Identifying Socio-Demographic Variability of Shared Micromobility Usage with Moran's Eigenvector Spatial Filtering

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ABSTRACT

The emergence of energy-efficient and more accessible mobility systems, such as shared free-floating e-scooter and bicycles, offer a unique opportunity to understand how people move within the urban space. Empirical data suggests that access to these services remains disproportionate across socio-demographic factors. How socio-demographics influences these mobility patterns or how these patterns vary within and across cities remains understudied. In this preliminary analysis, we examine micromobility usage patterns in Washington, DC using socio-demographic attributes (age, income, race, and gender) and built environment factors (walkability, street intersection density, employment-residential mix). We establish a new computational framework for micromobility data, that quantifies spatial patterns at multiple spatial scales using eigenvectors. Non-spatial and spatial models developed using Moran's Eigenvector Maps (MEM) and Eigenvector Spatial Filtering (ESF) are compared. Models that account for spatial structure at multiple spatial scales substantially outperform non-spatial models. Relative neighborhood graph and geographic distance based spatial weights matrices are tested within a MEM and ESF framework. Maps computed on geographic distance threshold perform better than relative neighborhood graph. Findings from this study may serve as a guide for future urban mobility decisions, that consider the distinct socio-demographic composition, built environment, and trip characteristics to address mobility inequity.

1. Introduction

Shared micromobility services, such as free-floating e-scooters, have established themselves as viable transportation alternatives for moving within a city. These services have been able to rapidly expand their market share across the globe due to their low carbon footprint and minimal dependence on transportation infrastructure. However, mobility providers often prioritize areas where they expect the largest return on their investment. Therefore, multiple corporate micromobility providers compete in the same consumer market and consequently serve people from similar backgrounds (Dill & McNeil, 2020).

Inequitable access to shared micromobility systems is apparent across cities in North America, with disparities reported across socio-demographics (Hosford & Winters, 2018; Meng & Brown, 2021). A free-floating e-scooter pilot program in Baltimore reports that 75% of its users were white despite only making up 30% of the population (*Baltimore City Dockless Vehicle Pilot Program Evaluation Report*, 2019). The usage of micromobility services by distinct socio-demographic segments remains understudied despite inequitable access to urban mobility observed across systems.

This project seeks to investigate how socio-demographic, built environment and trip characteristics influence micromobility usage in Washington, DC. The study employs Moran's Eigenvector Maps (MEM) and Eigenvector Spatial Filtering (ESF) techniques to account for spatial dependence in the study area. MEM and ESF techniques have been commonly used in ecological research; however, little work has investigated their suitability for mobility or transportation research.

Prior research has observed a high level of spatial dependence in micromobility, demographic and, built environment data (Aman et al., 2021). The validity of the independence assumption may be violated without the application of any spatial correction. The problem of spatial dependence can be accounted for using Moran's I, Geographic Weighted Regression (GWR), spatial lag, or spatial error (regression) models by considering the influence of neighboring values. MEM and ESF techniques address this issue in a different way, namely through the computation of "spatial predictors" based on any spatial weights matrix. The matrix can be generated using geographic distances between all locations or a graph-based neighbor specification. The resulting eigenvectors represent underlying spatial patterns, which are omitted in non-spatial models. ESF selects a subset of the eigenvectors produced that reduce model residuals.

1.1 Research Questions

Three research questions are explored through this preliminary work:

RQ 1. Do trip, socio-demographic (age, income, race, gender) and built environment data explain micromobility usage in Washington, DC?
RQ 2. Are there underlying spatial patterns in the data? Can they be identified using Moran's Eigenvector Maps and Eigenvector Spatial Filtering techniques?
RQ 3. Do spatial predictors strengthen the model?

2. Data & Methods

2.1 Data

Free-floating e-scooter usage data is retrieved from four micromobility providers in Washington, DC (Lime, Razor, Skip, Spin) for June-July 2019 and 2021. 2020 was excluded from the study due to mobility restriction measures enforced due to COVID-19. Each trip in the dataset contains origin-destination information as well as relevant timestamps. We use socio-demographics attributes from the U.S. Census Bureau's American Community Survey as user demographic data associated with trips are not released publicly. Previous work suggests that micromobility data is highly spatially correlated with age, gender, race, and income (McKenzie, 2019). Since the level of aggregation is crucial to our results, we choose data at the finest spatial resolution available, in this case, census block groups. Age, income, race, and gender data is retrieved for 449 census block groups in Washington, DC for 2019. National walkability index and street intersection density as reported by the U.S. Environmental Protection Agency at the census block group level is also included in the analysis. An entropy score for residential-employment mix at the census block group level where diverse employment and a greater number of occupied housing units are scored higher is also used.

Over 500,000 individual trips are aggregated to the census block group level based on trip origin. Raw trip origin counts are transformed using a rank normalization technique due to considerable

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imbalance in the trips taken in the downtown core as compared to outlying parts of the city. The percentile rank value for a given census block group represents the percentage of census block groups that experienced an equal or fewer number of trip origins. Average trip distance was calculated as the shortest path between origin and destination, along the OpenStreetMap road network.

2.2 Variable Selection

Existing micromobility literature reports that users of these services in the U.S. tend to be younger, white, male, and from higher income backgrounds (Meng & Brown, 2021; Shaheen et al., 2014). Free-floating trips are also reportedly higher in more walkable areas (Hosseinzadeh et al., 2021). Therefore, the following variables are given preference, to reduce issues with multicollinearity: (1) walkability index, (2) population between the ages of 25 to 34, (3) white, (4) income over \$200k, and (5) male. A maximum Pearson correlation threshold value of 0.5 is applied to remove any variables that are strongly correlated with these variables. Only variables with a variance inflation factor (VIF) < 10 are included in the model to ensure low correlation amongst the independent variables. Eleven variables are selected: walkability index, average trip distance, race (white, others), income less than \$10,000, median age, and five age segments (under 5, 5 to 9, 10 to 17, 25 to 34, over 85). All variables selected are statistically significant predictors of the response variable, trip origins.

2.3 Spatial-Autocorrelation at Multiple Spatial Scales

We use Moran's I autocorrelation coefficient to detect any underlying spatial structure in the socio-demographic, trip, and built environment attributes. A positive Moran's I statistic implies that similar values in the data are clustered in space whereas a negative value indicates dispersion. Spatial correlograms of the Moran's I indicate the presence of positive spatial autocorrelation in variables at multiple distance thresholds *(Figure 1)*. A p-value of less than 0.05 (highlighted in red) indicates statistically significant spatial autocorrelation.

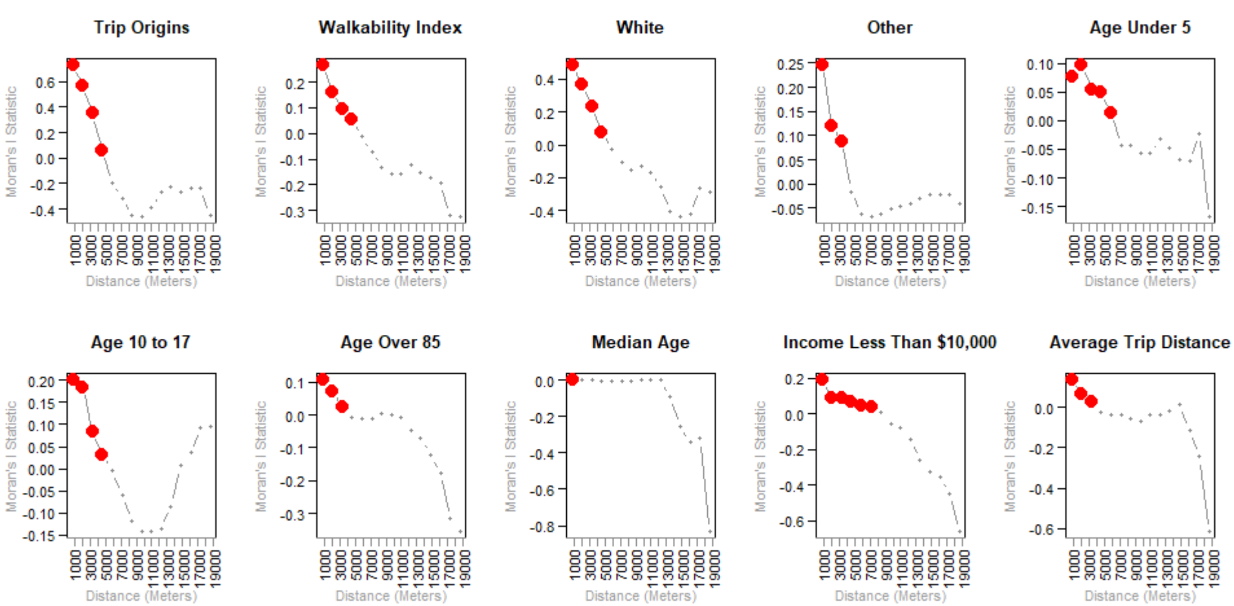

Figure 1: Moran's I Spatial Correlograms at multiple spatial scales

Strong spatial autocorrelation is evident in the dependent variable– trip origins— at distances between 0 to 4 kilometers. A similar pattern can be observed with race, income, walkability, as well as average trip distance. Statistically significant Moran's I indicate the presence of underlying spatial structures that must be accounted for through more spatially explicit modelling approaches.

2.4 Moran's Eigenvector Maps (MEM)

The presence of significant spatial dependence in the response and independent variables can bias results in models for which spatial autocorrelation is unaccounted. Moran's Eigenvector Maps offer a solution to account for spatial autocorrelation using eigenfunctions. The MEM method generates orthogonal variables that represent underlying spatial patterns based on distances between *n* sites, using a spatial weights matrix (Dray et al., 2006; Wagner et al., 2017). The process involves the diagonalization of an *n x n* spatial weights matrix that computes *(n-1)* eigenvectors. These orthogonal vectors represent spatial variation within the data and can be used as explanatory variables for multivariate statistical models as spatial predictors (Brind'Amour et al., 2018).

Not all eigenvector maps generated through this process are useful in reducing spatial dependence in model residuals. Using a semi-parametric spatial filtering approach known as Eigenvector Spatial Filtering (ESF), a subset is selected from the (n-1) eigenvector maps, based on their ability to minimize spatial autocorrelation in the residuals (Thayn, 2017). This approach has been reported to reduce errors associated with spatial misspecification and improve model fit and normality of model residuals (Thayn & Simanis, 2013).

2.4.1 Spatial Weights Matrix

In this study, MEM and ESF techniques are tested on two spatial matrices: Geographical and Relative Neighborhood Graph (RNG). The geographical distance matrix is a doubly centered matrix that contains the great-circle distance between the latitude and longitude of all points in the data. The matrix contains zeros for all diagonal entries.

The RNG adjacency matrix is computed using the 'spdep' package in R (Murakami, 2022). Instead of a straight-line distance, the RNG determines neighbors if two given points are closer to each other than any other points on a Euclidean plane. The graph of census block group centroids is visualized in *Figure 2*. The census block group centroids have 2.7 number of links on an average.

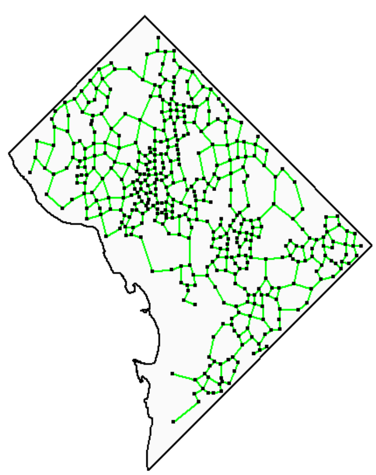

Figure 2: Relative Neighborhood Graph for Census Block Group Centroids in Washington, DC

 Volume DOI: 10.17605/OSF.IO/N6DU5

2.4.2 Eigenvector Spatial Filtering

Moran's eigenvector maps are generated for geographical and RNG matrices using the 'spmoran' package in R (Murakami, 2022). The geographical model produces 449 eigenvectors, based on (n-1) census block groups in the data whereas the RNG method produces 225 eigenvectors.

ESF is applied to resulting eigenvectors, to determine spatial patterns through a stepwise eigenvector selection, that minimizes model residuals. A minimum acceptable VIF value of 5 is applied to eigenvectors to remove any eigenvectors that may be correlated with other explanatory variables. Any eigenvector that does not meet this threshold is removed from the final model. Based on this criterion, 78/225 eigenvectors are selected with the RNG matrix, and 97/449 eigenvectors are selected with the geographical distance spatial matrix.

3. Results

Three models are compared to assess model performance: Model 1—a linear regression model with eleven non-spatial explanatory variables, Model 2 –a linear regression model with the same eleven explanatory variables and 78 spatially filtered eigenvectors from an RNG matrix and, Model 3— a linear regression model with eleven explanatory variables and 97 spatially filtered eigenvectors from a geographical distance matrix. Performance of models is contrasted in *Table 1*.

Model	Spatial Matrix	Spatial Predictors	Adj. R^2	RSE	AIC	BIC
Model 1	N/A	N/A	0.64	0.17	-280.63	-228.08
Model 2	RNG	78	0.89	0.095	-757.35	-383.60
Model 3	Geographical Distance	97	0.93	0.074	-967.74	-515.97

Table 1: Performance of Non-Spatial and Spatial models

Although Model 1 does not account for any underlying spatial structure in our data, the model produces an adjusted R^2 value of 0.64, a multiple R^2 of 0.65, and a residual standard error of 0.17 with 436 degrees of freedom. The model reveals a positive correlation between the dependent variable trip origin, and explanatory variables— white, other race, age under 25 to 34, and income less than $10,000. Negative coefficients for distance, age (under 5, 5 to 9, 10 to 17, over 85), and median age indicate an inverse relationship with trip origin.

With the same explanatory variables as Model 1 and 78 spatial predictors, Model 2 produces an adjusted R^2 value of 0.89. Model 3, with the same explanatory variables as Model 1, and 97 spatial predictors produces an adjusted R^2 of 0.93. The adjusted R^2 metric adjusts for variance explained based on the number of predictors in the model. The addition of spatial predictors in Model 2 and 3 improve the adjusted R^2, indicating a better fit. Walkability index, white, other races, age under 5, and income less than $10,000 remain significant in Models 2 and 3. Complete model results are summarized in the appendix (Tables 1, 2, and 3).

Akaike information criteria (AIC) and Bayesian Information Criterion (BIC) measures, which are commonly used to compare regression models suggest that Model 3 explains the largest amount of variation in the data, out of the three regression models compared. The decreasing Residual Standard Error (RSE) measure, which indicates the standard deviation of the error terms in the model, also suggests a better model fit for Model 3.

4. Discussion & Conclusion

In this study, we explore the feasibility of MEM and ESF techniques in addressing the issue of spatial autocorrelation with micromobility usage data. Model results reveal that a large portion of the variability in micromobility usage can be understood through socio-demographics (age, race, and income), built-environment (walkability), and average trip distance attributes. The addition of spatial predictors generated using a spatial weights matrix improves model fit. A geographic distance-based matrix performed slightly better than a RNG matrix for micromobility usage data.

Overall, the incorporation of spatial predictors improves our understanding of micromobility usage in Washington, DC. How the selection of spatial predictors affects model fit, and how these results compare against spatial lag or spatial error models will be explored in the future. Other network graphs such as Delaunay triangulation or Gabriel graph can also be tested for micromobility data. Spatial predictors are limited in their transferability to other cities due to dependence on the spatial structure of the underlying data. However, the feasibility of leveraging spatial predictors for understanding the temporal dimension of the data can be explored in the future.

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Appendix

Observations: 449
Dependent Variable: Trip Origins
Type: Linear Regression

MODEL FIT:

$R^2 = 0.65$
Adj. $R^2 = 0.64$
AIC = -281.48

Standard errors: OLS

	Est.	S.E.	t val.	p
(Intercept)	0.33	0.19	1.69	0.09
Walkability Index	0.04	0	9.23	0
Race-White	0	0	10.43	0
Race-Other	0	0	3.26	0
Age under 5	0	0	-2.41	0.02
Age 5 to 9	0	0	-2.78	0.01
Age 10 to 17	0	0	-4.07	0
Age 25 to 34	0	0	4.02	0
Age over 85	0	0	-2.96	0
Income Less than $10,000	0	0	5.29	0
Average Trip Distance	0	0	-4.54	0
Median Age	-0.44	0.18	-2.49	0.01

Table 1: Results for Model 1 (Linear Regression with 11 socio-demographic, built environment, and trip characteristics variables)

Volume DOI: 10.17605/OSF.IO/N6DU5

Observations: 449
Dependent Variable: Trip Origins
Type: OLS Linear Regression with Spatial Predictors

MODEL FIT:
R^2 = 0.91
Adj. R^2 = 0.89
AIC = -757.35

Standard errors: OLS

	Est.	S.E.	t val.	p
(Intercept)	0.18	0.12	1.42	0.16
Walkability Index	0.03	0	9.49	0
Race-White	0	0	5.02	0
Race-Other	0	0	2.05	0.04
Age under 5	0	0	1.86	0.06
Age 5 to 9	0	0	-1.18	0.24
Age 10 to 17	0	0	-0.27	0.79
Age 25 to 34	0	0	0.84	0.4
Age over 85	0	0	0.93	0.35
Income Less than $10,000	0	0	3	0
Average Trip Distance	0	0	-1.19	0.24
Median Age	-0.15	0.11	-1.33	0.18
Spatial Predictor 5	-2.74	0.13	-20.7	0
Spatial Predictor 2	-1.78	0.13	-13.45	0
Spatial Predictor 7	-1.22	0.12	-10.19	0
Spatial Predictor 11	-0.99	0.1	-9.51	0
Spatial Predictor 1	1.1	0.11	9.72	0
Spatial Predictor 26	0.63	0.1	6.41	0
Spatial Predictor 3	-0.41	0.11	-3.66	0
Spatial Predictor 34	0.58	0.1	5.79	0
Spatial Predictor 20	0.52	0.1	5.31	0
Spatial Predictor 36	0.44	0.1	4.49	0
Spatial Predictor 21	0.46	0.1	4.63	0
Spatial Predictor 27	0.31	0.1	3.07	0
Spatial Predictor 93	-0.43	0.1	-4.44	0
Spatial Predictor 9	-0.49	0.1	-4.94	0
Spatial Predictor 58	-0.3	0.1	-3.12	0
Spatial Predictor 39	-0.37	0.1	-3.82	0

Spatial Predictor 13	0.44	0.1	4.44	0
Spatial Predictor 8	0.59	0.11	5.53	0
Spatial Predictor 130	0.34	0.1	3.54	0
Spatial Predictor 4	-0.42	0.1	-4.08	0
Spatial Predictor 29	-0.32	0.1	-3.3	0
Spatial Predictor 215	-0.32	0.1	-3.35	0
Spatial Predictor 28	-0.3	0.1	-3.05	0
Spatial Predictor 24	-0.26	0.1	-2.7	0.01
Spatial Predictor 41	0.3	0.1	3.09	0
Spatial Predictor 193	0.24	0.1	2.5	0.01
Spatial Predictor 175	-0.25	0.1	-2.6	0.01
Spatial Predictor 84	-0.26	0.1	-2.75	0.01
Spatial Predictor 44	0.3	0.1	3.03	0
Spatial Predictor 16	-0.31	0.1	-3.06	0
Spatial Predictor 79	-0.28	0.1	-2.93	0
Spatial Predictor 14	0.27	0.1	2.82	0.01
Spatial Predictor 136	-0.27	0.1	-2.81	0.01
Spatial Predictor 33	-0.24	0.1	-2.51	0.01
Spatial Predictor 188	-0.25	0.1	-2.58	0.01
Spatial Predictor 86	-0.25	0.1	-2.6	0.01
Spatial Predictor 74	-0.24	0.1	-2.47	0.01
Spatial Predictor 49	-0.24	0.1	-2.45	0.01
Spatial Predictor 67	-0.2	0.1	-2.12	0.03
Spatial Predictor 192	0.21	0.1	2.23	0.03
Spatial Predictor 17	-0.23	0.1	-2.29	0.02
Spatial Predictor 89	0.2	0.1	2.09	0.04
Spatial Predictor 55	0.22	0.1	2.34	0.02
Spatial Predictor 64	0.21	0.1	2.12	0.03
Spatial Predictor 81	-0.22	0.1	-2.24	0.03
Spatial Predictor 100	0.22	0.1	2.33	0.02
Spatial Predictor 82	-0.2	0.1	-2.08	0.04
Spatial Predictor 88	0.23	0.1	2.42	0.02
Spatial Predictor 19	-0.23	0.1	-2.35	0.02
Spatial Predictor 85	0.21	0.1	2.17	0.03
Spatial Predictor 94	0.21	0.1	2.16	0.03
Spatial Predictor 221	-0.21	0.1	-2.23	0.03
Spatial Predictor 65	0.2	0.1	2.09	0.04
Spatial Predictor 6	-0.2	0.1	-2.02	0.04
Spatial Predictor 22	0.19	0.1	1.94	0.05
Spatial Predictor 97	0.19	0.1	1.95	0.05
Spatial Predictor 189	-0.18	0.1	-1.81	0.07
Spatial Predictor 116	-0.19	0.1	-1.99	0.05
Spatial Predictor 109	-0.19	0.1	-2.01	0.04

Volume DOI: 10.17605/OSF.IO/N6DU5

Spatial Predictor 66	0.18	0.1	1.87	0.06
Spatial Predictor 46	0.19	0.1	1.98	0.05
Spatial Predictor 101	0.19	0.1	1.94	0.05
Spatial Predictor 30	-0.19	0.1	-1.97	0.05
Spatial Predictor 128	0.19	0.1	1.94	0.05
Spatial Predictor 126	-0.18	0.1	-1.88	0.06
Spatial Predictor 87	-0.18	0.1	-1.85	0.07
Spatial Predictor 223	-0.18	0.1	-1.86	0.06
Spatial Predictor 45	0.17	0.1	1.78	0.08
Spatial Predictor 38	-0.17	0.1	-1.78	0.08
Spatial Predictor 211	0.17	0.1	1.78	0.08
Spatial Predictor 138	-0.17	0.1	-1.73	0.09
Spatial Predictor 63	-0.17	0.1	-1.73	0.08
Spatial Predictor 163	-0.16	0.1	-1.68	0.09
Spatial Predictor 199	0.16	0.1	1.69	0.09
Spatial Predictor 54	-0.16	0.1	-1.69	0.09
Spatial Predictor 56	0.16	0.1	1.7	0.09
Spatial Predictor 202	-0.16	0.1	-1.65	0.1
Spatial Predictor 31	0.16	0.1	1.65	0.1

Table 2: Results for Model 2 (linear regression with 11 socio-demographic, built environment, and trip characteristics variables and 78 spatially filtered eigenvectors from an RNG matrix)

Observations: 449	
Dependent Variable: Trip Origins	
Type: Linear Regression with Spatial Predictors	

MODEL FIT:

$R^2 = 0.95$
Adj. $R^2 = 0.93$
AIC = -967.7423

Standard errors: OLS

	Est.	S.E.	t val.	p
(Intercept)	0.34	0.1	3.52	0
Walkability Index	0.02	0	10.39	0
Race-White	0	0	8.39	0
Race-Other	0	0	2.6	0.01
Age under 5	0	0	-2.03	0.04
Age 5 to 9	0	0	0.9	0.37
Age 10 to 17	0	0	1.23	0.22
Age 25 to 34	0	0	0.66	0.51
Age over 85	0	0	0.97	0.34
Income Less than $10,000	0	0	3.46	0
Average Trip Distance	0	0	1.52	0.13
Median Age	-0.3	0.09	-3.54	0
Spatial Predictor 447	-3.54	0.11	-31.31	0
Spatial Predictor 448	-1.38	0.1	-13.96	0
Spatial Predictor 449	-1.08	0.12	-9.39	0
Spatial Predictor 446	0.65	0.08	7.65	0
Spatial Predictor 424	0.62	0.08	8.01	0
Spatial Predictor 430	0.67	0.08	8.74	0
Spatial Predictor 432	-0.59	0.08	-7.68	0
Spatial Predictor 429	-0.44	0.08	-5.81	0
Spatial Predictor 420	-0.55	0.08	-6.9	0
Spatial Predictor 444	-0.52	0.08	-6.55	0
Spatial Predictor 317	0.37	0.08	4.96	0
Spatial Predictor 440	-0.35	0.08	-4.58	0
Spatial Predictor 434	-0.34	0.08	-4.26	0
Spatial Predictor 313	0.3	0.08	3.99	0
Spatial Predictor 425	-0.37	0.08	-4.8	0
Spatial Predictor 188	-0.34	0.08	-4.47	0
Spatial Predictor 439	-0.33	0.08	-4.27	0

 Volume DOI: 10.17605/OSF.IO/N6DU5

Spatial Predictor 393	-0.31	0.08	-4.15	0
Spatial Predictor 360	-0.31	0.08	-4.06	0
Spatial Predictor 385	0.3	0.07	4.04	0
Spatial Predictor 351	-0.28	0.08	-3.68	0
Spatial Predictor 410	-0.27	0.08	-3.61	0
Spatial Predictor 390	0.26	0.08	3.43	0
Spatial Predictor 427	0.26	0.08	3.43	0
Spatial Predictor 443	0.27	0.08	3.33	0
Spatial Predictor 311	0.24	0.08	3.18	0
Spatial Predictor 296	-0.25	0.08	-3.34	0
Spatial Predictor 320	0.25	0.07	3.27	0
Spatial Predictor 418	-0.24	0.08	-3.24	0
Spatial Predictor 377	0.2	0.08	2.64	0.01
Spatial Predictor 132	-0.24	0.08	-3.22	0
Spatial Predictor 391	0.26	0.08	3.4	0
Spatial Predictor 302	-0.21	0.08	-2.8	0.01
Spatial Predictor 306	-0.25	0.07	-3.31	0
Spatial Predictor 185	-0.24	0.07	-3.25	0
Spatial Predictor 310	0.22	0.08	2.97	0
Spatial Predictor 126	-0.23	0.07	-3.13	0
Spatial Predictor 186	-0.2	0.07	-2.67	0.01
Spatial Predictor 312	0.23	0.08	3.05	0
Spatial Predictor 442	0.24	0.08	3.09	0
Spatial Predictor 342	-0.2	0.08	-2.68	0.01
Spatial Predictor 295	-0.23	0.07	-3.1	0
Spatial Predictor 413	0.22	0.08	2.95	0
Spatial Predictor 398	0.16	0.08	2.14	0.03
Spatial Predictor 124	-0.2	0.07	-2.74	0.01
Spatial Predictor 107	-0.21	0.08	-2.84	0
Spatial Predictor 346	0.22	0.08	2.89	0
Spatial Predictor 233	-0.21	0.08	-2.73	0.01
Spatial Predictor 401	0.19	0.08	2.5	0.01
Spatial Predictor 24	0.21	0.08	2.78	0.01
Spatial Predictor 44	0.2	0.07	2.68	0.01
Spatial Predictor 237	-0.21	0.08	-2.83	0
Spatial Predictor 298	-0.21	0.07	-2.81	0.01
Spatial Predictor 428	0.18	0.08	2.35	0.02
Spatial Predictor 218	-0.2	0.07	-2.68	0.01
Spatial Predictor 154	0.21	0.07	2.8	0.01
Spatial Predictor 260	0.2	0.08	2.63	0.01
Spatial Predictor 163	-0.19	0.07	-2.56	0.01
Spatial Predictor 111	-0.21	0.07	-2.77	0.01
Spatial Predictor 40	0.17	0.08	2.31	0.02

Spatial Predictor 7	0.2	0.07	2.63	0.01
Spatial Predictor 171	0.22	0.08	2.88	0
Spatial Predictor 294	-0.19	0.08	-2.5	0.01
Spatial Predictor 53	0.22	0.08	2.79	0.01
Spatial Predictor 93	0.17	0.08	2.26	0.02
Spatial Predictor 249	-0.18	0.07	-2.41	0.02
Spatial Predictor 316	-0.19	0.08	-2.51	0.01
Spatial Predictor 415	-0.18	0.08	-2.43	0.02
Spatial Predictor 309	0.18	0.08	2.37	0.02
Spatial Predictor 39	0.18	0.07	2.45	0.01
Spatial Predictor 365	0.18	0.08	2.36	0.02
Spatial Predictor 99	-0.18	0.07	-2.37	0.02
Spatial Predictor 141	0.16	0.07	2.16	0.03
Spatial Predictor 216	0.2	0.07	2.68	0.01
Spatial Predictor 417	-0.18	0.08	-2.33	0.02
Spatial Predictor 441	0.2	0.08	2.57	0.01
Spatial Predictor 392	0.19	0.08	2.45	0.01
Spatial Predictor 423	0.2	0.08	2.61	0.01
Spatial Predictor 388	0.18	0.08	2.34	0.02
Spatial Predictor 59	-0.17	0.07	-2.3	0.02
Spatial Predictor 379	-0.17	0.08	-2.2	0.03
Spatial Predictor 169	0.18	0.08	2.36	0.02
Spatial Predictor 431	0.18	0.08	2.38	0.02
Spatial Predictor 85	-0.18	0.08	-2.34	0.02
Spatial Predictor 156	-0.16	0.08	-2.16	0.03
Spatial Predictor 358	-0.16	0.08	-2.17	0.03
Spatial Predictor 264	0.17	0.07	2.29	0.02
Spatial Predictor 402	0.16	0.08	2.08	0.04
Spatial Predictor 396	-0.17	0.08	-2.25	0.03
Spatial Predictor 272	-0.16	0.08	-2.15	0.03
Spatial Predictor 343	0.16	0.08	2.08	0.04
Spatial Predictor 376	0.16	0.07	2.14	0.03
Spatial Predictor 397	0.15	0.08	1.97	0.05
Spatial Predictor 414	-0.16	0.08	-2.05	0.04
Spatial Predictor 197	0.16	0.08	2.1	0.04
Spatial Predictor 350	0.16	0.08	2.05	0.04
Spatial Predictor 35	-0.16	0.08	-2.04	0.04

Table 3: Results for Model 3 (linear regression with 11 socio-demographic, built environment, and trip characteristics variables and 97 spatially filtered eigenvectors from a geographical distance matrix)

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