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Impact of Transitways on Travel on Parallel and Adjacent Roads and Park-and-ride Facilities

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IMPACT OF TRANSITWAYS ON TRAVEL ON PARALLEL AND ADJACENT ROADS AND PARK-AND-RIDE FACILITIES

FINAL REPORT

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EXECUTIVE SUMMARY

Transitways such as light rail transit (LRT) and bus rapid transit (BRT) provide fast, reliable and high-capacity transit service, mostly for longer trips. Transitways have the potential to attract more riders and take a portion of the auto mode share, reducing the growth of auto traffic. Studying such an effect and validating it with real data are crucial for future transit planning and evaluation. Park-and-ride (PNR) facilities can complement transit service by providing a viable choice for residents who are without walking access to transit or those who prefer better transit service such as LRT or BRT. Little is known about how PNR users choose the location where they park and take transit, or whether they consider network topology, PNR types, daily activities, etc. In this study, we conduct two research tasks. One is to examine the impact of the operation of the Green Line LRT on the annual average daily traffic (AADT) of its adjacent roads, and the other is to estimate the PNR location choice model in the Twin Cities metropolitan area in Minnesota.

In the first task, we examined the impact of the Green Line LRT on road traffic. Using traffic data before and after its opening, we applied a quasi-experimental design to compare AADT on the roads within and outside of the LRT-influence areas. We employed multivariate analyses to control for confounding factors such as transit service, land-use variables, and road-function classes. We found that compared with the roads outside the influence area, the Green Line reduced AADT on the roads within its influence area by about 22% in the first two years of operation. In the next two years, the AADT bounced back by about six percentage points. These findings suggest that rail transit can reduce traffic on adjacent roads, but there is a rebound effect.

In the second task, we provided insight into the travel behavior and preferences of PNR users in the Twin Cities. From an on-board survey conducted by Metro Transit in 2016, we used 1,690 PNR users' route choices to estimate a discrete choice model. We applied the precise coordinates of their origin, destination, and parking location to calculate travel time experienced by each PNR user, as well as aspects of their transit path, such as walking time, waiting time, and required number of transfers. Further, we used attributes of each PNR facility to model preferences for quality of service. We considered route overlap and measured it with a path size factor and a nested logit model. The estimated models showed significant evidence that travel time with a car is perceived as approximately four times more costly/burdensome than the same amount of time traveled by transit. We also found that PNR users do not strictly minimize total travel time when choosing their commute route. Ultimately, the best-fitting model correctly predicted the PNR choice for 64% of users in a test sample. We extended this study to define travelsheds for people commuting to the University of Minnesota using the previously estimated multinomial logit model. After assigning each travel analysis zone (TAZ) in the Twin Cities metropolitan area to a given PNR travelshed, the total population served by each PNR facility was inferred.

The contribution of this study to the literature is threefold. First, it uses a quasi-experimental design and controls for confounding factors to study the causal relationship between rail transit deployment and vehicular travel demand. Thus, it produces more accurate estimates of rail transit effects than previous studies. Second, our empirical model shows that the Green Line reduced road traffic, but its effect decreased over time. These findings suggest that both induced demand and induced development could be at work. Third, we consider overlapping routes in studying PNR choice. While previous literature on station choice has investigated the relationship between routes that share a transit path, no studies specific to PNR choice have considered the matter.

CHAPTER 1: INTRODUCTION

Rail transit has been deployed to mitigate vehicular travel demand and stimulate transit-oriented development in the US. Total vehicle miles traveled (VMT) in the US were 3.25 trillion in 2019, 20% more than 20 years ago (FHWA, 2020). The increase in vehicular travel lessons various transportation-related issues, such as traffic congestion and air pollution. For example, the average daily congestion time[1] among the 52 largest metropolitan areas in the US exceeded four hours in 2018 (FHWA, 2019). To promote transit use and slow the growth in VMT, many regions have built rail transit systems that offer better quality of service (such as, higher reliability and frequency) than traditional buses. In 2017, the number of rail transit systems in the US totaled 88, 70% more than 20 years before (APTA, 2019). The total length was 11,498 miles in 2017, among which light rail transit (LRT) accounted for 17.7% (BTS, n.d.).

Because rail transit requires high subsidies, quantifying its effectiveness is critical for policymakers to garner public support for rail transit investment. For example, the Blue Line LRT commenced in the Minneapolis-St. Paul (Twin Cities) metropolitan area in 2004 and the capital cost of this 12-mile route was greater than $700 million (Metropolitan Council, 2011). Furthermore, rail transit is becoming more expensive. The Green Line extension, a 14.5-mile route under construction, has an initial budget of about $2 billion (Metropolitan Council, 2020). Given this, planners and policymakers must assess the benefits of rail transit to justify their investment.

To evaluate its transportation impact, many scholars have examined the influence of rail transit on road traffic (Bhattacharjee & Goetz, 2012; Ewing, Tian, Spain, & Goates, 2014; Giuliano, Chakrabarti, & Rhoads, 2016). For example, Bhattacharjee and Goetz (2012) compared VMT on highway road segments before and after the opening of three light rail lines in Denver, CO, between 1992 and 2008. They suggested that the three lines reduced the increase in highway traffic.

Previous studies, however, often have two limitations. First, they do not account for the effects of confounding factors (such as transit supply and land use along the roads) on road traffic, and omitting these important confounders leads to biased estimates of the rail transit effects. In particular, when a rail transit line is deployed in a corridor, transit agencies adjust bus routes as necessary in and/or near the corridor to optimize the benefits of the transit system. For instance, the Green Line LRT in the Twin Cities completely replaced Route 50 bus service and substantially reduced the service frequency of Route 16 (Metro Transit, 2014). Changes in bus supply may alter the vehicular travel demand in the corridor. In addition, individual responses to rail transit depend on land-use patterns within its vicinity (Huang, Cao, Yin, & Cao, 2019). For example, commercial and industrial uses may generate different travel outcomes. Second, few studies test whether the impact of rail transit on road traffic changes over

[1]Congestion time is the number of hours "when freeways operate less than 90% of free-flow freeway speeds" (FHWA, 2019, p. 2). It is measured from 6 am to 9 pm on weekdays.

time. Rail transit can generate new development along the corridor (Cervero, 1994; Guthrie & Fan, 2013), resulting in an increase in trips to the corridor (Cervero, 2003).

Park-and-ride (PNR) facilities can complement transit service by providing a viable choice for residents who are without walking access to transit or those who prefer better transit service such as LRT or BRT. Little is known about how PNR users choose the location where they park and take transit, or whether they consider network topology, PNR types, daily activities, etc. The Twin Cities metropolitan area offers more than 100 PNR facilities served by express bus, heavy rail, and light rail that give commuters a variety of ways to reach their destination. Between 2004 and 2015, PNR usage in the Twin Cities grew by nearly 60% but has decreased slightly since 2015 (Nelson, 2017). As parking becomes more difficult to find in downtown Minneapolis and Saint Paul, improving PNR service will be essential to the region's pursuit of mobility and environmental goals.

To address these gaps, we conduct two research tasks in this study. In the first task, we examine the impact of the Green Line LRT on road traffic in the Twin Cities using traffic data before and after its opening. This task applies a quasi-experimental design to compare the annual average daily traffic (AADT) on the roads within and outside of the LRT-influence areas. We employ multivariate analyses to control for confounding factors including transit service, land-use variables, and road-function classes. This task attempts to answer the following two research questions: (1) How does LRT influence AADT of the road segments within its service area? And (2) how does the influence change over time?

In the second task, we provide insight into the travel behavior and preferences of PNR users in the Twin Cities. From an on-board survey conducted by Metro Transit in 2016, we use 1,690 PNR users' route choices to estimate a discrete choice model. We apply the precise coordinates of their origin, destination, and parking location to calculate the travel time experienced by each PNR user, as well as aspects of their transit path, such as walking time, waiting time, and required number of transfers. Further, we use the attributes of each PNR facility to model preferences for quality of service. Given the PNR that each user chose to use, we generate a choice set of reasonable alternatives from the facilities shown in Figure 1. We consider route overlap and measure it using a path size factor and a nested logit model. Finally, we conclude this task with an application of the estimated choice model to determine PNR travelsheds for those commuting to the University of Minnesota. For each travel analysis zone (TAZ) in the metropolitan region, commuters are assigned to the most likely PNR based on the previously estimated choice model, resulting in a spatial understanding of the areas and populations served by each PNR facility.

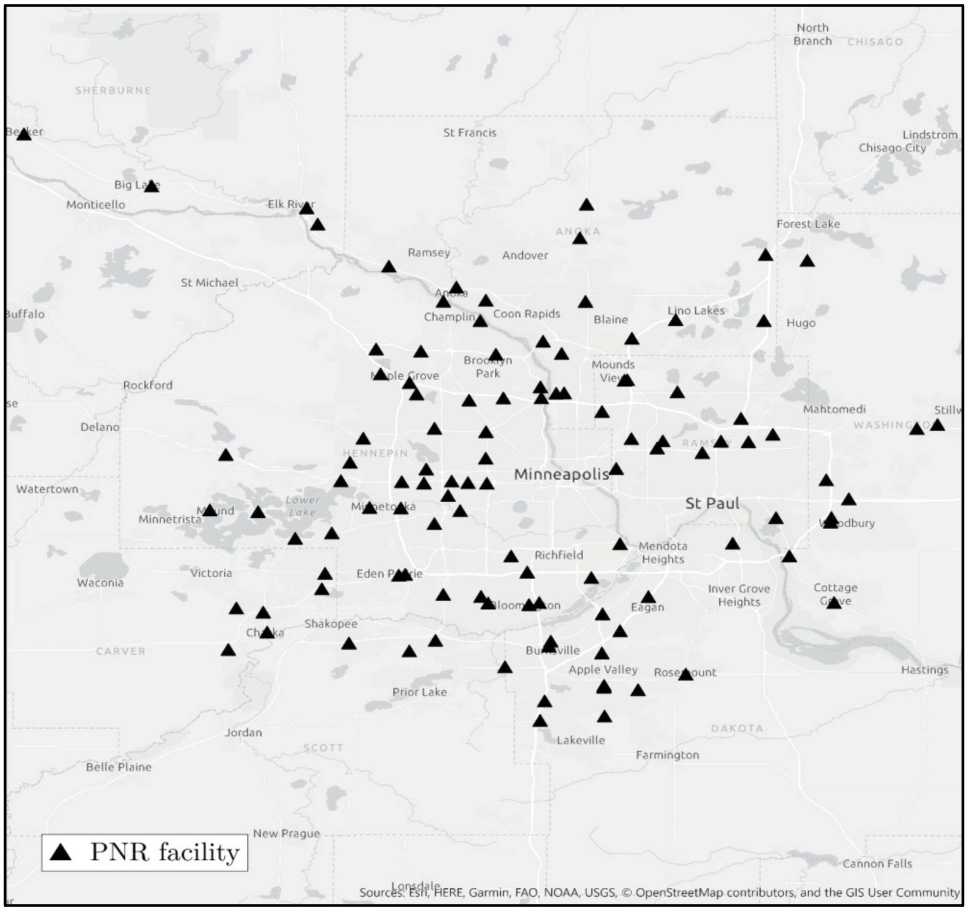

Figure 1. Twin Cities park-and-ride facilities

The rest of the report is organized as follows. Chapter 2 reviews the current literature about the impact of rail transit on travel demand and PNR location choice. Chapter 3 introduces the method and results of the first task. Chapter 4 then introduces method, results, and application of our second task. And finally, we conclude our research in Chapter 5.

CHAPTER 2: LITERATURE REVIEW

2.1 LITERATURE ON THE IMPACT OF RAIL TRANSIT ON TRAVEL DEMAND

Many studies examine the influence of rail transit on vehicular travel demand. Scholars address this issue through both disaggregate and aggregate studies. Disaggregate studies focus on travel demand of individuals or households (Cao and Ermagun 2017; Spears, Boarnet, and Houston 2017; Jiang and Mondschein 2019). For example, Spears, Boarnet, and Houston (2017) surveyed 285 households near the Exposition light rail in Los Angeles, CA and compared their daily VMT before and after its opening. They found that households living within one-kilometer of the rail transit drove approximately ten miles fewer than those living farther away.

Disaggregate studies unveil how rail transit influences vehicular travel demand at the individual level, such as mode choice, trip frequency, and VMT. They have a few limitations. First, respondents may underreport their daily travel or vehicle use (Wolf, Oliveira, & Thompson, 2003). For example, individuals may misunderstand the meaning of trips in travel diaries or forget to record short trips. This underreporting results in inaccurate estimates. Second, although travel behavior analysis provides information on the impact of rail transit on individuals, it often does not consider complementarity and competition among travelers in a constrained transportation system (Levinson & Krizek, 2018, p. 11). People make trade-offs when facing constraints. However, once the constraints are relaxed, latent demand is unleashed. For example, after individuals switch from driving to rail transit after its opening, road congestion (and travel cost) decreases, making room for new vehicular trips that would have not occurred otherwise or the trips shifting from other routes, times, and modes. Third, by using travel diaries, transportation engineers and planners do not know when and where individual trips occur in the transportation system. However, understanding temporal and geographical distributions of vehicular travel is essential to effective transportation system management and travel demand management.

Aggregate studies explore the influence of rail transit on vehicular demand in the transportation system (Bhattacharjee & Goetz, 2012; Giuliano et al., 2016). Compared with disaggregate studies, they do not suffer from those aforementioned issues. In aggregate studies, variables of interest are attributes of road segments or specific areas, such as travel speed, VMT, and AADT. For example, Giuliano and her colleagues (2016) compared rush-hour travel speeds of highway segments adjacent to the Exposition light rail before and after its opening finding that it has no significant effect. By contrast, Bhattacharjee and Goetz (2012) concluded that LRT in Denver reduced the growth in VMT on the highways in its influenced areas. Ewing et al. (2014) compared AADT of road segments before and after the opening of two extensions of the TRAX line at the University of Utah. They found that the extensions reduced AADT. These studies provide insights on rail transit effects on the performance of transportation systems and thus offer technical evidence for policymaking.

Another way to assess the role of transit is to examine the impact of a transit strike, an immediate shock to the transportation system (Adler & van Ommeren, 2016; Lo & Hall, 2006). Adler and van Ommeren (2016) measured the performance of transportation systems during transit strikes in Rotterdam, Netherlands and compared it with that during regular days. They found that the strike substantially increased the travel time on the roads in the inner city, but marginally affected the performance of ring roads. This study illustrates the role of transit in mitigating traffic by examining traffic conditions without transit. However, since transit strikes are scarce events, studies on their effect are limited. More importantly, as a response to short-lived transit strikes, individuals choose lower-cost strategies to mitigate the impacts (Mokhtarian, Raney, and Salomon 1997; Cao, Wongmonta, and Choo 2013). This incorrectly estimates the importance of transit in the transportation system.

The divergent impacts of the transit strike in Rotterdam on traffic in different areas suggest that individuals' responses are confounded by third-party variables. Urban areas have better transit services and are more densely developed than suburban areas, so urban residents use transit more often than suburbanites. Once transit becomes unavailable, urban residents are more likely than suburbanites to switch travel modes. Therefore, it is plausible that a more substantial impact was observed in the inner city. Similarly, the impact of rail transit on road traffic may be confounded by transit supply and land uses. For example, feeder buses help connect rail transit with riders outside of its catchment areas. More feeder buses attract more auto drivers to use rail transit (Ding, Cao, & Liu, 2019; Gan, Yang, Feng, & Timmermans, 2020). Moreover, rail transit increases property values (Cao and Lou 2017; Mathur 2020) and stimulates new development (Cao and Porter-Nelson 2016) along the corridor. Land use changes likely alter travel demand. However, few studies control for confounding variables when examining the effects of rail transit.

The influence of rail transit on road traffic may change over time, but few studies examine how the change evolves. Firstly, the traffic in the vicinity of rail transit is likely to rebound gradually. Downs (1992) proposed the *principle of triple convergence*: capacity increase or reduced vehicular demand attributable to policy interventions (e.g., telecommuting or transit-oriented development) will be offset by the demand switched from other modes, times, and routes. After the opening of a rail transit line, some individuals switch from driving to transit. As a result, roads adjacent to the rail line become less congested. Because it is more convenient to use these roads, individuals who use alternative roads change their routes. Similarly, some transit users switch back to driving and those who change their trip departure time to beat the traffic may also switch back. Sooner or later, the roads will become congested again. Second, transit investments, particularly rail transit, can bring about changes in population, employment, and land uses around transit station areas (Baker & Lee, 2019; Cervero, 1994). Induced development will attract more traffic to the corridor (Cervero, 2003). Therefore, the effect of rail transit on vehicular travel demand in its vicinity should be dynamic. Some studies discuss this in their results. Giuliano, Chakrabarti, and Rhoads (2016) speculated that the insignificant effect of the Exposition light rail was due to the large latent travel demand in the corridor. Bhattacharjee and Goetz (2012, p. 262) claimed that rail transit could slow down the increase of highway travel demand "for a short period of time." However, most studies do not differentiate the impacts of rail transit in the after-opening period.

2.2 LITERATURE ON PARK-AND-RIDE LOCATION CHOICE

Station choice modeling first appeared in academic literature in the mid-1970s, and is now an established application of discrete choice modelling (Young & Blainey, 2018). Most often, researchers have used revealed preference data to frame station choice as a utility maximization process. Among the most common findings in station choice modelling is a negative effect of distance from origin to station on station choice (Chakour & Eluru, 2014; Debrezion, Pels, & Rietveld, 2009; Kastrenakes, 1988). In the earliest study to report this finding the researcher created a binary variable indicating if a station was ”local” to a given user, and found this variable along with access time to be the most influential factors in station choice (Kastrenakes, 1988). Another study modeled Dutch Railway station choice as a share of postcode area demand, and not only found a negative effect of access distance, but found a steeper negative effect of access distance on non-motorized access modes compared to motorized access modes (Debrezion et al., 2009). Finally, a study of commuter train station choice around Montreal validated these results, showing a negative effect of access time by mode on station choice (Chakour & Eluru, 2014). Transit frequency has also commonly been found to have a positive effect on station choice (Chakour & Eluru, 2014; Debrezion et al., 2009). Due to differences between transit networks, some of these key findings should be interpreted with caution. For example, studies that found a positive effect of transit frequency on station choice were conducted on rail transit systems with regular headways. In the Twin Cities, PNR facilities are largely served by express buses with irregular headways, and therefore station choice may have a different relationship with transit frequency.

The relatively limited body of literature specific to PNR station choice may offer the most relevant findings to this study. A study from Perth, Australia used a stated preference survey to estimate a multinomial logit model for PNR station choice along a rail network (Olaru, Smith, Xia, & Lin, 2014). The findings indicate that quality of facilities and surrounding land-use most significantly influence PNR station choice. Similar to station choice literature which found access distance to be significant, this study observed 60% of PNR users boarding at the nearest station to their origin. These results may not be widely applicable, however, as each PNR user is assumed to face a choice between exactly two PNR locations. This limitation is partially addressed by a study of PNR station choice in Toronto, in which train riders face a choice between the five nearest stations and subway riders choose between the three nearest stations (Mahmoud, Habib, & Shalaby, 2014). The study found that access distance and the direction of the station from their origin were the strongest predictors of station choice. The study is further limited by a lack of driving and transit path attributes. A study from Austin, Texas provides the most relevant framework for analyzing PNR station choice in the United States (Pang & Khani, 2018). The authors used on-board survey data to estimate passenger’s travel path, using a street network representation to model shortest-path access times, and a schedule-based shortest path algorithm to model transit paths (Khani, Hickman, & Noh, 2014). Among the findings are preferences for higher transit frequency, transit in-vehicle time less than ten minutes, and shorter walking times. This recent study is significant for including detailed transit path information, as well as its application of choice modelling to a transit system where express buses are the dominant service.

Across the literature, several methodological themes exist. First, most studies define a choice set such that each user’s station choice is between a fixed number of stations (Debrezion et al., 2009; Mahmoud et al., 2014; Olaru et al., 2014; Sharma, Hickman, & Nassir, 2017), while a minority of studies define a more flexible choice set (Chakour & Eluru, 2014; Pang & Khani, 2018). Fixed choice sets are easy to define and manage, but may also be highly influential in a model’s understanding of choice behavior.

Flexible choice sets are formed using some criteria to determine which stations are reasonable or unreasonable alternatives for a given user. For example, one study defines a reasonable alternative path as one whose total travel time does not exceed the shortest total travel time plus 50 minutes (Pang & Khani, 2018). This type of choice set definition is preferable to a fixed definition as it does not dictate the size of a choice set, but rather eliminates extreme alternatives based on observed behavior. Second, most studies use Euclidean distance to measure the distance between a user's origin and each reasonable station (Debrezion et al., 2009; Kastrenakes, 1988; Mahmoud et al., 2014). One study improved upon this methodology by using a network representation of the roads in Austin, Texas to approximate each user's experiences driving time (Pang & Khani, 2018). A variety of methods are used to estimate transit travel times including a Google Maps based algorithm (Chakour & Eluru, 2014) and a schedule-based shortest path algorithm proposed by Khani (Khani et al., 2014). These methods are preferable to simple measures of travel time, because they include more detailed information about the experienced walking time, waiting time, and number of transfers on a transit path. Finally, the studies reviewed in this section were selected for their application of discrete choice modelling. More specifically, each study estimates a multinomial logit model, and some estimate a mixed logit or nested logit model for station choice. The mixed logit model provides a more flexible framework than the multinomial logit model, allowing random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time (Train, 2009). These benefits only carry the burden of increased computation time. In the context of station choice, the nested logit model has only been used for situations where a traveler has a two-stage choice between stations and station access mode (Debrezion et al., 2009). In this study, the nested logit will be adapted to capture substitution patterns between the different transit modes available throughout the Twin Cities PNR system.

Literature on PNR station choice has yet to consider similarities between routes or overlapping routes. When two different routes share part of a transit route, there exists a statistical correlation between the alternatives that should be accounted for when estimating a discrete choice model. The most related work in the context of PNR station choice comes from a study in Brisbane, Australia which uses a modeling framework called Random Regret Minimization (RRM) that is notable for its accommodation of the "Compromise Effect" (Sharma et al., 2017). A compromise alternative is one with generally intermediate performance across several attributes, in contrast to an alternative with extreme performance. For example, a PNR facility that is an average driving distance from a user's origin and provides average transit speed would be a compromise alternative. The popularity of compromise alternatives has been well-documented in many decision-making contexts, but is often overlooked in transportation applications (Chorus & Bierlaire, 2013). While this framework acknowledges a trade-off relation between alternatives, it does not explicitly account for or measure route overlap. Outside of PNR choice literature, a multimodal path size factor has been developed to measure subroute overlap, and will be adapted for this study. Three different path size factor formulations are proposed by Hoogendoorn-Lanser and Bovy, each accommodating a slightly different multimodal path scenario. Ultimately, the study finds that the inclusion of a path size factor in their discrete choice model significantly improves model performance (Hoogendoorn-Lanser & Bovy, 2007).

CHAPTER 3: AADT ANALYSIS BEFORE AND AFTER LRT OPENING

3.1 METHOD

3.1.1 Research design

This study applied a quasi-experimental (before-after and treatment-control) design to explore the impact of rail transit on vehicular travel demand on adjacent road segments. The treatment is the Green Line light rail in the Twin Cities. It connects downtown Minneapolis and downtown Saint Paul, along University Avenue and Washington Avenue. The 11-mile route has 18 new stations and five stations shared with the Blue Line. The Green Line replaced limited stop service Route 50, which had an average weekday ridership of 6,886 in 2010. The parallel Route 16, a high-frequency local service with an average weekday ridership of 16,880 in 2010, was reduced to a low-frequency service (Metro Transit, 2012, p. 52). In 2019, the average weekday ridership of the Green Line was 44,004, exceeding the projected ridership in 2030 by 10% (Metro Transit, 2020). These statistics imply that about 40-50% of Green Line riders are new to transit.

We defined treatment and control groups as follows. We selected the one-mile buffer along the Green Line as the LRT-influence area (the pink area shown in Figure 2). The treatment group constitutes all road segments within the LRT-influence area (see Figure 13 in the Appendix). Non-influence areas include one-mile buffers along the interstate highways within the beltway (the blue areas shown in Figure 2). The control group constitutes all road segments within these non-influence areas. We used the control group to account for the influences on vehicular travel demand of third-party variables, such as gasoline prices and region-wide transportation policies. We excluded the road segments within the two downtown areas from our analysis because they were affected by road traffic in both LRT-influence and non-influence areas.

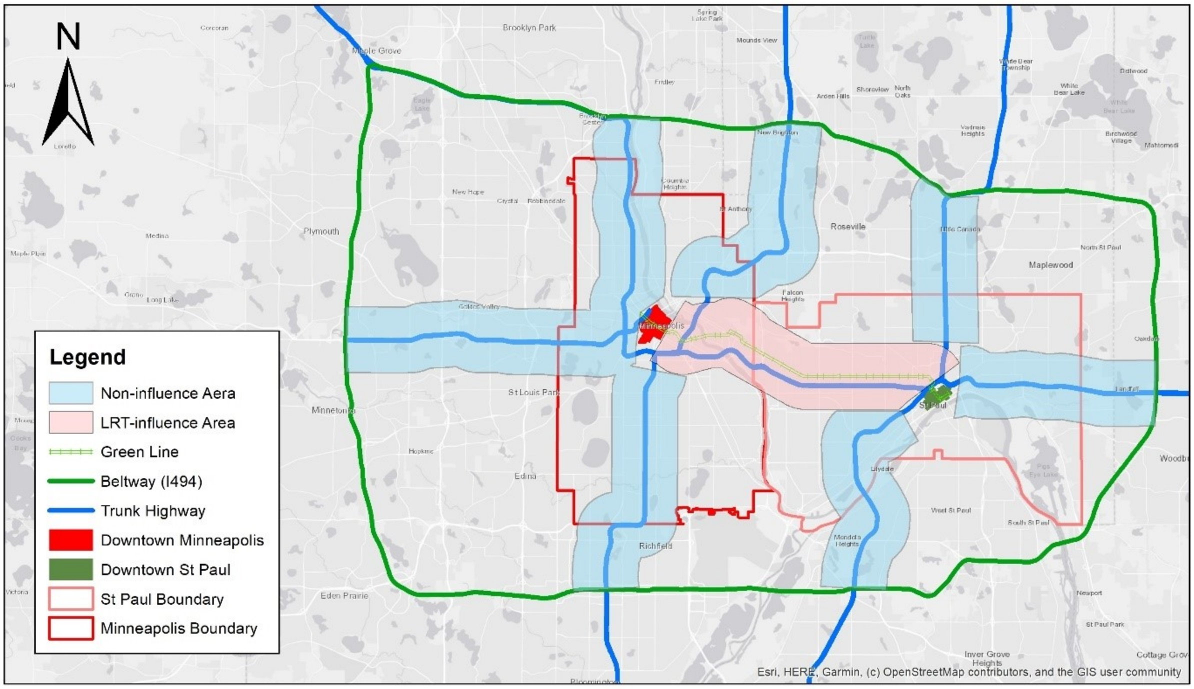

Figure 2. LRT-influence area and non-influence areas

We defined before and after periods as follows. We chose years of 2009-2010 as the before period and years of 2015-2018 as the after period. The Green Line started construction in late 2010 and began revenue service in June 2014. We excluded the years of 2011-2014 from our analysis because the construction of the Green Line could disrupt the performance of adjacent road networks.

3.1.2 Data

We used annual average daily traffic to measure vehicular travel demand. AADT is an index to estimate vehicular traffic within road segments for both directions on any given day during a year (MnDOT, 2020). This information can be used to calculate annual VMT, helping the Federal Highway Administration (FHWA) for travel analysis and funding (MnDOT, 2020). We obtained AADT data during 2009-2018 from the Minnesota Department of Transportation (MnDOT). It is worth noting that not all road segments have AADT data in a given year. The frequency of collecting AADT of a road segment depends on its importance in the transportation network. MnDOT collects AADT of the road segments in the state trunk highway system biennially (MnDOT, 2020). The AADT data of other roads are collected at a lower frequency. To obtain traffic data of all trunk highways, we integrated AADT data of two consecutive years. Accordingly, we produced AADT data for three periods: 2009-2010, 2015-2016, and 2017-2018. Figure 13-Figure 16 in the Appendix illustrate the road segments with AADT data at different periods. Appendix Table 2 presents the number of road segments for each period.

We also acquired datasets of road classification from MnDOT, land use from the Metropolitan Council, and transit supply from the Metro Transit. MnDOT classifies road segments into four categories: principal arterial, minor arterial, collector roads, and local road. In general, a higher road classification is associated with a larger volume. Land uses along a road segment affect its travel demand. To capture the influence of land uses, we computed the areas of commercial uses, industrial uses, institutional uses, and residential uses within the half-mile buffer of the segment. Transit supply measures the average number of transit service trips per hour in the quarter-mile buffer of the segment. Table 1 defines the variables used in this study and Table 2 presents their descriptive statistics.

Table 1. Variable Definition

Variables		Definition
Dependent variable		
Travel Demand	**AADT**	Normalized AADT in number of vehicles for both directions of the road segment[1]
Independent variables		
	LRT	Dummy variable indicating the road segment intersects the LRT influence area
Period	**Opening**	Dummy variable indicating AADT is collected after the opening of the Green Line
	Year1718	Dummy variable indicating AADT is collected in 2017 or 2018
	Year1516	Dummy variable indicating AADT is collected in 2015 or 2016
	Year0910	Dummy variable indicating AADT is collected in 2009 or 2010, the reference category for the other two periods
Road Classification[2]	**Principal Arterial**	Dummy variable indicating the road segment is classified as principal arterial
	Minor Arterial	Dummy variable indicating the road segment is classified as minor arterial
	Collector Road	Dummy variable indicating the road segment is classified as collector road
	Local Road	Dummy variable indicating the road segment is classified as local road, the reference category for the other three types of road classification
Land Use[3]	**Commercial Area**	Commercial area in acres in the half-mile buffer of the road segment
	Industrial Area	Industrial area in acres in the half-mile buffer of the road segment
	Institutional Area	Institutional area in acres in the half-mile buffer of the road segment
	Residential Area	Residential area in acres in the half-mile buffer of the road segment
Transit Supply[4]	**Transit Frequency**	Daily average number of transit service trips per hour in the quarter-mile buffer of the road segment[5]

Notes:
1. As wider roads tend to accommodate larger volumes, we normalized AADT of a road segment (dividing AADT by travel width). Travel width measures the drivable surface from shoulder to shoulder of a road segment. It does not consider passing lanes, turn lanes, auxiliary lanes, or shoulders.
2. Road classification is consistent within the study period.
3. We applied land use data in 2010 for the period of 2009-2010, 2016 for 2015-2016, and 2018 for 2017-2018.
4. We applied transit supply data in autumn 2010 for the period of 2009-2010, autumn 2016 for 2015-2016, and autumn 2017 for 2017-2018. We chose the data in autumn 2017 for the last period because transit data in autumn 2018 are unavailable.
5. We counted only the transit service with stops in the quarter-mile buffers. Transit service includes urban local bus, suburban local bus, express bus, the North Star commuter rail, and the Blue Line light rail.

Table 2. Variable Statistics

Variables	Total (N = 2,718)				Year0910 (N = 943)				Year1516 (N = 657)				Year1718 (N = 1,118)			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
AADT	393.43	524.78	0.42	2,652.78	387.35	482.59	3.54	2,652.78	483.69	602.28	7.68	2,569.44	345.52	503.30	0.42	2,416.67
LRT	0.18	0.38	0	1	0.15	0.35	0	1	0.18	0.39	0	1	0.21	0.41	0	1
Opening	0.65	0.48	0	1												
Year1718	0.41	0.49	0	1												
Year1516	0.24	0.43	0	1												
Year0910	0.35	0.48	0	1												
Principal Arterial	0.17	0.37	0	1	0.16	0.37	0	1	0.23	0.42	0	1	0.14	0.34	0	1
Minor Arterial	0.40	0.49	0	1	0.47	0.50	0	1	0.39	0.49	0	1	0.34	0.48	0	1
Collector Road	0.21	0.41	0	1	0.14	0.35	0	1	0.26	0.44	0	1	0.23	0.42	0	1
Local Road	0.23	0.42	0	1	0.23	0.42	0	1	0.12	0.33	0	1	0.29	0.45	0	1
Commercial Area	152.83	102.35	0.08	576.96	146.59	104.14	0.28	564.41	158.24	102.21	2.45	576.96	154.91	100.72	0.08	530.51
Industrial Area	61.03	81.26	0	502.04	51.16	73.12	0	502.04	60.21	87.36	0	435.34	69.84	83.12	0	486.68
Institutional Area	31.93	51.72	0	431.29	40.77	56.84	0	429.46	27.74	49.23	0	431.29	26.93	47.52	0	408.47
Residential Area	336.91	164.95	3.00	1,266.57	339.43	164.69	5.75	1,251.40	372.48	174.90	3.00	1,266.57	313.90	155.13	3.00	1,245.14
Transit Frequency	3.84	5.20	0	41.81	3.11	4.55	0	37.43	4.22	4.63	0	37.91	4.24	5.91	0	41.81

Notes:
N = Sample Size; SD = Standard Deviation; Min = Minimum; Max = Maximum

3.1.3 Models

As presented in Figure 3, we assume that while the operation of LRT influences AADT in a given year, other factors, such as land use, transit supply, and road classification, also contribute to the AADT. Therefore, we need to account for their influences in the model.

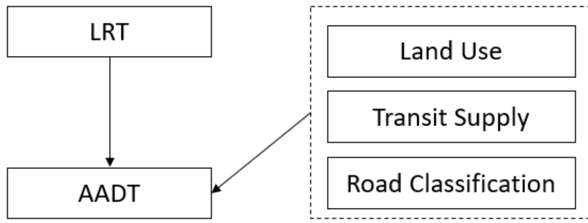

Figure 3. Conceptual framework of this study

We applied negative binomial regression to analyze the assembled data based on the conceptual framework. The dependent variable is AADT of road segments and the other variables in Table 1 are independent variables. We chose negative binomial model because AADT is skewed to the right and its variance is larger than its mean.

We constructed two models: Model 1 examines the difference in vehicular travel demand before and after the opening of the Green Line. Model 2 shows the changes in vehicular travel demand over the study period. Besides measures of road classification, land use, and transit supply, Model 1 (shown in Equation 1) includes the treatment variable LRT, the period variable $Opening$, and their interaction term:

$$AADT = f(LRT, Opening, LRT \times Opening, \\ Road\ Classification, Land\ Use, Transit\ Supply). \tag{1}$$

In a difference-in-difference model like Equation 1, the interaction term is the policy variable (Billings, Leland, & Swindell, 2011; Hurst & West, 2014). A significantly negative coefficient suggests that the opening of the Green Line reduces vehicular travel demand of the road segments in the LRT-influence area, compared with those in the non-influence areas. All else being equal, the effect of an independent variable on vehicular travel demand can be calculated as:

$$\Delta = \left(e^{\hat{\beta}} - 1\right) \times 100\%, \tag{2}$$

where Δ is the relative change in percentage, and $\hat{\beta}$ is the estimated coefficient of the independent variable.

Model 2 (shown in Equation 3) includes the treatment variable LRT, two period variables ($Year1516$ and $Year1718$), and two interaction terms and controls for the same three types of variables as Model 1:

$$AADT = f(LRT, Year1516, Year1718, LRT \times\ Year1516, \\ LRT \times Year1718, Road\ Classification, Land\ Use, Transit\ Supply). \tag{3}$$

A significantly negative coefficient of the interaction term implies that the Green Line reduces travel demand of the road segments in the LRT-influence area during the corresponding period (years 2015-2016 or years 2017-2018), compared with those in the non-influence areas during the years 2009-2010. The relative change in AADT could be calculated using Equation 2.

3.2 RESULTS

Table 3 presents two model results. Model 1 focuses on the change in vehicular travel demand after the opening of the Green Line, and Model 2 emphasizes how this change evolves over time. These two models have a similar fitness to the dataset based on the pseudo adjusted R squared: both are around 0.1.

Table 3. Model Results

Variable	Model 1			Model 2		
	Coefficient	P-value	Relative Change (%)	Coefficient	P-value	Relative Change (%)
Opening	0.04	0.194				
$\mathbf{LRT \times Opening}$	-0.20	0.003	-18.23			
LRT	0.33	0.000		0.33	0.000	
$\mathbf{LRT \times Year1516}$				-0.25	0.003	-22.18
$\mathbf{LRT \times Year1718}$				-0.18	0.015	-16.19
Year1516				0.04	0.275	
Year1718				0.03	0.264	
Principal Arterial	2.81	0.000	1,562.65	2.81	0.000	1,564.32
Minor Arterial	1.19	0.000	227.72	1.19	0.000	227.72
Collector Road	0.45	0.000	56.31	0.45	0.000	56.30
Commercial Area	8.60×10^{-4}	0.000	0.09	8.53×10^{-4}	0.000	0.09
Industrial Area	-7.22×10^{-4}	0.000	-0.07	-7.09×10^{-4}	0.000	-0.07
Institutional Area	1.19×10^{-3}	0.000	0.12	1.18×10^{-3}	0.000	0.12
Residential Area	1.66×10^{-4}	0.051	0.02	1.67×10^{-4}	0.052	0.02
Trip Frequency	-0.02	0.000	-1.91	-0.02	0.000	-1.90
Constant	4.25	0.000		4.25	0.000	
Dispersion Factor	2.6937			2.6947		
Pseudo Adjusted R^2	0.1015			0.1014		
Sample Size	2,718			2,718		

3.2.1 Model 1: Before and after comparison

Model 1 shows that the coefficient of the interaction term between LRT and opening is -0.20 and significant, after controlling for other variables. This means that after the opening of the Green Line, the AADT of the road segments in the LRT-influence area decreases by approximately 18%, compared with that in the non-influence areas. Therefore, the Green Line reduces vehicular traffic of adjacent road segments. This result is consistent with the literature (Bhattacharjee & Goetz, 2012; Ewing et al., 2014) and the rising transit ridership in the corridor.

All, but one, of the control variables have significant relationships with vehicular travel demand at the 5% level, while residential area is marginally significant. Road classification variables show significant associations with AADT. Specifically, principal arterials, minor arterials, and collector roads carry approximately 1,563%, 228%, and 56% more vehicles than local roads, respectively. This pattern is logical as the volumes of different service levels of the roads follow their importance hierarchy in the transportation system. Regarding land use variables, commercial area, institutional area, and residential area are positively associated with AADT. Among the three, institutional area has the largest effect. In particular, for each one-acre increase in institutional use, AADT grows by about 0.12%. By contrast, industrial area is negatively associated with AADT. The negative relationship might be because land-intensive industrial uses generate lower traffic than other types of land uses. Transit frequency has a negative correlation with AADT. This relationship is plausible because transit competes with personal vehicles. An increase of one transit trip per hour is associated with an approximate 2% reduction in AADT.

3.2.2 Model 2: Trend over time

All control variables in Model 2 have the same relationships with AADT as those in Model 1. The two interaction terms between the period variables and LRT are both negative and significant. The coefficient of the interaction term between year1516 and LRT is -0.25, showing that the AADT of the road segments in the LRT-influence area decreases by about 22% in the period of 2015-2016, compared with the period of 2009-2010. The coefficient of the interaction term between year1718 and LRT is -0.18. It means that the decrease in the AADT of the road segments in the LRT-influence area is around 16% in the period of 2017-2018, compared with the period of 2009-2010. These results suggest that the opening of the Green Line reduces vehicular travel demand on adjacent roads during the first two years of operation, but vehicular traffic rebounds during the following two years (Figure 4). This finding is likely attributable to the *principle of triple convergence*, as discussed in the literature review. Transit-induced development is another cause.

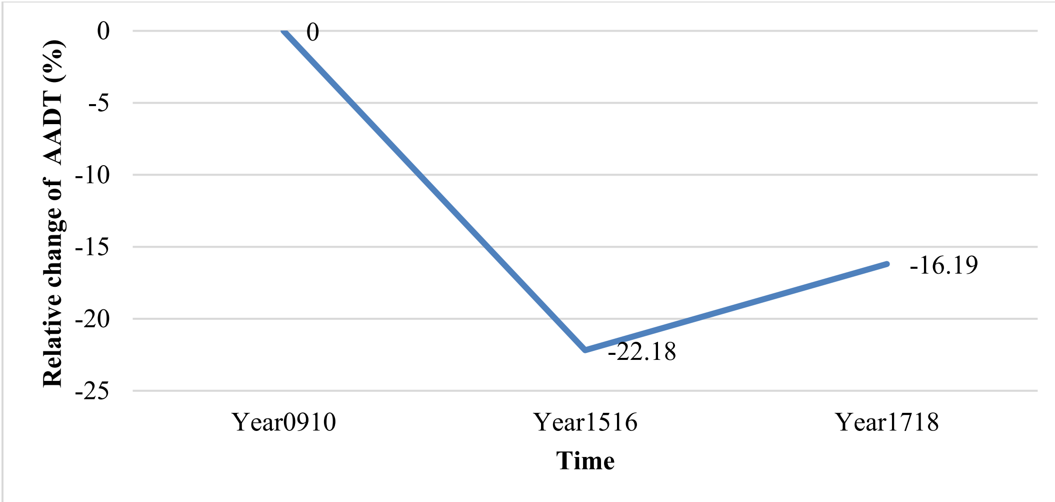

Figure 4. Relative change of AADT in the LRT-influence area

The Green Line increases property values and attracts real estate development along its route, such as apartments, retail stores, and restaurants. Cao and Lou (2017) found that the commencement of the Green Line improved housing values by $13.7 per square foot. Cao and Porter (2016) also showed that the funding announcement of the Green Line increased building activities in the station areas by approximately 24%. The Metropolitan Council (2018) reported that outside of downtown Minneapolis, new developments of $2.9 billion have been announced, under construction, or in use along the Green Line corridor by February 2018. New development induces more people to travel to and from this area.

3.2.3 Models without control variables

We also estimated the effects of the Green Line on AADT using models without controlling for confounding variables. These models illustrate the magnitude of omitted variable bias. The effects of the Green Line would be substantially overestimated if we did not account for the influences of the confounding variables. As shown in Table 4, the estimated reduction in AADT in the after-opening period is 35.8%, which almost doubles the effect (18.2%) when controlled for the confounding variables (Table 3). Therefore, when quantifying the independent effect of rail transit on vehicular travel demand, it is necessary to include confounding variables in the model to account for their influences.

Table 4. Model Results without Controlling for Confounders

Variable	Model 1			Model 2		
	Coefficient	P-value	Relative Change (%)	Coefficient	P-value	Relative Change (%)
Opening	0.10	0.038				
$\mathbf{LRT \times Opening}$	-0.44	0.000	-35.81			
LRT	0.41	0.000		0.41	0.000	
$\mathbf{LRT \times Year1516}$				-0.46	0.002	-37.12
$\mathbf{LRT \times Year1718}$				-0.41	0.002	-33.38
Year1516				0.30	0.000	
Year1718				-0.04	0.410	
Constant	5.89	0.000		5.89	0.000	
Dispersion Factor	0.8204			0.8294		
Pseudo Adjusted R^2	0.0003			0.0013		
Sample Size	2718			2718		

3.3 LIMITATION

This research has some limitations that are avenues for future research. First, although AADT illustrates where individual trips aggregate in the transportation network, it cannot show when the trips occur. Therefore, we are unable to examine the effect of rail transit on traffic congestion. Future research could use travel speed of road segments to compute congestion time and use it as the dependent variable. However, the concern remains regarding how to choose critical travel speeds for different types of roads, such as principal arterials and local roads. Secondly, because of a lack of archived data, we could not include information on regional road construction projects in the models, although it is desirable to capture their influence on AADT. Third, we used four years of data to examine the effect of rail transit over time. While four years may be adequate to capture the influence of induced traffic and triple convergence, it takes a much longer time to observe the effect of induced development. Therefore, future studies should test the dynamics of rail transit effects over an extended time frame.

CHAPTER 4: PARK-AND-RIDE LOCATION CHOICE MODEL ESTIMATION

4.1 METHOD

4.1.1 Origin-destination data

This study is made possible by an on-board survey conducted by Metro Transit, in which transit riders were asked to answer questions about the origin and destination of their trip, access mode, boarding time, transit route(s), trip purpose, and demographic information. The survey received 30,491 responses between April 2016 and February 2017, of which 4,033 (13.2%) recorded using a designated PNR facility. Only PNR users whose trip origin was their home or a hotel and whose transit trip started at a PNR facility were ultimately selected from the survey for further analysis (1,895 users). While each respondent was asked to record the transit routes they took to reach their destination, this information may be unreliable or incomplete. This study uses the geospatial coordinates of each respondent's home, chosen PNR location, and destination to approximate each respondent's travel time and route (hereafter referred to as their "observed route"). After calculating a path for each respondent and cleaning the data, 1,690 records with complete information remained and were used to produce the results of this study.

Previous studies have shown a significant relationship between socio-economic factors and station choice, such as age and income (Pang & Khani, 2018). This study will consider four individual-specific attributes when modeling station choice: income, age, gender, and disability status. Each respondent of the on-board survey reported their household income as one of seven brackets (e.g. $49,000 - $64,999, $150,000 or more). These brackets have been coded and ordered for use in the model estimation. Age is reported in a similar fashion, with 5 distinct age ranges. Finally, disability status is treated as a binary variable, in which each respondent with a disability that effects their use of transit is marked as having a disability, while all others are marked as not having a disability.

4.1.2 Park-and-ride facility attributes

Model estimation uses several facility-specific attributes from a dataset downloaded from MN Geospatial Commons (Minnesota Geospatial Commons, 2017). The Twin Cities has three transitways that serve PNR facilities: the Northstar commuter rail, the Blue Line light rail transit (LRT), and the Red Line bus rapid transit (BRT). These lines are distinct from standard express bus service in quality and frequency of service. The Northstar is a commuter train that provides peak hour service with irregular headways, while the Blue Line has a ten-minute headway for most of the day, and is used for both commuting and intra-city travel. Finally, the Red Line is a bus service that acts as an extension of the Blue Line, with 30-minute headways during peak hours. These transitways first appear in the logit models as explanatory variables, and later as a nest designation in the nested logit model. Detail is provided later in the model construction. Another facility-specific variable, Amenities, counts how many of the surveyed features exist at a given facility. The complete set of amenities is presented below:

- Electric vehicle charging station
- Shelter
- Indoor waiting area
- Lighting
- Drop off area
- Bench
- Trash
- Public restroom
- Elevator
- Escalator
- Bike racks
- Bike lockers

4.1.3 Street network shortest path

Using the origin coordinates of each survey respondent, the free-flow driving time and distance to each PNR facility were calculated using the python package Osmnx (Brathwaite & Walker, 2018). This package uses OpenStreetMap's API to download street geometries and provides a built-in function to find the shortest path through the street network between any two coordinate pairs. In the Twin Cities metropolitan area, OpenStreetMap has complete information about the classification of each road segment, but for the majority of segments is missing a speed limit. Thus, it was straightforward to calculate a distance-based shortest path, but more information was needed to calculate a time-based shortest path. The road classification for each road segment was used to approximate speed limits: any segment labeled 'motorway' received a speed limit of 55 miles per hour, while every other classification was given a speed limit of 30 miles per hour. Assuming that free-flow travel time is equivalent to driving at the speed limit, a time-based shortest path was calculated from every origin location to every PNR facility. In estimating logit models, both driving time and distance will be tested separately as explanatory variables. If they both prove to be significant predictors of PNR facility choice, only the more significant one will be included in the final model due to the close relationship between driving time and distance.

4.1.4 Schedule-based transit shortest path

In contrast to the street network shortest path, a transit path depends on both direction and time of travel. Finding a path through a transit path is a much more complicated process as a result, and is performed using a previously developed algorithm (Khani et al., 2014). Using General Transit Feed Specification (GTFS) data, a time-expanded network is constructed from the transit schedule (Minnesota Geospatial Commons, 2019b, 2019a). Nodes are used to represent transit stops at a particular point in time, thus the connection between nodes depends on spatiotemporal proximity. In the transit network, Node A is connected to node B with a directed link if node B follows node A in any transit route's stop sequence. Node A can also be connected to node B if they are within a tenth of a mile and within a 120-minute time window of each other. In other words, transit passengers can only make a transfer if it requires less than a tenth of a mile of walking, and the required waiting or walking time is less than 120 minutes. Given a transit schedule, the algorithm generates a path through the network in which features of a transit path can be weighted to mimic rider preferences. A previous study found the disutility of transferring to be roughly equivalent to 35 minutes of walking time (Pang & Khani, 2018). With the intention of incorporating this finding as well as maintaining a flexible shortest-path algorithm, transit paths generated for this study will have a transfer disutility penalty equal to 15 minutes of walking or waiting time. This has the effect of forcing the algorithm to avoid paths with a high number of transfers; it does not mean that transit paths with a transfer are estimated to take longer than actually experienced.

In the context of PNR travel behavior in the Twin Cities, observed transit paths are fairly predictable. Commuters park adjacent to their boarding stop, board an express bus or train, and most often require no more than one transfer to reach their destination. Based on this behavior, the path generated for each user has the following characteristics:

1. Maximum walking distance of 0.25 miles from parking location to initial boarding stop
2. Maximum walking distance of 1 mile from final egress stop to destination
3. High transfer penalty

In the on-board survey, respondents are asked to provide the hour window in which their trip began (e.g., 8:00 - 9:00 AM). Travel time is relatively sensitive to departure time for irregular transit routes, so several precautions were taken to limit inaccuracies in the travel times associated with generated paths. Each path is generated such that the trip starts and ends within two hours of the beginning of the stated time window. For a passenger departing between 8:00 and 9:00 AM, the transit path is constrained to arrive at their destination by 10:00 AM. Crucially, the shortest-path algorithm has been written in a way that does not penalize early arrival or late departure. Thus, the assigned transit path is simply the lowest cost trip within two hours of the surveyed boarding time. Once the path is generated, the initial transit boarding time is inferred as the arrival time minus the travel time. The transit path may include in-vehicle time, waiting time at a transfer point, walking time between transfer points, and walking time from the final egress stop to a destination. Because the initial departure time is not provided in the survey, waiting time at the initial boarding stop is not included in total travel time.

Finally, the schedule-based shortest path algorithm is written to find a transit path backwards through the transit network, as it greatly reduces computational time. In its simplest form, Dijkstra's shortest path algorithm finds the travel cost from one node to every other node in the network. For this study, we are interested in finding the travel cost from many PNR facilities to one destination. The problem is inverted, thus the algorithm is inverted as well.

4.1.5 Choice set generation

Table 5. Explanatory Variables

Variable	Description	Mean	Std. Dev.
Individual Attributes			
Age	Survey response category (e.g. 18-24, 55-64)	35-44	
Income	Survey Response category (e.g. \$49,000 - \$64,999, \$150,000 or more)	\$60 - \$100k	-
Disability status	Survey Response; 1 = disability impacting transit use, 0 = otherwise	0.04	-
Female	Survey Response; 1 = female, 0 = otherwise	0.6	-
Path Attributes			
In-transit time	Total time spent in a bus or train (minutes)	36.6	13.0
In-car time	Total time spent driving (minutes)	10.3	12.2
Driving distance	Total distance driven (miles)	5.9	7.7
Walk time	Total time spent walking (minutes)	6.0	4.1
Wait time	Total time spent waiting between transfers (minutes)	0.4	1.7
Transfers	Number of transfers on a transit path	0.13	0.4
Average headway	Average time between buses/trains for the route boarded at a PNR, during the time period of boarding	30.4	24.6
Distance ratio	Measure of how directly a path goes from origin to destination (see Figure 2)	1.1	0.1
Time ratio	Measure of how much longer a given path takes than the fastest path available for each individual, see Equation (2.1)	1.2	0.2
Park-and-ride Attributes			
Lot Capacity	Number of parking spaces at a park-and-ride facility	692.9	439.8
# Routes served	Number of unique transit routes that stop at a given park-and-ride facility	3	2.3
Structured	1 = facility has a structured parking lot, 0 = otherwise	0.5	-
Transitway	1 = facility is served by Blue Line, Red Line, or Northstar, 0 = otherwise	0.3	-
Amenities	Number of amenities available at a facility	6.6	2.6

Note: Std. Dev. = Standard Deviation

In generating a choice set for each PNR user, this study solely considers PNR location alternatives to the observed route. Thus, the option of driving the complete distance from origin to destination is beyond the scope of this study. To generate the choice set for each user, an auto path and a transit path are calculated for all 111 PNR locations. Many of these alternative routes may be unreasonable. In the interest of reducing each user's choice set to only include reasonable options, the distribution of observed route travel times was examined to inform two route-eliminating criteria. For this study, a reasonable route has the following features:

1. **Time criterion:** travel time ratio less than a threshold A = 1.657
2. **Distance criterion:** distance ratio less than a threshold B = 1.361

where,

$$Time\ Criterion\colon \frac{tt_{n,i}}{tt_{n,*}} < A \tag{4}$$

$$Distance\ Criterion:\ \frac{X_{n,i} + Y_{n,i}}{Z_n} < B \tag{5}$$

The first criterion aims to reduce each user's choice set by eliminating routes with a particularly long total travel time. The total travel time associated with the route through PNR_i for user n, $tt_{n,i}$, is equal to the sum of the driving time from origin to PNR_i, and the time spent in transit between PNR_i and the destination. For each user, the PNR location that provides the shortest possible total travel time (and may differ from the user's observed route) is identified and assigned the $tt_{n,*}$ designation. So, the ratio of $tt_{n,i}$ to $tt_{n,*}$ is simply a measure of how much longer a given route takes compared to the fastest possible route available to each user. Finally, the threshold A is set to capture 95% of observed route time ratios, thus eliminating the most extreme 5% of observed routes along with all other routes with a time ratio greater than A.

Similar to the first criterion, the second constrains the choice set based on the straight-line distance from origin to destination. For each PNR location alternative *i* and user *n*, three straight-line distances are calculated, as shown in Figure 2. $X_{n,i}$ is the straight-line distance from a user's origin to a PNR location, while $Y_{n,i}$ is the straight-line distance from PNR location to the user's destination. This criterion measures how "out of the way" each alternative PNR location is compared to a straight path from origin to destination, Z_n. The threshold B is set to capture 95% of observed routes, and eliminate all alternative routes with extreme distance ratios. These criteria firmly ground each user's choice set in both time space and Euclidean space, and reduce the dataset to 1,690 users. On average, each user is faced with about 19 reasonable alternatives to their observed route. Choice set summary statistics are provided in Table 5.

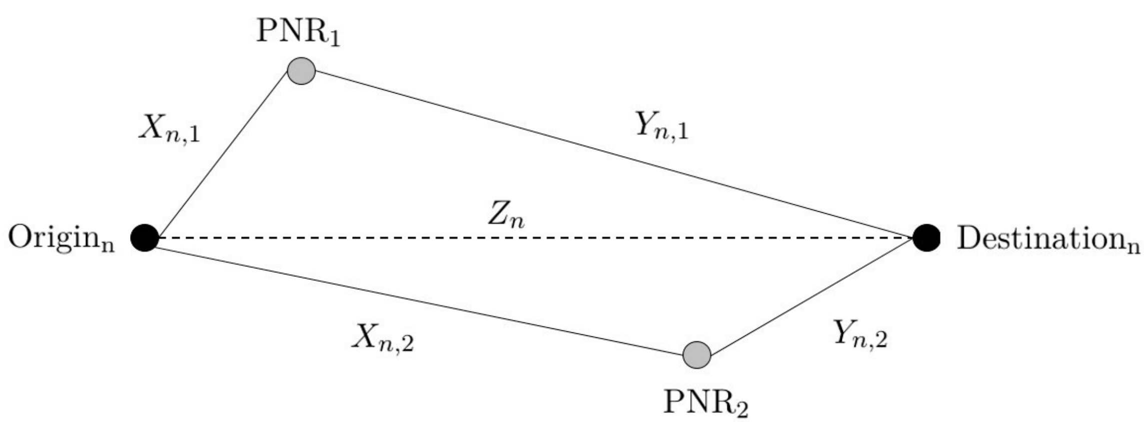

Figure 5. Distance ratio

4.1.6 Model construction

This study fits a multinomial logit model, mixed logit model, and nested logit model to the data, and compares their respective predictive abilities. The base multinomial logit model frames expected utility as the sum of observed and unobserved components:

$$U_{n,i} = \beta x_{n,i} + \varepsilon_{n,i} \tag{6}$$

In Equation 6, $U_{n,i}$ is the expected utility that user *n* derives from alternative *i*. The righthand side of the equation shows a vector $x_{n,i}$ of observed variables related to alternative *i*, β which is a vector of coefficients to be estimated, and the unobserved random error $\varepsilon_{n,i}$. For this equation, the logit probabilities are:

$$P_{n,i} = \frac{e^{\beta x_{n,i}}}{\sum_{i \epsilon I} \beta x_{n,i}} \tag{7}$$

In Equation 7, *I* is the complete set of alternatives faced by user *n*. This probability expression assumes that user *n* will choose the alternative with the highest utility. Further, this model assumes proportional substitution patterns across alternatives, known as the Independence of Irrelevant Alternatives (IIA) property (Train, 2003). This assumption may be unrealistic, and can be overcome in a variety of ways. First, if a relationship is known between alternatives, they can be nested together in the aptly named nested logit model (Figure 6). In this model, the alternatives *i* are partitioned into non-overlapping subsets $B_1, B_2, \ldots, B_k$. The utility function becomes:

$$U_{n,i} = W_{n,k} + Y_{n,i} + \varepsilon_{n,i} \tag{8}$$

In this equation, $W_{n,k}$ depends on variables that describe nest *k*. Similarly, $Y_{n,i}$ represents the variables that describe alternative *i* (Train, 2009). The choice probabilities are an extension of Equation 7, where the probability of choosing alternative *i* in nest *k* is:

$$P_{n,i} = P_{n,i|B_k} P_{n,B_k} \tag{9}$$

where,

$$P_{n,B_k} = \frac{e^{W_{n,k} + \lambda_k Q_{n,k}}}{\sum_{l=1}^{K} e^{W_{n,l} + \lambda_l Q_{n,l}}} \tag{10}$$

$$P_{n,i|B_k} = \frac{e^{\frac{Y_{n,i}}{\lambda_k}}}{\sum_{i \epsilon B_k} e^{\frac{Y_{n,i}}{\lambda_k}}} \tag{11}$$

$$Q_{n,k} = ln \sum_{i \epsilon B_k} e^{\frac{Y_{n,i}}{\lambda_k}} \tag{12}$$

The nest parameter λ_k measures the degree of independence in unobserved utility between alternatives in nest *k*, and is between 0 and 1 in the context of utility maximization. When $\lambda_k = 1$, this model reduces to the multinomial logit model, indicating that no correlation exists between alternatives in nest *k*. Conversely, a small value for λ_k indicates correlation in unobserved utility within nest *k*. One of the most common applications of the nested logit model is in transportation mode choice, as alternative modes have been shown to have disproportionate substitution rates (Debrezion et al., 2009).

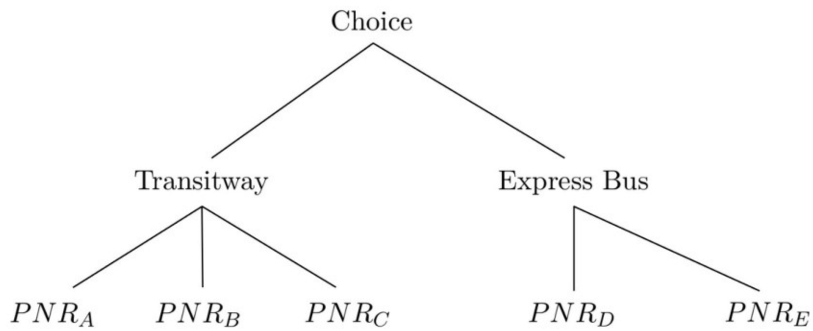

Figure 6. Nested logit structure

Even more flexible than the nested logit model is the mixed logit model. While the previous two models are deterministic, the mixed logit is a simulation-based model that allows for random taste variation across users, unrestricted substitution patterns, and correlation in the unobserved factors (Train, 2009). The mixed logit choice probabilities can be expressed as:

$$P_{n,i} = \int \frac{e^{\beta x_{n,i}}}{\sum_{i \epsilon I} \beta x_{n,i}} f(\beta) d\beta \tag{13}$$

In Equation 13, the mixed logit probability is a weighted average of the probability described in Equation 7 evaluated for different values of β, where the values of β are taken from the density function, $f(\beta)$. The main distinction here is that β is not treated as a fixed number, but instead a random variable whose density, $f(\beta)$, is a function of the mean and covariance of β across the population (Train, 2009).

All three of these logit models were estimated using the pylogit package in Python (Brathwaite & Walker, 2018). Three different nesting setups were tested for the nested logit model, and the model described in Figure 6 was ultimately selected. In estimating the simulation-based mixed logit model, 500 draws were taken from the distribution of the random coefficients. For all three models, all variables listed in Table 5 were initially included as predictors, and insignificant variables were incrementally eliminated until every remaining variable was significant at the 0.05 level.

4.1.7 Overlapping routes

It has been acknowledged that a shortcoming of the multinomial logit model is its failure to account for overlapping routes, and as a result may produce unrealistic choice probabilities (Hoogendoorn-Lanser & Bovy, 2007). Introducing a path size factor to the logit model addresses this problem by measuring the extent to which a given route overlaps with other routes and adjusting utility accordingly. For this study, a path size factor is calculated solely for the transit sub-route of a given path. The factor is calculated as the following:

$$PS_{irn} = \frac{1}{L_{ir}} \sum_{a \epsilon A_{ir}} \frac{l_a}{N_{na}} \tag{14}$$

where, A_{ir} is the set of legs in a subroute *r* of path *i*, L_{ir} is the total length in minutes of a subroute, and *l* is the length in minutes of a leg of the subroute. For any leg of a subroute, a, N_{na} is the number of distinct routes sharing that leg. Crucial to the calculation of the path size factor is complete information about the transit stops passed through on a given transit path. First, L_{ir} is set equal to the difference between the first boarding time and the final egress time on a transit path. When the path includes a transfer between transit routes, the access and egress points will not be connected by a single transit route. Next, A_{ir} is found by creating an ordered list of transit stops that each path passes through. While the time at which the stop was passed through is critical to determine the order of the stops, the time is not considered when comparing two transit paths. In other words, two paths that cover the same stretch of road at different times during the day are considered to be overlapping routes. Once the ordered set of stops is found for each transit path in the choice set of user *n*, N_{na} increases by one for every occurrence of two consecutive transit stops in the choice set of user *n*. Finally, the length of overlap is determined by the length of time scheduled between two consecutive transit stops. For example, if it a transit route is scheduled to pass through stop B three minutes after stop A, the length of overlap on that leg of the transit path would be three minutes.

4.2 RESULTS

4.2.1 Model results

Table 6 shows the estimation results for the multinomial, nested, and mixed logit models. Among all of the variables tested, only those that are significant at the 95% were used to estimate the final models. Based on McFadden's R^2 and log-likelihood measures, the multinomial and mixed logit models provide a significantly better fit to the data than the nested logit model. All three models agree on the relative effect of each variable; the sign of each coefficient is consistent across all three models. The in-transit and in-car coefficients tell us that PNR users generally choose a larger percentage of their total trip time to be spent on transit as opposed to in a car. The distance ratio coefficient indicates that PNR users prefer to be moving in the direction of their destination. Given the insignificance (and exclusion) of the time ratio coefficient, PNR users are more sensitive to in-car travel time as opposed to total travel time. In summary of the average behavior, PNR users perceive higher disutility by driving time and distance traveled than total travel time.

Table 6. Logit model results

Variable	MNL	Nested	Mixed
In-transit time	-0.092***	-0.054***	-0.11***
In-car time	-0.39***	-0.11***	-0.52***
Walk time	-0.067***	-0.025***	-0.079**
Transfers	-1.61***	-0.39***	-2.0054***
Average headway	-0.015***	-0.005***	-0.016***
Distance ratio	-3.81***	-	-4.67***
Lot Capacity	0.0014***	0.0009***	0.002***
Transitway	1.53***	-	1.73***

Structured lot	0.47***	-0.32***	0.56***
Number of routes available	-0.13***	-0.047***	-0.21***
Path size	0.56*	-	-
Transitway nest		0.54	
Bus nest		0.38**	
***σ* in-car time**			0.17***
***σ* walk time**			0.20***
***σ* # routes available**			0.40***
Adjusted R^2	0.595	0.426	0.609
Log-Likelihood	-1,280.19	-2,387.82	-1,232.92
Predictive Ability	64.3%	53.4%	63.7%

Note: Significance level notation: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Coefficients for walk time and transfers offer insight into preferences along a transit path. Adding a transfer to the transit path has a marginal rate of substitution of 17.5 with transit time. In other words, PNR users are likely to choose transit paths with no transfers over paths that are 17.5 minutes faster but include a transfer. A similar interpretation can be given for the transitway coefficient: PNR users have no preference between a Transitway route and an express bus route that is 16.6 minutes faster. This finding alone emphasizes the success of investing in transitway infrastructure along PNR routes. Finally, the coefficient found for the number of routes available variable does not lend itself to an intuitive explanation. The sign is negative, indicating that PNR users have a positive perception of facilities with fewer transit routes available. It may be the case that this variable has some unrepresented spatial component. For example, PNR facilities nearest to downtown Minneapolis may serve the most routes, while those that are farther away serve fewer routes. If this is the case, the negative coefficient may reflect the finding that PNR users perceive transit time less negatively than in-car time.

The purpose of fitting a nested logit model was to explain differences between service types based on intuition, however the nest specification ultimately gave a significantly worse fit to the data than the other models. While further work should be done on mode nesting, it appears that the effect of transit type is more effectively captured by the transitway variables in the multinomial and mixed logit models. The variance of every variable was tested for heterogeneity across users in the mixed logit model, and three were found to vary significantly. As a result, this variance is reflected in the model by the three sigma terms. Finally, it is worth noting a few variables that were tested but insignificant across all models tested. Individual attributes such as income and gender as well as several interaction terms were found to be insignificant, as was the number of amenities available at each PNR facility.

All three models presented in Table 6 are estimated using a random sample of 70% of the PNR users and validated against the remaining 30% of PNR users. This process was repeated for ten random samples and the average predictive ability is reported for each model. For simplicity of interpretation, the predictive ability is the percentage of observed routes that have the highest choice probabilities among each user's choice set of alternatives. The highest predictive ability indicates that the multinomial logit model correctly identified the chosen PNR facility for 64.3% of the test sample.

4.2.2 Multimodal behavior

Following the results of the logit models, Figure 7 contrasts the total travel time for observed routes and all other routes in choice sets. First, the scale of the distributions are different because there are a total of 33,822 routes considered while only 1,690 were chosen by surveyed individuals. Still, only 1.6% of chosen routes exceed 100 minutes of total travel time and have an average total travel time of 46.9 minutes. In contrast, 8.6% of non-chosen routes exceed 100 minutes and have an average total travel time of 63 minutes.

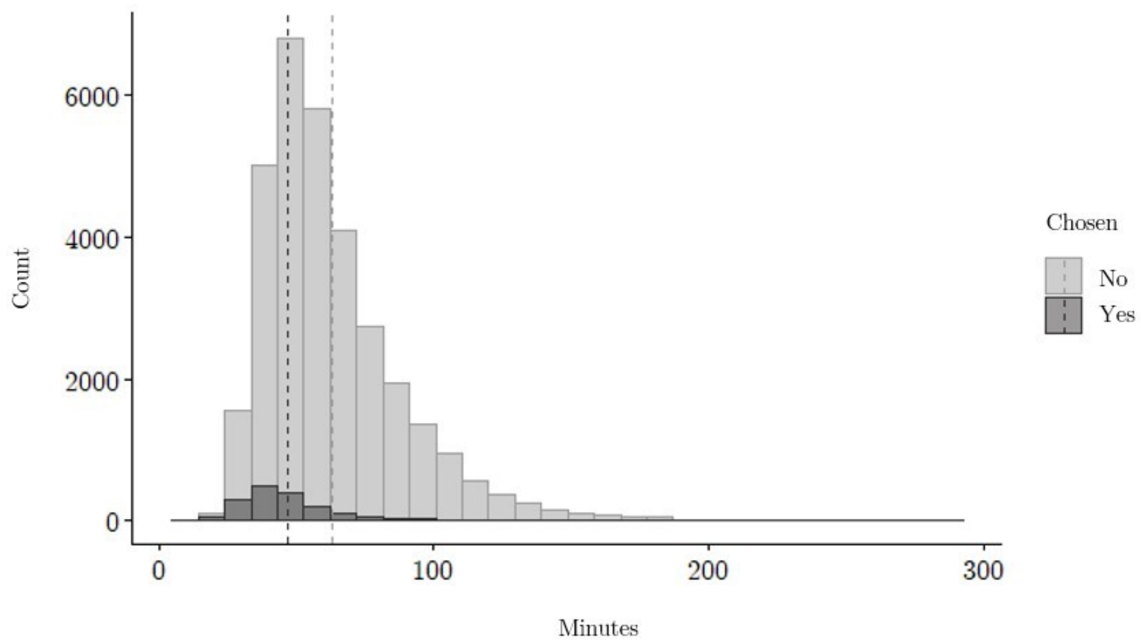

Figure 7. Total travel time (dashed line shows the mean travel time)

Figure 8 shows the time ratio for each surveyed individual, which is a ratio of the travel time of their chosen route compared to the travel time of the fastest route available. While a significant proportion have a ratio value of one indicating that they chose the fastest route available, the overall distribution shows that surveyed individuals are not strictly time minimizing. On average, they chose a route that is 17% longer than the shortest route available to them. As discovered from the logit model coefficients, PNR users prefer to minimize driving time and total distance before minimizing total travel time. In Figure 8, the otherwise smooth distribution appears to be interrupted by a sudden drop around the 1.02 mark. This could be explained by the distribution of PNR facilities throughout the Twin Cities. PNR facilities are often associated with specific commuter communities, such as Burnsville, Maple Grove, and Inver Grove Heights. The gap in the figure may reflect the gap in space between the locally serving PNR facility for these communities and the next nearest selection of suburban PNR facilities. In other words, the figure shows that choice sets are often missing alternatives that are 2-4% longer than the fastest alternative available.

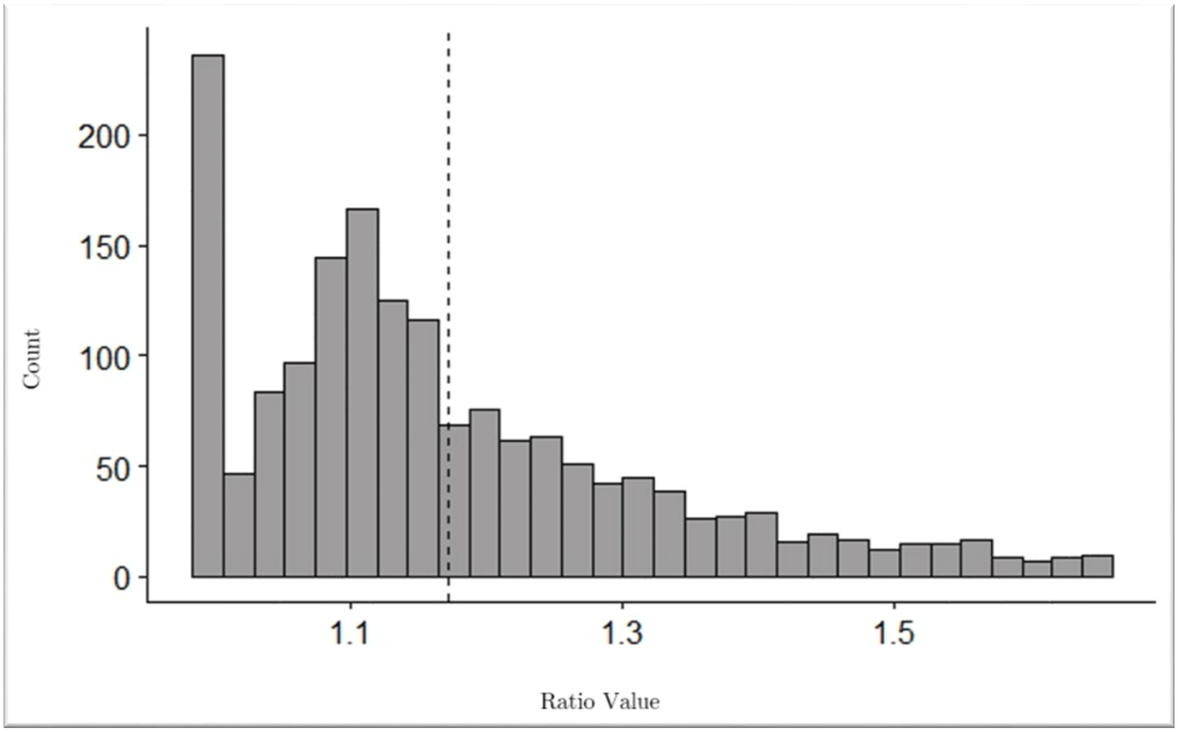

Figure 8. Time ratio for chosen routes (dashed line shows the mean ratio value)

In both the multinomial and mixed logit model estimations, the Transitway variable was found to be significantly positive, meaning that PNR users perceive the Transitway routes to have higher utility than comparable express bus routes. In the multinomial logit model, the Transitway coefficient has a magnitude equivalent to about 23 minutes of walk time. That is, average users are likely to consider a transitway route over an express bus route even if it takes up to 23 minutes longer to access the transitway. This relationship can be further explored by plotting the density curves for walk time by transit service, as shown in Figure 9. We can see that PNR users who chose to use transitway routes walked on average about three minutes longer than express bus users. For PNR users, very little walk time is incurred at the start of a transit trip because the PNR parking facilities usually sit very near to the transit stops. Thus, the density curves shown in Figure 9 mainly capture the walking time between the alighting stop and final destination. It can be interpreted that PNR users are less likely to consider taking an express bus route than a transitway service if the express bus route does not stop very near to their destination. This could have major implications for transit planners aiming to serve large areas without expanding the number of transit routes available – transitway riders are willing to walk further distances to reach their destination from their alighting stop.

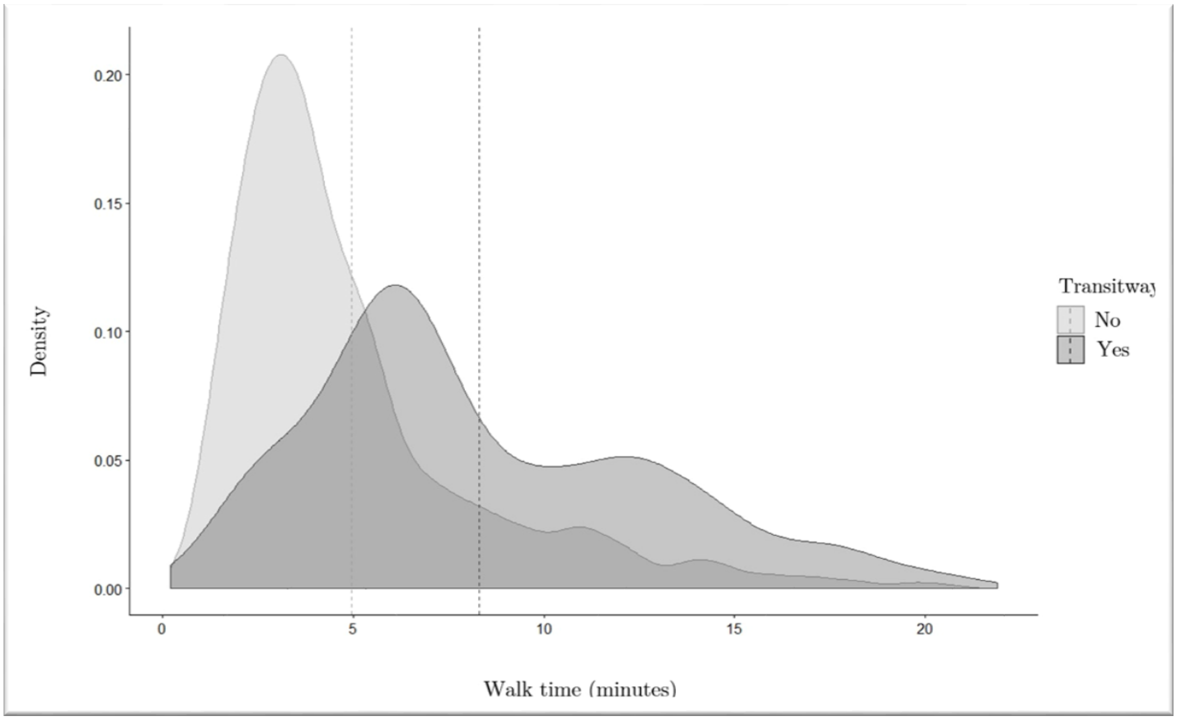

Figure 9. Walk time on chosen routes (dashed line shows the mean walk time)

4.2.3 Same route, different station

To better understand the predictive ability of these models, we can further explore the nature of the prediction error. Upon estimating the multinomial logit model and calculating the choice probabilities for each alternative, each user's set of alternatives is put in one of two groups: those with the same first transit route as the observed path, and those with a different first transit route. Across all user choice sets, same-first transit-route alternatives made up about 5% of alternatives, while other alternatives made up the remaining 95%. Figure 10 shows the normalized choice probability densities for these two groups. The Kolmogorov-Smirnov test gives significant evidence that these density functions come from different distributions (Massey Jr., 1951). Further, same route alternatives generally have higher choice probabilities, and thus higher utility. This means that the multinomial logit model may be better at predicting a PNR user's route than their exact boarding station. To test this, we compare the observed transit route to the predicted transit route, and find a 75% match rate, showing a substantial increase over the 64% match rate for station prediction.

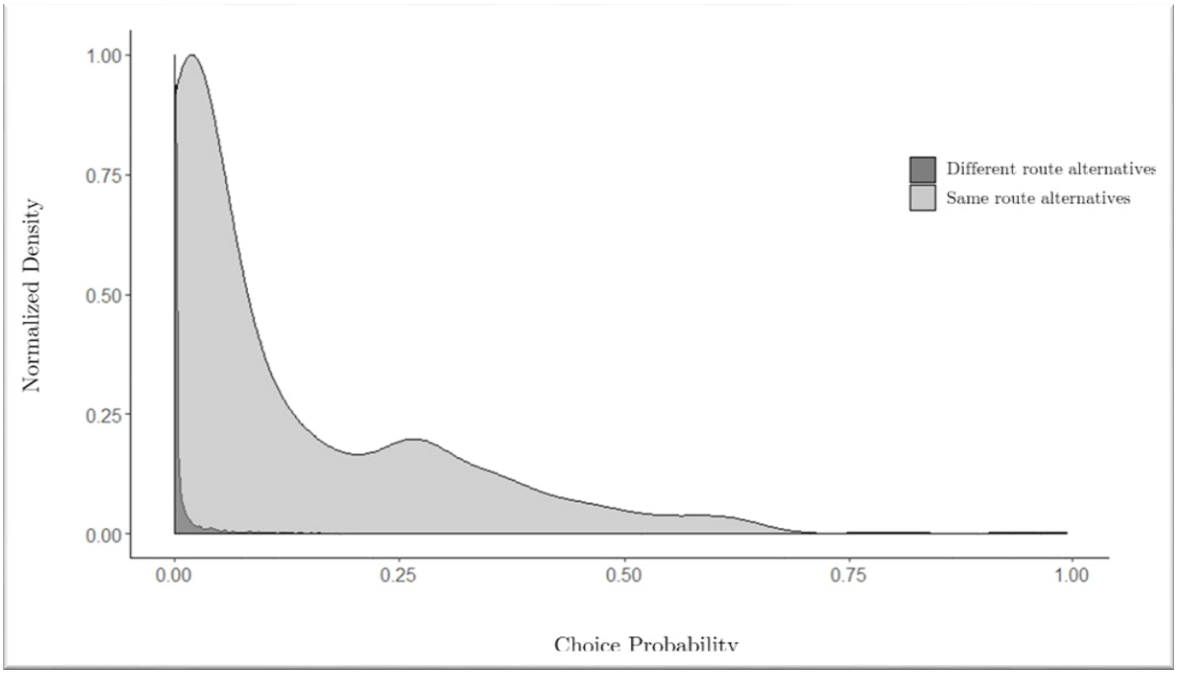

Figure 10. Alternative choice probabilities

4.3 APPLICATION: TRAVELSHED ANALYSIS

4.3.1 Objective

This section will explore the process of defining commuter travelsheds for commuters to the University of Minnesota using the multinomial logit model estimated in the previous section. Travelsheds for each PNR facility are defined analogously to a catchment area in human geography: the area from which a PNR facility attracts users. Defining these areas can be useful to planners interested in better understanding which areas are underserved by PNR facilities in the commuter region. Travelsheds can also inform the expected growth in usage for each facility over time by associating population growth projections from each TAZ with a PNR facility. The following section will explain the data and methodology used to calculate travelshed regions, followed by an analysis and discussion of limitations.

4.3.2 Data and methods

Similar to the model estimation that relied on a dataset containing origin-destination coordinate pairs for PNR users, this portion of the study will require generating a set of origin-destination pairs. The Twin Cities Traffic Analysis Zone (TAZ) dataset was downloaded from Minnesota Geospatial Commons - these 3,030 zones will act as the origin locations representative of commuters throughout the region (Minnesota Geospatial Commons, 2019c). TAZs are defined as bounded areas, so the coordinate pairs of each TAZ centroid will be used when generating travel times. Next, the Coffman Union transit station was used as the destination associated with every TAZ. This destination was chosen because all commuter bus routes that serve the university pass through the Coffman Union transit station, and it is relatively central to the University campus. Using TAZs centroids together with the previously estimated utility model will answer the following question: given a commuter's origin location, which PNR commute alternative to the University of Minnesota campus will yield the highest utility?

For many TAZs, using a PNR facility to reach campus will be unreasonable or may not be the best transit option. For example, it will be much faster for many commuters from downtown Minneapolis to take the Green Line train to campus. Similarly, many areas within City of Minneapolis limits are served by local transit routes that go directly to the Coffman Union transit station. To most accurately define commuter travelsheds for each PNR facility, TAZs were only considered if a PNR facility was the fastest transit option available. In other words, transit travel times were calculated from every TAZ to Coffman Union, and those for which a local transit route was faster than the fastest PNR option were removed from the dataset.

4.3.3 Choice set generation

Unlike the choice set generation performed for the initial model estimation, only the PNR facilities that directly serve Coffman Union with no required transfers were considered in the choice set generation for each TAZ. These 21 PNR facilities are listed by name in Table 7. The methodology from Section 4.1.5 was adopted for each TAZ's choice set, eliminating the PNR alternatives that did not meet the Time and Distance criteria. All PNR alternatives remained in the choice set for all TAZ origins, meaning the two criteria did not eliminate any alternatives. This is likely an outcome of previously filtering each choice set to only include direct transit routes to Coffman Union. Three TAZs were eliminated from the dataset due to missing data, leaving 3,027 TAZs each with 21 PNR facility alternatives to reach Coffman Union.

4.3.4 Results

Figure 11 and Figure 12 show the Twin Cities Metropolitan Area with TAZs color coded by which PNR facility a commuter would most likely use if traveling to the University of Minnesota between 7 and 9 am. Using the multinomial logit model previously estimated from survey data, the utility of each PNR facility for each TAZ was modeled, translated to a choice probability, and the PNR facility with the highest probability was selected as the most likely option. Several findings from the multinomial logit model are apparent in travelshed patterns. First, travelsheds are largest furthest away from the University of Minnesota. This reflects the finding that PNR users choose the facility with the shortest driving distance from their origin because the PNR facilities farthest from the University often present the travel path that involves the least driving. Second, some of the travelsheds are composed of non-contiguous TAZs, which may be explained by the use of travel time as opposed to distance. Due to varying driving speeds by road classification, some TAZs are closer in travel time to a given PNR facility than other TAZs that are closer in space. In the center of Minneapolis, grey TAZs are those for which using a PNR facility was slower than taking a local transit route to reach Coffman Union. Similar to the shaping of travelsheds, the grey region is defined by transit speed as opposed to transit distance.

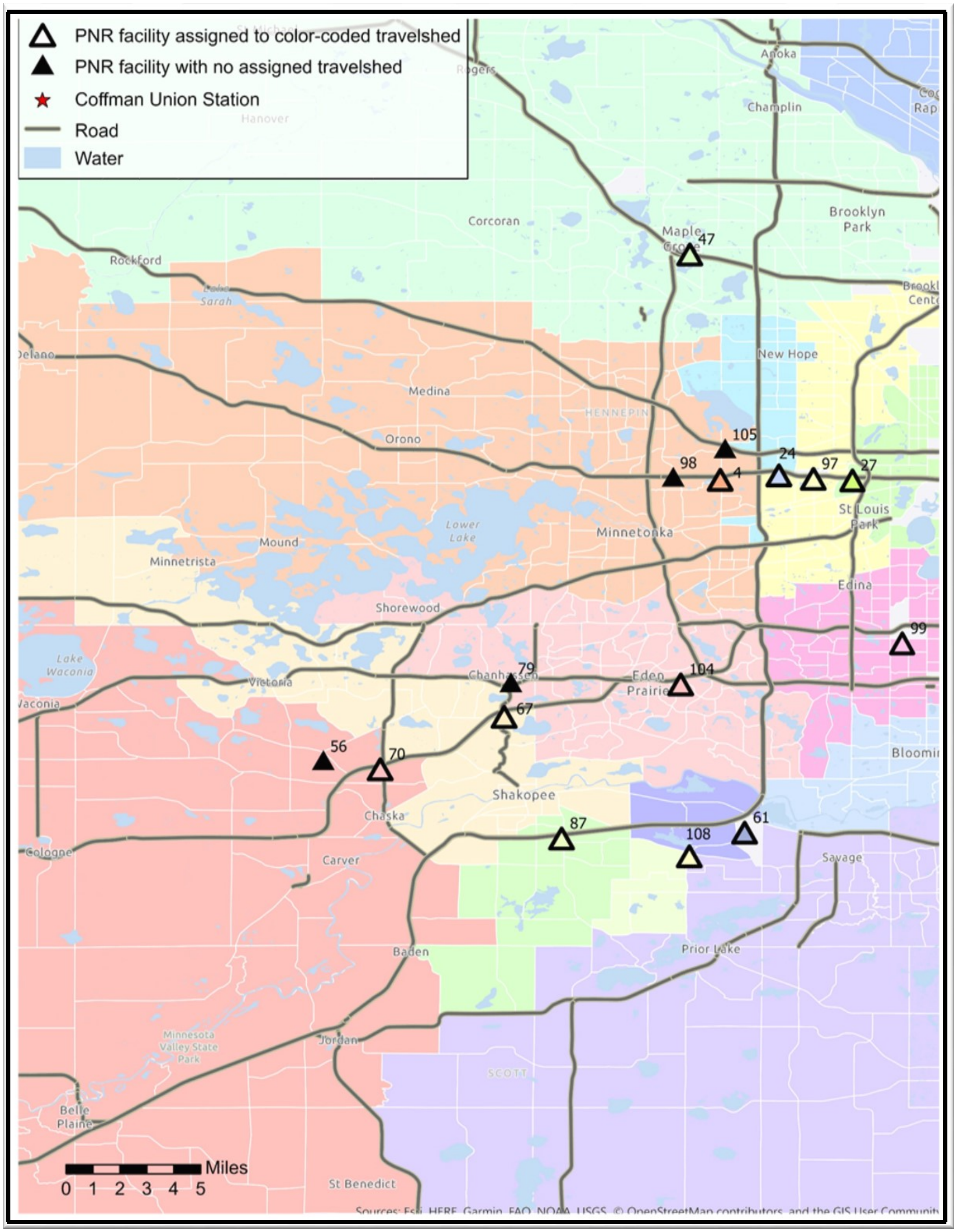

Figure 11. Travelshed for PNR facilities serving the University of Minnesota, West Metro Area

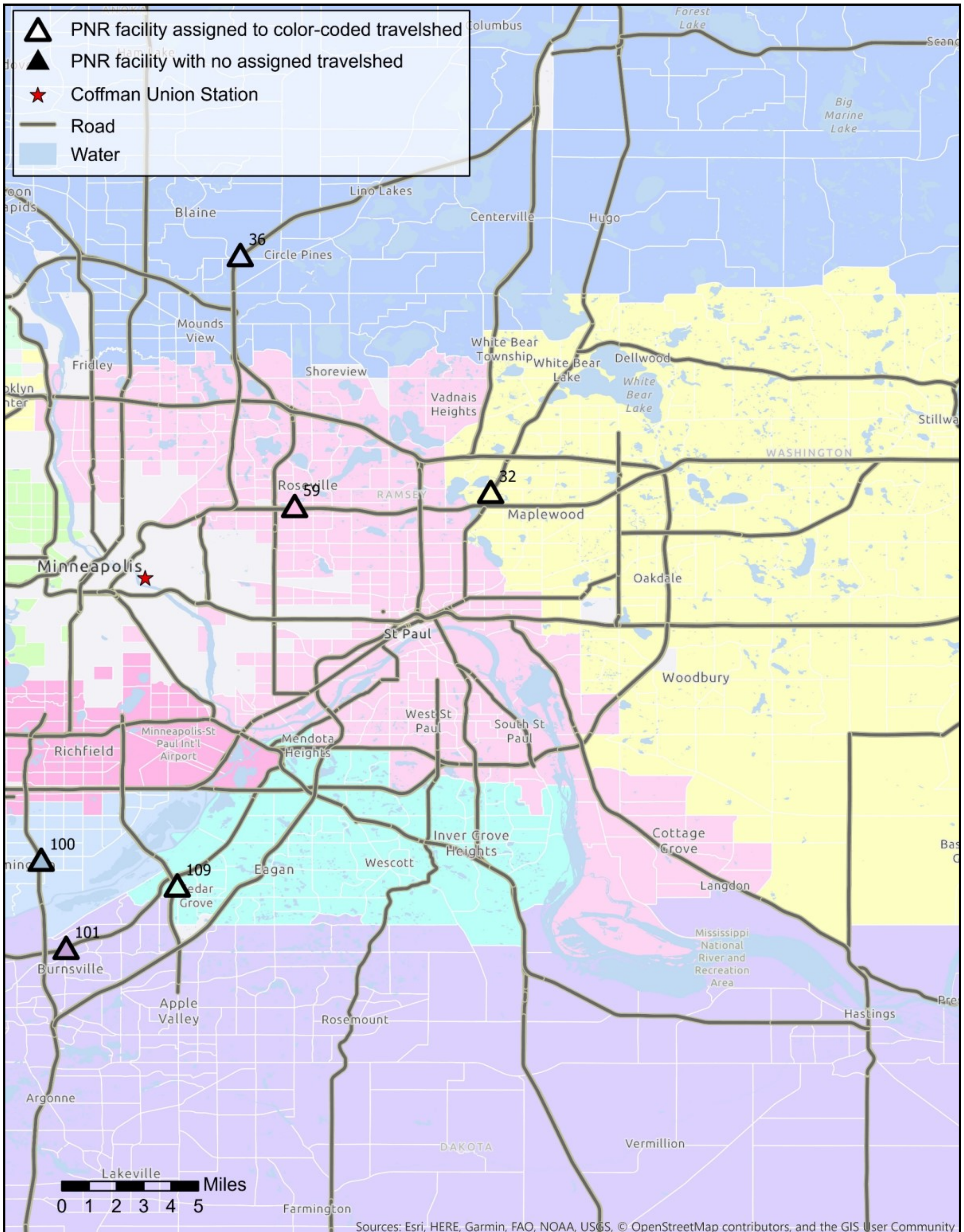

Figure 12. **Travelshed for PNR facilities serving the University of Minnesota, East Metro Area**

Table 7. Travelshed results

Name	ID	Employed pop. 2020	Employed pop. 2030	Change (%)	Attractiveness
Grace Church	59	245,967	257,932	4.9	88.1
Burnsville Transit Station	101	173,785	188,695	8.6	79.3
I-35W & 95th Ave	36	172,595	188,081	9	93.4
Maple Grove Transit Station	47	171,473	189,867	10.7	81.2
Hwy 61 & Co Rd C	32	139,569	150,804	8	76.3
Southdale Transit Center	99	130,935	139,531	6.6	80.6
SouthWest Station	104	89,409	95,680	7	76.1
Co Rd 73 & I-394 South	4	84,628	90,787	7.3	49.3
Cedar Grove Transit Station	109	82,684	89,974	8.8	70.2
Louisiana Ave Transit Center	97	74,003	77,590	4.8	44.5
South Bloomington Transit Center	100	62,712	68,169	8.7	73.5
General Mills Blvd & I-394	24	62,039	65,513	5.6	41.4
Park Place & I-394	27	56,489	58,703	3.9	73.9
East Creek Station	70	33,503	38,269	14.2	61.9
SouthWest Village	67	30,959	34,346	10.9	42.3
Plymouth Road Park & Ride	98	16,705	17,987	7.7	0.0
Southbridge Crossing	61	7,312	8,026	9.8	38.2
Marschall Road Transit Station	87	6,769	7,731	14.2	37.9
Eagle Creek Transit Station	108	5,560	6,200	11.5	34.3
Station 73	105	4,662	5,008	7.4	0.0
Chanhassen Transit Station	79	4,006	4,351	8.6	0.0

Note: PNR 98, 105, and 79 have a choice probability between zero and a tenth of a percent, and appear as zero due to rounding

4.3.5 Park-and-ride facility comparison

A significant body of literature exists on the optimal placement of PNR facilities – that is, if a transit provider were to create a new PNR facility or move an existing one, where should it be placed? A related question has been less-often explored in academic literature but remains of interest to planners: which PNR facilities are providing the least value and can thus be eliminated? Table 7lists each PNR facility that serves the University of Minnesota, as well as some information that may inform the answer to that question. Based on official employed population projections for each TAZ, the total employed population that is served by each PNR facility is shown for both 2020 and 2030, calculated as:

$$Emp_j = \sum_{i \in I}^{n} Emp_i * P(ij) \forall j \in J \quad (15)$$

where ”Emp” is an abbreviation of ”Employed Population Served”, *J* is the set of all PNR facilities, *I* is the set of all TAZs, and *P*(*ij*) is the probability that a commuter from TAZ *i* would choose to use PNR facility *j*. These projections can be used to estimate the potential volume of ridership for each PNR facility. Similarly, employed population growth can be used to predict the change in ridership for each PNR facility. It should be noted that these population numbers represent the whole of the population, while this application only considers PNR routes to the University of Minnesota. If a planner is only interested in forecasting ridership to the University, these employed population numbers should be multiplied by some estimated proportion of the total employed population that commutes to the University of Minnesota. Estimating total PNR ridership for a given facility will require further study. Many PNR facilities that have attractive service to the University of Minnesota have relatively unattractive service to downtown Minneapolis. It is easy to see that, depending on the destination of a PNR user, the attractiveness of each PNR facility will change significantly. If this method is used for PNR demand forecasting, a planner should be equipped with information about the proportions of employees who work in various employment hubs throughout the metropolitan area. Simply, they could consider employees as working in one of three locations: the University of Minnesota campus, downtown Minneapolis, and downtown Saint Paul.

In addition to considering the total employed population served, the logit choice probabilities can help us understand the relative attraction of each PNR facility given a destination. In Table 7, ”Attractiveness” records the following measure:

$$Attractiveness_j = \frac{\sum_{i \in I}^{n} P(ij) * z_{ij}}{\sum_{i \in I}^{n} z_{ij}} \ \ \forall j \in J \quad (16)$$

$$z_{ij} = 1: P(ij) > P(ik) \ \ \forall j \in J$$

$$z_{ij} = 0: otherwise$$

where *J* is the set of all PNR facilities, *I* is the set of all TAZs, *P*(*ij*) is the probability that a commuter from TAZ *i* would choose to use PNR facility *j*, and z_{ij} is a binary variable indicating if *j* is the highest probability alternative for commuters from TAZ *i*. The Attractiveness measure for each PNR facility can be interpreted as the average choice probability among TAZs within its travelshed. A higher value means that the PNR alternative is relatively more attractive compared to other alternatives in the choice set. Similarly, a low probability means that the PNR facility did not stand out from other alternatives and was selected somewhat agnostically. For example, if a choice set consists of three alternatives and each has a choice probability of one third, the PNR user will randomly choose between the alternatives.

Some trends emerge when comparing PNR Attractiveness and Employed Population Served. First, PNR Attractiveness has a statistically significant positive relationship with Employed Population Served. This trend is particularly evident at the extremes, where highly attractive facilities serve a large population while the least attractive facilities serve relatively few. This trend is a combination of more attractive facilities drawing more users, and the effects of some TAZs having higher populations than others. In between, variation within the trend may give reason to investigate the overall success of a given PNR facility. PNR 100 and 24 serve a very similar number of employed individuals, but PNR 100 has an Attractiveness score of 73.5 which dwarfs the 41.4 rating for PNR 24. This means that PNR 100 is a clear choice for its users while PNR 24 is competing closely with other PNR facilities for its users. The importance of understanding these numbers in context cannot be understated. PNRs can differentiate themselves in unobserved ways - the availability of land, service to marginalized communities, or service to underserved destinations. These numbers can, however, serving as a starting point to understand where a surplus or deficit of PNR service exists throughout the metropolitan area.

4.4 LIMITATIONS

While this travel-shed analysis can paint in broad strokes the behavior we would expect to see from commuters to the University of Minnesota, analysis is limited in several ways by the aggregate nature of the data. First, it is assumed that all commuters are traveling to Coffman Union station. While this point is central to much of the university campus, it may not capture the full extent of many commutes. For example, walk time from the final alighting stop to any destination is effectively ignored in travel time calculations by setting the transit stop as the destination itself. Second, assigning the entire employed population from each TAZ to a PNR facility may not have a strong relationship with the number of expected commuters to the university, as university employees are not uniformly distributed throughout the metropolitan area. Lastly, some TAZs were eliminated from travelsheds because it would be faster for a commuter from that TAZ to ride transit without driving at all. This measure was likely unable to identify all of the TAZs from which its residents ride local transit instead of using a PNR facility. This comes about because comparing local transit to PNR routes based solely on travel time ignores the disutility of driving compared to not driving. Even if a PNR facility can offer the fastest commute time for a commuter, it may be preferable to ride transit the whole distance and avoid driving all together. Thus, some of the travelsheds generated for each PNR facility will include too many TAZs.

CHAPTER 5: CONCLUSION

In this study, we conduct two research tasks. One is to examine the impact of the operation of Green Line LRT on the AADT of its adjacent roads, and the other is to estimate PNR location choice model in the Twin Cities area.

In the first task, we applied a quasi-experiment (before-after, treatment-control) research design to examine the effects of the Green Line LRT on vehicular travel demand on the roads in its vicinity. We developed two difference-in-difference models with a negative binomial link function. The first model emphasized annual average daily traffic (AADT) before and after the opening of the Green Line. The second one examined AADT changes over three time periods. To identify the independent effects of the Green Line on AADT, both models controlled for confounding variables, including road classification, land use, and transit supply. This task offered critical insights into the effect of rail transit on road traffic.

- All else being equal, the Green Line reduced AADT of adjacent road segments by 18%. This finding emphasized the critical role of rail transit in travel demand management.
- While the Green Line reduced road traffic in the first two years of operation, the effect became smaller in the next two years. Specifically, the effect decreased from 22% to 16%. The decreasing effect was likely attributable to land-use development induced by the Green Line and travel demand that switched from other routes and modes. Given that more development will occur in the corridor, we expect the effect of the Green Line on road traffic to continue to decrease, a hypothesis to be tested.
- It is crucial to control for confounding factors such as road classification, land use, and transit supply. Otherwise, we are likely to substantially bias the estimates of rail transit effect.

Overall, rail transit has a significant influence on road traffic and its influence is dynamic. The transportation system benefits from rail transit in several ways. First, auto users find rail transit more attractive than bus service. By replacing regular bus service, the Green Line drastically enhances transit ridership along the corridor. Substituting rail transit for driving reduces VMT and its associated negative externalities, such as traffic congestion, air pollution, and crash risk. Second, although the effect of the Green Line on road traffic appears to decrease over time, it improves system efficiency and traveler well-being. Because of the opening of the Green Line, some travelers who used other routes or other modes of transport other than driving, switched back to driving on the roads in the surrounding areas. However, the capacity of the entire transportation system has increased. Furthermore, travelers' behavioral changes make them better off. The travel benefits for those using rail transit have not been diminished. If the decreasing effect is due to land development induced by the Green Line, this is desirable. It shows that rail transit is effective in shaping urban form. New developments around rail transit stations encourage additional auto users to change travel modes. Since the Green Line opened in 2014, the line's ridership has continued to rise. In particular, annual ridership grew from 12.4 million in 2015 to 13.8 million in 2018 (Metro Transit, 2016, 2019). Rising ridership partly substantiates the effect of induced development on transit use.

In the second task, we test several PNR choice models and find that the multinomial and mixed logit models most accurately reveals PNR user preferences from the Metro Transit On-Board Survey data. The model shows that PNR users choose travel paths with a high proportion of time spent on transit and PNR locations with a small distance ratio, where distance ratio measures how "out of the way" a PNR location is when travelling from origin to destination. Interestingly, the model indicates that PNR users are not necessarily looking to use the PNR lot that minimizes their overall travel time. It may be incorrect to draw the conclusion that PNR users do not value shortening travel time. Instead, additional travel time may not be as burdensome as some other factors, such as transferring between transit routes. This outcome is most likely a result of the choice set definition, where some alternative routes may in practice be unreasonable despite their competitive travel time. One particularly meaningful comparison is that of the coefficients of driving time and transferring. The multinomial logit model shows that adding a transfer to a transit path has a disutility equivalent to an additional 17.5 minutes of transit time. PNR users also exhibit facilities preferences; structured lot facilities are preferred to surface parking facilities, and facilities that serve more unique transit routes are perceived negatively. Lastly, the presence of a transitway route in the multinomial logit model makes a PNR location more attractive, meaning transitway routes are sought out in higher proportion than their representation in users' choice sets.

This research task joins a small body of literature on PNR location choice and is innovative in its inclusion and analysis of overlapping routes. First, we estimate a nested logit model to capture substitution rates between transitway routes and express bus service. This model gives an inferior fit to the data compared to the multinomial and mixed logit models. Second, we calculate a sub-route path size factor for the transit leg of each path and find it is significant in the multinomial logit model estimation. This model successfully predicts the PNR location choice of 64.3% of users when tested on a sample set of PNR users, and then is used to generate travelsheds for each PNR facility that serves the University of Minnesota. We use the centroids of all 3,030 TAZs in the Twin Cities metropolitan area to represent commuters to the University of Minnesota and assign them to the PNR facility with the highest choice probability among their choice set alternatives. In addition to creating a spatial representation of the areas served by each PNR facility, this simulation provides the total employed population served by each PNR facility as well as a measure of attractiveness for each. While this application outlines the methodology for generating travelsheds, future work should include information about the spatial distribution and proportion of those commuting to the University of Minnesota to produce more refined results.

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APPENDIX A: ROAD SEGMENTS USED IN THE LRT IMPACT ANALYSIS

Table 8. Number of road segments for each study period

	All	Principal Arterial	Minor Arterial	Collector Road	Local Road
Year0910	943	152	444	131	216
Year1516	657	151	254	170	82
Year1718	1118	152	385	262	319

Note: Almost all principal arterials were included in the three periods.

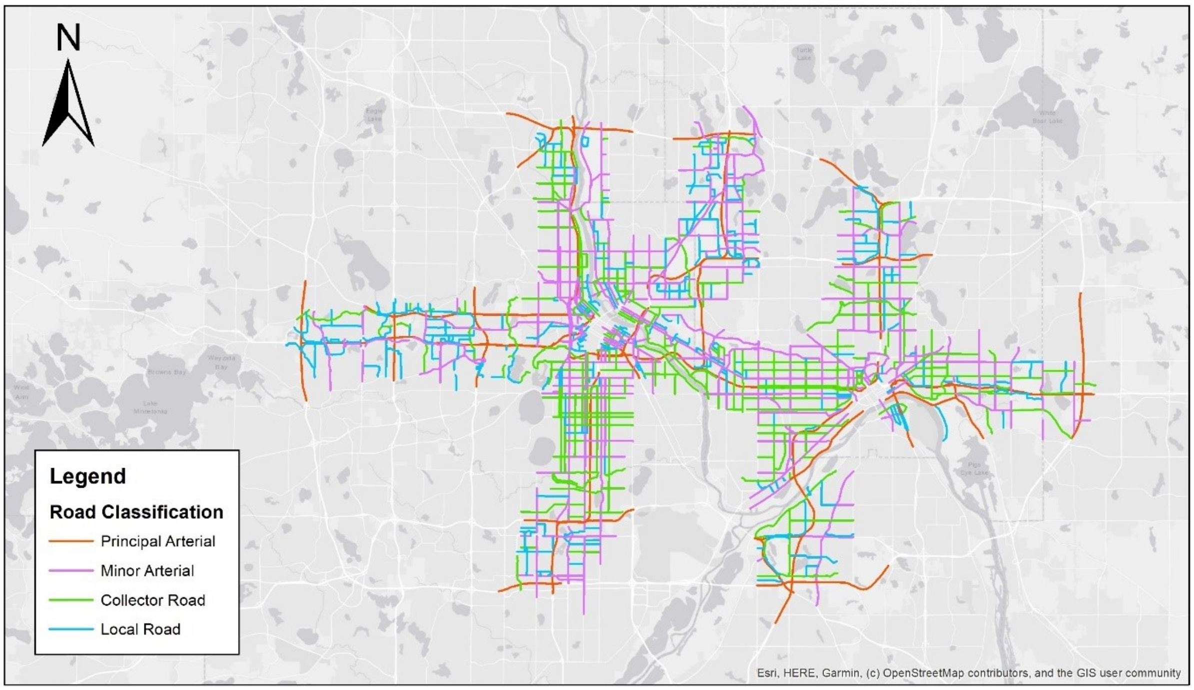

Figure 13. All road segments

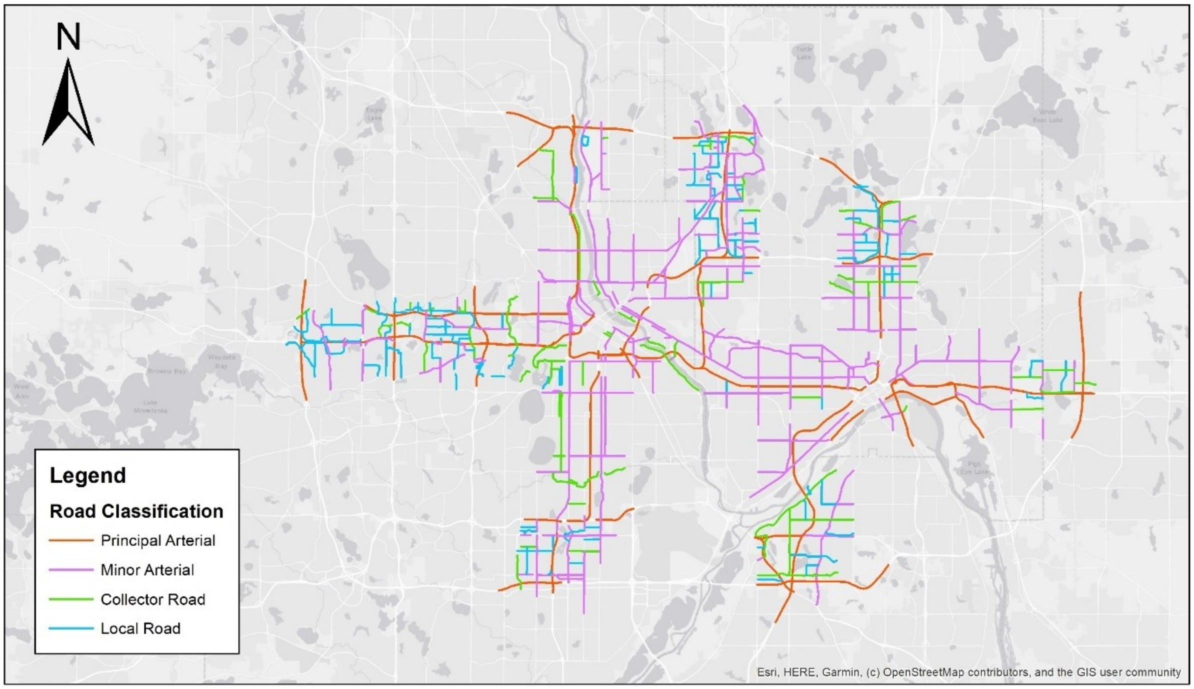

Figure 14. Road segments in 2009-2010

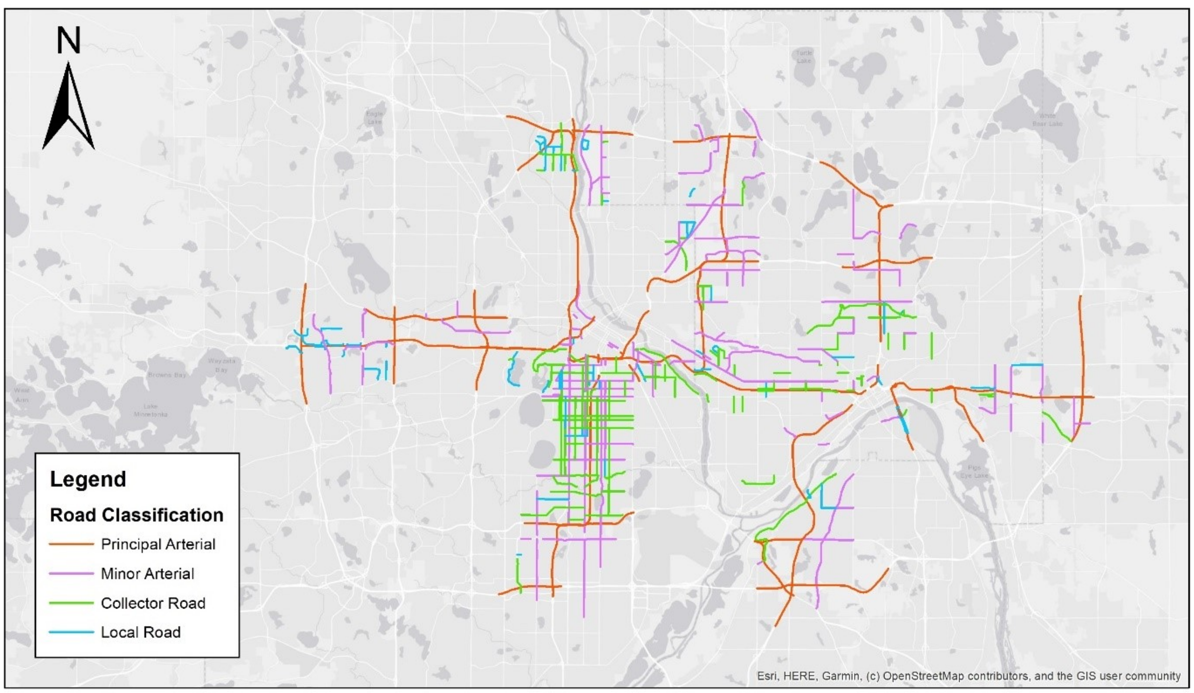

Figure 15. Road segments in 2015-2016

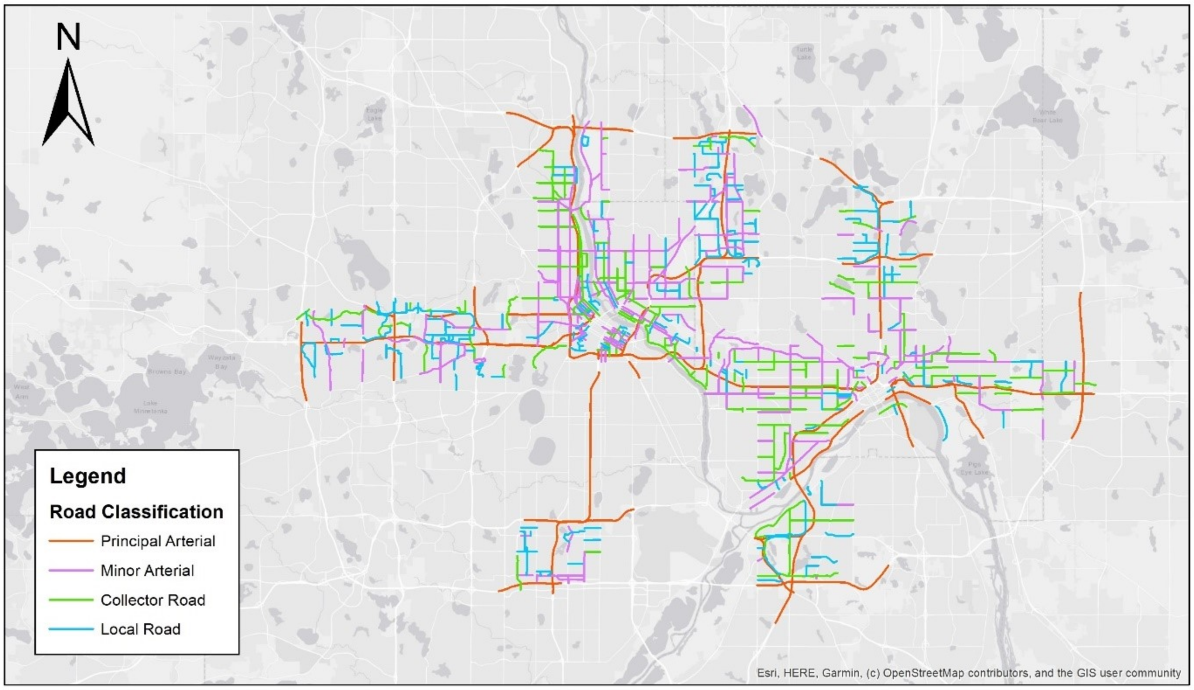

Figure 16. Road segments in 2017-2018