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Exploring the interaction effect of poverty concentration and transit service on highway traffic during the COVID-19 lockdown

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Abstract: During COVID-19 lockdowns, transit agencies need to respond to the decline in travel but also maintain the essential mobility of transit-dependent people. However, there are a few lessons that scholars and practitioners can learn from. Using highway traffic data in the Twin Cities, this study applies a generalized additive model to explore the relationships among the share of low-income population, transit service, and highway traffic during the week that occurred right after the 2020 stay-at-home order. Our results substantiate that transportation impacts are spread unevenly across different income groups and low-income people are less able to reduce travel, leading to equity concerns. Moreover, transit supply influences highway traffic differently in areas with different shares of low-income people. Our study suggests that transportation agencies should provide more affordable travel options for areas with concentrated poverty during lockdowns. In addition, transit agencies should manage transit supply strategically depending on the share of low-income people to better meet people's mobility needs.

Keywords: COVID-19, stay-at-home order, social equity, transit service, transportation, low-income people

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1 Introduction

The pandemic of COVID-19 has drastically changed people's outdoor activity participation and travel behavior (Beck & Hensher, 2020; de Haas et al., 2020; De Vos, 2020), particularly after governments issued the stay-at-home order. Aiming to avoid contact, the lockdown order required residents to stay at home as much as possible, except for front-line workers and essential trips. As a result, road traffic in the US decreased by 40% in April 2020, compared with April 2019, with a monthly reduction of 196 billion vehicle kilometers (FHWA, 2020). Likewise, transit trips dropped by 41% in March 2020, compared with March 2019 (APTA, 2020). In the Minneapolis-St. Paul (Twin Cities) metropolitan area, highway traffic reduced by nearly 70% (Asmus & Ehrlich, 2020), and transit ridership declined by approximately 60% (Lind, 2020) by the end of March 2020. Moreover, the decline in mobility is spread unevenly across the region. In Florida, for example, the reduction of traffic volumes varies between urban and rural areas and between highways and local roads (Parr et al., 2020).

When the stay-at-home order was in effect, all Americans were affected, but low-income people faced disproportionally greater challenges than before. Low-income people need to travel for several

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possible reasons. First, many low-income people are essential workers who are employed in front-line industries so they have to commute. A survey by the Center for Economic and Policy Research (Rho et al., 2020) showed that although low-income people (those lower than 200% poverty line) accounted for 20.6% of all workers in the US, they accounted for 30.1% of workers in grocery, convenience, and drug stores, and 42.4% of workers in building cleaning services. Although some low-income people are not essential workers, the nature of their jobs does not allow them to work remotely or their home conditions are not suitable for telecommuting. These contribute to travel behavior changes of low-income people during the pandemic. Second, although online shopping has proliferated during the lockdown period (Redman, 2020), low-income people are less likely to benefit from high technology. It is known that income is positively associated with the frequency of online shopping (Cao et al., 2012; Saphores & Xu, 2020). This digital divide makes low-income people more likely to conduct shopping activities at brick-and-mortar stores than others. Furthermore, low-income people are more likely to travel for food at local food banks during the pandemic (Cole, 2020). Third, low-income people tend to live closer to their family members and are more likely to travel for caregiving (Rihl, 2020).

The literature offers some empirical evidence on socioeconomic disparities in travel behavior associated with the COVID-19. Using mobile phone tracking data in King County, WA, Brough et al. (2020) found a sharp decline in the mobility of all people. Further analysis suggested that higher-income and more-educated people are more likely to shift from public transportation to private vehicles than lower-income and less-educated ones, and that the differential changes in transit usage between these two groups of people are not attributable to transit supply. They concluded that the burden of COVID-19 varies among different socioeconomic groups. Hu and Chen (2021) also reached a similar conclusion in their study on transit use in Chicago, IL.

Although low-income people may not be able to reduce their travel as much as they prefer, the reduction in transit capacity makes transit-dependent people struggle for mobility instruments. According to the National Household Travel Survey (NHTS), households earning $20,000 or less use transit 2.6 times as frequent as other households (Renne & Bennett, 2014). Some low-income people rely on transit for their daily activities, even during the pandemic (Brough et al., 2020). However, because many choice riders stop using transit (Bucsky, 2020), transit agencies reduce services as a response to the declining demand. Furthermore, to maintain social distancing among passengers, the capacity of transit services decreases greatly. For example, Metro Transit in the Twin Cities allows 10 or fewer riders on a 40-foot bus and 15 or fewer passengers on a 60-foot bus (Metro Transit, 2020). These changes in transit services disproportionally affect the accessibility and well-being of low-income people.

In the Twin Cities, Metro Transit faced the challenges associated with unpredictable demand for transit services, social distancing requirements, and uncertainty of transit drivers, while attempting to maintain mobility of front-line workers and essential trips during the lockdown (Lind, 2020). Since the pandemic of COVID-19 is unique in contemporary society, transit agencies do not have much to learn from past experiences. After deliberation, Metro Transit reduced its services to mimic holiday schedules, reducing light rail transit service span and frequency and cutting about 40% of weekday bus trips (Lind, 2020). As transportation agencies are adjusting their policies to address the unprecedented challenges, there are many unanswered questions. For example, how do transit service changes meet riders' mobility needs? How do transit supply and the concentration of low-income people jointly affect travel demand? How can transportation agencies better prepare for the next possible lockdown? The answers to these questions are essential to maintaining mobility needs of transportation-disadvantaged groups in the worst scenario.

Using highway traffic data in the Twin Cities, US, during the week right after the stay-at-home order, this study employs a generalized additive model to examine the relationships among low-income people, transit service, and highway traffic, while controlling for confounding factors. It aims to address

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the following two research questions to help transit agencies better understand people's travel behavior and allocate the valuable and scarce transit resource to those who need it most during the pandemic: (1) How do low-income people travel on the highway amid the stay-at-home order? (2) How is the relationship between transit supply and highway use moderated by the concentration of low-income people?

This study contributes to the literature in that, moving beyond descriptive analyses of transportation impacts of COVID-19 commonly seen in the literature (Bucsky, 2020; Teixeira & Lopes, 2020), it uncovers the interaction effect of transit supply and the concentration of low-income people on highway traffic. Furthermore, our findings provide transit agencies guidance on how to manage scarce resources to keep the mobility of those who need it during future lockdowns.

The remainder of this paper is organized as follows. Section 2 presents the data and the modeling approach used in this study. Section 3 discusses the research results. The final section replicates key findings and discusses associated policy implications.

2 Research methods

2.1 Data and variables

We used traffic data published by the Metropolitan Council (Met Council & Metropolitan Council, 2020), which include locations, observed and predicted daily vehicular traffic of 2,685 nodes in the highway system in the Twin Cities, US. The observed daily traffic was recorded by loop detectors built in the nodes. The predicted daily traffic was estimated by a statistical model using historical traffic data of three years (2018, 2019, and 2020 up to March 1st). We used traffic data from 1,341 nodes on entrance and exit ramps as proxies for highway travel demand in the areas nearby (Figure 1). We excluded the nodes on the trunk lines to remove the observations of through traffic. After data cleaning, we included 1,251 observations for data analysis.

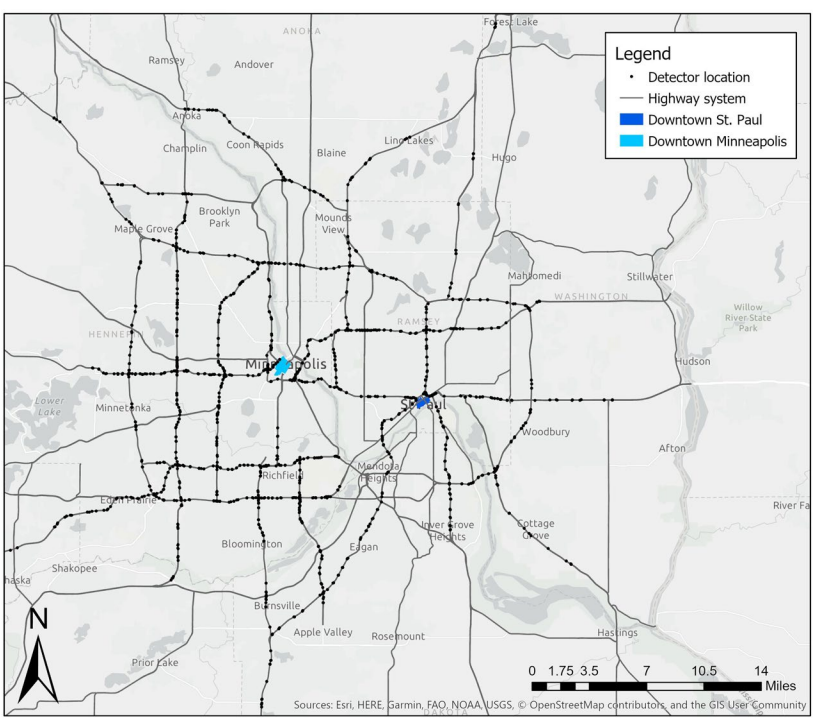

Figure 1. Study area

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Our study period is from March 28th to April 3rd, 2020, the week right after the stay-at-home order took effect (March 27th). We chose this period in our study for two reasons. First, it is the week when the traffic changed most since March 1st (Figure 2). It reflects the most influential impact of the pandemic and the lockdown policy on people's travel behavior, which deserves specific investigation. Second, the research findings related to this period provide implications of how transportation agencies can deal with this level of extreme cases. The dependent variables of this study are two indices measuring traffic changes during this week. In particular, weekday traffic percentage is the average ratio between observed and predicted daily traffic during the five weekdays, and weekend traffic percentage is the mean ratio during the weekend. Figure 3 shows the distribution of average traffic percentage on weekdays and that on weekends. The traffic percentage on weekends is lower than that on weekdays. Weekdays and weekends show similar spatial patterns. For example, the nodes in the southwestern metro have relatively lower traffic percentages than other areas.

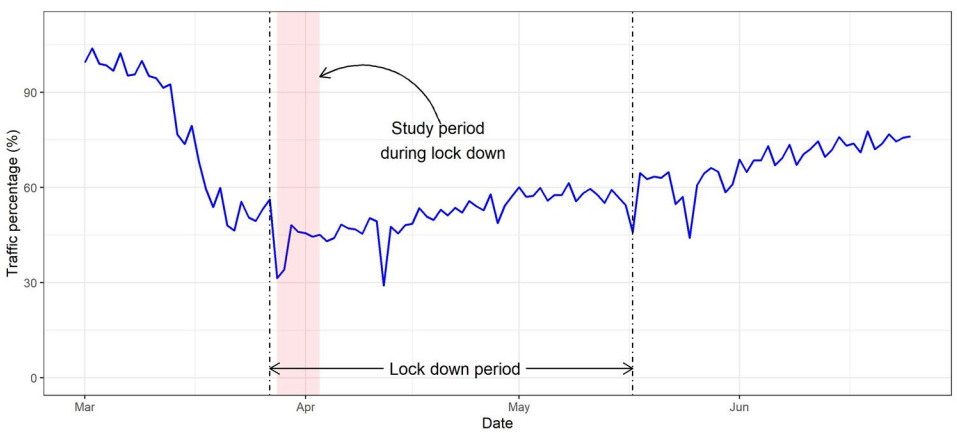

Figure 2. The trend of traffic percentage from March 1 to June 25 in 2020 (Lockdown period is March 27 to May 17; study period during the lockdown is March 28 to April 3)

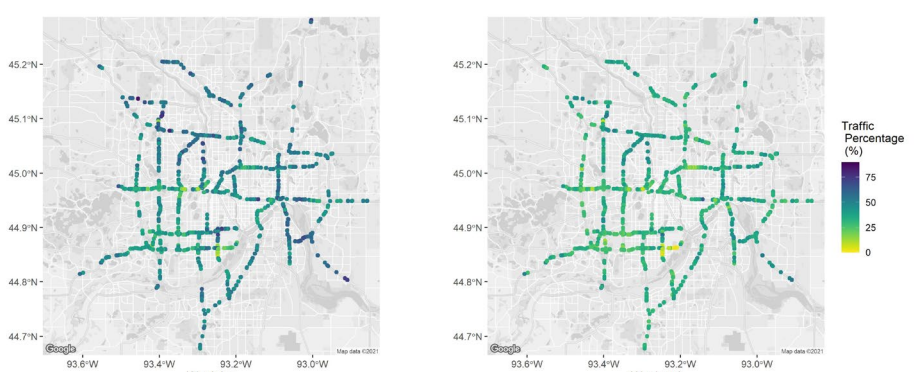

Figure 3. Distribution of average traffic percentage on weekdays and on weekends (March 28 to April 3)

We considered three types of independent variables: socioeconomic variables, built environment characteristics, and spatial location (Table 1). The socioeconomic variables include attributes related to household structure, vehicle ownership, and poverty level. The built environment contains measures pertinent to the size of lands for different uses, road network connectivity, and transit service level. Spatial locations are measured by the longitude and latitude of transportation nodes. Table 2 lists the descriptive statistics of these variables.

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Table 1. Variable definition and source

Variables	Definition	Sources
Weekday traffic percentage	The average ratio (in percentage point) between observed daily traffic and predicted daily traffic on weekdays (Mar. 28 - Apr. 3)	Met Council
Weekend traffic percentage	The average ratio (in percentage point) between observed daily traffic and predicted daily traffic on weekends (Mar. 28 - Apr. 3)	Met Council
Socioeconomic variables		
Share of children	Percentage of population age under 18 in the census block group (CBG) where the node is located	ACS
Share of seniors	Percentage of population age over 65 in the CBG where the node is located	ACS
Share of males	Percentage of men in the CBG where the node is located	ACS
Average household size	Average household size in the CBG where the node is located	ACS
Average number of vehicles	Average number of vehicles per household in the CBG where the node is located	ACS
Number of households with zero vehicles	Number of households with zero vehicles in the CBG where the node is located	ACS
Share of low-income population	Percentage of population with income less than 185% of poverty threshold in the CBG where the node is located	ACS
Built environment variables		
Commercial area	Commercial area (in hectare) within the 1609-meter (one-mile) buffer of the node	MGC
Industrial area	Industrial area (in hectare) within the 1609-meter buffer of the node	MGC
Office area	Office area (in hectare) within the 1609-meter buffer of the node	MGC
Residential area	Residential area (in hectare) within the 1609-meter buffer of the node	MGC
Park area	Park area (in hectare) within the 1609-meter buffer of the node	MGC
Number of dead ends	Number of dead ends within the 1609-meter buffer of the node	MGC
Number of intersections	Number of intersections within the 1609-meter buffer of the node	MGC
Weekday transit frequency	Daily average number of transit trips per hour within the 1609-meter buffer of the node on weekdays (Mar. 28 - Apr. 3)	Metro Transit
Weekend transit frequency	Daily average number of transit trips per hour within the 1609-meter buffer of the node on weekends (Mar. 28 - Apr. 3)	Metro Transit
Number of transit stops	Number of transit stops within the 1609-meter buffer of the node	Metro Transit
Spatial Location		
Longitude	Longitude of the node's location	Met Council
Latitude	Latitude of the node's location	Met Council

Notes:
ACS = American Community Survey;
MGC = Minnesota Geospatial Commons.

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Table 2. Variable descriptive statistics

Variables	Mean	Standard Deviation	Minimum	Maximum
Weekday traffic percentage (%)	46.53	12.21	0.58	86.66
Weekend traffic percentage (%)	33.09	8.69	0.4	85.75
Share of children	0.21	0.08	0	0.51
Share of seniors	0.15	0.10	0	0.66
Share of males	0.49	0.07	0.32	0.77
Average household size	2.34	0.47	1.02	4.55
Average number of vehicles	1.62	0.45	0.09	2.64
Number of households with zero vehicles	0.11	0.14	0	0.91
Share of low-income population	0.26	0.21	0	0.92
Commercial area (hectare)	55.87	40.58	0	196.04
Industrial area (hectare)	67.18	65.13	0	343.81
Office area (hectare)	70.46	45.22	0	233.91
Residential area (hectare)	326.85	129.9	0	653.85
Park area (hectare)	95.42	57.23	3.34	361.38
Number of dead ends	38.62	18.71	4	122
Number of intersections	92.97	75.12	4	340
Weekday transit frequency (trips/hour)	4.66	7.51	0	39.44
Weekend transit frequency (trips/hour)	3.61	5.85	0	28.04
Number of transit stops	56.75	56.03	0	287
Longitude	-93.25	0.14	-93.61	-92.86
Latitude	44.96	0.10	44.64	45.28

2.2 Modeling approach

We applied the generalized additive model (GAM) approach to estimate the influences of socioeconomic variables, built environment characteristics, and spatial location on traffic percentage. Compared with the traditional ordinary least squares (OLS) method, the GAM approach has several advantages. First, using non-parametric smooth terms, GAM can automatically seek the potential nonlinear relationships between dependent and independent variables. By contrast, when used to estimate a nonlinear relationship, OLS needs prior knowledge on the shape of the nonlinear relationship. If the knowledge is absent, the nonlinear model is likely to be falsely specified. Second, GAM can model a variety of nonlinearities whereas OLS can model only a limited number of nonlinearities such as logarithmic and polynomial forms. That is, GAM is more flexible than OLS. Third, although OLS can estimate an interactive effect by including an interaction term of two independent variables, GAM can model their interactive nonlinear effect more conveniently than OLS.

In mathematic notations, a GAM model can be expressed as follows:

$$y = \beta_0 + \beta_1 x_1 + s(x_2) + s(x_3,x_4) + \epsilon,\ \epsilon \sim N(0,\sigma^2), \quad (1)$$

where β_0 is the constant term, β_1 is the coefficient for x_1, and ϵ is the residual and assumed to follow a normal distribution. These terms are the same as those in linear regression models. $s(x_2)$ is a non-para-

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metric smooth term used to estimate the non-linear relationship between x_2 and y. It can be expressed in the following equation (Lin & Zhang, 1999):

$$s(x_2) = \sum_{k=1}^{K} \beta_k b_k(x_2), \quad (2)$$

where $b_k(x_2)$ is the kth basis function and β_k is the corresponding coefficient. Similarly, $s(x_3, x_4)$ is a non-parametric interaction term between x_3 and x_4. In this study, we applied the thin-plate spline smoother (one type of basis functions) to fit the non-linear relationships, which usually provides better fitting results (Wood, 2003, 2020).

In this study, we hypothesized that transit frequency and share of low-income people have an interactive effect on traffic percentage. First, planners can manipulate transit frequency immediately in response to the pandemic. On the other hand, other variables such as land use and vehicle availability may change over a long term. That is, this study emphasizes transit frequency, controlling for these other variables. Moreover, previous studies have shown that individuals' responses to transit service changes vary by their income level (Blumenberg, 2017; TCRP, 2013). Compared with low-income people, high-income people, among whom many are choice transit riders, will switch from driving to transit when transit service reaches a higher threshold. Therefore, it is reasonable to expect that the association between transit frequency and traffic percentage be moderated by income. We are interested in the potential nonlinear effects of transit frequency and share of low-income people on traffic percentage. Accordingly, we employed smooth functions to examine the effect of their interaction.

Furthermore, we accounted for spatial autocorrelation in our models for a couple of reasons. First, previous studies have shown that travel demand is spatially correlated (Hu et al., 2018; Kerkman et al., 2018; Shen et al., 2020). A fundamental assumption for statistical inference is that residuals are independent. If they are dependent and the dependency is not addressed, p-values of model coefficients are invalid. Accounting for spatial autocorrelation in the model can help address this issue. Second, the distribution of traffic percentage in Figure 3 clearly shows that it is spatially correlated. For example, traffic percentage in the southwestern part of the study area is lower than that in other areas. In addition, the Moran's I indices for weekday and weekend traffic percentages are both 0.2 and significant, indicating the existence of spatial autocorrelation. Many studies on travel demand analysis have controlled for spatial dependence in their models (Hu et al., 2018; Kerkman et al., 2018; Shen et al., 2020). For example, Hu et al. (2018) constructed a GAM to estimate carsharing demand in Shanghai, China, and they applied an interactive smooth term between the longitude and latitude of carsharing stations to account for the spatial autocorrelation of carsharing demand. Following Hu et al. (2018), we addressed spatial dependence among residuals by including a smooth of geographical locations (longitude, latitude) in the model. With these considerations, our model is specified as follows:

$$\begin{aligned} &\textit{Traffic percentage} = \beta_0 + \boldsymbol{\beta}_x \boldsymbol{X} + \\ &s(Ln(\textit{Transit frequency}+1), \textit{Share of poor population}) + s(\textit{Longitude}, \textit{Latitude}), \end{aligned} \quad (3)$$

where $s(Ln(\textit{Transit frequency}+1)$,Share of poor population) specifies the interaction term between transit supply and share of low-income population; $s(\textit{Longitude,Latitude})$ is the interaction term between the longitude and latitude of node locations; $\boldsymbol{X}$ is the matrix of other independent variables, and $\boldsymbol{\beta}_x$ is the corresponding vector of coefficients; and β_0 is the constant. We used the "mgcv" package (Wood, 2017, 2018) in R 3.6.3 to estimate the models.

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3 Results

We first developed a GAM for weekday traffic percentage. We considered spatial locations, and all the socioeconomic and built environment variables in Table 1 as independent variables. To obtain a parsimonious model, we kept variables significant at the 0.1 level in the model and manually dropped insignificant variables. Table 3 presents model results. Five linear terms are statistically significant in the model. Because the five variables are specified in the form[1] of Y = In(X+1), they have non-linear relationships with weekday traffic percentage. For such a model specification, the coefficient (2.16) of residential area roughly means that associated with a one-percent increase in residential area, weekday traffic increases by 2.16/100 percentage points. Despite the stay-at-home order, a larger residential area means more essential trips made by people living in the area. Therefore, it is plausible that residential use is positively associated with vehicular traffic. By contrast, commercial area, office area, and park area have negative associations with weekday traffic percentage. Relative to residential use, these land uses experience a reduction in weekday traffic. Furthermore, office use has the largest coefficient (in terms of absolute values) among the three variables. That is, office use experiences the largest reduction in weekday traffic. This result makes sense because most office employees are required to work at home during the stay-at-home period. It is worth noting that industrial use is insignificant in the model. Industrial use includes both essential industries and non-essential industries. Presumably, essential industries are positively associated with weekday traffic whereas non-essential ones have a negative association. Collectively, the effects of these two types of industrial use cancel each other out. Average number of vehicles per household has a positive association with weekday traffic percentage. This finding is consistent with our expectation: the higher the number of vehicles is, the more the vehicular trips are.

Table 3. The weekday model result

Linear terms	**Estimate**	**P-value**
Ln(Residential area + 1)	2.18	0.000
Ln(Commercial area + 1)	-1.47	0.000
Ln(Office area + 1)	-2.16	0.000
Ln(Park area + 1)	-1.32	0.016
Ln(Average number of vehicles + 1)	4.61	0.069
Constant	50.91	0.000
Smooth terms	**EDF**	**P-value**
s(Ln(Weekday transit frequency + 1), Share of low-income population)	8.44	0.000
s(Longitude, Latitude)	22.90	0.000
R^2	0.354	
Sample size	1251	

Note: EDF = estimated degree of freedom. An EDF value close to 1 indicates an approximately linear relationship with the dependent variable.

Figure 4 illustrates the joint effects of transit supply and share of low-income people on weekday traffic percentage. In general, transit frequency is negatively associated with its effect on weekday traf-

[1] When conducting the logarithmic transformation, we added 1 to these variables because they contain zeros.

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fic. This negative relationship implies that without transit services during the pandemic, people will be forced to use highways (e.g., driving and carpooling). Share of low-income people has a positive association with its effect on weekday traffic. As described in Section 1, low-income people are more likely to be front-line workers (such as employees of grocery stores, trucking and warehouse, food manufacturing, and so on) and visit physical stores for essential daily activities. Therefore, the more the low-income people are, the smaller the traffic drop is.

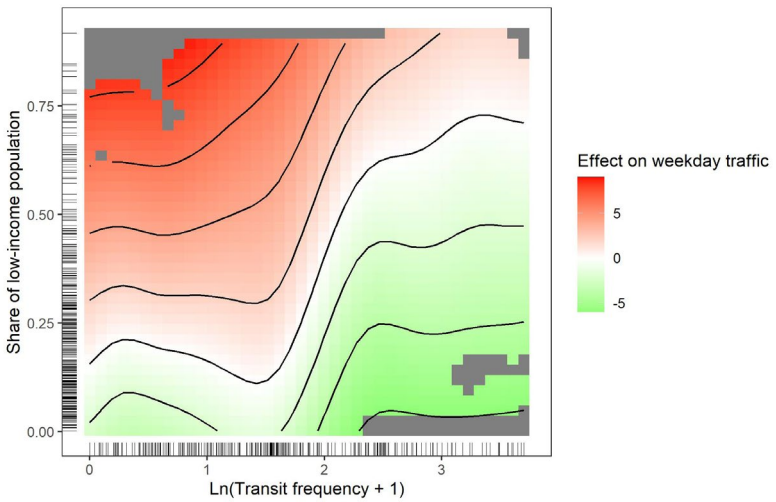

Figure 4. Joint effect of transit frequency and share of low-income people on weekday traffic (Black lines are contour lines. The distance between two contour lines is 2 percentage points. Grey areas present no value. The tick marks on the axes indicate the distributions of the corresponding variables.)

More importantly, transit frequency and share of low-income people interact with one another when affecting weekday traffic. The EDF for the smooth term is 8.44 and statistically significant (Table 3), so the smooth term has a non-linear effect on weekday traffic. To better illustrate this non-linear effect, we used Figure 5, which is derived from Figure 4, to show how the effect of transit frequency on weekday traffic varies in areas with different shares of low-income population. Specifically, we chose six shares of low-income population (0, 0.17, 0.33, 0.5, 0.66, 0.82), which are evenly distributed between 0 and 1. The first two subplots in Figure 5 illustrate the relationships between transit frequency and traffic percentage when the share of low-income population is low (i.e., 0 and 0.17). When transit frequency is smaller than 2.8 trips per hour[2], it is positively associated with traffic percentage. Although this relationship appears counterintuitive, it is plausible. The CBGs these two subplots illustrate are more likely to be located in suburban areas. Among these CBGs, transit service is often deployed in the areas where vehicular traffic is high; in the areas with low traffic, transit service is limited or not available. That is, the positive relationship between transit frequency and traffic percentage is more of an outcome of travel mode diversification. When transit frequency exceeds the threshold, it has a negative association with traffic percentage. That is, a large transit supply is associated with a large decrease in vehicular traffic during the lockdown period. This substitution relationship is consistent with our expectation. When transit frequency reaches 10.8 trips per hour[3], its association with traffic percentage becomes trivial, suggesting that the transit demand has been mostly met at this frequency.

[2] When *Ln*(*Transit frequency* + 1)=1.33, transit frequency is exp (1.33) – 1=2.8 trips per hour.

[3] When *Ln*(*Transit frequency* + 1)=2.47, transit frequency is exp (2.47) – 1=10.8 trips per hour.

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In the next two subplots where the share of low-income population is medium (i.e., 0.33 and 0.5), the negative associations between transit frequency and traffic percentage have two thresholds. The lower threshold (2.8 trips per hour) suggests the presence of dose response: transit supply has to reach a certain threshold to be effective. The upper threshold (10.8 trips per hour) suggests the effect of diminishing returns, as presented in the previous paragraph. In the last two subplots where the share of low-income population is high (i.e., 0.66 and 0.82), transit supply has a negative association with traffic percentage, congruent with our expectation.

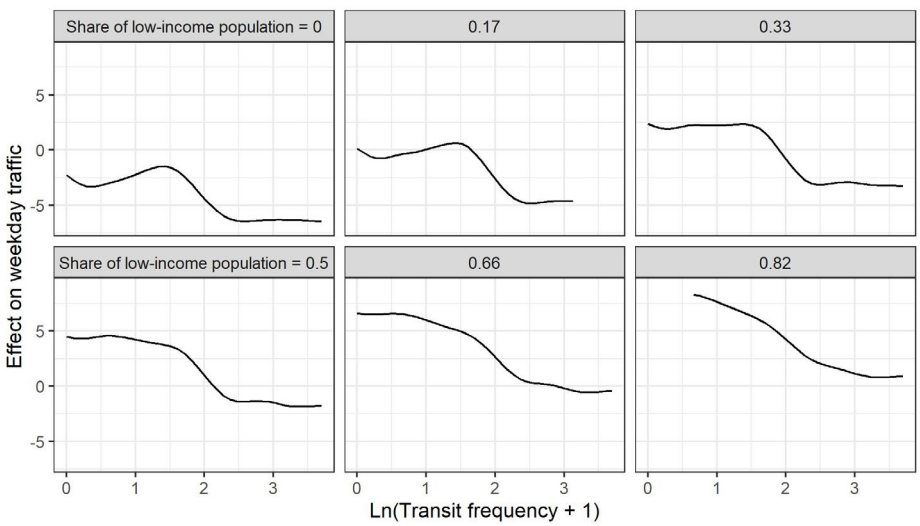

Figure 5. Effect of transit frequency on weekday traffic in areas with different shares of low-income population (cross-sections)

Figure 6 shows weekday traffic percentage by geographical location. After controlling for all aforementioned variables, weekday traffic shows clear spatial dependence. In particular, southwest and south metro areas (particularly Edina, Minnetonka, Eden Prairie, and Egan) experience a larger decrease in weekday traffic than north metro areas (such as Brooklyn Park, Brooklyn Center, and Columbia Heights) and southeast metro areas (such as South St. Paul and Inner Grove Heights). Roughly speaking, the former areas have lower share of low-income population and are the most affluent areas in the Twin Cities, whereas the latter areas have higher share of low-income population and are economically struggling (Figure 7). Furthermore, the areas adjacent to highways connecting outer metro areas tend to show a strong spatial dependence. Overall, both the EDF of $s(Longitude,Latitude)$ and Figure 6 suggest that we need to model spatial dependence while exploring the correlates of highway traffic. The inclusion of this smooth term also substantially improves model performance (see Appendix).

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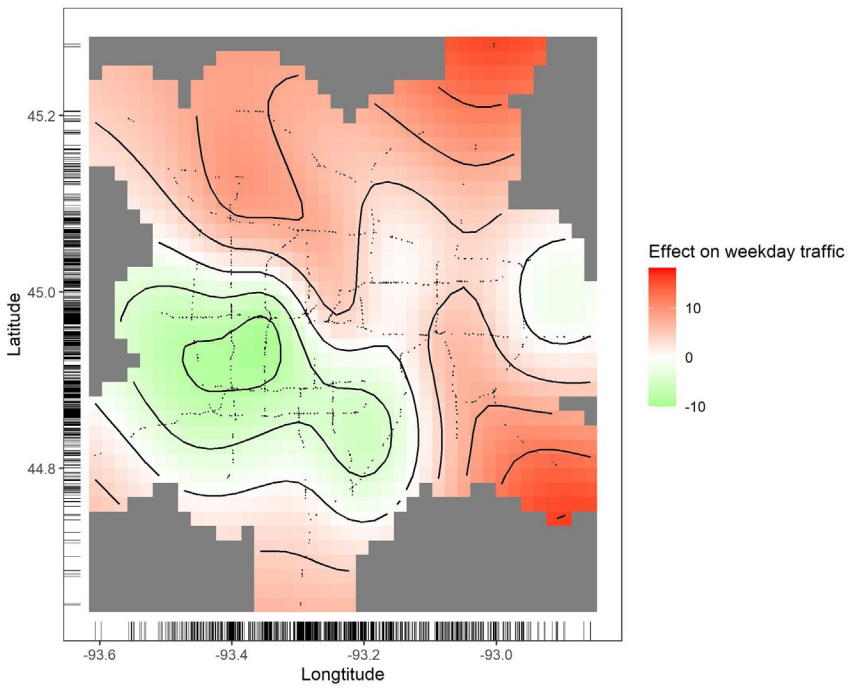

Figure 6. Effect of spatial location on weekday traffic (Black lines are contour lines. The distance between two contour lines is 4 percentage points. Grey areas present no value. Black dots are traffic detector locations. The tick marks on the axes indicate the distributions of the corresponding variables.)

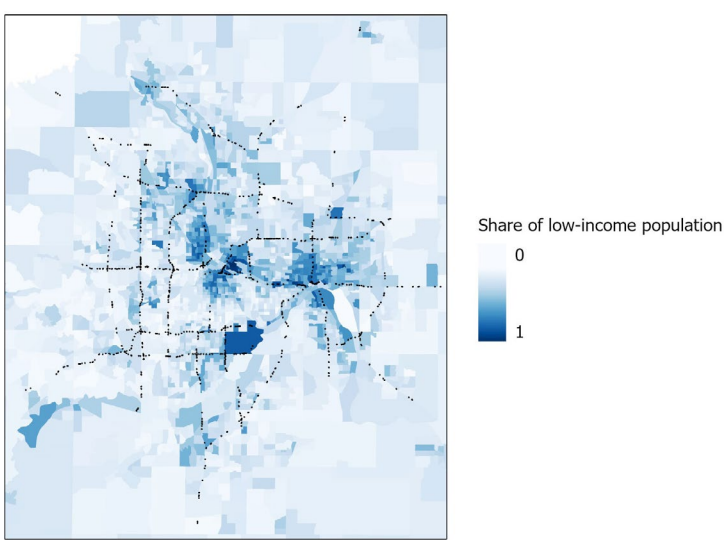

Figure 7. Distribution of share of low-income population in the Twin Cities (Black dots are traffic detector locations.)

We also developed a model for weekend traffic percentage (Table 4). The results between weekday traffic and weekend traffic are mostly consistent as the signs of variable coefficients are the same. However, park area becomes insignificant in the weekend model. People may use parks for exercise on weekends, which was allowed as long as maintaining social distancing. The coefficient of residential use becomes larger whereas the coefficients for commercial use and office use become smaller. These changes are plausible because weekend traffic is less commuting-related. Transit supply and share of low-income

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people also have an interactive effect on weekend traffic percentage (Figure 8 and Figure 9). However, the patterns are less straightforward than those on weekdays. The ambiguity makes sense because weekend traffic is more diverse in purpose and mode choice than weekday traffic. Weekend traffic is also spatially dependent (Figure 10). The pattern of spatial dependence on weekends is mostly similar to that on weekdays. However, the degree of spatial dependence on weekends is weaker than that on weekdays.

Table 4. The weekend model result

Linear terms	**Estimate**	**P-value**
Ln(Residential area + 1)	3.24	0.000
Ln(Commercial area + 1)	-0.93	0.002
Ln(Office area + 1)	-1.12	0.002
Ln(Park area + 1)	-0.49	0.220
Ln(Average number of vehicles +1)	3.34	0.074
Constant	21.71	0.000
Smooth terms	**EDF**	**P-value**
s(Ln(Weekend transit frequency + 1), Share of low-income population)	13.74	0.000
s(Longitude, Latitude)	23.18	0.000
R^2	0.338	
Sample size	1251	

Note: EDF = estimated degree of freedom.

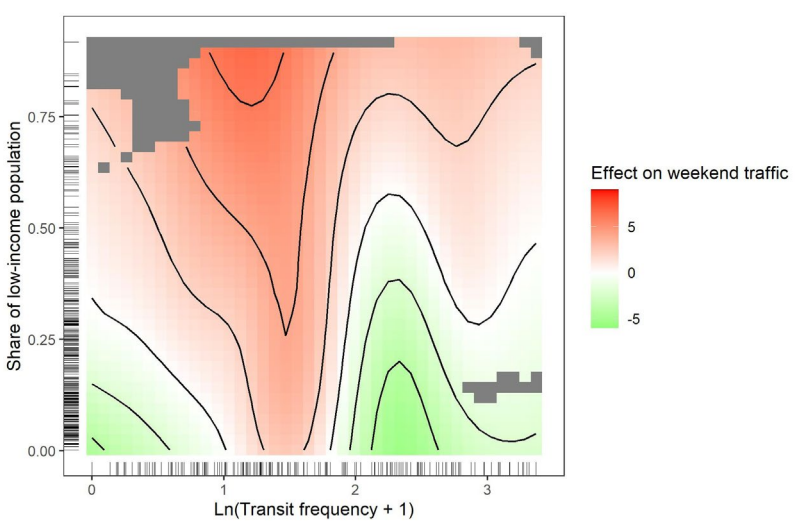

Figure 8. Joint effect of transit frequency and share of low-income people on weekend traffic (Black lines are contour lines. The distance between two contour lines are 2 percentage points. Grey areas present no value. The tick marks on the axes indicate the distributions of the corresponding variables.)

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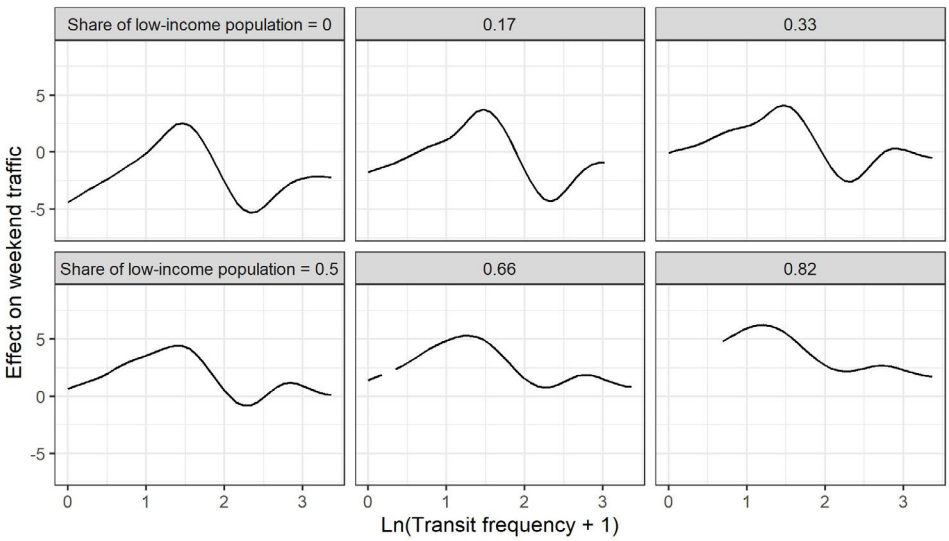

Figure 9. Effect of transit frequency on weekend traffic in areas with different shares of low-income population (cross-sections)

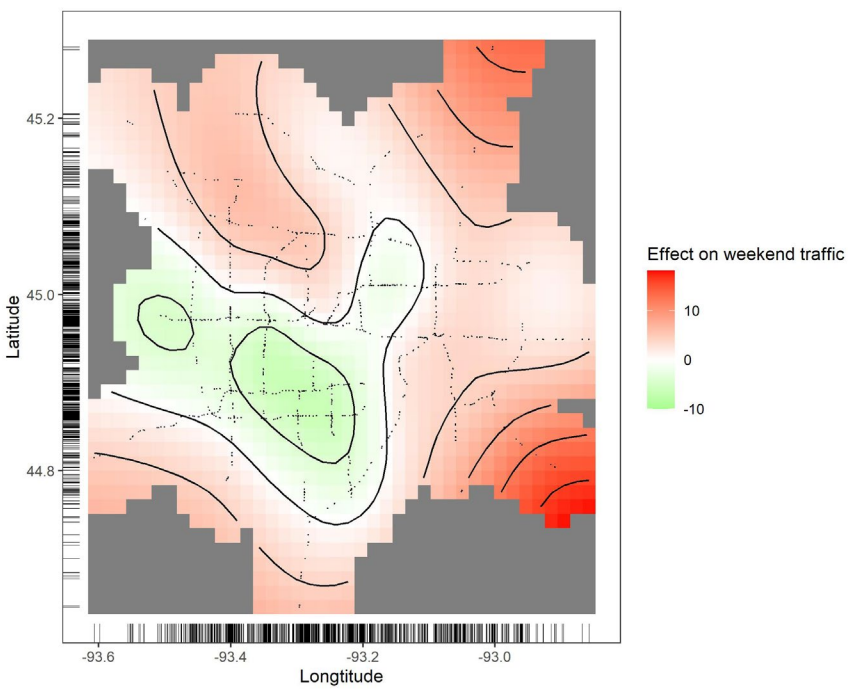

Figure 10. Effect of spatial location on weekend traffic (Black lines are contour lines. The distance between two contour lines is 4 percentage points. Grey areas present no value. Black dots are traffic detector locations. The tick marks on the axes indicate the distributions of the corresponding variables.)

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4 Conclusions

In this study, we estimated two GAMs to explore the relationships among low-income people, transit supply, and highway traffic in the Twin Cities during the week right after the State of Minnesota implemented the stay-at-home order. This study has two limitations. First, we employed highway traffic detected on entrance and exit ramps as proxies for travel demand in the areas nearby. However, these ramps are not originations or destinations of people's trips. These data are useful for macro-level analysis, but disaggregated data such as travel surveys or GPS trace data can offer more direct and accurate evidence on individuals' travel choices. Second, we are reluctant to transfer the findings in the Twin Cities to other regions. Because stay-at-home orders by different states had varying requirements and transit agencies in different regions adopted different responses to the lockdown, people's travel behavior is likely to vary by region. More studies in other regions are needed to examine the generalizability of the results. Nevertheless, this study provided a preliminary but insightful understanding of the relationships among low-income people, transit service, and vehicular demand.

Our results confirmed that low-income people have less flexibility in reducing travel during the stay-at-home order than other people, consistent with Brough et al. (2020). In the weekday model, the share of low-income people is positively correlated with highway traffic. In addition, the spatial pattern of traffic percentages showed that the areas with more disadvantaged people have higher highway traffic than other areas. In the US, low-income people have been marginalized in the transportation system for decades (Blumenberg, 2017). Our finding raises an additional equity concern. During the lockdown period, low-income people risked their lives to work in the front lines but had fewer options to travel because of transit service adjustment. This imposed disproportional burdens on low-income people who have already faced many challenges amid the pandemic. As low-income people are less able to reduce travel, it is important for governments to provide the areas of concentrated poverty more affordable options, such as transit and subsidized taxi and MaaS (Mobility as a Service).

We also found that transit supply impacts highway traffic differently in areas with different proportions of low-income people. There are threshold effects in the areas where low-income people account for 50% or less of the total population. Transit frequency has a slightly positive or trivial influence on weekday traffic when it is smaller than 2.8 trips per hour within the 1609-meter (one-mile) buffer of the highway node. However, transit supply substantially reduces highway traffic when it increases from 2.8 to 10.8 trips per hour. After 10.8 trips per hour, the influence of transit frequency on weekday traffic percentage becomes stable. When more than 50% of people live in low-income households, transit frequency has a monotonically negative effect on highway traffic. Overall, the relationship between transit supply and highway traffic is moderated by the share of low-income people.

During the pandemic, the revenues of transit agencies drop drastically. Thus, it is important for them to manage scarce resources to better serve the areas where transit service is needed most. Based on our results, we recommend that in the areas with 50% or less than 50% of low-income people, transit agencies should offer at least 1.33 transit trips per hour per square kilometer[4] to maximize the benefits of transit. In areas with more low-income people, transit agencies could provide as many transit trips as possible to satisfy people's mobility needs.

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[4] 10.8 transit trips per hour in a 1609-meter (one-mile) buffer area is equal to 10.8÷3.14÷2.58=1.33 trips per square kilometer.

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Appendix

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