020. <https://www.uber.com/us/en/price-estimate/>.

Figure 10.1.2 shows the distance from transit stops to the designated Direct Connect stops. All of the bus stops are within three miles of the nearest selected station, so the Uber ride from the bus

stop to the nearest designated station is the minimum fare. In other words, the additional travel fare for the passengers who need to use Uber service to reach the nearest designated Direct Connect stops is the minimum Uber fare. Depending on the type of Uber service, users would have to pay a total of \$242,053 to \$913,410 per year after accepting a \$5 subsidy per ride.

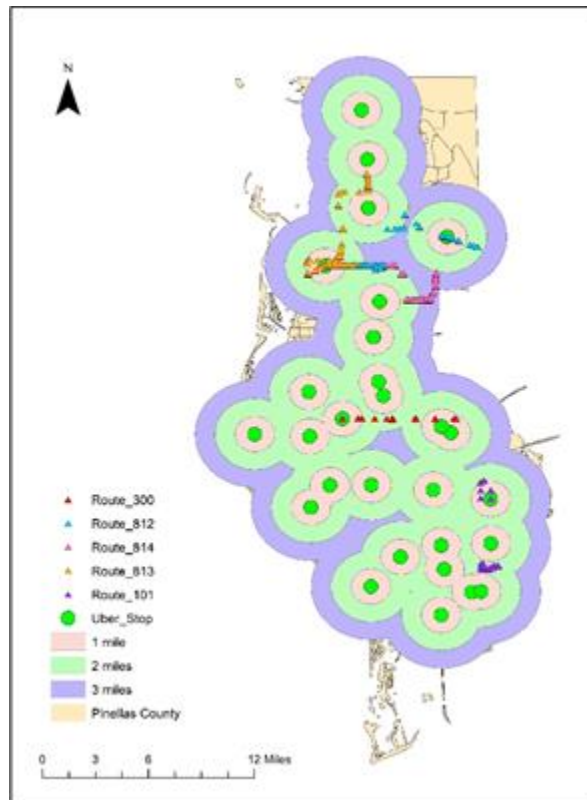


Figure 10.1.2 The Distance from Transit Stops to Designated Direct Connect Stops

Table 10.1.3 Users' Costs of Scenario 1

	UberPool	UberX	UberXL	Select	Uber Black
Total Ridership	91,341	91,341	91,341	91,341	91,341
Full Trip Fare	\$698,758	\$657,655	\$863,172	\$1,045,854	\$1,370,115
Passenger pays	\$242,053	\$200,950	\$406,467	\$589,149	\$913,410

Cost per passenger pays	\$2.65	\$2.20	\$4.45	\$6.45	\$10.00
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In summary, for the public transit agency, the use of Uber services to replace the less cost-effective bus route services has significant cost-saving potential. For transit users, this measure increases their travel costs. However, according to the estimated results above, the net benefit of the transit agency is \$2,077,185, which is much larger than the user’s increased cost, from \$242,053 to \$913,410. If the public transit agency increases the subsidy for each Uber trip to cover the minimum Uber fare, the public transit agency can still have a net benefit with the amount from \$1,163,775 to \$1,835,132 while offsetting the additional travel cost of users.

10.2 Evaluation of Scenario 2

The proposed measure in scenario 2 is to use PSTA’s own small vehicles to replace Uber’s role and provide the same first/last mile service as the recent Direct Connect program. The service offered by PSTA’s own small vehicles is free for users. The cost that this change will bring to PSTA, compared to the existing Direct Connect program, is the operating cost of the small vehicles, including the cost of the vehicle rental or purchase, maintenance, employee’s salaries, fuel, and other fees. The benefit brought to PSTA is the saving of the subsidy cost (\$5 per TNC ride) required by the original partnership program. There is no additional cost to the user because this measure provides the same services as the Direct Connect program. Since the proposed measure is a free service, users will also save the Uber fees that would be paid by themselves.

There is a program in Tampa, Florida called Downtowner, which provides microtransit service and works similarly to the measure proposed in this scenario. Downtowner is a free, on-demand

ridesharing service to fill the existing mobility gap of the transit system, ease the parking needs, and revitalize the local economy. The service time period is from 6 AM to 11 PM on weekdays and from 11 AM to 11 PM on weekends (Peng, 2020).

The Downtowner program leases small vehicles from leasing partners and operates them to offer ridesharing services to passengers. There were a total of five kinds of vehicles in operation, namely Gem, Bolt, Tesla, ADA, and Kia. The total Downtowner rides generated in 2017 and 2018 were 119,956 and 126,976. The annual budget of Downtowner operation is shown in Table 10.2.1, including vehicle costs, personnel costs, and management costs. Driver salary and field management fee, vehicle leasing fee, and program technology and management fee represented the largest portion of the total annual budget, all of them exceeding one hundred thousand dollars.

Table 10.2.1 Annual Budget of the Downtowner Operation

Budget Items	2017	2018	2019
Driver Salary and Field Management Fee	578,720	585,866	515,314
Vehicle Leasing Fee	136,691	136,568	104,228
Vehicle Storage Fee	4,525	10,630	13,755
Fuel	12,403	13,627	16,156
Maintenance	42,202	49,488	53,542
Vehicle Devices	4,789	4,496	5,081
Insurance	95,499	101,490	62,468
Other Expenses (e.g., vehicle cleaning)	8,689	8,809	6,846
Program Technology and Management	150,000	143,332	120,831
Total	1,005,340	989,113	877,524

Source: Evaluating the effectiveness and funding mechanism of the Downtowner service in Tampa, Florida for the statewide application, Peng, Z.R., 2020.

Since the mode of operation in the Downtowner program is similar to the proposed service in this scenario, the annual budget of the Downtowner program was used as a reference to estimate the small vehicle operating expenses of PSTA.

According to the report named evaluating the effectiveness and funding mechanism of the Downtowner service in Tampa, Florida for the statewide application, the service area of Downtowner was about 2.02 square miles and the ridership in 2018 was 119,956 (Peng, 2020). The population density in Downtown Tampa was 7,200 persons per square mile. Figure 10.2.1 shows the origin and destination pattern of the Downtowner rides. From this O-D pattern, the trip distances could be calculated based on Google Maps. The distance of most Downtowner rides was about 1.2 miles. The average wait time for each trip was about 17.5 minutes and the average trip time was about 6 minutes in 2019 (Peng, 2020). Also, there was a total of 12 vehicles operated by Downtowner service. Table 10.2.1 presents the annual budget of the Downtowner operation compared to the Direct Connect program. Driver salary and field management fee, vehicle leasing fee, vehicle storage fee, vehicle device, insurance, and other expenses were fixed costs, which were closely related to the number of vehicles, while fuel and maintenance costs were closely related to the trip distance. Program technology and management costs did not easily change with the number of vehicles and the number of trip miles (Peng, 2020).

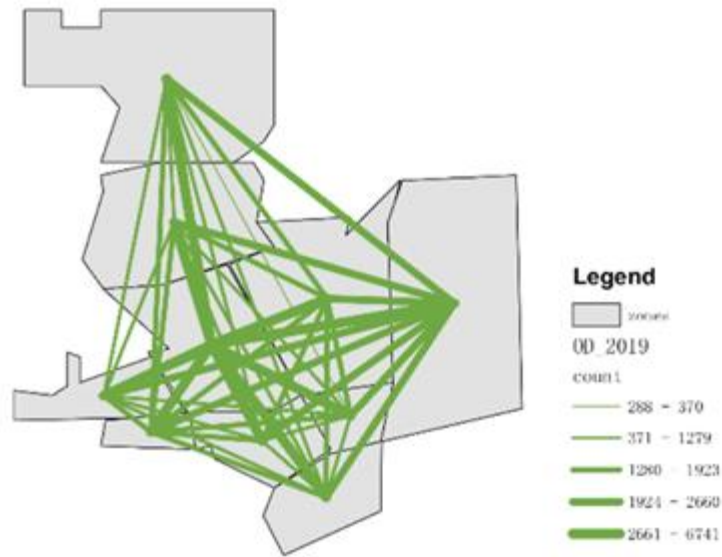


Figure 10.2.1 O-D Pattern of Downtowner Rides in 2019

Source: Evaluating the effectiveness and funding mechanism of the Downtowner service in Tampa, Florida for statewide application, Zhong, Z.R., 2020.

In terms of the Direct Connect program, the service area was 274 square miles, which was approximately 136 times the Downtowner service area. The population density of Pinellas County was about 3,558 persons per square mile. However, the annual ridership of the Direct Connect program in 2019 was 34,700, which was just 29% of the Downtowner riders. The average trip time was about fifteen minutes in 2019. The average trip distance of the Direct Connect program was 3.13 miles.

Table 10.2.2 Information about the Downtowner and the Direct Connect Program

	Service Area	Annual Rides	Population Density	Average Trip Mile	Area Covered/Vehicle	Average Trip Time
Downtowner	2.02 square miles	119,956	7,200 person/square mile	1.20 miles	1.44 square miles	6 min
Direct Connect	274 square miles	34,700	3,558 person/square mile	3.13 miles	9.79 square miles	15 min

Among all of the above conditions, we selected travel time as a measure to estimate the number of vehicles needed in the proposal and associated costs. The reason for choosing travel time over other conditions for the estimation is that it can include the time picking up passengers, the trip time driving passengers to the destinations, wait time, and the vehicle idle time, which is the time that there is no passenger on board. However, if other conditions are used for estimation, like service area and trip miles, only the trip time driving passengers to the destinations would be included in the estimation, while other kinds of times would be excluded, which can also generate operating costs. Then such an estimation method would lead to biased estimates. Therefore, to make a more accurate estimation of the number of vehicles and the costs in the proposal, the travel time was used.

The first step was to estimate the total travel time of the Downtowner program and calculate the travel time per vehicle per day. The total travel time includes the wait time, trip time, and vehicle idle time. According to the equations below, the travel time of the Downtowner in 2019 is 49,990 hours and the travel time that each vehicle needs to operate to meet the travel time demand is 11.4 hours per vehicle per day.

$$\text{Total Travel Time} = \text{Total Wait Time} + \text{Total Trip Time} + \text{Total Idle Time}$$

$$\text{Time/Vehicle} = \text{Total Travel Time} / N(\text{Vehicle})$$

Where,

Total Travel Time is the total travel time of the Downtowner in 2019;

Total Wait Time is the sum of the wait time for each trip of the Downtowner in 2019;

Total Trip Time is the sum of the trip time for each trip of the Downtowner in 2019;

Total Idle Time is the total idle time of the Downtowner in 2019;

Time/Vehicle is the travel time that each vehicle of the Downtowner operates in one day to meet the travel time demand;

N(Vehicle) is the number of the vehicle in the Downtowner program.

The second step was to estimate the travel time demand in Pinellas County. The number of trips and average trip time of the Direct Connect was used to make the estimation. According to the Uber data, the number of Uber trips in the Direct Connect program varies greatly at different time periods. 6 AM to 10 AM is the peak time period of the Uber trips. Because the vehicle services of the proposal need to meet the resident's travel demand in every time period, the peak time period, 6 AM – 10 AM, was selected for the estimation. If the number of vehicles in Pinellas County could meet the resident's travel demand in the peak time period, it can satisfy the travel demand in other time periods. The number of trips in Pinellas County from 6 AM to 10 AM in 2019 was 14,248. We assume the wait time for each trip in Pinellas County is 17.5 minutes (the same as the average waiting time as the Downtowner service). Additionally, we used the portion of idle time in the

total travel time in the Downtowner to estimate the idle time in Pinellas County. The total travel time demand in the peak time period is 28.7 hours.

Table 10.2.3 Travel Time Demand of the Peak Time Period of One Day in the Pinellas County Based on Two Wait Time Assumptions

Wait Time	Total Trip Time in Peak Time Period	Total Wait Time in Peak Time Period	Total Idle Time in Peak Time Period	Travel Time Demand in Peak Time Period
10 minutes/trip	21 hours	6.5 hours	1.2 hours	28.7 hours
17.5 minutes/trip	21 hours	11.4 hours	1.4 hours	33.8 hours

The third step was to estimate the number of vehicles needed in Pinellas County. According to the results in the first step, the travel time that each vehicle operates to meet the travel time is 11.4 hours per vehicle per day in the Downtowner. Because the peak time period in Pinellas County is four hours, the travel time for each vehicle in the Downtowner should be adjusted to four hours, which is 1.9 hours per vehicle per four-hours. According to the equation below, the number of vehicles needed in Pinellas County is 15 and 18 respectively.

$$Vehicle(P) = \frac{Travel\ Time\ Demand(P)}{Vehicle\ Travel\ Time\ (D)}$$

Where,

Vehicle(P) is the number of vehicles needed in Pinellas County;

Travel Time Demand(P) is the travel time demand of the peak time period in Pinellas County;

Vehicle Travel Time (D) is the travel time that each vehicle in the Downtowner operates in every four hours.

The fourth step was to estimate the costs of the proposal. In our estimation, the travel time of each vehicle is fixed, which means that the costs, including fixed cost and operating cost of each vehicle, are the same. Therefore, the ratio of the number of vehicles between the Downtowner and Pinellas County can be used to estimate the costs of the proposal in Pinellas County. However, the management and technology fare cannot be estimated according to the ratio of the number of vehicles, which should be the same for both programs. The results showed that if the number of vehicles in Pinellas County is 15, the annual cost of the proposal is \$1,066,697. If the number of vehicles in Pinellas County is 18, the annual cost of the proposal is \$1,255,870.

$$Cost(P) = Cost(D) * \frac{NVehicle(P)}{NVehicle(D)} + Administrative\ Expense(D)$$

Where,

Cost(P) is the annual costs of the proposal in Pinellas County;

Cost(D) is the annual costs of the Downtowner, except for the management and technology fare;

Administrative Expense is the management and technology fare of the Downtowner;

NVehicle(P) is the number of vehicles in Pinellas County;

NVehicle(D) is the number of vehicles in the Downtowner.

The last step was to compare the costs with the benefit. Two assumptions are made here. the first one is that if this service is the free service as described before, then the benefit of this proposal is the saving of the subsidy cost of the Direct Connect program, which is estimated based on the annual Uber rides. The benefit is about \$173,500. However, the costs of the proposal are \$1,066,697 and \$1,255,870 respectively, which far outweigh the benefit. The second assumption

is that this service is not free, and it will charge passengers \$3.90 for each trip. In the Direct Connect program, the average trip fare that passengers need to pay after receiving the subsidy is \$3.90. The reason why the service fee is set as \$3.90 is that we want to keep the trip fare of passengers the same as the Direct Connect program, which would not affect the passenger's travel demand. Under such a background, the benefit is the fare revenue and the saving of the subsidy cost of the Direct Connect program. Therefore, the benefit is \$308,830, which is still less than the costs of the proposal.

In summary, under the two assumptions of the service fare, when compared with the Direct Connect program, the costs of the proposal far outweigh the benefit. It means that the cost-saving ability of the transit-TNCs partnership is far greater than that of the proposal in Scenario 2 in which the transit agency operates its own vehicles to provide first/last mile service.

11. Result of Customer Satisfaction Survey

The objective of the surveys is to provide an overview of the performance of the Direct Connect and TD Late Shift services. Both Direct Connect and TD Late Shift Program were initiated in 2016. However, because of the COVID-19 pandemic, the people's daily traveling has been significantly influenced since March 11th, 2020. To better evaluate the performance of two programs, we design two circumstances for some survey questions: before and during the COVID-19. Detailly, the surveys intend to answer the following questions:

Users of Direct Connect Survey:

1. What is the background of the Direct Connect service users?
2. How do users know the Direct Connect service?
3. What is the travel behavior of Direct Connect service users (before and during the COVID-19)?
4. What are the users' concerns and suggestions?

Non-users of Direct Connect Survey:

1. What is the background of the Direct Connect service non-users?
2. What is the travel behavior of Taxi/Lift/Uber users (before and during the COVID-19)?
3. What is the travel behavior of Car users (before and during the COVID-19)?
4. What is the travel behavior of Transit users (before and during the COVID-19)?
5. What are the non-users' attitudes to the Direct Connect service?

TD Late Shift Users Survey:

1. What is the background of the TD Late Shift users?
2. How did the users know the TD Late Shift users?
3. What is the travel behavior of TD Late Shift users (before and during the COVID-19)?
4. What is the value of the TD Late Shift service (before and during the COVID-19)?
5. What are the users' concerns and suggestions?

The research team conducted customer satisfaction surveys by distributing questionnaires to Direct Connect Users, Direct Connect Non-users, and TD-Late shift users via email.

11.1 Direct Connect Users

The questionnaires for Direct Connect Users were distributed by the research team via email. The questionnaires were collected during the period from February 1st to March 31st in 2021. Among the total 70 collected questionnaires, 51 questionnaires were valid.

11.1.1 Background of the Users

Table 11.1.1 indicates that 96.08% of Direct Connect service users are “Residents”, while only 3.92% of users are “Tourists/Visitors”.

Table 11.1.2 shows that 82.35% of Direct Connect service users are in "36 – 64" age group and 13.73% of users are in ">65" age group. Table 11.1.3 & 11.1.4 presents that 64.71% of Direct Connect service users are male and white people (64.71%) are the main respondents.

Table 11.1.5 indicates that 37.25% of Direct Connect service users are “Employed full-time job”, 15.69% of users are “Employed part-time”, and 17.65% of users are “Retired”. Table 11.1.6 shows that 33.33% of users have annual household income “below \$25,000” and 31.37% of users have annual household income “\$25,000-\$49,999”.

Table 11.1.1 Direct Connect Service Users' Residence Status.

Answer	%	Count
Resident	96.08%	49
Tourist / Visitor	3.92%	2
Total	100.00%	51

Table 11.1.2 Direct Connect Service Users' Age-group Status

Answer	%	Count
18 - 34	3.92%	2
35 - 64	82.35%	42
65+	13.73%	7
Total	100.00%	51

Table 11.1.3 Direct Connect Service Users' Gender Status

Answer	%	Count
Female	35.29%	18
Male	64.71%	33
Total	100.00%	51

Table 11.1.4 Direct Connect Service Users' Ethnicity Status

Answer	%	Count
White	64.71%	33
African American	13.73%	7
Asian	5.88%	3
Hispanic	5.88%	3
Other	3.92%	2
I'd prefer not to answer	3.92%	3
Total	100.00%	51

Table 11.1.5 Direct Connect Service Users' Income Status

Answer	%	Count
Below \$25,000	33.33%	17
\$25,000-\$49,999	31.37%	16
\$50,000-\$99,999	15.69%	8
\$100,000-\$149,999	3.92%	2
Other / I'd prefer not to answer	13.73%	8
Total	100.00%	51

Table 11.1.6 Direct Connect Service Users' Employment Status

Answer	%	Count
Student	1.96%	1
Employed full-time	37.25%	19
Employed part-time	15.69%	8
Retired	17.65%	9
Unemployed, active job seeker	7.84%	4
Unemployed, not currently seeking a job	1.96%	1
Stay-at-home parent	3.92%	2
Other / I'd prefer not to answer	11.76%	7
Total	100.00%	51

11.1.2 How did the users know the Direct Connect Service?

Table 11.1.7 The Information Source to know Direct Connect Service

Answer	%	Count
PSTA website	43.14%	22
My employer/ colleague told me about the service	5.88%	3
Saw posters/flyers around	21.57%	11
Word of mouth/ friends/ family	13.73%	7
Other	15.69%	8
Total	100.00%	51

Table 11.1.7 shows that 43.14% of Direct Connect service users learned from “PSTA’s website”, while 21.57% of users learned from “Saw posters/flyers around”

11.1.3 Travel Behavior and Direct Connect Service Reflection

Table 11.1.8 shows that 45.10% of Direct Connect service users indicated it is very easy to use this service, and 33.33% of users indicated “Somewhat easy”. Table 11.1.9 presents that, before the COVID-19 outbreak, 39.22% of Direct Connect service users use the service “1 to 3 times per week” and another 39.22% of users use the service “4 to 6 times per week”. During COVID-19, 33.33% users use the service “0 times per week” and 39.22% users use the service “1 to 3 times per week”.

Table 11.1.10 indicates that 80.39% of Direct Connect service users use the latest service on weekdays, while only 33.33% of users use the latest service on weekends. Table 11.1.11 shows that 41.03% of users last used the service in the period between 01/2021 to 03/2021.

According to Table 11.1.12, before the COVID-19 outbreak, “Home” (76.47%) and “Workplace” (58.82%) are the most frequent origin and destination, and “Retail stores” (54.90%) are also a frequent origin and destination. During COVID-19, “Home” (52.94%) and “Workplace” (41.18%) remained the most frequent origin and destination.

Table 11.1.8 Direct Connect Service Users’ Attitude to the Ease of Using Transit Service

Answer	%	Count
Very challenging	1.96%	1
Somewhat challenging	9.80%	5
Neutral	9.80%	5
Somewhat easy	33.33%	17
Very easy	45.10%	23
Total	100.00%	51

Table 11.1.9 Direct Connect Service Users' Service Usage Frequency

Answer	BEFORE COVID-19		DURING COVID-19	
	%	Count	%	Count
0 times per week	3.92%	2	33.33%	17
1 to 3 times per week	39.22%	20	39.22%	20
4 to 6 times per week	39.22%	20	19.61%	10
7 to 9 times per week	5.88%	3	3.92%	2
Over 9 times per week	11.76%	6	3.92%	2
Total	100.00%	51	100.00%	51

Table 11.1.10 Direct Connect Service Users' Last Time Usage

Answer	%	Count
Weekday	80.39%	41
Weekend	19.61%	10
Total	100.00%	51

Table 11.1.11 Direct Connect Service Users' Last Time Usage (specific time)

Answer	%	Count
Earlier than 01/2020	10.26%	4
01/2020 - 06/2020	25.64%	10
06/2020 - 12/2020	23.08%	9
01/2021 - 03/2021	41.03%	16
Total	100.00%	39

Table 11.1.12 Direct Connect Service Users' Service Origin and Destination (Option to select more than one answer)

Answer	BEFORE COVID-19		DURING COVID-19	
	%	Count (out of 51)	%	Count (out of 51)
Home	76.47%	39	52.94%	27
Workplace	58.82%	30	41.18%	21
School	7.84%	4	3.92%	2
Retail Stores	54.90%	28	37.25%	19
Bank/Other Office	31.37%	16	23.53%	12
Restaurant	27.45%	14	7.84%	4
Hospital/Doctor	33.33%	17	23.53%	12
Place of Worship	9.80%	5	3.92%	2
Recreation Place	17.65%	9	9.80%	5
Hotel	0.00%	0	1.96%	1
College/University	9.80%	5	3.92%	2
Airport	11.76%	6	3.92%	2
Other	15.69%	8	11.76%	6
I didn't use the service BEFORE/DURING COVID-19	3.92%	2	25.49%	13

11.1.4 Suggestions of Direct Connect Users

Table 11.1.13 indicates 37.25% of Direct Connect service users chose “None” for service shortcomings, and 49.02% of users indicated “Other”. The Other suggestions (Table 11.1.14) include five aspects of service shortcomings: Difficulty using service, App related issues, Fares and Bonus related issues, Limited Direct Connect service, and Lack of TD-late Shift availability. In the future, PSTA needs to focus on those aspects to improve Direct Connect service.

Table 11.1.15 indicates that 50.98% of Direct Connect users do not need to transfer to transit service. Table 11.1.16 shows that 41.18% of users are “Satisfied” with the service, and 29.41% of users indicated “Very satisfied”.

Table 11.1.17 indicates that 49.02% of Direct Connect users would select “Uber/Lyft” if the Direct Connect service had not been available, 47.06% of users would select “Public bus”, and 39.22% of users would choose to “Walk”.

Table 11.1.18 shows that 68.63% of Direct Connect users use Direct Connect Service due to “Lower travel cost”, 52.94% of users are Unable to drive themselves, and 50.98% benefit from reduced travel time. The other suggestions show that Direct Connect service is user-friendly for disabled people and saves time over transit alone.

Table 11.1.13 Direct Connect Service Users' advice about Service Shortcomings (Option to select more than one answer)

Answer	%	Count (out of 51)
None	37.25%	19
Fares too expensive	11.76%	6
No bus services	13.73%	7
Cleanliness	1.96%	1
Too many transfers	5.88%	3
Commute takes too long	7.84%	4
Other [short answer]	49.02%	25

Table 11.1.14 Current Shortcomings of the Direct Connect Service – Other suggestion

- Difficulty using service
It is difficult to find Uber.
Some UBER staff is not familiar with the Direct Connect program.
Limited availability of Direct Connect service during busy times.
Direct Connect service is sometime unavailable.
- App related issues
Hard to get stop name correct.
Lack of clear service guide.
Unclear exact pickup site on App.
- Fares and Bonus related issues
Sometimes Direct Connect service is more expensive than UberX service.
Uber Direct Connect discount is not consistent.
- Limited Direct Connect service
Limited number of direct connect stops.
Need a designated pick-up spot.
- Lack of TD-late Shift availability
Some respondents complain about Direct Connect service is unavailable late night.

Table 11.1.15 Whether the users need to transfer to transit service after using Direct Connect service

Answer	%	Count
Yes	49.02%	25
No	50.98%	26
Total	100%	51

Table 11.1.16 Direct Connect Service Users' Satisfaction Level about Service

Answer	%	Count
Very satisfied	29.41%	15
Satisfied	41.18%	21
Neither satisfied or dissatisfied	11.76%	6
Dissatisfied	13.73%	7
Very dissatisfied	3.92%	2
Total	100%	51

Table 11.1.17 Direct Connect service Users' Alternative Travel Modes (Option to select more than one answer)

Answer	%	Count (out of 51)
I would not have made these trips	3.92%	2
Driven my own car	5.88%	3
Public bus	47.06%	24
Ride from friend or family	13.73%	7
Uber/Lyft	49.02%	25
Taxi	1.96%	1
Bicycle	13.73%	7
Walk	39.22%	20
Other, please specify	3.92%	2

Table 11.1.18 Direct Connect Service Users' Reason(s) to use this Service (Option to select more than one answer)

Answer	%	Count (out of 51)
Lower travel cost	68.63%	35
More comfortable	21.57%	11
Safety	29.41%	15
It reduces my travel time	50.98%	26
Unable to drive myself	52.94%	27
Other [short answer]	11.76%	6

11.2 Direct Connect Non-Users

The questionnaires for Direct Connect Non-users were distributed by the research team through the research team via email. The questionnaires were collected during the period from February 1st to March 31st in 2021. Among the total 24 collected questionnaires, 17 questionnaires were effective.

11.2.1 Background of the Direct Connect Non-users

Table 11.2.1 shows that all the Direct Connect service non-users are residents of Pinellas County. Table 11.2.2 indicates that 70% of Direct Connect service non-users are in the "36 – 64" age group, and over 20-percent of respondents are in ">65" age group. Tables 11.2.3 & 11.2.4 show that over 60% of non-users are female and white people (52.94%) are the majority of non-users.

Table 11.2.5 presents that 35.29% of Direct Connect service non-users have a full-time job, and 23.53% of non-users have a part-time job. Table 11.2.6 shows that 58.82% of non-users have an annual household income of less than \$25,000.

Table 11.2.7 indicates that 47.06% of Direct Connect service non-users choose "Transit" as their primary travel mode, 35.29% of non-users choose "Driving", and 11.76% and 5.88% of non-users choose "Uber/Lyft" and "Walk" respectively. Table 11.2.8 shows that 58.82% of non-users know about the Direct Connect Service. The following sections pertain to each type of Direct Connect non-user who took the survey.

Table 11.2.1 Direct Connect Service Non-users' residence Status

Answer	%	Count
Resident	100%	17
Tourist / Visitor	0%	0
Total	100%	17

Table 11.2.2 Direct Connect Service Non-users' Age-group Status

Answer	%	Count
18-34	5.88%	1
35-64	70.59%	12
>65	23.53%	4
Total	100%	17

Table 11.2.3 Direct Connect Service Non-users' Gender Status

Answer	%	Count
Female	64.71%	11
Male	29.41%	5
Other / I'd prefer not to answer	5.88%	1
Total	100%	17

Table 11.2.4 Direct Connect Service Non-users' Ethnicity Status

Answer	%	Count
White	52.94%	9
African American	17.65%	3
Hispanic	17.65%	3
Other / I'd prefer not to answer	11.76%	2
Total	100%	17

Table 11.2.5 Direct Connect Service Non-users' Income Status

Answer	%	Count
\$25,000-\$49,999	23.53%	4
< \$25,000	58.82%	10
Other / I'd prefer not to answer	17.65%	3
Total	100.00%	17

Table 11.2.6 Direct Connect Service Non-users' Employment Status

Answer	%	Count
Student	5.88%	1
Employed full-time	35.29%	6
Employed part-time	23.53%	4
Retired	17.65%	3
Unemployed, active job seeker	5.88%	1
Unemployed, not currently seeking a job	5.88%	1
Other / I'd prefer not to answer	5.88%	1
Total	100.00%	17

Table 11.2.7 Direct Connect Service Non-users' Main Travel Mode

Answer	%	Count
Driving	35.29%	6
Transit	47.06%	8
Uber/Lyft	11.76%	2
Walk	5.88%	1
Total	100.00%	17

Table 11.2.8 Do Non-users know about the Direct Connect Service in the Pinellas County

Answer	%	Count
Yes	58.82%	10
No	41.18%	7
Total	100.00%	17

11.2.2 Travel behavior – Taxi/Lyft/Uber Users

Table 11.2.9 shows that, before and during COVID-19, one Direct Connect service non-user used Taxi/Lift/Uber 1 to 2 times per week, while another one shows 6 to 8 times per week. Table 11.2.10 presents that, before the COVID-19 outbreak, one non-user spent less than \$10 per week and another one spent \$16-20 per week. During COVID-19, one non-user indicates he/she spent more than \$26 per week another one spent \$16-20 per week.

Table 11.2.9 Taxi/Lyft/Uber Users’ Travel Frequency

Answer	BEFORE COVID-19 outbreak		DURING COVID-19 outbreak	
	%	Count	%	Count
0 times	0	0	0	0
1-2 times	50%	1	50%	1
3-5 times	0	0	0	0
6-8 times	50%	1	50%	1
>8 times	0	0	0	0
Total	100%	2	100%	2

Table 11.2.10 Taxi/Lyft/Uber Users' Travel Cost

Answer	BEFORE COVID-19		DURING COVID-19	
	%	Count	%	Count
< \$10	50%	1	0	0
\$11-15	0	0	0	0
\$16-20	50%	1	50%	1
\$21-25	0	0	0	0
> \$26	0	0	50%	1
zero use BEFORE/DURING COVID-19	0	0	0	0
Total	100%	2	100%	2

11.2.3 Travel Behavior – Car Drivers

Table 11.2.11 shows that, before the COVID-19 outbreak, 50% of Direct Connect service non-users who choose driving as their main travel mode drive more than 8 times per week; whereas during COVID-19, 50% of these non-users drove 1 to 2 times per week. According to Table 11.2.12, the cost of parking per week has no statistical difference before and during COVID-19 and 83.33% of non-users spend less than 10 dollars for car parking in both periods.

Table 11.2.11 Car Drivers' Travel Frequency per Week

Answer	BEFORE COVID-19		DURING COVID-19	
	%	Count	%	Count
0 times	0	0	16.67%	1
1-2 times	0	0	50.00%	3
3-5 times	16.67%	1	33.33%	2
6-8 times	33.33%	2	0	0
>8 times	50.00%	3	0	0
Total	100%	6	100%	6

Table 11.2.12 Car Drivers' Parking Cost per Week

Answer	BEFORE COVID-19		DURING COVID-19	
	%	Count	%	Count
< \$10	83.33%	5	83.33%	5
\$11-15	16.67%	1	16.67%	1
\$16-20	0	0	0	0
\$21-25	0	0	0	0
> \$26	0	0	0	0
zero use BEFORE/DURING COVID-19	0	0	0	0
Total	100%	6	100%	6

11.2.4 Travel Behavior – Transit Users

Table 11.2.13 shows that, before the COVID-19 outbreak all Direct Connect service non-users who choose transit as their main travel mode indicated it is extremely easy or somewhat easy to use transit service, whereas during COVID-19 25% of them showed somewhat difficult to use transit service. According to Table 11.2.14, the travel methods to bus stops have no statistical difference before and during COVID-19 and 75% of non-users choose to walk to bus stops both two periods.

Table 11.2.15 shows that there is a similar trend before and during COVID-19; 65% of Direct Connect service non-users who choose transit as their main travel mode spend more than 15 min traveling from home to bus stops. According to Table 11.2.16, before and during COVID-19, 37.5% of non-users spend more than 15 min traveling from workplace to bus stops; however, non-users who spend less than 5 min traveling to bus stops decreased from 3 to 2 persons.

Table 11.2.17 shows that, before the COVID-19 outbreak, 62.5% of Direct Connect service non-users who choose transit as their main travel mode traveled more than 8 times per week, while, during COVID-19, 37.5% of transit users traveled more than 8 times per week.

Table 11.2.13 Transit Users' Attitude to the Ease of Using Transit Service

Answer	BEFORE COVID-19		DURING COVID-19	
	%	Count	%	Count
Extremely easy	50.00%	4	37.50%	3
Somewhat easy	50.00%	4	37.50%	3
Neither easy nor difficult	0	0	0	0
Somewhat difficult	0	0	25.00%	2
Extremely difficult	0	0	0	0
Total	100%	8	100%	8

Table 11.2.14 Transit Users' Travel Methods to Transit Stops

Answer	BEFORE COVID-19		DURING COVID-19	
	%	Count	%	Count
Walk	75.00%	6	75.00%	6
Bicycle	12.50%	1	12.50%	1
Scooter	0	0	0	0
Transit	12.50%	1	12.50%	1
Drive	0	0	0	0
Uber/Lyft	0	0	0	0
Others	0	0	0	0
zero use BEFORE/DURING COVID-19	0	0	0	0
Total	100%	8	100%	8

Table 11.2.15 Transit Users' Travel Time from Home to Transit Stops

Answer	BEFORE COVID-19		DURING COVID-19	
	%	Count	%	Count
< 5 min	37.50%	3	25.00%	2
5-10 min	0	0	12.50%	1
10-15 min	0	0	0	0
> 15 min	62.50%	5	62.50%	5
zero use BEFORE/DURING COVID-19	0	0	0	0
Total	100%	8	100%	8

Table 11.2.16 Transit Users' Travel Time from Workplace to Transit Stops

Answer	BEFORE COVID-19		DURING COVID-19	
	%	Count	%	Count
< 5 min	37.50%	3	25.00%	2
5-10 min	0	0	0	0
10-15 min	0	0	12.50%	1
> 15 min	37.50%	3	37.50%	3
zero use BEFORE/DURING COVID-19	25.00%	2	25.00%	2
Total	100%	8	100%	8

Table 11.2.17 Transit Users' Travel Frequency per Week

Answer	BEFORE COVID-19		DURING COVID-19	
	%	Count	%	Count
0 times	0	0	0	0
1-2 times	0	0	25.00%	2
3-5 times	25.00%	2	12.50%	1
6-8 times	12.50%	1	25.00%	2
>8 times	62.50%	5	37.50%	3
Total	100%	8	100%	8

11.2.5 Non-user's Attitudes

Table 11.2.18 shows that 64.71% of Direct Connect service non-users think that commuting takes too long via public transportation and 35.29% of non-users show other concerns. Non-users' other suggestions include two aspects: low bus route frequency and inconvenient transfer. Some of them say that they usually wait 30 minutes for a bus, and one of them suggests there were too many passengers during peak hours. Moreover, some non-users point out that the instructions for transfer connections on a mobile phone application are not clear.

Table 11.2.19 shows that 41.18% of Direct Connect service non-users indicated that they don't know how to use the App, 23.53% of non-users indicated that they drove their own car, and 29.41% of non-users indicated "Other reasons". Non-users' other suggestions show that the limited daily time period (the Direct Connect service is only provided before 8 pm) is one of reasons why they did not use this service, and poor routes and schedule are also reasons.

Table 11.2.20 shows that 47.06% of Direct Connect service non-users are willing to use Direct Connect service and 47.06% of non-users answer they may try it later.

Table 11.2.18 Direct Connect Service Non-users' Suggestions about Public Transportation
(Option to select more than one answer)

Answer	%	Count (Out of 17)
Fares too expensive	0.00%	0
Difficult to get to transit stations	11.76%	2
No bus services	5.88%	1
Cleanliness	11.76%	2
Too many transfers	17.65%	3
Commute takes too long	64.71%	11
Others	35.29%	6

Table 11.2.19 Direct Connect Service Non-users' Reason(s) for Not Using this Service (Option to select more than one answer)

Answer	%	Count (Out of 17)
My trip is within walk distance	11.76%	2
Drive my own car	23.53%	4
There are no bus servicing and destinations	5.88%	1
Don't know how to use the App	41.18%	7
Bus station is accessible	0.00%	0
The subsidy is too little	0.00%	0
Long time to wait the Uber	0.00%	0
Taking transit is time-consuming	5.88%	1
It is inconvenient to shift travel mode	0.00%	0
Worry about the safety issue	5.88%	1
Other reasons:	29.41%	5

Table 11.2.20 Direct Connect Service Non-users' Interest about this Service

Answer	%	Count
Yes	47.06%	8
Maybe	47.06%	8
No	5.88%	1
Total	100.00%	17

11.3 TD-Late Shift Users

TD-Late Shift questionnaire were distributed by the research team through mail. The questionnaires were collected during the period from February 1st to March 31st in 2021. 55 responses were collected, and 30 of them were effective.

11.3.1 Background of the TD-late Shift Users

Table 11.3.1 shows that all the users of the service are “residents” of Pinellas County.

Table 11.3.1 TD-late Shift Users’ Residence Status

Answer	%	Count
Resident	100.00%	30
Tourist/Visitor	0.00%	0
Other	0.00%	0
I'd prefer not to answer	0.00%	0
Total	100%	30

Table 11.3.2 TD-late Shift Users’ Age Group Distribution

Answer	%	Count
Under 18	0.00%	0
18 - 35	16.67%	5
36 - 64	80.00%	24
65+	3.33%	1
I'd prefer not to answer	0.00%	0
Total	100%	30

Table 11.3.3 TD-late Shift Users' Gender Distribution

Answer	%	Count
Male	36.67%	11
Female	60.00%	18
Non-binary / third gender	0.00%	0
I'd prefer not to answer	3.33%	1
Total	100%	30

Table 11.3.4 TD-late Shift Users' Ethnicity Distribution

Answer	%	Count
White	46.67%	14
Black or African American	36.67%	11
American Indian or Alaska Native	0.00%	0
Asian	6.67%	2
Native Hawaiian or Pacific Islander	0.00%	0
Other	6.67%	2
I'd prefer not to answer	3.33%	1
Total	100%	30

From Table 11.3.2, 11.3.3, and 11.3.4, we know that most of the users (80%) are in the "36 – 64" age group. 16.67% of people are in the "18 – 35" age group. 60% of the users are "female". "Black" people (36.67%) and "White" people (46.67%) are the two major user groups of the service.

Table 11.3.5 TD-late Shift users' Employment Status Distribution

Answer	%	Count
Employed full-time	56.67%	17
Employed part-time	30.00%	9
Stay-at-home parent	3.33%	1
Unemployed, active job seeker	10.00%	3
Unemployed, not currently seeking a job	0.00%	0
Retired	0.00%	0
Student	0.00%	0
I'd prefer not to answer	0.00%	0
Total	100%	30

About half of the users are “Employed full-time” (56.67%), some of the users are “Employed part-time” (30%), and 10% of them are “Unemployed, active job seeker”.

Table 11.3.6 TD-late Shift Users' Income Distribution

Answer	%	Count
Below \$25,000	86.21%	25
\$25,000-\$49,999	13.79%	4
\$50,000-\$99,999	0.00%	0
\$100,000-\$149,999	0.00%	0
Over \$150,000	0.00%	0
I'd prefer not to answer	0.00%	0
Total	100%	29

Most of the users are low-income people (86.21%), “Below \$25,000 per year”. A few people have an income between “\$25,000-\$49,999” (13.79%).

Table 11.3.7 TD-late Shift Users' Car Ownership Distribution

Question	0 cars	Count	1 car	Count	2 cars	Count	More than 2 cars	Count	Total
Before COVID-19	93.33%	28	6.67%	2	0.00%	0	0.00%	0	30
During COVID-19	90.00%	27	10.00%	3	0.00%	0	0.00%	0	30

Before COVID-19, 93.33% of users did not own a car, 6.67% of users had “1 car”, and no users had more than 1 car. During the COVID-19, 90% of users do not have a car, and 10% of users have “1 car”. We now know that some users bought cars during COVID-19.

Table 11.3.8 TD-late Shift Users' Special Transportation Need Distribution

Answer	%	Count
Yes	23.33%	7
No	73.33%	22
I'd prefer not to answer	3.33%	1
Total	100%	30

Table 11.3.9 TD-late Shift Users' Wheelchair Use Distribution

Answer	%	Count
Yes	6.67%	2
No	93.33%	28
I'd prefer not to answer	0.00%	0
Total	100%	30

In terms of the special transportation needs, about 23.33% of users have special transportation needs, and 6.67% of users use a wheelchair.

11.3.2 How do users found out about the TD-late Shift Service

Table 11.3.10 The Way that the Users Know the Service

Answer	%	Count
The TD Late Shift Website	14.55%	8
Social Media	0.00%	0
Word of mouth/ friends/ family	45.45%	25
Posters/Flyers	21.82%	12
Bus operators	3.64%	2
Other [short answer]	12.73%	7
I don't know the service	1.82%	1
Total	100%	55

45.45% of users learned about the service by “Word of mouth/friends/family”, and 21.82% of users learned through “Posters/Flyers”. 14.55% of users learned about the service through the official “TD Late Shift Website”, and 12.73% of users found out other ways.

11.3.3 Travel Behavior

Table 11.3.11 Last 12 Months Usage Distribution

Answer	%	Count
Yes	64.81%	35
No	35.19%	19
Total	100%	54

Table 11.3.12 Time of Last Service Use

Answer	%	Count
Within 1 Week	60.61%	20
Within 1 Month	9.09%	3
Within Last 3 Months	0.00%	0
Within Last 6 Months	30.30%	10
Total	100%	33

Table 11.3.11 and Table 11.3.12 show how frequent the users use the TD-Late Shift service. We can see 64.81% of users used the service within last 12 months. Among these users, 60.61% of users used the service “Within the 1 week”. 30.3% of users used the service “Within Last 6 Months”, and 9.09% of users used the service within the last month. We have no users whose last usage of the service is between 3 months and 1 month ago.

Table 11.3.13 Usage per Month

Question	1-5	Count	6-10	Count	11-20	Count	More than 20	Count	I don't use this service	Count	Total
Before the COVID-19	13.33%	4	3.33%	1	10.00%	3	73.33%	22	0.00%	0	30
During the COVID-19	6.67%	2	6.67%	2	16.67%	5	53.33%	16	16.67%	5	30

Furthermore, if we look at the usage per month, before COVID-19, 73.33% of users used the service “More than 20” times per month. 13.33% and 10% of users used the service “1-5” times and “11-20” times per month respectively. During COVID-19, 53.33% of users used the service “More than 20” times per month, and 16.67% of users used the service “11-20” times per month. 16.67% of users do not use the service at all.

Table 11.3.14 Time Spent Distribution (Before the Service was Provided)

Answer	%	Count
Less than 5 minutes	3.03%	1
6-15 minutes	18.18%	6
16-30 minutes	18.18%	6
31-60minutes	15.15%	5
More than 60 minutes	42.42%	14
I don't know	3.03%	1
Total	100%	33

Table 11.3.14 indicates that if the service was not provided, on average, 42.42% of users would spend “More than 60 minutes” getting to their destinations, 18.18% of users would spend “16-30 minutes”, and another 18.18% would spend “6-15 minutes”.

Table 11.3.15 Time Spent Distribution (After the Service was Provided)

Question	Before COVID	During COVID
< 5 min	13.33%	0.00%
Count	4	0
6-15 min	43.33%	50.00%
Count	13	15
16-30 min	36.67%	26.67%
Count	11	8
31-60 min	3.33%	3.33%
Count	1	1
> 60 min	3.33%	6.67%
Count	1	2
I don't know	0.00%	0.00%

Count	0	0
I don't use this service	0.00%	13.33%
Count	0	4
Total	30	30

After the service was provided, and before COVID-19, 43.3% of users spent “6-15 min” getting to their destinations. 36.67% of users spent “16-30 min”. After the service was provided, and during COVID-19, 50% of users spent “6-15 min” getting to their destinations. 26.67% of users spent “16-30 min”, and 13.33% of users stopped using the service. We can conclude that the service helps users save commuting time, and COVID-19 increased users' commuting time in general.

Table 11.3.16 Frequent Destination Distribution

Question	Before COVID	During COVID
Home	34.92%	29.31%
Count	22	17
Workplace	44.44%	41.38%
Count	28	24
School/ Daycare	1.59%	0.00%
Count	1	0
Bank/ Other Office	3.17%	3.45%
Count	2	2
Restaurant	3.17%	1.72%
Count	2	1
Hospital/Doctor	3.17%	5.17%
Count	2	3
Place of Worship	1.59%	1.72%
Count	1	1

Recreation Place	1.59%	1.72%
Count	1	1
Hotel	0.00%	0.00%
Count	0	0
The Second Home	3.17%	3.45%
Count	2	2
College/University	1.59%	1.72%
Count	1	1
Airport	1.59%	1.72%
Count	1	1
I don't use this service	0.00%	8.62%
Count	0	5
Total	63	58

Before COVID-19, 34.92% of users' frequent destination was "Home", and 44.44% was "Workplace". During COVID-19, 29.31% of users' frequent destination was "Home", and 41.38% was "Workplace". 8.62% of users did not use the service during COVID-19.

Table 11.3.17 Waiting Time Distribution

Question	1-5	Count	6-15	Count	16-30	Count	Over 30	Count	I don't use this service	Count	Total
Before COVID	26.67%	8	73.33%	22	0.00%	0	0.00%	0	0.00%	0	30
During COVID	13.33%	4	43.33%	13	20.00%	6	10.00%	3	13.33%	4	30

As for the service waiting time before COVID-19, 73.33% of users' service waiting time was "6-15" min. 26.67% of users waited "1-5" min for TD-Late Shift service. During COVID-19, 43.33%

of users' service waiting time was “6-15” min, and 13.33% waited “1-5” min. There was an obvious increase of service waiting time during COVID-19.

11.3.4 The Value of the Service

Table 11.3.18 Alternative Travel Modes Distribution (If the Service is not Provided)

Question	Before COVID	During COVID
I would not have made the trip	29.63%	34.00%
Count	16	17
Private Car	0.00%	4.00%
Count	0	2
Public Bus	25.93%	24.00%
Count	14	12
Ride from friend or family	11.11%	8.00%
Count	6	4
Uber/Lyft	11.11%	8.00%
Count	6	4
Taxi	0.00%	0.00%
Count	0	0
Bicycle	1.85%	2.00%
Count	1	1
Walk	20.37%	20.00%
Count	11	10
Total	54	50

Now, we discover the value of the service, as shown in the Table 11.3.18. Before COVID-19, if the service was not provided, 29.63% of users say “I would not have made the trip”. 25.93% of users would have taken “Public Bus”, 20.37% of users would have traveled by “Walk”, and 11.11% of users would have taken “Uber/Lyft”. During COVID-19, if the service was not

provided, 34% of users say “I would not have made the trip”. 24% of users would have taken “Public Bus”, 20% of users would have traveled by “Walk”, and 4% of users would have used the “Private Car”.

Table 11.3.19 Values Brought to Users Distribution

Question	New Job	Count	More Income	Count	Lower Travel Cost	Count	Safety	Count	More time with family	Count	I don't use this service	Count	Total
Before COVID	12.94%	11	22.35%	19	18.82%	16	23.53%	20	21.18%	18	1.18%	1	85
During COVID	11.43%	8	24.29%	17	15.71%	11	21.43%	15	18.57%	13	8.57%	6	70

Before COVID-19, 23.53% of users think the greatest value of the service for them is “Safety”. 22.53% of users think the service brought “More Income”, 18.82% of users think the service “Lower(s) Travel Cost”, and 12.94% of users think the service gives them or makes them a chance to have a “New Job”. During COVID-19, 24.29% of users think the service brought “More Income”. 21.43% of users think it increases “Safety”, 15.71% of users think the service “Lower(s) Travel Cost”, and 11.43% of users think the service gives them or makes them a chance to have a “New Job”.

11.3.5 Users' Concerns and Advice

Table 11.3.20 Concerns Before COVID-19 Distribution (With 1 Being the Most Important and 6 Being the Least Important)

Question	1	Count	2	Count	3	Count	4	Count	5	Count	6	Count	Total
Cleanliness	20.00%	6	6.67%	2	13.33%	4	13.33%	4	10.00%	3	36.67%	11	30
Expand Service Area	0.00%	0	30.00%	9	23.33%	7	20.00%	6	20.00%	6	6.67%	2	30
Add More Trips per Month	20.00%	6	23.33%	7	23.33%	7	16.67%	5	10.00%	3	6.67%	2	30
Lower Fares	6.67%	2	13.33%	4	16.67%	5	20.00%	6	26.67%	8	16.67%	5	30
Reduce Waiting Time	3.33%	1	13.33%	4	13.33%	4	26.67%	8	20.00%	6	23.33%	7	30
Expansion of Service Hour	50.00%	15	13.33%	4	10.00%	3	3.33%	1	13.33%	4	10.00%	3	30

Table 11.3.20 shows Users' Concerns and Advice before COVID-19. 50% of users think that "Extend the Service Time" is their first need. 30% of users think "Expands Service Area" is the second need. The least important need is "Cleanliness".

Table 11.3.21 Concerns during COVID-19 Distribution (With 1 Being the Most Important and 7 Being the Least Important)

Question	1	Count	2	Count	3	Count	4	Count	5	Count	6	Count	7	Count	Total
Cleanliness	10.00%	3	16.67%	5	16.67%	5	13.33%	4	6.67%	2	16.67%	5	20.00%	6	30
Expand Service Area	3.33%	1	20.00%	6	16.67%	5	23.33%	7	20.00%	6	13.33%	4	3.33%	1	30
Add more Trips per Month	26.67%	8	13.33%	4	20.00%	6	10.00%	3	10.00%	3	10.00%	3	10.00%	3	30
Lower Fares	0.00%	0	10.00%	3	13.33%	4	16.67%	5	26.67%	8	23.33%	7	10.00%	3	30
Reduce Waiting Time	10.00%	3	10.00%	3	6.67%	2	20.00%	6	13.33%	4	26.67%	8	13.33%	4	30
Expansion of Service Hour	23.33%	7	20.00%	6	13.33%	4	10.00%	3	13.33%	4	0.00%	0	20.00%	6	30
Sanitary Safety (related to the COVID)	26.67%	8	10.00%	3	13.33%	4	6.67%	2	10.00%	3	10.00%	3	23.33%	7	30

On the contrary, during COVID-19, 26.67% of users think that " Sanitary Safety (related to the COVID) " is the first need, and another 26.67% think "Add More Trips per Month" is also the first need. 20% of users think "Expansion of Service Hours" is the second need, and another 20% of users think "Expand Service Area" is also the second need. The least-desired need is still the "Cleanliness".

Table 11.3.22 Shortcomings of the Service (Users' Opinion)

Question	Before the COVID	During the COVID
Fares Too Expensive	9.80%	12.73%
Count	5	7
25 Trips per Month is not Enough	35.29%	29.09%
Count	18	16
Cleanliness	9.80%	10.91%
Count	5	6
Too Many Transfers	5.88%	1.82%
Count	3	1
Commute Takes Too Long	9.80%	7.27%
Count	5	4
Safety	15.69%	16.36%
Count	8	9
Sanitary Concern (related to COVID-19)	13.73%	21.82%
Count	7	12
Total	51	55

The shortcomings of the service from user's opinions before COVID-19 are shown in Table 11.

3.5.3. 35.29% of users think "25 Trips per Month is not Enough". 15.67% of users think the

shortcoming is “Safety”. During COVID-19, 29.09% of users still think the shortcoming is “25 Trips per Month is not Enough”. 21.82% of users think the shortcoming is “Sanitary Concern (related to COVID-19)”. 16.36% of users think “Safety” is a shortcoming, which implicates the users expect the protective measures of COVID-19 can be further improved.

Table 11.3.23 Satisfaction Level

Question	Before COVID	During COVID
Very Satisfied	73.33%	60.00%
Count	22	18
Satisfied	16.67%	10.00%
Count	5	3
Neither Satisfied nor Unsatisfied	6.67%	6.67%
Count	2	2
Dissatisfied	0.00%	0.00%
Count	0	0
Very Dissatisfied	0.00%	6.67%
Count	0	2
I don't use this service	3.33%	16.67%
Count	1	5
Total	30	30

For the overall satisfaction level before COVID-19, 73.33% of users are “Very Satisfied”, and 16.67% of users are “Satisfied”. 6.67% of users are “Neither Satisfied nor Unsatisfied”. During COVID-19, 60% of users are “Very Satisfied”. 10% of users are “Satisfied”. 6.67% of users are “Very Dissatisfied”. 16.67% of users did not use the service during COVID-19. The overall satisfaction level decreased during COVID-19.

Table 11.3.24 Other Opinions from Users

Service Time & Area related	Lower monthly cost and do 30 days instead of 25.
	Standard service from 10 p.m. to 7 a.m.
	Full - month trip, Shorter Wait time with lower fare.
	Expanding service area.
Disability related	Driver Must Have Space in His Car trunk for disable people's walker.
Safety Concern	Background checks for the drivers.
	Please always have a cab company as an option because I would never take an Uber or Lyft for safety concerns.
Others	Made it easier to be eligible and to be manage in the transportation Apps.

Other opinions from users can be separated into four categories: Service Time & Area, Disability, Safety Concern, and others. In the Service Time & Area, most of the users would like the service to have a higher monthly cap and a longer running time. In the Disability category, users prefer the service provide more space for disabled people. As for the Safety Concern, users would like the service carrier to improve the safety of the service. Others are related to the improvement of the service App.

12. Panel Data Model Analysis

12.1 Data source

In panel data (Table 12.1.1), the study used bus ridership data from PSTA as a dependent variable and the Direct Connect ridership data from Uber Technologies, Inc as an independent variable. Because the bus stops' ridership is highly related to employment, population, income-level, car-ownership, and accessibility to jobs in surrounding blocks, the study added those factors as control variables into the panel data model. In terms of bus ridership data, the study used the average four-month bus onboarding ridership on weekdays and weekends at 130 bus stops from July 2018 to February 2020. In terms of the Direct Connect ridership data, this study used the four-month Direct Connect offboarding ridership on weekdays and weekends at 26 eligible stops in the same period. Moreover, this study took the natural logarithm of each variable.

Table 12.1.1 Variable description and data source in Panel data model.

Variables	Description	Data sources
Dependent variables		
ln(BusRide.a)	The average number of bus onboarding ridership for weekdays in four months [Busridership/month] (in natural logarithm form)	PSTA
ln(BusRide.b)	The average number of bus onboarding ridership for weekend in four months [Busridership/month] (in natural logarithm form)	
Independent variables		
ln(Uber.a)	The average number of Uber offboarding ridership for weekdays in four months in Eligible stops	Uber Technologies, Inc.,

	[Uberridership/month] (in natural logarithm form)	
ln(Uber.b)	The average number of Uber offboarding ridership for weekend in four months in Eligible stops [Uberridership/month] (in natural logarithm form)	
ln(Income)	Median household income in \$1000 (in natural logarithm form)	ACS ^a
ln(Access)	Total jobs by cumulative accessibility within 30 mins transit weighted by employment (in natural logarithm form)	Access Across America: Transit 2017
a. American Community Survey (ACS) Source: U.S. Census Bureau, 2015. Selected demographic characteristics, 2015–2019, American Community Survey 5-year estimates. Retrieved on 6.2021, from https://www.fgdl.org/metadateexplorer/explorer.jsp		

12.2 Methodology

This study uses panel data models to explore whether the Direct Connect program positively impacts transit ridership in Pinellas County. The panel data models can estimate the influence of the Direct Connect trips on the bus ridership with data across time and individuals. Since the number of bus ridership is changing over time as well as the number of Direct Connect riders, it is necessary to consider the impacts of the increase of the Direct Connect trips on each bus stop in different time periods. If the study uses only the cross-sectional data to investigate the impact of average Direct Connect ridership in a year on the average bus ridership in the same periods, it is ambiguous whether the increase of Direct Connect ridership significantly influences the bus ridership every month or only in certain periods.

Moreover, the panel data model can also increase observations to better estimate the influence of the Direct Connect ridership on bus ridership. Since the Direct Connect ridership dataset contains only information in 26 eligible stops, observations recording the impacts of Direct Connect

ridership in each eligible stop on the surrounding ridership of bus stops are insufficient. By recording the DC ridership in multiple time periods, panel data models can duplicate the number of observations.

This study assumes that the Direct Connect ridership in one eligible stop directly influences the ridership of bus stops located within its surrounding 800-foot buffer. Due to lack of data recording the transfer process of the Direct Connect users, this study has only two datasets: the data recording the number of bus onboardings and offboardings at each bus stop from July 2018 to February 2020 and the data recording the number of the Direct Connect onboardings and offboardings in each eligible stop from the same period. Because the Direct Connect policy requires users' trips to stop at a place within the 800-foot buffer of eligible stops, this study assumes that the Direct Connect users usually transfer from the Direct Connect service to transit service at those bus stops within 800 feet of eligible stops. Therefore, the hypothesis in this study supposes that the increase or decrease of Direct Connect ridership at one eligible stop has direct impacts on the number of ridership at bus stops within the 800-foot buffer of this eligible stop.

The methodology to explore the impact of the Direct Connect offboardings on the amount of bus onboardings is Pooled Ordinary Least Squares (OLS) regression. According to Greene (2003), the basic framework of models for panel data is shown below:

$$y_{it} = x'_{it}\beta + z'_i\alpha + \varepsilon_{it}$$

In the model for panel data, the study uses subscript i and t to denote individuals and time. The individual in this study is each eligible stop. For instance, the observation y_{it} is observed for the cumulative bus onboarding within 800 feet of eligible stop $i = 1, \dots, K$ across time periods $t = 1, \dots, T$. In this equation, x_{it} includes the number of Uber trips ended within 800 feet of eligible

stop $i = 1, \dots, K$ across time periods $t = 1, \dots, T$. Moreover, $z'_i \alpha$ is the heterogeneity that z_i contains a constant term and a set of individual or group-specific variables (i.e., income level and access to job), which could be observed or unobserved, and all of them are taken to be constant over time t . And ε_{it} is the error term. In accordance with Greene (2003), various cases should be considered in this model. Here is the situation to use Pooled OLS model: when z_i is observed for all individuals or contains only a constant term, the entire model can be viewed as “an ordinary linear model and fit by least squares” (Greene, 2003).

12.3 Results

In the Pooled OLS model, about 47-percent of observations on weekdays and weekends can be explained by the model. There is more than a 90-percent confidence level that the increase of 1 percentage of Direct Connect trips ending at the surrounding area will lead to a 0.116 percentage increase of onboarding riders for bus stops on weekdays. However, the impact of Direct Connect ridership is not significant on the number of bus onboarding on weekends. In the Pooled OLS model, access to jobs shows a positive influence on bus onboarding. However, the median income level in the surrounding area of bus stops has negative impacts on onboarding.

Table 12.3.1 Estimation Results for Panel Models (Weekdays)

Variables	Pooled OLS
lnUber.a	.116*
lnIncome	-1.891***
lnAccess	.931***
Constant	6.107***
R-squared	0.470
observation	135
***significant at 1 percent; **significant at 5 percent; *significant at 10 percent.	

Table 12.3.2 Estimation Results for Panel Models (Weekends)

Variables	Pooled OLS
lnUber.b	.087
lnIncome	-2.261***
lnAccess	.876***
Constant	7.858***
R-squared	0.460
observation	135
***significant at 1 percent; **significant at 5 percent; *significant at 10 percent.	

13. Summary

We explored the spatiotemporal characteristics of users (research question 1), conducted the spatiotemporal analysis and summarized the change of Uber ridership and public transit ridership over the three years, and analyzed the Direct connect service trip patterns and fare of trips in different periods of a day and in different days of a week. To understand the determining factors influencing the trips of the Direct Connect program (research question 2), we have conducted the geographically weighted regression model (GWR) to analyze the local relationship between the Uber ridership in the weekday and weekend and the predicted factors. To figure out whether the partnership can improve the cost-effectiveness or reduce the cost of the transit system and what are the alternative funding strategies to make the program sustainable (research question 3), we evaluated the impact of the transit-TNCs partnership on transit ridership and whether the alternatives can reduce more costs than the current partnership; however, more evidence needs to be found to determine whether the transit-TNCs partnership was the cause of the cost-effectiveness decline. Finally, we analyzed the customer satisfaction surveys to understand how people use the Direct Connect service and their customer experience, what main travel modes non-users use and their attitudes towards the Direct Connect program, and how people use TD-Late shift and their suggestions.

13.1 Spatiotemporal Pattern

To explore the spatiotemporal characteristics of users who participated in the Transit-TNC partnership program, we had conducted a spatiotemporal analysis on the Direct Connect rides over the past three years (2018 to 2020). Collectively, we summarized the following three conclusions that correspond to the abovementioned research questions:

(1) Overall, between the second quarter of 2018 and the first quarter of 2020, Uber's quarterly travel volume rose significantly before declining from the third quarter of 2019. The growth time period coincides with the implementation of the third phase of the Direct Connect program, which shows that the Direct Connect program has contributed greatly to the increase of Uber travel. Uber's monthly travel trends are consistent with quarterly travel trends. However, in February 2020, there was a significant drop due to the spread of COVID-19; the stay-at-home order constrained people's mobility. The peak hours of Uber travel are 6am to 10am and 3pm to 7pm; the average number of Uber trips between 6am and 10am and between 3pm and 7pm are significantly higher than that in other time periods. Between April 2018 and March 2020, the daily average Uber ridership varied widely. The daily Uber ridership on Monday to Thursday is the highest (129 trips per day), which is about four times the daily Uber ridership on Saturday and Sunday (33 trips per day). The daily Uber ridership on Friday is slightly the lowest with 11 trips per day.

Between February 2018 and January 2020, public transit ridership showed an overall trend of growth, with a total increase of about 22,000 trips. According to the ridership data from American Public Transportation Association (APTA), since 2014, national transit ridership has continued to decline. The ridership in 2018 was reduced by 2.5% from the previous year, which has dropped below 10 million trips, returning to the level of 2005 (Mallett. M., 2019). Therefore, compared with the national trend of transit ridership, Pinellas transit ridership increased greatly due to the Direct Connect Program.

In line with Uber's trips, Monday to Thursday is also the peak period for public transit; the ridership of each day of which was significantly higher than that on Friday and during

the weekend by roughly 10,000 trips. The performance of each bus line also varies widely, with ridership ranging from 1,300 trips to 461,105 trips per four months. Routes 52, 18, 34, 4, 35, 19, and 59 are the fixed-routes with the highest ridership, while Routes 0, 813, and 812 are the lowest-performing routes.

- (2) Time of Day Pattern: By reviewing trip patterns and fare of trips in different periods of a day, we find that peak hours are during the periods from 6 am to 10 am and 3 pm to 7 pm, which have more blocks and stops with trips. Based on origins, we find the census blocks located in the east part of the county and the pilot stops located in the south part of the county have more trips and higher fares. Although there are more trips and higher mean fare at census blocks located in the east part of the county based on destinations, the destination pilot stops with more trips are spread all over the county. Moreover, OD patterns in time of day represent that Park St & S Garden Ave at the northwest, Pinellas Park Transit Station at the southeast, and Pasadena Ave & Sun Island Dr S at the south side of the county are traveling centers, which have the most origins and destinations.
- (3) Day of week Pattern: As for the day of week pattern, trips that occurred from Monday to Thursday hold the main share of the overall trips that happened in a week. The weekend also accounts for several trips in a week, and Friday has the least share of the total trips in a week. Mostly, from Monday to Thursday, trips start from areas around Missouri Ave N, Seminole Blvd, Ulmerton Rd, 34th St N, U.S. 19, and Grandy Blvd, and end in areas similar to the departure areas. Origins and destinations of trips that happened on Friday and during the weekend are quite evenly distributed. When we see trips from the perspective of pilot stops, most of the pilot stops are used frequently (over 6 trips per day

on average, either the origin or destination stops) from Monday to Thursday. Few pilots have more than 6 trips on average on either Friday or during the weekend.

In terms of fare, from Monday to Thursday, areas around the intersection of Ulmerton Rd and 66th St N have higher fare, but the same is not true for Friday or the weekend. Most origin stops with an average fare over \$5 are located on U.S. 19 and 66th St. N on any given day. A few destinations stops had an average fare exceeding \$5 on different days of a week; and they are located on Ulmerton Rd, 66th St N and Seminole Blvd.

13.2 GWR Regressions for the Determining Factors

13.2.1 GWR for Direct Connect Program

Table 13.2.1 Summary of GWR regressions result.

Variable	Model for Weekday			Model for Weekend		
	Significance Level	Coefficient Estimates	Spatial Difference	Significance Level	Coefficient Estimates	Spatial Difference
Education level	Significant	Negative	South part of county	Significant	Negative	Southeast part of the city
Median income	Significant	Negative	South part of county	Significant	Negative	Southwest part of the city
Median age	Significant	Negative	The whole county	Limited Significant	Negative	Northeast part of the city
Population density	Insignificant			Insignificant		
Employment density	Insignificant			Insignificant		
Percentage of Female	Significant	Positive	North part of county	Insignificant		

Percentage of Black	Significant	Positive & Negative	North & South part of county	Insignificant		
Percentage of Hispanic	Significant	Positive	Northwestern part of the county	Insignificant		
Road network density	Insignificant			Insignificant		
Sidewalk density	Insignificant			Insignificant		
Land use mix	Insignificant			Insignificant		
Access to jobs	Significant	Positive	North part of county	Limited Significant	Positive	The most north part of the city
Note: Limited Significant means that the variable is significant at 90 percent confidence level at some places at best. Spatial difference represents the place with the highest Significant Level.						

The geographical weighted regression analysis indicates that seven variables including Female percentage, Hispanics percentage, Black percentage, education level, median income, median age, and access to the job have significant impacts on weekday Uber ride demand. In the north part of the county, the Uber ridership is positively affected by Female percentage, Black percentage, and Access to job. In the south part of the county, the Uber ridership is negatively influenced by Black percentage, education level, and median income. Moreover, in the northwestern part of the county, the percentage of Hispanics has a positive impact on the Uber ridership. It is worth noting that the increase of median age can cause a negative impact on Uber ridership in almost the whole county. We also found employment and population density, land use mix, road network density and sidewalk density are not significantly correlated to the Uber ridership.

We tested 12 independent variables for the average daily Uber trip demand during the weekend; however, compared to the weekday model, the results are quite different. Eight independent

variables are totally insignificant (Percentage of Female, Percentage of Black, Percentage of Hispanic, Population Density, Employment Density, Land Use Mix, Road Network Density, and Sidewalk Density), two independent variables are partly significant at 90% confidence level (Median Age and Access to Job), and only two independent variables are significant but have a limited impact on the dependent variable (Education Level and Median Household Income). Among these four significant variables, the Education Level is the most influential variable among all variables affecting the travel demand during the weekend.

In short, for the average daily Uber trip demand during the weekend, the Education Level and Median Household Income are the two variables that should be taken into account. Other variables are either totally insignificant or have a too weak relationship with the travel demand to be considered.

13.2.2 GWR for TD-Late Shift Program

GWR model results imply the spatial pattern of ridership and the spatial relationship between the ridership and socio-demographic and built environment variables. For the socio-demographic variables, education level has a negative impact on the ridership at the county center, this is because people with a higher education level probably will not have a job at late night, and TD-Late Shift is targeting low-income people who normally have a lower education level. And as shown in Figure 8.1.2.2 (a) and Figure 8.1.2.4, blocks with lower education level overlap with blocks with high poverty rate at county center, and people with high education level are clustered at the peripheral of the county. Therefore, the blocks at the center are mainly resided by people with lower education level, so they might have a job at night and hence having a positive impact on the TD-Late Shift ridership. This negative correlation counters the findings of Yu & Peng (2019) and Correa et al. (2017). This is caused by the differences between this late-night shift program and

other types of programs. Percentage of black has positive impacts at county center and south part of the county. This can also be explained by the target population of the TD-Late Shift program and black people are more likely to be low-income people in Pinellas County, which is shown by the overlaps between the high percentage of black blocks and high poverty rate blocks in Figure 8.1.2.2 (b) and Figure 8.1.2.4. This positive relationship is more evident at the center than that in the south part of the county, because there are many people work at the county center which generates many to-home ridership, resulting in the more intense positive relationship between percentage of black and the ridership. Percentage of male is not significant enough but still have a positive impact at county center. The reason for this is because male is more likely to have a job at late night or in early morning than female does, the result of TD-Late Shift User Survey proves that by showing most of users (61.29%) are male, but this difference is not obvious enough to make the percentage of male have a stronger significant impact on the ridership. Alemi et al. (2018) used female as a dummy variable and found female has a positive impact on the Uber ridership, but what they analyzed is the normal daily ride demand of Uber which is different from the specific ride demand at late night or early morning in our analysis. Percentage with a disability is not significant in this study. For built environment variables, household density has a negative impact at the county center, this negative relationship contradicts the finding of Yu & Peng (2019); Correa et al. (2017), Zhang (2016). And one reason for this negative correlation is that the household density at the county center is low as shown in Figure 8.1.2.3 (a), causing less to-work ridership and more to-home ridership originated from the census blocks at county center. So, there are less household density at the county center but there still will be many to-home ridership. For other parts of the county, the inconsistent relationship between the household density and ridership resulted in the insignificant relationship. Population to employment entropy has a negative impact

at the middle part of the county which is in consistence with the findings of Yu & Peng (2019). It means the census blocks with a better balance between employment and population tend to have a lower ridership. This negative correlation can be explained by the theory that a balanced land use planning (commercial and residential) can mitigate the usage of motorized mode and encourage the usage of non-motorized mode (Wedagama, 2006) and this theory is also true for this late-night shift program. Insignificant relationship is observed in other parts of the county, this is caused by the variation of the relationship between population to employment entropy and ride demand. Access to job has a positive impact on the ridership at most of parts of the county except for the upper-center part, and this positive impact is stronger toward the county center which is resulted from the higher marginal growth of ridership than that of access to job. Yu & Peng (2019) also proved a same correlation for ridership of TNCs in Austin. This is intuitive since the census block with higher accessibility to job tend to have more to-work ridership. The less significant level at the upper-center part of the county is caused by some degree of inconsistent relationship exists between access to job and rider demand. Celsor & Millard-Ball (2017) and Correa et al. (2017) proved the 0-car ownership will increase the ridership of TNCs. In our study, percentage of household with 0 vehicle also has a positive impact on the ridership at the south part of the county. This is because most of households who have no car are located at the south and middle-west parts of the county (as indicated in Figure 8.1.2.3 (d)), and the TD-Late Shift service connected their home to workplace. But the percentage of household with 0 vehicle at middle-west part displays different impacts on the ridership and therefore resulting in an insignificant impact (Figure 8.1.2.3 (d) and Figure 8.1.2.1). Road density has a positive impact on ridership at the south part of the county where the census blocks with higher poverty rate clustered. Same correlation was found by Yu & Peng (2019), Correa et al. (2017) and Qian & Ukkusuri (2015). However, this correlation

does not have a strong significant level which implies that the road density is not an influential variable for the rider demand of TD-Late Shift program.

13.3 Cost Efficiency

The purpose of this research was to evaluate the TNC-Transit partnership program to figure out the impacts of partnership on the transit ridership and whether the partnership can improve the cost-effectiveness or reduce the cost of the transit system. To achieve the research purpose, three questions should be answered. The first question is what is the impact of the transit-TNCs partnership on transit ridership? The second one is what is the impact of the transit-TNCs partnership on the cost-effectiveness of the public transportation system? The third one is whether the alternatives can reduce more costs (from the perspective of transit agency and users) than the current partnership? This research successfully answered the first and third questions, while the second question was not fully answered. The research only evaluated and compared the cost-effectiveness of the entire transit system. However, further research that contains the cost-effectiveness analysis of the Direct Connect program is needed to answer whether the decline of the cost-effectiveness of the transit system was caused by the partnership.

There are three major findings in this research. The first one was that the transit-TNCs partnership had a significant positive impact on transit ridership. With every increase of one unit in the Uber trip, the transit ridership would increase by seven units. The second finding was that the cost-effectiveness of the entire Pinellas County transit system kept declining from FY 2011 to FY 2019. However, further research containing the cost-effectiveness analysis of the Direct Connect program was needed to prove that the transit-TNCs partnership was the cause of the cost-effectiveness decline. The third finding was about the cost-saving potential of the improvement of

the partnership. It was found that replacing the five least-utilized fixed routes of the Pinellas transit system with Uber service had significant cost-saving potential for the transit agency. However, the alternative that using the transit agency's own vehicles to replace the transit-TNCs partnership could not achieve the cost-saving goal and even resulted in more cost to the transit agency.

The findings concluded in this research could serve as the evidence and reference for policymakers or transportation planners to make policy decisions. This also provided new ideas or alternatives for people who seek to form transit-TNCs partnerships in the future. The major findings in this research suggested that the transit-TNCs partnership had the potential to increase transit ridership and reduce costs. This partnership can be a choice for policymakers to solve the service problems where the transit system is not cost-effective, or where the first/last mile connection service is lacking. What is more, this study adopted a quantitative research method to evaluate the performance and economy of the Direct Connect program in Pinellas County, which enriched the current single evaluation method of the transit-TNCs partnership, the qualitative case study.

13.4 Customer Satisfaction Survey

13.4.1 Direct Connect User

For the Direct Connect service, most of users are low-income residents of Pinellas County in age group between 35 to 64 years old. In terms of information source to know Direct Connect services, 43.14% of users know it from PSTA website. As for the users' travel behavior, most of users (78.43%) use the service 1 to 6 times per week before COVID, however, 72.55% of users use the service 0 to 3 times per week. In terms of users' service origin and destination, Home and Workplace are the most frequent origin and destination before and during COVID. According to the survey, service advice suggested by 49.02% of users include five aspects of service

shortcomings: Difficulty to use service, App related issues, Fares and Bonus related issues, Limited Direct Connect service, No Introduce to TD-late Shift. Moreover, most of Direct Connect service users are satisfied with the service, and their major alternative travel modes are public bus, Uber/Lyft, and walk. As for the reasons that respondents use Direct Connect service, Lower travel cost, Unable to drive myself, and It reduces users' travel time are the main reasons.

13.4.2 Non-Direct Connect User

For the respondents who do not use Direct Connect service, most of them are low-income residents of Pinellas County in the age group between 35 to 64 years old. In terms of non-users' main travel mode, 47.06% of Direct Connect service non-users choose transit as their primary travel mode, 35.29% of non-users choose drive, and 11.76% and 5.88% of non-users choose Uber/Lyft and Walk respectively. For car users before the COVID-19 outbreak, 50% drive more than 8 times per week, whereas during COVID-19, 50% of non-users drive 1 to 2 times per week. 62.5% of Direct Connect service non-users who choose transit as the main travel mode travel more than 8 times per week before COVID, while only 37.5% of transit users travel more than 8 times per week during COVID. Moreover, 65% of Direct Connect service transit users spend more than 15 min traveling from home to bus stops before and during COVID, and 37.5% of them spend more than 15 min traveling from workplace to bus stops before and during COVID. As for the non-users' attitudes to public transit, 64.71% of Direct Connect service non-users think that commute by bus takes too long. In terms of the reasons for not using Direct Connect service, 41.18% of Direct Connect service non-users indicate that they Don't know how to use the App, 23.53% of non-users indicate that they Drive their own car, and 29.41% of non-users indicate other reasons.

13.4.3 TD Late Shift users

For the TD Late Shift service, most of the users are low-income residents of the Pinellas County, and most of them (93.33%) have No “Private Car”. In terms of the way they know about the service, about half of users (45.45%) know the service “By the Word of Mouth/Friends/Family”. As for the users’ travel behavior, more than half of them (73.33%) use the service “20 times a month” before COVID; however, during COVID, this percentage has decreased to 53.33%. According to the survey, the service decreased the average commuting time after the service was provided. But during COVID, user’s average commuting time had been increased. Before COVID, the travel destination of 34.93% of users was “Home”, and 44.44% was “Workplace”; these percentages remained nearly unchanged during COVID. Definitely, COVID increased the service waiting time, and more users would not make trip during COVID. For the value of the service before COVID, “Safety” is most valued by users (23.53%); whereas, during COVID, “More Income” brought by the service is most valued by users (24.29%), and “Safety” is at the second place (21.42%). There are also some concerns and suggestions from users. Before COVID, 50% of users think the “Service Time” should be extended, and 30% of users think the “Service Area” should be extended as well. During COVID, both “COVID Sanitary Concern” and “More Trips per Month” are the first concerns of users. Also, the satisfaction level has decreased during COVID (60% users are “Very Satisfied” compared to 73.33% before the COVID). The suggestions for the service are related to “More Trips per Month”, “Longer Service Time” and “Larger Service Area”. Needs of persons with disabilities and safety are also mentioned.

13.5 Panel Data Model Results

According to the results from Pooled OLS model, one percentage increase of Direct Connect trips that ended in the surrounding area will increase about 0.116 percentage of onboarding for

all nearby bus stops on weekdays. In addition, the Direct Connect Program has increased residents' accessibility and mobility even when some Direct Connect trips do not result in adding to the bus trips. Moreover, the study found that access to jobs has a positive influence on the bus ridership, while household median income has a negative impact on the bus ridership. Erhardt et al. (2021) also found that accessibility has a positive and significant influence on the transit service. Furthermore, Erhardt et al. (2021) pointed out that the areas with proximity to low-income households are related to higher transit ridership.

13.6 Recommendation

13.6.1 Direct Connect Program

This study provides several recommendations to improve the existing Direct Connect Program. First, the study suggests increasing service accessibility (i.e., more eligible stops) at the middle-west and southeast parts of Pinellas County since the Direct Connect trips were mainly generated and distributed in those areas.

Second, the study found that people living in the neighborhoods with lower income and education levels are more likely to use this program; therefore, service accessibility should be increased in those areas.

Third, the study recommends replacing the least cost-effective fixed routes (i.e., route 300, 812, 813, and 814) with the Transit-TNC partnership.

Finally, according to the questionnaire survey results, the study suggests providing more detailed mobile phone application instructions since the many users indicate that it is hard to find the exact pickup site on App and the instruction on App is not clear and sufficient.

However, although the impacts of the Direct Connect program on transit ridership could be estimated through using regression models, data sharing and collecting are still the main barriers for program's service improvement. Due to private companies' concerns about the business secret and privacy of their data, there are two different sets of data to analyze the performance of the Direct Connect program. Therefore, the analysis of the Direct Connect program's performance could only be estimated rather than observed. The study believes that data-sharing agreements between TNCs and public agencies, which allow them to track user transfer process, would largely improve the service quality of the Direct Connect program.

13.6.2 TD-Late Shift Program

The GWR model determines the spatial relationship between the ridership of the TD-Late Shift program and the socio-demographic and built environment variables. The results indicate that at the center of the county, education level and household density have significant negative impacts and the percentage of black residents has a significant positive impact on the ridership.

Population to employment entropy has a significant negative impact on the ridership in the middle part of the county. At the south part of the county, the percentage of black residents and households with no vehicle have significant positive impacts on ridership. Resident access to jobs has a significant positive impact on the ridership in most parts of the county, except for the upper-middle part. Therefore, in order to increase the ridership of the program, the policy makers should promote the TD-Late Shift service according to these spatial ride demand characteristics.

The survey results indicate that the COVID-19 pandemic increased the average waiting time of the service and overall commuting time of users. And COVID-19 also made people focus more on attaining more income instead of attaining safety from the service. The service cap per month needs to be expanded and service area or service hour need to be extended too, as

indicated by the users before and during the COVID-19 period. Furthermore, the survey presented that there are two groups of users holding different attitudes towards COVID-19; therefore, both the improvements of sanitary safety and extending the service hours during COVID-19 should be considered. The overall satisfaction level decreased during the COVID-19 pandemic. All in all, the program is still significant to users and competitive since the results reveal a similar percentage of people before and during COVID-19 would not have made the trip if the TD-Late Shift service was not provided. To further improve the service, the policy makers should first consider extending the monthly cap, service hour or service area. Then, during COVID-19, more preventive measure should be conducted to solve the sanitary concerns of users. For example, PSTA can ask Uber to distribute free sanitizers to drivers and riders. Masks could be required for both riders and drivers, and the punishment mechanism should be applied for the violation of mask regulation. Other improvements could include more disability care and better service Apps, as indicated in the last open-ended question. For instance, the App could offer the option of larger accommodating vehicles for disabled people to store their crutches or wheelchairs.

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