INTERACTIVE TRAVEL MODES: UBER, TRANSIT AND MOBILITY IN NEW YORK CITY.

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ABSTRACT

Smartphones have progressively become an essential tool to help people produce or achieve mobility by providing contextual wayfinding information and serving as a key asset in enabling new shared-mobility services.

Using two unique data sets this paper explores how smartphone applications may enable multi-modal transport behavior. The data sets are user-level interactions from a smartphone application called *Transit* (which seeks to easily informs users of transit, bikeshare, carshare, and Uber access based on their geographic position), and Uber ride-hail origin data released publicly through the New York City Taxi and Limousine Commission. It is believed that users who request Uber through the Transit app are signaling their intent to try transit first, but are willing to move on to other modes when transit does not meet their needs. Thus, Transit application users are more likely to request an Uber near a subway station as complement (for example, instead of a transfer) or a substitute (to avoid a long wait) to transit.

After organizing data by location, this paper finds that Transit app users request Ubers at a higher rate both within 250 feet of a transit station and with greater dispersion across the entire city than the general population of Uber ride-hails. This suggests that Transit app users are attempting to use Uber to make up for gaps in their transit options. This finding aligns with previous studies where people have indicated that the tools on their smartphone allow them to assert more control over their transportation outcomes, particularly when they choose not to drive.

INTRODUCTION

Smartphones have progressively become a tool to help people produce or achieve mobility. Using increasingly robust, yet easily interpretable data about various transport options, smartphone users can choose between a wide and growing number of transport services to plan their journeys and make the process of mobility easier. This collection of services includes:

1. Interactive transit schedules and real-time public transit information;
2. Live traffic congestion data;
3. Shared-economy services – this includes new travel mode categories such as bike share and car share; and new challengers in existing modes such as Uber and Lyft towards taxi services.

Often, these transportation services are studied independently. However, a user of one of these services is typically using a smartphone and can just as easily access information about the other services by switching apps. Some apps, such as the *Transit* app[1] – which will be a focus in this paper – present much of that information in one interface known as a mobility aggregator. Mobility aggregators have easy-to-follow information that makes it much easier and more reasonable for a traveler to execute a multi-modal journey.

Despite the availability of mobility aggregators like the Transit app, the majority of these services tend to operate independently. Further, most of the 'shared-economy' services described above are run by private companies who have no obligation to make their data available to the public. Therefore, very little is known about how these services interact with each other and other mobility aggregators as travelers make their way from origin to destination with the assistance of their smartphones.

RESEARCH QUESTION

This paper will use two unique data sets to explore how smartphone applications focused on transport services encourage multi-modal transport behavior. The data sets consist of user-level interactions in the Transit application (a smartphone application that easily informs users of transit, bikeshare, carshare, and Uber access based on their geographic position), and the general population Uber ride-share origin data released publically through the New York Taxi and Limousine Commission (TLC). This paper is based on the assumption that users who request Uber through the Transit app are signaling their intent to try transit first, but are willing to move on to other modes when transit does not meet their needs. Based on this assumption, we hypothesize that Transit app users will request Ubers near transit stations at higher rates than the general population of Uber users. If this hypothesis is correct, it would align with previous studies in which travelers have indicated that the tools on their smartphone allowed them to make more informed transportation decisions *[1]*, particularly when they choose not to drive *[2]*.

[1] *Transit* (the smartphone application) was originally called the *Transit App.* In order to avoid confusion between *Transit* (the app) and transit (the general name for mass transport), this paper will refer to the smartphone application as the 'Transit app' or the 'Transit application.'

LITERATURE REVIEW

The rise of Transportation Network Companies (TNC) such as Uber, and mobility aggregators like Transit app is due to vast improvements in information and communication technology (ICT), which are exemplified by the smartphone. Changes in transportation have long been linked to changes in communication technology, as both activities are complimentary and substitutable *[3]*. Increasingly, travelers are using digital information communicated via their smartphones to achieve more reliable mobility outcomes. The rise of the mobile phone has allowed users to communicate without remaining at fixed locations *[4]*, which can then "permit new practices and innovation in our relationship with space and travel" *[5]*. In fact, mobile devices are purposefully meant to interact with the environment *[6]*. Ubiquitous computing platforms like smartphones often have the ability to modify, control, utilize, and regulate space (such as a surveillance system, digital thermostat, or traffic signal). Increasingly, with their connected devices, people can now proactively manage their use of space and time. New digital services allow people to use their personal ICT devices to plan a trip, find a ride, share bikes or cars, or avoid traffic congestion in real-time *[7][1]*.

ICTs in particular have enabled significant new forms of travel at mass market scales *[8]*. An overwhelming majority of these forms of travel are now shared transportation modes in which users can utilize excess capacity of discrete goods/services for travel *[9][10]* . Unlike traditional transportation systems that are publicly maintained, many new ICT-based transportation services are often private start-ups. These ICTs include car share (ZipCar, Car2Go), ride-sourcing (Uber, Lyft) and some bike-sharing services (CitiBike, Zagster). These new travel options, combined with improved transit and road congestion information made available by mobility aggregators, produce a curated travel experiences for users based on their exact location, the time of day, and accessible transportation alternatives.

Yet, these new transport services are not without their controversy. For example, many localities - even whole countries - have attempted to ban Uber, as most government entities were not prepared for Uber's meteoric rise *[11]*. Regulatory bodies and incumbent actors were surprised and challenged by the new technology and did not have the necessary frameworks to handle the Uber service *[12]*. While these agencies have more-or-less come to accept the new challenges of TNCs, the costs and benefits of ride-sourcing are understood much more anecdotally than quantitatively. The services are clearly well used and expanding every day, but detailed data on ride-sharing's tangible social costs and benefits are inconsistent and hard to come by.

By contrast, the passenger benefits of real-time travel information, particularly in public transportation, has been increasingly well-documented using widely available data. Implementation of real-time arrival systems have led to increased ridership, satisfaction, and perceptions of control *[13][14][15]*. In a series of focus groups conducted in late 2013, smartphone users expressed an improved ability to travel to new parts of town, try different travel modes, and manage their time more effectively due to newly available real-time travel information. In fact, the users acknowledged an actual, and growing dependence on this *[2]*.

Fueled by technology and information, people increasingly use their smartphones as their primary source of mobility information.

Hence, it is logical that some travelers would combine shared mobility services with transit information to better achieve their transport preferences for speed, convenience and costs.

DATA

This paper's analysis utilizes two unique datasets related to Uber use in New York City. The first data set, is a sample of Uber trip origins for a six-month period in 2014. The second is comprised of Uber requests summoned through the Transit app. These datasets are described in detail in the following paragraphs.

TLC Uber data

Rules about for-hire-vehicles (FHVs) in New York City require all FHV drivers to be licensed by the Taxi and Limousine Commission and associated with a dispatch base. Uber is considered one of these FHVs under New York law. As a result of evolving FHV reporting rules, Uber origin data has been reported to the TLC from the dispatch bases since 2014. Since this data was now in the hands of a public agency, it became a candidate for a Freedom of Information Law (FOIL) request. The data-journalism blog FiveThirtyEight.com conducted a FOIL request for the Uber origin data and was rewarded with six months (April through September 2014) worth of Uber origin data by latitude/longitude, and six months (January – June 2015) of Uber origin data by 'taxi zone' (a TLC specific geographic unit a bit smaller than a zip code). They used this data to examine several claims about Uber use and traffic congestion on their popular blog *[16][17]*.

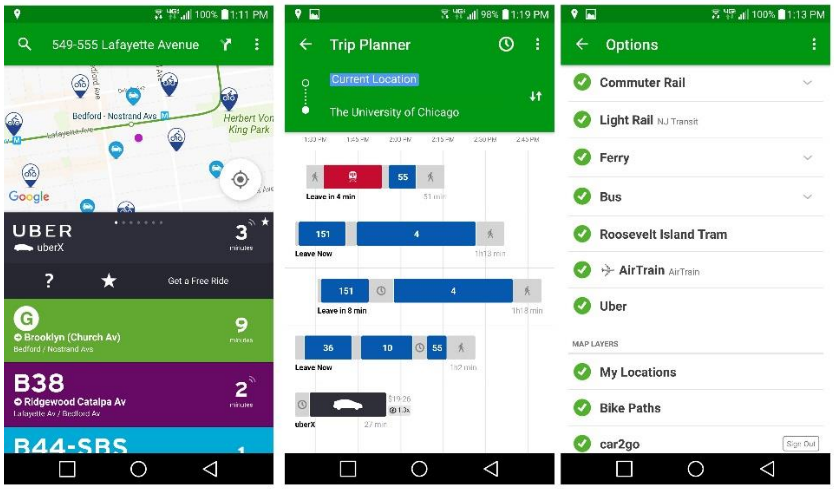
FiveThirtyEight then made this data accessible to the public along with the FOIL documentation on a GitHub repository in 2015 *[18]*. Currently, the 2014 TLC dataset of Uber origins published by FiveThirtyEight is the only publically available large scale view into Uber origins at the fine resolution provided by latitude/longitude coordinates. Both the 2014 and 2015 data sets reveal only origin location and timestamp data.

Transit app Uber data

The Transit application agreed to disclose their data to this paper's research team for academic inquiry. As its name implies, Transit app primarily focuses on providing information about transit services, but as of 2015 it also integrates several 'shared' mobility services including an ability to reserve a Car2Go (car-share), Uber (ride-share/ride-source), and find availability on most bike share systems. Because of these features, Transit app has become one the more popular public transit related apps and concurrently one of the larger referrers to the Uber system. Part of its popularity lies in the application's ability to provide comprehensive mobility information in an easy-to-read interface with minimum input from the user.

The Transit app works by sending the user's GPS coordinates to a server, which then returns schedule and real-time information for all nearby transit lines and supported mobility services. The results for the user are a series of tiles (an interactive list) of transit lines with the next scheduled departure clearly displayed for each service, as well as a map of nearby car-share and bike-share services. Embedded within the transit information is an Uber tile that displays an estimated pickup time from the user's location (see Figure 1). Tapping this tile launches the Uber app and starts the process for a ride request.

Figure 1: Screenshots of the Transit app show the availability of multiple travel modes



The Transit app dataset analyzed for this paper contains records of user interactions with the software interface and is considered a form of data exhaust *[19]*. This dataset is necessary for the application to know what information to serve to which user at the transaction level, but can be used for a secondary purpose to discern systemic patterns. The user interactions in the dataset include opening the app, tapping a tile for more information, asking for directions, or reserving a shared mobility service. To provide transportation information to the users, the application needs to identify individual user devices and the locations of those devices. While the dataset is very detailed in terms of activities and data queries, it is geared towards the operation of the smartphone application, as opposed to answering research questions. Names or demographic variables are not requested nor stored, which protects the anonymity of users.

DATA HARMONIZATION AND DESCRIPTIVE STATISTICS

While both representing Uber rides, the TLC and Transit app data sets have differences that need to be addressed in order to make proper comparisons.

Probably the largest limiting factor is the restriction to New York City. Both the Transit app and Uber operate globally, thus both companies have the potential to produce similar data sets across jurisdictions. This parallel in itself can be valuable for transportation researchers who are typically limited by data collected by government authorities serving specified geographies. However, in this case, while the available Transit app data is global, the available Uber origin data was filtered through the New York TLC. As a result, this paper's analysis is limited to comparing Uber trips against Transit app activity in New York City only.

Further, while both the TLC and the Transit app have Uber data from 2015, the binning of the more recent 2015 TLC data into taxi zones is a very rough spatial resolution, which results in difficulty spatially assessing whether a trip was influenced by the transit system. Alternatively, the raw latitude/longitude coordinates found in the 2014 TLC data allow us to look at the dispersion of Uber origins with higher precision. Unfortunately, the Transit app did not offer the Uber Request feature until 2015. Therefore, we are left comparing data from consecutive years (TLC-Uber in 2014 to Transit app-Uber in 2015). While this would be nearly a non-issue for established transport services, major differences might be present for these fast growing start-ups in the span of one year.

To understand if the TLC data is spatially different in different years, the 2014 TLC data was put into the same taxi zone bins as the 2015 data. The result was that even though the growth in the total number of trips was substantial, the proportional change per taxi zone was small. By broadly aggregating trips that originated inside the Central Business District (CBD) versus outside of it, the percentage of trips outside the CBD increased by just 6.3% of total trips, even though the total count of trips grew by nearly 225% system wide.

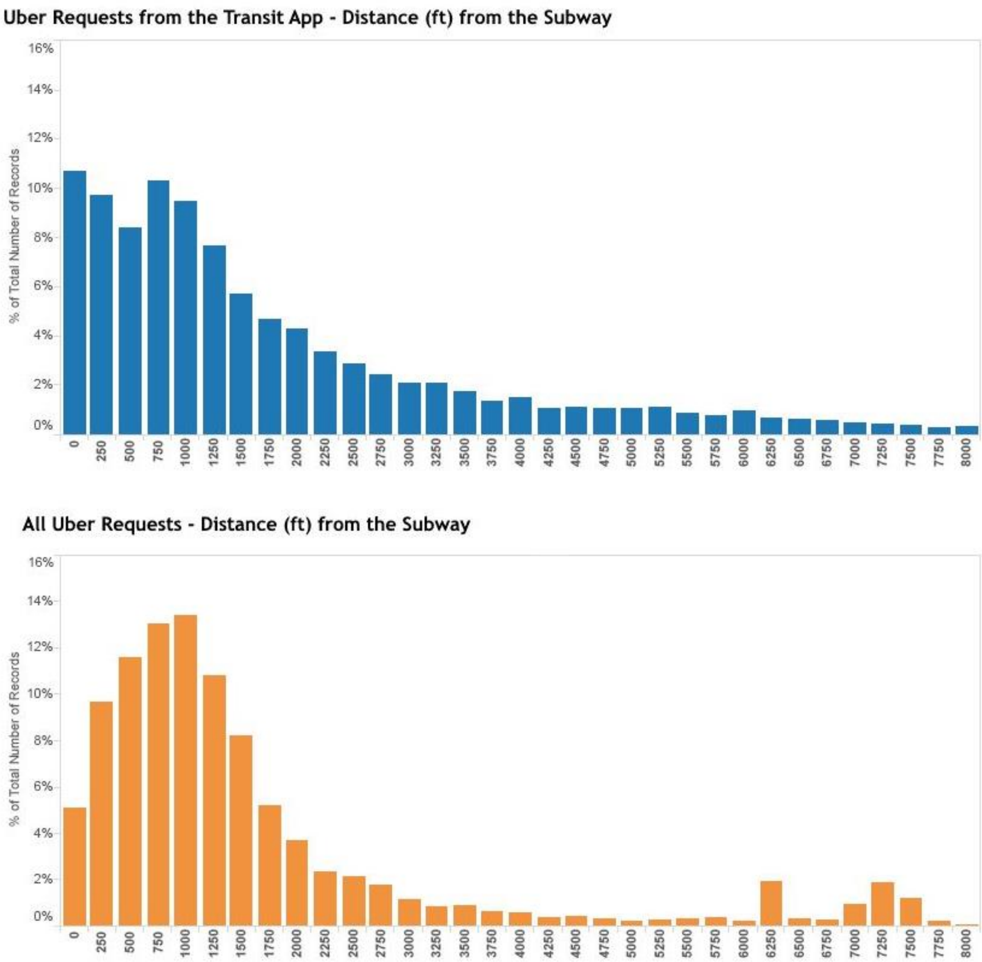
Table 1: Basic comparisons between data sources.

Year	Time frame	*n*	Growth	In CBD*	%CBD	Data type
TLC - Uber origins						
2014	6-mo (Apr-Sept)	4,412,080	NA	3,360,280	76.2%	Lat/Long
2015	6-mo (Jan-June)	14,271,895	223.5%	9,974,257	69.9%	Binned by zones
Transit application - Uber requests						
2015	6-mo (Apr-Sept)	32,398	NA	4,205	13.0%	Lat/Long

*CBD (Central Business District) is defined as Manhattan south of 110th St and is based on the exclusive service area for Yellow Taxis

Viewing the table above, an immediate comparison between the TLC and the Transit app data is apparent. It is clear that unlike the TLC population data set, the Transit app population is strongly dispersed outside of the CBD. In the 2015 sample, nearly 87% of Transit app Uber requests occurred outside of the CBD, while just 30% of total Uber trips occurred outside of the CBD. Further confirming this dispersion is a GIS kernel density analysis. The maps in Figures 2 & 3 show the relative density of Uber origins for the TLC and Transit app samples. These maps lay bare two observations: 1) that the TLC-Uber sample is highly concentrated into the Manhattan CBD, and 2) that the Transit app-Uber sample shows a higher cluster of activity near subway stations - especially outside the CBD. This observation is further confirmed with an exploratory histogram of the two data sets (Figure 4). The Transit app has a much higher percentage of trips within 250 feet of a transit station than the TLC data set. Additionally, the entire dataset is more gradually distributed than the TLC data. Further exploration of these key observations is the main focus of this paper.

Figure 4: Histogram of Uber requests by data set and distance from the subway.

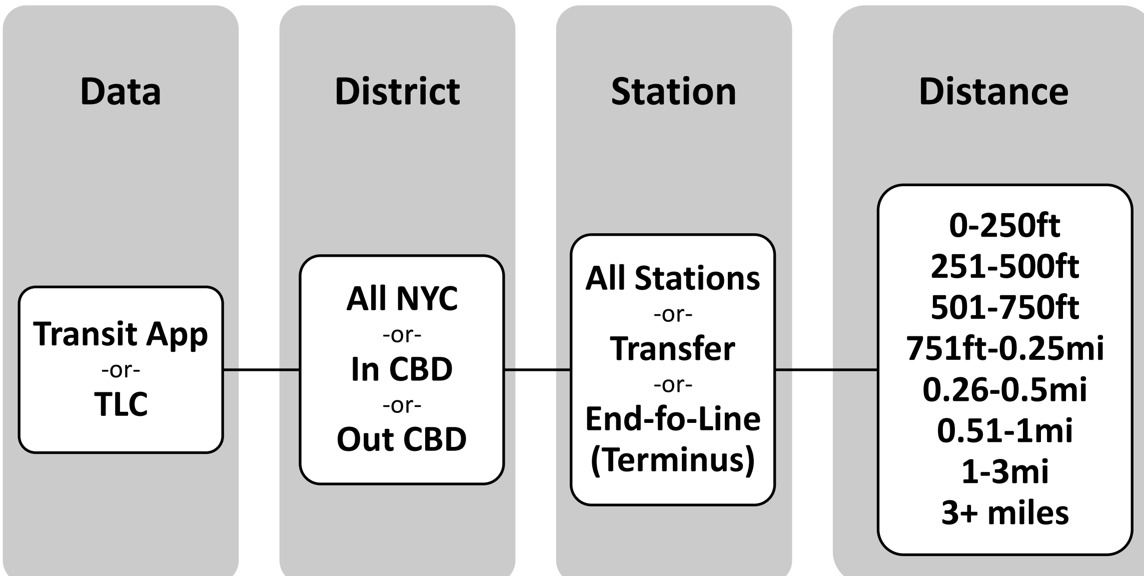


METHODOLOGY

In order to relate Uber trip origins to transit locations, both data sets needed to be spatially related using a GIS system and then tabulated. This relationship allowed for a calculation of the distance from each Uber origin point to the nearest transit station. Stations were further designated as transfer stations (where users could change lines other than between local and express), and end-of-line stations at the terminus. These designations added a dimension that permitted evaluation of whether people were more likely to request an Uber near transit where a transfer would also be likely due to the presence of other high frequency services.

Another important grouping of the data sets involved determining if an origin point occurred in the Manhattan Central Business District. For the purposes of this paper, that area is defined as Manhattan south of 110th Street, which is also the exclusive service territory for Yellow taxis. (In 2013 the Green Taxi program was started to serve upper Manhattan and the Boroughs as approximately 80% of all Yellow taxi trips began and ended south of Harlem. A Green taxi ride must either begin or end outside of this zone.) The CBD designation is important because the geography, density, and land-use of this area of Manhattan means that nearly all activities will occur near subway service, so it is more tenuous to connect Uber activity directly to subway activity in this area rather than outside of it. For this reason, this paper evaluated the data from the CBD separately from the other data points. To count the records, this paper assigned each record in a 100% sample of the Transit app 2015 data (n=32,398) and a 5% random sample of the much larger TLC 2014 data (n=220,604 of 4,412,080) with a subway, transfer, and end-of line distance field as well as a CBD flag. Using these calculations, the records were sorted into 144 bins following the organization in Figure 5.

Figure 5: Record characterizations resulting in 144 unique bins



Due to a difference in the size of the samples, the bins were compared by calculating the percent in each bin of the total sample size for each dimension. Bins were sorted and compared using ESRI ArcMap GIS, Tableau, and R.

FINDINGS

A comparison of the bins is presented in Table 2. Transit app-Uber origins are more likely to be closest to subway stations than the general TLC sample of Uber origins. As discussed above, more attention is being paid to origins outside the CBD since travel activity near non-CBD subway stations is more likely to be related to those stations, though there are also some notable observations inside the CBD as well.

Consistently, a higher percentage of origins in the ‘0-250 ft’ distance from station bins occur in the Transit app data set. For example, outside of the CBD 9.6% of Uber origins from the Transit app occurred within 250 feet of a subway station, compared to 4.3% of origins from the TLC data. Calculating a ratio of the difference in proportion between the Transit app and the TLC reveals that the Transit app saw a 55% higher proportion of Uber origins at all Subway stations, 24.6% higher proportion of origins at Transfer stations, and 90.2% higher proportion of origins at End-of-Line stations when compared to the TLC data. However, this relationship deteriorates rapidly past 250 feet. Both data sets have approximately 75% of activity (TA = 74.1%, TLC=77.6%) occurring more than 750 feet from All Subway stations outside of the CBD.

The Transit app's strongest and most consistent advantage was when Uber users requested rides near end-of line stations. The Transit app had a 370% higher proportion of Uber requests than the TLC data within 750ft of these stations. All end-of-line stations are outside of the CBD.

TABLE 2

Proportion of Uber Origins by data source, distance and type of subway station

Distance		0-250 ft	250-500 ft	500-750 ft	750ft-0.25 mi	0.25-0.5 mi	0.5-1 mi	1-3 mi	3+ miles	Sum	Bin Size
District	Closest Station	**Transit app - Uber Origins (Apr-Sept 2015)**									
All Stations	Any Station	***10.7%***	10.1%	8.8%	20.6%	***21.7%***	***13.6%***	***12.1%***	***2.4%***	100%	32,398
	Transfer	2.7%	2.0%	1.9%	4.7%	10.2%	***19.4%***	***47.0%***	***12.0%***	100%	
	End-of-line	***0.8%***	***0.7%***	***0.5%***	***1.3%***	***5.2%***	***15.7%***	***54.4%***	21.5%	100%	
Inside CBD	Any Station	***18.3%***	***19.2%***	16.7%	24.3%	***16.7%***	***4.8%***	0.0%	0.0%	100%	4,205
	Transfer	***10.6%***	***8.0%***	9.4%	21.2%	23.8%	***14.9%***	***12.2%***	0.0%	100%	
	End-of-line	***0.0%***	0.0%	0.0%	0.0%	0.0%	0.0%	***14.9%***	85.1%	100%	
Outside CBD	Any Station	***9.6%***	***8.7%***	7.6%	20.0%	22.4%	***14.9%***	13.9%	***2.8%***	100%	28,193
	Transfer	***1.6%***	1.1%	0.8%	2.3%	8.2%	20.0%	***52.2%***	***13.8%***	100%	
	End-of-line	***0.9%***	***0.8%***	***0.6%***	***1.5%***	***6.0%***	***18.0%***	***60.2%***	***12.0%***	100%	
District	Closest Station	**TLC- Uber Origins (Apr-Sept 2014)**									
All Stations	Subway	7.9%	***16.1%***	***19.0%***	***29.5%***	18.1%	4.2%	5.1%	0.1%	100%	220,604
	Transfer	***3.2%***	***6.4%***	***8.5%***	***21.6%***	***27.1%***	17.9%	14.8%	0.5%	100%	
	End-of-line	0.0%	0.0%	0.1%	0.1%	0.5%	1.4%	18.4%	79.5%	100%	
Inside CBD	Subway	9.1%	18.6%	***21.9%***	***30.8%***	***16.3%***	3.3%	0.0%	0.0%	100%	167,760
	Transfer	3.8%	7.7%	***10.5%***	***26.7%***	***30.3%***	***13.8%***	7.2%	0.0%	100%	
	End-of-line	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	11.2%	***88.8%***	100%	
Outside CBD	Subway	4.3%	8.2%	9.9%	25.2%	23.7%	6.8%	21.4%	0.4%	100%	52,844
	Transfer	1.2%	2.2%	***2.2%***	***5.5%***	***16.9%***	31.0%	***38.8%***	2.3%	100%	
	End-of-line	0.1%	***0.1%***	***0.2%***	***0.5%***	***2.1%***	***5.9%***	41.1%	50.0%	100%	

Bold figures in the Transit app data are greater than the equivalent cell in the TLC data, and vice-versa. Users of the Transit app were more likely to book an Uber within 250 feet of a subway station than the general (TLC) population of Uber users.

The TLC data has one small, but interesting advantage against the Transit app when evaluating the proportion of trips for 0-250 feet from Transfer stations across the entire city (2.7% of Transit app-Uber origins versus 3.2% of TLC-Uber origins). However, when this proportion is broken into districts of inside and outside of the CBD, the Transit app has the advantage in both categories. This advantage is due to the TLC data's being heavily concentrated in the dense CBD where many transfer stations are located, resulting in a closer median distance to transfer stations for the entire TLC data set. However, when sorting into Inside and Outside the CBD for both data sets, the Transit app actually reveals a higher concentration around transfer stations in both districts compared to the TLC data. The kernel density map in Figures 2 & 3 explains this paradox: it shows that in the CBD, the Transit app has a high concentration of trips near major transfer hubs such as Penn Station, Grand Central Terminal, Fulton St and the Port Authority Bus Terminal, while the TLC data is most concentrated in commercial and office districts such Midtown East and nighttime entertainment districts like the Meat Packing District and the Lower East Side. Thus a higher proportion of origins in the CBD leads to a closer median value for the entire TLC data, but the Transit app data is actually more concentrated near major transfer points inside and outside the CBD.

DISCUSSION AND FUTURE RESEARCH

By combining the wealth of transportation options made visible by mobility aggregators such as the Transit app, with TNCs such as Uber, travelers have more tools to enable them to execute trips that match their preferences for speed, convenience, and cost. The Transit app in particular is geared towards smartphone users who would like to consider transit options first, while also helping them find other modes of transport as a part of their journeys.

The results of this specific analysis provide early evidence of the idea that utilizing interactive, dynamic and contextual transport information about many modes on a modern smartphone can result in multi-modal trips. Our key finding is that Transit app users have a higher incidence of Uber requests immediately next to a subway station than the general population of Uber users. If the user did not hope to take transit, it is unlikely that they would have opened the Transit app just to request an Uber when the Uber app would still have to be used to complete the transaction. The Transit app's data suggests that for a Transit app user the TNC acts as an accessible transit complement helping people if the user's public transit option was not suitable or desirable for that particular trip. For some trips, the TNC may act as a substitute for transit after viewing options on the Transit app. However, this behavior still complements a general habit of using transit. The improved ease of accessing the different options may sustain the use of public transit in general, thus still behaving as a complement to the transit system overall.

The strength of the findings – both in its logic and in the data – is strongest for origins closest to the transit stop, particularly outside of dense activity areas such as Manhattan's Central Business District. Continued research involving the evidence presented here is proceeding with statistical analysis to quantify the significance of these findings. As research into this relationship progresses into the future, new data should also be made available to researchers and transportation departments to understand how these services can impact public infrastructure and policy needs. Future qualitative research should include travel surveys to verify how people use mobility aggregators to complete specific trips that may involve more than one travel mode.

The phenomenon of shared mobility and real-time transport information is evolving quickly due to the transformations wrought by the prevalence of TNCs and mobility aggregators worldwide. Both services were barely available 5-years ago, but have grown to be quite prevalent in urban environments. As these services continue to evolve new transportation behaviors will evolve around them. This area of research should grow in significance as the use of TNCs and mobility aggregators continue to revolutionize users' abilities to control their own transportation outcomes.

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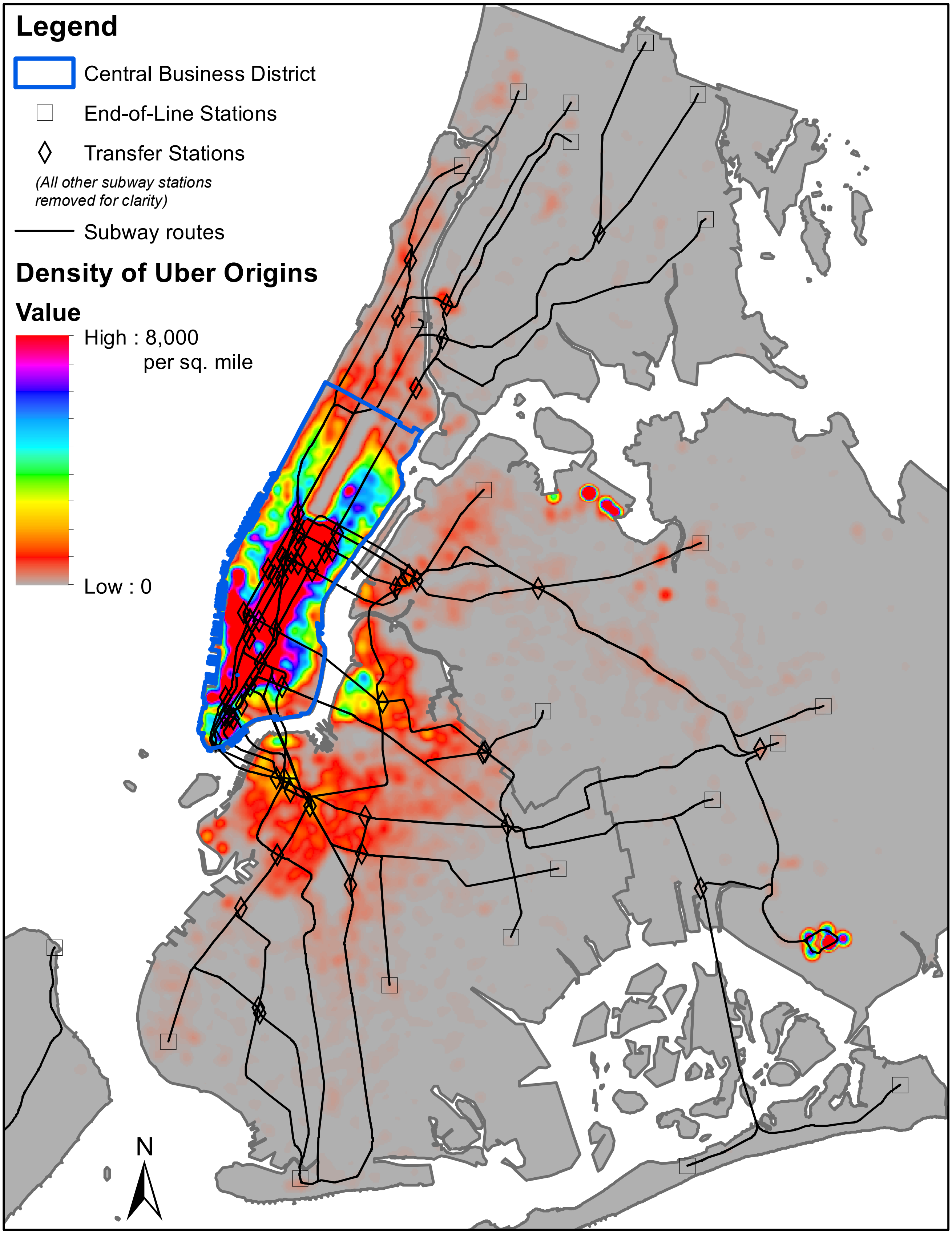
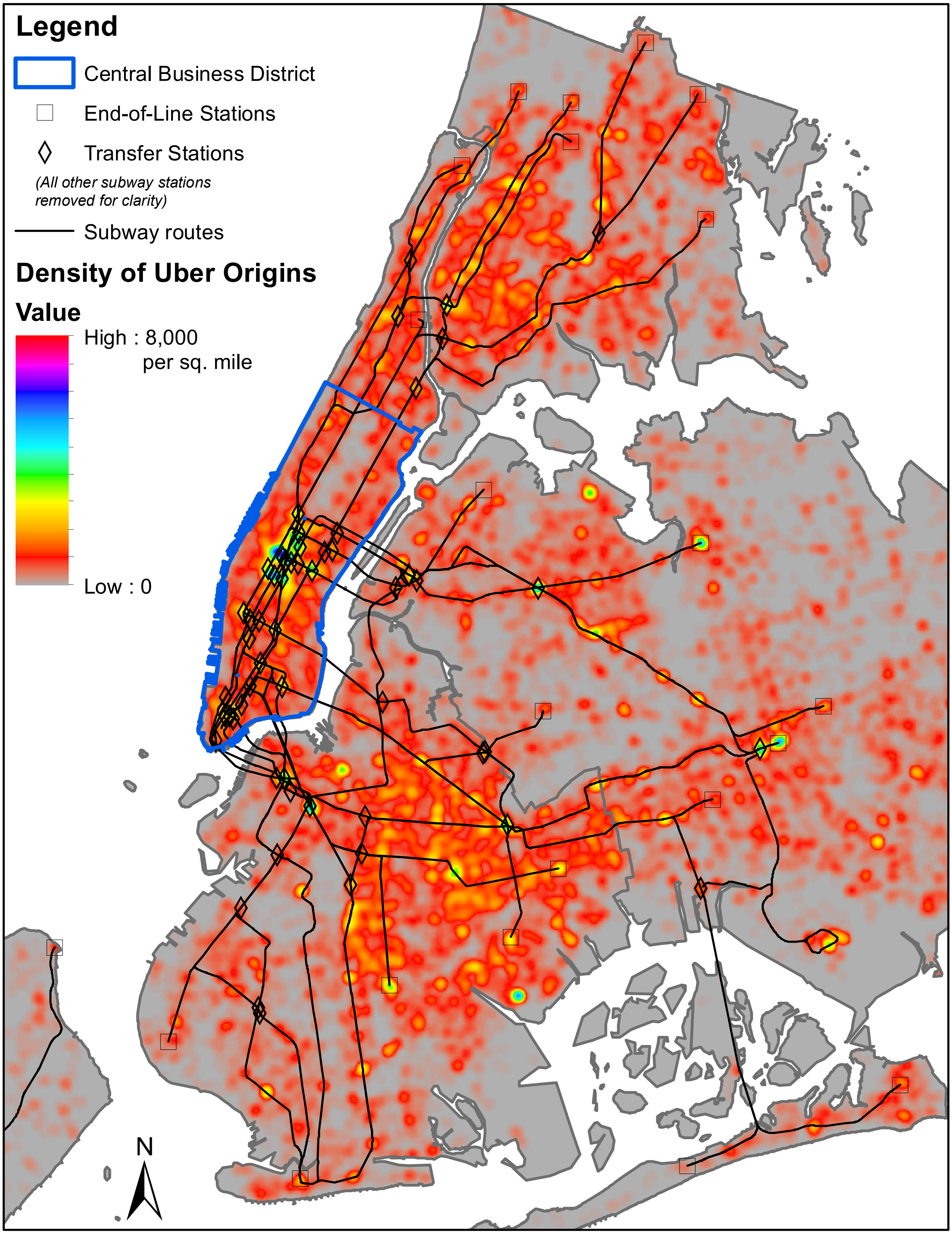
Figure 2. Density of Uber Origins reported by the TLC for 2014



Source: New York City Taxi and Limousine Commission via FiveThirtyEight.com (2015)

Figure 3.

Density of Uber Origins from the Transit App for 2015



Source: The Transit App (2016)