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Exploring the influence of built environment on Uber demand

Sadegh Sabouri[a,*], Keunhyun Park[b], Amy Smith[c], Guang Tian[d], Reid Ewing[a]

[a] Department of City & Metropolitan Planning, University of Utah, 375 S 1530 E, Room 235, Salt Lake City, UT 84112, USA
[b] Department of Landscape Architecture and Environmental Planning, Utah State University, 4005 Old Main Hill, Logan, UT 84322, USA
[c] Uber Technologies, 1455 Market Street, San Francisco, CA 94103, USA
[d] Department of Planning and Urban Studies, University of New Orleans, 2000 Lakeshore Drive, New Orleans, LA 70148, USA

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ABSTRACT

Ride-sourcing services have made significant changes to the transportation system, essentially creating a new mode of transport, arguably with its own relative utility compared to the other standard modes. As ride-sourcing services have become more popular each year and their markets have grown, so have the publications related to the emergence of these services. One question that has not been addressed yet is how the built environment, the so-called D variables (i.e., density, diversity, design, distance to transit, and destination accessibility), affect demand for ride-sourcing services. By having unique access to Uber trip data in 24 diverse U.S. regions, we provide a robust data-driven understanding of how ride-sourcing demand is affected by the built environment, after controlling for socioeconomic factors. Our results show that Uber demand is positively correlated with total population and employment, activity density, land use mix or entropy, and transit stop density of a census block group. In contrast, Uber demand is negatively correlated with intersection density and destination accessibility (both by auto and transit) variables. This result might be attributed to the relative advantages of other modes – driving, taking transit, walking, or biking – in areas with denser street networks and better regional job access. The findings of this paper have important implications for policy, planning, and travel demand modeling, where decision-makers seek solutions to shape the built environment in order to reduce automobile dependence and promote walking, biking, and transit use.

1. Introduction

Transportation planning is reaching a point where transformative innovations change the way we look at the future, in some ways making it less predictable than at any time since the advent of the automobile. Imminent technological advances such as driverless vehicles have transportation researchers postulating about how the current paradigm will adapt to the implementation of these new technologies. Even relatively new innovations that have already been implemented are just starting to be understood.

Ride-sourcing services or what most practitioners call transportation network companies (TNCs), such as Uber and Lyft, have made significant changes to the transportation system, essentially creating a new mode of transport, arguably with its own relative utility compared to the other standard modes. Ride-sourcing is a new type of shared mobility occurring when a passenger requests a ride using a mobile device and an application. Uber has grown rapidly since it first launched in San Francisco in 2009, now operating in more than 700 cities across 69 countries on six continents (Uber Technologies Inc, 2019). This wide geospatial range, and Uber's

* Corresponding author.
E-mail addresses: Sadegh.Sabouri@utah.edu (S. Sabouri), keunhyun.park@usu.edu (K. Park), amy.smith@uber.com (A. Smith), gtian@uno.edu (G. Tian), ewing@arch.utah.edu (R. Ewing).

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detailed trip data now makes it possible to analyze the impact of this transport technology on the transportation system.

One question that has not been addressed as yet is how the built environment affects demand for ride-sourcing services. The so-called D variables of the built environment are now well established in their ability to affect vehicle miles traveled (VMT), walking, biking, and transit use, with Ewing and Cervero (2010) concluding that the combined effects of development density, land use diversity, street network design, distance to transit, and destination accessibility on travel outcomes are quite large. In general, studies have found that VMT reduction and car shedding occur as the Ds increase (or inversely, as the distance to transit decreases), and as a result, motivate more non-motorized and public transit travel. Understanding the relationship between the built environment and travel behavior is important for a wide range of applications, including the development of sustainable city planning strategies and effective transportation policies.

The objective of this study is to fill gaps in existing research by providing a robust data-driven understanding of how ride-sourcing demand is affected by the built environment. Is ride-sourcing like other modes, affected by the D variables, or is it somehow different and unique? The first of its kind, this study answers this question by merging built environment and socioeconomic characteristics with actual Uber trip data aggregated at the Census Block Group (CBG) level for 24 diverse regions across the United States. The results indicate that the built environment affects ride-sourcing in much the same way it affects travel by other modes, underscoring the role of the built environment in shaping travel choices, including those that involve newer, technology-enabled services such as ride-sourcing.

To answer the research question, we present a trip distribution model that considers the built environment impacts of CBGs both at the origin and destination of the trips. We have generated consistent measures of built environment variables for 24 regions of the U.S. The model developed in this study has a multilevel structure to account for the dependence of trips in the same region on regional characteristics. Additionally, the data structure requires a multiple membership model since trips generated from one CBG to multiple CBGs and trips attracted to one CBG from multiple CBGs, each of them considered as one observation. Therefore, our trips are nested within three higher-level units, i.e., origin, destination, and region.

The remainder of this paper is organized as follows. Section 2 contains a review of the few studies that assessed the impact of sociodemographic characteristics of households and built environment characteristics of neighborhoods on ride-sourcing demands. Section 3 describes the data, and statistical methods used to estimate the trip distribution model. Section 4 presents the results of the best-fit multi-level multiple membership model and discusses the results. Finally, Section 5 presents the conclusions.

2. Literature review

There is a vast body of literature that has studied and analyzed the linkage between the built environment and travel behavior over the past decades. Studies have found that an individual's mode choice is a function of both socioeconomic characteristics of the household and the built environment characteristics of the surrounding area, characterized by the so-called D variables (Ewing and Cervero, 2010). The first three of them known as density, diversity, and design were coined by Cervero and Kockelman (1997), and then, Ewing and Cervero (2001) added destination accessibility and distance to transit to this list.

Higher population and job densities, greater retail floor area ratio, more diverse land use characteristics, shorter distance to jobs and social amenities, well-connected streets, and diversity of local transport have all been claimed to encourage more people to walk, bike, and use transit (Hamre and Buehler, 2014; Ozbil, Peponis, and Stone, 2011; Wang and Lin, 2013; Ewing et al., 2014; Zailani et al., 2016). There are of course specific features associated with each mode as well which will encourage more people to travel by that mode. For instance, a smaller fraction of cul-de-sac streets, more sidewalk coverage, and wider sidewalks increase the likelihood to walk (Ozbil, Peponis, and Stone, 2011; Ewing et al., 2004, 2009; Aziz et al., 2018). On the other hand, bicycling facilities and bike lanes are motivating factors for bicycling (Hamre and Buehler, 2014).

In terms of ride-sourcing services, over the past few years, a number of attempts—both qualitatively and quantitatively—have been made to explore the relationship between ride-sourcing demands and socioeconomic and built environment factors. Studies have found that there is a higher demand for TNCs from younger, more-affluent, and well-educated individuals (Alemi et al., 2018; Gerte et al., 2018; Rayle et al., 2016; Circella et al., 2018; Lavieri et al., 2018; Reinhart, 2018). In addition, households who own more vehicles tend to use ride-sourcing services less frequently (Correa et al., 2017; Dias et al., 2017).

Only a handful of studies have explored ride-sourcing demand in the context of the built environment, and they only focus on a single region and a few D variables such as density and destination accessibility. These include studies conducted in San Francisco, CA, New York City, NY, Chicago, IL, and Austin, TX. In the first two regions, researchers accessed TNC data through TNCs' Application Programming Interfaces (API). In New York City, researchers as well as journalists (e.g., see Silver and Fischer-Baum, 2015) have studied TNC activity using data available through the Taxi and Limousine Commission's data portal, available at the official website of the City of New York. In Austin, rideAustin data is publicly available at the most disaggregated level, allowing researchers to derive useful information from it.

To date, only Yu and Peng (2019a,b) have examined the impacts of the arguably full range of the built environment factors (i.e., 5Ds), using the rideAustin data. What differentiates their study from ours is their ability to distinguish weekday trips from weekend trips since the true nature of these trips can be very different. The authors used a geographically weighted regression (GWR) model, and therefore the Ds' impacts vary from one census block group (their unit of analysis) to the next. The researchers found that most of the areas with a larger population, higher road and sidewalk densities, land use mix, and transit accessibility are positively associated with rideAustin demand across the study region, while job-population balance is negatively associated with this demand.

In New York City, using Uber pickup data in 2015, Gerte et al. (2018) found that the total built area (as a measure of overall intensity of each taxi zone), the percent of residential floor area, and the percentage of retail by floor area are positively associated with the Uber demand. They did control for other relevant variables such as bus stops, subway stops, and the percentage of the overall parking. However, none of them were statistically significant and were dropped from the analysis.

Bao et al., 2017 also analyzed Uber data from New York City. They selected a single week of Uber trip data in 2014 and conducted their study of 167 ZIP code tabulation areas (ZCTA). In contrast to the previous study, they found that the number of parking spaces, the ratio of floor area allocated for commercial use, and the subway accessibility in each ZCTA were significant and positively correlated with the Uber usage. They also found that the number of unemployed population in each ZCTA is negatively correlated with Uber usage.

Other findings on the impact of the built environment on Uber demand in New York City come from Correa et al. (2017). They found higher expectancy of Uber demand in areas where roadway length and job opportunities are higher, and on the other hand, transit access time is lower.

Another set of findings derives from the study of Alemi et al. (2018) in California. Using the California Millenials dataset (N = 1975) and estimating binary logit models, they found that land use diversity and destination accessibility have positive impacts on Uber demand. In addition, the study found a greater chance of using TNCs for longer distance business trips and also, among the individuals who travel by plane more frequently.

To our knowledge, the only study outside the U.S. was done by Li et al. (2019). The authors investigated the impacts of built environment variables on DiDi's (a ride-sourcing service in China) demand. They found that the recreation and entertainment point of interest (POI) and residential district POI make the biggest contribution to night online ride-sourcing travel. Note that POI, which is unclearly defined by the authors, is their geographic unit of analysis. Control variables included population and road density, distance to central business district (CBD), and land-use mix. Of these, only the land-use mix was found to be significant and positively correlated with ride-sourcing demand.

Apart from the fact that limited efforts have been made to shed light on the relationships between the built environment variables and TNCs demand, there are two main problems with the existing literature. First is the lack of external validity. Studies have mostly focused on one metropolitan region (e.g., Austin and New York City) and many of them explicitly warned the readers that their findings might not be transferable to other regions. Second, researchers did not control for the effect of all D variables in their studies, except Yu and Peng (2019a,b), which can prevent them from capturing the full effect of the built environment and might lead to biased results.

3. Data and method

3.1. Uber data and study regions

Although we had consistent built environment data for 34 regions, Uber data was provided where ride-sourcing services are available. Therefore, in this study, we were able to compile datasets for 24 regions across the U.S. A region is a metropolitan area of a designated Metropolitan Planning Organization (MPO). The boundary of a region was adopted from the boundary defined by each MPO, which consists of one or multiple counties. The regions are as diverse as Boston, MA, and Portland, OR, at the compact end of the urban form continuum, and Houston, TX, and Atlanta, GA, at the sprawling end of the continuum. To our knowledge, this is the largest sample of ride-sourcing data ever assembled for such a study. Table 1 shows the study regions with their population and information about the number of CBGs both at the origin and destination. Trip volumes are not presented in Table 1 since these data are proprietary.

Uber data was aggregated and anonymized to protect user privacy. It is challenging to assemble databases that meet the criteria needed for a detailed analysis of the built environment-travel behavior relationship, as confidentiality concerns may prevent both metropolitan planning organizations and private companies from sharing data about individuals' travel patterns. However, we were able to identify a level of aggregation that both protected individuals' privacy and served the needs of the study.

Limitations of the data include the filtering of Uber data after aggregation to prevent re-identification of personal location information as well as temporal constraints. Data were provided for CBG pairs with more than 30 Uber trips per month. The time range of the Uber data encompasses the first three months of 2017, aggregated at the monthly level. In order to reduce variation in different months, we averaged the monthly trip aggregates for each CBG. Where three months of data were not available after the filtering step, CBGs were removed from the dataset, and only those with information for all three months were considered. After filtering, as it is shown in Table 1, the resulting pooled data set consists of ride volumes between 71,789 CBGs. Due to the limited time period, we did not control for seasonal variation in Uber trips.

3.2. Variables and data sources

In this study, we controlled for five socioeconomic variables at the CBG level: average household size, median age of households, average household income, average household vehicle ownership, and average number of employed persons in the household. For the first three variables, we obtained information in 2017 from the American Community Survey (ACS), using the 5-year range (2013–2017) data. For the employment data, we used the Longitudinal Employer-Household Dynamics (LEHD) database which is assembled by the U.S. Census Bureau and is available from 2002 to 2015 at the census block level. In this study, LEHD data were downloaded, aggregated to the CBG level, and processed for the year 2015.

We described built environment variables earlier in this study. Table 2 is the summary of the description, measurement in this study, and the source of data for each of the D variables. Note that to compute most of the D variables in this study, we have used data

Table 1
Study regions with their population and number of CBGs.

Region	Population	# Unique CBG Origin	# Unique CBG Destination	# Flows between CBGs[1]	Total # of CBGs in Each Region
Atlanta, GA	5,173,196	989	925	8150	2565
Boston, MA	4,459,130	1271	1077	17,759	3316
Charleston, SC	621,695	117	111	923	325
Dallas, TX	6,374,031	727	687	4699	4182
Denver, CO	2,863,897	407	386	3000	1550
Detroit, MI	4,814,667	40	37	274	1583
Greensboro, NC	516,753	53	50	205	292
Hampton Roads-Norfolk, VA	1,627,273	154	138	524	1123
Houston, TX	5,675,998	548	507	4099	2998
Indianapolis, IN	1,803,042	195	192	753	1139
Kansas City, MO	1,745,073	85	89	586	1405
Madison, WI	488,073	65	61	762	310
Miami, FL	2,475,945	841	779	11,051	1576
Minneapolis-St. Paul, MN-WI	2,727,273	358	302	1617	2024
Orlando, FL	1,891,633	332	316	2815	683
Phoenix, AZ	4,405,623	582	529	2923	2670
Portland, OR	1,612,200	267	228	1359	1037
Richmond, VA	1,166,276	97	92	806	600
Sacramento, CA	1,933,143	61	52	164	1021
Salt Lake City, UT	1,569,022	145	147	596	912
San Antonio, TX	1,828,412	169	152	791	1085
Seattle, WA	3,810,659	636	505	5630	2643
Springfield, MA	621,570	39	45	197	442
Tampa, FL	2,882,353	417	400	2106	2065
Total	–	8595	7807	71,789	37,546

[1] Number of unique O-D pairs with at least 30 Uber trips on average per month.

Table 2
The D Variables (revised from Ewing et al., 2015).

D Variable	Description	Measurement in this study	Data source
Density	A variable of interest per unit of area. Population and employment are sometimes summed to compute an overall activity density.	Activity density = Sum of population and employment per square mile	Sociodemographic data for CBGs from ACS
Diversity	Diversity measures pertain to the number of different land uses in a given area and the degree to which they are balanced. Entropy measures of diversity, wherein low values indicate single-use environments and higher values more varied land uses, are widely used in travel studies. Jobs-to-housing or jobs-to-population ratios are also used.	Entropy index = −[residential share * ln (residential share) + commercial share * ln (commercial share) + public share * ln(public share)]/ln(3), where ln is the natural logarithm.	Parcel-level land use map from county tax assessors
Design	Design measures include average block size, proportion of four-way intersections, and number of intersections per square mile. Design is also occasionally measured as sidewalk coverage, average building setbacks, or numbers of pedestrian facilities (e.g., crossings, street trees).	1. Intersection density = The number of intersections per square mile 2. Percentage of four-way intersection = the number of four-way intersections divided by the total number of intersections	A GIS layer for street networks and intersections from VMT growth database (Ewing et al., 2015)
Destination accessibility	Ease of access to trip attractions. Regional accessibility may be a distance to CBD or the number of jobs or other attractions reachable within a given travel time, which tends to be highest at central locations and lowest at peripheral locations.	1. Percentage of regional employment within 10, 20, and 30 min by car = % of jobs that can be reached within 10-, 20-, and 30-min by automobile 2. Percentage of regional employment within 30 min by transit = % of jobs that can be reached within 30-min by transit	Sociodemographic data for CBGs from ACS *and* Travel time skims matrix from MPOs
Distance to transit	Usually measured as the shortest street routes to the nearest rail station or bus stop. Alternatively, it may be measured as transit route density, distance between transit stops, or the number of stations per unit area.	Transit density = the number of stops per square mile	General Transit Feed Specification (GTFS) from https://gtfs.org/

Table 3
Descriptive statistics of variables.

Variable	Description	N	Mean	S.D.
Uber variables				
lnrides	**Dependent variable** – natural log of average number of trips between each two CBGs (provided by Uber)	71,789	NA[a]	NA[a]
avg_duration	Average trip duration in minutes between each two CBGs (provided by Uber)	71,789	14.30	8.13
Socio-demographic variables (aggregated at the CBG level) at the origin CBG				
o_hhsize	Average household size	8542	2.54	0.68
o_median_age	Median age of households	8564	37.23	8.63
o_vehicle	Average number of vehicles per household	8595	1.65	0.37
o_employed	Average number of employed persons in household	8542	1.33	0.38
o_lnincome	Natural log of average household income	8542	11.24	0.44
Socio-demographic variables (aggregated at the CBG level) at the destination CBG				
d_hhsize	Average household size	7754	2.53	0.70
d_median_age	Median age of households	7777	37.22	8.77
d_vehicle	Average number of vehicles per household	7807	1.64	0.38
d_employed	Average number of employed persons in household	7754	1.34	0.40
d_lnincome	Natural log of average household income	7754	11.23	0.44
Measures of size at the origin CBG				
o_area	Gross land area of CBG in square miles	8595	0.91	3.18
o_totpop	Total population within CBG	8595	1817.18	1901.71
o_totemp	Total employment within CBG	8595	1772.09	4292.22
Built environment variables at the origin CBG				
o_actden	Activity density within CBG (pop + emp per square mile in 1000 s)	8590	13229.4	24910.1
o_entropy	Land use entropy	8586	0.52	0.27
o_pct4way	Percentage of 4-way intersections within CBG	8584	35.21	21.11
o_intden	Intersection density within CBG per square mile	8595	200.96	173.74
o_transitden	Transit stop density per square mile	8595	48.61	80.22
o_pctemp10a	% Regional employment within 10 min by auto	8595	7.69	7.69
o_pctemp20a	% Regional employment within 20 min by auto	8595	30.45	20.08
o_pctemp30a	% Regional employment within 30 min by auto	8595	55.25	23.59
o_pctemp30t	% Regional employment within 30 min by transit	8595	24.02	18.63
Measures of size at the destination CBG				
d_area	Gross land area of CBG in square miles	7807	1.05	4.82
d_totpop	Total population within CBG	7807	1861.88	1980.78
d_totemp	Total employment within CBG	7807	1923.24	4475.99
Built environment variables at the destination CBG				
d_actden	Activity density within CBG	7801	13632.1	26004.2
d_entropy	Land use entropy	7797	0.53	0.27
d_pct4way	Percentage of 4-way intersections within CBG	7796	35.34	21.03
d_intden	Intersection density within CBG per square mile	7807	198.02	176.51
d_transitden	Transit stop density per square mile	7807	49.01	82.26
d_pctemp10a	% Regional employment within 10 min by auto	7807	7.79	7.83
d_pctemp20a	% Regional employment within 20 min by auto	7807	30.45	20.17
d_pctemp30a	% Regional employment within 30 min by auto	7807	55.22	23.84
d_pctemp30t	% Regional employment within 30 min by transit	7807	23.89	18.78
Regional variables				
regpop000	Regional population in 1000	24	2628.62	1721.36
regemp000	Regional employment in 1000	24	1322.78	887.24
regpopden	Population density within the region	24	783.26	725.69
gasprice	Average gasoline price in the region	24	2.86	0.120

[a] This data is proprietary.

from MPOs, state departments of transportation, transit agencies, county assessors, and other sources.

Table 3 shows the dependent and independent variables used in this study, as well as the sample sizes and descriptive statistics. We have covered most of the D variables considered in the built environment literature, from density to demographics. All in all, a total of 39 independent variables are available to explain Uber demand. All variables are consistently defined from region to region.

3.3. Statistical analysis

Our data and model structure are hierarchical, with CBGs nested within regions. Ewing et al. (2015) argue that multilevel modeling (MLM) is “the best statistical approach for nested data” since it accounts for “spatial dependence among observations.” MLM is also called hierarchical linear modeling (HLM). Single-level statistical methods produce biased standard errors and inefficient regression coefficients. In some settings, MLM overcomes these limitations, accounting for the dependence among observations and producing more useful coefficient and standard error estimators (Raudenbush and Bryk, 2002).

Trip production in a region such as Portland is likely to have very different characteristics compared to a region such as Atlanta, regardless of census block group (or neighborhood) characteristics. MLM partitions variance between the CBG level (Level 1) and the regional level (Level 2) and considers simultaneously the variance associated with these two levels.

In addition, the data structure requires a multiple membership model. In multiple membership data, lower-level units do not need to belong to only one higher-level unit. There are multiple trips produced by a single CBG and attracted to multiple CBGs. Similarly, there are multiple trips attracted to a single CBG from different near and far CBGs. Hence, trips can be described as being "multiple members" of a CBG.

The models in this study can be written as:

$$y_{i(j_1,j_2)k} = \beta_0 + \beta_1 x_{1i(j_1,j_2)k} + \beta_{\mathrm{m}} x_{2j_1k} + \beta_{\mathrm{n}} x_{3j_2k} + \beta_{\mathrm{o}} x_{4k} + u_{j_1k} + u_{j_2k} + v_k + e_{i(j_1,j_2)k}$$

where $y_{i(j_1,j_2)k}$ is the natural log of average Uber rides (*lnrides*) between origin block group j_1 and destination block group j_2 in region k, β_0 is the mean *lnrides* across all CBGs and regions, $\beta_0 + \beta_1 x_{1i(j_1,j_2)k} + \beta_{\mathrm{m}} x_{2j_1k} + \beta_{\mathrm{n}} x_{3j_2k} + \beta_{\mathrm{o}} x_{4k}$ is termed the fixed part of the model and $u_{j_1k} + u_{j_2k} + v_k + e_{i(j_1,j_2)k}$ is termed the random part of the model. The fixed part of the model specifies the overall mean relationship between the response (*lnrides*) and the predictor variables applied in the average origin-destination block group pair. The random part specifies how the region and origin/destination CBG specific relationships differ from this overall mean relationship.

In the fixed part of the model, $x_{1i(j_1,j_2)k}$ is the predictor variable—*avg_duration*—between the origin CBG j_1 and the destination CBG j_2 in region k with the slope coefficient β_1, x_{2j_1k} represents a set of predictor variables (i.e., socio-demographic, measures of size, and D variables) at the origin CBG j_1 in region k with the slope coefficient β_{m}, x_{3j_2k} is a set of predictor variables (i.e., socio-demographic, measures of size, and D variables) at the destination CBG j_2 in region k with the slope coefficient β_{n} (m and n represent each of the socio-demographic, measures of size, and D variables), $\beta_{\mathrm{o}} x_{4k}$ denotes the regional variables with their corresponding slope coefficients in region k, and $e_{i(j_1,j_2)k}$ is the residual error term for Uber rides between block groups j_1 and j_2 in region k.

The multiple membership multilevel model, developed by Hill and Goldstein (1998), takes the complexity in travel flow or trip distribution data into consideration. It should be noted that multiple membership multilevel model is also referred to as a cross-classified random effects model (see Raudenbush and Bryk, 2002; Ewing et al., 2005). In this case, Uber rides are cross-classified by origin and destination at the CBG level. To generate our cross-classified random effects model, we used *lmer* function (*lmerTest* package) in R 3.4.3 software.

4. Results and discussions

Before describing the best-fit model results, it should be noted that we used *lnrides* (log-transformed value) rather than the average number of rides (or rounded to the nearest integer to be compatible with a count regression model) since the result of the k-fold cross-validation suggested that the root mean squared error (RMSE) of the model with *lnrides* is substantially lower than the model with rides. In k-fold cross-validation, trip data were randomly split into k equal-sized groups. k-fold cross-validation (here, k = 5) considers training on all but the k$^{\mathrm{th}}$ part, and then validating on the k$^{\mathrm{th}}$ part, iterating over k = 1, …, 5. We then, assessed and compared the models using the RMSE defined as (n = observations):

$$RMSE_p = \sqrt{\frac{(\hat{y}_i - y_i)^2}{n}}$$

RMSE measures the prediction error or standard deviation of the residuals. Lower RMSE indicates that the model has better predictive accuracy. Also, note that we computed leverage values using Cook's Distance method. In this method, the effect of each observation on the fitted response values is measured. Observations with high leverage (such as Universal Studio and Disney World in Florida which might also be outliers) can have negative impact on the accuracy of the model. For our model using *lnrides* as our dependent variable, none of the observations were dropped since leverage values did not exceed the 0.2 rule of thumb (de Vaus, 2002).

We also used variance inflation factor (VIF) to check for the multicollinearity (i.e., high correlation among predictors) in our model since by including most of the socio-demographic and D variables both at the origin and destination, some of them might be highly correlated with each other. The highest VIF in our model was 2.77 which did not exceed the 10 (or sometimes 5) rule of thumb. With these three considerations, the final best-fit model of Uber trip distribution – excluding statistically non-significant variables – is shown in Table 4.

According to Table 4, there is considerable variation in the intercept at level 2 (regions), and among the CBGs (members) both at the origin and the destination. This suggests that the relationships between the built environment and sociodemographic factors and ride-sourcing demand are to some degree dependent on the region in which they are located. After grouping the origins and destinations (i.e., origin-CBG level and destination-CBG level), the results show that the cross-classified random effects model performs better compared to the single-level model due to the significant group-level variances. That is, the cross-classified random effects model provides a better fit to the data.

The following sub-sections describe the sociodemographic and built environment factors most strongly linked to Uber demand, and relate these findings to known relationships with other modes of travel drawn from the built environment-travel behavior literature.

Table 4
Estimation results of the trip distribution model.

Variable Type	Variables	Coef.	Elasticity	t value	p value
	(Intercept)	1.856	–	5.770	< 0.001
Trip	avg_duration	−0.065	−0.927	−170.620	< 0.001
Socio-demographic at the origin CBG	o_hhsize	−0.055	−0.140	−3.928	< 0.001
	o_median_age	−0.010	−0.367	−11.196	< 0.001
	o_vehicle	−0.445	−0.734	−14.352	< 0.001
	o_employed	0.091	0.121	4.307	< 0.001
	o_lnincome	0.225	0.225	11.048	< 0.001
Measures of size at the origin CBG	o_totpop	0.00004	0.069	12.063	< 0.001
	o_totemp	0.00004	0.073	30.648	< 0.001
Built environment at the origin CBG	o_actden	0.000001	0.013	3.956	< 0.001
	o_entropy	0.319	0.166	13.547	< 0.001
	o_intden	−0.0004	−0.080	−8.481	< 0.001
	o_transitden	0.0004	0.017	4.510	< 0.001
	o_pctemp10a	−0.0077	−0.059	−5.407	< 0.001
	o_pctemp30t	−0.0023	−0.055	−3.849	< 0.001
Socio-demographic at the destination CBG	d_hhsize	−0.041	−0.104	−2.841	0.004
	d_median_age	−0.008	−0.303	−8.332	< 0.001
	d_vehicle	−0.362	−0.594	−11.146	< 0.001
	d_employed	0.105	0.141	4.793	< 0.001
	d_lnincome	0.137	0.137	6.451	< 0.001
Measures of size at the destination CBG	d_totpop	0.00003	0.058	9.858	< 0.001
	d_totemp	0.00004	0.073	29.233	< 0.001
Built environment at the destination CBG	d_actden	0.000001	0.013	3.911	< 0.001
	d_entropy	0.318	0.168	12.771	< 0.001
	d_intden	−0.0005	−0.103	−10.921	< 0.001
	d_transitden	0.0004	0.022	5.546	< 0.001
	d_pctemp10a	−0.013	−0.099	−8.561	< 0.001
	d_pctemp30t	−0.0038	−0.091	−6.262	< 0.001
Regional	regpop000	−0.0001	−0.263	−2.186	0.041
Variation at Different Levels					
Var(cons)-origin					0.162 (N = 8526)
Var(cons)-destination					0.170 (N = 6902)
Var(cons)-region					0.153 (N = 24)
Model Evaluation					
Log-Likelihood (LL(β))					89225.9
McFadden R2					0.332
AIC					89291.9
BIC					89590.7
RMSE					0.379

4.1. Socio-demographic and travel time variables

In general, the results demonstrate both similarities and differences compared to those in the current travel behavior literature. Uber demand declines with larger household size and the median age of the residents. Traveling by Uber may become more difficult and potentially more expensive relative to using a personal vehicle as household size increases (Gerte et al., 2018). Trip-chaining and household travel behavior become more complex for larger household sizes. For example, while a personal car could be used to conduct three separate trips with extended stops in between, with ride-sourcing and similar on-demand transportation services, each trip would need to be requested and paid for separately. This could result in ride-sourcing being a relatively inconvenient and expensive option for daily transportation needs. We presume that larger households generally use their private cars as a primary mode of transportation over other alternatives.

Previous research indicates that younger age groups tend to use Uber more (Gerte et al., 2018; Rayle et al., 2016; Yu and Peng, 2019a,b; Circella et al., 2018). This trend is also reflected in the model results. Possible explanations for this relationship are an affinity for technology among younger people and existing mode bias (Gerte et al., 2018). Uber is an emerging technology, and younger people are more inclined to adopt technological innovations.

In terms of the duration of trips, the result of our analysis indicates that Uber users tend to request rides for trips that take less time and to some extent, shorter trip distances. This makes intuitive sense since longer ride-sourcing trip distances cost more, especially during peak travel periods. Other temporally isolated conditions not studied here may also affect demand, such as inclement weather.

As expected, vehicle ownership is negatively correlated with Uber demand at both the origin and destination CBGs, when everything else is equal. This means that households who own more vehicles have higher propensities to make trips using their personal vehicles since they might find it more convenient and flexible, especially for trips that consist of multiple stops. In addition, vehicle deficiency can play a role, as individuals without private cars and with limited alternatives may use transit, ride-sourcing, and other services to meet their travel needs. Other studies have found a similar relationship (e.g., see Correa et al., 2017; Gerte et al., 2018).

Uber demand is positively associated with the household's income and the number of employed persons in households both at the origin and destination. That is, more affluent households have higher propensities to use Uber. Cost considerations likely play a role in the decision to use ride-sourcing services. This is consistent with previous studies which have shown that higher income is associated with more vehicle trips and VMT (Cervero and Murakami, 2010; Ewing et al., 2014). Concerns have been raised regarding ride-sourcing usage imbalance due to income differences (see Griswold, 2016). However, more recent research indicates ride-sourcing could be helping to fill in mobility gaps in traditionally underserved areas. A 2018 study in Los Angeles found that ride-sourcing services like Lyft and Uber improve access to low-income communities (Brown, 2018).

The positive relationship between the number of workers and Uber demand, while holding other variables constant, is counter-intuitive at first glance since, as with household size, the number of workers is directly related to the number of vehicles owned by households (e.g., see Kitamura et al., 2001; Pinjari et al., 2011). Viewing it differently, employment status of household members affects overall household income, which is known to be strongly linked to affordability of travel at the household level. These results suggest that household-level affordability of ride-sourcing services may similarly be affected when a greater number of household members are employed. Ride-sourcing may also have lower disutility relative to personal vehicles for some trip purposes, such as trips in which the inconvenience of finding a parking spot and the cost associated with it plays a significant role in mode choice.

4.2. Measures of size and built environment variables

Uber demand is positively associated with population and employment at both the origin and the destination. Total population and total employment have a direct relationship to total demand, as in the conventional gravity model. The results show that higher population and/or higher employment in a CBG are correlated with an increase in Uber requests. To put it simply, more people means more trip productions, and more jobs mean more trip attractions. This is the essence of the gravity model used in four-step travel demand modeling (interzonal flows are directly proportional to trip productions at the origin and trip attractions at the destination and inversely related to travel time between zones).

Regarding density, we can see that higher activity density is associated with more Uber demand both at the origin and destination. This might be due to the fact that generally, CBGs with high activity density will have more and faster Uber service, lower rates of auto ownership, and higher parking charges (e.g., see Kennedy, 2016). This is consistent with previous research on the relationship between density and ride-sourcing demand. Even other measures of density such as residential density, residential floor area, and the ratio of floor area allocated to commercial use have been found to have a positive influence on Uber demand (Bao et al., 2017; Dias et al., 2017; Gerte et al., 2018).

In terms of diversity, land-use mix—measured as an entropy index—is positively correlated with Uber demand. The possible reason for this relationship is that CBGs with greater land use mix provide diverse services through commercial, residential, and public buildings and spaces which may attract more travel than other CBGs. These results indicate that this applies to ride-sourcing as well. This finding is consistent with recent studies such as Circella et al. (2018), Li et al. (2019), and Yu and Peng (2019a,b). Previous research has also shown that higher entropy can reduce car travel frequency and encourage non-motorized travel (Ewing et al., 2014; Ewing & Cervero, 2010). Our new result suggests that higher entropy may affect motorized alternatives as well.

Regarding design variables, intersection density was found to be significant and negatively correlated with Uber demand both at the origin and the destination while holding other variables constant. This finding is in contrast with Yu and Peng (2019a,b), who found that ride-sourcing trips increase as road network density increases. They argue that this is mainly due to the "higher exposure to available RideAustin vehicles" and "less response time to ride requests" (Yu and Peng, 2019a,b). Similar to the known connection between land use diversity and travel behavior, design variables have historically been shown to be positively associated with non-motorized trips (Ewing and Cervero, 2010; Frank et al., 2008). Greater non-motorized demand may, in turn, reduce ride-sourcing demand.

In terms of transit stop density, previous studies have shown that areas with higher transit accessibility have higher propensities for Uber and other ride-sourcing services (e.g., see Bao et al., 2017; Correa et al., 2017; Yu and Peng, 2019a, 2019b). Our results support this finding and show a positive relationship both at the origin and destination. This is consistent with the theory that ride-sourcing services can complement transit service by accommodating first-mile and last-mile trips. Intuitively, it is expected to see more ride-sourcing demand if either the origin or destination of a trip is in those block groups with poor/no transit services. Otherwise, trips both from/to transit rich block groups can actually show the substitution effect (during transit operating hours).

On the other hand, the percentage of employment accessible within 30 min by transit is significant and negatively associated with Uber demand both at the origin and destination. That means individuals in CBGs that are less accessible to jobs by transit (e.g., suburban and exurban areas) tend to use Uber more. Therefore, since transit is not a reliable mode (in terms of frequency, routes, etc.) to access the jobs from these areas, users may be more likely to substitute their transit (if available in their CBG) trip with a ride-sourcing trip. All in all, our results suggest that Uber is acting both as a complement and substitute for transit. It is not possible to determine a priori which effect is dominant. Previous researchers have reached mixed conclusions (Schaller Consulting, 2018; Clewlow and Mishra, 2017; Rayle et al., 2016).

Job accessibility by automobile (within 10 min) is significant and negatively associated with Uber demand at both the origin and the destination. This finding suggests that Uber may be a less competitive alternative to private cars for trips that are quick and inexpensive by automobile. Also, we can expect to see more walking and biking as destination accessibility both by automobile and transit increases (Ewing and Cervero, 2010).

Finally, regional population has a negative and significant relationship to Uber flows when everything else is equal at both the origin and destination CBGs. It should be noted that at the CBG level, population represents productions and attractions for all modes of travel. At the regional level, however, population represents the size of metropolitan area and the average distance traveled, which relates to the cost of ride-sourcing trips. We have already controlled for the population and employment of CBGs, so this means that Uber rates of usage are lower in large regions. The base rate is determined by the time and distance of a trip (Uber, n.d.). In this study, we have controlled for the travel time as well. But travel distance is known to be longer in large regions because residences and workplaces, as well as commercial and public spaces, tend to be farther apart. A simple computation of travel distance for different population size categories using the National Household Travel Survey (2017) reflects this fact. Also, transit levels of service are better in large regions (Ewing et al., 2014), decreasing transit's disutility relative to other modes, including ride-sourcing. Taxi services may also be more competitive with ride-sourcing services, for instance if one compares Dallas or Seattle (where Taxi services are generally available) to a typical small region like Greensboro, NC (where Taxi services are not as common).

We have also computed the elasticity of the predictors in Table 4. An elasticity is a percentage change in one variable with respect to one percent change in another variable. For a log-linear model, the elasticity is equal to the regression coefficient times the mean value of the independent variable (Ewing and Cervero, 2010). Note that two independent variables were used in the log form (i.e., natural log of income at both the origin and destination CBGs). For these variables, the elasticity is equal to their coefficients.

Average trip duration and the number of household vehicles have the greatest influence on the level of Uber demand, a negative relationship in both cases. Average income and land use mix (entropy) have the greatest influence on the level of demand in the positive direction. In principle, we can conclude that the elasticities of built environment variables are low-to-moderate relative to socioeconomic variables and travel time, but still significant.

5. Conclusion

It has been almost a decade since ride-sourcing services—pioneered by Taxi Magic, but well-established by Uber and Lyft—launched in many of our cities and since then, they have had significant impacts on travel behavior of residents and visitors. These services are getting more popular each year, and their markets are expanding. But what factors contribute to their widespread adoption? This study has sought to provide an answer within the context of metropolitan areas and their built environments.

This study is a first of its kind in that we were able to build a constructive partnership with a private company with a shared goal of contributing new knowledge to the body of research around ride-sourcing. In this study, by analyzing millions of trips between almost 72,000 CBGs in 24 regions, we have established that the built environment affects ride-sourcing in much the same way it affects travel by other modes. The built environment, the so-called D variables, have an influence on travel demand beyond simple socio-demographics.

Uber demand is positively correlated with total population and employment, activity density, land use mix or entropy, and transit stop density of a CBG. CBGs having more people, jobs, transit services, as well as diverse commercial, residential, and public places and services to visit (and travel to) have a higher travel demand overall, including a higher Uber demand. On the other hand, Uber demand is negatively correlated with intersection density and destination accessibility (both by auto and transit) variables. This might be attributed to the relative advantages of other modes – driving, taking transit, walking, or biking – in areas with denser street networks and better regional job accessibility. Individuals and households derive varying levels of utility from travel options in different built environments: e.g., in dense, congested street networks, the disutility of public transit or active modes relative to that of ride-sourcing is expected to be different compared with lower density areas where transit is limited or unavailable.

The findings of this paper have important implications for policy, planning, and travel demand modeling, where decision-makers are increasingly seeking solutions to shape the built environment in order to reduce automobile dependence and promote walking, biking, and transit use. This study can also benefit ride-sourcing companies in terms of business strategies that align with cities' sustainability goals. In combination with previously established knowledge of how the built environment affects traditional modes of travel, these results can inform collaboration and cooperation between local governments, planners, and TNCs to develop holistic policy initiatives, regulations, and planning strategies that leverage the potential benefits of ride-sourcing and minimize its negative impacts.

We think the ultimate potential of ride-sourcing to reduce the negative externalities associated with auto ownership and use lies in the area of car shedding and associated parking reductions (Sabouri et al., 2020). If the availability and economy of ride-sourcing allows households to own fewer automobiles (while early evidence suggests that this may be the case in some locations, more research is needed to determine a causal effect) all alternatives to private vehicle use will become more attractive. In trip generation studies and models, and in mode choice studies and models, a key variable is vehicle ownership. By allowing households to shed a car from three down to two or from two down to one, walking and biking can become more attractive for short trips, transit use can become more attractive on somewhat longer trips (with ride-sourcing covering the first and/or last mile of the trip), shared ride-sourcing can become more attractive for repeated trips as a means of economizing on travel cost, and some parking lots can be converted to higher and better uses. In order to inform sustainable planning strategies and transportation policies, further research is needed into how urban design affects personal vehicle reliance and the degree to which the availability of ride-sourcing affects that reliance in different types of environments.

This study is subject to some limitations. Issues regarding confidentiality, aggregation bias, and a relatively short period—three months—of the Uber data were explained in the Data and Method section. In addition, trips in our dataset were not distinguishable in terms of trip purpose and time of travel. Ostensibly, the impact of the built environment will be different for separate trip purposes (e.g., home-based work, home-based shopping, home-based school) and at different times of the day (e.g., social activity at night, work trip in the morning) or week (e.g., weekday vs. weekend) (Frank et al., 2008; Limtanakool et al., 2006; Salon, 2015). Although we covered the standard D variables, we still omitted certain variables (e.g., parking supplies and prices, the number of drivers in a household, local destination accessibility, and even weather conditions) that have presumptive effects on individuals using TNCs. Uber is not the only available TNC in our sample of 24 regions. Although we have contacted Lyft as well, we were not able to acquire their data, which would substantially help us to better capture the influence of the built environment on TNC demand. Residential self-selection is another important confounder that we were not able to account for in this study.

Last but not least, spatial autocorrelation was not controlled in our model. Spatial autocorrelation in TNC demand means that TNC pickups and dropoffs in one CBG might be affected by, or correlated with, those in neighboring CBGs. This might occur by clustering of TNC availability, trip attractions, demographic attributes of the neighborhood, to name a few. The spatial relationship has been analyzed or controlled in some of the previous studies (Bao et al., 2017; Correa et al., 2017; Yu and Peng, 2019a, 2019b) when a spatial unit is an administrative boundary (e.g., ZIP code, CBG). But in the current paper, an origin-destination pair of two CBGs is the spatial unit, which makes it less meaningful to consider spatial relationships between different pairs while significantly increasing modeling complexity. Instead, two regional job accessibility variables—pctemp10a and pctemp30t—at both the origin and destination as well as a regional population variable were added to capture the influence of contextual effects.

CRediT authorship contribution statement

Sadegh Sabouri: Conceptualization, Methodology, Data curation, Formal analysis, Validation, Writing - original draft. **Keunhyun Park:** Methodology, Data curation, Formal analysis, Writing - review & editing. **Amy Smith:** Resources, Supervision, Writing - review & editing, Project administration. **Guang Tian:** Data curation, Writing - review & editing. **Reid Ewing:** Conceptualization, Investigation, Project administration, Supervision, Writing - review & editing.

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