Poster session 4065

Poster number: TRBAM-23-00006

Scheduled time: Wed, 1/11/2023, 10:15 AM-12:00 PM

Examining the Nonlinear Effects of Ridesharing on Public Transit Usage: An Empirical Study Based on the Hierarchical Negative Binomial Generalized Additive Model

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Background

Ridesharing services might complement or substitute public transit systems.

- Complement effects: address the first-and-last mile issues and improve the accessibility of public transit.
- Substitution effect: competition between the two alternatives.

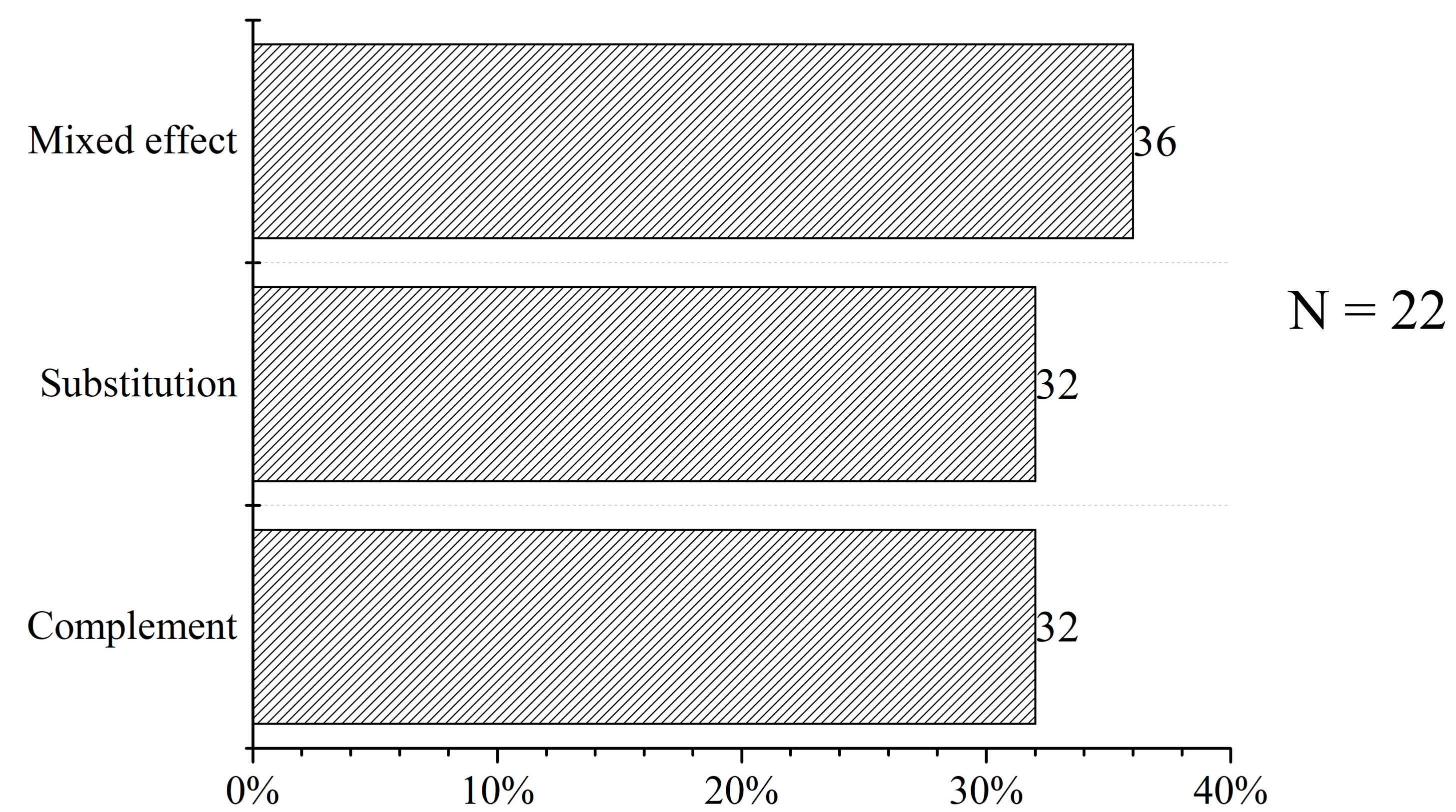

Fig.1. Impacts of ridesharing on public transit usage in prior literature

Motivations

- A dummy variable (0: without ridesharing services, 1: with ridesharing services) was too mechanical to profile the ridesharing use frequency.
- Ignoring nonlinear effects between the two alternatives will lead to biased estimation and inference of the relationships between the two alternatives.
- Travel patterns with the same census tract are usually correlated or spatially dependent.

Objective

Investigate the nonlinear effects of ridesharing use frequency on public transit usage.

- The hierarchical negative binomial generalized additive (HNBGAM) model was specified.
- Jointly account for the nonlinear effects and spatial dependence.
- Provide a reference to classify the contributing covariates and reveal the nonlinear effects.

The full text is available in the Journal of Transport Geography.

QR code:

Data

2017 National Household Travel Survey (NHTS)

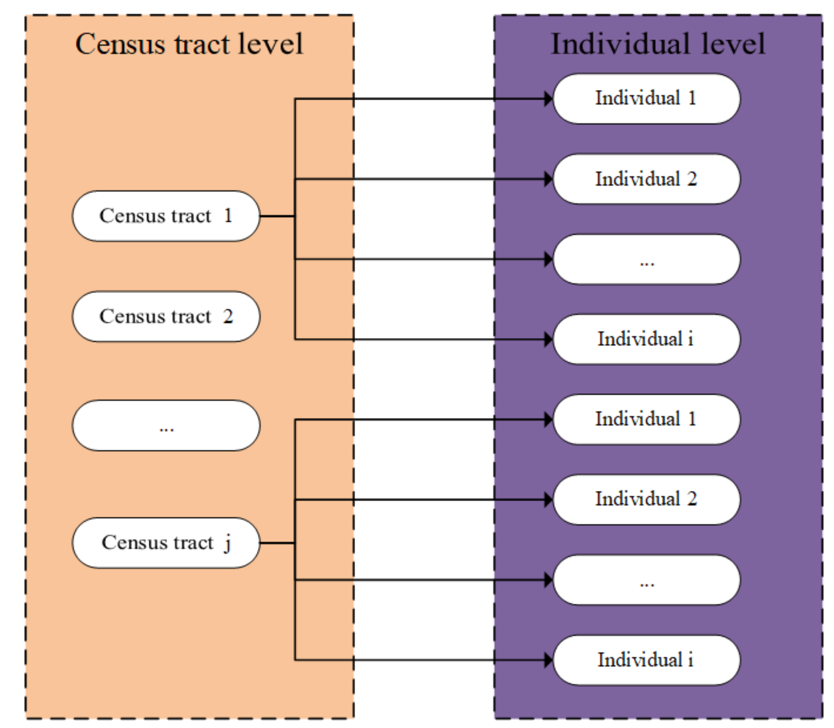

Fig.2. Two-level hierarchical structure

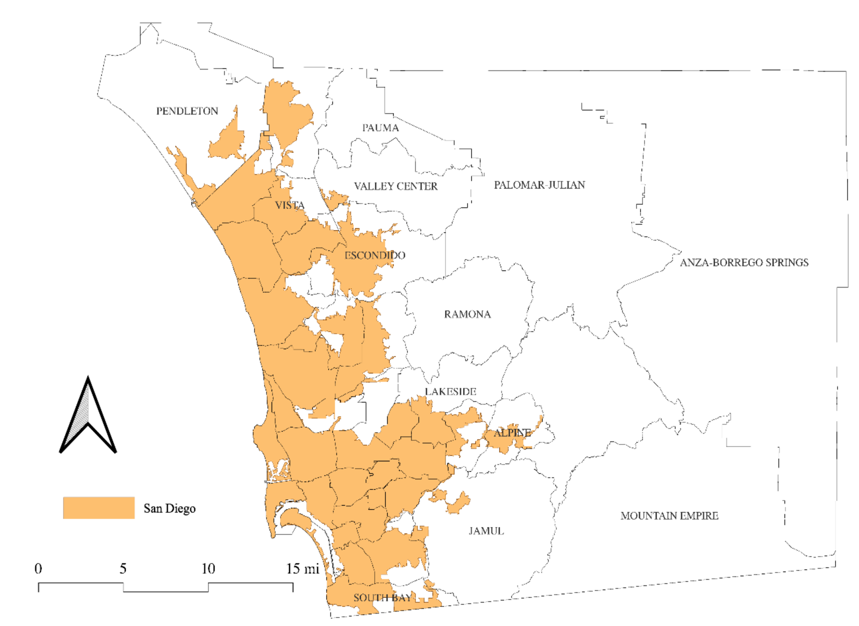

Fig.3. San Diego NHTS areas

Data description

Table 1. Comparisons between ridesharing users and regular travelers

Key variables	Ridesharing users		Regular travelers		*p*-value
	Mean	S.D.	Mean	S.D.	
Public transit usage	1.74	5.11	1.02	4.03	< 0.01
Ridesharing use frequency	4.36	4.50	0.83	2.60	< 0.01

Methodology

HNBGAM

Level 1:

$$\log(\theta_{ij}) = \beta_{0j} + f_1(RS_{ij}) + f_2(RA_{ij}) + \sum_{p=1}^{P} \beta_{pj} X_{pij}$$

Level 2:

$$\beta_{0j} = \gamma_{00} + \sum_{q=1}^{Q} \gamma_{0q} Z_{qj} + \varepsilon_{0j}$$

- θ_{ij} is the expectation of response variable y_{ij} for ridesharing user i in census tract j.
- ε_{0j} is the random effect at census tracts where $\varepsilon_{0j} \sim N(0, \sigma_\varepsilon^2)$.
- RS_{ij} and RA_{ij} are ridesharing use frequency and age for ridesharing user i in census tract j, respectively.
- The smoothers $f_1(.)$ and $f_2(.)$ called thin plate regression splines are applied here for versatility.

Results & Discussions

Variables	NBGLM Coef.	S.E.	HNBGLM Coef.	S.E.	HNBGAM Coef.	S.E.
Fixed effect						
Intercepts	0.24***	0.02	-4.03***	0.72	-0.39***	0.05
Key factor						
Ridesharing use frequency	**0.03*** **	**<0.01**	**0.04*** **	**<0.01**	**0.41*** **	**0.13**
Socio-demographic factors						
Respondent age	0.01***	<0.01	0.01***	<0.01	0.13***	0.05
Respondent race	-	-	-	-	0.26***	0.02
Respondent gender	-0.13***	<0.01	-0.29***	0.01	-0.47***	0.01
Highly educated respondent	0.40***	0.01	0.44***	0.01	0.86***	0.01
Driver license	-1.52***	0.01	-1.25***	0.01	-1.35***	0.03
Number of household children	-0.56***	<0.01	-0.72***	0.01	-1.02***	0.01
Household size	0.42***	<0.01	0.47***	<0.01	0.51***	0.01
Low-level annual household income	0.42***	0.01	0.55***	0.01	0.27***	0.02
Household vehicle ownership	-0.11***	<0.01	-0.07***	<0.01	-0.32***	0.01
Built environment factors						
Population density	0.19***	<0.01	2.14***	0.67	0.74***	0.01
Percentage of rental houses	0.86***	0.02	-	-	0.77***	0.05
Random effects						
sd (intercepts)	-	-	17.21***	4.15	0.73***	0.01
sds (ridesharing use frequency)	-	-	-	-	6.50***	0.13
sds (respondent age)	-	-	-	-	0.43***	0.06
Smooth terms					EDF	p-value
f(ridesharing use frequency)	**-**	**-**	**-**	**-**	**6.00** **	**< 0.01**
f(respondent age)	**-**	**-**	**-**	**-**	**8.00** **	**< 0.01**
Statistical performance						
AIC	1,420,985		1,309,228		1,207,484	

Note:
1. Significance codes: * p<0.05, ** p<0.01, *** p<0.001.
2. sd (intercepts) shows the standard deviation of the coefficient for the intercept across census tracts.
3. sds (Z) describes the standard deviation of the coefficients forming the smoothing spline for the variable Z's fixed effect.

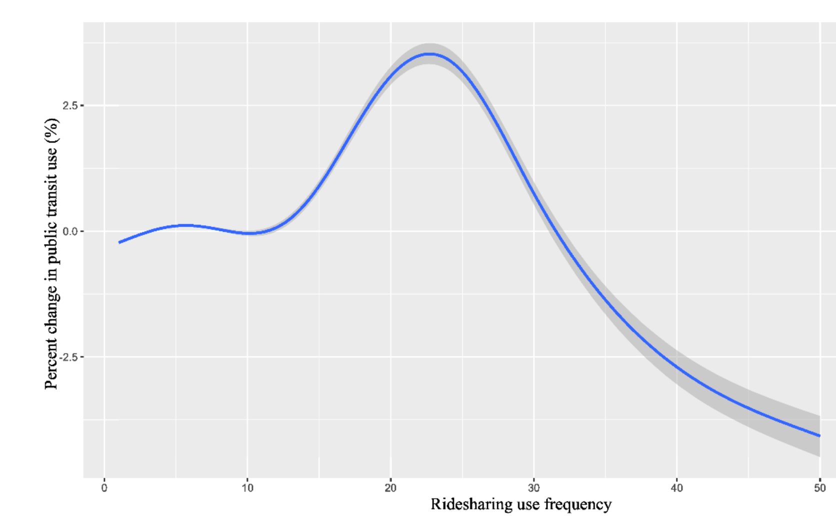

Fig.4. Nonlinear effects between ridesharing and public transit

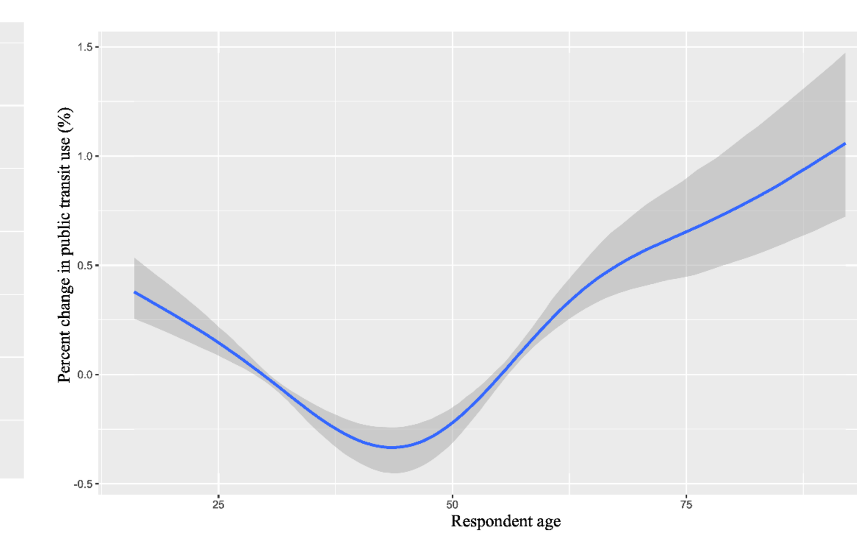

Fig.5. Nonlinear effects between respondent age and public transit

Conclusions

- A negligible impact on public transit usage for occasional ridesharing use (from one to eleven times per month).
- A complementary effect for regular ridesharing use (from eleven to thirty-two times per month).
- A substitution effect for active ridesharing use (more than thirty-two times per month).
- Possible solutions: schedule planning for public transit, demand-responsive feeder transit systems, and transit transfers and travel time.

Acknowledgements

The work was partially funded by the Transportation Informatics Lab, Department of Civil & Environmental Engineering at Old Dominion University (ODU). The work described in this paper was also supported by the National Natural Science Foundation of China (71861167001) and the National Science Fund for Distinguished Young Scholars (72025104).