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The Road Less Traveled: Does Rail Transit Matter?

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Abstract
Quantifying the effect of rail transit on vehicular traffic helps policy makers understand its transportation benefits. Previous studies seldom consider the effect over time and the influence of confounding factors. We apply a quasi-experiment research design to explore the evolving impact of the Green Line light rail transit on vehicular traffic in the Twin Cities, controlling for road classification, land use, and transit supply. The results show that rail transit is a substitute for automobile traffic, but induced and diverted trips gradually reduce the substitution effect. The reduced effect suggests that rail transit improves transportation system performance.

Keywords
quasi-experiment, light rail transit, AADT, auto use, induced demand

Abstract
Cuantificar el efecto del tránsito ferroviario en los viajes vehiculares ayuda a los legisladores a comprender sus beneficios de transporte. Los estudios anteriores rara vez consideran el efecto a lo largo del tiempo y la influencia de los factores de confusion. Aplicamos un diseño de investigación cuasi experimental para explorar el impacto evolutivo del tránsito del tren ligero de la Línea Verde en el tráfico vehicular en las Ciudades Gemelas, controlando la clasificación de las carreteras, el uso del suelo y el suministro de tránsito. Los resultados muestran que el transporte ferroviario es un sustituto del tráfico de automóviles, pero los viajes inducidos y desviados reducen gradualmente el efecto sustitución. El efecto reducido sugiere que el tránsito ferroviario mejora el desempeño del sistema de transporte.

Keywords
Cuasi experimento, tránsito de tren ligero, AADT, uso automático, demanda inducida

摘要
量化轨道交通对车辆出行的影响有助于政策制定者了解其运输效益。 先前的研究很少考虑混淆因素及随时间推移所产生的影响。 本文在控制道路分类、土地使用和公交供给的同时， 采用准实验研究设计来探索绿线轻轨交通对双子城车辆出行的影响。 结果表明，轨道交通替代汽车出行，但诱导需求和分流出行使替代效应逐渐降低。 这些被降低的效应展示出轨道交通提高了交通系统的性能。

关键词
准实验, 轻轨交通, 年平均日交通量, 汽车使用, 诱导需求

Introduction

Rail transit has been deployed to increase transit ridership and mitigate the growth of vehicular travel demand in the United States. Total vehicle miles traveled (VMT) in the United States were 3.27 trillion in 2019, 20 percent more than twenty years ago (Federal Highway Administration [FHWA] 2020). The increase in vehicular travel lessens various transportation-related issues, such as traffic congestion

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and air pollution. For example, the average daily congestion time[1] among the fifty-two largest metropolitan areas in the United States 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 United States totaled eighty-eight, 70 percent more than twenty years before (American Public Transportation Association 2019).

Because rail transit requires high subsidies, quantifying its effectiveness is critical for policy makers to garner public support for rail transit investment. Taking the Blue Line light rail transit (LRT) commenced in the Minneapolis–St. Paul (Twin Cities) metropolitan area in 2004 as an instance, the capital cost of this twelve-mile route is 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 policy makers 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 and Goetz 2012; Ewing et al. 2014; Giuliano, Chakrabarti, and 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, from 1992 to 2008. They suggested that the three lines reduced the increase in highway traffic.

Previous studies, however, often have two limitations. First, they do not simultaneously 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 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 in its vicinity (Huang et al. 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 time. Rail transit can generate new development along the corridor (Cervero 1994; Guthrie and Fan 2013) resulting in an increase in trips to the corridor (Cervero 2003).

To address the two research gaps, 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 study applies a quasi-experimental design to compare the annual average daily traffic (AADT) on the roads within and outside LRT-influence areas. We employ multivariate analyses to control for confounding factors including transit service, land use variables, and road function classes. This study attempts to answer the following two research questions:

Research Question 1: How does LRT influence AADT of the road segments within its service area?
Research Question 2: How does the influence change over time?

This study contributes to the literature in two important ways. 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. In particular, although rail transit reduces road traffic at the beginning of its operation, the trips that switched from other modes and other routes gradually fill up the roads. Furthermore, the new development induced by rail transit attracts additional trips to the corridor.

The rest of this paper is organized as follows. We review the literature on the influence of rail transit on vehicular travel demand in the next section. In the "Method" section, we introduce the research design, data, and models. The model results are presented and discussed in the "Results" section. We conclude our research and provide policy-related implications in the final section.

Literature Review

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; Jiang and Mondschein 2019; Spears, Boarnet, and Houston 2017). 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, and 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 and Krizek 2018, 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. 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 and Goetz 2012; Giuliano, Chakrabarti, and Rhoads 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, Chakrabarti, and Rhoads (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 policy making.

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 and van Ommeren 2016; Lo and 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, as 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 (Cao, Wongmonta, and Choo 2013; Mokhtarian, Raney, and Salomon 1997). 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, and Liu 2019; Gan et al. 2020; Shao et al. 2020). Moreover, rail transit increases property values (Cao and Lou 2018; 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. It is worth noting that Ewing et al. (2014) considered transit supply when studying the short-term effect of the TRAX line on nearby traffic and land use change when studying its medium-term effect. However, they did not consider them simultaneously.

The influence of rail transit on road traffic may change over time, but few studies examine how the change evolves. First, the traffic in the vicinity of rail transit is likely to rebound gradually. Downs (1992) proposed the *principle of triple convergence*: additional capacity 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 and 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, 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.

The literature shows that although many aggregate studies assess the effect of rail transit on road traffic, few account for the influence of confounding factors, and few explore the influence of rail transit over time. To fill these research gaps, we propose a conceptual framework to control for potential confounding variables in a longitudinal setting. To the best of

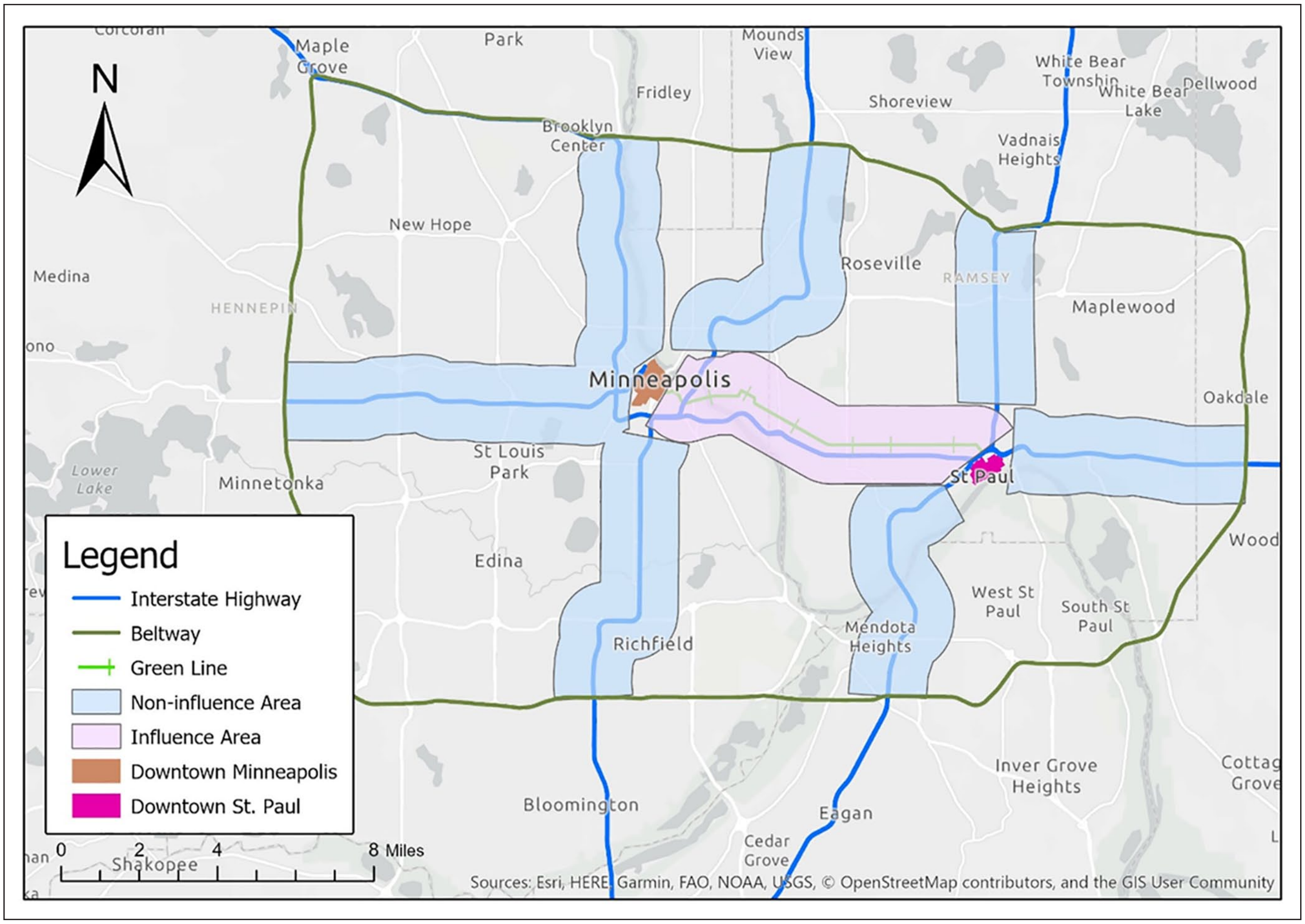

Figure 1. LRT-influence area and non-influence areas.
Note: Interstate highways include I94, I35W, I35E, and I394. Beltways include I494 and I694. LRT = light rail transit.

our knowledge, this is the first aggregate study that includes confounders in the models to study the influence of rail transit on vehicular travel demand. Furthermore, we examine different after-opening periods to illustrate the dynamic effects of rail transit on road traffic.

Method

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 of adjacent road segments. Our key interest is the Green Line light rail in the Twin Cities. It connects downtown Minneapolis and downtown St. Paul, along University Avenue and Washington Avenue. The eleven-mile route has eighteen 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, 52). In 2019, the average weekday ridership of the Green Line was 44,004, exceeding the projected ridership in 2030 by 10 percent (Metro Transit 2020). These statistics imply that about 40 to 50 percent of Green Line riders are new to transit.

In this study, 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 may disrupt the performance of adjacent road networks.

We deliberately chose treatment and control groups. We selected the one-mile buffer along the Green Line as the LRT-influence area (the pink area shown in Figure 1). All road segments within the LRT-influence area constituted the treatment group (see Figure A2 in the appendix). We assumed that before the opening of the Green Line, drivers would choose adjacent minor arterials to detour when the streets where the Green Line is located were congested. Because the adjacent minor arterial on the north side is far from the Green Line and about one mile away, we selected one mile as the size of the buffer. Furthermore, the one-mile buffer covers most residents nearby who may switch from driving to transit. It is worth noting that we also used one-km buffers as our study areas to test the robustness of the results and found that the relationships among the same set of variables (not shown) are consistent with what we reported in the "Results" section. In the remainder of this paper, we reported only the results based on the one-mile buffers.

Ideally, the control corridor should be the same as the treatment corridor before the treatment in a quasi-experiment because the treatment is unable to be randomly assigned. Otherwise, confounding factors may be a concern. However, no two corridors are alike in a metropolitan area and it is hard to find a perfect match. When choosing control corridors, we adopted two approaches to minimize the confounding effect on vehicular travel demand. First, we regarded one-mile buffers along the interstate highways within the beltway (the blue areas shown in Figure 1) as non-influence areas, and all road segments within these non-influence areas constituted the control group (Figure A2 in the appendix). The non-influence areas are similar to the LRT-influence area because both of them are served by the backbones of the road network in the Twin Cities metropolitan area. In particular, both areas are along the interstate highways which play an important role in assembling and distributing travel demand in the Twin Cities. Furthermore, both are located in the area within the beltway, which covers most of the urbanized area and people's trip destinations in the region. Both are also connected to the two downtowns (St. Paul and Minneapolis) in the metro area.

Second, we tried to control for confounding factors in the models of vehicular travel demand. Although the LRT-influence area and non-influence areas are comparable to a certain degree, they differ in their surrounding built environment. As presented later in the "Models" section, we accounted for the influences of land use and transit supply in the models. Statistical control is a commonly used approach to address the confounding issue. For example, when examining the influence of the Hiawatha LRT on land use change in Minneapolis, Hurst and West (2014) selected the observations within the influence area of the LRT as the treatment group and all the observations outside the influence area as the control group, and then included other variables related to the observations to control for the differences between the treatment and control groups.

Although imperfect, our approaches represent an improvement compared with previous studies. When exploring the impact of LRT lines on VMT in Denver, Bhattacharjee and Goetz (2012) compared the level of traffic on the highway segments within the LRT-influence zone and on all other highway segments outside of the influence zone (excluding two segments under construction during the study period). However, they did not consider the differences between treatment and control groups prior to the operation of the LRT lines and hence ignored the influence of potential confounding factors. When investigating the influence of the Expo Line on freeway speed in Los Angeles, Giuliano, Chakrabarti, and Rhoads (2016) chose the areas adjacent to the influence area of the Expo line as controls. Although they stated that the treatment and control areas are similar, they did not justify their choice and did not control for potential confounding factors in their difference-in-difference models. Ewing et al. (2014) represents an improvement. They chose two north–south streets as the control group for the east–west LRT line because these two streets had similar vehicular traffic before the treatment. However, because the control streets intersect with the treatment street, the traffic on the control streets is likely to be affected by the LRT.

By adopting the treatment–control design, we also accounted for the influences on vehicular travel demand of third-party variables, such as gasoline prices and region-wide transportation policies. It is worth noting that 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.

Data

We used AADT 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 (Minnesota Department of Transportation [MnDOT] 2020). This information can be used to calculate annual VMT, helping the FHWA for travel analysis and funding (MnDOT 2020). We obtained AADT data during 2009–2018 from the 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. Table 1 illustrates the number of road segments by road classification in the three periods. MnDOT classifies road segments into four categories: principal arterial, minor arterial, collector roads, and local road (see Table 2 for definition and Figure A1 in the appendix for an illustration). In general, a higher road classification is associated with a larger volume. Figures A2 to A5 in the appendix illustrate the road segments with AADT data available at different periods.

Table 1 shows that almost all principal arterials in the study area are included in the three study periods. However, the numbers of minor arterials, collector roads, and local roads vary. This is because not all road segments have AADT data in a given period as we presented in the last paragraph. In this study, we pooled all observations in the three periods as our working data. Alternatively, we could use a panel dataset containing the same observations appearing in all the three periods. Compared with the panel data, our working data have a larger sample size. In particular, the sample size

Table 1. Number of Road Segments by Study Period.

	All	Principal arterial	Minor arterial	Collector road	Local road
Year0910	943	152	444	131	216
Year1516	657	151	254	170	82
Year1718	1,118	152	385	262	319

Table 2. Variable Definition.

Variables		Definition
Dependent variable		
Travel demand	AADT	Normalized AADT in number of vehicles for both directions of the road segment[a]
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[b]	Principal Arterial	Dummy variable indicating the road segment is classified as principal arterial, including interstate highways, and other freeways and expressways which provide the highest level of mobility
	Minor Arterial	Dummy variable indicating the road segment is classified as minor arterial, which provides relatively lower level of mobility than principal arterials
	Collector Road	Dummy variable indicating the road segment is classified as collector road, which gathers trips from local roads and funnels them into arterials
	Local Road	Dummy variable indicating the road segment is classified as local road, which provides limited mobility but the highest level of accessibility; it is the reference category for the other three types of road classification
Land Use[c]	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[d]	Transit Frequency	Daily average number of transit service trips per hour in the quarter-mile buffer of the road segment[e]

Note: AADT = annual average daily traffic; LRT = light rail transit.
[a]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.
[b]Road classification is consistent within the study period. The definition of each road class is from the Federal Highway Administration (2013). Figure A1 presents an example of each type of road classification.
[c]We applied land use data in 2010 for the period of 2009–2010, 2016 for 2015–2016, and 2018 for 2017–2018. We assumed that travel demand of road segments is correlated with land use within their half-mile buffers.
[d]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.
[e]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.

of the final models increased from 735 to 2,718. Enlarging sample size increases the precision of the estimators and the power of the test statistics (Wooldridge 2012). To account for the differences among road segments in different study periods, we controlled for the characteristics that vary by road segment as we specified in equation (1) later.

This type of quasi-experimental research design with a pooled dataset has been applied in many studies (Benson and Cao 2020; Billings 2011; Cao and Lou 2018; Cho, Kim, and Lee 2020; Kiel and McClain 1995; Sunak and Madlener 2016). For example, Kiel and McClain (1995) applied a quasi-experimental design to study the influence of an undesirable land use, an garbage incinerator, on housing values in North Andover, MA. They designed seven study periods and included 416, 481, 595, 302, 662, 711, and 323 houses sold in these periods in their study, respectively. To control for the differences among these different groups of houses, they included housing features (such as age, living area, and number of bath rooms) as control variables in their pooled estimation model. Cao and Lou (2018), a recent publication

Table 3. Variable Statistics.

Variable	Year 2009–2010 (N = 943) Treatment group (n = 137) M	SD	Control group (n = 806) M	SD	Year 2015–2016 (N = 657) Treatment group (n = 120) M	SD	Control group (n = 537) M	SD	Year 2017–2018 (N = 1,118) Treatment group (n = 232) M	SD	Control group (n = 886) M	SD
AADT	543.83	521.57	360.75	470.85	462.81	611.34	488.35	600.71	346.62	489.03	345.23	507.24
Principal Arterial	0.19	0.39	0.16	0.36	0.21	0.41	0.23	0.42	0.11	0.31	0.14	0.35
Minor Arterial	0.72	0.45	0.43	0.50	0.39	0.49	0.39	0.49	0.42	0.50	0.32	0.47
Collector Road	0.08	0.27	0.15	0.36	0.32	0.47	0.25	0.43	0.31	0.47	0.21	0.41
Local Road	0.01	0.12	0.27	0.44	0.08	0.28	0.13	0.34	0.16	0.36	0.32	0.47
Commercial Area	163.11	105.84	143.78	103.65	146.91	86.77	160.77	105.26	161.91	100.59	153.08	100.73
Industrial Area	48.45	62.46	51.62	74.81	103.93	106.69	50.44	79.30	73.04	88.95	69.00	81.56
Institutional Area	66.56	68.66	36.38	53.40	47.47	60.99	23.33	45.09	50.90	62.67	20.66	40.44
Residential Area	238.91	112.99	356.51	166.04	251.77	119.51	399.45	174.01	247.06	123.06	331.40	157.93
Transit Frequency	7.96	7.14	2.28	3.30	7.94	5.77	3.39	3.89	9.14	6.92	2.95	4.86

Note: N = sample size; AADT = annual average daily traffic.

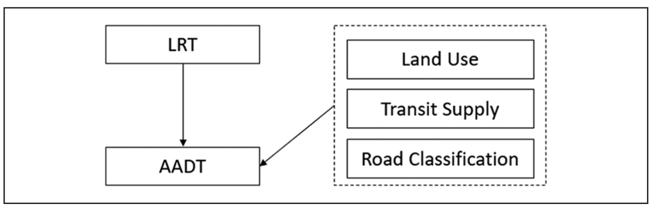

Figure 2. Conceptual framework of this study.
Note: AADT = annual average daily traffic; LRT = light rail transit.

of this journal, also employed the similar control approach to examine the influence of the Green Line on housing sales price.

We also acquired land use data from the Metropolitan Council, the regional Metropolitan Planning Organization, and transit supply data from the Metro Transit. 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 2 defines the variables used in this study and Table 3 presents their descriptive statistics.

Models

As presented in Figure 2, 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.

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 2 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, and Swindell 2011; Hurst and 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. The coefficient of the dummy variable $Opening$ measures the temporal trend of travel demand before and after the operation of the Green Line, which is not related to the locations of road segments. On the contrary, the coefficient of the dummy variable LRT indicates the spatial difference of travel

Table 4. Model Results.

Variable	Model 1 Coefficient	Model 1 *p* value	Model 1 Relative change (%)	Model 2 Coefficient	Model 2 *p* value	Model 2 Relative change (%)
Opening	0.04	.194				
LRT × Opening	−0.20	.003	−18.23			
LRT	0.33	.000		0.33	.000	
LRT × Year1516				−0.25	.003	−22.18
LRT × Year1718				−0.18	.015	−16.19
Year1516				0.04	.275	
Year1718				0.03	.264	
Principal Arterial	2.81	.000	1,562.65	2.81	.000	1,564.32
Minor Arterial	1.19	.000	227.72	1.19	.000	227.72
Collector Road	0.45	.000	56.31	0.45	.000	56.30
Commercial Area	8.60×10^{-4}	.000	0.09	8.53×10^{-4}	.000	0.09
Industrial Area	-7.22×10^{-4}	.000	−0.07	-7.09×10^{-4}	.000	−0.07
Institutional Area	1.19×10^{-3}	.000	0.12	1.18×10^{-3}	.000	0.12
Residential Area	1.66×10^{-4}	.051	0.02	1.67×10^{-4}	.052	0.02
Transit Frequency	−0.02	.000	−1.91	−0.02	.000	−1.90
Constant	4.25	.000		4.25	.000	
Dispersion factor	0.3712			0.3711		
Pseudo-adjusted R^2	.7229			.7230		
Sample size	2,718			2,718		

Note: LRT = light rail transit.

demand between the influence and non-influence areas, which does not distinguish the temporal difference. These two variables are the base terms for the interaction term. It is worth noting that if an interaction term in a difference-in-difference model is statistically significant, we cannot interpret the coefficients of its base terms independently from the interaction term. In this case, the influence of one base term depends on the value of the other base term.

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). The coefficients of the dummy variables $Year1516$ and $Year1718$ differentiate the temporal impacts of the second and third time periods. We calculated variation inflation factors (VIFs) for the variables in the two models. All of them are smaller than five, suggesting that multicollinearity is not an issue.

Results

Table 4 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^2: both are around .72.

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 percent, 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 and 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 percent 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 percent 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

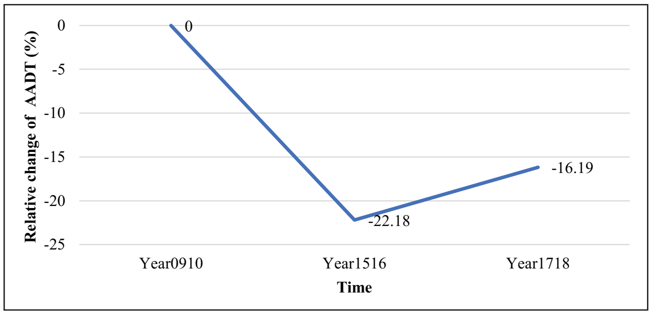

Figure 3. Relative change of AADT in the LRT-influence area.
Note: AADT = annual average daily traffic; LRT = light rail transit.

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 percent. 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 percent reduction in AADT.

It is worth noting that we also tested the influence of the number of jobs[2] along the road segment in our models. This variable was negatively associated with AADT. We then checked its bivariate correlation with Ln(AADT) and found that the correlation coefficient was miniscule and statistically insignificant. A further diagnostics showed that the negative coefficient of the number of jobs in the multivariate model was caused by commercial area. If we removed it from the model, the number of jobs became insignificant. Because the negative influence of the number of jobs is counterintuitive and inconsistent with previous studies (Selby and Kockelman 2013; Zhao and Chung 2001), we dropped it from the models.

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 percent 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 percent 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 3). This finding is likely attributable to the *principle of triple convergence*, as discussed in the literature review. Transit-induced development is another cause.

The Green Line increases property values and attracts real estate development along its route, such as apartments, retail stores, and restaurants. Cao and Lou (2018) found that the commencement of the Green Line improved housing values by $13.7 per square foot. Cao and Porter-Nelson (2016) also showed that the funding announcement of the Green Line increased building activities in the station areas by approximately 24 percent. 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.

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 5, the estimated reduction in AADT in the after-opening period is 35.8 percent, which almost doubles the effect (18.2%) when controlled for the confounding variables (Table 4). 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.

Conclusion

In this study, we applied a quasi-experiment (before–after treatment–control) research design to examine the effects of the Green Line light rail 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 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 research has several limitations that are avenues for future research. First, there are no perfect matches to a treatment corridor in a metropolitan area. To address this intrinsic shortcoming, it is better to account for the influences of any differences between treatment and control corridors in statistical models. Although we have addressed some factors that may confound the association between LRT deployment and AADT, future studies should control for as many confounding variables as possible. Second, because of a lack of archived data, we could not include information on regional

Table 5. Model Results without Controlling for Confounders.

	Model 3			Model 4		
Variable	Coefficient	*p* value	Relative change (%)	Coefficient	*p* value	Relative change (%)
Opening	0.10	.038				
LRT × Opening	−0.44	.000	−35.81			
LRT	0.41	.000		0.41	.000	
LRT × Year1516				−0.46	.002	−37.12
LRT × Year1718				−0.41	.002	−33.38
Year1516				0.30	.000	
Year1718				−0.04	.410	
Constant	5.89	.000		5.89	.000	
Dispersion factor	1.2189			1.2057		
Pseudo-adjusted R^2	.0057			.0179		
Sample size	2,718			2,718		

Note: LRT = light rail transit.

road construction projects in the models, although it is desirable to capture their influence on AADT. Third, 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. In addition, AADT does not measure the origins and destinations of the trips and, thus, cannot differentiate local trips starting or ending within the study areas and through traffic. As rail transit influences local trips and through traffic differently, future research could study local trips specifically if related data (such as mobile phone data or big data with geographical location information) are available. Fourth, we used four years of data to examine the effect of rail transit over time. Although 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 period.

Nevertheless, this study offers critical insights into the effect of rail transit on road traffic.

- All else being equal, the Green Line reduces AADT of adjacent road segments by 18 percent. This finding emphasizes 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 becomes smaller in the next two years. Specifically, the effect decreases from 22 to 16 percent. The decreasing effect is likely to be attributable to land use development induced by the Green Line and travel demand 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 will 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 aspects. First, rail transit is more attractive to auto users 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 of those using rail transit have not been diminished. If the decreasing effect is due to land development induced by the Green Line, this is more 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 its opening in 2014, the Green Line ridership has kept rising. In particular, the annual ridership grew from 12.4 million in 2015 to 13.8 million in 2018 (Metro & Transit 2016, 2019). The rising ridership partly substantiates the effect of induced development on transit use.

Appendix

Road Segments Considered in This Study

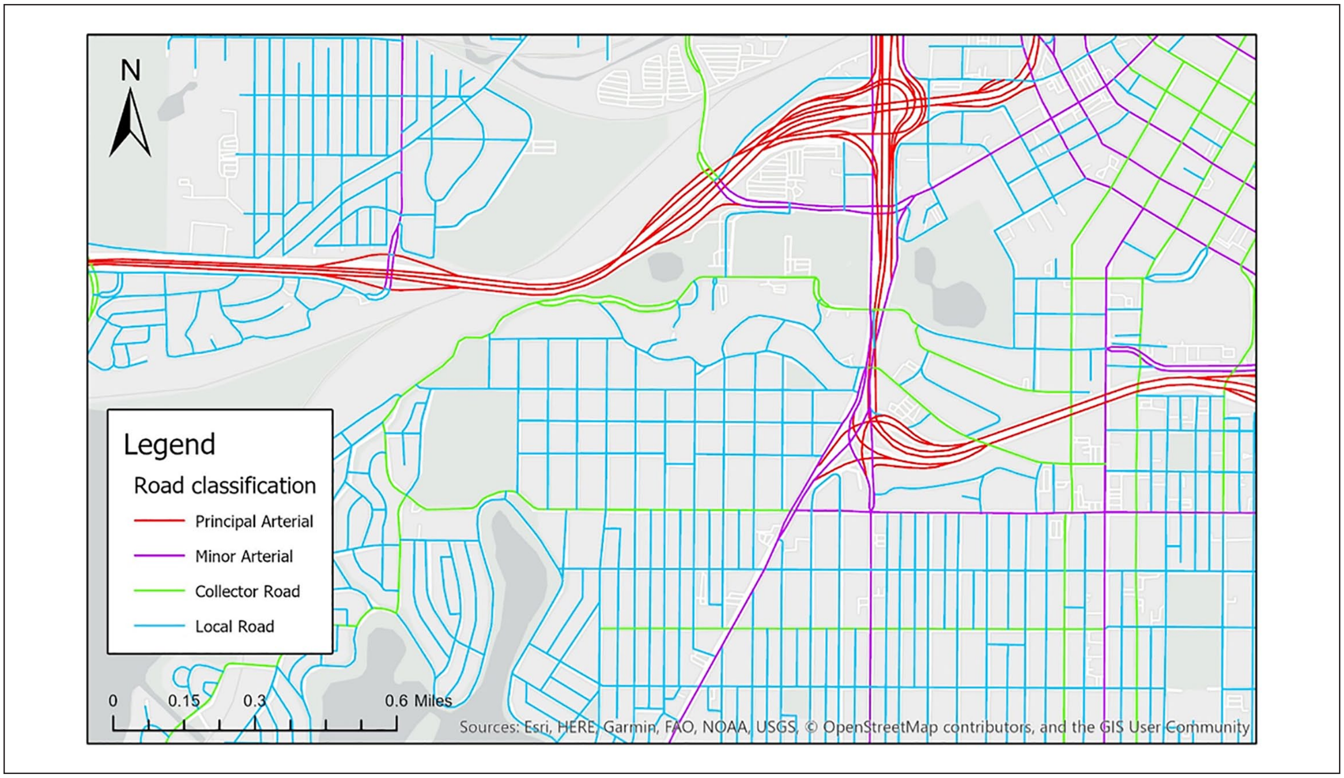

Figure A1. An illustration of road classification.

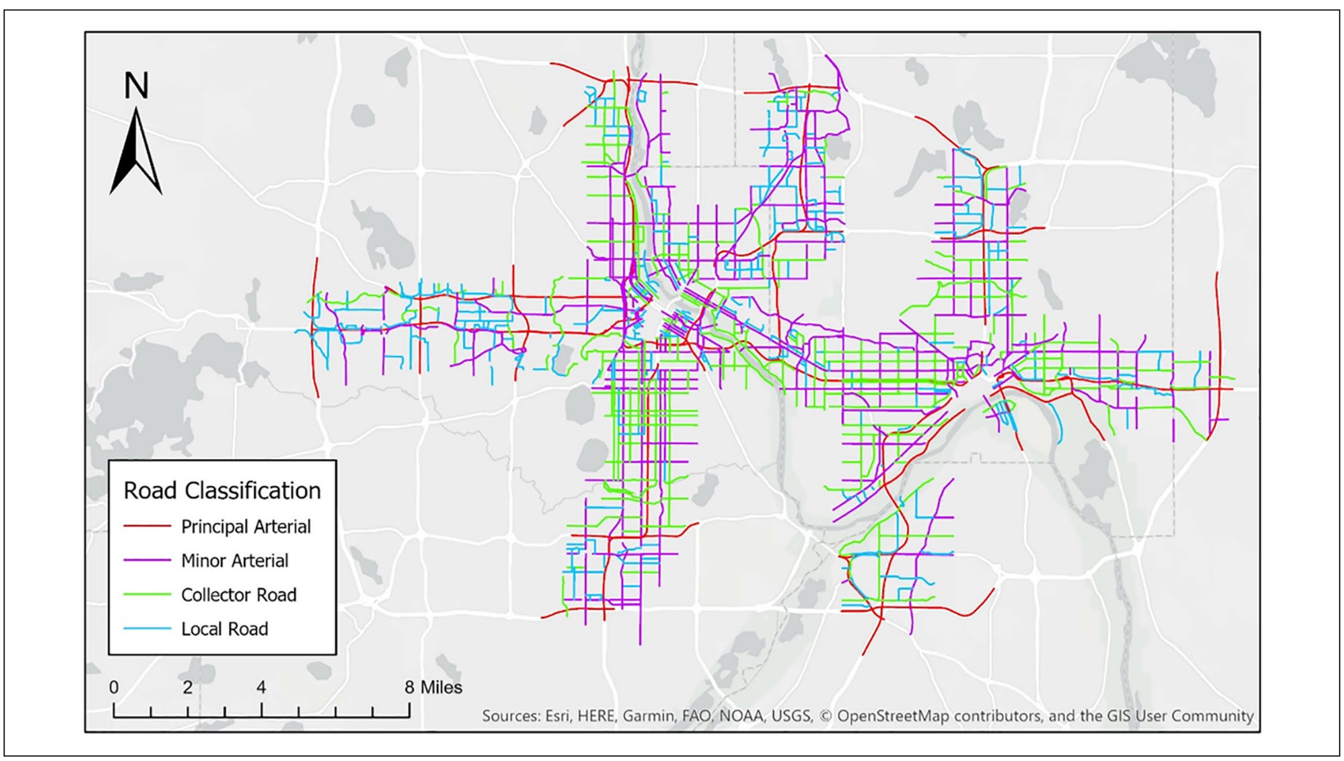

Figure A2. All road segments.

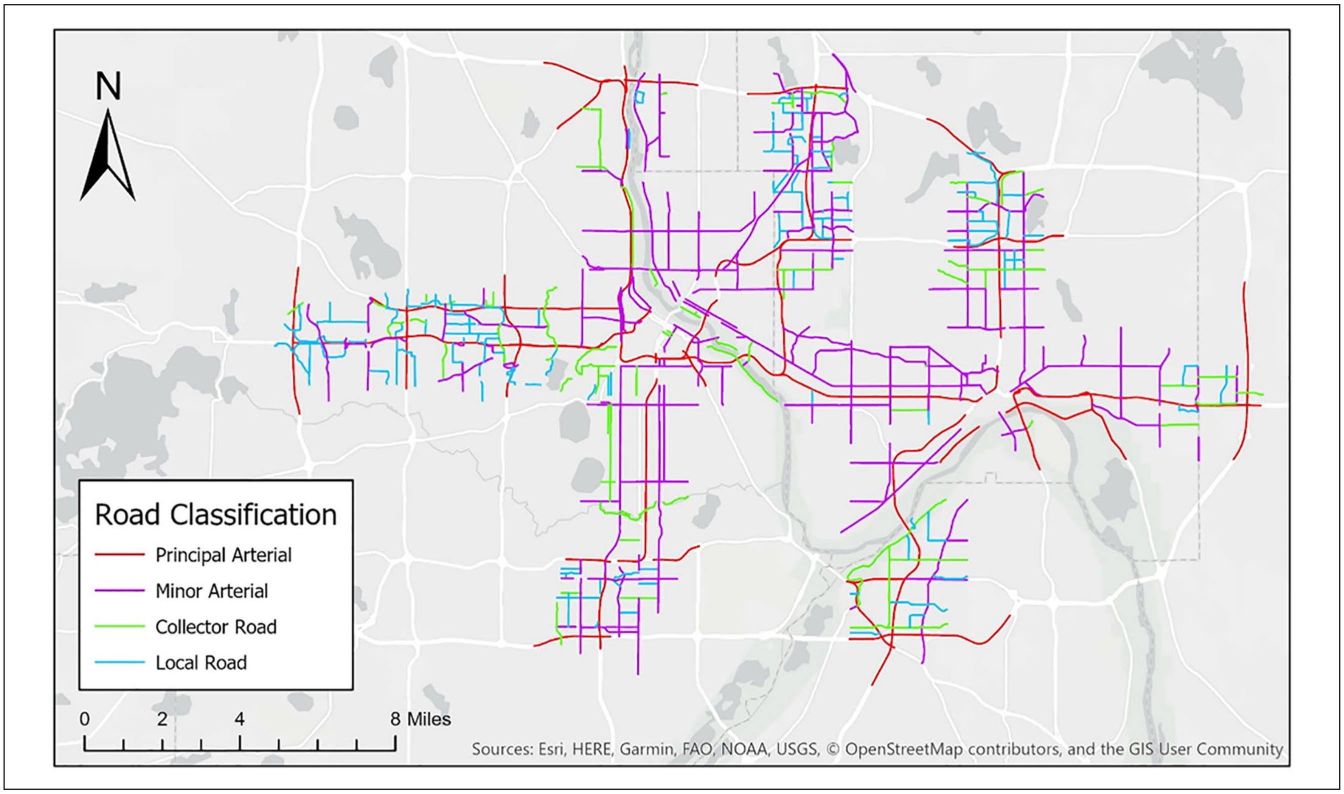

Figure A3. Road segments in 2009–2010.

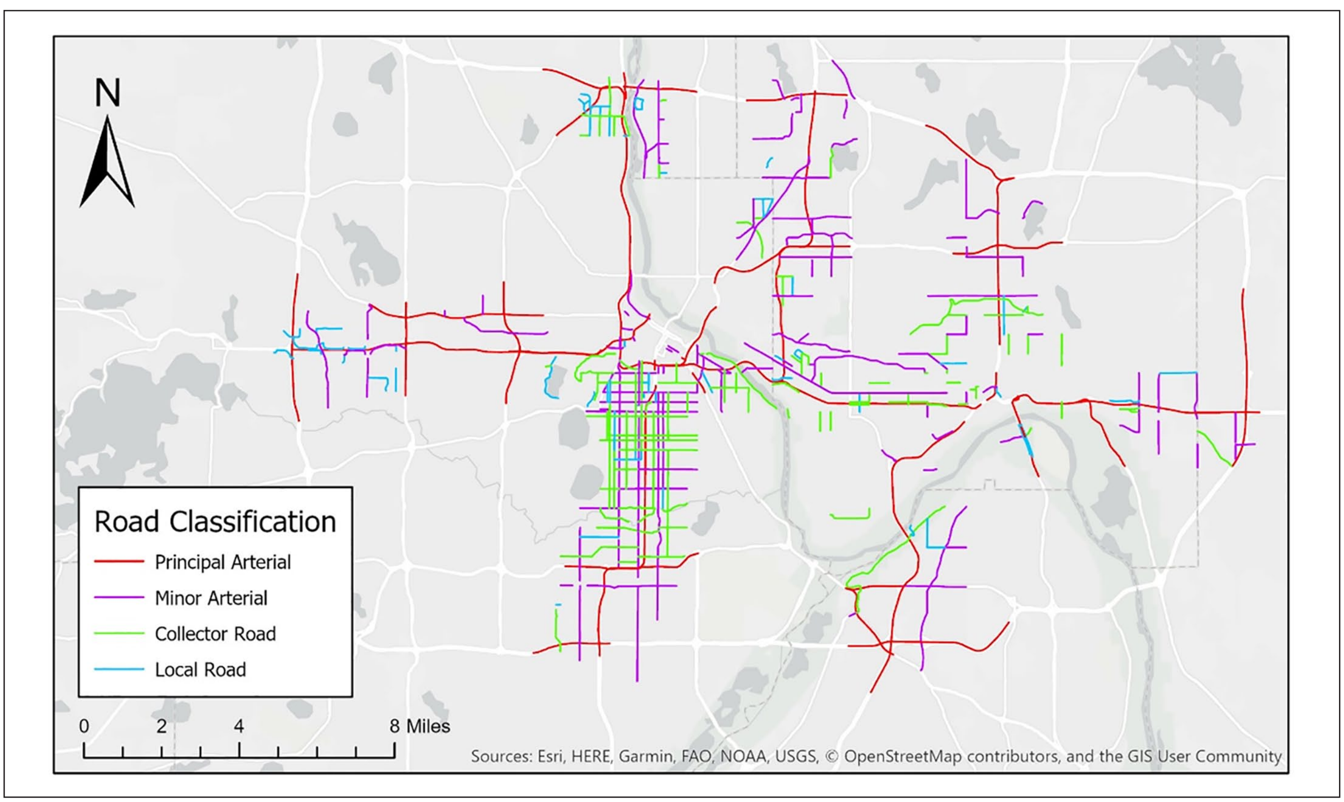

Figure A4. Road segments in 2015–2016.

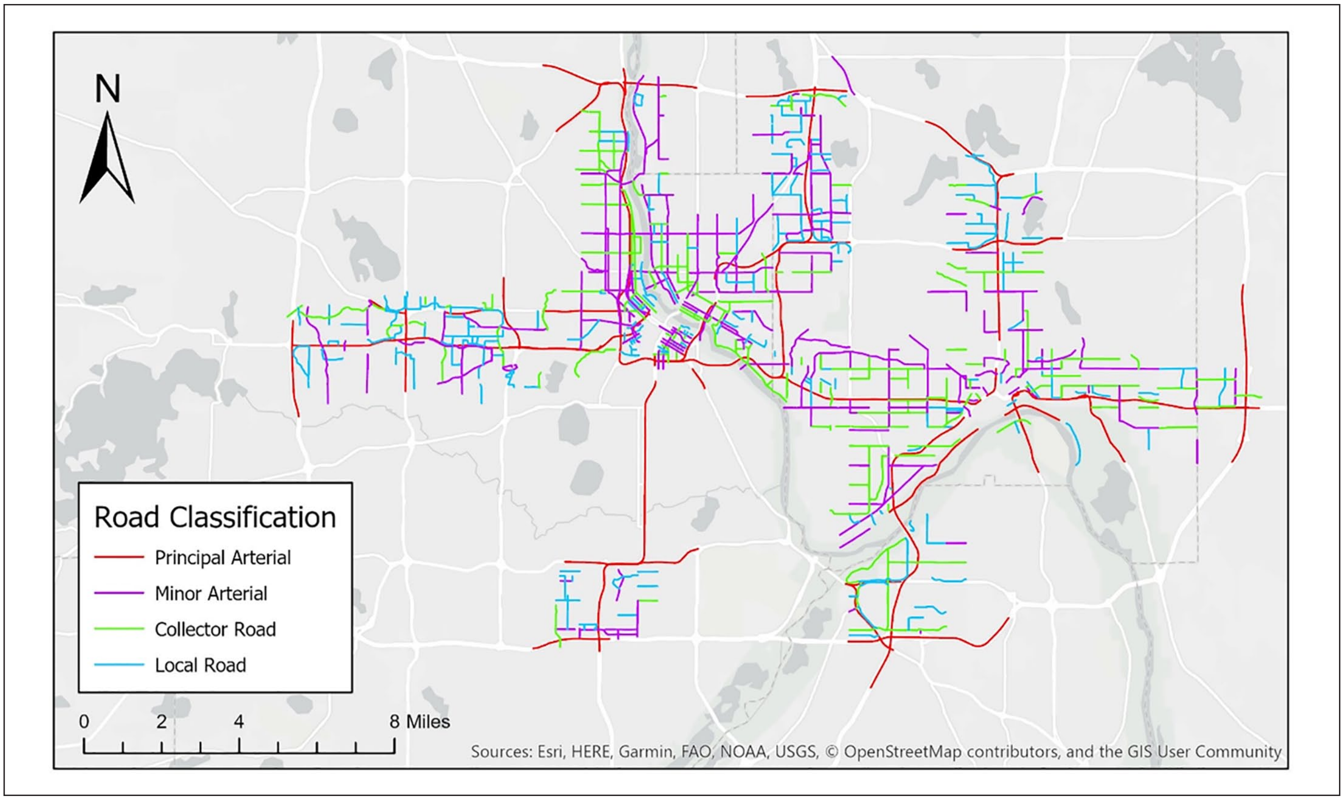

Figure A5. Road segments in 2017–2018.

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Notes

1. Congestion time is the number of hours "when freeways operate less than 90 percent of free-flow freeway speeds" (Federal Highway Administration [FHWA] 2019, 2). It is measured from 6 a.m. to 9 p.m. on weekdays.
2. The number of jobs was measured in the half-mile buffer of road segments during the corresponding study periods. We downloaded the job dataset from the Center for Economic Studies (https://onthemap.ces.census.gov/). We applied job data in 2010 for the period of 2009–2010, 2016 for 2015–2016, and 2018 for 2017–2018.

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