Transportmetrica A: Transport Science

ISSN: 2324-9935 (Print) 2324-9943 (Online) Journal homepage: http://www.tandfonline.com/loi/ttra21

Shared-use mobility competition: a trip-level analysis of taxi, bikeshare, and transit mode choice in Washington, DC

Timothy F. Welch, Steven R. Gehrke & Alyas Widita

To cite this article: Timothy F. Welch, Steven R. Gehrke & Alyas Widita (2018): Shared-use mobility competition: a trip-level analysis of taxi, bikeshare, and transit mode choice in Washington, DC, Transportmetrica A: Transport Science, DOI: 10.1080/23249935.2018.1523250

To link to this article: https://doi.org/10.1080/23249935.2018.1523250

Accepted author version posted online: 11 Sep 2018.
Published online: 21 Sep 2018.

TRANSPORTMETRICA A: TRANSPORT SCIENCE
https://doi.org/10.1080/23249935.2018.1523250

Taylor & Francis
Taylor & Francis Group

Shared-use mobility competition: a trip-level analysis of taxi, bikeshare, and transit mode choice in Washington, DC

Timothy F. Welch[a], Steven R. Gehrke [b] and Alyas Widita[c]

[a]Center for Quality Growth and Regional Development, School of City and Regional Planning, Georgia Institute of Technology, Atlanta, GA, USA; [b]Department of Civil and Environmental Engineering, Portland State University, Portland, OR, USA; [c]School of City and Regional Planning, Georgia Institute of Technology, Atlanta, GA, USA

ABSTRACT

The emergence of new shared-use mobility options such as bikeshare and ride-hailing services render the traditional dichotomy between personal vehicles and public transit somewhat irrelevant. Transportation planners and policymakers have yet to conclude whether these mobility technologies are complementing or competing against existing public transit services. The understanding of this relationship is vital given the increasing uncertainty of funding sources for transit services, but limited by the scarcity of meaningful data provided by the private ride-hailing industry. This study applies big data analytic tools on a unique travel data set to uncover the predictors motivating a half-billion transit, taxi, and bikeshare trips in rail station walksheds across Washington, DC. Study findings indicate travel cost and natural environment factors as well as land use diversity and network connectivity metrics significantly impact the likelihood for an individual to travel via taxi or bikeshare rather than rail.

ARTICLE HISTORY
Received 1 September 2017
Accepted 10 September 2018

KEYWORDS
Taxi ridership; public transit; bikeshare; big data; mode choice

Introduction

Competition among transportation modes has traditionally been categorized as a choice between personal vehicles and public transit. Transportation policies that seek to guide individual mode choice towards public transit or seek to reduce auto-related traffic congestion have generally focused on this traditional dichotomy. Yet, until recently, an evolving and increasingly meaningful array of non-public transportation options made available to urban travelers has been commonly unaddressed by these policies. While many individuals have the option to travel by either public transit or personal vehicle, the rise of the sharing economy has opened the doors to non-traditional transportation services that urban policy has not fully addressed. Whether travelers choose to hail a taxi, temporarily rent a bike, or summon a shared ride via their mobile phone; these transportation options are becoming

CONTACT Steven R. Gehrke sgehrke@pdx.edu Department of Civil and Environmental Engineering, Portland State University, Portland, OR 97207, USA

much more prevalent in fulfilling daily urban mobility needs. What planners and urban policymakers have not yet figured out is whether these services round out an important mix of multimodal transportation options or compete directly with public transit services.

Fixed rail transit is a major public investment in the jurisdictions it serves. The extent to which the aforementioned non-public transportation options compete with traditional fixed rail systems may necessitate additional transportation policy options. If these alternative modes are highly complementary, providing a wider breadth of travelers – particularly those beyond walking distance from a rail station – feasible access to the rail system, then planners should consider ways to make such services available to a broad variety of potential users. However, if non-public modes tend to replace rail transit trips, serving travelers whose origins and destinations are within close proximity to rail stations, urban transport policy should address the reasons riders choose the non-public mode over rail service.

Transportation options that are competitive with rail service are not likely to fundamentally alter public transit system viability; however, under the current regime of historically shrinking public transportation funding, every rider makes a difference. Much of the research that attempts to measure the competitive effects of alternative transportation modes tend to focus on a restricted number of travel surveys. These studies attempt to determine the nature of the public transit and non-public transportation service relationship. This type of information is useful, but also limited in what it can tell planners about the motivations that drive underlying travel behavior. In order to better understand the role of a rapidly expanding slate of alternative transportation modes, a more comprehensive investigation of the links between the natural environment, built environment, and these expanding transportation networks with the individual decision process is demanded.

To examine the influence of these described factors on the travel decision-making process, this study applies the latest tools in big data analysis on a travel data set collected in Washington, DC. Specifically, a multinomial analysis is adopted to uncover the predictors motivating a half-billion public transit, taxi, and bikeshare trips within rail station walksheds. By doing so, we attempt to define a variety of significant factors influencing travelers' decision to take alternative modes of transportation to destinations that are easily served by rail. Our analysis provides valuable insights for planners and decision-makers interested in directing more trips to their rail transit systems via alterations to the built environment.

Literature review

The rise of ubiquitously available alternative transportation modes has created a new urban landscape comprised of many options for a traveler to make an intra-city trip. But, the implications for public transportation brought by the rise of emerging and existing ridesharing services – the latter of which includes taxi services – has yet to be fully studied by researchers, practitioners, and policymakers (Austin and Zegras 2012; Kamga, Yazici, and Singhal 2015; Wang and Ross 2017). This notion may be somewhat surprising given that researchers have suggested the importance of rideshare modes in shaping many facets of urban transportation systems since the 1970s (Kamga, Yazici, and Singhal 2015; Wohl 1975). In an article dating back to 1975, Wohl suggested that taxis in the US at that time managed to 'handle almost 40 percent more passengers than do all US rapid transit systems combined,' in which he further stressed that taxis even 'carry about 60 percent as many passengers as all bus transit systems.' In a more recent study based on the 1996 and 2001

Canadian Census, Kattan, de Barros, and Wirasinghe (2010) highlighted the role of taxis in reducing parking demand in the urban core and providing transportation services to disadvantaged populations in areas that had relatively limited transit options (e.g. low income, senior citizens). Nonetheless, scholarly investigations on taxis and new ridesharing modes have remained conspicuously sparse compared to the persistent and continuous attention given to other transport modes (Austin and Zegras 2012; Kamga, Yazici, and Singhal 2015; Wohl 1975; Qian and Ukkusuri 2015). Part of the absence of research in this area is likely due to a burdensome task of collecting ridesharing trip data through roadside assessments, as has been conventionally conducted in the past (Yang et al. 2000).

The relatively recent arrival of spatial data sources, which implement GPS tracking systems on a large number of taxi fleets (and by proxy ride-hailing travel modes) across the world, has enabled researchers to shed additional light on a variety of aspects pertaining to taxis, and thus further the literature (Kamga, Yazici, and Singhal 2015; Ferreira et al. 2013). Austin and Zegras (2012) categorized the current evidence base on taxis into three tiers. The first tier focuses on the role that taxis play in addressing the last-mile problem of other public transportation modes considering that taxi serves door-to-door travel (Qian and Ukkusuri 2015; King, Peters, and Daus 2012). The second tier focuses on the regulatory aspects of the taxi industry, while the final tier examines the potential use of optimization tools, often through technological means, to enable more efficient taxi operation and provide more convenient travel for customers.

The inquiry regarding the role of taxis in urban areas tends to center on the relationship between taxis and other mass transit. In a circumstance where taxi services operate in areas served by public transit, researchers have suggested that taxis would theoretically complement transit (Design Trust for Public Space 2007; Schaller Consulting 2006). Several recent empirical studies seem to corroborate that hypothesis, but with some caveats. Using data of Boston taxi trips, Austin and Zegras (2012) developed four models representing different times of the day to estimate the impact of distance to the city's rail and bus routes, while controlling for built environment and socioeconomic measures, on the number of taxi trips generated within a block group. Their study findings suggest taxis are both complementary and substitutional to rail transit. Yang and Gonzales (2014) developed multiple linear regression models representing each hour of the day to estimate the impacts of population, transit access time, median age, education level, income, and total number employment on taxi trips, aggregated to a traffic analysis zone.

Also using New York City taxi data, Qian and Ukkusuri (2015) found that subway accessibility and a set of sociodemographic and built environment factors including education level, proportion of commercial area, and road density positively correlated with taxi trips aggregated at a ZIP code tabulation area. The geographically weighted regression (GWR) used by the authors outperformed their ordinary least squares model, and was thus determined a more appropriate method for dealing with spatial heterogeneity; especially, when considering the disproportionate share of taxi trips in Manhattan compared to the other four boroughs.

A third study using New York City taxi data also addressed the relationship between taxi and transit use (Hochmair 2016). Using a series of nonspatial negative binomial regression models, the results of this study indicated that the number of taxi trips was positively correlated with the number of subway and train stations; however, an inverse relationship was identified between the number of bus stops and taxi trips. The nonspatial regression results should be interpreted with care, though, since the spatially filtered model suggested there was no clear statistical connection between public transit and taxi trips (Yang and Gonzales 2014).

To further understand the nature of taxi trips and how it relates to transit, Wang & Ross (Wang and Ross 2017) proposed a categorization of their relationship as transit-competing, transit-extending, and transit-complementing. Based on 983,053 taxi trips in New York City, they found that transit-extending trips accounted for 7.64% of the observed trips while transit-competing and transit-complementing trips accounted for 58.54% and 33.82% of observed trips, respectively. Using binary logit models and controlling for sociodemographic, built environment, and weather data, their study findings suggest transit-competing taxi trips are likely to decrease during rush hour, indicating that travelers opted to ride transit in order to avoid the expected roadway congestion during peak hour. Whereas, transit-extending taxi trips tend to occur in the morning and evening peak periods and less so in the late night, which may be partially explained by personal security concerns.

Methods

Data development

Washington, DC is a dense urban city with an extensive public transportation system that includes heavy rail, commuter rail, and bus networks. Figure 1 provides a map of the study area identifying the locations of Washington Metropolitan Area Transit Authority (WMATA) Metrorail stations, a quarter-mile transit walkshed around these stations, and the Capital Bikeshare stations within the city boundary and the greater metro region. Forty heavy rail stations, comprising the WMATA Metrorail system, extend across the Washington, DC metropolitan region. In 2016, an average of over 75,000 daily WMATA Metrorail trips originated and terminated in the municipal boundary of Washington, DC. Trip-level ridership data spanning the entire 2016 calendar year was collected for this study, which included more than one half-billion trips that were aggregated based on day of the year and time of day. Of these data, 55,427,089 station-to-station trips were completed within the city boundary of Washington, DC.

These data detailed station-level characteristics including the station identification number, trip entry and exit time, trip travel time, fare payment method, and fare type (full price or discounted). From these data, a composite distance for each station pair that mirrors WMATA's fare policy was calculated by the authors. WMATA's fare policy applies a distance-based charge using the average of rail distance and straight-line distance between stations. Fares are then further distinguished between peak periods (system opening to 9:30am and 3:00pm to 7:00pm) and off-peak periods. Finally, discounted fares for seniors and people with disabilities represented half of the full fare price.

The city also has an extensive regulated taxi service and expansive bikeshare network. In this study, these private taxi services were used as a proxy for all hired-ride services (e.g. Uber, Lyft). Although the authors acknowledge traveler behavior and service usage is likely somewhat different between these alternatives, a lack of publicly available data covering private ride-hailing services necessitated the use of the District's extensive taxi data. In this study sample, a total of 2,469,592 DC Taxi trips that occurred in 2016 had both trip ends

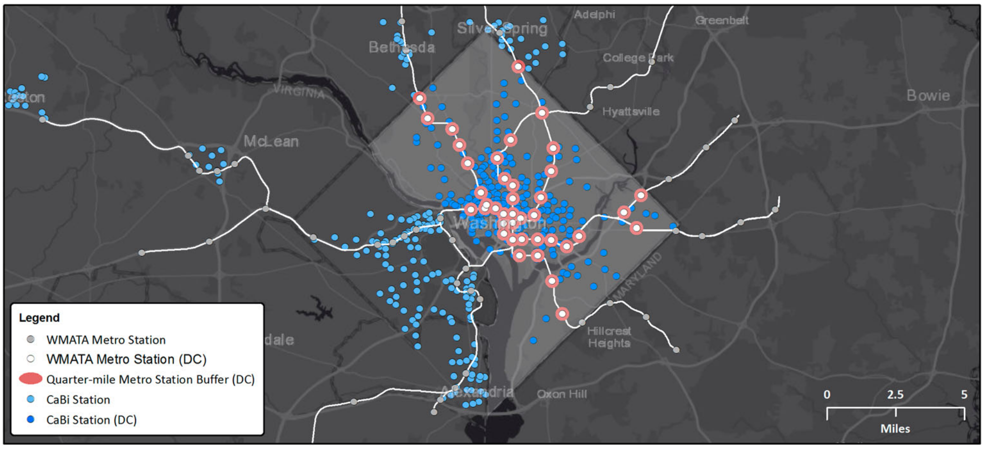

Figure 1. Map of WMATA Metrorail Stations and Capital Bikeshare Stations in Washington, DC.

Table 1. Trip Characteristics by alternative travel mode.

Travel Mode	Average Daily ridership	Average Trip cost	Average Trip distance
WMATA Metrorail	75,706	2.18	3.21
Capital Bikeshare	2039	2.90	1.28
DC Taxi	6710	10.59	1.29

fall within a quarter-mile distance of a Metrorail station. In terms of Capital Bikeshare ridership, there were 740,337 trips in 2016 that both originated and terminated at a biking dock located within the defined transit walkshed. Table 1 summarizes the average daily ridership, trip cost, and trip distance of the study sample.

After compiling the annual taxi, transit, and bikeshare trip-level data within metro station walksheds, information on the minimum and maximum temperatures, average wind speed, and precipitation for the travel day was appended to each record. The inclusion of these control variables is posited to help explain non-policy related reasons as to why travelers might choose or oppose to conduct their travel via taxi or bikeshare rather than rail.

Built environment characteristics and transportation network connectivity is also expected to influence a traveler's decision of whether or not to take public transit or another form of urban mobility option. To control for these effects, built environment and connectivity measures at the block level were calculated by using US Census, American Community Survey (ACS), Longitudinal Employer-Household Dynamics (LEHD), and General Transit Feed Specificastion (GTFS) data. A subset of built and natural environment variables as well as trip-related attributes explored in this study, reduced to only list those variables that are specified in the final model, is provided in Table 2.

To account for as much of the decision process as possible absent detailed travel surveys, we computed all built environment, connectivity, and socioeconomic variables at both the origin and destination of the trip. Adoption of this strategy allowed for measurement of the impact that these variables potentially have on a traveler's decision to take a travel mode when conditions at both the start and end of their trip are considered. The intuition here

Table 2. Variables used in final model specification and associated data sources.

Variable	Data Source
Trip cost	WMATA, DC Taxi, CaBi
Weekend trip	WMATA, DC Taxi, CaBi
Trip during Metrorail operating hours	WMATA, DC Taxi, CaBi
Network trip distance	WMATA, DC Taxi, CaBi
Rain during travel day	NOAA
Mean temperature on day of trip	NOAA
Mean wind speed on day of trip	NOAA
Activity density (origin/destination)	ACS, US Census, LEHD
Employment-population balance (origin/destination)	ACS, US Census, LEHD
Land use entropy (origin/destination)	ACS, US Census, LEHD
Intersection density (origin/destination)	OpenStreetMap
Cul-de-sac density (origin/destination)	OpenStreetMap
Link density (origin/destination)	OpenStreetMap
Connected node ratio (origin/destination)	OpenStreetMap
Beta index (origin/destination)	OpenStreetMap
Network distance to nearest bus stop (origin/destination)	OpenStreetMap

is that should a traveler live and work within a quarter-mile walkshed of a rail station, and their residence is located in an area with a well-connected transportation network, a lack of density at the work end of the trip may be the major factor that resulted in a taxi trip.

Analytic approach

In this study, small samples of detailed travel diaries were substituted with very large samples of detailed trip and environmental data. To isolate trips that directly compete with rail transit, only taxi and bikeshare trips with both their origin and destination within a quarter-mile areal buffer around a rail station were selected. This subset of trips represented those that may be considered easily completed via rail with a short walk to and from a rail station on both trip ends.

To measure the impact that these trip-related and contextual variables have on an individual traveler's decision to use a new shared-use mobility option over public rail transportation, a non-linear multinomial logistic (MNL) regression-based approach was utilized. The MNL approach enabled a comparison of the impacts that changes in the mode specific characteristics and environmental factors have on the probability that a trip between two station areas will occur by a given mode. An MNL modeling approach examines the relative probabilities of a given outcome when that outcome has more than two alternatives. In this study, those trips that occur across three modes (WMATA Metrorail, taxi and bikeshare) were examined. To measure the probability that a given mode will be selected, the probability that traveler (i) will select a given mode (j) was modeled, represented in Equation (1).

$$\sigma_{ij} = Pr\{Y_i = j\} \tag{1}$$

For example, σ_{itaxi} would be the probability that the *i*-th traveler took a taxi for their trip. Since each mode is mutually exclusive, as only unlinked trips were examined, $\sum_j^J = 1, \sigma_{ij} = 1$ for each i (the probability for each traveler sums to one). Our data is based on individual trips for each mode. For these data, $n_i = 1$ (the number of modes a traveler can take per unlinked trip) and Y_{ij} is transformed to a dummy variable with the value of 1 if the *i*-th traveler selected the *j*-the mode and 0 otherwise. Following the mutually exclusive travel mode requirement, $\sum_j y_{ij} = 1$, because one of the dummy variables y_{ij} can take the value of 1 for each trip.

The resulting mode choice probability distribution of all Y_{ij} for the total n_i is a multinomial distribution of the form given in Equation (2).

$$Pr\{Y_{i1} = y_{i1}, \ldots, Y_{iJ} = y_{iJ}\} = \binom{n_i}{y_{i1}, \ldots, y_{iJ}} \sigma_{i1}^{y_{i1}} \ldots \sigma_{iJ}^{y_{iJ}} \tag{2}$$

To model this multinomial mode choice distribution, we assume the log-odds of each mode choice outcome follows the non-linear model of Equation (3). Here, log-odds represent the log transformation of odds which itself is simply the probability of a traveler selecting a specific mode.

$$\mu_{ij} = \log \frac{\sigma_{ij}}{\sigma_{iJ}} = \alpha_j + x_i'^{\beta_j} \tag{3}$$

where α_j is a constant, x' is a vector of independent variables and β_j is our vector of regression coefficients, for $j =$ *taxi*, *bikeshare*, ..., J – 1, .

Metrorail was chosen as the reference case for this MNL analysis to permit a comparison of the choice probabilities of this alternative with the modal decision to choose either taxi or bikeshare. The ability to estimate the effect of trip-related and contextual factors on an individual's decision to select a mode other than Metrorail for travel between two locations was of particular interest in this study. An MNL modeling framework also allowed a comparison of the impact of individual determinates on the probability of one outcome occurring over another. In other words, the model predicts the change in probability that a traveler will choose either a taxi or bikeshare trip over a rail transit trip for each unit change in the corresponding independent variable. The relative risk or odds ratio of each mode along the vector of dependent variables, derived by the exponentiation of each regression coefficient ($\exp(\beta_j)$), is also reported. This calculation provides an elasticity-like term describing the likelihood that a given traveler (*i*) will choose a mode (*j*) *over* our reference mode of WMATA Metrorail given a one unit change in the corresponding independent variable.

Results

Of the trips for the three travel modes that originated and terminated within a quarter-mile of a Metrorail station, the majority were conducted by rail. However, a significant number of trips are assumed to have occurred in these locations on modes other than rail. Table 3 describes the variables used in the MNL analysis. In total, 16 variables were selected to represent the most important trip-related, natural environment, built environment, and network factors that influence alternative travel mode choice.

The results of our MNL model analysis provide the increasing or decreasing likelihood that a trip will occur by a travel mode other than WMATA rail, for each unit change in the underlying variable. Table 4 shows the model results, indicating that all variables were significant to the 99th percentile confidence interval. These factors are all significant due to the large amount of data used to estimate the non-linear MNL model, which sought to assess the probabilities that a traveler will select one mode over another.

The cost of the trip or 'fare' was a significant determinant of whether a traveler will select rail, when modal access is strong, rather than an alternative mode. Model results show that

Table 3. Descriptive statistics of sampled trips ($n = 4{,}837{,}099$).

Variable	Mean	St. Dev.	Min	Max
Trip cost	6.61	5.36	0.01	74.97
Weekend trip	0.23	0.42	0.00	1.00
Trip during Metrorail operating hours	0.96	0.20	0.00	1.00
Network trip distance	2.31	2.14	0.00	13.33
Rain during travel day	0.02	0.16	0.00	1.00
Mean temperature on day of trip	60.64	16.72	20.00	91.00
Mean wind speed on day of trip	8.81	3.27	0.00	23.00
Activity density (origin)	157.39	158.07	0.00	600.00
Activity density (destination)	152.98	154.91	0.00	600.00
Employment-population balance (origin)	317.33	572.52	0.00	3467.00
Employment-population balance (destination)	299.02	555.49	0.00	3467.00
Land use entropy (origin)	0.53	0.15	0.00	0.81
Land use entropy (destination)	0.53	0.15	0.00	0.81
Intersection density (origin)	6.84	6.05	0.00	45.86
Intersection density (destination)	6.84	6.20	0.00	45.86
Cul-de-sac density (origin)	0.42	1.53	0.00	10.79
Cul-de-sac density (destination)	0.43	1.55	0.00	10.79
Link density (origin)	18.10	16.15	0.00	102.52
Link density (destination)	17.96	16.44	0.00	102.52
Connected node ratio (origin)	0.85	0.35	0.00	1.00
Connected node ratio (destination)	0.85	0.35	0.00	1.00
Beta index (origin)	2.24	1.10	0.00	5.00
Beta index (destination)	2.21	1.09	0.00	5.00
Network distance to nearest bus stop (origin)	0.12	0.12	0.00	0.89
Network distance to nearest bus stop (destination)	0.12	0.12	0.00	0.89

when considering Metrorail or taxi, a traveler is 12 times more likely to take a taxi for each dollar that the WMATA fare increases. Similarly, a traveler is five times more likely to use bikeshare for each dollar increase in WMATA fares. Weekend travelers are about 30% more likely to take WMATA Metrorail over bikeshare and 50% less likely to take a taxi. This provides an indication that, at least on weekdays, taxis are more likely to be competitors to rail transit, particularly when the cost of the taxi trip compares favorably.

The idea that rail trips primarily serve as a commute-based mode while our two alternative shared-mobility modes compete directly for other trip purposes is reinforced by Figure 2. The graphic shows the distribution of trips by mode and time of day. During peak periods rail is the dominate mode, but bikeshare and taxi are heavily concentrated in the urban core where employment entropy is high. Evening off-peak trips occurring in the core are highly centered towards taxi trips, while the light rail usage tends to be more spread out across the study area.

Trip distance also plays a significant role, with travelers about 70% and 85% less likely to take bikeshare and taxi, respectively, with each mile increase in trip distance. Bikeshare riders are more likely to take rail as trip distances increase, showing the significant impact an additional mile of peddling has on riders. Taxis are dramatically less attractive than rail for each additional mile of travel which is likely a result of the high cost associated with this mode.

In terms of the impact of weather on mode choice, model results indicate that travelers are about 40% less likely to use bikeshare on days with measurable rainfall, but 1.5% more likely to cycle for each degree increase in mean temperature. Wind speed seems to have a marginal effect on the decision to use either of the alternative modes.

Table 4. Multinomial logistic regression (MNL) model results.

Reference Case:	Metrorail	
Alternative Mode Choice:	Bikeshare	Taxi
Independent Variable	*Coefficient*	*Coefficient*
(constant)	0.001	0.000
Trip cost	5.537	12.697
Weekend trip	0.724	0.525
Trip during Metrorail operating hours	1.495	0.400
Network trip distance	0.318	0.157
Rain during travel day	0.635	0.742
Mean temperature on day of trip	1.015	0.998
Mean wind speed on day of trip	0.991	1.003
Activity density (origin)	1.000	1.002
Activity density (destination)	1.001	1.002
Employment-population balance (origin)	1.000	1.000
Employment-population balance (destination)	1.000	1.000
Land use entropy (origin)	34.462	17.606
Land use entropy (destination)	53.886	28.614
Intersection density (origin)	1.149	1.030
Intersection density (destination)	1.180	1.093
Cul-de-sac density (origin)	0.766	0.808
Cul-de-sac density (destination)	0.728	0.757
Link density (origin)	0.951	0.980
Link density (destination)	0.944	0.962
Connected node ratio (origin)	4.060	4.338
Connected node ratio (destination)	2.700	3.232
Beta index (origin)	0.883	0.955
Beta index (destination)	1.013	1.054
Network distance to nearest bus stop (origin)	4.945	13.306
Network distance to nearest bus stop (destination)	7.160	15.453
Interaction Variables		
Activity density (origin * destination)	1.000	1.000
Employment-population balance (origin * destination)	1.000	1.000
Land use entropy (origin * destination)	0.003	0.003
Intersection density (origin * destination)	0.997	0.998
Cul-de-sac density (origin * destination)	1.008	1.023
Link density (origin * destination)	1.000	1.000
Connected node ratio (origin * destination)	0.810	0.665
Beta index (origin * destination)	0.923	0.930
Network distance to nearest bus stop (origin * destination)	0.002	0.000
Model Summary		
Akaike Information Criterion (AIC)	2,559,070	

Notes: All independent and interaction variables significant at $p < .01$ level.

While the natural environment determinants of mode choice are important to recognize, a primary objective of this study is to uncover environmental factors that planners may perceivably alter to encourage travelers to adopt public transit over alternative non-public modes. Accordingly, this study examined the influence of three land development measures and six network connectivity measures, specified at each trip end, on mode choice. Activity density and employment-population balance had virtually no influence on a traveler's decision to take an alternative mode; however, employment entropy at both ends of the trip had an outsized impact on mode choice.

Travelers are about 34 to 53 times more likely to choose bikeshare over rail as the diversity of employment options increased. We attribute this effect to the increased level of

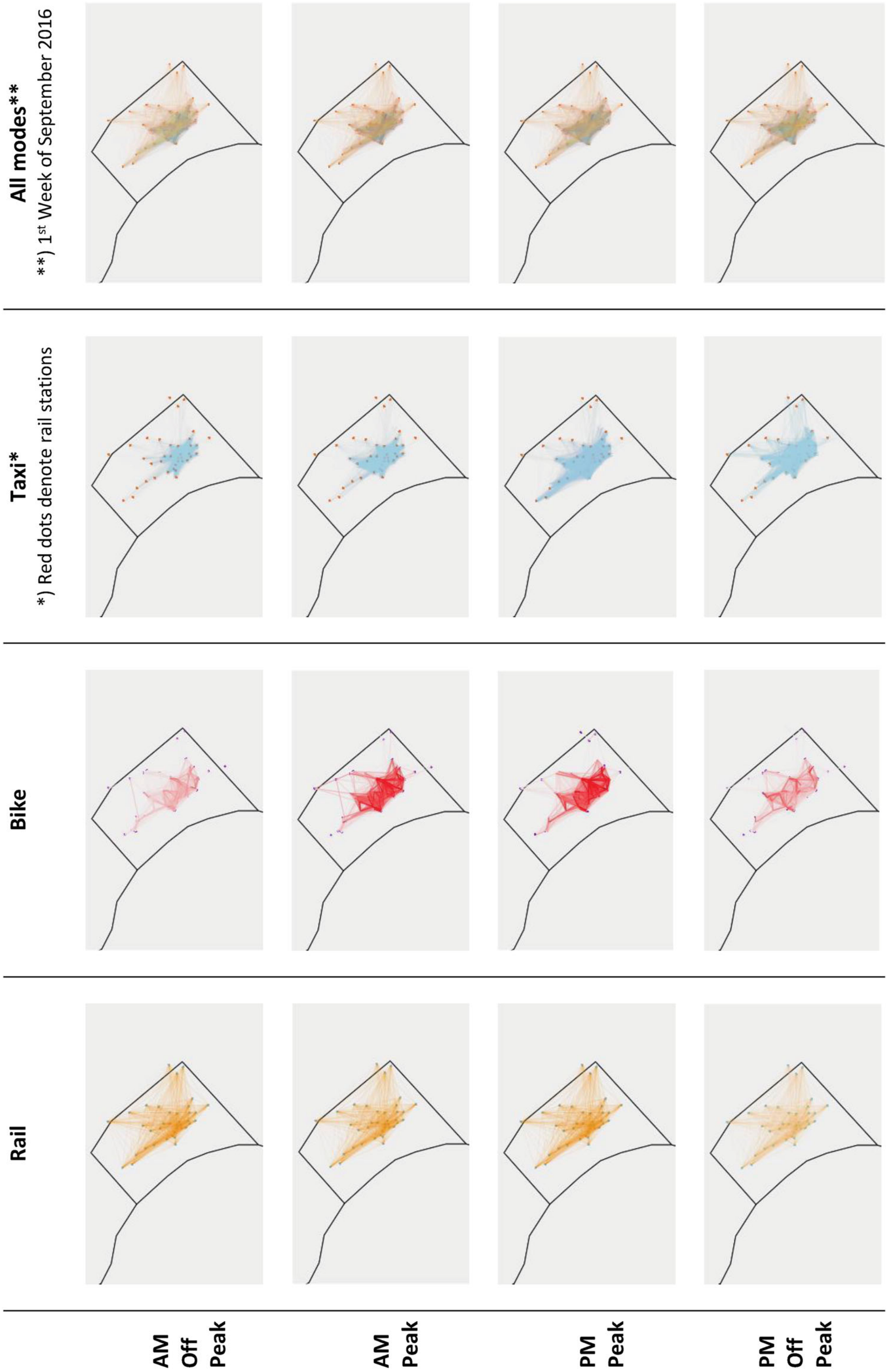

Figure 2. Trip Distributions by Time Period Across Travel Modes in Washington, DC during September 2016.

accessibility, which means travelers could accomplish multiple tasks within a more confined geographic area rather than necessitate travel by rail to conduct activities that are more spatially separated. There is a slightly smaller impact for taxis, with travelers about 17 to 28 times more likely to choose a taxi when the origin or destination have a highly-diverse set of employment options. The tendency for travelers to favor alternative modes over public transit when the diversity of employment opportunities is higher likely indicates that rail serves a more limited set of travel purposes. Commute trips are primarily conducted by rail, while travelers may prefer shared-ride modes when conducting non-work travel.

In regard to network connectivity, intersection density at the destination was a significant determinant of a traveler choosing a travel mode. While there is a slight increase in bikeshare and slight decrease in taxi trips when intersection density at the origin increased, the modal decision is primarily influenced by the characteristics of the destination. Travelers are about 10% more likely to take bikeshare with each unit increase in intersection density at the destination and about seven percent more likely to take a taxi. The results indicate that higher rail is less attractive when the destination has a higher density road network. Link and cul-de-sac density both increase the likelihood that travelers will take transit while the connected node ratio, a measure of the ratio of three- and four-way intersections to all intersections, also pushes individuals away from transit and toward alternative shared-use travel modes.

Finally, the potential interaction between origin and destination variables was modeled to determine which trip end characteristic had a stronger impact on the decision-making process. Generally, the same factor at either end of the trip had an equal influence on mode choice with notable exceptions for land use entropy and the connected node ratio. As described above, travelers were much more influenced by greater land use diversity and a traditional gridded street pattern at the destination end of their trip.

Conclusions

The presence of alternative shared-use travel options such as bikeshare, taxi, and ride-hailing services (e.g. Uber, Lyft) appear to compete with transit, but are not likely to fundamentally alter the viability of public transit systems. However, as the funding resources for public transportation services continue to shrink at a staggering rate, the retention of its ridership is more important than ever to maintaining the vitality of transit systems. Therefore, it is critical for planners and transport policymakers to better understand the reach of these non-public transportation options. This study investigated the role of the built environment, natural environment, and other contextual factors in influencing an individual's decision to use bikeshare or taxi services for travel between activity locations adequately served by transit. In doing so, a multinomial analysis was conducted on a big data set of a half-billion transit, taxi, and bikeshare trips conducted within Washington, DC.

Study findings confirmed that travelers of public transit and emerging shared-use mobility options are cost sensitive. Results revealed that when considering rail or taxi, a traveler is 18 times more likely to take a taxi for each dollar that the WMATA fare increases. Similarly, a traveler is seven times more likely to choose bikeshare rather than Metrorail for each dollar increase in transit fare. From the built environment perspective, travelers appear to favor alternative modes over rail when job diversity is high. In addition, fewer roads and cul-de-sacs, particularly in relationship to the number of intersections, make shared-use mobility modes more attractive than rail transit. These findings are likely an indication that rail is more often chosen for commute trip purposes, while shared-use modes may be preferred when travelers are conducting non-work-related tasks.

While these factors are influential in mode choice decisions, planners and policymakers can modify policies that influence the factors that impact public transit ridership. Offering transit service that is more conducive to a range of activities rather than catering to commute trips will make rail relatively more attractive to riders. In turn, the continued work in reducing the prevalence of cul-de-sacs and instituting policies that reduce the number of road links in the network may encourage the adoption of alternative travel modes such as bikeshare. The establishment of greater efficiencies in the built environment, rather it be via diversifying the types of locations near a rail station to better serve a range of activities or by enhancing the network connectivity in a station area, carries the prospect of ensuring that rideshare modes are either extending or complementing existing rail services.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Steven R. Gehrke http://orcid.org/0000-0001-9355-5571

References

Austin, D., and P. Zegras. 2012. "Taxicabs as Public Transportation in Boston, Massachusetts." *Transportation Research Record: Journal of the Transportation Research Board* 2277: 65–74. doi:10.3141/2277-08.

Design Trust for Public Space. 2007. *Taxi 07: Roads Forward*. New York City Taxi and Limousine Commission.

Ferreira, N., J. Poco, H. T. Vo, J. Freire, and C. T. Silva. 2013. "Visual Exploration of Big Spatio-Temporal Urban Data: A Study of New York City Taxi Trips." *IEEE Transactions on Visualization and Computer Graphics* 19 (12): 2149–2158. doi:10.1109/TVCG.2013.226.

Hochmair, H. H. 2016. "Spatiotemporal Pattern Analysis of Taxi Trips in New York City." *Transportation Research Record: Journal of the Transportation Research Board* 2542: 45–56. doi:org/10.3141/2542-06.

Kamga, C., M. A. Yazici, and A. Singhal. 2015. "Analysis of Taxi Demand and Supply in New York City: Implications of Recent Taxi Regulations." *Transportation Planning and Technology* 38 (6): 601–625. doi:10.1080/03081060.2015.1048944.

Kattan, L., A. de Barros, and S. C. Wirasinghe. 2010. "Analysis of Work Trips Made by Taxi in Canadian Cities." *Journal of Advanced Transportation* 44 (1): 11–18. doi:10.1002/atr.102.

King, D. A., J. R. Peters, and M. W. Daus. 2012. "*Taxicabs for Improved Urban Mobility: Are We Missing an Opportunity?*" Presented at the transportation research board 91st annual meeting Transportation Research Board.

Qian, X., and S. V. Ukkusuri. 2015. "Spatial Variation of the Urban Taxi Ridership Using GPS Data." *Applied Geography* 59: 31–42. doi:10.1016/j.apgeog.2015.02.011.

Schaller Consulting. 2006. *The New York City: Taxicab Fact Book*. Schaller Consulting, Brooklyn.

Wang, F., and C. L. Ross. 2017. "New Potential for Multimodal Connection: Exploring the Relationship Between Taxi and Transit in New York City (NYC)." *Transportation*, 1–22. doi:10.1007/s11116-017-9787-x.

Wohl, M. 1975. "The Taxi's Role in Urban America: Today and Tomorrow." *Transportation* 4 (2): 143–158. doi:10.1007/BF00164684.

Yang, C., and E. Gonzales. 2014. "Modeling Taxi Trip Demand by Time of Day in New York City." *Transportation Research Record: Journal of the Transportation Research Board* 2429: 110–120. doi:org/10.3141/2429-12.

Yang, H., Y. W. Lau, S. C. Wong, and H. K. Lo. 2000. "A Macroscopic Taxi Model for Passenger Demand, Taxi Utilization and Level of Services." *Transportation* 27 (3): 317–340. doi:10.1023/A:1005289504549.