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Uber service area expansion in three major American cities

Steven R. Gehrke

Department of Geography, Planning, and Recreation, Northern Arizona University, Flagstaff, AZ 86011, United States of America

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ABSTRACT

Chiefly led by Uber, on-demand ride-hailing services have transformed the urban American transportation landscape in merely the past decade. Utilizing the proliferation of internet-enabled smartphones, this app-based company has provided city inhabitants with a convenient and reliable door-to-door mobility service, which has arguably improved car-based accessibility while also generating a host of negative environmental and societal externalities. While to date the utilization of Uber has largely been an urban phenomenon, the lasting success of this new mobility option likely rests within its ability to expand its services into suburban communities. Yet, given the competitive nature of the ride-hailing marketplace and genuine concerns over passenger and driver anonymity, transportation planners and urban policymakers have been stymied in their ability to access the disaggregate data sets needed to help assess whether these services are in fact extending beyond city centers and identify which factors may be contributing to any expansion into more peripheral suburban neighborhoods. By introducing a creative strategy using the privacy-related suppression processes of Uber Movement data, this study quantifies the continued expansion of Uber's ride-hailing service into outlying communities from 2016 to 2018 by employing a multilevel modeling approach to recognize the neighborhood-level socioeconomic and built environment factors most related to this service expansion in three major American cities: Boston, San Francisco, and Washington, DC.

1. Introduction

Since its introduction to American cities a decade ago, the adoption of Uber as a ride-hailing service platform has substantially grown. Uber's development—along with other private ride-hailing businesses—has corresponded with the common adoption of internet-enabled smartphones, which facilitate individuals to conveniently schedule the door-to-door, on-demand vehicle services offered by such app-based mobility services (Shaheen and Cohen, 2019; Anderson, 2014). However, this enhancement in auto transportation accessibility throughout urban communities also generates defensible concerns regarding increased traffic congestion (Erhardt et al., 2019), competition with more sustainable mobility options (Gehrke et al., 2019), and other environmental and societal consequences passed onto city residents, workers, and visitors.

To date, ride-hailing services largely remain an urban phenomenon, with sparse evidence to denote if these companies will be able to expand service availability into more peripheral suburban and rural areas where residents are more dependent on private vehicles and traditional taxi services (Schaller, 2018). An expansion into suburban neighborhoods, where most of the population of American cities resides, will be sought-after by private ride-hailing companies (Clewlow and Mishra, 2017) seeking economic viability. In response, researchers and policymakers, who generally lack access to meaningful data needed to identify and plan for the initial and immediate impacts of ride-hailing services on more urban districts, will continue to look for new insights—derived from various data sources and unconventional collection methods—into the factors connected with service area expansion or changes in the composition of ride-hailing adopters.

This study, which addresses this need for further empirical evidence in the face of limited ride-hailing data availability, aims to confirm whether Uber has in fact been successful in expanding it services beyond city centers and better understand what factors may be associated with any identified service area expansion. Specifically, by using publicly-available Uber Movement data for three similarly populated and spatially distributed American cities across three time periods, this study's objectives are to (i) measure the extent to which Uber service in American cities is either increasing or plateauing with regard to service area and (ii) identify neighborhood-level socioeconomic and built environment factors most associated with any changes to Uber service area size.

E-mail address: steven.gehrke@nau.edu.

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2. Literature review

This section synthesizes findings from past studies conducted in the United States and Canada that examine the socioeconomic and environmental factors associated with ride-hailing service adoption. In general, this evidence base has found that early adopters of ride-hailing services have tended to be young, educated, and wealthy. An intercept survey of ride-hailing passengers by Rayle et al. (2016) found survey respondents were generally younger and better educated than an average San Francisco resident; whereas, income distributions of passengers mimicked that of City residents, except for low-income households who were underrepresented. Henao and Marshall (2019), who conducted an in-vehicle intercept survey, reported early ride-hailing adopters in Denver had comparable socioeconomic characteristics when matched to the City's population. Clewlow and Mishra (2017) noted only 4% of survey respondents in seven metro regions aged 65 and older had utilized ride-hailing services in comparison to 36% of respondents aged 18 to 29 years, with college-educated, affluent Americans adopting ride-hailing services at double the rate of less educated, lower income populations. In Boston, Gehrke et al., 2018 found a majority of ride-hailing passengers were under 35 years old, had at least a four-year college degree, and were White, non-Hispanic/Latinx. Yet, ride-hailing adoption was popular on both tails of the income spectrum, with those households in the lowest income cohort more likely to substitute ride-hailing for travel via transit (Gehrke et al., 2019).

In general, early ride-hailing adopters were more likely to be male; however, mixed results concerning race and ethnicity are evident in the literature. Feigon and Murphy (2018) noted that zip codes with higher levels of high-income households, young adults, White residents, and educational attainment were more likely to adopt ride-hailing services in five metro regions including Washington, DC. In a study of predictors of ride-hailing adoption in California, Alemi et al. (2018a) discovered that younger, better-educated individuals and individuals of non-Hispanic origin were more likely to adopt on-demand services. Analyzing National Household Travel Survey data, others have found that higher income households use ride-hailing services more often, as do males, individuals aged between 20 and 40 years, and Asian individuals, who also tend to earn more than White individuals in the United States (Conway et al., 2018). Although in a study of 6.3 million Lyft trips in Los Angeles, Brown (2019) found that US Census tracts of Asian or Hispanic majority had a negative association with neighborhood-level Lyft trip frequency.

Early ride-hailing adopters also tended to have lower rates of personal car ownership. In her aforementioned study, Brown (2019) found that neighborhoods with a higher share of zero vehicle households and residents aged 15–34 years positively predicted neighborhood-level Lyft trip frequency in Los Angeles. Likewise, Feigon and Murphy (2018) noted zip codes with smaller household sizes and fewer vehicles per household had higher ride-hailing adoption rates. In Toronto, Young and Farber (2019) described ride-hailing adoption as largely a younger generation phenomenon, with a majority of ride-hailing passengers also being wealthy and having lower car ownership rates. The latter finding may be partially explained by the downtown study area in which households living in this planning district were more likely to have low car ownership rates to begin with.

Given the above socioeconomic findings, it's no surprise that early ride-hailing adopters tended to not have children and resided in smaller households. Employing a latent class choice modeling approach, Alemi et al. (2018b) found the market segment of higher-educated, independent millennials who lived in urban areas without children were most inclined to adopt ride-hailing services. Meanwhile, Spurlock et al. (2019) noted that younger generations were both more likely to have already adopted both single and pooled ride-hailing services, but that individuals with a higher-income were only significantly more likely to have adopted non-pooled ride-hailing services and that having children under 8 years old had a significant negative impact on the interest in adopting pooled services.

As for environmental context, ride-hailing service adoption to-date has been a largely urban phenomenon. Clewlow and Mishra (2017) noted 29% of survey respondents who resided in urban neighborhoods had adopted ride-hailing services and continue to adopt these services more regularly, while only 7% of suburban residents utilize them to travel within their metro region. In quantifying a previously unknown ride-hailing service market size in San Francisco, Cooper et al. (2018) discovered ride-hailing trip origins and destinations were concentrated in the most developed, northeastern quadrant of the City. Conway et al. (2018) found at highest densities, residents were far more likely to adopt ride-hailing services; positing this relationship to be the result of more nearby destinations, which make these services relatively inexpensive and associated wait/travel times shorter.

Finally, the evidence base has largely concluded that ride-hailing service adoption has adversely impacted areas with strong local and regional accessibility. In a pair of studies, Alemi et al. (2019) found an increase in activity density (number of jobs and housing units per acre) at the block group-level predicted an increase in ride-hailing frequency, and that increased land use mixing and regional auto accessibility also increased the likelihood of service adoption (Alemi et al., 2018a). Echoing the former finding, Brown (2019) concluded that neighborhoods with higher levels of activity density were predictive of increased neighborhood-level Lyft trip frequency in Los Angeles, as were factors related to increased transit density and road network density. Gehrke et al., 2019 discovered that residing in a zip code with a high employment-to-population ratio was more likely to predict the substitution of ride-hailing services for walking, biking, transit, or no travel at all than the substitution of ride-hailing services for vehicle travel. Also, residents of environments with a gridded street network, as described by a high connected node ratio (defined as ratio of three- and four-way intersections to all intersections) and low gamma index (defined as ratio of observed street links to maximum number of possible street links), were more likely to substitute ride-hailing services for transit than they were to substitute ride-hailing for travel in another auto vehicle.

This study intends to build upon the reviewed literature by addressing a handful of identified gaps. Foremost, this study investigates ride-hailing adoption using a panel data set collected for multiple cities; an improvement over most previous work that has analyzed cross-sectional data. Another contribution of this study is its examination of ride-hailing service area growth; an aggregate outcome unique from current literature that often investigates individual responses to ride-hailing introduction whether it be adoption or frequency of use. Finally, past studies have generally focused on a narrow selection of neighborhood-level socioeconomic and built environment features in their analyses. This multi-city study, in turn, investigates the neighborhood effects of many socioeconomic characteristics—often only inspected at an individual-level—as well as a robust list of built environment features describing a neighborhood's land development patterns, urban design, and transportation system on Uber service area growth over multiple time periods.

3. Methods

3.1. Data

Introduced in January 2017, Uber Movement (UM) was launched by Uber Technologies, Inc. as a platform for the ride-hailing company to share anonymized and aggregated travel time information with planning agencies and researchers eager to gain insight into the impact of the mobility service on their cities (Gilbertson, 2017). These zone-to-zone travel times, which are synthesized from GPS trace pings collected every four seconds from an Uber driver's smartphone, are made available at a census tract or traffic analysis zone geography and are the

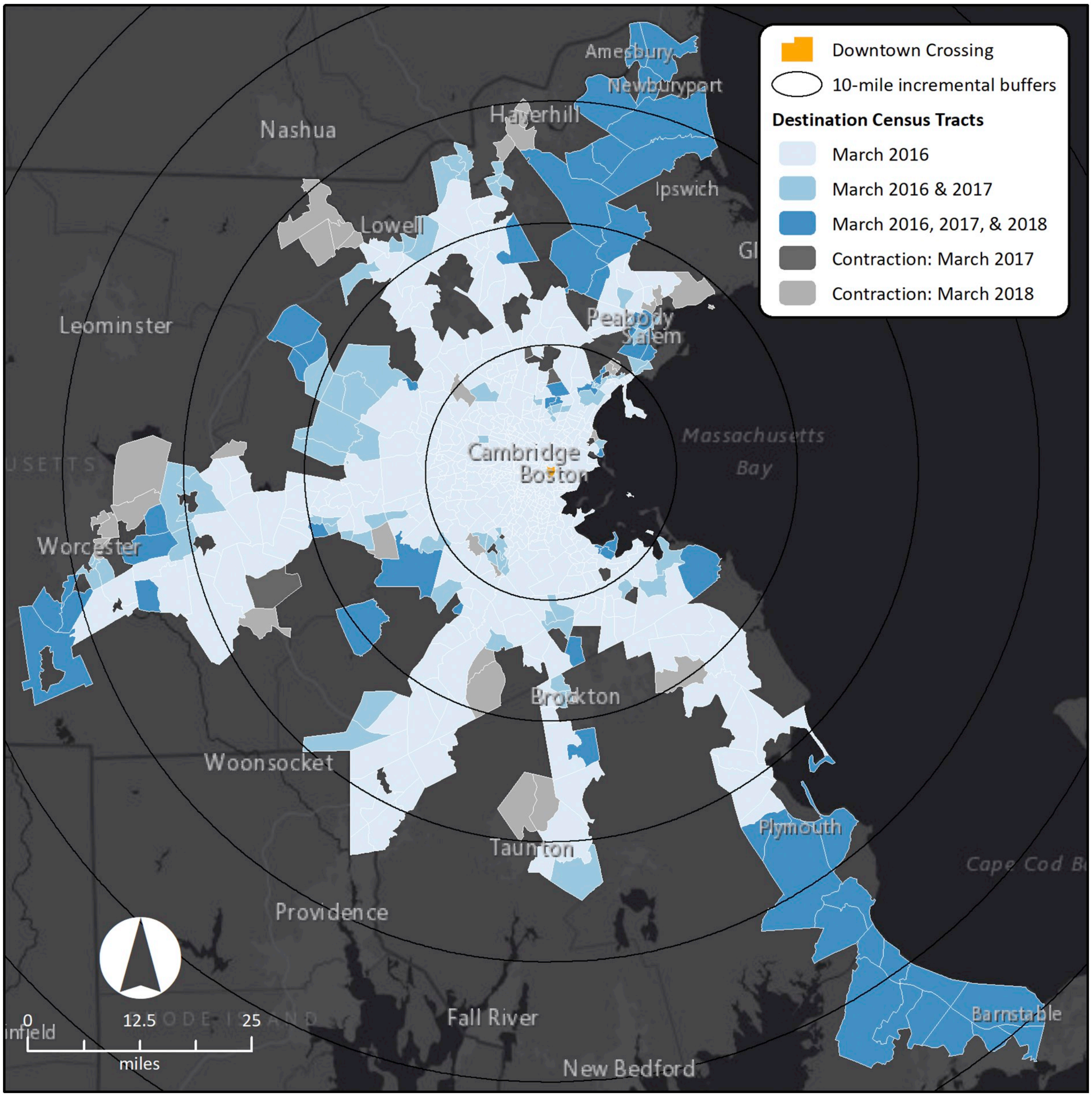

Fig. 1. Three-year Uber service area expansion for morning peak passengers from Boston's Downtown Crossing.

product of a six-step process to ensure ride-hailing rider privacy is preserved. One step in this process is the suppression of travel time information for zone-to-zone pairings that either do not meet a minimum number of trips or a minimum count of unique riders (Uber Technologies, Inc., 2019). The likelihood of any zone-to-zone pairing failing to meet either of these criteria increases as the UM platform user specifies a more restricted period (i.e., smaller hour-by-hour or day-of-the-week time increments) for their travel time query. Accordingly, with a refined search of travel time information across unrelated time points, a UM platform user can view how the distribution of destination zones with published UM travel data changes for any given origin zone. When assessed for many origin zones, this more refined search of UM data can provide information about the expanse and robustness of the Uber network in a city.

In fact, an identification of the ride-hailing company's network expansion is likely one of the few areas of insight that can be gleaned from the publicly-available UM data set, whose utility is limited beyond a basic understanding of aggregate mode-specific travel patterns, times, and speeds, for a select number of cities. Hence, these data have been of minimal benefit to transportation planners and researchers who need robust data on trip volumes between zones; average travel distances with and without a rider; disaggregate locations of trip pick-ups and drop-offs; and attributes of the vehicle, driver, rider, and trip context to inform nuanced policy and research questions. Regrettably, Uber, Lyft, and other ride-hailing services are reluctant to provide these desirable insights to decisionmakers, and few state or local governments have mandates requiring this information to be reported to those agencies who can address their continued impact on cities. A pair of notable exceptions can be found in New York City, where Uber is mandated to provide the Taxi and Limousine Commission with spatiotemporally disaggregate trip information in order to operate on the City's streets, and Massachusetts, where Uber and other ride-hailing companies have been required to report municipal-level trip and safety data to the Commonwealth's Department of Public Utilities.

For this study, the author leveraged the travel time data suppression steps used for the public UM data sets to analyze how Uber's service area has changed in three cities: Boston, Massachusetts; San Francisco, California; and Washington, District of Columbia. These cities were

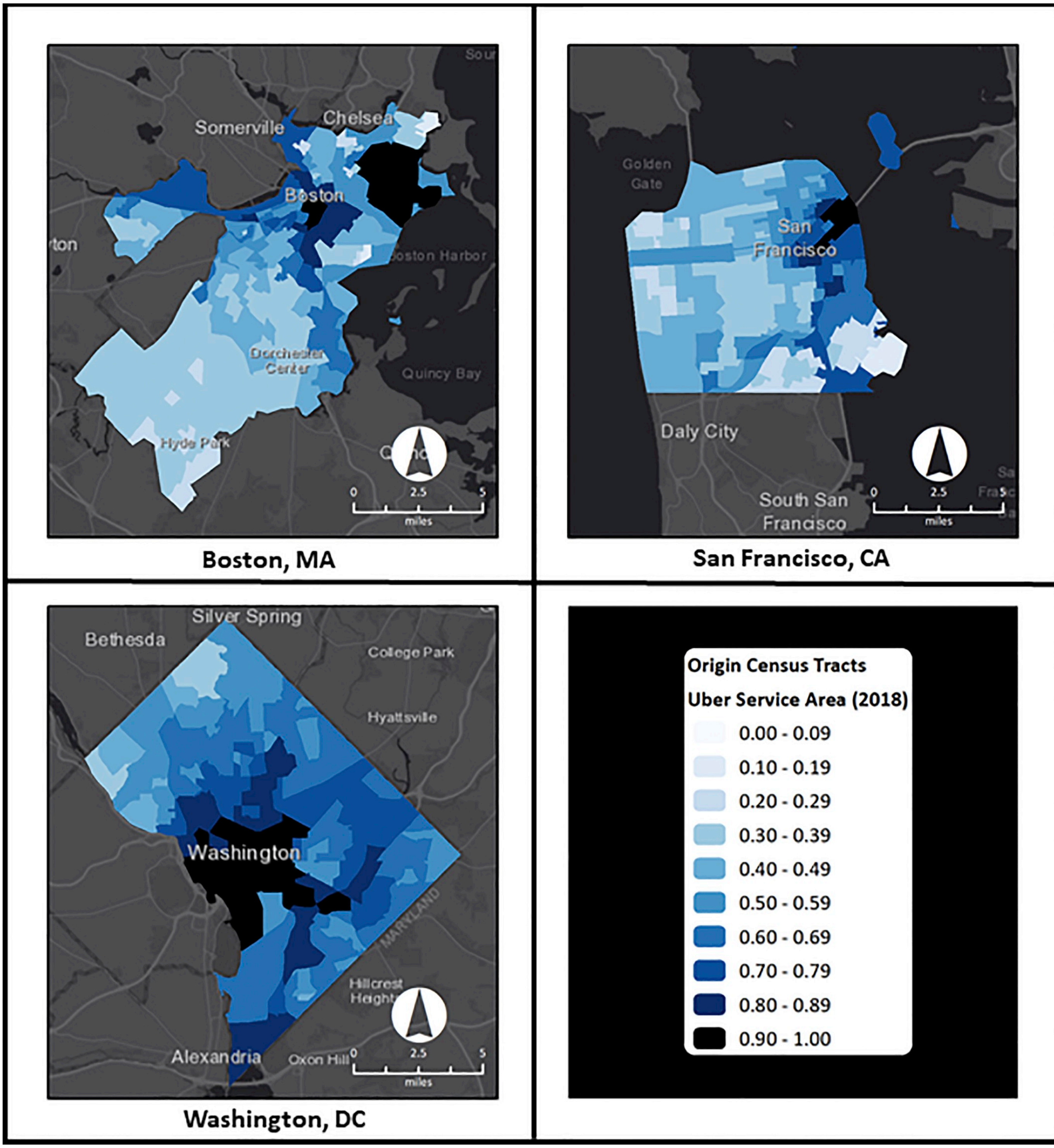

Fig. 2. Census tract-level illustration of Uber service area expansion for March 2018 in three American cities.

chosen based on similarities in population size and the arrival of Uber to their markets as well as differences in their spatial distribution. Travel times were collected for every census tract in the three city boundaries for the morning peak period (6-10 am) on weekdays in March 2016, 2017, and 2018. Morning peak period was analyzed, as this travel time reflects a routine pattern of high-volume auto traffic where an increased Uber service area would suggest further roadway congestion and decline in sustainable travel mode adoption for commuting purposes. The month of March was chosen because it was the most current month with available UM data at the time of data collection and adequately exemplifies typical travel conditions as there are no holidays, schools are in session, and weather in the three cities is mild. From the downloaded files, the number of destination tracts with unsuppressed travel time information (Uber service area) for a particular origin tract was provided for the three time periods. Fig. 1 provides an illustration of change in Uber service area from 2016 to 2018 for one census tract in downtown Boston. From this origin, there were 528 census tracts with unsuppressed travel time information in March 2016, 629 destination census tracts in March, 2017, and 660 destination census tracts in March 2018; while, three census tracts contracted between 2016 and 2017, another three census tracts contracted between 2016 and 2018, and 30 census tracts between 2017 and 2018.

Extending this strategy for conceptualizing Uber service area, a next step was to operationalize a measure (Uber service area ratio) that could be analyzed to identify the neighborhood-level predictors of service expansion (or contraction). Given that spatial information is not published by UM for all census tracts within each city's metropolitan region, to limit spatial attenuation effects, only census tracts in the three city boundaries were considered as origins. There were 196 origin tracts in San Francisco, while Boston and Washington, DC each had 179 origin census tracts with travel time information for a set of tract-level destinations. Uber service area for a census tract was quantified as the count of destinations with unsuppressed data divided by the census tract in its city with the highest count of destination tracts of any year. Using the example in Fig. 1, where 528 census tracts had unsuppressed travel time information in 2016, 629 in 2017, and 660 in 2018 for the Downtown Crossing census tract, these three counts were then normalized by the maximum count of destinations with unsuppressed information for any origin tract in Boston over the three periods ($n = 712$) to create an Uber service area ratio of 0.74 in 2016, 0.88 in 2017, and 0.93 in 2018. This destination ratio was computed for every census tract in the three study cities and was the dependent variable in this study's analytic approach described in Section 3.2.

All independent variables examined in this study were similarly measured at a 2010 US Census geography and reflected the socioeconomic context and built environment of this neighborhood unit. Demographic data on the share of residents in a census tract by different sex, age, education, and race or ethnicity categories as well as neighborhood-level data on annual household income, tenure of occupied housing units, and household vehicle ownership rates were derived from 2013 to 2017 American Community Survey (ACS) Five-Year Estimates. These socioeconomic variables were complemented by a set of built environment metrics of the origin tract describing its land development patterns and transportation system (Gehrke and Welch, 2017). Specifically, measures of density (population, employment, and activity density), land use mix (jobs-population ratio), urban design (intersection density and connected node ratio), and transportation infrastructure (percent of primary, secondary, and local roadways) for each census tract were constructed using ACS data along with 2015 Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics and 2018 Topologically Integrated Geographic Encoding and Referencing (TIGER) data sets.

3.2. Analytic approach

Hierarchical linear models are an extension of multiple linear regression models which account for distinct unexplained sources of variability at each level of a specified nesting structure (Snijders and Bosker, 2012). The dependent variable of interest, Uber service area, is a continuous measure of repeated census tract-level observations where inference strength for one time period or group is borrowed from data for the other groups. Accordingly, the independent observations assumption is violated and a multilevel model to account for the variation at the group-level is suggested. This study adopts the simpler case of a random intercept model with two levels in its nesting structure to account for the within-group variation across different census tracts and between-group variations of the three time periods.

The random intercept model has two components which enable the testing of multiple fixed effects—the various aforementioned socioeconomic context and built environment variables—and the random effect or heterogeneity of regression slopes for the three different groups. The following model form describes a random intercept multilevel model (Snijders and Bosker, 2012):

$$Y_{ij} = \beta_{0j} + \beta_1 x_{ij} + \beta_2 x_{ij} + R_{ij} \tag{1}$$

$$\beta_{0j} = \gamma_{00} + U_{0j} \tag{2}$$

where, Y_{ij} is the continuous outcome of Uber service area for census tract (level-one unit) i of time period (level-two unit) j. In Eq. (1), β_1 and β_2 are non-stochastic coefficients of the level-one socioeconomic and built environment predictors, respectively. β_{0j} is a level-two random intercept containing the average intercept γ_{00} with the group-level deviation U_{0j}. Both random model parts, U_{0j} and the observation-level deviation R_{ij}, are mutually independent with zero means given the values of predictors x_{ij}. The residuals are drawn from normally distributed populations with the variance of level-one residuals denoted by σ^2 and level-two residuals denoted by $\tau_0{}^2$.

Each of the three city-specific multilevel models and the multi-city pooled model employed a maximum likelihood estimator. Model specification used a backwards-elimination process with variables in the pooled data set that were strongly correlated with each other or weakly correlated with the dependent variable removed from consideration in all models, as a first step. Next, level-one predictors that were not statistically significant ($p < 0.10$) of Uber service area were then iteratively removed from the full model until all predictors were significant and the elimination of a predictor resulted in a log-likelihood ratio test (LRT) between the tested model and a prior specification that was non-significant ($p > 0.05$). The iterative process described in the last two sentences was then repeated for each city-specific model with variables in each city's data set until a final model was determined. Unlike the city-specific models, the specification process for the pooled three-city model started with an empty model with a level-one dummy variable for San Francisco and Washington, DC, which enabled the testing of city-level differences in Uber service area expansion. By estimating this pooled model, insights into the neighborhood-level determinants of Uber service area change across three time periods were provided for multiple cities, offering greater sample heterogeneity and potentially more generalizable findings.

4. Results

4.1. Descriptive statistics

Fig. 2 provides citywide visualizations of Uber service area expansion for the three cities investigate in this study. In Boston, the origin census tract with the most destination tracts with unsuppressed travel time information—quantified by a ratio value of one and reflected by the darkest color shade—was Logan International Airport, located in the northeastern corner of the city. Other areas in Boston with high Uber service area expansion during the morning peak period include a stretch along the Charles River extending eastward from the Allston neighborhood in the northwest to the city's downtown districts and along the I-93 corridor south to Dorchester. In San Francisco, two census tracts in the South of Market neighborhood had the highest ratios of Uber service area expansion. The Financial District to the north and census tracts located near US-101 in the Mission District and Portola neighborhoods to the south were also observed to have far-reaching Uber service areas. Finally, in Washington, DC, Uber service area ratios were highest for census tracts covering the National Mall and the city's downtown districts.

Temporal insights into the Uber service area extent across the three cities can be gleaned from examining the descriptive statistics provided in Table 1. In each city, the average Uber service area ratio for all origin census tracts during the morning peak period increased from March 2016 to March 2017 and March 2017 to March 2018. The average service area expansion across these cities was highest during the first interval, with ratios across the three time periods being nearly identical in magnitude for Boston and San Francisco. However, the average Uber service area ratio for Washington, DC census tracts was highest, which may signify less tract-to-tract variation within its city boundary than the former two cities. The range of Uber service area ratios was 0.13 to

Table 1
Descriptive statistics for census tracts in three cities.

Variable	Boston, MA		San Francisco, CA		Washington, DC	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Uber service area^						
2016	0.36	0.13	0.35	0.13	0.49	0.13
2017	0.42	0.16	0.42	0.15	0.60	0.15
2018	0.46	0.16	0.46	0.16	0.68	0.13
Socioeconomic context						
Sex: Share of male residents	0.47	0.11	0.51	0.07	0.48	0.06
Sex: Share of female residents	0.50	0.11	0.48	0.07	0.52	0.06
Age: Share of residents less than 18 years old	0.15	0.09	0.13	0.06	0.18	0.09
Age: Share of residents 18–34 years old	0.38	0.20	0.30	0.11	0.34	0.15
Age: Share of residents 35–44 years old	0.12	0.05	0.16	0.04	0.14	0.05
Age: Share of residents 45–64 years old	0.20	0.08	0.25	0.06	0.22	0.06
Age: Share of residents 65 years old or more	0.11	0.11	0.15	0.07	0.12	0.06
Education: share of adults less than Bachelor's	0.34	0.18	0.35	0.15	0.32	0.18
Education: share of adults Bachelor's	0.18	0.12	0.27	0.10	0.17	0.09
Education: share of adults Master's or PhD	0.15	0.12	0.18	0.10	0.23	0.16
Race/ethnicity: white, non-Hispanic	0.46	0.30	0.42	0.22	0.34	0.29
Race/ethnicity: black/African American	0.23	0.26	0.06	0.09	0.50	0.35
Race/ethnicity: asian	0.09	0.10	0.32	0.19	0.04	0.04
Race/ethnicity: latinx/Hispanic	0.08	0.09	0.06	0.04	0.04	0.04
Race/ethnicity: other distinctions	0.12	0.10	0.13	0.09	0.07	0.06
Income: share of households less than $35,000	0.32	0.18	0.23	0.15	0.29	0.18
Income: share of households $35,000–$75,000	0.23	0.10	0.19	0.07	0.22	0.08
Income: share of households $75,000-150,000	0.24	0.12	0.27	0.08	0.26	0.09
Income: share of households $150,000 or more	0.16	0.13	0.31	0.15	0.23	0.18
Tenure: share of owner-occupied housing units	0.34	0.22	0.39	0.24	0.42	0.22
Tenure: share of renter-occupied housing units	0.62	0.24	0.61	0.24	0.57	0.23
Vehicles: share of households 0 cars	0.23	0.17	0.21	0.19	0.25	0.15
Vehicles: share of households 1 car	0.39	0.13	0.36	0.13	0.43	0.11
Vehicles: share of households 2 cars	0.24	0.15	0.27	0.13	0.24	0.12
Vehicles: share of households 3 cars or more	0.09	0.11	0.15	0.14	0.08	0.08
Built environment						
Persons per acre	39.19	28.32	48.22	34.96	28.08	18.95
Jobs per acre	27.59	65.69	32.13	75.04	19.76	54.74
Persons and jobs per acre	66.78	74.01	80.34	87.54	47.84	58.02
Jobs-population ratio	2.47	10.38	1.37	6.01	5.63	59.91
Intersections per acre	0.50	0.28	0.38	0.18	0.27	0.15
Connected node ratio	0.83	0.11	0.90	0.12	0.92	0.09
Percent of primary roads	0.02	0.06	0.02	0.05	0.02	0.06
Percent of secondary roads	0.06	0.10	0.02	0.05	0.03	0.07
Percent of local roads	0.91	0.13	0.96	0.09	0.95	0.09
Half-mile rapid transit shed	0.76	0.43	0.34	0.47	0.78	0.42

Notes. ^ For each Census tract, the count of destination tracts with Uber Movement travel times for the AM peak period of weekdays in March, normalized by the tract with the highest count in each city.

0.77 in 2016, 0.17 to 0.95 in 2017, and 0.17 to 1 in 2018 for Boston; 0 to 0.80 in 2016, 0 to 0.93 in 2017, and 0 to 1 in 2018 for San Francisco; and 0.24 to 0.92 in 2016, 0.31 to 0.99 in 2017, and 0.38 to 1 in 2018 for Washington, DC. The Uber service area ratios for all census tracts increased or remain unchanged from March 2016 to March 2018; however, 11 (6%) origin tracts in Boston, 4 (2%) of tracts in San Francisco, and 1 (<1%) of tracts in Washington, DC had a contracted service area between March 2017 and March 2018.

The remaining variables described in Table 1 represent the tract-level predictors of socioeconomic context and the built environment tested in the multilevel models. In terms of socioeconomic context, the average share of census tract residents in San Francisco are male, while tracts in Boston and Washington, DC tend to be female majority. Unlike San Francisco, the average share of residents in census tracts of these latter two cities are mostly under 35 years old and most likely to report an annual household income below $35,000. In contrast, the average census tract in San Francisco was most likely to have the highest share of households earning more than $150,000, annually. San Francisco and Boston tracts were most likely to have the highest share of residents reporting to be White (non-Hispanic), while the largest share of DC residents reported being Black/African American. Across all cities, the average census tract had a higher share of renter-occupied housing units and one-car households. Turning to the built environment, census tracts in San Francisco tend to have higher rates of population and employment density, whereas, Boston tracts have the smallest share of local roads and greatest density in intersections. Washington, DC has the highest jobs-person ratio per census tract and a more traditional grid-based street network, reflected by its high mean connected-node ratio, of the three cities. Over three-quarters of tracts in Washington, DC and Boston intersect a one-half-mile areal buffer surrounding stations of their respective regional rail transit systems, while one-third of tracts in San Francisco intersect a Bay Area Rapid Transit station walkshed.

4.2. Modeled predictors of Uber service area expansion

4.2.1. Individual city models

The results of three city-specific random intercept multilevel models of Uber service area expansion are shown in Table 2. Each final model specification included both significant socioeconomic context and built environment predictors and was found to produce a significant improvement in model fit from the empty (base) model specification. The final Boston model produced a log likelihood statistic of 550.86 versus the base model, which produced a log likelihood of 258.46

Table 2
Results for three city-specific random intercept multilevel models of Uber service area expansion.

Effect	Variable	Boston, MA		San Francisco, CA		Washington, DC	
		Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Random	Intercept: Level 2	0.04		0.04		0.08	
	Residual: Level 1	0.08	0.03	0.08	0.03	0.07	0.03
Fixed	Intercept: Level 1	0.32***	0.03	0.16***	0.03	0.16**	0.07
	Socioeconomic context						
	Sex: Male					0.37***	0.06
	Age: Less than 18 years old	−0.19***	0.05				
	Age: 18–34 years old			0.15***	0.04		
	Age: 35–44 years old			0.38***	0.10		
	Age: 45–64 years old					−0.19***	0.07
	Education: Master's or PhD	0.07**	0.03	0.12***	0.04	0.05*	0.03
	Income: $35,000-75,000					−0.15**	0.06
	Vehicles: 0	0.05*	0.03	0.17***	0.03	0.16***	0.03
	Vehicles: 1					0.18***	0.03
	Built environment						
	Jobs per acre (x1,000)	0.39***	0.07	0.58***	0.06	0.56***	0.07
	Intersections per acre			0.05**	0.02	0.09***	0.03
	Connected node ratio					0.09**	0.04
	Percent of primary roads	1.44***	0.07	1.87***	0.08	1.09***	0.06
	Percent of secondary roads	0.26***	0.04	0.37***	0.08	0.37***	0.06
	Half-mile rapid transit shed	0.06***	0.01	0.03***	0.01	0.06***	0.01
	Summary statistics						
	Number of observations	537		588		537	
	Number of groups (years)	3		3		3	
	Log likelihood	550.86		618.52		604.62	

Notes. * *p*-value <.10, ** p-value <.05, and *** p-value <.01.

($LRT = 584.79$, $p < 0.01$). For San Francisco, the base model log likelihood was 279.80 ($LRT = 590.27$, $p < 0.01$); while, the empty model for Washington, DC produced a statistic of 309.49 ($LRT = 677.45$, $p < 0.01$).

4.2.1.1. Boston, MA. In Boston, an increase in the share of residents under 18 years of age in a census tract was found to be negatively associated with Uber service area expansion across the three time periods, with a one unit increase in the share of this characteristic predicting a decrease in Uber service area ratio by 0.19 units ($\beta = -0.19$, $SE = 0.05$). In turn, tracts with a higher share of zero-car households ($\beta = 0.05$, $SE = 0.03$) and a adults with an advanced university degree ($\beta = 0.07$, $SE = 0.03$) observed a significant expansion in Uber service area during the weekday morning peak period over the three time periods. As for tract-level built environment predictors of service area expansion, an increase in job density ($\beta = 0.39$, $SE = 0.07$) and share of primary ($\beta = 1.44$, $SE = 0.07$) or secondary ($\beta = 0.26$, $SE = 0.04$) roads were found to be significant in the Boston model. Census tracts within a half-mile walkshed of a rapid transit station were positively associated with three-year Uber service area expansion during the morning peak ($\beta = 0.06$, $SE = 0.01$).

Many of the socioeconomic context findings are perhaps unsurprising and corroborate results from individual-level studies that highlight individuals with higher educational attainment and without access to a personal vehicle were early adopters of ride-hailing services. However, the negative relationship of Uber service area growth in neighborhoods with higher rates of children—a finding corroborated in the reviewed literature—potentially points to the industry's cooler reception by residents of Boston's suburban neighborhoods; at least in this initial stage of ride-hailing adoption. Nevertheless, a continued expansion of Uber's service area in Boston's densest areas and in neighborhoods with good access to Massachusetts Bay Transportation Authority rapid transit station should be of concern to public officials vested in promoting public transit and reducing roadway congestion.

4.2.1.2. San Francisco, CA. Also, in the San Francisco model, high-capacity roadways—primary ($\beta = 1.87$, $SE = 0.08$) and secondary ($\beta = 0.37$, $SE = 0.08$) designations—were significant predictors of a neighborhood's morning peak period service area expansion. Neighborhoods with high employment density ($\beta = 0.58$, $SE = 0.06$), increased density of roadway intersections ($\beta = 0.05$, $SE = 0.02$), and which are located in close proximity to a rapid transit station ($\beta = 0.03$, $SE = 0.01$) were similarly found to have more destination tracts with unsuppressed Uber travel time information. As for neighborhood socioeconomic characteristics, tracts with a higher share of zero-car households ($\beta = 0.17$, $SE = 0.03$) and residents with advanced college degrees ($\beta = 0.12$, $SE = 0.04$) were associated with an increase in Uber service area across the three periods. Uber service area expansion during the morning peak period in San Francisco was also evident in tracts with a higher share of residents between 18 and 34 years old ($\beta = 0.15$, $SE = 0.04$) as well as residents between the ages of 35 and 44 years ($\beta = 0.38$, $SE = 0.10$).

Largely echoing the Boston case study, San Francisco's most urban neighborhoods—characterized by a traditional gridded street network, high concentration of jobs, and strong access to the region's network of rail stations—witnessed the greatest growth in Uber service area coverage during the morning peak periods in March 2016, March 2017, and March 2018. However, those neighborhoods with a higher rate of households living car-free had a stronger association with Uber service area expansion than neighborhoods in Boston, partially supporting a hypothesis that access to this emergent mobility service may be allowing residents to forego personal vehicle ownership. Moreover, neighborhoods with a higher share of residents between 35 and 44 years old had a greater increase in the adoption of ride-hailing services for longer trips than their millennial generation counterparts; perhaps, underscoring an expanding demographic market for ride-hailing utilization in San Francisco.

4.2.1.3. Washington, DC. The final city-specific model had the greatest number of neighborhood predictors of Uber service area expansion. Regarding the built environment, an increase in tract-level job density ($\beta = 0.56$, $SE = 0.07$), intersection density ($\beta = 0.09$, $SE = 0.03$), and connected node ratio ($\beta = 0.09$, $SE = 0.04$) had a significant positive link to higher Uber service area ratios in Washington, DC. As for

Table 3
Results for pooled three-city random intercept multilevel models of Uber service area expansion.

Effect	Variable	Coef.	Std. Err.	t-value	p-value
Random	Intercept: Level 2	0.06			
	Residual: Level 1	0.08	0.03		
Fixed	Intercept: Level 1	0.21	0.04	5.41	< 0.01
	City				
	Boston, MA^				
	San Francisco, CA	0.04	0.01	6.26	< 0.01
	Washington, DC	0.17	0.01	28.16	< 0.01
	Socioeconomic context				
	Age: 18–34 years old	0.08	0.17	4.47	< 0.01
	Education: Master's or PhD	0.13	0.02	6.71	< 0.01
	Income: $35,000-75,000	−0.08	0.03	−2.69	< 0.01
	Vehicles: 0	0.11	0.02	6.19	< 0.01
	Built environment				
	Jobs per acre (x1,000)	0.53	0.04	13.53	< 0.01
	Jobs-population ratio (jobs x1,000)	0.12	0.07	1.81	< 0.10
	Connected node ratio	0.05	0.02	2.43	< 0.05
	Percent of primary roads	1.38	0.04	33.68	< 0.01
	Percent of secondary roads	0.29	0.03	9.01	< 0.01
	Half-mile rapid transit shed	0.06	0.01	10.42	< 0.01
	Summary statistics				
	Number of observations	1662			
	Number of groups (years)	3			
	Log likelihood	1626.50			

Notes. ^ Reference category.

transportation access, census tracts with a higher proportion of primary ($\beta = 1.09$, $SE = 0.06$) and secondary ($\beta = 0.37$, $SE = 0.06$) roads in addition to neighborhoods within a half-mile walkshed of a Washington Metropolitan Area Transit Authority rail station ($\beta = 0.06$, $SE = 0.01$) were all associated with three-year Uber service area expansion during the morning peak.

Neighborhoods with a higher share of residents in the 45 to 64 age cohort ($\beta = -0.19$, $SE = 0.07$) were found to have lower levels of Uber service area expansion in the morning peak, as were census tracts with a greater proportion of households earning between $35,000 and $75,000 ($\beta = -0.15$, $SE = 0.06$). In contrast, tracts with a higher share of zero-car ($\beta = 0.16$, $SE = 0.03$) and car-lite ($\beta = 0.18$, $SE = 0.03$) households positively predicted an extended Uber service area. However, unlike Boston and San Francisco, an increase in the proportion of adult residents with advanced college degrees ($\beta = 0.05$, $SE = 0.03$) was only marginally significant in Washington, DC census tracts. Also, unique to this city-specific model, an increase in the share of male residents was associated with an increased Uber service area ratio; a study finding that warrants future investigation, but which supports the reviewed evidence that early ride-hailing adopters were more likely to be male.

Of the three cities in this study, the reluctance of certain market segments to adopt Uber appeared most pronounced in Washington, DC, where census tracts with more middle-aged residents and households reporting a modest annual income had a negative relationship with service area expansion over time. As with the other cities, neighborhoods with good rail transit access were more likely to experience a growth in new destination tracts served by Uber during the morning peak period over the three time periods, which suggests the new mobility service's growing competitive edge over transit during popular commute times.

4.2.2. Pooled cities model

A fourth random intercept multilevel model was next estimated for the pooled three-city data set with city-level control fixed effect variables to understand what census tract-level factors of Uber service area expansion may be common across the study areas. Table 3 provides the results of the final model specification, which significantly improved upon the specification with only city-level dummy variables ($LRT = 1{,}563.91$, $p < 0.01$). The significant coefficient for the San Francisco and Washington, DC control variables points to citywide differences in morning peak period Uber service area growth with the reference case of Boston; offering further justification for estimations of the three city-specific models. However, a smaller coefficient for the San Francisco dummy variable highlights the closer parallels that San Francisco and Boston have regarding temporal trends in Uber's growing popularity and reach.

Looking at the different level-one socioeconomic context predictors of Uber service area expansion across the three years, tracts with a higher share of households earning between $35,000 and $75,000 ($\beta = -0.08$, $SE = 0.03$) experienced smaller service areas. Meanwhile, neighborhoods with a higher proportion of residents between 18 and 34 years of age ($\beta = 0.08$, $SE = 0.02$), residents with higher educational attainment ($\beta = 0.13$, $SE = 0.02$), and households without a private vehicle ($\beta = 0.11$, $SE = 0.02$) were associated with farther-reaching Uber service areas. As for the built environment context, neighborhoods with higher levels of job density ($\beta = 0.53$, $SE = 0.04$), more jobs than residents ($\beta = 0.12$, $SE = 0.07$), heightened street network connectivity ($\beta = 0.05$, $SE = 0.02$), and stronger access to primary ($\beta = 1.38$, $SE = 0.04$) and secondary ($\beta = 0.29$, $SE = 0.03$) roads were linked to greater Uber service areas during the morning peak period. As with each of the city-specific models, tracts intersecting a half-mile walkshed of a rapid transit station ($\beta = 0.06$, $SE = 0.01$) were also associated with an increase in Uber service area expansion.

5. Conclusions

This study has contributed to a limited but growing evidence base seeking to identify the extent to which ride-hailing services are changing America's transportation landscape by examining the growth of Uber's service area. By introducing a creative strategy to utilize the privacy-related suppression processes of a rare publicly-available data set (Uber Movement), the author was able to quantify the continued expansion of Uber services into outlying communities and recognize the neighborhood-level socioeconomic and built environment factors most associated with this expansion in three major American cities. Descriptively, this rise in service area coverage for the morning peak period was greatest between 2016 and 2017 for all three cities, with Boston and San Francisco tracts displaying comparable rates of growth and Washington, DC experiencing a stronger yet more uniformed distribution in service area expansion over the three-year period. An expanding service area that is likely accompanied by increased technology adoption and lengthier ride-hailing vehicle trips that have notable environmental and societal implications including more traffic congestion (Erhardt et al., 2019) and energy consumption (Wenzel et al., 2019) as well as lower financial resources for more sustainable and affordable mobility options (Gehrke et al., 2018).

These challenges faced by city leaders appear more daunting when assessing this study's multilevel model results that find walkable areas with high levels of activity density are experiencing the greatest increase in service area expansion. In Boston, San Francisco, and Washington, DC, census tracts with high employment density—like those located in central business districts—and those characterized by strong public transit access were the most likely to have higher service area ratios during the morning commute period. A finding which fits the growing narrative of direct mode competition between ride-hailing and public transit services, resulting in the loss of passengers using the latter more sustainable mobility option (Gehrke et al., 2019; Graehler

Jr. et al., 2019); although, the positive coefficient could highlight some synergies of Uber as a possible first and last mile connection to rapid transit services. Additionally, transportation infrastructure access had the strongest effect size of Uber service area growth in the pooled and all city-specific models. An intuitive outcome also highlighting the likelihood that ride-hailing services add to traffic congestion on primary and secondary roads, which may consequently reduce the efficiency of buses or streetcars without dedicated lanes of travel. In response, city planners and officials must continue to pursue the effectiveness of roadway pricing schemes or similar policies aimed at properly assessing the growing negative externalities of popular ride-hailing services.

In regard to the socioeconomic factors of Uber service area expansion, neighborhoods with a higher share of residents with advanced college degrees or fewer vehicles were most characteristic of larger service areas. Considered conjointly, these city-specific results and pooled model findings that tracts with a higher share of households earning between $35,000 and $75,000 had less sizeable service areas and tracts with a higher proportion of younger adult residents had greater service areas, ride-hailing services appear to remain most attractive to city residents with less ownership-related obligations and disposable incomes. These findings are in-line with other studies and may be related to greater societal changes that are shaping mobility preferences (Spurlock et al., 2019). City planners and leaders should be responsive to such findings that underscore a reluctance over time for households with modest incomes to adopt ride-hailing services for longer trips by ensuing high-quality public transportation services are provided to areas with lower-income residents and other vulnerable populations who may be unable to regularly afford the more expensive price of ride-hailing services or have limited access to a personal vehicle.

Building on its contributions, future extensions of this work should seek to address its limitations. First, while adoption of a random intercept multilevel modeling framework enabled estimation of data nested by time periods, a random slope model would permit an exploration of how different socioeconomic and built environment predictors of Uber service area expansion changed over time. Second, UM travel time data are available for several other American cities and could be incorporated in subsequent analyses. By adding more study areas, a three-level model specification—where city is a level-two group instead of a level-one control variable—may become feasible from an empirical standpoint. Third, only morning peak period travel was examined in this study, but future research should also evaluate Uber service area changes during other daily periods (e.g., evening) in which ride-hailing services may have a higher demand. Fourth, it is important to recognize that the dependent variable created for this study is likely an imperfect operationalization of the service area concept, but an inventive metric that utilizes one of the few sources of publicly-available data on ride-hailing travel in an unintended manner. The aggregated nature of UM data has limited its utility to transportation researchers to date (Wu, 2019); however, its suppression of origin-destination pairs with limited travel information permitted this study's exploration of neighborhood factors behind Uber's ever-growing service area. Fifth, in regard to the UM data source, tract-level data are unavailable for all zones across the regions of this study's three cities. In response, tracts within city boundaries were selected to reduce spatial attenuation, but the number of tract destinations with unsuppressed travel time data may be more than what is publicly shared by Uber. This data availability limitation was likely to have limited the Uber service ratio values for Washington, DC, where many tracts in Montgomery and Prince George's County, Maryland were missing UM data. Finally, at present, ride-hailing service in the United States is a duopoly between Uber and Lyft. While Uber appears to dominate the current market share (Shaheen et al., 2018), future research must continue to examine the transportation and land use impacts of their combined services in our urban areas.

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