An Alternative to Slow Transit, Drunk Driving, and Walking in the Rain: An Exploratory Study of Ridesourcing Trip Patterns and Mode Choice

1. Introduction

One of the most dramatic changes to urban transportation in recent years has been the rise of app-based transportation providers such as Uber, Lyft, DiDi Chuxing, Ola Cabs, and Grab. Sometimes called real-time ridesharing or transportation network companies, these companies typically connect customers seeking transportation with drivers of personally-owned vehicles via a mobile phone app. After Rayle et al. (2016) we use the term *ridesourcing* for these services, since rides are purchased and usually not shared among multiple riders. In less than ten years since the founding of market leader Uber in 2009, ridesourcing companies have seen rapid growth in many cities worldwide, and by 2018 several market research firms estimate roughly one-third of Americans had ever used these services (Molla, 2018). An analysis of the 2017 US National Household Transportation Survey found 9.8% ± 0.4 of respondents had used ridesourcing at least once in that year, and although their use was growing rapidly ridesourcing encompassed 0.50% ± 0.08 of all trips (Conway et al., 2018).

The advent of a new mode of urban transportation has resulted in the urgent need for research, especially that which investigates the geographic nature of this mode of travel and which draws on detailed information from travelers. To meet this need, this paper reports on results obtained from an exploratory survey of ridesourcing riders in Washtenaw County, Michigan, which includes the cities of Ann Arbor and Ypsilanti. Although the study is limited by the use of a convenience sample resulting in unknown representativeness of the respondents, the resulting rich linked demographic and travel information is used to analyze the travel geography and decision-making among respondents. The findings show users and younger and more female than the population at large, and most trips are chosen over transit. A geographic analysis of the trips show most occur in a relatively few, high-density neighborhoods, although the data suggest important differences between city-based trips and those originating in suburban areas.

1.1 Background

The rapid adoption of ridesourcing by urban travelers has important consequences for urban transportation systems. Although more convenient and often less expensive than traditional taxis, ridesourcing users tend to be well-educated, higher income, employed, and residing in high-density areas (Conway et al., 2018; Dias et al., 2017). Others have documented unique barriers for their adoption by low-income users such as digital access and literacy (Dillahunt et al., 2017). Furthermore, there is a growing perception that the benefits ridesourcing offers riders have been accompanied by undesirable public side-effects, such as a decline in public transit ridership and an increase in driving and traffic congestion in some cities (San Francisco County Transportation Authority, 2017). A recent national survey found that ridesharing users reported a decrease in public transit use, and that approximately one-half of trips would have been made by walking, biking, transit, or avoided altogether (Clewlow and Mishra, 2017). As a consequence of these findings, this paper examines ridesourcing from a sustainable mobility paradigm, which replaces the traditional transportation focus on individual cost-minimization and system focus on optimization with an interest in the social factors influencing travel and transportation system sustainability (Banister, 2008; Sultana et al., 2017).

Research is needed on ridesourcing for two reasons. First, to shed light on their current use and more deeply understand the spatial nature of this new transportation mode today. Second, research on ridesourcing today may shed light on future urban transportation issues. This is because ridesourcing companies may be the first site of mass deployment of automated vehicles in the future, since they are among those most intensively investing in this technology. Since this is expected to further reduce the cost of ridesourcing services, understanding their use today may shed light on what might emerge as an ever more widely used transportation mode tomorrow—automated ridesourcing.

A growing body of research has resulted in a deeper understanding of ridesourcing, but two topics have been relatively neglected: the types and locations of specific travel destinations for ridesourcing trips, and the particular motivations for choosing ridesharing over other available transportation modes. These questions are difficult to answer due to the limited access to ridesourcing company data and difficulty collecting information from representative samples of users. Nonetheless, two recent reports by public agencies characterize the extent of ridesourcing in urban centers. Through analysis of data obtained via creative data collection from Uber and Lyft’s public-facing APIs, the San Francisco County Transportation Authority (SFCTA) mapped ridesourcing pickup hotspots, showing high usage in San Francisco’s downtown area, but since the study relies on system-level data it did not analyze specific trips or riders (San Francisco County Transportation Authority, 2017). A study conducted by Boston's Metropolitan Area Planning Commission utilized in-vehicle rider intercept surveys to provide insights into rider demographics and trip characteristics, showing that many ridesourcing trips were chosen as substitutes for public transit (42%) or walking and biking (12%) (Gehrke et al., 2018). However, this study did not collect detailed origin and destination data and therefore was only able to map the density of trips beginning or ending at rider's homes, summarized by zip codes. Focused on U.S. metropolitan regions with the first- and third-highest per capita use of ridesourcing services, it is unclear how these findings translate to other types of cities (Conway et al., 2018).

Academic studies provide some greater detail on the issues of trip characteristics and traveler motivations. Utilizing intercept surveys conducted in known ridesourcing hotspots in San Francisco, Rayle et al. (2016) explores rider demographics, trip details, and mode choice, although it is difficult to know whether the sampling approach introduces a bias in the results. Researchers with access to ridesourcing system data have gained operational insights, but are not able to examine rider backgrounds or decisions (Dong et al., 2018; Hughes and MacKenzie, 2016; Komanduri et al., 2018; Wang and Mu, 2018). As a consequence, the present study investigates the research question: *What explains why travelers choose ridesourcing over other travel modes available to them: driving a personal automobile, riding transit, walking, or biking?*

The geographic nature of ridesourcing travel is also not well known. Although there is a growing awareness of the characteristics of places with high ridesourcing demand, the exact relationships between ridesourcing use and place have not been carefully examined. Hoffman et al. (2016) found ridesharing and public transit are both substitutes and complements, since their use in particular areas is correlated, but that ridesourcing use increased after local subway stations closed. Yet, this aggregate observational study isn't able to probe individual travelers regarding their decisions. The vague findings about ridesourcing demand stands in contrast to other forms of travel behavior, such as mode choice or overall vehicle kilometers traveled, which have been subjects of intensive empirical research (e.g., Ewing and Cervero, 2001). This research stream typically analyzes travel behaviors against a set of built environment factors, including density, diversity, design, and destinations. Yang et al.'s (2018) study of taxi demand in Washington, D.C. uses a similar design as these studies, finding demand related to population and employment density but not mixed land uses, and the paper calls for new research to see whether ridesharing follows similar patterns. Therefore, the study seeks to answer the second research question: *What are the built environment characteristics which explain ridesourcing trip demand?* To contextualize these results, the demographics of the survey respondents and the trip destination categories are compared with those obtained by other researchers.

2. Methods

To understand why travelers choose ridesourcing over other travel models, we utilized a voluntary survey, available online via a responsive survey tool suitable for mobile phones or desktop computers. The survey contained sections about the respondent's demographic and household characteristics, as well as trip-level information for up to five recent ridesourcing trips. We advertised the survey in Washtenaw County, Michigan in the months of April and May 2018, through several means: (1) geographically targeted Facebook and Google Adwords ads, (2) flyers posted at busy public places, and (3) an advertisement displayed on the interior of 25 city buses for one month. Google Adwords resulted in 160 visitors and Facebook resulted in 517 visitors to the survey landing page, but visitors from the flyers and bus ad were not tracked.

We obtained a total of 189 valid responses, defined as respondents who reported using a ridesourcing service at least once in the past year on the survey's first question. These respondents provided information for 195 trips with valid information for both the origin and destination. The provided addresses were geocoded using a combination of OpenStreetMap's Nominatim geocoding API and Google geocoding API. For both APIs, we set the search area variable to Washtenaw County. During geocoding, 98.5% of the addresses (384 out of 390) were matched. The resulting data were mapped using the ArcGIS software, and the statistical analysis conducted via Stata.

For the destination analysis, the trips were summarized to the 251 Census block groups in Washtenaw County using a spatial join function. This analysis made use of the US EPA Smart Location Database (SLD), a nationwide geographic data resource for analyzing travel behavior (Ramsey and Bell, 2014). It includes variables describing characteristics such as housing density, diversity of land use, neighborhood design, destination accessibility, transit service, employment, and demographics. Most attributes are available for every census block group in the United

States. The destination analysis also made use of two additional variables which were constructed to complement those in the SLD due to the unique nature of ridesourcing travel described by previous research. The first is the density of bars and restaurants for each Block Group. To create this variable, we searched the D&B Hoovers commercial database for all businesses in Washtenaw County categorized under NAICS code 164 (Restaurants and Bars). The resulting records were geocoded using the same method described above, and the density was computed by calculating the kernel density (search radius of 1,790 m, determined by default algorithm), and then applying zonal statistics to find the mean density for area within each census block group. The kernel density geoprocessing used default searching radius and cell size. We also created a dummy variable for block groups included in the area served by the Ann Arbor Downtown Development Authority (DDA), which encompasses the downtown area. This area contains the highest density of commercial land uses in the study area, and where almost all parking is provided DDA at a modest hourly rate (around $1.60 USD/hour) through parking garages, lots, and on-street metered spaces.

In order to understand how the built environment factors related to ridesourcing use, we conducted a multivariate analysis relating the trip density (or number) for each block group with these built environment variables. We fit two types of multivariate regressions on our data. For the trip density outcome, we fit a linear regression to explore relationships. For the number of trips for each block group, we fit a Poisson regression appropriate for count data. Since many block groups had no trips, we considered fitting a zero-inflated model, which model two processes: one set of variables explaining whether trips occur, and another to predict the number (Long and Freese, 2006). However, we decided this was not theoretically appropriate in our case since trips can (and did) occur in all parts of the county. We decided the Poisson regression is the most appropriate model, since it is fit based on the full set of observations and zero-trip block groups reflect areas of low demand.

Washtenaw County, Michigan had a population of 344,791 in the 2010 Census, and is part of the Detroit-Warren-Ann Arbor Combined Statistical Area. Located west of Metropolitan Detroit, the two primary cities in the County are Ann Arbor and Ypsilanti, and the county contains many smaller cities, villages, and townships in rural areas. The largest employer is the University of Michigan, a large public university which operates a major regional hospital complex. Separate from the University there are clusters of information technology and automotive-related firms. The largest industries by employment are healthcare and social assistance (27.4%), retail trade (12.3%), accommodation and food services (11%), professional, scientific and technical services (9.9%), and manufacturing (9.8%) (U.S. Census Bureau, 2012). Public bus transportation is provided by the Ann Arbor Area Transportation Authority (AAATA) in Ann Arbor and Ypsilanti, with limited services in some surrounding townships. The University of Michigan operates multiple bus routes connecting University properties. Sidewalks are available on almost all streets within the city, and many major routes have bike lanes.

Ridesourcing has been available in Washtenaw County since 2014, with Uber entering the market in April and Lyft in May (Allen, 2014). The AAATA system ridership has increased from 2014, reaching record ridership in fiscal year 2017 (Stanton, 2018). However, this is likely due in part to a service expansions funded by a transit tax approved in May 2014, as well as continued commercial and residential growth in areas served by transit, therefore this study cannot characterize the specific impact of ridesourcing on transit ridership.

3. Results

The study results are presented below in four parts. First, to contextual the survey respondents, the demographic profile of the resulting ridesourcing users is compared with the demographics of the county, and that obtained by Rayle (2017). Second, trip destination types and spatial distribution are presented. Third, data about respondent's choices to utilizing ridesourcing over other modes are presented. Fourth, the results of the analysis of built environment factors are presented.

3.1 Rider Demographics

The demographics of ridesourcing users who responded to the survey are presented in Table 1, which also contains similar demographics from Rayle et al. (2016) and the American Community Survey 1-year estimates for Washtenaw County for 2016 (the most recent year available). Overall, respondents had a wide variation of incomes, although most were under 34 (67%) and female (67%). Many respondents (32%) reported only some college, although a majority had already obtained a bachelor's or graduate degree. Respondent's race roughly mirrored the county, although the percentage of white respondents (77%) slightly exceeded the county (74%). Although many respondents reported having no vehicle available to them (27%), the majority had vehicle access.

Table 1. Ridesourcing survey respondent demographics.

Demographic Categories	Ridesourcing #	Ridesourcing %	Rayle (2017)	Washtenaw County ACS 1-year (2016)
Household Income				
Less than $25,000	40	38	n/a	19.8+/-0.7
$25,000 - $50,000	24	22	n/a	21.3+/-0.8
$50,000 - $100,000	21	20	n/a	27.8+/-0.8
$100,000 - $200,000	17	16	n/a	23.1+/-0.6
More than $200,000	3	3	n/a	8.0+/-0.4
Age				
18-24	32	33	16	18.8+/-0.2
25-34	33	34	57	14+/-0.1
35-44	15	15	19	12+/-0.1
45-54	10	10	6	12+/-0.1
55-64	6	6	1	12+/-0.1
65-74	2	2	0	8+/-0.1
75+	0	0	0	6+/-0.1
Gender				
Female	72	67	40	51+/-0.1
Male	33	31	60	49+/-0.1
other	2	2	n/a	n/a
Vehicle Availability				
1	47	44	n/a	23+/-0.2
2	22	21	n/a	44+/-0.2
3+	9	8	n/a	29+/-0.2
None	29	27	43	4+/-0.1
Educational Attainment				
High school or less	7	7	n/a	20+/-1.26
Some college or associate’s degree	34	32	n/a	7+/-0.8
Bachelor’s degree	31	29	54	27+/-1.1
Graduate or professional school degree	35	33	27	28+/-1.3
Race and Ethnicity				
White	82	77	n/a	74+/-0.0
Asian	7	7	n/a	9+/-0.0
Black or African American	10	10	n/a	12+/-0.1
Two or more or some other race	8	7	n/a	6+/-0.1

3.2 Trip Origins and Destinations

The location of trips origins and destinations from survey trips is shown in Figure 1, which shows the count of origins and destinations for each block group. Many block groups in low-density rural areas, as well as many predominantly residential areas within the cities of Ann

Arbor and Ypsilanti had no trips in the dataset. All remaining block groups had between 1 and 10 trips, except for two: one at a shopping mall with 12, and one in downtown Ann Arbor with 45.

To facilitate comparison, these counts were divided by the block group area (Figure 2).

Figure 1 - Map of Origins and Destinations

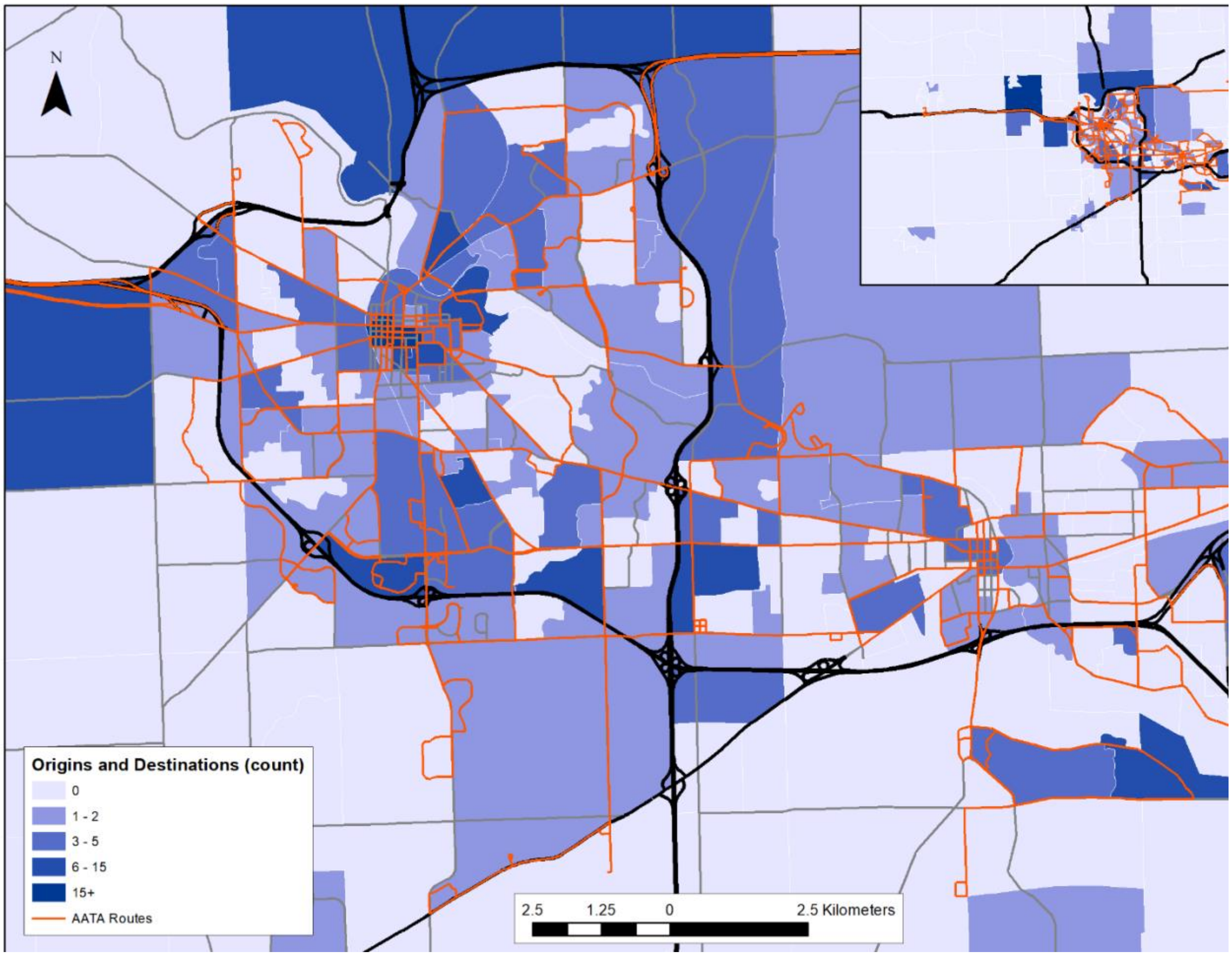
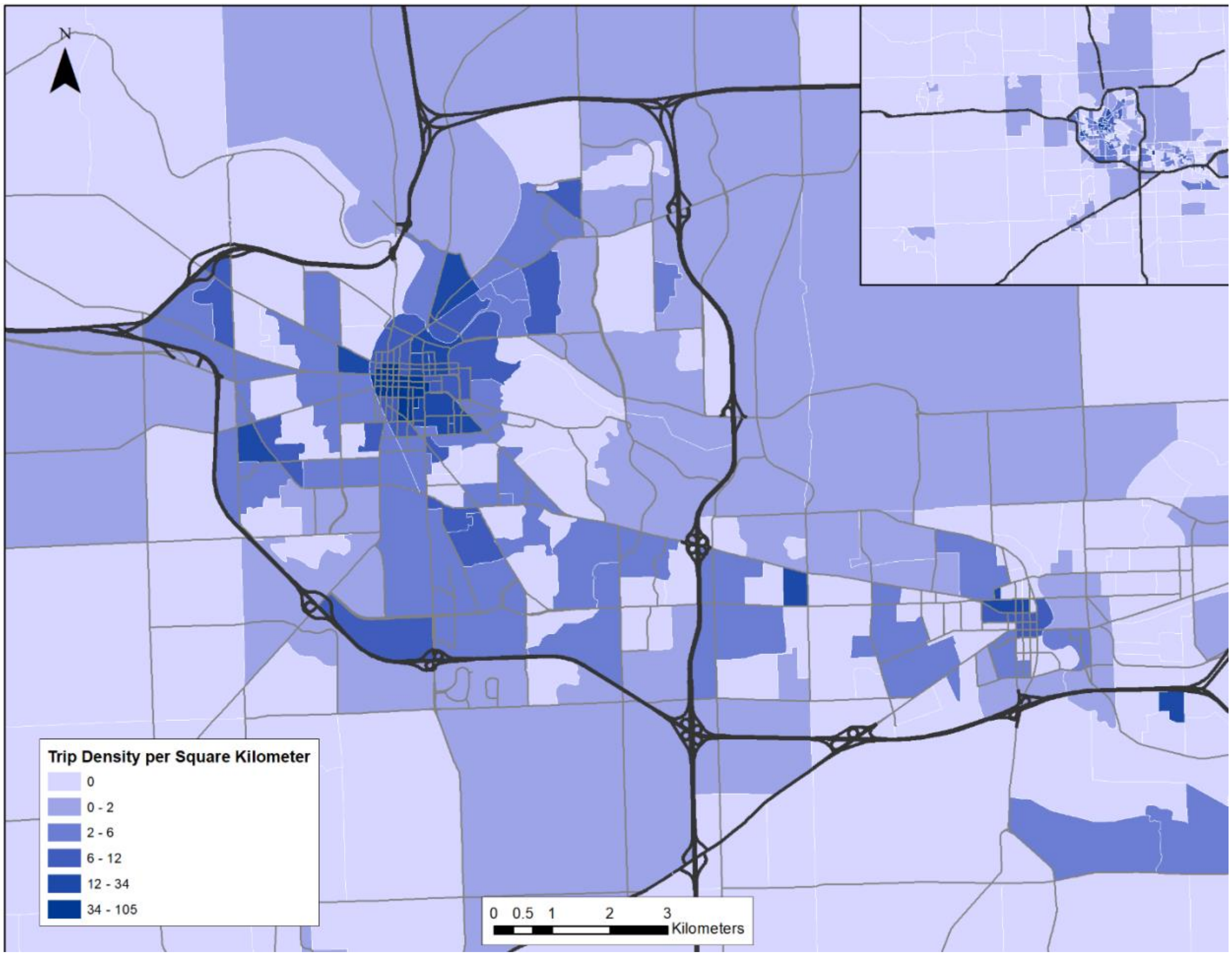


Figure 2 – Ridesourcing Trip Density



The information provided about destination type is reported in Table 2. The most popular destinations were home (32%), work or school (20%), or social and recreational (18%), with a smaller number of trips for other purposes, like the airport, medical or dental services, or shopping.

Table 2. Destination Types

Type	All		DDA		City of Ann Arbor		Outside of city boundaries		Totals	Percentage of Total
	O	D	O	D	O	D	O	D		
Home	102	60	5	1	67	43	5	16	162	43%
Work or School	21	36	4	6	19	26	5	1	57	15%

Social or recreational	24	34	12	19	20	29	1	2	58	15%
Medical or dental services	6	12	1	0	4	7	4	1	18	5%
Family or personal obligations	4	8	1	0	3	5	2	0	12	3%
Shopping or errands	12	8	1	1	6	6	0	3	20	5%
Airport or train station	6	12	0	0	2	5	3	0	18	5%
Arts and culture	3	7	2	2	3	4	0	0	10	3%
Other	9	12	5	2	10	5	4	1	21	6%
Totals	187	189	31	32	134	131	24	24	376	100%

O: Origins; D: Destinations

3.3 Trip Choice Analysis

For each trip provided, we asked respondents whether four alternative modes of travel were available to them for this trip, and if they answered yes, we asked more detailed questions on why they chose to use ridesourcing over the alternative mode. Among the trips, 63% were chosen over transit, 36% over driving a personal vehicle, 32% over walking, and 18% over biking. The survey allowed respondents to provide choice information for multiple modes. To simplify the presentation, reasons which received a mean importance rating corresponding with the option "Slightly important" or less (ratings of <2) are reported in the table captions.

The ratings for provided reasons for choosing ridesourcing over transit is shown in Table 3. The top-rated reason is frequency or speed of route (4.3), and the second and third top-rated reasons are to avoid walking and due to the weather, although only the frequency or speed of route received a mean rating greater than the option for very important (4).

Table 3. Reasons for choosing ridesourcing over transit.

Reason	**Mean importance (Std. Dev.)**
Frequency or speed of route	4.3 (1.2)
Less walking	3.4 (1.5)
Weather	3.2 (1.6)
Transit ease of use	3.1 (1.5)

Transit less comfortable and pleasant	2.7 (1.5)
Concern about Transit reliability	2.4 (1.5)
Transit service hours concern	2.2 (1.5)
Carry Heavy Item	2.1 (1.5)

Scale: Extremely important (5), very important (4), moderately important (3), slightly important (2), not important at all (1). Reasons with mean rating for slightly or less: less expensive for travel with a group (1.6), transit knowledge (1.7), and personal safety (1.8), more convenient for travel with a group (1.9). n=113-118.

The ratings provided for reasons for choosing ridesourcing over driving a personal vehicle, walking, and biking are shown in Table 4. The highest-rated reason for not using a personal vehicle is "alcohol, tiredness, or medication," with parking cost and availability also rated as moderately important. Lack of a driver's license and vehicle characteristics were not highly rated reasons. Weather is the top-rated reason for both walking and biking, with distance also moderately important for walking, and bike availability and infrastructure each rated between slightly and moderately important for biking.

Table 4. Reasons for choosing ridesharing over personal vehicle, walking, and biking.

	Reasons	**Mean Importance rating (Std. Dev.)**
Personal Vehicle	Alcohol, tiredness, medication	3.3 (1.9)
	Parking cost or availability	3.0 (1.6)
	Stress	2.7 (1.3)
Walking	Weather	3.4 (1.6)
	Distance	3.2 (1.4)
Biking	Weather	3.2 (1.4)
	Availability of bike	2.8 (1.8)
	Infrastructure	2.4 (1.6)

Reasons with mean rating of slightly or less for driving: driver's license (1.1), injury or illness (1.4), characteristics of vehicle (1.2), personal vehicle reliability (1.2), sustainability (1.5); for Biking: distance (1.8); for walking: infrastructure (1.8). Scale: Extremely important (5), very important (4), moderately important (3), slightly important (2), not important at all (1).
Driving N=62-66; walking N=59, Biking N=32-33.

3.4 Demand Analysis

The set of built environment variables used for the demand analysis is shown in Table 5. Our initial model included variables well-established in the transportation literature for explaining mode choice, falling into the categories of density, land use diversity, design, destination accessibility, and distance to transit (known as the "five Ds") (Ewing and Cervero, 2010) using the EPA Smart Location Database. The additional variables bar and restaurant density and DDA area are shown in Figure 3.

Figure 3. Bar and Restaurant Density and DDA Area

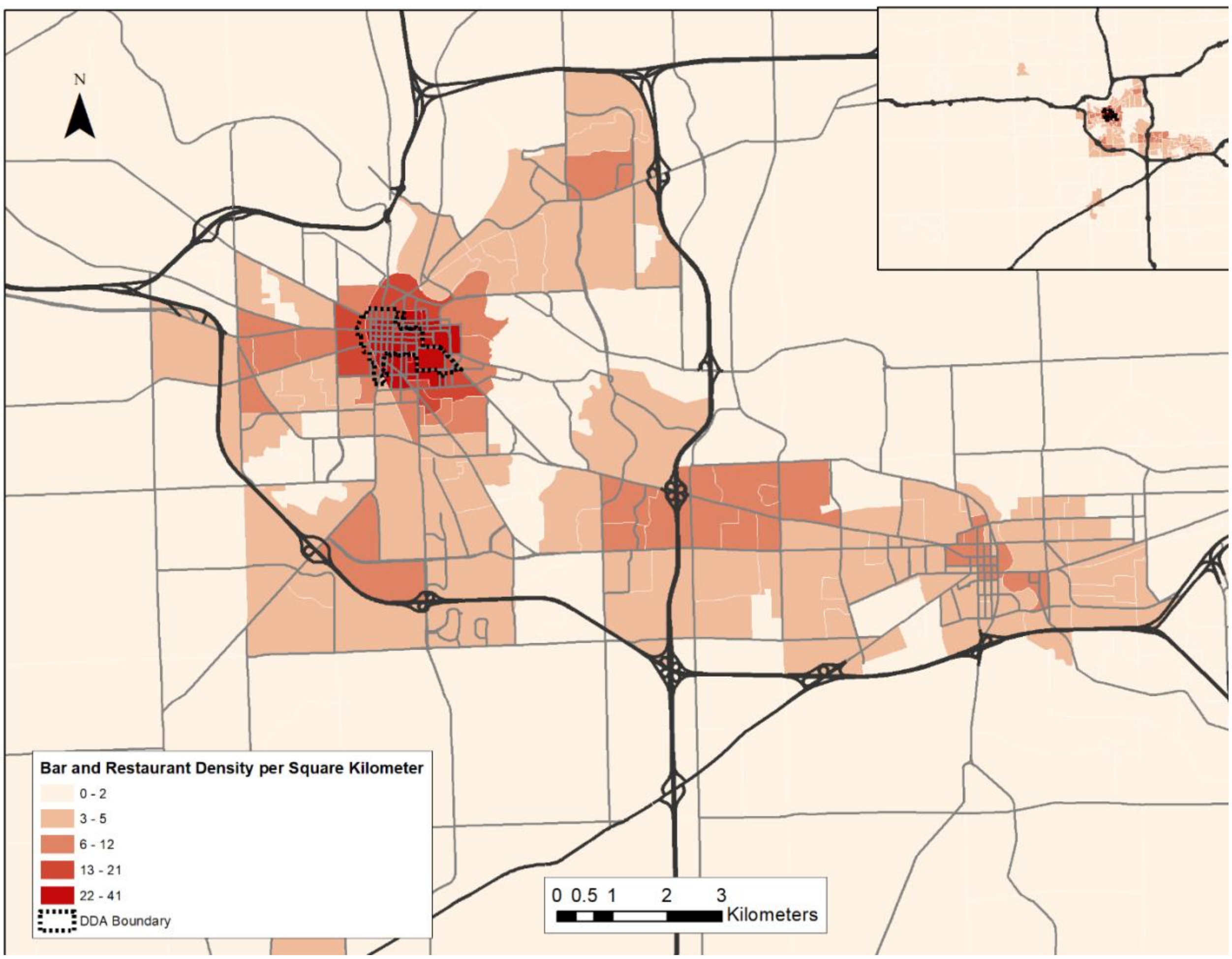


Table 5. Demand Analysis Variables

Category	**Variable**	**SLD Variable Name**	**Description**
Density	Population Density	D1b	Gross population density (people/acre) on

			unprotected land
	Job Density	D1c	Gross employment density (jobs/acre) on unprotected land
Diversity	Land use mix	D2b_E5Mix	5-tier employment entropy (denominator set to observed employment types in the CBG)
	Jobs-housing balance	D2a_EpHHm	Employment and household entropy
Design	Intersection density	D3b	Street intersection density (weighted, auto-oriented intersections eliminated)
	% 4-way intersections	D3bmm4	Intersection density in terms of multi-modal intersections having four or more legs per square mile
Destination accessibility	Job accessibility by auto	D5cr	Proportional Accessibility to Regional Destinations - Auto: Employment accessibility expressed as a ratio of total MSA accessibility
	Job accessibility by transit	D5dr	Proportional Accessibility of Regional Destinations - Transit: Employment accessibility expressed as a ratio of total MSA accessibility
Distance to transit	Distance to nearest transit stop	D4a	Distance from population weighted centroid to nearest transit stop (meters)
Ridesourcing-Specific Variables	Bar and restaurant density	bardensity	Density of businesses categorized under NAICS code 164 (Restaurants and Bars)
	Entertainment job density	E5_ENT10	Density of entertainment industry jobs.
	DDA Area	touch_dda	Dummy variables for block group in DDA area
	Auto Ownership	AUTOOWN0	Percentage of households with access to one or more automobiles.

Although the dependent variable is highly skewed, due to the continuous nature of the variables and exploratory nature of the study we fit a standard multiple linear regression with trip density as the dependent variable. Among the independent variables, 15 of the pairwise correlations are greater than 0.5, with most of these affecting the employment-related variables (See Appendix A). We fit three linear regression models, reported in Table 6 below. To simplify interpretation, beta coefficients are reported. Model 1 includes all variables, Model 2 removes variables without significant coefficients and removes two of the three correlated employment-related variables to avoid multicollinearity, and Model 3 includes an alternative employment variable (office jobs). Auto ownership is included in Model 2 but not Model 3 since it is correlated with office job density (r=0.54). The signs and magnitudes of the significant beta coefficients are consistent across all three models except for the coefficients for employment in Model 1, two of which are negative due to multicollinearity.

The variables with the strongest relationship with trip demand are bar and restaurant density, and entertainment and office job density. Auto ownership is significant in Model 2, but with a small magnitude. Variables with a negative relationship with ridesourcing demand include population density, jobs-housing balance, and DDA area. Model 3 explains roughly 73% of the variation in the dependent variable using five variables.

Table 6. Multivariate analysis of ridesourcing trip demand.

Category	**Variable**	**SLD Variable Name**	**OLS Model 1**	**OLS Model 2**	**OLS Model 3**
Density	Population Density	d1b	-.076	-.189***	-.152***
	Job Density	d1c	-.124**		
	Entertainment jobs density	D1c8_Ent10	-.168**	.338***	
	Office jobs density	D1c8_Off10	.694***		.502***
Diversity	Land use mix	D2b_E5Mix	.036		
	Jobs-housing balance	D2a_EpHHm	-.102**	-.131**	-.097***
Design	Intersection density	D3b	-.020		
	% 4-way intersections	D3bmm4	.027		
Destination accessibility	Job accessibility by auto	D5cr	-.005		
	Job accessibility by transit	D5dr	-.005		
Distance to transit	Distance to nearest transit stop	D4a	.023		
Ridesourcing-Specific Variables	Bar and restaurant density	bardensity	.662***	.771***	.738***
	DDA Area	touch_dda	-.102*	-.130**	-.156***
	Auto Ownership	AUTOOWN0	.008	.133***	
		Adj R-squared	.738	.658	.729

Dependent variable: trip density per square kilometer. Beta coefficients reported. * $P < .10$ **$P < .05$ *** $P < .01$. $N = 251$.

A Poisson regression fit on the count of ridesourcing trips (origins or destinations) for each block group resulting in overall results with some notable variable-level differences. Table 7 shows two models, Model 1 which includes all variables, and Model 2 which includes all variables which were significant along with office jobs density. To facilitate interpretation, a standardized factor change has been provided for the variables in Model 2. This value represents the expected change factor to counts for a standard deviation change in each independent variable. For a one standard deviation increase in job accessibility by transit, the count of ridesourcing trips increases by a factor of 1.559, holding other variables constant. Comparing Model 2 to the results of the linear regression, DDA Area and population density are no longer significant, and intersection density, land-use mix, job accessibility by transit, and distance to nearest transit stop are significant.

Table 7. Poisson Regression of ridesourcing trip demand.

Category	**Variable**	**SLD Variable Name**	**Model 1 Coefficients**	**Model 2 Coefficients**	**Model 2 std. factor change**
Density	Population Density	d1b	-.11		
	Job Density	d1c	.002		
	Entertainment jobs density	D1c8_Ent10	.021		
	Office jobs density	D1c8_Off10	-.010	.084***	1.104
Diversity	Land use mix	D2b_E5Mix	.708***	.579**	1.215
	Jobs-housing balance	D2a_EpHHm	.648*	.826**	1.222
Design	Intersection density	D3b	-.010***	-.009***	.684
	% 4-way intersections	D3bmm4	.007		
Destination accessibility	Job accessibility by auto	D5cr	169.524		
	Job accessibility by transit	D5dr	99.339***	107.422***	1.559
Distance to transit	Distance to nearest transit stop	D4a	6.27e-06***	7.87e-06***	1.476
Ridesourcing-Specific Variables	Bar and restaurant density	bardensity	.029**	.015*	1.089
	DDA Area	touch_dda	-.520		
	Auto Ownership	AUTOOWN0	.001		
		Pseudo R-squared	.347	.340	

Dependent variable: count of trip origins and destinations. Beta coefficients reported. * $P < .10$ **$P < .05$ *** $P < .01$. N = 251.

4. Discussion

We begin with a discussion of the demographics of the survey respondents, and proceed to discuss the results of the study's two research questions. A section discussing the significance for an understanding of the geography of urban travel concludes.

4.1 User Demographics

By definition, convenience samples do not result in statistically representative samples from a broader population, however a consideration of the results of this study in light of other works helps contextualize the findings. Although statistical methods exist for making inferences from non-representative samples (such as weighting), they require precise information about the population which does not exist for ridesourcing. Furthermore, even if precise population information existed, the user population is rapidly changing. Whereas a Pew Research survey found that 15% of Americans in 2015 had used a ridesourcing service, private sector data providers who use credit card data to track spending patterns found that between 32% and 43% of card holders had used a ridesourcing service in 2018 (Molla, 2018). In 2015, the Boston Federal Reserve found 76.9% of Americans hold a credit card (Green et al., 2017). Combining the two statistics results in an estimate that between 24.6% and 33.0% use ridesourcing services. Since card holders tend to live in urban areas and are wealthier than the population at large, the rate for Washtenaw County is likely higher than this. Clewlow and Mishra's survey (2017) found 21% of adults in a survey had used ride-hailing services, and an additional 9% used it with friends but were not account holders themselves.

The detailed demographic profile obtained in this study resembles those found in previous research. Clewlow and Mishra (2017) and Dawes (2016) both found the service to be used by more women than men, although Clewlow and Mishra report a much less dramatic differences than Dawes and the findings here. Similarly, although the response categories differ slightly, most users in both of these studies are young (under 34 in Dawes and under 49 in Clewlow and Mishra). The main discrepancies between this survey and the results here probably reflect unique characteristics of the geographic area studied here. The higher proportion of "some college" and users in lower income categories than in either of these surveys is likely due to the large population of current college students in Washtenaw County.

4.2 Choice Analysis

Overall, the observed reasons for choosing ridesourcing closely aligns with the findings of Rayle et al. (2016) from data collected in San Francisco in 2015. In that study, more than 20% of respondents reported a desire to not drink and drive, which was among the top five reasons riders opted for ridesourcing over driving a personal vehicle. The second top-rated reason in this study, parking, also rated highly among the Rayle et al. (2016) respondents. The reasons for riders who chose ridesourcing over transit are similar as well, with trip time and convenience topping both lists. These results are similar to those found in a survey conducted as part of a recent master's thesis by Dawes.

Overall, the data here seem to confirm the finding by Dawes (2016) that ridesourcing is used primarily for special purpose trips, like avoiding driving while intoxicated or traveling to the airport, and not regular commuting. Examining the spatial pattern of trips shown in Figure 1 provides additional insights to this data. Most trips occurred within the city, where transit service and pedestrian and bicycle facilities are generally available. However, a consideration of the block groups with high density of origins and destinations outside of the city provide insights into 36% of trips chosen over driving a personal vehicle, since these areas have little to no transit service. The block groups located to the north and northwest of the city and outside of the freeway loops are primarily residential areas with no transit service to the city, and limited number of commercial destinations of any type. The block group immediately to the west of the city contains a cluster of automotive dealerships and repair facilities, as well as a large apartment complex and some other commercial destinations. Similarly, the block groups in areas surrounding Ypsilanti also have limited transit service and limited access to commercial amenities.

Although all ridesharing trips share similar user and destination characteristics, from a transportation point of view the data suggests they can be grouped into two categories. Some trips use ridesourcing as a substitute for public transit, and to a lesser extent bicycling and walking. Since the respondents report transit is an option, we can assume the trip origins and destinations are both somewhat transit-accessible. Although the issue requires further research to fully investigate, the data above suggests that weather, distance, and transit convenience are factors for these trips. The data also suggests that the ridesourcing niche may exclude the shortest trips where other modes are preferred, since distance (presumably, longer trips) was rated as an important factor for choosing ridesharing over walking. Other trips to or from largely auto-oriented suburban and rural areas, for which transit is generally not an option. Analyzing these trips may identify opportunities for public transit service expansion, although the low population densities and occasional use of ridesourcing may mean traditional scheduled, fixed-route transit service may not be viable in these areas.

It is important to note that this analysis is conducted at the scale of particular trips, and does not extend to the broader question of what explains the adoption of ridesharing services in general (e.g., installing the app, signing up, and learning to use the service). Studying the adoption of car sharing services, Kent et al. (2017) concluded based on a qualitative analysis of interviews that such decisions are driven by disruptions—such as a single large event, or a constellation of events. However, adoption also required willingness and ability as two important preconditions. Future research could fruitfully probe these issues in the context of ridesourcing adoption.

4.3 Destination Analysis

The destination analysis above provides additional nuanced insight into the picture emerging from the data. Overall, the variables with the strongest relationship to ridesourcing demand are office jobs, entertainment jobs, and the density of bars and restaurants. Paradoxically, the variable for block groups located within the DDA area was negatively related to ridesourcing demand in the linear regression model, even though these areas generally have expensive and limited parking supply and a high density of destinations. However, these areas are generally very walkable, bikeable, and well-served by the city's transit system, which has a radial organization from two central depots in the downtowns of Ann Arbor and Ypsilanti. The positive coefficient on auto ownership in the linear regression supports the idea that ridesourcing is used as an alternative for driving by some users. The models present inconsistent results for jobs-housing balance.

The Poisson regression results finds statistically significant relationships with several additional variables: land-use mix, job accessibility by transit, and distance to nearest transit stop, and does not find DDA area and auto ownership to be significant. These differences most likely reflect the nature of the different dependent variables, but do not lead to major differences in the substantive interpretation. Instead, the results support the survey data indicating that for many users, ridesourcing is a substitute for traditional public transit.

Since the linear regression models explains nearly three-quarters of the variation in ridesharing demand, the results from the multivariate analysis could be converted into a planning tool to predict demand for areas undergoing development, or create maps to estimate ridesourcing demand in existing cities or as part of future land-use scenarios. Given the reluctance of ridesourcing companies to share demand data, this may prove useful for transportation planners to understand where to provide facilities such as dedicated drop-off spaces, or where improvements to transit may capture trips currently being taken through ridesourcing.

4.4 Insights on the Geography of Urban Travel

Urban travel has long had a complex geographic nature, since city residents can chose from a variety of transportation modes, and these choices are strongly influenced by aspects of the urban built environment and the location of fixed transit networks. The recent introduction of ridesourcing has raised the question of how the settled patterns of transportation in cities would evolve in light this new option. The results described in this paper provide some insights into this transition. First, in contrast with the statements by ridesourcing companies which envision their services as replacements of cars suitable for all forms of travel, the survey here found that ridesourcing was used for certain types of trips in certain places. Although most respondents had access to a vehicle, most reported that for the particular trip where they chose ridesourcing, they chose it over public transit. As a result, the data shows a striking spatial pattern with the highest densities of demand occurring in the study area’s two downtowns, each with a high density of commercial services and high levels of transit service. Future research could probe more deeply which neighborhoods see the greatest adoption as a proportion of all travel, and further explore the relationship between ridesourcing and other modes.

5. Conclusions

Ridesourcing has been one of the most notable transportation innovations in recent years, with the number of users rocketing from zero to roughly one-third of Americans in less than a decade. This had been especially notable in big cities like New York and San Francisco, with large populations of young, tech-savvy residents eager to try new innovations, and which have historically supported large taxicab fleets as part of complex multi-modal transportation networks. Even where their impacts have grown, the role of ridesourcing within the broader suite of transportation options and the spatial nature of ridesourcing use has been unclear due to a lack of data. Furthermore, it is not clear whether adoption patterns in smaller cities is similar to closely studied big city markets.

This paper reported the results of an exploratory survey on ridesourcing use in Washtenaw County, Michigan, the location of the cities of Ann Arbor and Ypsilanti. To collect detailed information about ridesourcing use, survey respondents were recruited through a variety of online and offline advertisements, resulting in a convenience sample of 189 corresponding with 195 trips. Despite relying on a non-random sample, the demographics of respondents are broadly similar to those obtained from national sample surveys. The lower educational attainment and income of the study sample are likely due to the prevalence of current college students in the area. However, the sampling approach means the results should be interpreted with care.

Overall, the paper provides needed geographical context to the patterns of ridesourcing use which research has begun to describe. Respondents reported that many trips were chosen over public transit, for reasons such as speed and convenience. Among the riders choosing ridesourcing over driving, the top three reasons for this choice were to avoid driving under the influence of alcohol, parking costs, and to avoid the stress of driving. Finally, some trips were chosen over walking or biking, with the top cited reason as weather. Areas with the highest demand tended to have high office and entertainment employment and high density of bars and restaurants. Paradoxically, population density a downtown area with limited parking (but high transit access and walkability) were related to lower ridesourcing demand, perhaps because trips in these areas were taken by other modes.

Overall, the results suggest that for cities like Ann Arbor, ridesourcing fills a niche in the transportation system for certain types of travel, but has seemingly not displaced traditional travel modes for routine travel. Most survey respondents reported selected ridesourcing over the city's public transit system, or over privately owned cars. Although it seems plausible that extremely low-cost, automated ridesourcing could result in greater mode shift from transit, it may not result in shifts from private auto trips, where ridesourcing is taken only for particular trip types (such as where parking is expensive or alcohol consumption is planned). In sum, the results suggest that for markets like Ann Arbor, ridesourcing may be reaching saturation among the market of likely trips. However, this is not to minimize the potential for greater market shares in cities with relatively wealthy residents with large mode share on public transportation systems facing operational problems (such as New York or Washington, D.C.). But the likely future for most other U.S. cities seems to be the emergence of a more complex transportation system where ridesourcing coexists with existing modes.

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Appendix A. Trip Analysis Variable Correlation Matrix

	tripden	d1b	d1c	d1c8_en~	d1c8_o~0	d2b_e5~x	d2a_ep~m	d3b	d3bmm4	d5cr	d5dr	d4a	mean	touch_~a	autoown0
tripden	1														
d1b	0.4626	1													
d1c	0.3095	0.4859	1												
d1c8_ent10	0.6316	0.3738	0.5357	1											
d1c8_off10	0.7249	0.3496	0.5487	0.8898	1										
d2b_e5mix	0.113	-0.1123	-0.0313	0.163	0.1333	1									
d2a_ephhm	0.1336	-0.1204	-0.0174	0.2925	0.195	0.6942	1								
d3b	0.263	0.529	0.1309	0.2135	0.181	-0.0898	-0.0453	1							
d3bmm4	0.3506	0.3616	0.0663	0.2508	0.2598	0.0435	0.0983	0.4915	1						
d5cr	0.2908	0.4936	0.1701	0.2489	0.1924	-0.0981	0.0853	0.5691	0.2941	1					
d5dr	0.4766	0.5498	0.2662	0.4411	0.3947	0.0075	0.1364	0.6161	0.3374	0.6263	1				
d4a	0.234	0.4431	0.1138	0.1886	0.1421	-0.0964	0.0894	0.5633	0.3052	0.6999	0.5933	1			
mean	0.7369	0.6961	0.3309	0.5167	0.497	0.1268	0.1842	0.3927	0.3787	0.4474	0.6257	0.3536	1		
touch_dda	0.5724	0.5503	0.3912	0.4712	0.4565	0.1448	0.1363	0.3253	0.1686	0.3155	0.5201	0.2138	0.8088	1	
autoown0	0.4846	0.3397	0.1106	0.4989	0.5404	0.0644	0.1429	0.1849	0.2443	0.2445	0.3094	0.2412	0.3993	0.3182	1

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