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Understanding Spatiotemporal Growth of Ride Source Services In New York City

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3.0 INTRODUCTION:

Ride source as a method of transportation has spread globally and increased in popularity at a rate that cannot be ignored since operation of UberCab began in San Francisco in late 2010. The emergence of ride source services has been assisted by the growing acceptance of the market segment known as the sharing economy in combination with increasing smart phone ownership and internet use. The sharing economy allows independent contractors to offer a variety of goods and services to customers through a third party online platform or marketplace. These third party companies main function is to connect sellers and buyers (1). The sharing economy ranges from selling used goods (Ebay) and odd job tasks (Task Rabbit) to space (AirBnB). The sharing economy reached into the transportation market with carshare (Zipcar) and more recently ride source services (Uber).

In the case of ride source services, Transportation Network Companies (TNCs) serve as the third party company that match a user to a driver in order to fulfill a door to door trip through a smart phone application. The method of transportation that ride source most closely resembles is taxi. While taxi rides can be booked using a phone, the typical method of hailing a taxi is by street hail. Ride source separates itself from taxi by solely operating through smart phone applications. The innovative functionalities that are offered theoretically should alter a user's transportation decision making process. Advances in smartphone GPS capabilities allow matching algorithms to find a driver that might otherwise be out of range for a street hail. In addition, TNC offer dynamic pricing that is at its root based on the supply of drivers and demand of trips in an area. Users are able to track the price of a trip and book it when it falls in their price range. Payment for a trip is exclusively made by credit card through the application. Lastly, users can specify the size of vehicle needed based on the number of people taking the trip.

Despite the number of technology advantages ride source services have over traditional taxi, at its core, ride source is a taxi service. Even though they are a taxi service, TNCs have not been regulated as such for the majority of their existence. The lack of regulation of ride source has allowed them to grow unchecked within urban areas around the world. For example, Uber, the largest TNC, operates in 600 cities across 78 countries (2). Many professionals in the transportation sector are concerned that ride source services are currently negatively impacting public transit ridership while increasing motor vehicle congestion (3, 4). A comprehensive understanding of how ride source is changing transportation systems in a variety of transportation environments does not exist due to the limited open source ride source trip data available to cities and transportation professionals. This has stunted policy makers ability to pass legislation that promotes context sensitive integration of ride source services into the existing transportation system.

The largest ride source dataset available exists for New York City. The analytics company FiveThirtyEight filed a Freedom of Information Law request to Uber resulting in a set of trip origin data from April to September 2014 being released by Uber. The dataset included pickup time and location information for trips picking up or dropping off within New York City. Following this release, the New York City Taxi and Limousine Commission publishes ride source trip data for all TNCs in New York City. Current data released spans from January 2015 to December 2017. The availability of this data set has inspired a surge of research that uses innovative ways of visualizing and analyzing ride source data by researchers.

Cities have begun to recognize that ride source must be understood in order to create policies that focus on how ride source services operate. In 2018, New York City became the first U.S. city to enact policy that functions to limit the growth of ride source trips. In January 2019, a congestion pricing plan will take effect for trips within Manhattan. The Manhattan congestion pricing plan will include a tax on ride source trips that require driving in Manhattan (5). In addition, as recently as August 2018 an immediate freeze on newly licensed ride source drivers in New York City was passed. This caps the number of ride source vehicles operating in the city which recently had surpassed 80,000 vehicles (6). For comparison, yellow taxis in New York City are capped at about 13,500 vehicles. With the freeze on new licenses comes a requirement for more robust ride source trip data and a greater focus by New York City to study how ride source services effect the city's transportation system (6).

This thesis study aims to contribute to the effort by the transportation community to employ innovative research methodologies in order to understand how ride source is impacting transportation systems. The study used the ride source data available for New York City to understand if ride source is used differently in different areas of the city. New York City as a study area offers a wide range of neighborhood types to study due to the variety of socio-economic, transportation and activity density contexts that exist within its five boroughs. Using variables that theoretically inform the transportation decision making process, a K-means clustering analysis was used to identify similar types of neighborhoods in the study area. Growth and temporal patterns of use were analyzed by the resulting distinct neighborhood clusters within New York City.

While the study was exploratory in nature, it highlights important observations that will inform future confirmatory research methods regarding ride source in New York City. The study focuses on the following research questions:

1. *Are ride sourcing services being used differently depending on transportation, built environment intensity and social contexts?*

2. *How do the overall number of ride sourcing trips vary across different settings and how have they changed over time?*
3. *How have the temporal patterns of ride source use changed in different neighborhoods over time?*

This study aims to fill in a gap in the literature regarding ride source. Studies and articles have looked at ride source use spatially. Other studies have looked at the temporal patterns of ride source use. However, the understanding of spatiotemporal interactions of ride source is lacking. The following reports explore the spatiotemporal relationship of ride source service growth and use as well as how it relates to socio-economic, transportation and intensity of the built environment factors. As researchers target gaps in ride source research transportation experts and policy makers can have a more thorough comprehension of ride source use that allows nuanced ride source policies and regulations.

4.0 REPORT 1

UNDERSTANDING THE SURPRISING AND OVERSIZED USE OF RIDESOURCING SERVICES IN POOR NEIGHBORHOODS IN NYC

4.1 ABSTRACT

For-hire vehicle trips in the five boroughs of New York City from 2014 to 2017 increased by 82 million annually (46%). The biggest contributor is a 40-fold upsurge in ridesourcing trips originating in the outer boroughs, which now constitutes 56% of that market. Many of the outer borough neighborhoods in which ridesourcing trips originated are home to minority, relatively low-income populations, who are comparatively poorly-served by public transit, yet have 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, given that they 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 residents in the outer boroughs, then 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, any externalities being generated by this activity will negatively impact vehicle emissions, greenhouse gas emissions, and transportation safety, all of which impact a wide range of public policies/stakeholders. Third, local policy-makers need to be aware of these 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.

Keywords: Transportation Equity; Sustainable Transportation; Disruptive Transportation Technologies

4.2 INTRODUCTION

Mobility on Demand (MOD) describes a variety of new transportation technologies that allow consumers to access mobility, goods, and services at their own convenience. Passenger modes of travel that fall under the MOD category include bikesharing, carsharing, ridesharing, ridesourcing (also called transportation network companies (TNCs) in the non-academic literature), scooter sharing, microtransit, and shuttle services (1, 2). The most sophisticated versions of 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 four 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 such as ridesourcing have already begun to change how people travel (1). Impacts to the traditional taxi market have attracted the most attention to date in both the academic literature and the media (5, 6). Those in the taxi business have strongly objected to companies like Uber 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. 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.

Stakeholders involved in all aspects of transportation and land use need to have a clear understanding of the dynamics that are taking hold in ridesourcing, and how they vary according to context. All too often, pronouncements are being made in the media about the future of either cities or transportation—or both—that do not take into account the existing context. Blanket statements about the influence of emerging transportation technologies suggest a complete takeover of what already exists, yet these are often overly simplistic (7). It is difficult to imagine low-occupancy ridesourcing vehicles—either with a human driver or in an automated form—offering any improvement over what currently exists in some cities around the world. Examples include Tokyo and Zurich, which have extensive and efficient rail-based public transportation systems, and Amsterdam, whose biking culture creates one of the safest, lowest-carbon, transportation systems in the world, with the added benefits of promoting affordable, active transportation (8).

Whatever the immediate impacts of ridesourcing may be, the broader relevance of examining travel patterns relates to the fact that what has been introduced is merely the first stage of a whole host of ground-breaking transportation technologies expected to emerge over the coming years. Autonomous vehicles (AVs), currently being designed and tested in many cities around the world, appear to be looming on the horizon (9, 10, 11). Understanding the way in which ridesourcing is impacting the existing transportation system though geographic studies such as the one we describe here 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 factors that exist in that 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 trip in the five boroughs of New York City, how they vary across different settings, and how have they changed over time. The purpose is to understand how these contextual factors are shaping ridesourcing use.

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 & 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 to a levelling 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 the relevant literature about the impacts of disruptive transportation technologies, with specific focus 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 contains our findings, and is followed by a section containing conclusions and suggestions for future research.

4.3 METHODOLOGY

The overarching question guiding our study is: "*How do 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.

4.3.1 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 have identified two potential sources of inequity—one stemming from a digital divide, and another from discrimination of both riders and drivers (12). A third source, related to the fact that the app requires a bank card, may hinder access to those not in the formal banking system (15).

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 (16, 17). 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 (18). 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 (19). Half of all Americans (51%) were familiar with these services but had not actually used them, while one-third (33%) had never heard of these services. 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 to just 10% of people living in households of less than $30,000 (Smith 2016). This profile was echoed by two important studies that used surveys in San Francisco, and seven major cities between 2014 and 2016 (20, 14). The differential in adoption between those who are more educated and have higher incomes, and those who are not, were 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).

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 family of three) (21). The study, designed and implemented by a private consulting firm and funded by Uber, compared the relative performance of traditional taxis versus 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 to a taxi dispatched by telephone and cost less than half as much, even after accounting for "surge 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, who subsequently published several articles. Following this request, the NYC

TLC began to release limited ridesourcing data. A fuller discussion of this is contained in our sub-section on Data, but this does explain why trip data are publicly-available for NYC. A series of reports suggested that ridesourcing in NYC has begun to undermine public transportation (6) and is worsening congestion on city streets (22). Congestion pricing was therefore recommended to ease traffic and support public transit (23). 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 (24). What was eventually implemented, to take 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. This approach appears to completely ignore the dynamics unfolding outside of this geographic area. Furthermore, Uber appears to have begun a strategic marketing campaign to capture customers in the outer boroughs based on the message that their product fills an unmet need. Uber's website for the outer boroughs contains 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." (25)*

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. Uber has launched a strategic marketing campaign targeted specifically at lower-income neighborhoods with limited access to public transit. 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 (26, 27). Uber has also changed terms and conditions agreed with drivers at will, raising concerns about labor standards (5, 28, 29). 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 (30). 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 (31).

4.3.2 Study Area

New York conjures up 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 of the island have been labelled “subway deserts” and contain far fewer jobs and 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. More texture on how much these vary across the study area can be seen in Table 1 that presents the descriptive statistics for the variables used in our analysis.

Transportation theory emphasizes the importance of factors such as intensity of the built environment, 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 (32, 33). Distinct types of neighborhoods emerge with their own 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 describe various contexts.

4.3.3 Data

We used 17 variables to describe our study area, identified in Table 1. Subway and bus stops per square mile were calculated from data obtained from NYC Open Data, while car ownership rates were taken from the 2014 American Community Survey 5-year estimates. Data on jobs were obtained from the LEHD Origin-Destination Employment Statistics (LODES) dataset for New York. Eleven separate 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 that assigned Census Tracts to the taxi zone that contained the centroid. This join procedure was used because census tract and taxi zone borders closely align with each other. Figure 1 shows the typical discrepancy between borders using taxi zone 196 as an example along with the most extreme discrepancy taxi zone 2.

Figure 1: Alignment of Taxi Zones with Census Tracts Example

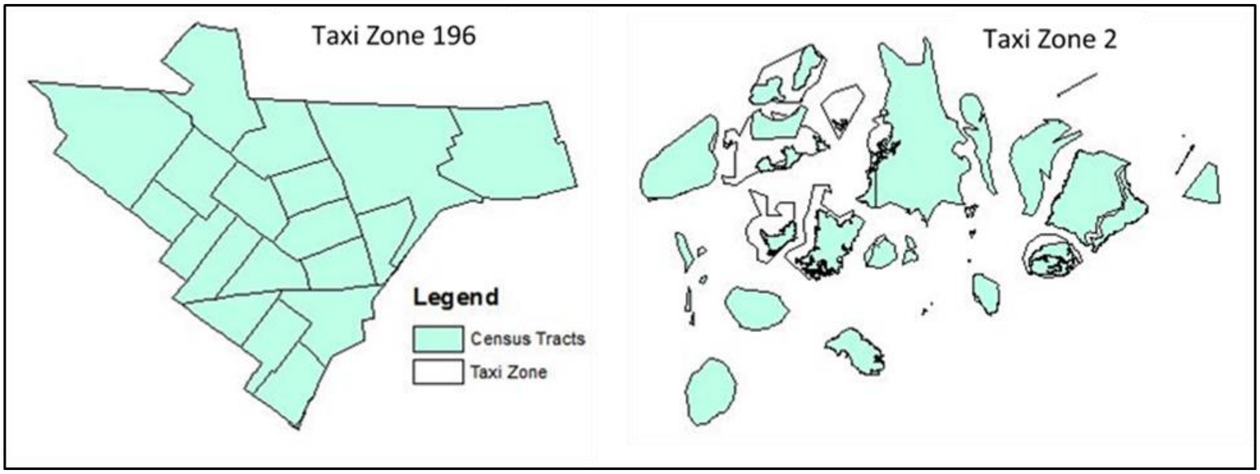

Table 1. Descriptive Statistics of Variables Used in Analysis Aggregated to the Taxi Zone

Variables	Minimum	Maximum	Mean	Standard Deviation
Transportation-Related Variables				
Subway Stops/SqMi	0	40.2	3.8	6.3
Bus Stops/SqMi	0	209.6	66.5	35.0
% Car Free Households	0	91.0%	49.9%	26.5%
Built Environment Intensity-related Variables				
Population/SqMi	0	191,520	41,563	34,664
Jobs/SqMi	0	525,749	27,920	77,692
Activity Density:(Pop+Job)/SqMi	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%

Data on for-hire vehicle trips were downloaded from the website of the NYC TLC, the government entity that regulates all for-hire vehicles across the New York boroughs. 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. Third, 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 Freedom of Information Law (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 timeframe are the taxi zone in which the trip originated, and the date and time of the trip. The study area contains 263 taxi zones of varying sizes created by the NYC TLC. As a result, our analysis focused on the taxi zone in which trips originated.

4.3.4 Methods

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. Five factors explained 78% of the variance in the data. These vectors were used in a K-Means cluster analysis. It was determined that eight unique clusters would yield groupings that were unique but not overly specialized. The K-Means cluster analysis was performed, selecting eight distinct groupings, or clusters.

4.4 FINDINGS

4.4.1 Neighborhood Typology

Our analysis generated eight distinct neighborhood types within the study area. The average values of each variable by Cluster (or neighborhood type) are shown in Table 2. Cluster 1 consists of 6 taxi zones, located entirely in Manhattan, distinctive because they have the highest density of subway stops per square mile (31.4% compared to 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 far less 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 is distinct because it has the lowest median household income of all the clusters ($36,027), has a majority of its population that 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 2.

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 these are a unique set of taxi zones that include parks, cemeteries, as well as the airports, that have their own dynamic.

Despite clustering on the vectors from the factor analysis, the cluster names were based on mean values for four selected variables that were used in the factor analysis. Names were based on mean variable values since they are easier to follow than the factor compositions. Variables selected to name clusters were variables that were distinct across clusters and describe spatial location of clusters, transportation opportunity, and ethnic composition.

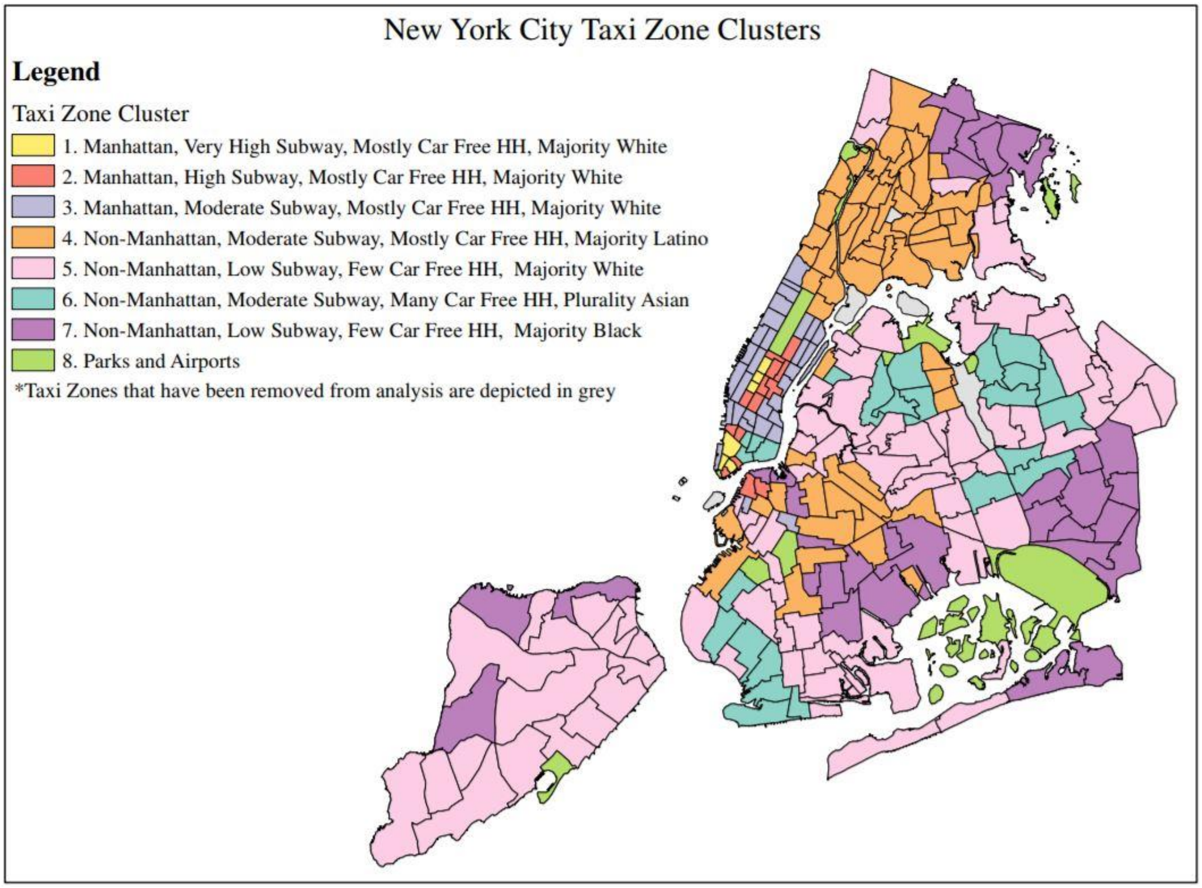

Figure 2: Types of Neighborhood Across New York's Five Boroughs

4.4.2 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 three-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 to the outer boroughs. In Manhattan, for-hire vehicle trips as a whole increased by only 10%. This was because ridesourcing trips increased while 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 towards 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.

Table 2. Mean Values of Characteristics Describing each Neighborhood Type

Variable	**Cluster Number**							
	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/SqMi	31.4	14.5	3.9	3.8	1.3	3.6	1.2	0.4
Bus Stops/SqMi	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/SqMi	42,048	47,572	93,524	59,817	23,745	44,795	27,150	0
Built Environment Intensity-related Variables								
Jobs/SqMi	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)/SqMi	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

Table 3. Average Number of Daily Trips

	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	4587%	-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	2420%	-40%	-4%	102%
7	385	878	1,330	2,594	27,021	451	1,481	28,952	6911%	-49%	11%	1016%
8	1,192	24,522	399	26,113	15,992	20,842	407	37,241	1242%	-15%	2%	43%
Total	23,017	436,463	34,214	493,695	390,105	298,599	31,248	719,952	1595%	-32%	-9%	46%

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, while 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 reveal that for trips originating in Manhattan, 73% drop off in Manhattan, compared to 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 5, and 7 are 40%, and 36% respectively.

Table 4. Pick-ups and Drop-offs for Randomly-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%

4.5 CONCLUSIONS & FUTURE RESEARCH

Our findings inform three important areas: equity, externalities, and public policy, each of which is detailed below. Within each sub-section, we suggest areas for future research.

4.5.1 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. 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 adopter 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 which 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, while drivers have been left open to changing terms and conditions of their flexible employment arrangements (26-

28). 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.

4.5.2 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. It is difficult to determine exactly how much additional VMT this translates into, in part because capacity utilization rates vary. Nevertheless, any increases in VMT will be accompanied by the usual negative externalities such as air pollution, traffic congestion, and traffic fatalities that have already been the focus on 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 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.

4.5.3 Public Policy

At the local level, all the emphasis on regulating ridesourcing appears is focused on Manhattan, motivated by growing congestion and a desire to maintain the existing public transit system. Following an examination of congestion in New York City, beginning in January 2019, a fee of $2.75/$2.50 will be imposed on ridesourcing vehicles/taxis for all trips originating south of 96th Street in Manhattan. 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 whether or not 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 may undermine important transportation sustainability goals.

The authors confirm contribution to the paper as follows: study conception and design: Carol Atkinson-Palombo and Norman Garrick; data collection: Lorenzo Varone; analysis and interpretation of results: Carol Atkinson-Palombo, Lorenzo Varone, Norman Garrick; draft manuscript preparation: Carol Atkinson-Palombo, Norman Garrick. All authors reviewed the results and approved the final version of the manuscript.

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5.0 REPORT 2

TRACKING THE EVOLVING ROLE OF RIDE SOURCING SERVICES WITHIN UNIQUE NEIGHBORHOOD TYPES IN NEW YORK CITY

5.1 ABSTRACT

Ride source is among the fastest growing services in the transportation sector. While the service initially served a niche market, ridership has boomed in recent years. Daily ride source pickups in New York City have increased from about 60,400 pickups in January 2015 to about 550,000 pickups in December 2017, an 810% increase. Even though ride source broke into the transportation landscape almost seven years ago, research studying its effects has been stunted by the limited open source data made available by TNCs. In order to help city officials make smart policy decisions regarding ride source, transportation experts must continue to advance the literature on ride source with the data available. This study aims to supplement existing research by analyzing temporal patterns of for-hire services in a range of transportation, land use and social contexts within New York City in order to understand how ride source was initially used and how it is used currently. We analyzed ride source, yellow taxi and green taxi temporal patterns by day of week and time of day for 2014 and 2017 and characterize these patterns in distinct neighborhood groupings. Using a set of demographic, social, economic, transportation and land use variables, A K-means Clustering Method will be used to identify similar taxi zones in order to define a set number of unique neighborhood clusters. The study finds that temporal trends in ride source and for-hire vehicle use have changed between 2014 and 2017, indicating that these services are being used differently now than at the beginning of the study period. Within Manhattan, ride source growth has mainly contributed to the increase late night trips. Outside of Manhattan all periods of the day have experienced a surge in pickups with the largest increase coming at night.

5.2 INTRODUCTION

Transportation has always been driven by the evolution of technology and the desire for efficiency. In many cases the emergence of new modes of transportation have proved disruptive to the transportation landscape when they were introduced. The most notable case being the invention of the automobile in 1885 and its emergence into popular use in 1908. Now more than ever, as advances in transportation become increasingly susceptible to advances in technology and transportation networks become more complex, transportation innovations are inherently disruptive. One of the most recent disruptive technologies to gain a strong foothold in transportation is ride sourcing.

Ride Source is a method of transportation that connects a user to a driver in order to facilitate a door to door trip. The service that links users to drivers is operated by a third party company commonly known as Transportation Network Companies (TNCs). TNCs provide this service through a smartphone application that takes advantage of smartphone location data (GPS) to match a user with a local driver and price a trip based on estimated travel time and distance. Location data has also recently been employed in judging the supply of drivers and demand of trips in an area in order to apply a demand tax referred to as surge pricing. The closest transportation counterpart to ride source service are taxi services. The most distinct difference between these two services is how a trip is arranged. Ride source trips are hailed on a smart phone, while taxi trips are typically hailed on the street or by the phone.

In cities where ride source is available, it is common for there to be more than one TNC option. In New York City, Uber, Lyft, Via, Gett and Juno make up the majority of the ride source market share. Uber began operation in New York City in May 2011, followed by Via and

Gett in June 2012. Lyft, owning the second largest ride source share, began service in July 2014. Lastly, Juno began in 2016 but was acquired by Gett in August 2017.

Even though ride source broke into the transportation landscape almost seven years ago, research studying its effects has been stunted by the limited open source data made available by TNCs. As ride source continues to grow in urban areas, city officials are motivated to enact policies that regulate ride source service. In order to help city officials make smart policy decisions regarding ride source, transportation experts must continue to advance the literature on ride source. This study aims to supplement existing research by analyzing temporal patterns of for-hire services in a range of transportation, land use and social contexts within New York City in order to understand how ride source was initially used and how it is used currently. New York City is a diverse setting and enables this study to capture ride source patterns for a variety of populations and land use configurations served by an array of transportation opportunities. This research, in conjunction with the current literature will hopefully influence context sensitive policies that promote equity and access in our transportation systems.

5.2.1 Taxi and Ride Source Operations in New York City

In a 2016 For-Hire Vehicle Transportation Study, The City of New York classifies both taxi and ride source under for-hire vehicle service. In New York City there are yellow taxis and green (or boro) taxis. Before ride source was introduced, yellow taxi essentially had a monopoly on for-hire vehicle service in New York City (*1*). Yellow taxis can make pickups in any taxi zone in New York City, including at airports. Taxi zones are a spatial unit regulated by the New York City Taxi and Limousine Commission (NYC TLC). The NYC TLC divides the study area into 263 taxi zones. Despite a lack in spatial regulation, yellow taxi mainly serves Manhattan. The New York City Taxi and Limousine Commission (NYC TLC) recognized this short coming in

2013 and attempted to address it by launching the green taxi in August (*2)*. In order to facilitate better availability of taxi service outside of Manhattan and perhaps limit competition with yellow taxi, green taxis are prohibited from making pickups in Manhattan taxi zones south of West 110 Street and East 96 Street as well as at the city's airports (*3)*.

Unlike the two taxi services, ride source pickups have yet to be restricted by any policy. Currently, ride source services can make pickups and drop offs anywhere within the five boroughs including the airports. The difference in regulation of these two major types (taxi and ride sourcing) of for-hire services extends into the number of vehicles allowed to operate in New York City. The city limits yellow taxi medallions in New York City to 13,587 medallions. In 2013, New York City sold 6,000 green taxi medallions with a planned 6,000 additional medallions to be sold the following two years (*2)*. Ride source vehicles have no regulation capping the number allowed to operate in the city.

5.2.2 Ride Source Regulation

Even though TNCs face full bans in countries such as Denmark and have encountered temporary bans over disputes in U.S. cities such as Austin, Texas, they have managed to operate in cities largely unregulated (*4, 5)*. Recent discussions have moved towards regulating the number of ride source vehicles since for-hire vehicles in New York City increased from 63,000 to over 100,000 vehicles since 2015 (*6)*. This has been met with opposition from TNCs, as Uber released an ad suggesting that the increased service they aim to provide for minority populations may no longer be possible with a vehicle limit (*7)*. However, legislation that applies a congestion charge on for-hire vehicle trips passing through Manhattan was passed and is scheduled to take effect in January 2019. A flat fee of $2.75 will be applied to ride source trips, $2.50 to taxi trips, and $.75 per passenger in shared options like Via, Uber Pool and Lyft Line (*8)*.

5.2.3 Overview of Study

The most complete ride source data available is the New York City dataset. Ride source data is available for April to September 2014 as well as January 2015 through December 2017 in two different formats. This study will use pickup time and location data aggregated to the taxi zone level for April to September 2014 as well as the same time period in 2017. We analyzed ride source temporal patterns by day of week and time of day for 2014 and 2017 and characterize ride source use in distinct taxi zones. Using a set of demographic, social, economic, transportation and land use variables, A K-means Clustering Method will be used to identify similar taxi zones in order to define a set number of unique taxi zone clusters.

5.3 REVIEW OF LITERATURE

In the following section a review of research relating to the objectives of this study is conducted. It will cover studies on ride source growth in New York City and their current impacts in order to understand the current state of understanding of magnitude of TNC use in New York City. Survey based studies will be reviewed to cover the current consensus on who is adopting ride source and for what purposes. In addition, limited studies on ride source temporal patterns will be discussed to get a sense of any current observations.

Following the initial release of ride source data and subsequent data sets researchers attempted to quantify and visualize the data to provide a top level analysis of ride source use and growth in New York City. Following their FOIL request, FiveThirtyEight has released an article that advanced the discussion of ride source's impacts on service in the outer boroughs. FiveThirtyEight made the observation that ride source appeared to serve the demand for for-hire vehicle trips in the outer boroughs better than taxi. As early as 2014, Uber held the highest share of any one service in the for-hire vehicle industry in the majority of the outer boroughs *(9).* Schaller Consulting has also steadily released articles concerning ride source growth in New York City. In February 2017, Schaller Consulting reported that ride source growth was the most significant in Manhattan, the most congested area of the city, and argued that ride source is an unsustainable means of improving shortcomings in city's transportation networks (*10).* In December 2017, it was reported that the increase in for-hire vehicle numbers and trips, as well as a high percentage of miles traveled without passengers between trips contributes to an average speed of less than 7 mph during the day in downtown Manhattan. This is the slowest speeds recorded in downtown Manhattan (*11).*

There have been a number of surveys conducted with the intent of capturing the subset of the population that most commonly uses ride source and what they are using it for. Clewlow and Mishra conducted a survey based on American Community Survey and Household Travel Surveys in seven U.S. cities including Boston, Chicago, Los Angeles, New York, San Francisco, Seattle and Washington D.C. Results from this study concluded that ride source is used predominately by individuals that are younger, well-educated individuals with higher income. Individuals living in urban areas are also more likely to use ride source services (*12).* Circella et al used survey data in order to estimate an ordered probit and zero inflated probit models. Important results include that sociodemographic factors help to explain adoption rates but not necessarily frequency of use. Activity density and car free households are good indicators of frequency of use (*13).* Henoa (*14*) drove for both Uber and Lyft in the Denver Metropolitan area and asked riders to complete a survey he curated to understand ride source adopters and their travel behaviors. He concluded that ride source users that typically drive a vehicle used the service for leisure trips, traveling to the airport and for trips taken while traveling away from home. Their decision to travel by ride source was based on avoiding searching for and paying for parking as well as to avoid the issue of driving home after drinking. As for users who do not drive a vehicle, they used ride source most commonly for work and school commute trips. The most popular reason to use ride source for these trips was due to lack of public transit options.

There have been limited studies that have considered comprehensive day of week and time of day patterns. One report by Feigon and Murphy analyzed day of week and time of day patterns for five metro areas after acquiring data from a major TNC. The dataset included hourly origin-destination data for Chicago, Los Angeles, Nashville, Seattle and Washington DC. The main take away from the temporal patterns of this study was that in all study areas the majority of ride source trips were made in the evening and on the weekend (*15)*. Using the datasets origin-destination data, the study also observed that most trips occurred in the downtown cores and, contrary to findings in Clewlow and Mishra (*14)*, stated that ride source trips occurred in areas of all income levels.

5.4 DATA

This section will provide an overview of the trip data obtained for yellow taxi, green taxi and ride source services as well as data used to characterize and group the taxi zones in NYC. It will describe where the data was obtained from in its raw format as well as the purpose of any additional data filtering and aggregation completed for this project. Trip data was acquired in order to understand changes in for-hire vehicle trips since 2012 as well as temporal patterns in 2014 and 2017. Transportation, land use, social, economic and demographic variables were used to characterize the taxi zones and to cluster them into groups of similar types. Data types were selected with the objective of capturing the different factors that might influence the transportation decision making process.

5.4.1 For-Hire Vehicle Data

Yellow Taxi data has been released by the NYC TLC for every month since January 2009. Green Taxi data has been released by the NYC TLC for every month since the service launched in August 2013. For yellow and green taxi, April to September 2014 trip data gives pickup location by latitude and longitude. April to September 2017 trip data gives pickup location aggregated to the taxi zone.

Even though ride source operation in New York City dates back to May 2011, the first ride source service data publicly available is an Uber dataset for New York City from April 2014 to September 2014. This data was released in response to a Freedom of Information Law (FOIL) request made by the analytics website FiveThirtyEight. Since this data was released, the NYC TLC now releases ride source service data as a part of their For Hire Vehicle (FHV) Trip Record data. The NYC TLC began releasing this data in January of 2015 and have released FHV data through December 2017. Only pickup data has been included in data releases for ride source trips up until June 2017. From June 2017 to December 2017 drop off data is also included. The lack of detail in the data released by TNCs as well as the omission of data from initial years of operation shows that these companies could be releasing more comprehensive open source data. For example, Uber and Lyft do not release data indicating whether a trip was made using their shared services UberPool and LyftLine or how many passengers there were for a given trip. This means that current data on pickups cannot be accurately translated to total ridership in New York City.

For the purpose of this study, temporal data of ride source, yellow taxi and green taxi was aggregated for April to September 2014 and April to September 2017. The 2017 period was selected to match the 2014 period to account for seasonal trends. Ride source service data for April to September 2014 only includes pickup data from the ride source company Uber and was gathered from the FiveThirtyEight Github page (*16)* The trip characteristics provided include the

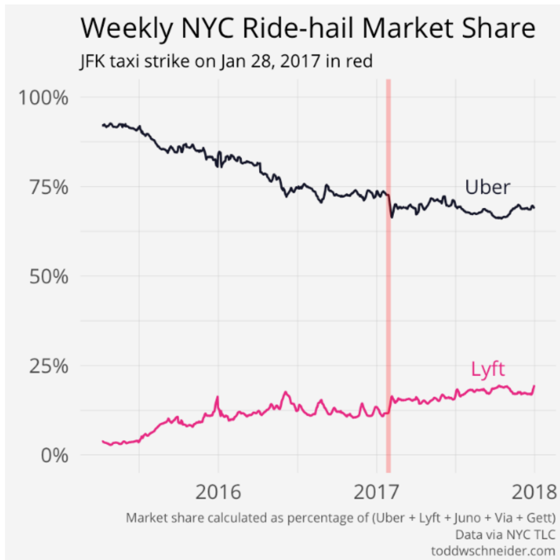


Figure 1. Uber and Lyft's Ride source Market Share (*17*)

date and time of the pick-up, the geographic coordinates of the pick-up in latitude and longitude and the Base Code. It is important to note that Via and Gett also operated in New York City during this entire time period and Lyft starting in July. In Figure 1 it is evident that Uber owned about 90 percent of the ride source market share in April 2015 (*17*). Therefore the 2014 Uber dataset representative of the ride source landscape in New York City during that period. Ride source service trip data for April to September 2017 was gather from the NYC TLC Trip Record page (*18*). This dataset provides pick up locations of individual trips at the taxi zone level. In this dataset one or more base codes are associated with each ride source company. The dataset was filtered using Todd Schneider's Github page of associated base codes to include only trips made by Uber, Lyft and Via (*19*). Gett and Juno trips do not provide pickup location information which is needed for this study's analysis. In order to keep the spatial unit of analysis constant, data for the 2014 time period was aggregated to the taxi zone level in ArcGIS to match the 2017 dataset using the taxi zone shape file downloaded from the NYC TLC (*18*).

5.4.2 Taxi Zone Characteristic Data

5.4.2.1 Transportation Related Variables

Subway and Bus stop locations were gathered from Subway and Bus Stops shape files from NYC Open Data (*20).* Stops per square mile were calculated by aggregating the number of stops in each taxi zone using a spatial join and executing the calculate area function for each taxi zone. Car Ownership Rates were gathered from the 2014 ACS 5-Year Estimates (*21).* Car Ownership rates were given at the census tract level and were aggregated to the taxi zone level.

5.4.2.2 Built Environment Intensity Related Variables

Population was gathered from the 2014 ACS 5 Year Estimate (*21*) and aggregated to the taxi zone level from census tract. Employment data was gathered from the LEHD Origin-Destination Employment Statistics dataset (*22*) for New York. Number of jobs were given by the census block level. Census block level data was aggregated to the taxi zone level. Lastly, a binary variable was created in order to identify whether a taxi zone was located in Manhattan or outside of Manhattan.

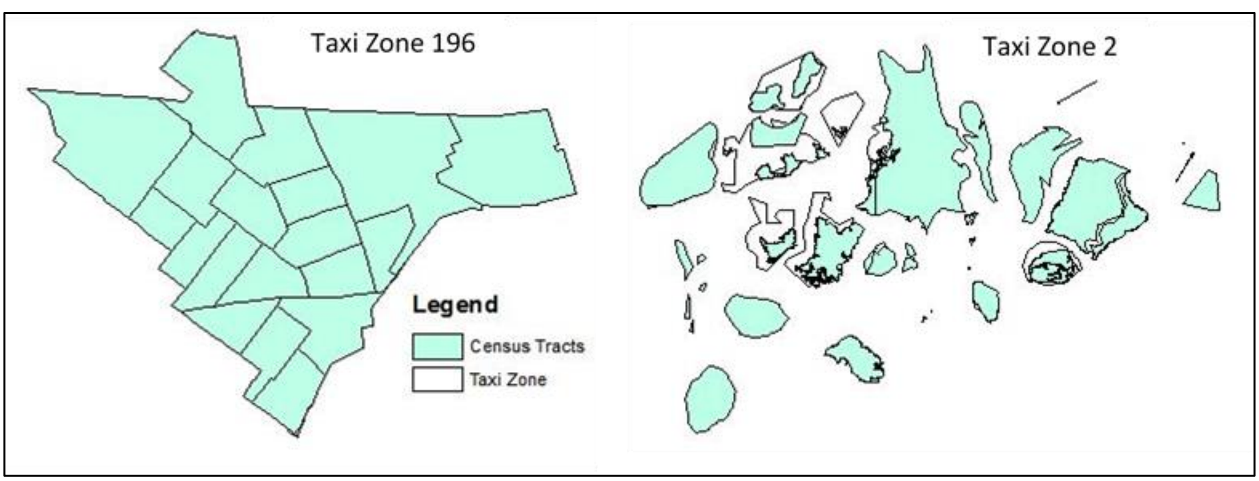
5.4.2.3 Social, Economic and Demographic Related Variables

Eleven variables that have been shown in studies to effect an individual's transportation decision-making process were gathered from the 2014 ACS 5-Year Estimates (*21*). These variables include Weighted Average Median Household Income, Average Household Size, Percent Households with People Younger than 18 Years Old, Percent Households Living Alone, Percent of People Older than 25 with a Bachelor's Degree, Percent Unemployed, Percent White, Percent Black, Percent Latino, Percent Asian and Percent Elderly. Census tract level data was aggregated to the taxi zone level.

5.4.2.4 Aggregation Procedure

Using the New York City 2010 Census Tract shape file gathered from the NYC Department of City Planning (*23*), census tract level data was matched to the census tract ID in the shape file. The census tracts were the spatially joined to the Taxi Zone shape file based on which taxi zone the center of each census tract fell within. This join procedure was used because census tract borders and taxi zone borders have nearly a one to one alignment throughout the city. Figure 2 shows the typical discrepancy between borders using taxi zone 196 as an example along with the most extreme discrepancy taxi zone 2.

Figure 2: Alignment of Taxi Zones with Census Tracts Example



Next, characteristic data was summed based on common taxi zone ID numbers. This same process was used for the Total Jobs data, however census block level data was aggregated to the taxi zone level. The New York State 2010 Census Block shape file was gathered from the New York City Department of Planning (*24*).

5.5 METHODOLOGY

In this section the steps taken to create the unique taxi zone clusters in SPSS will be described. The resulting neighborhood cluster characteristics and locations are then presented.

5.5.1 Taxi Zone Cluster Analysis

A Dimension Reduction-Factor Analysis with a varimax rotation was performed on the descriptive variables selected for the clustering analysis. The Factor Analysis was performed in order to identify a reduced set of unique factors that explain the variance within the total dataset. A varimax rotation was selected in order to account for multicollinearity between the variables selected for the clustering analysis. The factor analysis identified five unique factors. Together the five unique factors explain a total of 78.08% of the variance in the data. After completing the factor analysis, the five unique factors identified were used in a K-Means clustering analysis. It was determined that eight clusters would yield groupings that were unique but not overly specialized. K-Means cluster analysis was performed for eight clusters. The resulting clusters can be seen in Figure 3 below.

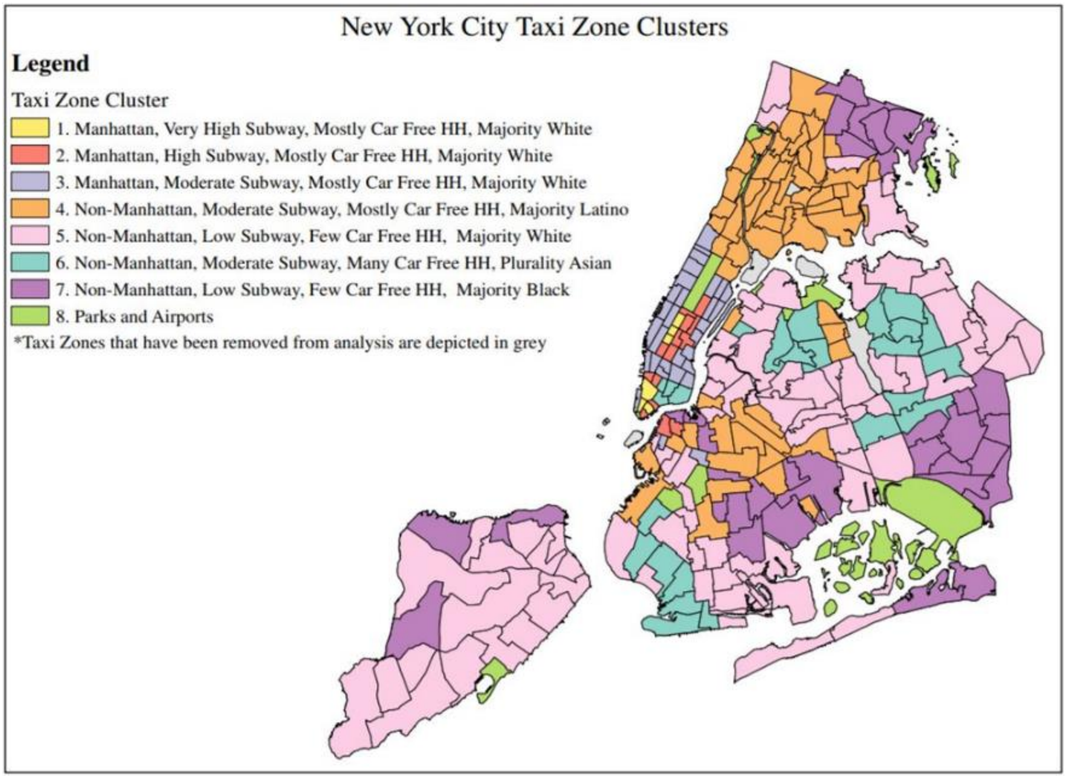


Figure 2. Taxi Zone Cluster Results and Cluster Descriptions

5.5.2 Taxi Zone Cluster Characteristics

The following section defines the criteria this study developed for top level cluster descriptions. Final top level cluster descriptions can also be found in Figure 3. Lastly, Table 1 displays mean values of variables that went into the cluster analysis for each cluster. A calculated variable, Jobs to Population Ratio, not included in the cluster analysis can also be found. This was included to understand the degree to which each cluster skews toward residential or commercial land use.

5.5.2.1 Framework for Top-Level Cluster Descriptions:

The framework developed for naming clusters is described below. Despite clustering on the vectors from the factor analysis, the cluster names were based on mean values for four selected variables that were used in the factor analysis. Names were based on mean variable values since they are easier to follow than the factor compositions. Variables selected to name clusters were variables that were distinct across clusters and describe spatial location of clusters, transportation opportunity, and ethnic composition.

- Manhattan vs Non-Manhattan:
    - Manhattan: >50% Manhattan Taxi Zones
    - Non-Manhattan: <50% Manhattan Taxi Zones
- Subway Access (Stop per Square Mile):
    - Very High: 20+
    - High: 10-20
    - Moderate: 2-10
    - Low: 0-2
- Car Free Households (%):
    - High: 75+
    - Moderate: 40-75
    - Low: <40
- Most Common Race (%)
    - Majority: >50%
    - Otherwise considered Plurality

Table 2. Mean Values of Characteristics Describing each Neighborhood Type

Variable	**Cluster Number**							
	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/SqMi	31.4	14.5	3.9	3.8	1.3	3.6	1.2	0.4
Bus Stops/SqMi	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/SqMi	42,048	47,572	93,524	59,817	23,745	44,795	27,150	0
Built Environment Intensity-related Variables								
Jobs/SqMi	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)/SqMi	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

5.6 DESCRIPTIVE ANALYSIS

In this section will place ride source growth in context among existing modes in New York City which include Taxi, Citi Bike and Subway. Overall trends in Subway and for-hire vehicle trips are discussed at a city wide level. Unique trends found in the Taxi Zone Clusters discussed in the previous section are also reviewed to understand how the for-hire vehicle market is changing in different areas.

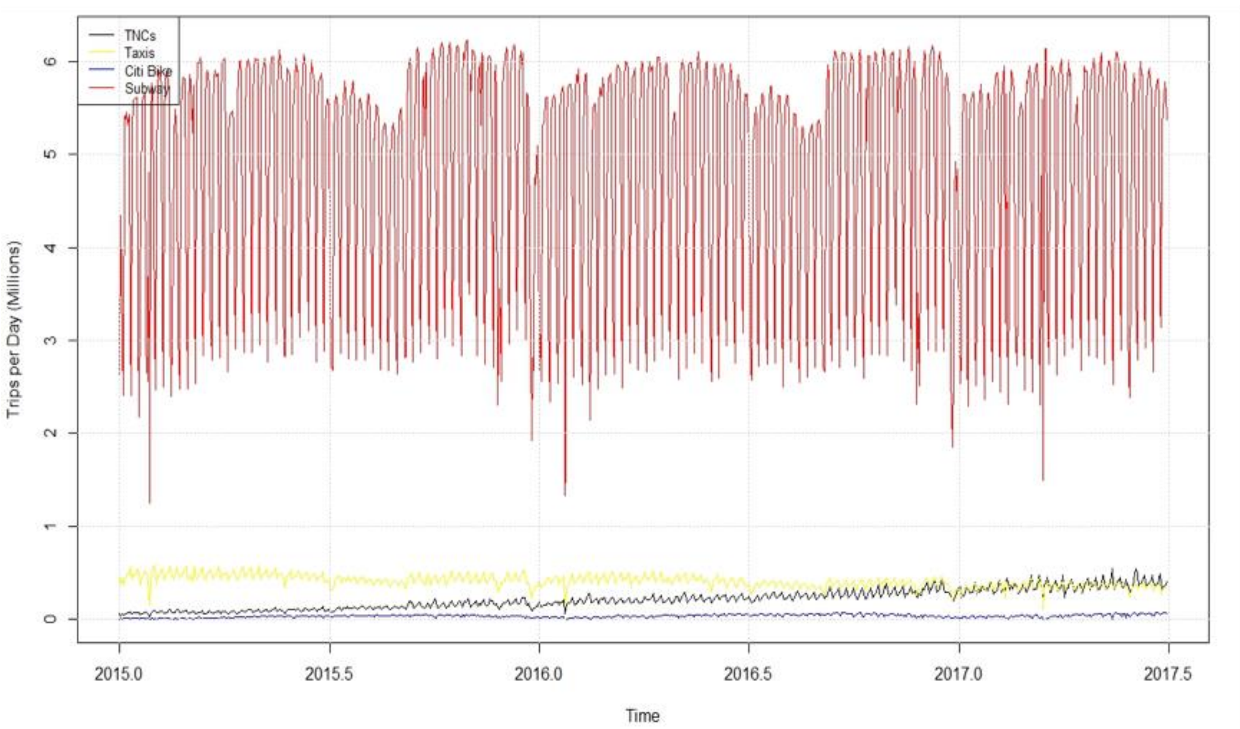


Figure 3. Daily Trips by Mode in New York City (*25*)

5.6.1 Subway Trips vs For-Hire Trips

Figure 4, developed in Gerte et al (*25*), puts into perspective the scale of ride source and taxi trips on a city wide level. Subway still holds a much greater share of trips in New York City compared to taxi and ride source. While subway trip trends show a seasonal effect, subway has not shown a discernable drop off in daily trip totals between 2015 and midway through 2017.

5.6.2 For-Hire Vehicle Trends

Figure 5 depicts the change in average daily pickups in New York City for each month by for-hire vehicle services. Ride source adoption did not happen overnight. However, in the scope of new transportation alternatives it grabbed a significant share of the for-hire vehicle market rather quickly. Since Uber went live in New York City in 2011, ride source pickups eclipsed green taxi in January 2015, and then the much bigger yellow taxi service in December 2016. Judging by the overall increase in for-hire vehicle pick-ups citywide, ride source does not appear to be merely eating into the taxi market, but might also be fulfilling a demand for for-hire services in the city that was not being met by taxi services. In January 2012, there were about 500,000 daily for-hire vehicle pickups citywide. By 2017, daily for-hire vehicle pickups had increased about 80 percent, reaching nearly 900,000 pickups.

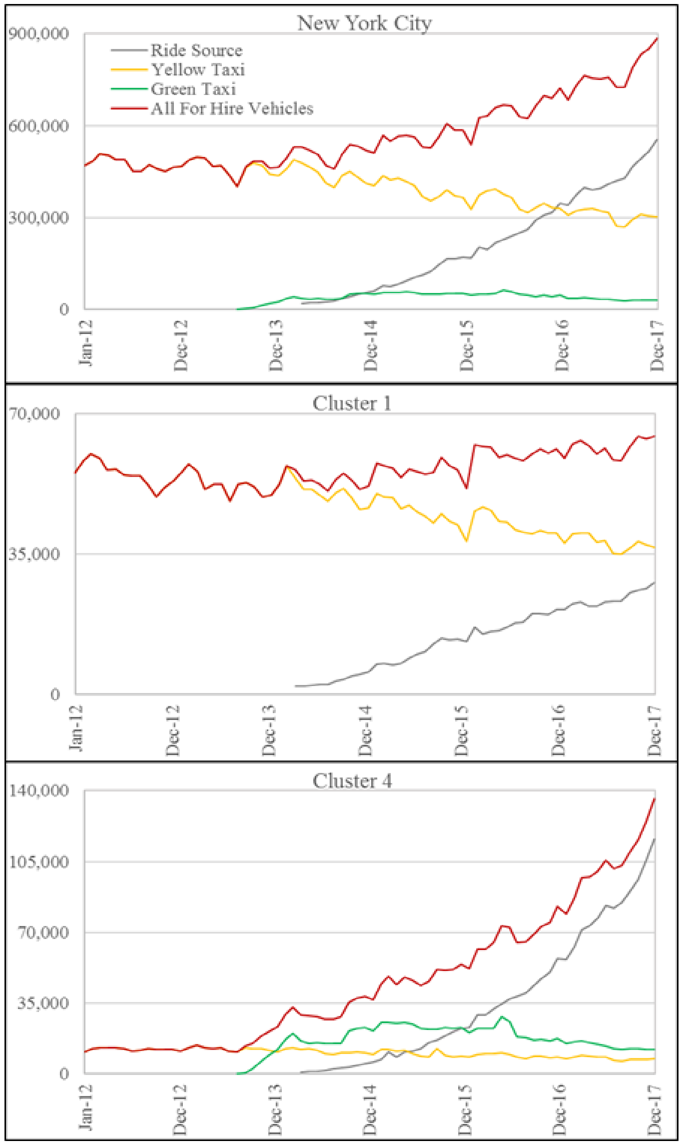


Figure 4 Daily Average Pickups by Month (January 2012-December 2017)

While the citywide numbers help to understand the overall trend, looking at the growth in different areas of the city paints a more nuanced picture of ride source and for hire vehicle growth. A similar chart depicting average daily pickups by month was created for the clusters of similar taxi zones that are discussed above. In general two distinct trends in growth were found. One for Manhattan centric clusters and another for Non-Manhattan centric taxi zone clusters.

Cluster 1, is typical of what happened in the three Manhattan taxi zone clusters. In this cluster of taxi zones, ride source growth has increased steadily, while yellow taxi pickups have declined concurrently on an almost one to one basis. The overall result is that total for-hire vehicle pickups have seen an uptick of 16% between January 2017 and December 2017. The trends in Manhattan suggest that ride source is largely replacing yellow taxi while perhaps also filling a small gap in unsatisfied for-hire service demand. The data hints at the possibility that ride source could soon reach a plateau in growth in Manhattan.

The results in Cluster 4, is typical of the four non-Manhattan residential taxi zone cluster. In this cluster, which is comprised of mainly of taxi zones in the Bronx and Brooklyn, there were minimal for-hire vehicle pickups prior to the introduction of ride source. While ride source use in these areas outside of Manhattan was also minimal before 2015, they have since taken off. The number of ride source pickups per day have increase sharply over the past two years. As a result daily pickups by for-hire vehicle services are over 1,000 percent higher than in January 2012. With ride source increasing at its highest rate over the past six months, it seems the leveling off point for for-hire service outside of Manhattan is not yet in sight.

5.7 RESULTS

The following section will discuss the day of week and time of day patterns within the unique taxi zone clusters discussed earlier. The discussion will focus on the distinct temporal patterns by cluster in each time period and how the patterns have shifted. Mean values for Taxi Zone Cluster characteristics found in Table 1 will be referenced in explaining why the temporal patterns observed are surprising or could be expected. The majority of variables used to characterize taxi zone clusters were not applicable to the taxi zones in Cluster 8. Therefore, Cluster 8 is not discussed in this paper.

5.7.1 Day of Week Analysis

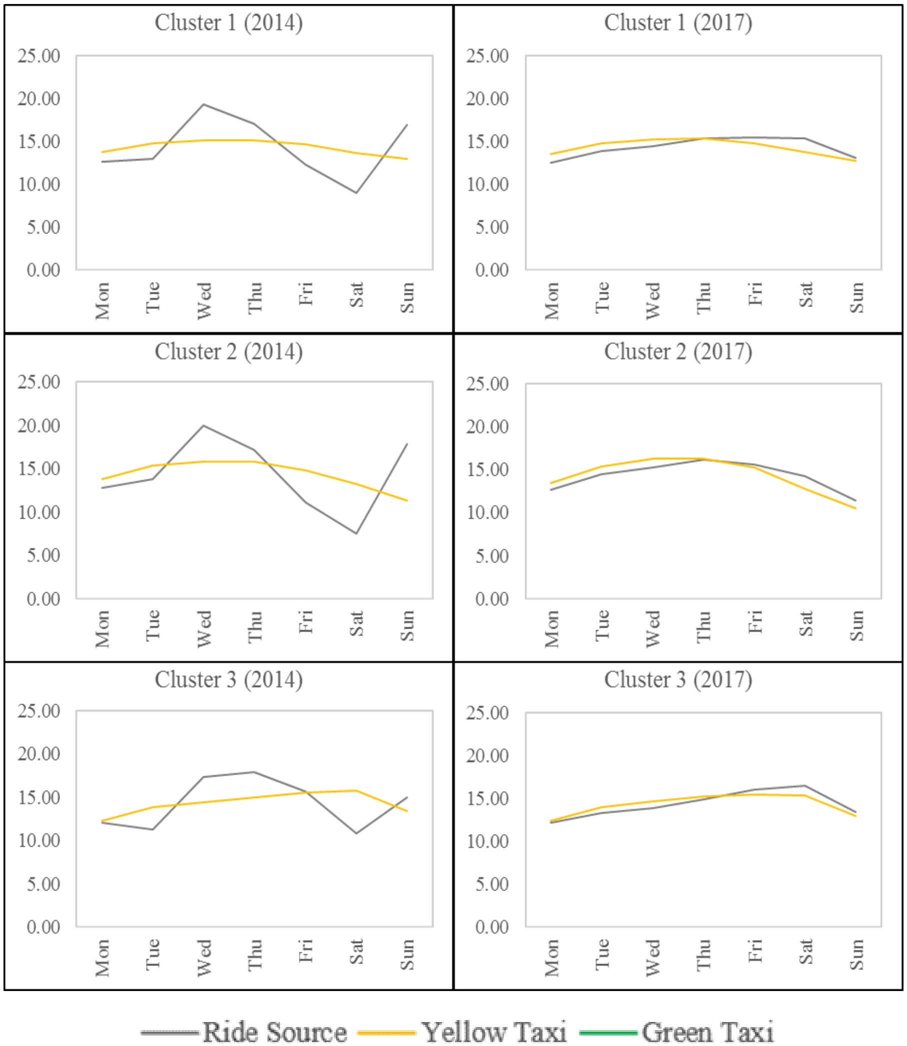


Figure 5. Percent of Pickups by Day of Week (Manhattan Clusters)

Figure 6. Percent of Pickups by Day of Week (non-Manhattan Clusters)

Figures 6 and 7 show the percentage of weekly trips by day of week for ride source and the taxi service with the higher number of pickups in a particular cluster (generally yellow taxi will be highest in Manhattan). In Figure 6 and 7, it is clear that ride source day of week patterns in 2014 and 2017 were distinctly different. In 2014, patterns in Manhattan clusters favored the middle of the week with the largest share of pickups on Wednesday or Thursday, while Tuesdays had the smallest share of ride source trips in all Manhattan clusters. In 2017, ride source patterns favor Saturday use in Cluster 1 and Cluster 3. Cluster 2 still favors mid-week use, however, the weekly distribution is more even throughout the week than in 2014. Weekly use in Manhattan clusters during 2017 also more closely resembles taxi use in 2017 where in 2014 it did not.

Non-Manhattan clusters display different day of week patterns from Manhattan clusters in 2014. In all four Non-Manhattan clusters, Fridays exhibited the largest weekly share of pickups. In every non-Manhattan cluster during 2017, the highest share of weekly trips for ride source shifted to Saturday. Though Saturday is favored in nearly every cluster in 2017, non-Manhattan clusters weekly share of pickups skew more heavily towards Saturdays than Manhattan clusters. The greater share of weekend pickups in non-Manhattan clusters suggests a stronger inclination to use ride source for leisure and entertainment trips

5.7.2 Time of Day Analysis

For the time of day analysis, only pickups made Monday through Thursday were considered. Trips being made on Saturdays and Sundays are largely assumed to be non-commute trips since they are outside the typical work week while Friday exhibits both weekday and weekend trends.

Figure 7. Percent of Pickups by Time of Day (Manhattan Clusters)

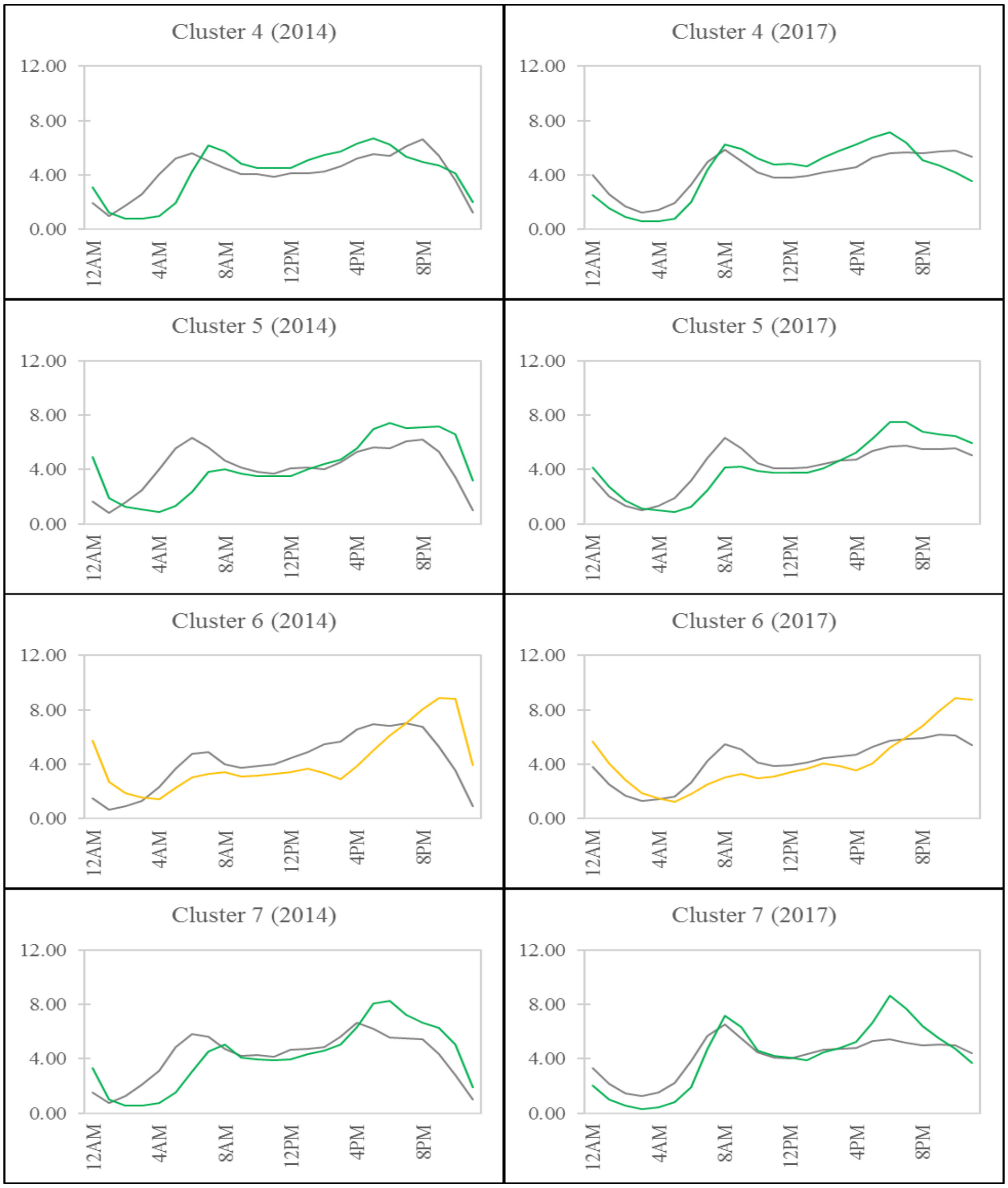


Figure 8 Percent of Trips by Time of Day (Non-Manhattan Clusters)

5.7.2.1 Ride Source 2014 Pattern

In 2014, ride source seemed to function largely as a supplement to taxi use in Manhattan. This is evidenced by the spikes in ride source percent use by time of day matching up with dips in time of day percent for yellow taxi in Figure 8. The dip in yellow taxi use matches up with the most common time for yellow taxi drivers to change shifts and not be available for pickups (*26).* Ride source also seemed to meet demand for travel in the morning before the typical taxi peak in cluster 3. In 2017, Ride source and yellow taxi presently see a much higher share of pickups by time of day occur in the late night hours between 9 PM and 12 AM. This appears to be a behavioral change in how for hire services are used.

5.7.2.2 Ride Source Time of Day Shift to Late Night Use

Similar to the overarching trends in day of week patterns, ride source time of day patterns (shown in Figure 8 and 9) have also shifted significantly from 2014 to 2017. The overarching change in ride source time of day distribution is that in 2017 a much higher percentage of ride source trips occur late at night compared to 2014. This change in time of day pattern is not isolated to any one part of the city. It is a city wide trend that shows up in every taxi zone cluster. This trend has emerged for all for-hire vehicle services. Ride source in Manhattan Clusters shown in Figure 8 and Non-Manhattan clusters shown in Figure 9 exhibit the same trend where daily share of pickups remains high from 9PM to 12 PM. Previously, in 2014, the percent of ride source pickups dropped off after 8 PM. Ride source is not the only service that has seen an increase in night time pickups. Both Yellow Taxi and Green Taxi have also seen a rise in percent of daily pickups during late night hours.

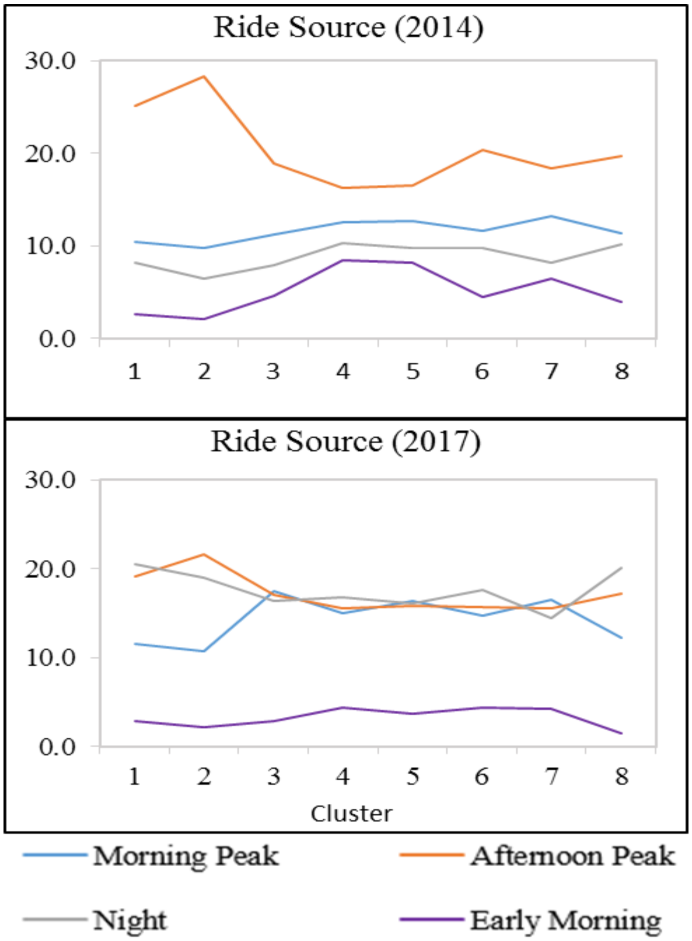


Figure 10 Change in Percent Pickups by Period of Day

5.7.2.3 For-Hire Service Time of Day Patterns Are Converging

Similar to how all for-hire vehicle services have converged from 2014 to 2017 in day of week use, for-hire vehicle service use by time of day has also become more similar over time. In 2014, there were clear differences in ride source time of day patterns between taxi zone clusters. For example, Manhattan taxi zone clusters 1 and 2 with very high job density have a much more pronounced afternoon ride source peak and dampened morning peak use. Comparatively, taxi zone clusters 3 through 7 with higher residential land use have a pronounced morning and afternoon peak. One might expect that because ride source operates similarly to taxi, that its time of day patterns would converge to how the 2014 taxi time of day pattern. However, the for-hire services have converged to a new pattern not previously observed in 2014. This indicates that for-hire vehicle travel behavior may be changing.

While the Figures 8 and 9 depicting time of day patterns by hour create a detailed picture of use, Figure 10 summarizes percent use during key periods of the day in 2014 and 2017. While initially the afternoon peak was favored in all clusters in 2014, the morning peak, afternoon peak and night period all share a more even percent of daily trips, especially in clusters 3 through 7. Total trips in 2014 and 2017 during these selected time periods as well as their percent changes are given in the following table in order to further characterize changes.

Table 3. Average Daily Pickups for Selected Periods of Day by Cluster

Cluster	Morning Peak (8-11 AM)	Afternoon Peak (4-7 PM)	Night (9PM-12AM)	Early Morning (2-5 AM)	Morning Peak (8-11 AM)	Afternoon Peak (4-7 PM)	Night (9PM-12AM)	Early Morning (2-5 AM)	Morning Peak (8-11 AM)	Afternoon Peak (4-7 PM)	Night (9PM-12AM)	Early Morning (2-5 AM)
	Ride Source 2014				Ride Source 2017				Ride Source % Change			
1	287	695	225	73	2,609	4,326	4,640	661	810%	523%	1963%	810%
2	694	2,026	457	154	5,802	11,661	10,218	1,167	736%	476%	2136%	659%
3	3,391	5,701	2,384	1,405	16,691	16,192	15,593	2,713	392%	184%	554%	93%
4	192	248	157	128	10,664	10,969	11,906	3,099	5446%	4321%	7465%	2313%
5	197	257	152	126	8,533	8,230	8,374	1,894	4238%	3099%	5414%	1400%
6	140	245	117	54	4,109	4,390	4,934	1,234	2831%	1689%	4104%	2168%
7	49	68	30	24	4,065	3,833	3,565	1,049	8191%	5501%	11627%	4241%
8	151	264	137	53	1,966	2,769	3,222	231	1198%	948%	2257%	334%
Total	5,101	9,504	3,660	2,018	54,440	62,370	62,453	12,049	967%	556%	1606%	497%
	For Hire Services 2014				For Hire Services 2017				For Hire Services % Change			
1	8,282	9,575	6,905	1,319	8,339	10,173	11,074	1,524	1%	6%	60%	16%
2	19,971	26,248	15,278	2,098	18,410	27,704	24,476	2,403	-8%	6%	60%	15%
3	34,508	42,381	26,957	6,751	40,227	38,958	36,346	5,650	17%	-8%	35%	-16%
4	3,273	4,216	3,231	1,047	13,877	14,440	14,414	3,686	324%	243%	346%	252%
5	1,617	2,384	2,896	909	9,798	9,892	10,303	2,378	506%	315%	256%	162%
6	1,859	3,081	3,689	1,010	5,222	6,182	7,614	1,945	181%	101%	106%	93%
7	278	449	354	78	4,381	4,205	3,850	1,082	1479%	835%	986%	1285%
8	4,133	5,101	3,214	415	5,665	7,009	6,833	423	37%	37%	113%	2%
Total	73,922	93,434	62,524	13,628	105,919	118,562	114,910	19,091	43%	27%	84%	40%

5.7.3 Increased Manhattan For-Hire Pickups During Night Period

In Table 3, the Manhattan clusters (1, 2 and 3) have a relatively muted increase, besides the night period, compared to the Non-Manhattan clusters. While the night period saw for-hire pickups increase 60 percent in Cluster 1 and 2 and 35 percent in Cluster 3, no other period saw greater than a 17% increase in for-hire vehicle pickups. While ride source pickups have increased by between 93 and 2,100 percent in the defined periods of the day, for-hire vehicle pickups have decreased in some cases. In Table 3 it can be seen that cluster 2 saw an 8 percent decrease in for-hire vehicle pickups in the morning period and Cluster 3 saw an 8 percent decrease in for-hire vehicle pickups in the afternoon peak. The most notable increase in for hire vehicle pickups occurred outside Manhattan in Cluster 7 with increases during periods of the day between 835% and 1480%.

5.7.4 Unexpected Ride Source Adoption

Cluster 7 lead all clusters in percent increase in for hire vehicle pickups for all selected time periods. It has few car free households, low subway access and the second lowest activity density. The literature highlighted suggested that areas of high car ownership and lower activity densities would expect less demand for ride source (12, 13). This extreme increase (up to 1,749% for the morning peak) suggests that cluster 7 has had an acute desire for for-hire services. In 2017, this demand is finally being met. In 2014, 30% of for-hire vehicle trips were made by ride source and in 2017 this number has increased to 90%. Cluster 7 experienced it’s most dramatic growth in the morning peak period.

Table 4. Pickups per Population plus Jobs by Time of Day Periods

Cluster	Morning Peak (8-11 AM)	Afternoon Peak (4-7 PM)	Night (9PM-12AM)	Early Morning (2-5 AM)	Morning Peak (8-11 AM)	Afternoon Peak (4-7 PM)	Night (9PM-12AM)	Early Morning (2-5 AM)
	Ride Source 2014				Ride Source 2017			
1	0.001	0.001	0.000	0.000	0.005	0.008	0.009	0.001
2	0.001	0.002	0.001	0.000	0.007	0.014	0.012	0.001
3	0.003	0.005	0.002	0.001	0.014	0.014	0.013	0.002
4	0.000	0.000	0.000	0.000	0.004	0.004	0.004	0.001
5	0.000	0.000	0.000	0.000	0.003	0.003	0.003	0.001
6	0.000	0.000	0.000	0.000	0.003	0.003	0.004	0.001
7	0.000	0.000	0.000	0.000	0.003	0.003	0.003	0.001
8	0.004	0.007	0.003	0.001	0.050	0.070	0.081	0.006
Total	0.000	0.001	0.000	0.000	0.005	0.006	0.006	0.001
	For Hire Services 2014				For Hire Services 2017			
1	0.016	0.019	0.013	0.003	0.016	0.020	0.021	0.003
2	0.023	0.030	0.018	0.002	0.021	0.032	0.028	0.003
3	0.029	0.035	0.023	0.006	0.034	0.033	0.030	0.005
4	0.001	0.001	0.001	0.000	0.005	0.005	0.005	0.001
5	0.001	0.001	0.001	0.000	0.004	0.004	0.004	0.001
6	0.001	0.002	0.003	0.001	0.004	0.005	0.006	0.001
7	0.000	0.000	0.000	0.000	0.003	0.003	0.003	0.001
8	0.104	0.129	0.081	0.010	0.143	0.177	0.172	0.011
Total	0.007	0.009	0.006	0.001	0.010	0.011	0.011	0.002

5.7.5 The Gap in Pickups per Capita still Favors Manhattan

In Table 4, ride source and for-hire vehicle pickups per cluster in 2014 and 2017 are normalized by the total sum of population plus jobs in each cluster. Even though Non-Manhattan clusters saw the largest percent increases in ride source and for-hire vehicle pickups (In Table 3), Manhattan clusters still have much greater pickups per capita. On average, Manhattan clusters in the night time period saw eighty-two percent more for-hire pickups per capita than non-Manhattan clusters. Clusters in the outer boroughs are still far behind Manhattan clusters in pickups per capita. A low pickups per capita in non-Manhattan clusters supports the trend observed in the Descriptive Analysis (Figure 5) that suggests ride source growth is much further from reaching a plateau than Manhattan clusters.

5.8 CONCLUSION

Observations regarding ride source and for hire temporal trends and their implications are discussed in this section. Long term impacts on New York City's transportation system if these observations hold true in future confirmatory research methods are discussed. Future research that can work to confirm or deny the observations in this study are also covered.

5.8.1 Behavioral Use of For-Hire Services

This study observed that there is a city wide trend that shows ride source service use to be favored on the weekend days in every cluster besides cluster 2. In addition, on weekdays, ride source use has seen the largest increase in use occur during the night time period in every cluster. As a whole, for-hire services are being used more heavily later at night in 2017 than they were in 2014. From the data available it cannot be confirmed if late night ride source pickups in a cluster are made by the population in the cluster. In addition, if the population in a cluster accounts for the majority of ride source pickups in a cluster, then surveys must be used to understand whether the population in a cluster using ride source is representative of the overall sociodemographic makeup of each cluster.

5.8.2 Increased Night Time Pickups in Manhattan by For-Hire Vehicles

The largest increase in for-hire vehicle pickups in all Manhattan clusters occurred during the night time period. Most reports highlighting congestion in Manhattan have focused on issues caused by an increase in for-hire vehicles during the afternoon peak (11). Further research may focus on understanding the night time ride source use in Manhattan. Survey data can isolate night time trip purposes as well as reasons for using ride source. For example, whether night time ride source trips consist of a high percentage of induced trips that would not have been made by another mode. This will help understand how much of the increase in for-hire vehicle trips in Manhattan are new trips and how many are replacing other modes such as personal vehicles, subway and bus.

5.8.3 Ride Source Adoption during Morning Peak Hours

In three out of four non-Manhattan clusters (5, 6 and 7) the morning peak period experienced the largest growth in for-hire vehicle. In Cluster 7, a growing portion of the population may be using ride source for their daily commute. Morning peak for-hire pickups increased nearly 1,500 percent in this cluster. This was a surprising result considering the high vehicle ownership of this cluster and the tendency of car owning individuals to not use ride source for commute trips discussed in the literature (*14*). Surveys conducted should also investigate the interplay of ride source with public transit especially in these outer borough clusters. It is important to know if people are using ride source to travel directly from home to work or using it to supplement their commute by transit by being dropped off at a transit station. Information on changes in vehicle ownership should also be collected to understand whether using ride source for commuting is leading to reduced vehicle ownership. It is important for planners to avoid relying on ride source to fill gaps in the transit network and service schedule. Instead of relying on these private companies further survey data can help transportation engineers and planners identify where to allocate transit funds that come from the new congestion pricing legislation.

The authors confirm contribution to the paper as follows: study conception and design: Carol Atkinson-Palombo and Norman Garrick; data collection: Lorenzo Varone; analysis and interpretation of results: Carol Atkinson-Palombo, Lorenzo Varone, Norman Garrick; draft manuscript preparation: Lorenzo Varone. All authors reviewed the results and approved the final version of the manuscript.

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6.0 CONCLUSION

Revisiting the initial research questions, the overarching question was "*Are ride sourcing services being used differently depending on transportation, built environment intensity and social contexts?"* Based on the findings in each of the reports it appears that there is reason to believe that ride sourcing is in fact being used for differently depending on context. There are distinct differences in the growth of ride source pickups as well as temporal patterns by neighborhood clusters.

In the first report the main focus was "*How do the overall number of ride sourcing trips vary across different settings and how have they changed over time?"* The observations that were the most important in this study were that ride source pickups are increasing the most in clusters with low income populations with low access to transit as well as low car ownership. It is assumed that low income populations will not use ride source since they likely cannot afford it (7). Therefore, further research must assess if ride source use in these areas is tied to low income populations and if so how frequently do they use it. This research is needed to inform how ride source policy should be handled in poorer areas. For purposes of equity, cities must be very careful of using ride source numbers to justify cutting transit service. Although an extreme case, Arlington, Texas has cut its only bus line in favor of partnering with the ride source company Via to operate micro-transit service in the city (8).

Ride source increased dramatically between the two study periods in this report. Fully understanding the externalities associated with this increase will be important to explore once more robust data is available for ride source trips. In order to estimate added VMT, air pollution and traffic safety implications, information regarding ride source trips length, passenger count, the indication of a shared ride, as well as time spent driving between trips will be vital. A combination of more transparent TNC data as well as survey data will be necessary to accomplish this research.

In the second report the focus was *"How have the temporal patterns of ride source use changed in different neighborhoods over time"* In the time between 2014 and 2017, city wide ride source temporal patterns of use have become more consistent geographically. In 2014, when ride source numbers were lower, day of week use as well time of day use was more sporadic. In 2017, clear patterns show ride source favors weekend use. In addition, weekends are more heavily favored in clusters located in the outer boroughs. Time of day use on weekends showed that ride source seems to be influencing increased demand of for-hire vehicle use during the late night hours. For Manhattan clusters, the night period saw the greatest increase in for-hire vehicle pickups. In non-Manhattan clusters the majority of increase during the day occurred either in the morning peak period or the night time period.

The findings from this study should be transferable to most urban areas due to the range of socio-demographic, transportation and built environment intensity contexts within New York City. The variety of neighborhood types analyzed should be sufficient to be applied to most cities. However, the methodology used in this study may not be applicable to cities with excessive urban sprawl.

The most important take away from this study is the need for survey data in order to fully comprehend who is using ride source in each neighborhood cluster developed in this study. In the coming year during the ride source driver licensing freeze in New York City, studies of this nature will have the capability of shaping ride source policy and regulation as well as policies that deal with the transportation sector as a whole.

7.0 STUDY LIMITATIONS

The overarching limitation of this study is the ride source data set itself. The time periods selected for 2014 and 2017 only allowed origin data to be compared. In addition, ride source and for hire vehicle data are now aggregated to taxi zones, a low resolution spatial unit which places a limitation on how finely grained the clustering analysis could be, as well as analyzing pick up locations. In addition, ride source data is lacking information regarding rides shared through pooled options as well as trip distance and cost. These characteristics are important for assessing transportation planning options.

One limitation to the study includes the assumptions made for allocating bus stops to taxi zones in order to determine bus stop density in each taxi zone. Since roadways in most cases define the boundaries between taxi zones, bus stops are located within close proximity to other taxi zones. In these cases, a stop is essentially accessible from the bordering taxi zone. In the case of looping bus routes, stops on either side of the road from the same route should account for this. However, in the case of one way bus routes or one way roads, the aggregation assumption used will not capture this.

In addition, spatial units of varying scales had to all be aggregated to the highest common spatial unit of the taxi zone. During the process of bringing all these spatial units to the same spatial resolutions, geographic inaccuracies in the spatial data may effect aggregation to a degree.

Another possible limitation exists in the procedure used for determining the neighborhood clusters. Once the five factors were determined in the factor analysis, the five vectors were not scaled to have all their variables in the same range. The range of all five factors are in Table 1 below. Most of the factors ranges are very similar and the only factor that may present a small issue was factor 4. There is a chance that scaling the factors would result in slightly different cluster groupings.

Table 1. Ranges of Factors Used in K-Means Clustering

	Min	Max	Range
Factor 1:	-3.17065	1.62513	4.795787
Factor 2:	-1.82094	2.69961	4.520543
Factor 3:	-1.93090	2.68152	4.612415
Factor 4:	-1.51757	6.01117	7.52874
Factor 5:	-2.02214	3.90644	5.928585

8.0 APPENDIX A

LIST OF REFERENCES FOR [3.0 INTRODUCTION] AND [6.0 CONCLUSION]

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