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Understanding the Surprising and Oversized Use of Ridesourcing Services in Poor Neighborhoods in New York City

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Abstract

For-hire vehicle trips in the five boroughs of New York City from 2014 to 2017 increased by 82 million annually (46%). This paper describes how factor analysis and cluster analysis were used to create a typology that was applied to quantify how usage patterns have evolved in different types of neighborhood. Having surged 40-fold, ridesourcing trips originating in the outer boroughs now constitute 56% of the overall market. Many of the outer borough neighborhoods in which ridesourcing trips originated are home to minority, relatively low-income populations with low car ownership rates. It is possible that these trips in the outer boroughs are being taken by local residents to fill gaps in mobility services, as these locations are less well-served by public transportation and other for-hire vehicles such as yellow taxis. The surge in ridesourcing trips in the outer boroughs is important for three reasons. First, if ridesourcing is being used to provide desired levels of accessibility by outer borough residents, having this need filled by for-profit entities with notoriously variable pricing structures could have long-term consequences for transportation equity. Second, if the trips represent induced travel, the associated externalities will negatively affect vehicle emissions, greenhouse gas emissions, and transportation safety. Third, local policy makers need to be aware of the dynamics unfolding in the outer boroughs because regulations that have been adopted to reduce congestion currently only apply to trips originating in Manhattan. Moreover, all stakeholders should reassess how disruptive transportation technology companies are regulated with respect to data sharing.

Mobility on Demand (MOD) describes new transportation technologies that allow consumers to access mobility, goods, and services at their own convenience. Passenger modes of travel in the MOD category include bikesharing, carsharing, ridesharing, ridesourcing (also called transportation network companies or TNCs), scooter sharing, microtransit, and shuttle services (*1*, *2*). The most sophisticated MOD passenger services combine trip planning and booking, payment capability, real-time information, and predictive analytics into a single user interface (*1*). Services provided by companies such as Uber and Lyft are particularly noteworthy because their usage has exploded. Uber, active in 600 cities across 78 countries, provided a stunning 4 billion rides in 2017 alone (*3*). Uber is just one of many technology companies competing for business in this market globally alongside entities such as Didi Chuxing in China and Ola in India (*4*).

MOD services have already begun to change how people travel (*1*). Impacts to the traditional taxi market have attracted the most attention to date in both academic literature and the media (*5*, *6*). Those in the taxi business have strongly objected to ridesourcing companies being able to operate in cities around the world with minimal regulations (*6*). That said, taxis constitute a relatively small portion of the overall transportation system throughout the United States. Important questions remain as to how, when, and where ridesourcing services may either complement or replace other modes of transportation (*7*, *8*). Impacts on public transit are especially important for places that have invested billions of dollars of public funds over decades to build and maintain their systems (*1*). Research into the impacts of ridesourcing on other modes of transportation is constrained by a paucity of data, which in a highly competitive market place, are considered proprietary and rarely shared by companies.

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Stakeholders involved in all aspects of transportation and land use need to have a clear understanding of what is happening in the ridesourcing market and how usage varies according to context. The broader relevance of examining travel patterns relates to the fact that ridesourcing is merely the first stage of a whole host of ground-breaking transportation technologies expected to emerge over the coming years. Autonomous vehicles (AVs) are currently being tested in selected cities around the world (*9–11*). Understanding the way in which ridesourcing is affecting the existing transportation system through geographic studies such as this one is essential to anticipating the potential impacts that other transportation innovations such as AVs may have going forward. The smartphone-enabled low-occupancy ridesourcing currently being provided by a human driver appears likely to become automated in the not-too-distant future. Ridesourcing services and their likely successor – low-occupancy AVs – may be attractive alternatives in specific contexts. But instead of being incorporated wholesale, emerging transportation technologies will have a distinct geography that will be shaped by the particular setting. For that reason, we echo a point that has been made by geographers for decades, and that has been addressed in some of the existing studies on emerging transportation technologies – that geography (or context) matters (*12*). Some types of MOD may fit for a particular location for a specific type of trip, but may not be suitable everywhere for every trip. Determining what might be suitable in what location requires understanding how contextual factors are shaping emerging transportation technologies. Accordingly, in this paper, we examine the overall number of ridesourcing trips in the five boroughs of New York City, how they vary across different settings, and how have they changed over time. We present here a baseline study that provides an overview of the general patterns of use that sets the stage for more in-depth analysis of the linkages between geographic setting and ridesourcing use. Because the insights from this paper provide a strong foundation for follow-up studies, suggestions for additional research are outlined in our conclusions.

We first compile variables that describe characteristics theoretically relevant to transportation decision-making. After aggregating the variables to the taxi zone, the spatial unit for which data on for-hire vehicles are compiled by the New York City Taxi and Limousine Commission (NYC TLC), we use factor analysis and cluster analysis to create a typology of eight distinct neighborhood types across the study area. Examination of for-hire vehicle data by neighborhood type yields the surprising finding that a majority of ridesourcing trips in 2017 (56%) originated in the outer boroughs in neighborhoods predominantly populated by relatively low-income minority residents with limited access to public transit and low car ownership rates. In 2014, only 24% of ridesourcing trips originated in the outer boroughs. The geographic shift in the concentration of activity from Manhattan to the outer boroughs resulted from a 40-fold increase in ridesourcing trips originating in the outer boroughs between 2014 and 2017, compared with a leveling-off of activity in Manhattan. It is possible that these trips in the outer boroughs are being taken by local residents to fill gaps in mobility services, given that they are less well-served by public transportation and other for-hire vehicles such as yellow taxis. This explanation would be consistent with Uber's strategic marketing campaign in the outer boroughs organized around the message that it is helping to fill gaps in public transit in areas long ignored by yellow taxis (*13*).

The paper is laid out as follows. Section 2 contains our Methodology, divided into four sub-sections covering (a) a discussion of literature about the impacts of disruptive transportation technologies, focusing on studies that have examined usage in low-income neighborhoods; (b) a description of the study area that motivates the creation of a neighborhood typology; (c) information about the data used in the analysis; and (d) our methods, primarily factor analysis, and cluster analysis. Section 3 summarizes the findings from the baseline study, and is followed by a section containing conclusions and suggestions for future research to build upon this preliminary analysis.

Methodology

The overarching question guiding our study is: How does the overall number of ridesourcing trips vary across different settings and how have they changed over time? The first sub-section focuses on literature pertaining to equity issues, along with work about our study area.

Literature Review

By way of a smart phone app, potential users of ridesourcing services such as Uber and Lyft can identify in real time the availability and cost of the service they wish to access and have the trip billed directly to a bank card associated with their account. Technology makes the trip easy to plan, information is readily available about expected travel time and cost, and the experience is more convenient and reliable than some other modes (*14*). The fact that services are accessed by a smart phone app has raised questions about equitable access. Existing studies, most prominently a comprehensive study of shared mobility and transportation equity, have identified a myriad of sources of inequity. In addition to concerns about the digital divide, discrimination of both riders and drivers (*12*), and the need to be part of the formal banking system (*15*), barriers can extend to language limitations and a lack of culturally inclusive marketing and outreach (*16*).

The extent to which lower-income populations may be able to access ridesourcing services could be important because studies have shown that they use taxis more often than their middle-income counterparts, possibly because they own fewer cars (*17*, *18*). A recent study of emerging transportation technologies has acknowledged that ridesourcing could improve the accessibility of low-income individuals if it were to provide a cheaper and more time-efficient alternative to taxis (*19*). However, some researchers have suggested that instead of promoting ridesourcing, a more appropriate strategy would be to improve public transit coverage and service frequency in low-income neighborhoods (*1*).

Despite their potential to provide mobility to lower-income populations, studies identified early adopters of ridesourcing as young, white, middle-class professionals. A study by the Pew Research Center published in 2016 found that only 15% of American adults had ever used services such as Uber or Lyft (*20*). Half of all Americans (51%) were familiar with these services but had not actually used them, whereas one-third (33%) had never heard of them. Ridesourcing was found to be popular among young adults, urbanites, and college grads. Along with young adults, usage and awareness of ridesourcing was highest for college graduates and the relatively affluent: 29% of college graduates had used ridesourcing services and just 13% were unfamiliar with the term. Among those who had not attended college, just 6% had used these services and half (51%) had never heard of them before. Twenty-six percent of American households with $75,000 or more had used these services compared with just 10% of people living in households of less than $30,000 (*20*). This profile was echoed by two important studies that used surveys in San Francisco, and seven major cities between 2014 and 2016 (*14*, *21*). The differential in adoption between those who are more educated and have higher incomes, and those who are not, was so pronounced that the authors of the seven city study cautioned that cities and transit agencies may need to address gaps in adoption among the wealthy and the poor when considering whether or not to integrate ridesourcing services into publicly subsidized transportation networks (*14*). That said, as this study was conducted only in English and via the Internet, the findings may have been undercounting some populations.

An important piece of evidence about the ability of ridesourcing services to cater to low-income populations came from an experiment conducted in low-income neighborhoods in Los Angeles (average household income <$50,000 for a family of three) (*22*). The study, designed and implemented by a private consulting firm and funded by Uber, compared the relative performance of traditional taxis with UberX rides and found that UberX was faster and cheaper than taxis. An UberX ride, booked using the app, arrived in less than half the time compared with a taxi dispatched by telephone and cost less than half as much, even after accounting for "surge pricing" (e.g., dynamic pricing). As researchers have noted, the results may overstate Uber's ability to serve the low-income neighborhoods as well as the study suggests because although riders were recruited from local employment agencies, they were provided with mobile devices, trained to use Uber's app, and had their trips billed to an "Uber for business" account (*12*).

Ridesourcing companies consider their data to be proprietary, limiting independent analysis. An early exception is New York City where selected data were released in 2014 in response to a Freedom of Information Law (FOIL) request made by the analytics website FiveThirtyEight, which subsequently published several articles. Following this request, NYC TLC began to release limited ridesourcing data. A fuller discussion of this is contained in our sub-section Data, but this does explain why trip data are publicly available for New York City (NYC). A series of reports suggested that ridesourcing in NYC has begun to undermine public transportation (*6*) and is worsening congestion on city streets (*23*). Congestion pricing was therefore recommended to ease traffic and support public transit (*24*). The final report was published around the same time that a task force, FixNYC, recommended a cordon-based congestion pricing system for the Manhattan Central Business District (defined as 60th Street to the Battery). The task force recommended a surcharge of $11.52 and $25.34 for passenger cars and trucks respectively, and a taxi/for-hire surcharge of up to $5 per trip (*25*). What was eventually implemented, which took effect in January 2019, is a fee of $2.75 for ridesourcing and $2.50 for taxis for all trips originating south of 96th Street in Manhattan. In other words, the regulatory focus is entirely on Manhattan. Furthermore, Uber has launched a strategic marketing campaign targeted specifically at lower-income neighborhoods to capture customers in the outer boroughs with limited access to public transit organized around the message that they fill unmet mobility needs, with the following pitch:

> Helping All New Yorkers Move Around Their Communities: From Bayside to Brownsville, Uber is proud to help all New Yorkers move around their communities, especially in areas long ignored by yellow taxis and where access to public transit is limited. Uber is helping to fill in

> gaps in public transit, ensuring that no matter where you live in New York City, you can always get an affordable and reliable ride in minutes (*26*).

In summary, the existing literature has characterized early adopters of ridesourcing as young, college-educated, white, urbanites. Capacity does seem to exist for ridesourcing to fill a niche in low-income neighborhoods, but affordability and access to smartphones and formal banking services may be limiting factors. One concern about Uber's focus on low-income neighborhoods relates to the lack of oversight of ridesourcing companies, especially with respect to pricing. Uber has been at the center of numerous high-profile complaints from both customers and drivers. "Surge pricing" charges premiums for trips taking place during especially busy periods (*27*, *28*). Uber has also changed terms and conditions agreed with drivers at will, raising concerns about labor standards (*5*, *29*, *30*). As some commentators have pointed out, despite their rapid growth in popularity, ridesourcing companies such as Uber have still not found a way to turn a profit, and are kept afloat by investors speculating on this latest technological innovation (*3*). Disruptors such as these have few obligations beyond their speculative investors, and their business priorities often clash with public policy goals to provide sustainable transportation (*32*).

Study Area

NYC evokes images of skyscrapers, congested city streets teaming with yellow taxis, and crowded sidewalks. The five boroughs that comprise our study area are far more diverse than this stereotypical image suggests. Parts of Manhattan contain some of the densest built environments in the United States fed by the subway system. Other parts have been labeled "subway deserts" and contain far fewer jobs and less housing. Land use- and transportation metrics in some part of the outer boroughs are more suburban in nature, with single-family housing and relatively high rates of car ownership. Transportation theory emphasizes the importance of factors such as intensity of the built environment, land-use mix, income, demographics, vehicle ownership, and access to other modes of transportation in shaping the context in which decisions are made. In many places, socio-spatial processes create patterns of segregation that result in many of the distinct variables affecting the transportation decision-making process being intricately interwoven (*33*, *34*). Distinct types of neighborhoods emerge with unique characteristics that blend together to form a specific context in which transportation decision-making occurs. This intermingling of human and built environment factors warrants the creation of a typology to capture various contexts.

Data

Seventeen variables identified from the literature as being important determinants of travel decision-making were used to describe our study area. Subway and bus stops per square mile were calculated from data obtained from NYC Open Data, whereas car ownership rates were taken from the 2014 American Community Survey (ACS) 5-year estimates. Data on jobs came from the Longitudinal Employer–Household Dynamics Origin-Destination Employment Statistics dataset for New York. Eleven social, economic, and demographic variables were obtained from the 2014 ACS 5-year estimates. The data were aggregated to the taxi zone spatial unit of analysis using a spatial join in a geographic information system (GIS) that assigned census tracts to the taxi zone containing the centroid. Descriptive statistics are shown in Table 1.

Data on for-hire vehicle trips were downloaded from the website of the NYC TLC, the government entity that regulates all for-hire vehicles in the study area. Data are partitioned into three separate categories: yellow taxis, green taxis, and ridesourcing vehicles. Yellow taxis operate via a medallion system that confers rights to pick up and drop off passengers throughout the study area, including airports. Green taxis were introduced to fill a gap in service because yellow taxis tended to concentrate in densely populated Manhattan. They also operate under a medallion system but are geographically constrained. They can be hailed in Manhattan north of East 96th Street and West 110th Street, and all outer boroughs except at the airports. The vehicles can drop passengers off anywhere, but are not able to pick up new passengers within the "yellow zone" (south of East 96th and West 110th Streets) or within airports. The third category is ridesourcing services, including vehicles operated by companies such as Uber and Lyft. No distinction is made between rides that are undertaken by a single passenger or group of passengers, and shared services such as UberPool and LyftLine that have been described in the literature as "ridesplitting."

The first data on ridesourcing services that were publicly released covered trips undertaken between April and September 2014, and resulted from a FOIL request made by the analytics website, FiveThirtyEight. The NYC TLC now includes ridesourcing data as a part of its for-hire vehicle trip records from January 2015 through December 2017. The only characteristics that are consistent across the entire time frame are the taxi zone in which the trip originated, and the date and time of the trip. The study area contains 363 taxi zones of varying sizes created by the NYC TLC. As a result, our analysis focused on the taxi zone in which trips originated.

Table 1. Descriptive Statistics of Variables Used in Analysis Aggregated to the Taxi Zone

Variables	Minimum	Maximum	Mean	Standard deviation
Transportation-related variables				
Subway stops/square mile	0	40.2	3.8	6.3
Bus stops/square mile	0	209.6	66.5	35.0
% car-free households	0	91.0%	49.9%	26.5%
Land-use mix and intensity-related variables				
Population/square mile	0	191,520	41,563	34,664
Jobs/square mile	0	525,749	27,920	77,692
Activity density: (pop + job)/square mile	0	556,230	68,767	89,038
Social, economic, and demographic variables				
Weighted avg median HH income ($)	0	250,000	62,713	36,661
Average HH size	0	4.35	2.44	0.82
% HH with people <18 years old	0	82.4%	28.2%	13.7%
% HH people living alone	0	70.2%	30.8%	14.4%
% people >25 w/bachelor's degree	0	88.3%	37.0%	24.5%
% unemployed	0	17.2%	5.8%	2.8%
% white	0	97.6%	37.1%	29.7%
% black	0	91.1%	17.5%	23.4%
% Latino	0	86.9%	24.3%	21.1%
% Asian	0	69.6%	12.4%	13.9%
% elderly	0	11.0%	2.0%	1.6%

Note: HH = households.

Methods

The combination of procedures used to create neighborhood types are established in the literature (*35*). Many of our 17 variables are highly correlated. We therefore used a dimension reduction-factor analysis with a varimax rotation to generate unique vectors that describe the dataset as a whole, after taking into account the correlation between the variables (*36*). Five factors explained 78% of the variance in the data. These vectors were used in a hierarchical clustering analysis using Ward's method and cluster distance measured by Euclidian distance. This method generates a series of groupings of observations from 1 (in which all observations belong to the same group), to n (where n = the number of observations), in which each observation is in its own unique group (*37*). The intervening options demonstrate the level of similarity between observations. From the range of options, generally displayed in a dendogram, the researcher can use judgment to select the number of groupings that provide an adequate amount of distinction between the groups, without being overly specialized. Once the number of desired clusters was identified, a K-means cluster analysis was performed, selecting eight distinct groups.

Findings

Neighborhood Typology

The analysis generated eight distinct neighborhood types. The average values of each variable by cluster (or neighborhood type) are shown in Table 2. Cluster 1 consists of six taxi zones, located entirely in Manhattan, with the highest density of subway stops per square mile (31.4% compared with the next highest level of 14.5%), and by far the highest activity density. This latter variable, comprised of the sum of population plus jobs per square mile, has an average value of 422,196 for Cluster 1, almost double that of the next highest group, Cluster 2. Cluster 3, also predominantly in Manhattan, has lower subway coverage (3.9 stops per square mile), and considerably lower activity density than either clusters 1 or 2. Clusters 4–8 are predominantly in the outer boroughs. Cluster 4 has the lowest median household income of all the clusters ($36,027), the majority of its population are Latino (52.8%) and, despite a comparatively low level of subway coverage (3.8 stops per square mile), has a large percentage of car-free households (68.9%). Cluster 5 has the lowest activity density of all the clusters, a moderate median household income at $69,338, is majority white (59.4%), and has the smallest percentage of car-free households of all the groups at 31.7%. The cluster locations, along with their descriptive names, are shown in the map in Figure 1.

Once we created our neighborhood types, we used GIS to join data on for-hire vehicle trips for each taxi zone and cluster. When conducting our in-depth analysis of ridesourcing trips in the outer boroughs we chose not to include Group 8 because this represents a unique set of taxi zones that includes parks, cemeteries, as well as the airports, that have their own dynamic.

Table 2. Mean Values of Characteristics Describing each Neighborhood Type

	Cluster number							
Variable	1	2	3	4	5	6	7	8
Number of taxi zones	6	5	31	59	73	25	32	16
% taxi zones in Manhattan	100.0	85.7	93.6	17.0	0.0	16.0	0.0	31.3
Transportation-related variables								
Subway stops/square mile	31.4	14.5	3.9	3.8	1.3	3.6	1.2	0.4
Bus stops/square mile	79.8	103.9	97.9	82.5	48.0	68.9	52.1	19.5
% car-free households	79.9	76.5	76.5	68.1	31.7	50.5	39.4	N/A
Population/square mile	42,048	47,572	93,524	59,817	23,745	44,795	27,150	0
Land-use mix and intensity-related variables								
Jobs/square mile	380,147	208,774	38,546	6,360	3,839	12,787	2,680	838
Job to population ratio	9.0	4.4	0.4	0.1	0.2	0.3	0.1	N/A
Activity density: (pop + job)/ square mile	422,196	256,346	132,070	66,176	27,584	57,582	29,830	838
Social, economic, and demographic variables								
Weighted avg median HH income	132,508	117,737	100,851	36,027	69,338	49,161	64,640	N/A
Average HH size	1.8	1.8	1.9	2.8	2.7	2.9	3.0	N/A
% HH with people <18 years old	12.4	12.0	15.3	37.7	30.6	30.9	40.1	N/A
% HH people living alone	51.5	52.5	50.0	31.0	28.2	27.0	23.5	N/A
% people >25 w/bachelor's degree	81.0	76.6	74.4	20.5	38.0	30.5	27.2	N/A
% unemployed	4.6	4.1	4.2	8.5	5.0	5.9	8.0	N/A
% white	62.3	71.0	66.4	10.9	59.4	27.7	13.0	N/A
% black	5.4	3.7	5.7	30.0	5.3	4.5	61.0	N/A
% Latino	8.1	8.7	13.1	52.8	18.7	22.6	19.1	N/A
% Asian	20.9	13.9	11.9	4.5	14.2	42.0	4.0	N/A
% elderly	1.8	1.3	1.6	3.0	1.7	3.4	1.5	N/A

Analysis of For-Hire Vehicle Data

Between 2014 and 2017, the total number of daily trips by for-hire vehicles increased from 493,695 to 718,952 (46%) across the entire study area (see Table 3). In this 3-year interval, ridesourcing trips increased by a factor of 16, from just over 23,000 to 390,000 per day. However, the rates of increase were significantly different in Manhattan compared with the outer boroughs. In Manhattan, for-hire vehicle trips as a whole increased by only 10%. This was because ridesourcing trips increased whereas yellow taxi trips decreased by 32% from 436,463 to 298,599. In clusters 4–7, total daily trips by for-hire vehicles increased by 242% from 72,668 to almost 248,204.

These data suggest that in clusters 1, 2, and 3 (primarily Manhattan) the overwhelming trend appears to be toward substitution between yellow taxis and ridesourcing with little increase in total trips. In clusters 4–7, some substitution appears to have occurred between green taxis and ridesourcing, with green taxi trips falling by 10% between 2014 and 2017. However, the overwhelming development in clusters 4–7 was a 40-fold surge in ridesourcing from just over 5,000 trips in 2014 to almost 200,000 in 2017. This dramatic increase is responsible for the vast majority of the overall increase in for-hire vehicles across our study area between 2014 and 2017.

Several months of the most recent ridesourcing data (June–December 2017) contain fields that describe both the pick-up and drop-off taxi zone, although not all of the fields were populated for every observation. To better connect origins and destinations, we used SPSS to randomly select a sample containing 10% of the trips ($n = 1{,}584{,}419$) for June 2017. Of those, a total of 1,148,561 observations (73%) had data for both pick-up and drop-off taxi zones. After recoding the data for taxi zone to its appropriate cluster, we cross-tabulated the pick-up and drop-off fields. Table 4, panel (a) contains a matrix of the number of pick-ups and drop-offs by cluster, whereas the data in panel (b) show percentage of trips by cluster.

The results of this supplementary analysis are consistent with the major finding from the examination of overall trips: that 56% of trips originate in the outer boroughs. The additional information gleaned from adding destination data reveals that for trips originating in Manhattan, 73% drop off in Manhattan, compared with 81% within the outer boroughs. Of particular note is that over 50% of trips originating in Cluster 4 also drop off in that cluster. The number of within-cluster trips for clusters 5 and 7 is 40% and 36% respectively.

Conclusions and Future Research

Our findings inform three important areas: equity, externalities, and public policy, each of which is

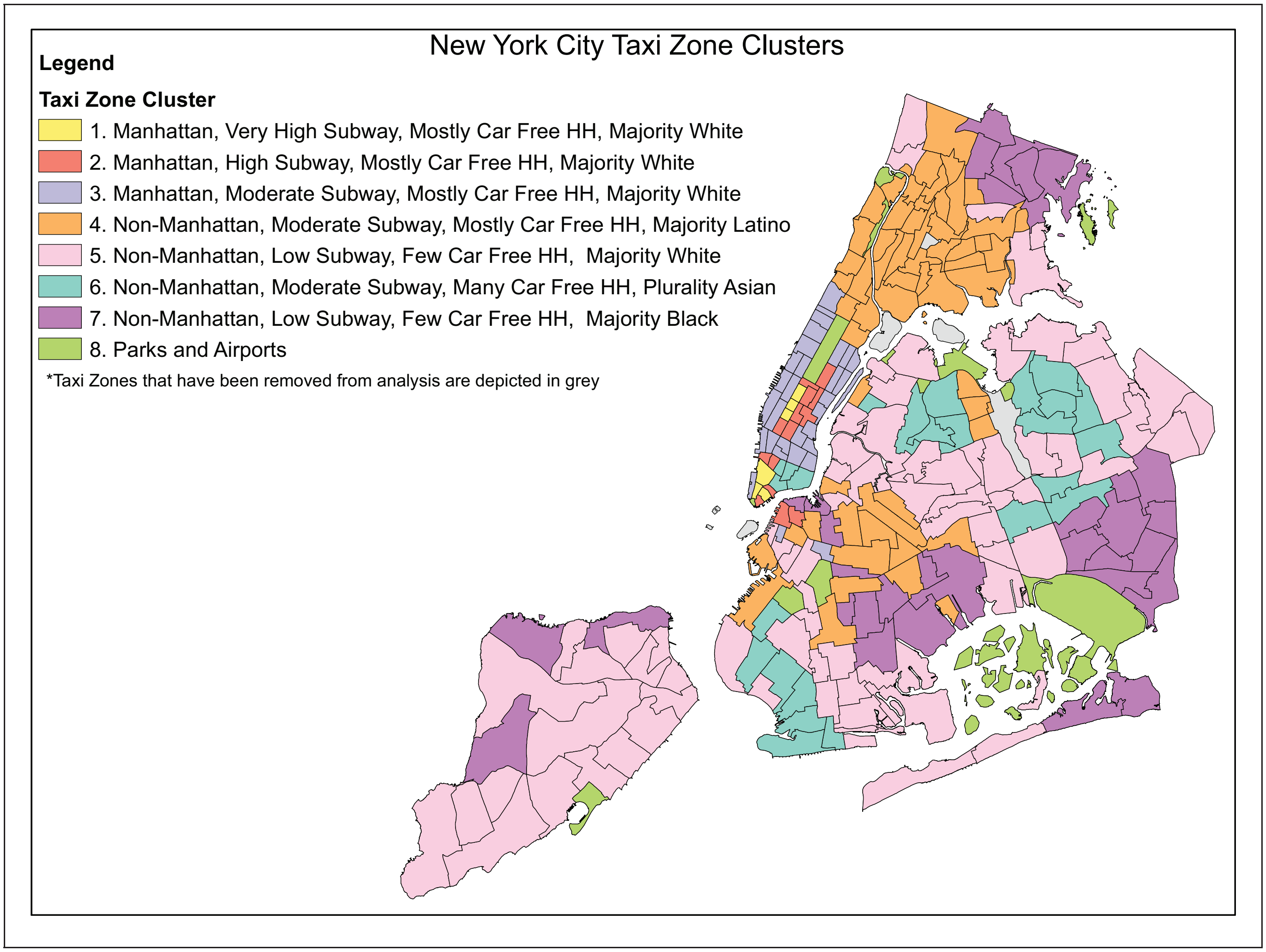

Figure 1. Types of neighborhood across New York's five boroughs.

Table 3. Average Number of Daily Trips by For-Hire Vehicles, Total and by Type

	2014				2017				% change, 2014/2017			
Cluster	Ride-sourcing	Yellow taxi	Green taxi	For-hire vehicles	Ride-sourcing	Yellow taxi	Green taxi	For-hire vehicles	Ride-sourcing	Yellow taxi	Green taxi	For-hire vehicles
1	2,344	50,404	N/A	52,750	22,952	36,938	N/A	59,891	879%	–27%	N/A	14%
2	5,851	117,355	1,025	124,230	52,259	81,199	1,487	134,945	793%	–31%	45%	9%
3	8,498	207,308	2,129	217,935	99,995	137,825	1,850	239,670	1077%	–34%	–13%	10%
4	1,728	10,962	15,345	28,035	81,015	7,574	13,418	102,007	4,587%	–31%	–13%	264%
5	1,768	7,903	9,636	19,308	59,345	3,499	8,424	71,268	3257%	–56%	–13%	269%
6	1,251	17,132	4,349	22,731	31,526	10,271	4,181	45,977	2,420%	–40%	–4%	102%
7	385	878	1,330	2,594	27,021	451	1,481	28,952	6,911%	–49%	11%	1,016%
8	1,192	24,522	399	26,113	15,992	20,842	407	37,241	1,242%	–15%	2%	43%
Total	23,017	436,463	34,214	493,695	390,105	298,599	31,248	719,952	1,595%	–32%	–9%	46%

detailed below. We acknowledge that this paper contains a useful baseline from which to conduct more detailed analysis, rather than more definitive findings. Accordingly, we suggest areas for future research within each sub-section that can extend this introductory analysis.

Table 4. Pick-ups and Drop-offs for a Random Selection of Data, June 2017

(a) Number of ridesourcing trips

		Drop-off cluster number								
		1	2	3	4	5	6	7	8	Total
Pick-up cluster number	1	6,239	12,757	23,885	5,141	4,065	4,409	1,109	5,001	62,606
	2	14,036	29,884	59,439	12,701	10,836	8,653	2,796	11,515	149,860
	3	27,316	64,249	115,722	29,045	16,572	15,055	3,646	16,915	288,520
	4	4,276	10,810	24,178	124,627	35,717	10,065	24,244	9,919	243,836
	5	3,562	9,415	14,568	36,243	75,145	23,490	12,310	10,376	185,109
	6	4,863	8,256	15,272	11,051	24,343	21,688	5,018	4,330	94,821
	7	1,030	2,651	3,415	23,677	12,031	5,238	29,165	3,653	80,860
	8	4,225	8,080	11,943	6,330	5,947	2,798	2,066	1,560	42,949
	Total	65,547	146,102	268,422	248,815	184,656	91,396	80,354	63,269	1,148,561

(b) Percentage of ridesourcing trips by cluster

		Drop-off cluster number								
		1	2	3	4	5	6	7	8	Total
Pick-up cluster number	1	10.0%	20.4%	38.2%	8.2%	6.5%	7.0%	1.8%	8.0%	100%
	2	9.4%	19.9%	39.7%	8.5%	7.2%	5.8%	1.9%	7.7%	100%
	3	9.5%	22.3%	40.1%	10.1%	5.7%	5.2%	1.3%	5.9%	100%
	4	1.8%	4.4%	9.9%	51.1%	14.6%	4.1%	9.9%	4.1%	100%
	5	1.9%	5.1%	7.9%	19.6%	40.6%	12.7%	6.7%	5.6%	100%
	6	5.1%	8.7%	16.1%	11.7%	25.7%	22.9%	5.3%	4.6%	100%
	7	1.3%	3.3%	4.2%	29.3%	14.9%	6.5%	36.1%	4.5%	100%
	8	9.8%	18.8%	27.8%	14.7%	13.8%	6.5%	4.8%	3.6%	100%

Equity

Our results show that ridesourcing trips have surged 40-fold in the outer boroughs between 2014 and 2017. From our data, it is not possible to determine who is using these services and for what purpose. The only consistent variable that we have on ridesourcing trips is the taxi zone in which the trip originated. We are therefore unable to ascertain who is using ridesourcing services and the possible trip route. Uber's marketing campaign, launched in these neighborhoods, and organized around the message that it can provide mobility in areas underserved by public transit and long ignored by yellow taxis (*13*, *25*), may be responsible for some of this increase. Prior studies showed that early adopters of ridesourcing systems were white, well-educated, middle class, young professionals (*14*, *19*, *20*). Our findings suggest that there may have been a broadening out of the market in NYC in terms of the demographics of the users. In 2014, for-hire services was a very small part of the transportation market in the outer boroughs. With the arrival of ridesourcing, this market has exploded. This suggests that there is a true gap in mobility services in the outer boroughs that may partly be due to inadequate public transit. Precisely what that gap is, for whom, and for what types of trips, and why it exists, is unclear and needs further investigation. What is clear though, is that filling such a gap with private sector for-profit rather than publicly funded services may generate considerable equity repercussions over the longer term. Ridesourcing companies are not subject to the same type of regulation as taxis, and Uber, in particular, has become notorious for its fluid pricing terms. Customers are subject to "surge pricing" that can fluctuate enormously during busy periods, whereas drivers have been left open to changing terms and conditions of their flexible employment arrangements (*27–29*). Additional research is needed to better understand what is happening in the outer borough neighborhoods to determine whether or not there is cause for concern regarding equity and what potential there may be for ridesourcing companies to partner with public transit agencies, as has been suggested by some researchers (*1*).

Externalities

The surge in ridesourcing resulted in a 46% increase in total for-hire vehicle trips between 2014 and 2017. This translates into approximately 226,000 extra trips each day, or over 82 million trips per year. Translating this into additional vehicle miles traveled (VMT) is difficult, because data on destinations (and therefore trip length) and number of passengers are unavailable for the period studied. Any increases in VMT would be accompanied by the usual negative externalities such as air pollution, traffic congestion, and traffic fatalities that have already been the focus of some academic and non-academic studies. It is notable that some of the largest increases in ridesourcing trips in absolute terms have occurred in the lowest income neighborhoods (Cluster 4 with a weighted average median household income of $36,027) with high levels of car-free households (68.1%). However, some of the neighborhoods (Cluster 5) have much less than half the level of car-free households (31.7%). Our results provide a solid foundation for a full assessment of externalities being generated by ridesourcing akin to recent studies that have already been undertaken, stratified by neighborhood type, on the basis that the dynamics may be different. A follow-up study is already underway using the data for which origins and destinations are available (June–December 2017) as well as surveys of residents in selected neighborhoods.

Public Policy

At the local level, all the emphasis on regulating ridesourcing is focused on Manhattan, motivated by growing congestion and a desire to maintain the existing public transit system. Following an examination of congestion in NYC, a fee of $2.75/$2.50 was imposed on ridesourcing vehicles/taxis for all trips originating south of 96th Street in Manhattan. This was set to begin in January 2019 but was temporarily delayed because of a lawsuit. This policy may address traffic congestion within Manhattan, but ignores the dynamics unfolding in the outer boroughs. Congestion is just one aspect of the externalities generated by low-occupancy vehicle travel. If the increase in ridesourcing trips represents induced demand rather than substitutions of other low-occupancy vehicle modes, there will be implications for air pollution, greenhouse gas emissions, and transportation safety. Additional research needs to be undertaken to determine whether or not these trips are induced travel – that is, additional VMT – or they replaced other modes of transportation such as the private car. Our initial findings, as well as the insights from future research, may be of interest to those focusing on climate action plans and initiatives in the transportation safety realm such as Vision Zero. Beyond the immediate geographic area, anyone interested in urban sustainability may find our research of importance because of the cross-cutting questions pertaining to equity and externalities that is raises, and the debates about regulation of emerging transportation technologies that it may spark.

Companies such as Uber are proving to be highly disruptive to the existing transportation system. With a remit to be entrepreneurial, disruptors are expected to be agile and respond to shifts in the regulatory landscape and marketplace in a highly fluid manner. This dexterity may produce both opportunities and challenges for cities. A city's transportation system is the foundation upon which its economy, vitality, and social welfare depend. Each component of the network creates both positive and negative spillover effects. Ridesourcing companies have at their disposal a wealth of data about customers, travel behavior, willingness to pay for different services at different times (including pooled services). Even though city governments have the remit to set the priorities and operating rules for their transportation system as a whole, it may be difficult for them to do so without access to data from emerging transportation technology companies. City governments need to consider whether or not they wish to allow ridesourcing companies to continue to operate without making firmer commitments to information sharing that would allow stakeholders to assess the potential externalities that may undermine important transportation sustainability goals.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: CA-P, NG; data collection: LV; analysis and interpretation of results: CA-P, LV, NG; draft manuscript preparation: CA-P, LV, NG. All authors reviewed the results and approved the final version of the manuscript.

References

1. Shaheen, S., and A. Cohen. Is it Time for a Public Transit Renaissance? Navigating Travel Behavior, Technology, and Business Model Shifts in a Brave New World. *Journal of Public Transportation*, Vol. 21, No. 1, 2018, pp. 67–81.
2. Cassetta, E., A. Marra, C. Pozzi, and P. Antonelli. Emerging Technological Trajectories and New Mobility Solutions. A Large-Scale Investigation on Transport-Related Innovative Start-Ups and Implications for Policy. *Transportation Research Part A: Policy and Practice*, Vol. 106, 2017, pp. 1–11.
3. Uber Powered Four Billion Rides in 2017. It wants to do more-and Cheaper–in 2018. https://www.recode.net/2018/1/5/16854714/uber-four-billion-rides-coo-barney-harford-2018-cut-costs-customer-service.
4. Chen, J. *Thrown under the Bus and Outrunning It! The Logic of Didi and Taxi Drivers' Labour and Activism in the On-Demand Economy*. New Media and Society, 2017. https://doi.org/10.1177/1461444817729149.
5. Cramer, J., and A. B. Krueger. Disruptive change in the taxi business: The case of uber. *American Economic Review*, Vol. 106, No. 5, 2016, pp. 177–182.

6. Schaller, B. *Unsustainable? The Growth of App Based Ride Services and Traffic, Travel, and the Future of New York City*. Schaller Consulting, 2017a.
7. Currie, G. Lies, Damned Lies, AVs, Shared Mobility, and Urban Transit Futures. *Journal of Public Transportation*, Vol. 21, No. 1, 2018, pp. 19–30.
8. Rabl, A., and A. de Nazelle. Benefits of Shift from Car to active Transport. *Transport Policy*, Vol. 19, No. 1, 2012, pp. 121–131.
9. Kellerman, A. *Automated and Autonomous Spatial Mobilities: Transport, Mobilities and Spatial Change*. Cheltenha, UK, Edward Elgar, 2018.
10. Speck, J. *Autonomous Vehicles and the Good City*. Speck & Associates LLC, 2017. https://www.cnu.org/publicsquare/2017/10/16/ten-rules-cities-about-automated-vehicles.
11. Lewis, P., G. Rogers, and S. Turner. *Beyond Speculation: Automated Vehicles and Public Policy: An Action Plan for Local, State, and Federal Policymakers*, E. C. f. Transportation, 2017.
12. Jin, S. T., H. Kong, R. Wu, and D. Z. Sui. Ridesourcing, the Sharing Economy, and the Future of Cities. *Cities*, Vol. 76, 2018, pp. 96–104.
13. Rivioli, D. Uber Launches New Ad Highlighting its Efforts to Serve New York's Outer Boroughs. *New York Daily News*, 2018.
14. Clewlow, R. R., and G. S. Mishra. *Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States*. Institute of Transportation Studies, University of California, Davis, 2017.
15. King, D. A., and J. F. Saldarriaga. Access to Taxicabs for Unbanked Households: An Exploratory Analysis in New York City. *Journal of Public Transportation* Vol. 20, No. 1, 2017, pp. 1–19.
16. Shaheen, S., C. Bell, A. Cohen, and B. Yelchuru. *Shared Mobility and Transportation Equity*. Federal Highway Administration, Washington D.C., 2017.
17. Pucher, J., and J. L. Renne. Socioeconomics of Urban Travel: Evidence from the 2001 NHTS. *Transportation Quarterly*, Vol. 57, No. 3, 2003, pp. 49–77.
18. Renne, J. L., and P. Bennett. Socioeconomics of Urban Travel: Evidence from the 2009 National Household Travel Survey with Implications for Sustainability. *World Transport Policy and Practice*, Vol. 20, No. 4, 2014, pp. 7–27.
19. National Academy of Sciences. *Engineering, & Medicine, Between Public and Private Mobility: Examining the Rise of Technology-Enabled Transportation Services*. TRB Special Report 319, 2016.
20. Smith, A. *Shared, Collaborative, and On Demand: The New Digital Economy*. Pew Research Center, 2016. http://www.pewresearch.org/wp-content/uploads/sites/9/2016/05/PI_2016.05.19_Sharing-Economy_FINAL.pdf.
21. Rayle, L., D. Dai, N. Chan, R. Cervero, and S. Shaheen. Just a Better Taxi? A Survey-Based Comparison of Taxis, Transit, and Ridesourcing Services in San Francisco. *Transport Policy*, Vol. 45, 2016. pp. 168–178.
22. Smart, R., B. Rowe, A. Hawken, M. Kleiman, N. Mladenovic, P. Gehred, and C. Manning. *Faster and Cheaper: How Ride-Sourcing Fills a Gap in Low-Income Los Angeles Neighborhoods*. BOTEC Analysis Corporation, 2015.
23. Schaller, B. *Empty Seats Full Streets*. Schaller Consulting, New York City, 2017a.
24. Schaller, B. Making Congestion Pricing Work for Traffic and Transit in New York City. Schaller Consulting, Brooklyn, N.Y., 2018.
25. Fix NYC Advisory Panel Report. 2018. http://www.hntb.com/hntb/media/hntbmedialibrary/home/fix-nyc-panel-report.pdf.
26. Uber. *Helping All New Yorkers Move around their Communities* 2018. https://uberconnectsnyc.com/. Accessed 9 July 2018.
27. Chen, L., A. Mislove, and C. Wilson. Peeking Beneath the Hood of Uber. *Proc., of the 2015 Internet Measurement Conference*, 2015, pp. 495–508.
28. Surowiecki, J. In Praise of Efficient Price Gouging. *Technology Review*, Vol. 117 No. 5, 2014, pp. 75–77.
29. Rogers, B. The Social Costs of Uber. *SSRN Electronic Journal*, Vol. 82, No. 1, 2015, pp. 85–102.
30. Rosenblat, A., and L. Stark. Algorithmic Labor and Information Asymmetries: A Case Study of Uber's Drivers. *International Journal of Communication* Vol. 10, 2016, pp. 3758–3784.
31. Sherman, L. Why Can't Uber Make Money? *Forbes Magazine*, 2017. https://www.forbes.com/sites/lensherman/2017/12/14/why-cant-uber-make-money/#618d798210ec.
32. Sherman, L. Is Uber for Everything A Good Thing? *Forbes Magazine*, 2018.
33. Logan, J. R., B. J. Stults, and R. Farley. Segration of Minorities in the Metropolis: Two Decades of Change. *Demography*, Vol. 41, No. 1, 2004, pp. 1–22.
34. Massey, D. S. American apartheid: segregation and the making of the underclass. *American Journal of Sociology*, Vol. 96, No. 2, 1990, pp. 329–357.
35. Atkinson-Palombo, C., and M. J. Kuby. The Geography of Advance Transit-Oriented Development in Metropolitan Phoenix, Arizona, 2000–2007. *Journal of Transport Geography* Vol. 19, No. 2, 2011, pp. 189–199.
36. Costello, A. B., and J. W. Osborne. Best Practices in Exploratory Factor Analysis: Four Recommendations for Getting the Most from your Analysis. *Practical Assessment, Research & Evaluation*, Vol. 10, No. 7, 2005.
37. Calinski, T., and J. Harabasz. *A Dendrite Method for Cluster Analysis*. *Communications in Statistics*, Vol. 3, No. 1, 1974, pp. 1–27.

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