

# Spatial disparities of Uber accessibility: An exploratory analysis in Atlanta, USA



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## ABSTRACT

Inequality of accessibility in transportation systems is a constant concern, which is intensified by the transportation economization process and the digital divide. How should the accessibility of crowdsourced transportation be measured and understood? Without any prior assumption, this paper openly explores spatial disparities of accessibility in the city of Atlanta, USA using both the UberX (the most popular Uber product) and the UberBLACK (the premium Uber product) data. Accessibility is measured by both the expectation and variability of Uber wait time. With spatial autoregressive models, we find that after controlling for other socioeconomic factors, wealth and race do not have significant associations with Uber accessibility. Additionally, higher road network density, population density, and less commuting time to work correlate with greater Uber accessibility. More public transport stops are related to better accessibility of UberX but worse accessibility of UberBLACK. Finally, implications for policy-makers are provided.

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## 1. Introduction

Transport equity is a constant concern by geographers, urban planners, and sociologists. Although the federal government of the U.S. has prioritized equity of accessibility by enacting its Ladders to Opportunity Program to ensure that our transportation system *will simultaneously expand economic opportunity and socioeconomic mobility* (U.S. Department of Transportation, 2016), transportation-related social exclusion can persist in numerous ways (Pearce, Witten, Hiscock, & Blakely, 2008; Scott & Horner, 2008). Many are interested in this controversial question: will the prevalence of information and communication technologies (ICTs) strengthen social exclusion and inequality, causing more digital divide, or will it mitigate some long-lasting sociospatial inequality?

How should we measure and understand the accessibility of crowdsourced transportation? When searching for the answers, we take Uber as an example. Without any prior assumption, this paper openly explores spatial disparities of accessibility in the city of Atlanta, USA using both the UberX (the most popular Uber product) and the UberBLACK (the premium Uber product) data. In recent years, there has been an increasing number of apps connecting smartphone users who are rider-seekers with rider-providers in the vicinity. Uber, today's ride-sharing market leader in the U.S., has attracted over 160,000 partnered drivers by the end of 2014 (Hall & Krueger, 2015). As of September 2016, Uber has been operated in over 503 cities across 77 countries. It is followed

by Lyft, who operates in 30 U.S. states, and Hailo, which is present in dozens of cities across Europe, the U.S., and Asia (Harding, Kandlikar, & Gulati, 2016). Instead of a taxi service company, Uber can be considered as an online transportation network company that develops, markets, and operates the Uber smartphone app, allowing consumers with smartphones to submit a trip request routed to Uber partnered drivers driving their private cars. Moreover, it does not own a fleet of cars.

The emergence of Uber has recently created ripples regarding some theoretical notions in the fields of geography and urban studies. Batty (2016) argues that the advent of Uber marks a major transition from the industrial to a post-industrial age, where old industries based on old organizational forms are replaced by new bottom-up, renegade forms of organizations. McNeill (2016) uses Uber as an example to illustrate the urban policy tensions associated with the sharing economy. However, there are only a handful of empirical studies that utilize Uber data (e.g., Hall & Krueger, 2015; Hughes & MacKenzie, 2016 and Zhou, Wang, & Li, 2017). In order to test if the accessibility of Uber service differs by neighborhood socioeconomic characteristics, e.g., wealth and race, this study provides empirical evidence from the city of Atlanta with spatial regression models to unveil their effects on both the expectation and variability of Uber accessibility.

## 2. Literature review and research questions

Literature from accessibility and mobility research has been reviewed for this study, as well as the critical studies on digitalism from geography and transportation. This section starts with the conceptualization of

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accessibility, followed by recent literature in spatial inequality of transportation and digitalization.

Accessibility is embedded in the concepts of “easiness” and “freedom”, where a more accessible area reflects a potential for reaching spatially distributed activities. In transportation studies, Hansen (1959) defines accessibility as how easily people interact with places. In geography, accessibility is measured by the freedom with which a person participates in activities (Kwan, 1998; Weibull, 1980). Accessibility not only reflects spatial development, transportation network, and the distribution of opportunities jointly (Páez, Scott, & Morency, 2012) but also can be construed as a temporal measure (Weber & Kwan, 2003). Importantly, when mirroring demographic, social, economic, and cultural constraints, time measure can be more sensitive than place-based measures (Miller, 2003). There has been a strand of work using travel time as a comparative measure to understand job-housing (im)balance and the underlying racial, economic, and gender disparities in the distribution in urban areas (Preston & McLafferty, 1999; Tribby & Zandbergen, 2012).

Geographers have critically analyzed transportation economization and inequality. Transportation economization refers to both practices of (re)constructing the economy through interventions in transport systems and (re)constituting of ‘old’ forms of transport, such as rail, as economical and efficient (Çalışkan & Callon, 2009; Schwanen, 2016). Importantly, Schwanen (2016) argues that the constitution of transportation has intensified socio-spatial polarization. Under neoliberal and post-neoliberal capitalism, transportation infrastructure is proposed to attract capital and provide employment opportunities with greater efficiency and higher competitiveness. Furthermore, the public transport investments in Chicago have enhanced the uneven spatial development to the benefit of ‘capital and the affluent’ while sacrificing the interests of the working class and ethnic minority residents (Farmer, 2011). Further evidence from Chicago and Toronto shows that such uneven development is likely to be perpetuated rather than fundamentally altered by the financial crises (Addie, 2013).

Coupled with transportation economization, digital social inequalities that have been provoked by the advancement in ICTs have been studied for a long time (Castells, 2011). Such digital social inequalities, or digital divides, demonstrate variegated forms, such as divisions between classes and urban location (Dodge, Kitchin, & Mould, 2001). More recently, the maturity of various forms of digital technology has intensified the digital divide, and such a gap has penetrated into daily life (Graham, 2011; Kleine, 2013). Additionally, the prevalence of smart city initiatives has also been criticized by its intrinsic neoliberal ethos of development that reinforces current politics and social and spatial inequality rather than eroding or reconfiguring them (Datta, 2015; Shelton, Poorthuis, & Zook, 2015).

In summary, the literature review helps us clarify the following understandings and outline our research questions.

- Time as a proxy for a measure of accessibility. When requesting Uber service, the estimated wait times are an intuitive proxy to accessibility. Therefore, we conceptualized the estimated wait times for both the low-cost and high-end Uber services as a time measure for accessibility in this study.
- From the critical perspective of transportation inequality, the emerging Uber platform can be considered as a virtual transportation infrastructure. Hence, a question of concern would be whether this new platform is related to aggravated sociospatial polarization in a neighborhood or more equitable access to all neighborhoods regardless of the socioeconomic profiles.

### 3. Data and variables

We accessed the Uber Developers Application Program Interface (API) portal (<https://developer.uber.com/>) and collected estimated wait times for all Uber products in Atlanta, USA over one month in 2016. During the time of our data collection, Uber had five different service models

in Atlanta, namely UberX, UberXL, UberSELECT, UberBLACK, and UberSUV. These service models are segmented by capacity and pricing strategies (Table 1). While UberX, the low-cost Uber, is the most popular Uber service model that most previous studies have used (Hughes & MacKenzie, 2016; Smart et al., 2015), UberBLACK, the original Uber, is the premium option. UberBLACK utilizes “black cars” that meet some specific vehicle standards as well as commercially licensed drivers who are usually employees or contractors for limousine companies that use the Uber App (Hall & Krueger, 2015). Our preliminary data collection and exploration showed two general groups in a waiting time, with a high degree of similarity between UberX and UberXL or UberSELECT, as well as between UberBLACK and UberSUV. In order to provide a more nuanced relationship between Uber accessibility and socioeconomic profiles, this study focused on the estimated wait times for UberX and UberBLACK service models, typical examples of both groups.

The city of Atlanta is composed of 102 neighborhoods under 25 Neighborhood Planning Units (NPUs). The NPU system of Atlanta was founded in 1974 to allow citizens to both receive information and participate in city plans and proposals regarding city functions and long-term visions. We used neighborhoods as the units of analysis in this study and collected Uber estimated wait times using a systematic sampling approach to ensure each neighborhood has at least one random sample point and every other square mile has at least one random sample point. Estimated wait times were quoted at all sample points approximately every 30 min for a whole month, and a total of over 360,000 data points were collected.

Socioeconomic data at the neighborhood level are obtained from Neighborhood Nexus (<http://dev.neighborhoodnexus.org/>), a regional information system which provides a dashboard to access data from different federal and state agencies, including the U.S. Census Bureau and American Community Survey. After a preliminary screening of the variables via simple correlation examinations, population density (*PopDen*), mean travel time to work (*TravelTime*), unemployment rate (*Unemp*), no vehicle rate (*NoVehicle*), and median house value (*HouseValue*) were populated from Neighborhood Nexus. Following Hughes and MacKenzie (2016), we calculated the minority rate (*Minor*) as the number of the non-white population divided by the total population of each neighborhood. Additionally, variables reflecting transportation infrastructure were included. The number of public transport (i.e., train and bus) stops (MARTA) was collected from the Metropolitan Atlanta Rapid Transit Authority (<http://www.itsmarta.com/>). Road data were downloaded from the Topologically Integrated Geographic Encoding and Referencing (TIGER) products provided by US Census Bureau, where road network density (*RoadDen*) was computed. Furthermore, urban land use intensity ratio (*UrbanIntensity*) was calculated as the total developed land divided by the total area of each neighborhood, where developed land was extracted from the most recent US National Land Cover Database (i.e., NLCD2011). As some of these socioeconomic data are missing for the airport neighborhood, our final samples contain 101 samples (Fig. 1) with selected socioeconomic variables (Table 2).

### 4. Methods

We employed a suite of four spatial regression models to explore empirical relationships between socioeconomic disparities and Uber accessibility. While we consider the mean value of estimated wait times as the *expectation*, its standard deviation can be used to measure *variability*. Therefore, we can decompose accessibility through a holistic view of expectation and variability. The mean value of estimated wait times for each neighborhood per Uber service model (i.e., UberX and UberBLACK in this paper) from collected data samples was calculated as the central tendency of accessibility, which reflects the average expected wait times for that Uber model in that neighborhood. Uber users in more accessible neighborhoods would expect to face shorter wait times when they request Uber service. Similarly, the standard deviation of estimated wait times for each neighborhood per Uber service model was calculated

**Table 1**  
Segments of Uber service models in Atlanta, GA, USA.

Name	Description	Capacity	Cost/min <sup>a</sup>	Minimum payment <sup>a</sup>	Cost/mile <sup>a</sup>	Base rate <sup>a</sup>	Cancellation fee <sup>a</sup>
UberX	The low-cost Uber	4	0.12	5.75	0.75	1	6
UberXL	Low-cost rides for larger groups	6	0.3	8.75	1.9	3	6
UberSELECT	The next step towards luxury	4	0.35	10.75	2	4	10
UberBLACK	The original Uber	4	0.4	15	3.25	7	10
UberSUV	Room for everyone	6	0.5	25	4	14	10

<sup>a</sup> Currency unit: USD.

as the variability measure of accessibility, indicating the dispersion or fluctuation of wait times. A more accessible neighborhood is less variable to the fluctuation of wait times, and thus has a less dispersed range of estimated wait time, in other words, a smaller standard deviation. We created four models, where the dependent variable is the mean of estimated wait times for UberX (*AvgX*), the standard deviation of estimated wait times for UberX (*StdX*), the mean of estimated wait times for UberBLACK (*AvgBlk*), and the standard deviation of estimated wait times for UberBLACK (*StdBlk*), respectively.

When measuring socioeconomic disparities, median house value (*HouseValue*) was taken as the proxy for wealth effect, and the minority rate (*Minor*) was used as the proxy for race effect. Additionally, a set of control variables is necessary as Uber accessibility may relate to more factors than just the hypothesized proxies for socioeconomic disparities. Specifically, control variables including population density (*PopDen*), mean travel time to work (*TravelTime*), unemployment rate (*Unemp*), no vehicle rate (*NoVehicle*), the number of public transport stop (*MARTA*), road network density (*RoadDen*) and urban land use intensity (*UrbanIntensity*) are included. Our model specification is as follows:

$$Y = \text{HouseValue} + \text{Minor} + \text{PopDen} + \text{TravelTime} + \text{Unemp} + \text{NoVehicle} + \text{MARTA} + \text{RoadDen} + \text{UrbanIntensity} + \varepsilon$$

where  $Y \in [\text{AvgX}, \text{StdX}, \text{AvgBlk}, \text{StdBlk}]$  and  $\varepsilon$  represents the unexplained error term. The variance inflation factor (VIF) tests were applied to

quantify the severity of multicollinearity. While it is recommended that 10 is the maximum acceptable value of VIF (Kennedy, 2003; Kutner, Nachtsheim, & Neter, 2004), a stricter acceptable value of 5 was also found in literature (Rogerson, 2001). Nevertheless, none of the VIFs surpasses 5 (*HouseValue* yields the largest VIF value of 4.91); therefore, multicollinearity is not a significant issue in our specification.

The framework of our regression analysis is adapted from Anselin (2013), which is summarized in the Appendix (Fig. A1). To control for the potential heteroscedastic variances in the error term ( $\varepsilon$ ), a natural logarithm was taken for all variables before the regression analysis. First, we started fitting our models with ordinary least square (OLS) estimator. The error term ( $\varepsilon$ ) is assumed to be at least independent and identically distributed. However, the nature of share-riding behavior within a city is deemed to be a spatialized phenomenon, where the estimated wait times for one locale depend on not only how many partnered vehicles are nearby but also how many passengers nearby are requesting the same service. Therefore, it is unlikely that the unexplained error term in OLS is independent. A row-standardized spatial weight matrix ( $W$ ) was constructed using queen contiguity with the first-order of neighbors. Residuals of OLS models were examined for spatial autocorrelation using Global Moran's I test. A significant positive Moran's I for the residual of OLS regression in all models is found, indicating that a spatial model is required in this study. Second, two Lagrange Multiplier (LM) tests were applied to test spatial dependence and to help select the spatial error model (SEM) or the spatial lag model (some refer to the spatial lag model as the spatial autoregressive model (SAM) and as such, we use these two terms interchangeably in this paper and use SAM to refer to either of them). If both LM tests for SEM and SAM are significant, robust LM tests are further applied. Empirical results indicate that SAM should be chosen over SEM for all the four models with  $Y = \text{AvgX}, \text{StdX}, \text{AvgBlk}, \text{StdBlk}$ , respectively. All four models are numbered in the headers of Tables 4 and 5. Finally, a SAM is estimated using maximum likelihood estimators (Eq. (1)):

$$y = \rho Wy + x\beta + \mu \quad (1)$$

where  $y$  is an  $N \times 1$  vector of dependent observations,  $Wy$  is an  $N \times 1$  vector of lagged dependent observations,  $\rho$  is a spatial autoregressive parameter,  $x$  is an  $N \times K$  matrix of exogenous explanatory variables,  $\beta$  is a  $K \times 1$  vector of respective coefficients and  $\mu$  is an  $N \times 1$  vector of independent error terms.

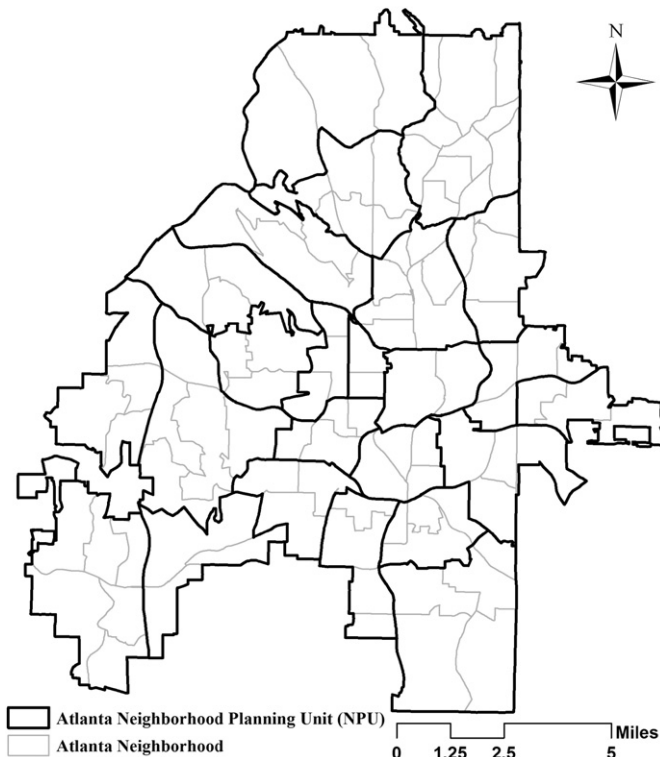
In the case of SAM, the coefficient estimates ( $\beta$ ) cannot be interpreted the same way as in OLS, because of the existence of spatial dependence. In SAM,  $\beta$  only represents the short-term direct impact of  $x_i$  on  $y_i$ . In fact, we must account for the indirect impact of  $x_i$  on  $y_i$ —the influence that  $y_i$  exerts on  $y_j$ , which in turn feeds back to  $y_i$ . Therefore, the total impact of a change in  $x_i$  on  $y_i$  can be expressed as:

$$E[dy] = (I_n - \rho W)^{-1} dx \quad (2)$$

where  $dx$  is a matrix of changes to the covariates;  $dy$  is the associated change in the dependent variable. The total impact reflects a global average impact of  $x$  on  $y$ .

## 5. Results

In order to reflect both the expectation and variability sides of accessibility concurrently, we mapped the average and the standard deviation



**Fig. 1.** Neighborhood Planning Units (NPUs) and neighborhood composition in the city of Atlanta (the airport neighborhood is excluded).

**Table 2**  
Summary statistics of explanatory variables (N = 101).

Variable	Description	Min	Max	Mean	Std. dev
<i>PopDen</i>	Population density	805.36	17,608.57	4124.07	2792.43
<i>TravelTime</i>	Mean time travel to work (in minutes)	17.20	40.70	27.08	5.59
<i>Unemp</i>	Unemployment rate	0.70	37.80	14.27	8.06
<i>NoVehicle</i>	No vehicle rate	0.70	65.50	19.32	13.89
<i>HouseValue</i>	Median house value (in USD)	69,280.00	904,698.00	237,122.40	180,918.50
<i>Minor</i>	Minority rate	0.00	99.70	66.64	35.05
<i>MARTA</i>	The number of public transport stops	0.00	188.00	39.69	29.58
<i>RoadDen</i>	Road network density (mi/sq. mi)	8.59	232.97	62.52	45.53
<i>UrbanIntensity</i>	Developed land divided by the total land area	0.43	1.00	0.81	0.17

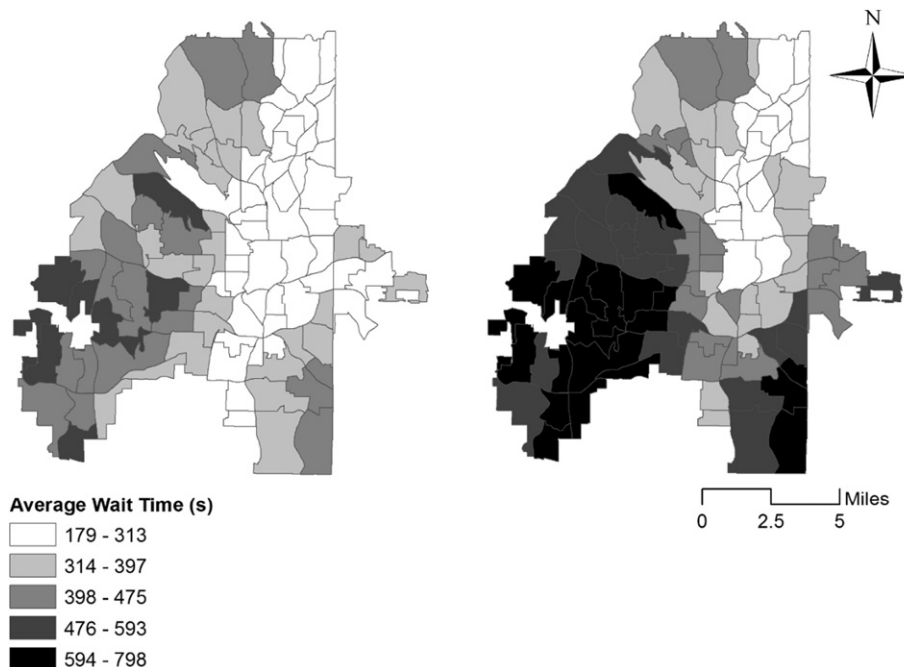
of estimated wait time (Fig. 2 and Fig. 3). For UberX, the average estimated wait time (*AvgX*) ranges roughly from 3 min to 10 min, with a mean value around 6 min; the standard deviation of that (*StdX*) spans from about 1 min to 3 min for all sampling sites, with a mean value of about 2 min. For UberBLACK, the average estimated wait time (*AvgBlk*) ranges roughly from 3 min to 13 min, with a mean value around 8 min; the standard deviation of that (*StdBlk*) spans from about 1 min to 3 min, with a mean value of about 2 min. It is not surprising that *AvgX* has a more concentrated distribution with a smaller mean number than *AvgBlk* does. After all, UberX is the most popular and cost-effective Uber service model while UberBLACK is a premium choice, which probably results in more UberX services in the market than the latter. Compared to UberX, UberBLACK will at least introduce three times the higher cost per minute and four times higher cost per mile (Table 1). In terms of the standard deviation, greater values of both *StdX* and *StdBlk* occur in the southwestern part of Atlanta. Compared to *StdX*, *StdBlk* has a larger range of value.

Based on the spatial model selection diagnostics (Table 3), there is a moderate positive spatial autocorrelation of the residual of OLS estimator (Global Moran's I,  $p < 0.005$ ) for all the four models. Noting that the Lagrange Multiplier diagnostics for both the spatial error model and the spatial lag model (LMerr and LMLag) are significant ( $p < 0.05$ ), Robust Lagrange Multiplier diagnostics were further examined. First, the Robust Lagrange Multiplier for the spatial lag model (RLMLag) is significant ( $p < 0.001$ ) in all four models. Second, the Robust Lagrange Multiplier for spatial error model (RLMerr) is only significant ( $p < 0.005$ ) in Model (4). Conceptually, ride-sharing activities involve a positive spillover

effect. First, Uber cars are free agents that move from point A to point B using an optimal route based on time and distance. They are not confined by boundaries of neighborhoods or NPU's. Second, if there is a high volume of Uber product supply in one neighborhood (resulting in lower expected estimated wait times), it is more likely that a neighborhood next to it will have lower expected estimated wait times. Therefore, the spatial lag model was applied to all four models.

Tables 4 and 5 summarize the regression results for UberX accessibility (Table 4) and UberBLACK accessibility (Table 5). In general, a positive Rho is found in all four models, suggesting there is a positive spatial autocorrelation in all models. Importantly, Likelihood Ratio tests are significant ( $p < 0.001$ ) for all models, suggesting that models have been improved with the addition of spatial lag term. Additionally, Wald statistic is significant ( $p < 0.001$ ) in all four models, showing that all of these explanatory variables are necessary for the model. Third, Lagrange multiplier test for residual autocorrelation is not significant in models (1), (2), and (4), indicating there is no more spatial autocorrelation; however, it is significant ( $p < 0.05$ ) in model (3), showing that spatial autocorrelation is not fully taken care of by adding a single spatial lag term.

In Table 4, neither median house value (*HouseValue*) nor minority rate (*Minor*) exerts a significant impact on the accessibility of UberX. In other words, there is no evidence showing that the most popular Uber product (UberX), a new platform, is associated with the aggravation of existing socio-spatial polarization in the neighborhoods of Atlanta. On the contrary, it generally provides equitable access to all neighborhoods regardless of the socioeconomic profiles (exemplified by wealth and race). Not



**Fig. 2.** The average wait time for UberX (left) and UberBLACK (right).



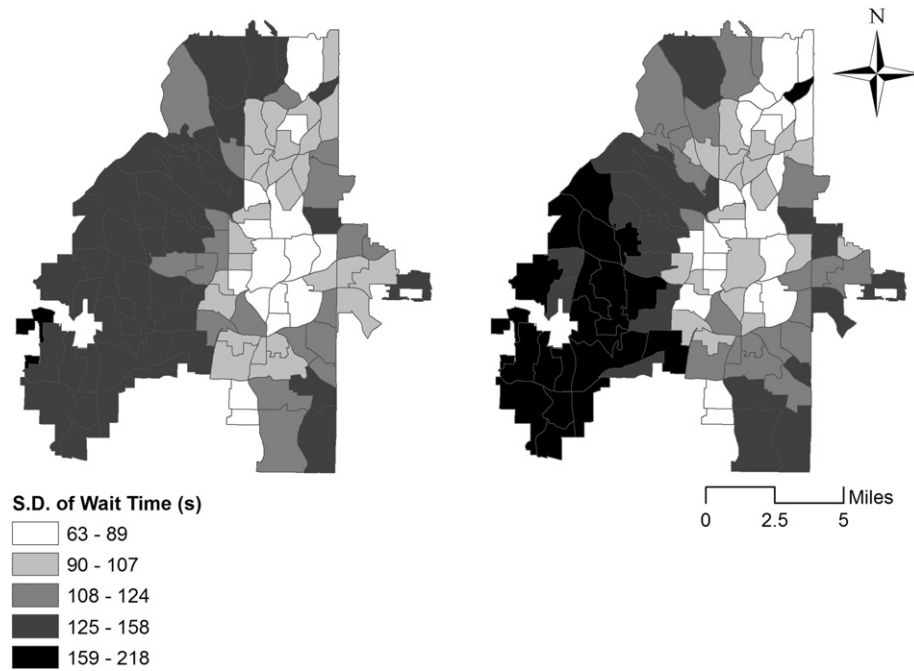


Fig. 3. The standard deviation (S.D.) of wait time for UberX (left) and UberBLACK (right).

surprisingly yet importantly, higher population density (*PopDen*) and road network density (*RoadDen*) are associated with better UberX accessibility. Specifically, controlling for other covariates, the associations are

- Positively related to UberX accessibility:
  - o A 1% increase in population density is associated with roughly 0.10% decrease in the average UberX wait time and 0.18% reduction in the standard deviation of UberX wait time.
  - o A 1% increase in road network density corresponds to 0.15% decline in average UberX wait time and 0.20% decrease in the standard deviation of UberX wait time.
  - o A 1% increase in no vehicle rate (*NoVehicle*) is associated with 0.11% reduction in the average UberX wait time.
  - o A 1% increase in the number of public transport stops (*MARTA*) is associated with 0.03% reduction in the average UberX wait time.
- Negatively related to UberX accessibility:
  - o Commuting behaviors such as the mean travel time to work (*TravelTime*). A 1% increase in *TravelTime* is linked to 0.54% more in the average UberX wait time.

Table 5 reports the regression results of UberBLACK accessibility. Similar to the results of UberX in Table 4, we found that neither median house value (*HouseValue*) nor minority rate (*Minor*) is significantly correlated with the accessibility of UberBLACK. To put it in another way, there is no evidence that the premium Uber product (UberBLACK) is linked to the aggravation of the current socio-spatial polarization in the neighborhoods of Atlanta. Controlling for other covariates, 1% increase

in road network density (*RoadDen*) is associated with 0.13% decrease in the average wait time and 0.22% reduction of the standard deviation of the wait time of UberBLACK. Similar to the findings of UberX, 1% increase in mean travel time to work (*TravelTime*) is associated with 1.11% increase in the average UberBLACK wait time; 1% growth in population density (*PopDen*) is linked to 0.22% decrease in the standard deviation of UberBLACK wait time. Lastly, 1% increase in public transport stops (*MARTA*) is related to 0.05% increase in the standard deviation of UberBLACK wait time.

## 6. Discussions and conclusion

Uber is indeed a disruptive market innovator of the taxi industry in the 'sharing economy'. On the one hand, it can be considered as a new (crowdsourced) transportation system, in which inequality of accessibility can be an issue and intensified by transportation economization

Table 4  
Spatial lag regression results of UberX accessibility.

DV	(1) AvgX				(2) StdX			
	Estimate	S.E.	p	Total	Estimate	S.E.	p	Total
(Intercept)	3.104	0.885	****	NA	2.343	0.886	**	NA
<i>PopDen</i>	−0.048	0.020	*	−0.095	−0.076	0.021	****	−0.178
<i>TravelTime</i>	0.272	0.091	***	0.536	0.140	0.097		0.330
<i>Unemp</i>	0.042	0.027		0.083	0.016	0.029		0.039
<i>NoVehicle</i>	−0.055	0.019	***	−0.108	−0.022	0.020		−0.051
<i>HouseValue</i>	−0.024	0.037		−0.047	0.018	0.039		0.044
<i>Minor</i>	−0.004	0.009		−0.008	−0.009	0.010		−0.022
<i>RoadDen</i>	−0.075	0.020	****	−0.147	−0.085	0.022	****	−0.201
<i>MARTA</i>	−0.014	0.007	.	−0.027	−0.001	0.008		−0.002
<i>UrbanIntensity</i>	−0.109	0.072		−0.215	0.081	0.073		0.192
Rho	0.492				0.576			
LR	24.381		****		28.698		****	
Wald statistic	35.717		****		43.494		****	
LL	83.257				74.624			
LM	0.019				5.116		*	

All variables are log-transformed. As the minimum number of *Minor* and *MARTA* was zero, a marginal value (of 0.001) was added to them before logarithm transformation. S.E. = standard error; Total = total effects; LR = likelihood ratio test value; LL = log likelihood; LM = Lagrange multiplier test for residual autocorrelation. Significant codes: .: 0.1, \*\*\* 0.05, \*\*\*\* 0.01, \*\*\*\*\* 0.005, \*\*\*\*\* 0.001.

Table 3  
Summary for spatial model selection diagnostics.

Model	DV	Moran's I	LMerr	LMlag	RLMerr	RLMlag
(1)	AvgX	0.184****	8.302***	21.291****	0.180	21.471****
(2)	StdX	0.209****	10.732***	28.392****	3.620	21.281****
(3)	AvgBlk	0.329****	26.441****	47.289****	0.056	20.904****
(4)	StdBlk	0.154***	5.802*	24.461****	9.532***	28.192****

DV = Dependent variable; Moran's I = Global Moran's I test for the residual of OLS estimator; LMerr = Lagrange Multiplier diagnostics for spatial error model; LMlag = Lagrange Multiplier diagnostics for spatial lag model; RLMerr = Robust Lagrange Multiplier diagnostics for spatial error model; RLMlag = Robust Lagrange Multiplier diagnostics for spatial lag model. Significant codes: \*\*\* 0.05, \*\*\*\* 0.01, \*\*\*\*\* 0.005, \*\*\*\*\* 0.001.

**Table 5**  
Spatial lag regression results of UberBLACK accessibility.

DV	(3) AvgBlk				(4) StdBlk			
	Estimate	S.E.	p	Total	Estimate	S.E.	p	Total
(Intercept)	1.504	0.986		NA	2.845	1.187	*	NA
PopDen	−0.039	0.025		−0.129	−0.099	0.030	***	−0.220
TravelTime	0.333	0.118	***	1.106	0.163	0.139		0.362
Unemp	0.048	0.034		0.161	0.019	0.041		0.042
NoVehicle	−0.032	0.024		−0.106	−0.033	0.029		−0.073
HouseValue	−0.008	0.046		−0.025	−0.015	0.056		−0.033
Minor	−0.009	0.011		−0.031	−0.017	0.014		−0.037
RoadDen	−0.078	0.026	***	−0.260	−0.058	0.031	.	−0.129
MARTA	−0.012	0.009		−0.040	0.021	0.011	.	0.047
UrbanIntensity	0.055	0.086		0.182	−0.032	0.106		−0.072
Rho	0.699				0.551			
LR	54.038		****		24.549		****	
Wald statistic	104.320		****		34.926		****	
LL	55.626				39.195			
LM	0.211				14.087		*	

All variables are log-transformed. As the minimum number of *Minor* and *MARTA* was zero, a marginal value (of 0.001) was added to them before logarithm transformation. S.E. = standard error; Total = total effects; LR = likelihood ratio test value; LL = log likelihood; LM = Lagrange multiplier test for residual autocorrelation. Significant codes: .: 0.1, \* 0.05, \*\*\* 0.01, \*\*\*\* 0.005, \*\*\*\*\* 0.001.

processes. On the other hand, as Uber is essentially a smartphone app that connects users, the problem of spatial disparities related to digitization and the digital divide also is also worthy of exploration. Importantly, as Uber has increasingly posted caused urban policy tensions and political controversy for governments and regulators (Dudley, Banister, & Schwanen, 2017; McNeill, 2016), it is deemed to be a social construct. Motivated to answer the question whether there are socioeconomic disparities in Uber service, we applied spatial regression models to analyze Uber accessibility in Atlanta, USA. This study contributes to accessibility research, especially the stream of transportation economization and digital social inequalities in the following two ways. Firstly, we have concretized accessibility by combining the dimensions of expectation and variability. A neighborhood with higher Uber accessibility is deemed to have less average wait times and lower standard deviation of such wait times. Secondly, we have materialized the accessibility of Uber through the case of UberX, the most popular Uber product, and UberBLACK, the high-end one.

With four spatial autoregressive models, we use the average wait time and standard deviation of that of UberX and UberBLACK as dependent variables. This study not only tests if the accessibility of different Uber products differs by neighborhood socioeconomic characteristics, (e.g., wealth and race), but also provides evidence of other influencing factors of Uber accessibility in the city of Atlanta, USA. The main conclusions are summarized as follows:

First, we did not find either wealth (exemplified by median house value) or race (illustrated by minority rate) is significantly associated with the accessibility of UberX or UberBLACK. In other words, there is no evidence either the most popular product (UberX) or the premium one (UberBLACK) has related to the aggravation or alleviation the existing socio-spatial disparities at the neighborhood level in Atlanta. This finding is consistent with Hughes and MacKenzie (2016), who found that in Greater Seattle, the accessibility to UberX is not restricted to 'white and wealthy' areas.

Second, higher road network density is associated with better Uber accessibility in all four models, and higher population density is related to greater Uber accessibility in all models expect for the average wait time of UberBLACK. The combined importance of road network density and population density implies the critical role that urban form plays in the accessibility of Uber products. Indeed, road network not only signifies the urban structure of a city but also defines where the Uber taxi can drive. A denser road network may imply that it is connected better in a neighborhood. Thus, the estimated average and the standard deviation of wait times and the standard deviation of that will be less in that

vicinity. Consequently, that area is more accessible to Uber services. Population density has long been used in urban form studies, and it provides proxies for the demand of Uber services.

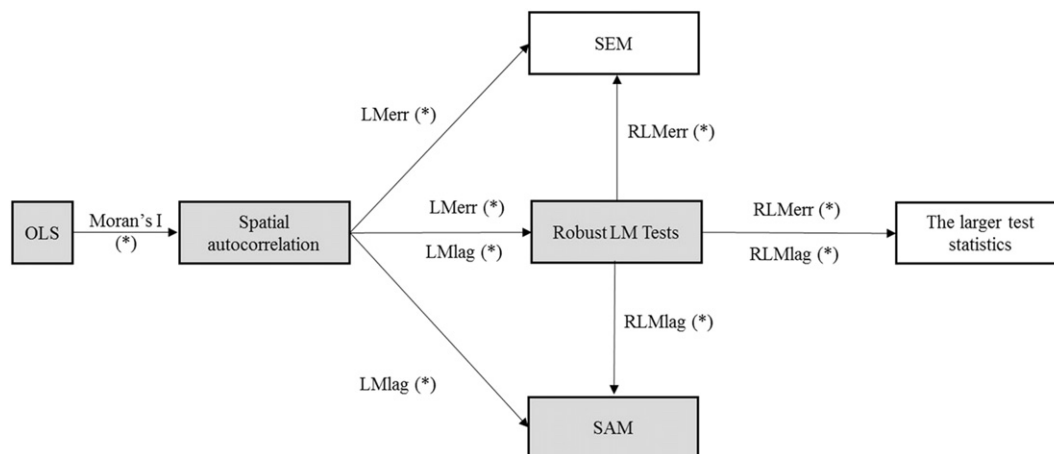
Third, commuting behavior exemplified by mean travel time to work is positively associated with the average wait time of both UberX and UberBLACK. In other words, the longer the average travel time to work, the worse the Uber accessibility. The mean travel time to work relates to the job-housing balance and rush-hour congestion. Long travel time to work implies a relatively imbalanced distribution of the ratio of the total numbers of employment to household count and inefficient transportation systems, where the wait time of Uber products can be used to delineate such urban form and functions. Furthermore, given the positive association between Uber wait time and travel time to work, Uber products may be utilized as a real-time traffic condition proxy monitor. Additionally, both no vehicle rate and the number of public transport stops are negatively related to the average wait time of UberX. As the mean wait time for UberX is less in a neighborhood with lower vehicle ownership rate and more public transport stops, it is possible that UberX serves as public transport functions. More recently, Uber launched a flat-fare package program, where any intra-city trips of UberX were charged a flat rate between \$4 and \$6.

Finally, the set of the factors influencing to UberX and UberBLACK are different, indicating that they are very different products (as they are named) and for various trip purposes. For example, a greater number of public transport stops is associated with better UberX accessibility, but worse UberBLACK accessibility, which implies that the two Uber products may serve different trip purposes. Indeed, while cars offering UberX service are everyday cars, UberBLACK cars are composed of typically high-end sedans with commercial registration and insurance. Regarding the average wait time, while that of UberBLACK is only associated with road network density and commuting behaviors, that of UberX is further related to population density, and public transport stops.

Based on this research, we make the following implications for policy-makers and regulators. First, our finding suggests that wealth and race, as well as the unemployment rate, are not significantly correlated with Uber accessibility. Typical social inequality issues associated with transportation economization and the digital divide may not be a severe problem in the ride-sharing cases such as Uber. Second, the fact that road network density, population density, and public transport availability do matter in Uber accessibility reiterates the importance of proper urban structure on accessibility and efficiency. Third, as the results indicate that urban land use intensity has no significant impact on Uber accessibility, a sustainable and less intense urban land use pattern (e.g., more green spaces) may not hamper the fruit of the 'sharing economy'. This study also intrigues us to dwell on Uber's role in the digital divide. Given that Uber operates entirely based on smartphone apps, will its intrinsically digital nature intensify the known digital divide or does it alleviate the tension of unequal accessibility? While our research may not be able to provide a simple answer to this bigger question, is sure it can help us identify future research directions.

Nevertheless, several limitations of this study are worth mentioning, as they provide additional directions for further research. Firstly, this study utilized neighborhood as the unit of analysis. Studies at a different scale may not reach the same conclusion. Given the uncertain geographic context problem (Kwan, 2012), multilevel and mixed level models (Mu, Wang, Chen, & Wu, 2015) can be applied in the future. Second, this study has focused on one particular city. With Uber's global footprint, it will be interesting to explore how cultural and political factors affect the spatial disparities of its accessibility. Thirdly, we have represented wealth and race each by a single and straightforward variable, which may not reflect some nuanced facets of social disparities. Lastly, while the Uber data were collected in 2016, the urban land use intensity was derived from the national land use database in an earlier time (i.e., NLCD 2011). It is worth to revisit this work when the NLCD 2016 is available to the public.

## Appendix A



**Fig. A1.** Flowchart of regression model selection, adapted from Anselin (2013). The shaded boxes indicate the model selection in this study. (\*) indicates the related statistical test is significant. LMerr = Lagrange Multiplier diagnostics for spatial error model; LMlag = Lagrange Multiplier diagnostics for spatial lag model; RLMerr = Robust Lagrange Multiplier diagnostics for spatial error model; RLMlag = Robust Lagrange Multiplier diagnostics for spatial lag model; SEM = spatial error model; SAM = spatial autoregressive model (spatial lag model).

## References

- Addie, J. -P. D. (2013). Metropolitics in motion: The dynamics of transportation and state reterritorialization in the Chicago and Toronto city-regions. *Urban Geography*, 34, 188–217.
- Anselin, L. (2013). *Spatial econometrics: methods and models*. Vol. 4. Springer Science & Business Media.
- Batty, M. (2016). How disruptive is the smart cities movement? *Environment and Planning B: Planning and Design*, 43, 441–443.
- Çalışkan, K., & Callon, M. (2009). Economization, part 1: Shifting attention from the economy towards processes of economization. *Economy and Society*, 38, 369–398.
- Castells, M. (2011). *The rise of the network society: The information age: Economy, society, and culture*. Vol. 1. John Wiley & Sons.
- Datta, A. (2015). New urban utopias of postcolonial India: 'Entrepreneurial urbanization' in Dholera smart city, Gujarat. *Dialogues in Human Geography*, 5, (pp. 3–22).
- Dodge, M., Kitchin, R., & Mould, A. (2001). *Mapping cyberspace*. Vol. 72. London: Routledge.
- Dudley, G., Banister, D., & Schwanen, T. (2017). The rise of Uber and regulating the disruptive innovator. *The Political Quarterly*.
- Farmer, S. (2011). Uneven public transportation development in neoliberalizing Chicago, USA. *Environment and Planning A*, 43, 1154–1172.
- Graham, M. (2011). Time machines and virtual portals: The spatialities of the digital divide. *Progress in Development Studies*, 11, 211–227.
- Hall, J. V., & Krueger, A. B. (2015). An analysis of the labor market for Uber's driver-partners in the United States. *Princeton University Industrial Relations Section Working Paper*, 587.
- Hansen, W. G. (1959). How accessibility shapes land use. *Journal of the American Institute of Planners*, 25, 73–76.
- Harding, S., Kandlikar, M., & Gulati, S. (2016). Taxi apps, regulation, and the market for taxi journeys. *Transportation Research Part A: Policy and Practice*, 88, 15–25.
- Hughes, R., & MacKenzie, D. (2016). Transportation network company wait times in greater Seattle, and relationship to socioeconomic indicators. *Journal of Transport Geography*, 56, 36–44.
- Kennedy, P. (2003). *A guide to econometrics*. MIT press.
- Kleine, D. (2013). *Technologies of choice?: ICTs, development, and the capabilities approach*. MIT Press.
- Kutner, M. H., Nachtsheim, C., & Neter, J. (2004). *Applied linear regression models*. McGraw-Hill/Irwin.
- Kwan, M. -P. (1998). Space-time and integral measures of individual accessibility: A comparative analysis using a point-based framework. *Geographical Analysis*, 30, 191–216.
- Kwan, M. -P. (2012). The uncertain geographic context problem. *Annals of the Association of American Geographers*, 102, 958–968.
- McNeill, D. (2016). Governing a city of unicorns: Technology capital and the urban politics of San Francisco. *Urban Geography*, 37, 494–513.
- Miller, H. J. (2003). What about people in geographic information science? *Computers, Environment and Urban Systems*, 27, 447–453.
- Mu, L., Wang, F., Chen, V. W., & Wu, X. -C. (2015). A place-oriented, mixed-level regionalization method for constructing geographic areas in health data dissemination and analysis. *Annals of the Association of American Geographers*, 105, 48–66.
- Páez, A., Scott, D. M., & Morency, C. (2012). Measuring accessibility: Positive and normative implementations of various accessibility indicators. *Journal of Transport Geography*, 25, 141–153.
- Pearce, J., Witten, K., Hiscock, R., & Blakely, T. (2008). Regional and urban-rural variations in the association of neighbourhood deprivation with community resource access: A national study. *Environment and Planning A*, 40, 2469.
- Preston, V., & McLafferty, S. (1999). Spatial mismatch research in the 1990s: Progress and potential. *Papers in Regional Science*, 78, 387–402.
- Rogerson, P. (2001). *Statistical methods for geography*. Sage.
- Schwanen, T. (2016). Geographies of transport I: Reinventing a field? *Progress in Human Geography*, 40, 126–137.
- Scott, D., & Horner, M. (2008). Examining the role of urban form in shaping people's accessibility to opportunities: An exploratory spatial data analysis. *Journal of Transport and Land Use*, 1.
- Shelton, T., Poorthuis, A., & Zook, M. (2015). Social media and the city: Rethinking urban socio-spatial inequality using user-generated geographic information. *Landscape and Urban Planning*.
- Smart, R., Rowe, B., Hawken, A., Kleiman, M., Mladenovic, N., Gehred, P., & Manning, C. (2015). *Faster and cheaper: How ride-sourcing fills a gap in low-income Los Angeles neighborhoods*. BOTEC Analysis Corporation, 2015 (Retrieved September).
- Tribby, C. P., & Zandbergen, P. A. (2012). High-resolution spatio-temporal modeling of public transit accessibility. *Applied Geography*, 34, 345–355.
- U.S. Department of Transportation (2016). *Ladders of opportunity*. (Accessed Nov 1, 2016) <https://www.transportation.gov/opportunity>.
- Weber, J., & Kwan, M. -P. (2003). Evaluating the effects of geographic contexts on individual accessibility: A multilevel approach. *Urban Geography*, 24, 647–671.
- Weibull, J. W. (1980). On the numerical measurement of accessibility. *Environment and Planning A*, 12, 53–67.
- Zhou, X., Wang, M., & Li, D. (2017). From stay to play - A travel planning tool based on crowdsourcing user-generated contents. *Applied Geography*, 78, 1–11.