Computers, Environment and Urban Systems 67 (2018) 169–175

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

journal homepage: www.elsevier.com/locate/ceus

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

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ARTICLE INFO

Article history:
Received 3 February 2017
Received in revised form 13 September 2017
Accepted 13 September 2017
Available online xxxx

Keywords:
Accessibility
Disparity
Crowdsourced transportation
Uber
Spatial autoregressive model

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 is 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.

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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https://doi.org/10.1016/j.compenvurbsys.2017.09.003
0198-9715/

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