A Model of Deadheading Trips and Pick-Up Locations for Ride-Hailing Service Vehicles

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ABSTRACT

The mode share of app-based ride-hailing services has been growing steadily in recent years and this trend is expected to continue. Ride-hailing services generate two types of trips – passenger hauling trips and deadheading trips. Passenger hauling trips are the trips made while transporting passengers between places. Virtually all other trips made by a ride-hailing vehicle when there are no passengers in the vehicle are called deadheading trips or empty trips. Trips between the drop-off location of one passenger and the pick-up location of the next passenger could comprise a substantial share of total travel by ride-hailing vehicles, both in terms of number of trips and miles of travel. This paper aims to model the deadheading trips produced by app-based ride-hailing services at the disaggregate level of individual trips. Passenger trip data published by the app-based ride-hailing company Ride Austin is used to impute deadheading trips. The pick-up locations of passengers are then modeled using a nonlinear-in-parameters multinomial logit framework, essentially capturing the deadheading that takes place from the drop-off of one passenger to the pick-up of the next passenger. The model is sensitive to socio-demographic characteristics, as well as employment opportunities and built environment characteristics of the study area. The model results shed light on the characteristics of deadheading trips at different locations and at different time periods in a day. The paper concludes with a discussion of how transportation planners and app-based ride-hailing companies may utilize knowledge about deadheading to enact policies and pricing schemes that reduce deadheading.

Keywords: Ride-hailing, TNC, deadheading, empty trips, Ride Austin, location choice model

1 INTRODUCTION

The past decade has seen a dramatic growth in the use of app-based ride-hailing (or ride-sourcing) services around the world (Statista, 2019). App-based ride-hailing is an internet platform-based service that facilitates the real-time matching of drivers who are willing to provide a ride and potential passengers based on the spatial proximity between the potential "matches". In app-based ride-hailing, provided by what are now labeled as Transportation Network Companies (or TNCs) (such as Uber, Lyft, Ola, and Didi) who use a dynamic matching algorithm, it is strictly necessary to request a ride in advance through a smartphone app. This is in contrast to traditional taxi-based ride-hailing services where riders physically hail a taxi from the street or elsewhere without prior notification/booking. App-based ride-hailing enables consumers to ascertain a vehicle's real-time location and estimated arrival time, and all monetary transactions are conducted through an on-line platform (Cohen and Shaheen, 2016; Shaheen *et al*., 2016). Further, app-based ride-hailing facilitates shared (pooled) travel in a seamless fashion for individuals who would like to share travel costs and reduce their carbon footprint. In many parts of the world, the difference between traditional taxi ride-hailing and app-based ride-hailing services, at least in terms of passenger service, is fading, with traditional taxi ride-hailing companies also allowing the use of a smart phone app to request a ride. App-based ride-hailing is the modern transformed version of the traditional taxi-based ride-hailing service that is here to stay (Komanduri *et al*., 2018). Because of this, the term "ride-hailing" has become synonymous to "app-based ride-hailing". In the rest of this paper, app-based ride-hailing will simply be referred to as "ride-hailing" unless explicitly mentioned otherwise.

Despite the numerous advantages of modern ride-hailing services, there are concerns that arise in the context of the increasing adoption of ride-hailing services. Perhaps the most pressing concern is the increased VMT due to deadheading trips or empty trips. These are trips that are made by ride-hailing vehicles when there are no passengers in the vehicle. While it behooves TNCs to match drivers and riders in ways that reduce deadheading time and distance (to minimize waiting time and maintain cost affordability), it is estimated that between 35% and 50% of the total distance traveled by ride-hailing vehicles is lost to deadheading (Cramer and Krueger, 2016; Henao and Marshall, 2019; Komanduri *et al*., 2018). This has led some to argue that ride-hailing is at least partially responsible for worsening traffic congestion in a number of cities (LeBlanc, 2018; Erhardt *et al*., 2019).

Even though deadheading trips constitute a significant share of the distance traveled by ride-hailing vehicles, until recently, most of the research on ride-hailing has focused on passenger trips (*i.e.*, trips involving transportation of passengers from pick-up locations to drop-off locations). Information on such passenger trips are easy to obtain by conducting surveys of individuals and eliciting responses to questions regarding ride-hailing use, purpose of ride-hailing trip, and spatial-temporal characteristics of the trips (see, for example, Clewlow and Mishra, 2017 and Lavieri and Bhat, 2019). However, it is more difficult to obtain survey-based diaries of deadheading trips from ride-hailing drivers, because ride-hailing drivers are a smaller segment of the population than those who request ride-hailing services. Another approach to obtain information on deadheading is through disaggregate trip-level data from ride-hailing vehicles. But such data were not easily available until 2017, when an app-based ride-hailing company "Ride Austin" released anonymized data on all ride-hailing passenger trips that were served on their platform over a ten month period between 2016 and 2017 (Ride Austin, 2017). The availability of this data presents an opportunity to impute and analyze deadheading trips at a disaggregate trip-level. Specifically, in this paper, we focus on the deadheading trips that are made in search of a new passenger after dropping off any previous passenger(s). One could also examine deadheading portions of trips in which there may be some passengers already in the ride-hailing vehicle, where the ride-hailing vehicle travels (with no benefit to existing passengers in terms of time or movement toward destinations) to pick-up an additional new passenger in a pooled/shared-ride mode of operation. However, given the very low use of ride-hailing in a pooled mode, at least in the U.S. (Lavieri and Bhat, 2019), and the inherent complexity in identifying deadheading portions of non-empty ride-hailing trips, the analysis (or inclusion) of this component of deadheading is left to a future research effort. Besides, as discussed later, the data used in this study precludes any shared/pooled ride-hailing, thus rendering the examination of deadheading portions of non-empty trips impractical.

In summary, in this paper, we develop a model to predict the location of the next passenger pick-up when the origin of the deadheading trip (or the drop-off location of the previous passenger) is known. An immediate reaction may be that such deadheading trips are simply a derivative of where passengers are picked up and dropped off. But this is not true, because deadheading trips, at a micro-level, are about which ride-hailing vehicle is assigned to a specific passenger pick-up. So, just knowing passenger pick-up locations and passenger drop-off locations do not provide information about deadheading. Of course, ride-hailing companies have a specific dynamic matching algorithm that matches ride-hailing vehicles to passenger pick-up requests, but TNCs consider the algorithm as being proprietary. Also, TNCs use such an algorithm to optimize business operations and revenue, while the emphasis in this research is to allow planners to account for the spatial-temporal patterns of deadheading trips in their urban and regional travel models to predict overall spatial-temporal patterns of traffic flow. In other words, while the goal of the models developed by TNCs would be to identify strategies for controlling ride-hailing demand and supply in a way that maximizes their revenue and profits, the goal of our model is to predict passenger pick-up patterns for ride-hailing vehicles based on historic data so that it can be simulated in travel demand forecasting frameworks. Two additional points along these lines. There is no doubt that fleet characteristics of the TNC, pricing considerations such as surge pricing, and related service characteristics, as well as driver attributes, can affect deadheading trips. But such characteristics are not available in the context of survey data used for traditional urban and regional travel demand models, and certainly are not available for use in forecasting with travel demand models. A second issue is that, in the U.S., TNCs assign pick-ups to a specific driver based on location proximity at non-airport locations or based on a digital queuing system (with the driver with the longest wait time in the queue) at airports (Griswold, 2018). Drivers are not provided information on where the assigned pick-up's drop-off point is until the driver gets to the pick-up point. This is done deliberately to avoid a situation where drivers do not accept a pick-up assignment based on where the pick-up is to be dropped. And drivers get steeply penalized if they do not accept, on a routine basis, assigned rides. In effect, driver attributes play a relatively small role in acceptance or not of pick-up rides assigned, which implies that driver attributes do not play a substantial role in deadheading trip patterns.[1] In recognition of these two issues, our model uses location specific attributes of the deadheading trip's origin as well as attributes of the potential destinations to predict the subsequent passenger pick-up location after a passenger drop-off within

[1] The situation is a little different in some places outside the U.S. For example, Didi, once it receives a ride request, sends that request to all nearby drivers (Xu *et al*., 2018; Jiang and Zhang, 2018). Drivers then respond positively or not to the request, and then Didi uses an algorithm to release the "deal" to a specific driver from among those who have responded (if no driver responds, the request is aborted). This is different from the operation of Uber and Lyft in the U.S., where the TNC directly assigns a pick-up to a specific driver (the driver has about 15 seconds to not accept, but routine non-acceptances get on the record of the driver).

the context of a regional travel demand model setting (as opposed to a micro-level profit-maximizing supply-demand matching setting). The location specific attributes used here include employment opportunities, built environment attributes, and socio-demographic characteristics. Such location-related variables are routinely used (typically at a traffic analysis zone or TAZ level) in travel demand model estimation and forecasting. A nonlinear-in-parameters multinomial logit model of pick-up location, given an earlier drop-off location, is estimated and the model results are used to gain insights on the factors that affect the propensity of passenger pick-ups at different locations and the distance that a ride-hailing driver travels in order to find a new passenger. When combined with a ride-hailing passenger drop-off model (essentially these would be determined within the context of the trip distribution model in traditional demand models), the current model provides the complete spatial-temporal pattern of predicted ride-haling deadhead trips (as discussed later in Section 6.3).

The remainder of this paper is organized as follows. Section 2 gives a brief overview of the past studies on ride-hailing. Section 3 presents a description of the data used in this study, while Section 4 explains the modeling methodology. Section 5 presents model estimation results. Section 6 presents a discussion of the potential planning and forecasting applications of the models developed in this study. Finally, Section 7 offers concluding thoughts.

2 LITERATURE REVIEW

Deadheading trips may be viewed as a corollary of passenger trips. After a passenger is served, a deadheading trip is very likely to take place as the ride-hailing driver proceeds to the next pick-up location. As such, deadheading trip destinations correspond to locations of ride-hailing passenger pick-up locations. In this section, we briefly introduce some of the studies on ride-hailing passenger trip pick-up locations and refer to them later in Section 5 to contextualize the results. Further, we explain in more detail other studies that use the Ride Austin dataset and study deadheading trips.

Many studies in the literature document the characteristics of ride-hailing service users and trip characteristics through a variety of surveys and secondary data collection efforts. One of the most comprehensive surveys on ride-hailing usage in the United States was conducted by Clewlow and Mishra (2017). They conducted a survey of ride-hailing users across seven major cities – Boston, Chicago, Los Angeles, New York, San Francisco, Seattle, and Washington D.C. Other studies that involved surveys of ride-hailing usage include Henao and Marshall (2019), Lavieri and Bhat (2019), and Rayle *et al*. (2016). Rayle *et al*. (2016) surveyed ride-hailing users in San Francisco, while Lavieri and Bhat (2019) surveyed commuters who used ride-hailing in the Dallas-Fort Worth metropolitan area. Henao and Marshall (2019) signed up to drive for ride-hailing companies, Uber and Lyft, in the Denver area and surveyed the passengers that rode in their vehicles. By serving as drivers, they were also able to estimate the distance traveled while deadheading. Some studies have attempted to derive insights on ride-hailing behavior from larger scale travel surveys (as opposed to targeted ride-hailing user surveys). Examples of such studies include: Dias *et al*. (2017), who studied ride-hailing usage using the 2017 Puget Sound regional household travel survey; Alemi *et al*. (2018), who used the 2015 California millennials survey; and Young and Farber (2019), who studied ride-hailing usage in Toronto.

Since TNCs were reluctant to release trip-level ride-hailing data until recently, a few studies, such as those by Cooper *et al*. (2018) and Kooti *et al*. (2017), have attempted to collect this data using novel data collection techniques. Cooper *et al*. (2018) obtained data on the movement of deadheading ride-hailing vehicles in the city of San Francisco directly through the

Application Programming Interfaces (API) of Uber and Lyft. They repeatedly queried the Uber and Lyft servers for the locations of vehicles that are available for hire around 200 synthetically generated clients spread around the city. Using this approach, they obtained the coordinate traces of deadheading Uber and Lyft vehicles in the city for a duration of 40 days. Kooti *et al*. (2017) extracted data on Uber's ride-hailing trips from Yahoo's email servers. They access the receipts sent by Uber to passengers as well as the reports sent by Uber to drivers and combine these reports with data on the owners of the email accounts to understand the socio-demographic profile of Uber passengers and drivers.

A few studies have attempted to address the issue of measuring and quantifying deadheading directly. Cramer and Krueger (2016) compared the deadheading durations of app-based ride-hailing and traditional taxis in the cities of Boston, Los Angeles, New York, San Francisco and Seattle. They measured the capacity utilization as the proportion of time for which there is a passenger in the ride-hailing vehicle to the total duration of operation of the vehicle. They were able to obtain the citywide percentages for capacity utilization directly from Uber. The same metric was computed for regular taxis using data from a wide range of sources. In virtually all cities, the capacity utilization for ride-hailing was higher than that for traditional taxis, with the difference being the smallest in New York. The capacity utilization for ride-hailing ranged from 43.6% in Seattle to 54.3% in San Francisco. They estimated the percentage of distance traveled while deadheading to be 35.8% in Los Angeles and 44.8% in Seattle. Henao and Marshall (2019) estimated the share of deadheading distance based on their own driving data when serving as drivers for Uber and Lyft. They report 40.8% of their total distance traveled (VMT) being lost to deadheading.

Ride Austin was one of the first TNCs to make data on individual passenger trips publicly available. Ride Austin is a non-profit that began operating in the city of Austin, Texas on June 16, 2016 when other companies, notably Uber and Lyft, were forced to cease operations because they were unable to abide by the city's regulations (Kelly, 2016). By the beginning of 2017, Ride Austin held around one-third of the ride-hailing market share in the city. Since the release of the trip-level data, a number of studies utilizing this data have been conducted (see, for example, Dias *et al.*, 2017, Lavieri *et al.*, 2018, Komanduri *et al.*, 2018, and Wenzel *et al.*, 2019). In the specific context of deadheading, the relevant studies are Komanduri *et al.* (2018) and Wenzel *et al.* (2019). Komanduri *et al.* (2018) assumed that a deadheading trip occurs whenever the time gap between consecutive passenger trips made by a driver is less than 30 minutes. The deadheading distances were calculated as the straight-line distances between the origins and destinations. If the time gap between passenger trips was more than 30 minutes, it was assumed that drivers would not deadhead for the entire time gap. Instead, they assumed that two deadheading trips with distances of two miles each and durations of five minutes each would have occurred within that interval. The first deadheading trip would occur immediately after the drop-off of one passenger and the next deadheading trip would occur immediately before the subsequent passenger pick-up. Based on these assumptions, they estimated the percentage of deadheading miles traveled by ride-hailing vehicles to be 37%. In a more recent study, Wenzel *et al*. (2019) also used a similar approach to identify deadheading trips. Unlike Komanduri *et al*. (2018), Wenzel *et al*. (2019) assumed that continuous deadheading occurs between consecutive passenger trips that are less than 60 minutes apart. They also used a correction factor for converting straight-line distances to network distances. They estimated the length of an average deadheading trip that occurs between consecutive passenger trips to be 55% of the average passenger trip length. Additionally, they imputed the location of residences of drivers based on the spatial median of their first pick-up and last drop-off locations from every shift. A new ride-hailing shift is assumed to have begun if a passenger is picked up eight hours after the previous passenger is dropped off. Using the imputed locations of driver residences, the deadheading distances at the beginning and ending of shifts were also computed. Using these assumptions, the overall percentage of deadheading distance was estimated to be 45%.

The approach adopted in this paper to identify deadheading trips is similar to that used by Komanduri *et al*. (2018) and Wenzel *et al*. (2019). In this paper, only the deadheading trips made for repositioning vehicles between drop-off and pick-up locations of consecutive passengers are considered. While other studies have largely estimated deadheading miles at an aggregate scale as a percentage of the total distance traveled (by ride-hailing vehicles), this paper makes an important contribution by modeling deadheading at the disaggregate level of individual trips. This provides a deeper understanding of the variations in deadheading patterns across time and space, while also identifying the key factors that contribute to deadheading variations. To build a model of deadheading (*i.e.*, pick-up location for next passenger) with a rich specification for use in travel demand models, the ride-hailing trip data needs to be fused with secondary data sources including socio-demographic data, network travel times and distances, built environment data, and employment data. The explanatory variables used in the model are variables that are regularly used in the context of travel demand forecasting. The insights from such a model would prove invaluable in predicting locations with high potential for deadheading (hotspots) and devising countermeasures to alleviate the adverse effects of deadheading mileage. Further, the modeling framework is such that it can easily be introduced into commonly used travel demand modeling frameworks such as the four-step model. To capture the variety of purposes for which ride-hailing trips are made at different times in a day, variables that measure employment opportunities at the potential destinations and identifiers for special generators, such as the Austin Bergstrom International Airport (ABIA) and the main campus of the University of Texas at Austin, are included in the model. Separate models are then estimated for different time periods of a day, thus providing an understanding of temporal variation in deadheading across the region.

3 DATA DESCRIPTION

The primary dataset used in this study is the dataset on ride-hailing passenger trips released by Ride Austin (2017). Deadheading trips were inferred and imputed based on the passenger trips in this dataset. The ride-hailing data was supplemented with data from several other sources. The Smart Location Database (SLD) was used to obtain data on socio-demographic, built environment, and other characteristics of census block groups in the study area (U.S. EPA, 2014). Some of the variables in the SLD were updated using more recent figures obtained from the 2016 American Community Survey (ACS) dataset. The network distances (skims) used in this study are based on the zoning and network information of the study area as used by the Capital Area Metropolitan Planning Organization (CAMPO) in their travel demand forecasting models. CAMPO is responsible for transportation planning in the city of Austin. The zoning and network information were acquired for the counties of Burnet, Bastrop, Caldwell, Hays, Travis and Williamson. The six counties comprise a total of 2102 traffic analysis zones (TAZs).

3.1 Ride Austin Passenger Trips Dataset

The Ride Austin dataset contains the anonymized records of every passenger trip made using the Ride Austin application between early-June 2016 and mid-April 2017. There are 1,494,125 trip records in this dataset. Very few trips were recorded in the initial months of the operation of Ride

Austin. To better capture ride-hailing usage patterns in steady state, only data for the period of October 2016 to mid-April 2017 (corresponding to 195 days of data) are used in this study. Each record in the dataset includes the coordinates of the origin and destination, the trip start and end times, and identifiers for the driver and passenger. The service did not allow for the sharing of rides between strangers. In other words, drivers would receive new ride requests only when there were no passengers in the vehicle. This is in contrast to the ride-sharing services provided by some of the competing TNCs (*e.g.*, Uber Pool and Lyft Shared) where new passengers may be picked up enroute to the destination of a passenger already in the vehicle. The lack of a ride-sharing option ensures that each passenger trip in the dataset is associated with only one passenger account.

The location coordinates in the dataset are censored to three decimal places to protect passenger privacy. If the coordinates were truncated to three decimal places and not rounded, this corresponds to a maximum radial error in distance measurement of approximately 147 meters (about 500 feet). The passengers may also have walked some distance from their original drop-off point to reach their final destination. The error in the observed location caused by these factors is unlikely to have a substantial impact on our modeling efforts because the attributes of an area generally would not vary significantly over a distance of 500 feet. Even if the designated area type changes within this distance, such as from urban to suburban, the variation is likely to be gradual so that it would be reasonable to consider either locations as suburban or urban. Besides, the average area of a traffic analysis zone (or TAZ) used as the spatial unit of analysis is of the order of 2.5 square miles (as presented later in Table 1). Assuming a square pattern, the size dimension of a TAZ is about 1.6 miles or 8500 feet. Thus, misclassifications of a location into a TAZ would be of the order of 10% [$(8500 \times 8500 - 8000 \times 8000) / (8500 \times 8500)$] which should not affect the model results in any substantial way.

Since it is computationally demanding to model locations as a continuous measure in the context of travel demand forecasting, all locations were mapped to their corresponding TAZs. A map of the average number of daily ride-hailing passenger trips generated by each TAZ (on a per square mile basis to account for differential TAZ sizes) is shown in Figure 1. The figure also shows the classification of the study area into urban, suburban and rural areas. Within the urban area, the central region with relatively high commercial and business activity is designated as the Central Business District (CBD). In terms of density of origin of passenger trips, the zones adjacent to the University of Texas and the CBD zones had the highest ride-hailing trip originations per square mile, consistent with students availing of ride-hailing services for their trips as well as patrons of bars and other entertainment places in the CBD. In terms of the total number of trip originations, the zone containing the ABIA generated the greatest number of ride-hailing passenger trips. This TAZ was also the destination for the greatest number of ride-hailing trips (this gets a little masked in Figure 1 because the zone containing the airport is a large one, leading to a density of originations that is less than that for the University and Austin downtown areas). In particular, 4.1% of all ride-hailing trips originated in the airport TAZ, and 6% of all ride-hailing trips ended there.

The average number of ride-hailing passenger trips generated by hour of the day and day of the week are shown in Figure 2. The demand for ride-hailing trips in Austin does not follow the usual time-of-day distributions of travel demand with peaks in the morning and the afternoon, a finding also reported by Komanduri *et al*. (2018). In Austin, the highest frequency of ride-hailing trips occurs on Friday and Saturday late night periods (and correspondingly Saturday and Sunday early morning periods). Since the purpose and frequency of ride-hailing trips vary by time-of-day, four separate models are estimated for the time periods of 7AM to 10AM, 10AM to 4PM and 4PM

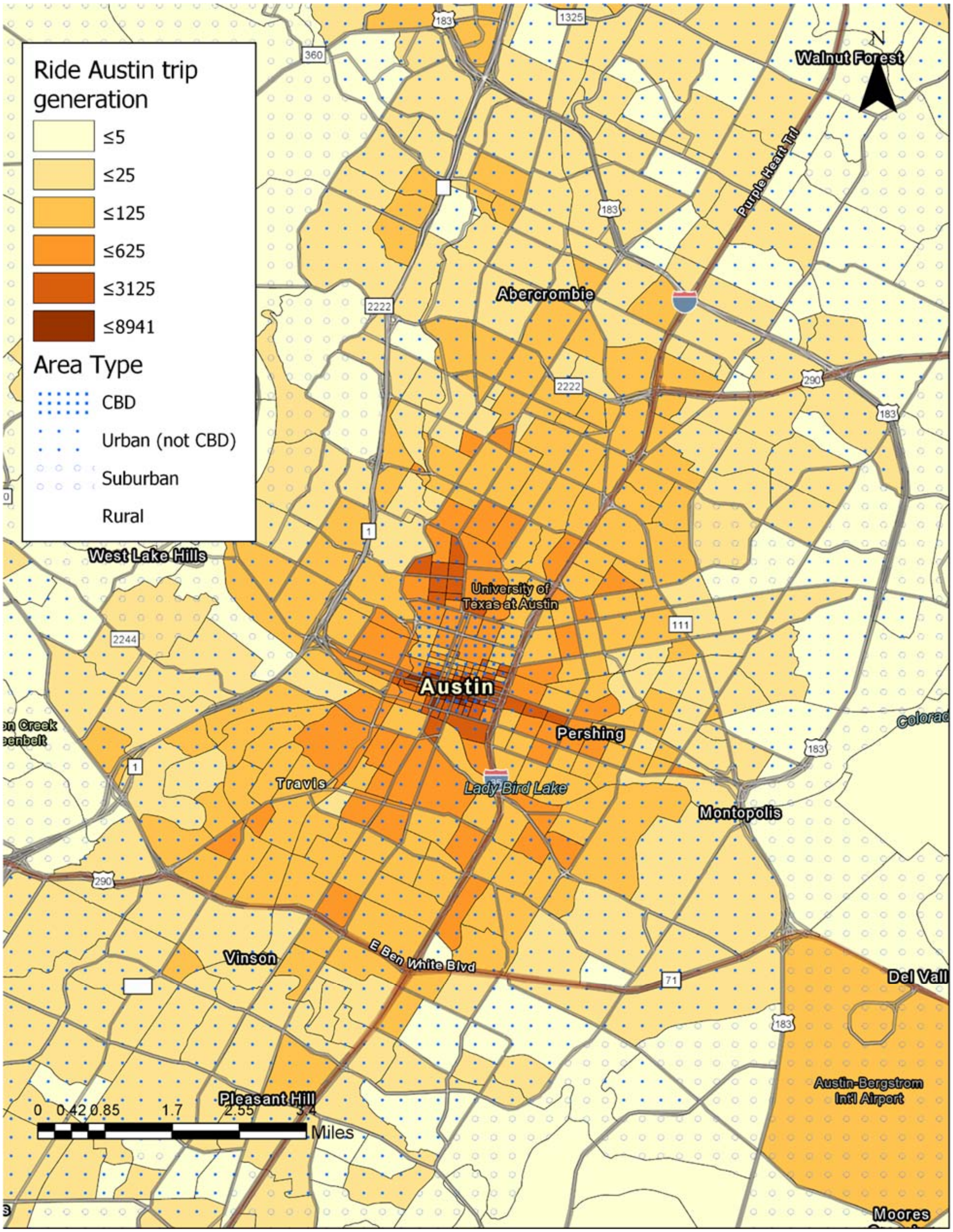

Figure 1 Average Number of Daily Ride-Hailing Passenger Trips Generated by Each TAZ (Per Square Mile)

to 7PM on weekdays, and 10PM to 1AM the next day on Friday and Saturday. In the remainder of the paper, these time periods are referenced as AM Peak, Mid-day, PM Peak and Weekend Night respectively.[2] The AM peak, mid-day and PM peak periods were selected for modeling because these are the four distinct time periods often considered in travel demand forecasting models (Cambridge Systematics *et al.*, 2012, Chapter 4). Additionally, the weekend night period is considered separately because of the exceptionally high rate of utilization of ride-hailing services in this period.

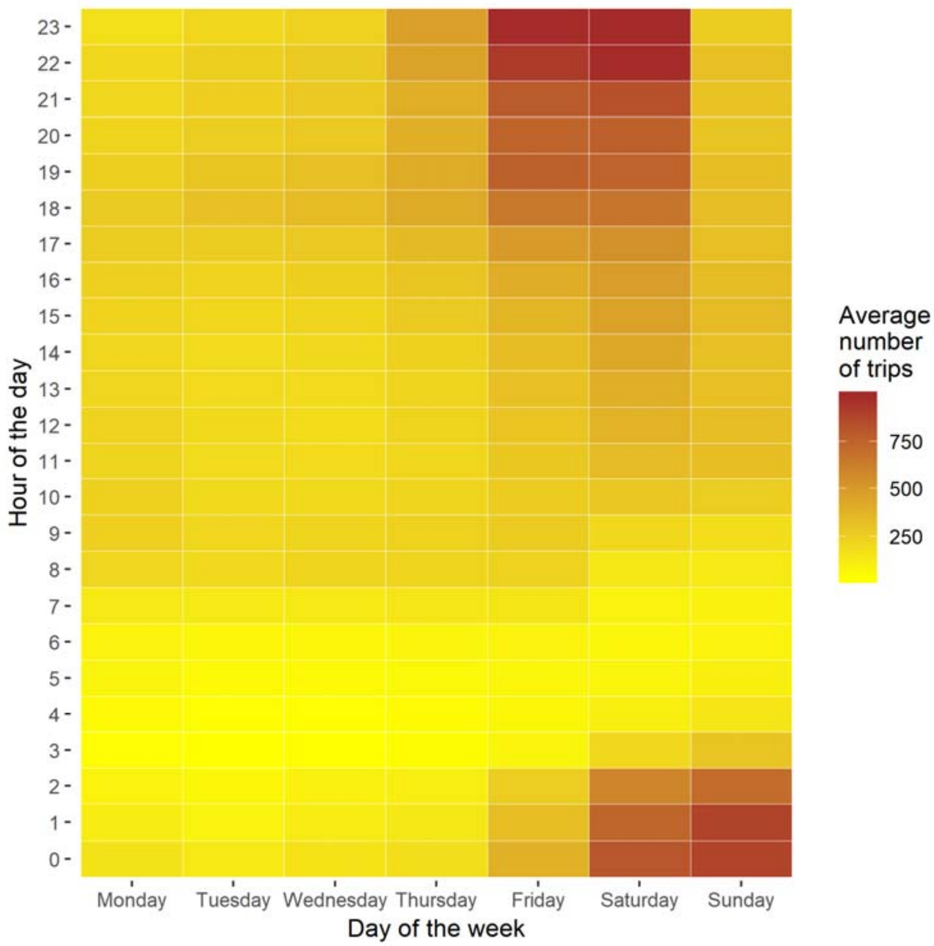

Figure 2 Average Number of Ride-Hailing Passenger Trips by Time-of-Day and Day-of-Week

3.2 Location Attribute Databases

Various socio-demographic, employment, built environment, and transportation network-related attributes of locations in Austin were obtained from the Smart Location Database (SLD), CAMPO travel model databases, and the American Community Survey (ACS) dataset. The SLD and the ACS datasets provide attribute values at the census block group level, while the CAMPO dataset

[2] To be precise, a deadheading trip is assigned to a particular time period if its destination time-stamp is within the time period. For example, if a deadheading trip's destination time-stamp is between 7AM and 10AM on a weekday, it is designated as an AM peak deadhead trip (that is, if a passenger is picked up between 7AM and 10AM, the previous deadheading trip leading up to the passenger pick-up is assigned to the AM peak).

provides attribute values at the TAZ level. Because the census block group boundaries did not match the TAZ boundaries exactly, GIS overlay techniques and weighted aggregation and allocation methods were employed to aggregate SLD and ACS data from the census block level to the TAZ level.

Descriptive statistics for TAZ attributes constructed from the SLD, ACS, and CAMPO datasets are presented in Table 1, by type of TAZ (CBD, urban, suburban, or rural). The variables in Table 1 are the ones considered in our model specification, though not all the variables in Table 1 appear in the final model specification.

Table 1 Descriptive Statistics for TAZ Attributes

	Average over TAZs in					**Data**	
	All	**CBD**	**Urban**	**Suburban**	**Rural**	**Source**	**Year**
Population							
Age < 18	228.6	2.4	225.0	348.1	129.5	ACS	2016
18 ≤ Age < 35	258.1	22.0	377.1	261.9	106.4	ACS	2016
35 ≤ Age < 65	366.1	23.5	385.2	513.8	214.1	ACS	2016
65 ≤ Age	92.5	5.4	81.6	133.1	70.8	ACS	2016
Caucasian	746.9	45.8	815.5	999.4	442.1	ACS	2016
African American	68.0	1.6	87.1	87.4	27.3	ACS	2016
Other race	130.5	5.9	166.3	170.2	51.4	ACS	2016
Employed	481.8	37.1	589.8	611.5	234.8	ACS	2016
Total	945.3	53.4	1068.9	1257.0	520.8	ACS	2016
No. of HH							
0 vehicle	17.5	3.3	32.7	11.0	4.2	SLD	2010
1 vehicle	122.2	22.4	187.7	113.7	47.9	SLD	2010
2+ vehicle	205.6	10.9	210.4	280.9	134.3	SLD	2010
Income < $50,000	130.5	7.3	186.0	124.8	66.1	ACS	2016
$50,000 ≤ Income < $100,000	108.4	8.3	132.0	136.0	55.1	ACS	2016
$100,000 ≤ Income < $150,000	55.5	5.3	56.9	84.0	28.9	ACS	2016
$150,000 ≤ Income	49.3	10.8	43.7	87.1	23.4	ACS	2016
HH Size = 1	95.8	19.1	146.7	93.3	34.6	ACS	2016
HH Size = 2	115.3	10.8	137.1	141.6	65.3	ACS	2016
HH Size = 3	53.4	1.4	60.0	74.8	26.4	ACS	2016
HH Size = 4+	79.2	0.5	74.8	122.2	47.2	ACS	2016
Total	343.6	31.8	418.6	432.0	173.5	ACS	2016
No. of employment							
Basic	93.8	28.2	159.5	80.3	23.5	CAMPO	2015
Retail	100.5	81.7	186.1	79.0	12.7	CAMPO	2015
Service	219.8	583.5	437.1	139.0	19.1	CAMPO	2015
Education (K-12)	23.1	1.4	28.9	31.2	8.9	CAMPO	2015
Education (Higher)	19.0	32.1	44.1	4.9	0.1	CAMPO	2015
Total	456.2	727.0	855.7	334.5	64.3	CAMPO	2015
Area (mi²) × 100	252.3	1.5	25.0	117.1	653.1	CAMPO	2015
Hourly frequency of transit per square mile at PM peak	283.1	2186.9	702.6	7.0	0.1	SLD	2012

There is some inconsistency in the year corresponding to different datasets. This is especially so for the SLD data on the number of vehicles (from 2010) and the hourly frequency of transit per square mile in the PM peak (from 2012). However, it is unlikely that there were substantial changes in these attributes at the zonal level within a span of six years or so, and thus the use of these attribute values as a means to explain the 2016-2017 ride-hailing travel patterns was considered acceptable. As shown in Table 1, the number of employment opportunities in a TAZ is disaggregated into four categories – basic, retail, service, and education, based on the Standard Industrial Classification (SIC) code of employment industry (U.S. DOL, 2019). This disaggregation is used to recognize the varying nature of ride-hailing trip demands based on activity purpose and time-of-day (see, for example, Lavieri and Bhat, 2019).

4 METHODOLOGY

The Ride Austin dataset provides information on passenger trips, including the time stamp and location of the beginning and end of every passenger trip. Deadheading trips occur between the drop-off and pick-up of consecutive passenger trips. Unless the drop-off location of one passenger coincides with the pick-up location for the next passenger, there will be some non-zero distance associated with deadheading. The driver cannot pick up a new passenger while transporting another passenger because a ride-sharing option was not available in the period during which this data was collected.

This section offers a detailed description of the procedure used to impute deadheading trips (Section 4.1), the econometric framework for modeling destination of deadheading trips (Section 4.2), the procedures used to construct the choice set of possible destinations for model estimation (Section 4.3), and the considerations involved in designing a valid specification for which all coefficients can be identified (Section 4.4).

4.1 Imputing Deadheading Trips

Using the unique driver identifier (ID) and the start and end times of passenger trips, it is possible to assemble the roster of passenger trips served by each driver over the 195-day period covered by the data. Between the drop-off of one passenger and the pick-up of the next passenger, the following may happen:

1. The driver begins searching for a new passenger immediately after dropping off the previous passenger. This process may involve the relocation of the ride-hailing vehicle to a location where the driver feels that passenger pick-ups are more likely, either based on past experience or because of surge pricing (surge pricing is a pricing scheme enacted by TNCs to manage ride-hailing demand and driver supply). When a passenger pick-up request is received, the driver proceeds to the pick-up location of the passenger. In this scenario, the travel between the drop-off location of one passenger and the pick-up location of the next passenger constitutes a single deadheading trip. This represents the first category of deadheading trips.
2. The driver may take a break from ride-hailing to perform other activities (such as eating out) or going home to rest. For example, consider a driver who drops off a passenger at location A, then travels to eat meal at location B, then travels home to location C, and then starts another round of ride-hailing by picking up a passenger at location D. In this case, what constitutes deadheading is somewhat ambiguous. For sure, the trip from location B to C (returning home to rest) is not a deadheading trip (in the context of the definition used in this paper). One may consider the trip from A to B to be a deadhead, but it is difficult to say for sure because location B is chosen by the driver voluntarily. The only trip in this chain that

may be considered a deadhead trip with certainty is the trip from C to D, as the driver starts a new chain of ride-hailing trips. The deadheading associated with these kinds of complex patterns (where the driver participates in personal activities and ceases service between ride-hailing trips) correspond to a second category of deadheading trips.

The Ride Austin data does not provide a clear way of distinguishing between these two types of deadheading categories. This is because the data only has the pick-up and drop-off time-stamps and locations of the ride-hailing trips, and no information on the ride-hailing vehicle location between passenger trips. Thus, in the second category above, the data would only show the time-stamp of the drop-off at location A and the time-stamp of the pick-up at location D. Assuming that all the travel between A to D constitutes a deadhead would be incorrect. It is necessary to identify only "true" ride-hailing deadhead trips, but this is not possible based on the information available in the Ride Austin data (for the second category noted above). Therefore, a rule-based approach was adopted to infer deadheading trips. The rule is based on the duration of the deadhead time window (that is, the time window between consecutive passenger trips of the ride-hailing vehicle).

The time spent by drivers in searching for a new passenger can vary widely based on the ride-hailing market. Based on anecdotal evidence (Uber Drivers Forum, 2017), the passenger search duration is in the order of minutes in highly populated cities such as Dallas-Fort Worth and Las Vegas while it can be more than an hour in small towns. Figure 3 shows the cumulative probability distribution of the time duration between the start of a passenger trip and the end of the previous passenger trip in the Ride Austin dataset for different periods of the day. This duration is generally longer for the weekday AM peak and shortest for the weekend night period. This is consistent with the high level of ride-hailing demand during the weekend night period, which naturally leads to more frequent passenger pick-ups. The elbowing of the cumulative distribution function near the one hour mark seems to indicate that, in most cases, the duration of time spent by drivers in searching for new passengers would be less than an hour (the same assessment was also made by Wenzel *et al*., 2019). Over a full day, the time gap between trips is less than one hour in 72% of the cases. If the time gap is more than an hour (between trips), it is more likely that the driver stopped serving passengers and made trips to perform other activities. Based on the above position, we assume that if the time gap between the consecutive passenger trips is less than one hour, the distance between the destination of the first passenger and the origin of the next passenger would constitute a true deadheading trip of the first category. Travel segments corresponding to time gaps in excess of one hour are ignored in this study due to the not unreasonable position that it is much less likely that such travel would constitute true deadheading.

Based on the one-hour rule noted above, a total of 46505, 109287, 88882, and 191849 deadheading trips were identified in the AM Peak, Mid-day, PM Peak and Weekend Night periods, respectively. The average shortest path distance between the origins and destinations of deadheading trips was found to be 2.54 miles, while the average shortest path distance of passenger trips in the dataset is 4.53 miles. An estimate of the deadheading distance as a percentage of the total distance traveled by ride-hailing vehicles is about 36%. This value is likely to be a lower bound because while the passenger trips are likely to be direct from origin to destination, the deadhead trips may not be as direct since ride-hailing drivers may cruise around while waiting for the next demand request.

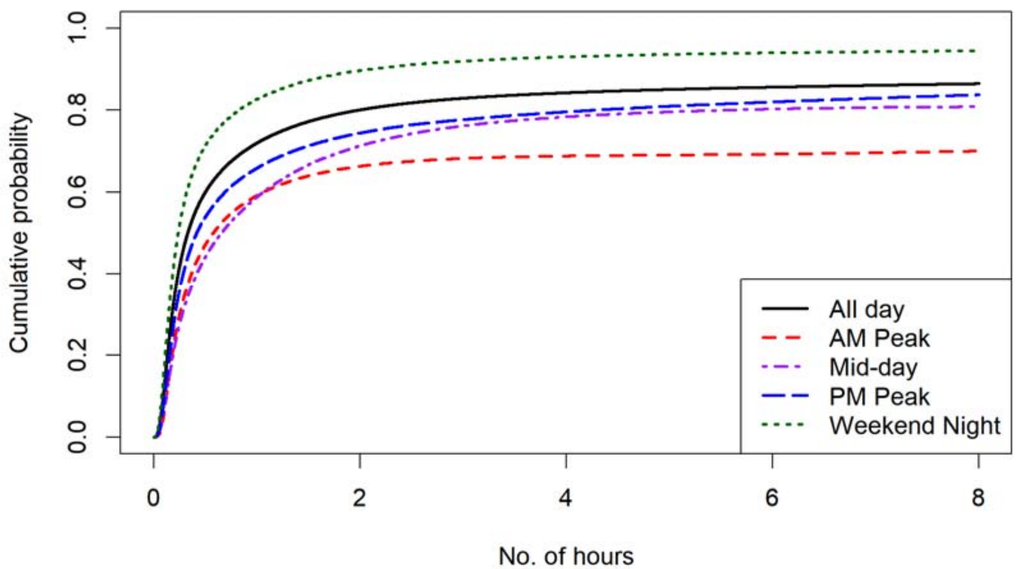

Figure 3 Distribution of the Time Gap Between Ride-hailing Trips by Time-of-Day

4.2 Econometric Framework

This study employs a random utility maximization framework to predict the destination TAZ of a deadheading trip, given the origin TAZ of the deadheading trip. Each TAZ has an intrinsic propensity (or utility) associated with being the destination of a deadheading trip. This may also be considered as a measure of the propensity of obtaining the next passenger pick-up in a TAZ location. TAZs generally cover a wide area and may comprise several elemental locations, each associated with a utility of being the destination. The utility of a TAZ, which is a measure of the propensity of obtaining the next pick-up from within the TAZ, may be viewed as an aggregate of the utilities of all elemental locations within the TAZ.

Let D_j be the number of deadheading destination points within TAZ *j*, or alternatively, the number of elemental passenger pick-up points within TAZ *j*. If D_j is relatively large (as is usually the case with passenger pick-up points within a zone), and assuming that the propensity distribution of passenger pick-ups at different points within the zone are about the same, the TAZ-level utility function of a destination TAZ *j* for a deadheading trip *n* originating in TAZ *i* may be written as (see Daly, 1982):

$$U_{nij} = \boldsymbol{\beta}'\boldsymbol{x_{ij}} + \eta \log(D_j) + \xi_{nij}, \tag{1}$$

where, $\boldsymbol{x_{ij}}$ is an independent variable vector that includes variables related to the impedance between zones *i* and *j*, the non-size characteristics of TAZ *j*, and interactions between impedance measures, characteristics of TAZ *i*, and characteristics of TAZ *j*. ξ_{nij} is a random term assumed to be distributed IID Gumbel across deadheading trips, zonal deadheading origins, and zonal deadheading destinations. $\boldsymbol{\beta}$ is a parameter vector and η is a scalar parameter to be estimated. In Equation (1), the log transformation for the size term is essential because it guarantees that if two destination zones (with identical non-size zone attributes) are merged into one, the probability of choosing the combined zone is exactly the sum of the probabilities of choosing the original two zones when η=1. D_j is not easily quantifiable. However, D_j may be represented by a set of proxy observable size variables such as employment in zone j, population of zone j, and land area of zone j. Let $\boldsymbol{z}_j$ represent a vector of proxy size variables for zone j and let $\boldsymbol{\delta}$ be a corresponding vector reflecting the contribution of the proxy size variables to the actual zone size D_j. Then, Equation (1) may be rewritten as:

$$U_{nij} = \boldsymbol{\beta}'\boldsymbol{x}_{\boldsymbol{ij}} + \eta \log(\boldsymbol{\delta}'\boldsymbol{z}_j) + \xi_{nij} = V_{ij} + \xi_{nij} \ . \tag{2}$$

The values of the elements of the $\boldsymbol{\delta}$ vector should be greater than or equal to zero, because increasing any proxy size measure for a zone must increase the chances that the zone will be a destination zone for a deadhead trip. Thus, the vector $\boldsymbol{\delta}$ vector itself is parameterized as $\boldsymbol{\delta} = \exp(\boldsymbol{\gamma})$, and the vector $\boldsymbol{\gamma}$ is estimated and then translated back into the vector $\boldsymbol{\delta}$. Also, for identification purposes, one of the elements of the $\boldsymbol{\delta}$ vector should be normalized to a specific value. Then, the coefficients on the other size variables provide the importance of these other size variables in attracting deadhead trips (*i.e.*, passenger trip originations from the zone) relative to the normalized attribute. Finally, V_{ij} represents the systemic component of the utility function in Equation (2). The magnitude of the parameter η in Equation (2) characterizes the presence of common unobserved zonal attributes affecting the attractiveness of all elemental alternatives in a zone as deadhead destinations. For example, consider a uniformly elevated attractiveness of elemental destinations within a zone. This results in cannibalization of sorts in terms of passenger pick-ups (because prospective passengers may go to any elemental location within a zone, all of which are highly favorable; and going to one elemental location implies a drop in pick-up at another elemental location). This parameter is expected to lie between 0 and 1, with a value of 1 denoting no cannibalization effects and a value of zero essentially indicating such a high cannibalization level that the number of elemental locations within a zone (*i.e.*, the zone size) does not matter. Another way to see this is to write the probability expression for a deadheading trip n with origin TAZ i and destination TAZ j as:

$$P_{n(i)}(j) = \frac{e^{V_{ij}}}{\sum_{k \in \Omega_i} e^{V_{ik}}} = \frac{(D_j)^{\eta} e^{\boldsymbol{\beta}'\boldsymbol{x}_{\boldsymbol{ij}}}}{\sum_{k \in \Omega_i} (D_k)^{\eta} e^{\boldsymbol{\beta}'\boldsymbol{x}_{\boldsymbol{ik}}}} = \frac{(\boldsymbol{\delta}'\boldsymbol{z}_j)^{\eta} e^{\boldsymbol{\beta}'\boldsymbol{x}_{\boldsymbol{ij}}}}{\sum_{k \in \Omega_i} (\boldsymbol{\delta}'\boldsymbol{z}_{\boldsymbol{k}})^{\eta} e^{\boldsymbol{\beta}'\boldsymbol{x}_{\boldsymbol{ik}}}} , \tag{3}$$

where Ω_i, is the choice set of possible destination TAZs for a trip originating in TAZ i. As η decreases from the value of 1, an increase in the size of a zone j, D_j, has less and less of an effect on the probability of choice of alternative j. The model in Equation (3) is a nonlinear-in-parameters multinomial logit model (NPMNL) because of the presence of the multiple size effects (as captured by the $(\boldsymbol{\delta}'\boldsymbol{z}_j)$ component in the utility function of Equation (2)).[3] The estimation of the model is

[3] Note that this NPMNL would collapse to a traditional multinomial model in the case when there is a single size measure. In such a case, the $(\boldsymbol{\delta}'\boldsymbol{z}_j)$ collapses to z_1 (with the normalization of 1 on this single size measure, as needed for identification), and the utility function of Equation (2) becomes $U_{nij} = \boldsymbol{\beta}'\boldsymbol{x}_{\boldsymbol{ij}} + \eta \log(z_1) + \xi_{nij}$. This is the familiar linear-in-parameters utility functional form, with a log-transformation of the single size measure. But when there are multiple size measures (say J size measures), the utility function takes the form $U_{nij} = \boldsymbol{\beta}'\boldsymbol{x}_{\boldsymbol{ij}} + \eta \log(z_1 + \delta_2 z_2 + \delta_3 z_3 + \ldots + \delta_J z_J) + \xi_{nij}$, with the parameter η as well as the parameters δ_j $(j = 2,3,\ldots J; \delta_1 = 1)$ to be estimated simultaneously. This results in the nonlinear in-parameters specification (see also Ben-Akiva and Lerman, 1985; page 260-261).

accomplished by using the maximum likelihood method in the GAUSS matrix programming language.

4.3 Choice Set Formation

In Equation (3), one could assume that the choice set Ω_i consists of all TAZs in the study area (2102 TAZs). However, in reality, only a subset of all possible TAZs will represent the potential destination choice set for any deadhead trip. This is because the behavioral and operational process determining deadhead trips is very likely to limit deadhead distance, as customers seek low wait times, and drivers and ride-hailing companies seek to minimize non-revenue time (miles). Ignoring this aspect of choice set determination will lead to inconsistent parameter estimates (Bhat, 2015). The issue then becomes one of determining an appropriate behavioral rule for the destination choice set generation process. In the Ride Austin dataset, 99.3% of all deadheading trips are less than 15 miles in length. Therefore, 15 miles is used as the threshold distance and the very small number of deadheading trips that had a distance greater than 15 miles were removed. Specifically, for a deadheading originating in TAZ *i*, the choice set Ω_i was formed by including only those TAZs that are within a distance of 15 miles (shortest network distance) from the origin TAZ. The sizes of the choice sets formed by applying this rule ranged between 12 and 949. The average choice set size for a deadheading trip was 865.41.

If the choice set used for estimation has a large number of alternatives, there will be several TAZs that have a near zero probability of being selected. This creates issues with convergence when using a maximum likelihood framework for estimating the values of β, δ, and η. To avoid this issue and to reduce computation time, we used only samples of the complete choice sets for estimation. As discussed in detail in McFadden (1978), in the case of the multinomial logit model (MNL) (in its linear-in-parameters or nonlinear-in-parameters form), the parameters are consistently estimated from a sample of alternatives. Nerella and Bhat (2004) further show that the true parameters are accurately recovered for the MNL even with a sample choice set of 1/40 of the actual choice set. In our estimation, we used a sample choice set of about 1/30 of the actual choice set; that is, we used 30 randomly selected TAZs from those that are within 15 miles of the originating TAZ for the deadheading trip. Specifically, for a trip *n* between origin *i* and destination *j*, the choice set sample $\tilde{\Omega}_n$ was generated by including the TAZ *j* and twenty-nine other TAZs chosen at random without replacement from the choice set Ω_i.[4]

4.4 Specification

The model specification was guided by the variables that were found to be significant for predicting ride-hailing demand in earlier studies and the attributes that were available through the ACS dataset and SLD. In addition, the model specification included a measure of impedance between the origin and destination and a measure of the spatial accessibility of the destination. A healthy dose of intuitive/conceptual reasoning and expectations were considered during the specification to ensure basic face-validity of the results.

[4] Sampling of choice sets is relatively common in logit based location choice modeling approaches, and enables the analyst to make a trade-off between the amount of information used for estimation and computational convenience. Previous studies have used choice set sample sizes of seven (Ben-Akiva *et al.*, 1984; Bhat *et al.*, 1998), 10 (Guo and Bhat, 2007; Lopez and Greenlee, 2016), 11 (Ben-Akiva *et al.*, 1984) and 30 (Zhang and Guhathakurta, 2018).

4.4.1 Impedance measure

The travel times between zones for the different times-of-day were generated using CAMPO's travel demand forecasting model. Any monotonic transformation of the travel time between an origin TAZ i and a destination TAZ j can be used as a measure of impedance. In our final specification, we use the square root of the travel time[5] between the TAZs ($\sqrt{t_{ij}}$) as the impedance measure. This choice of impedance measure was arrived at by comparing the goodness of fit that would be obtained when using different impedance measures with a simplified specification on a sample of the dataset. Specifically, the impedance measures that we compared were $\sqrt{t_{ij}}$, t_{ij}^2, $\ln(t_{ij})$, and t_{ij} itself. The impedance measures were evaluated based on the log-likelihood at convergence of the specification provided below in Equation (4), estimated on a sample dataset with 5000 observations from each of the four time periods:

$$U_{nij} = \beta_1 c(t_{ij}) + \beta_2 u_i c(t_{ij}) + \beta_3 r_i c(t_{ij}) + \beta_4 n_{ij} + \beta_5 s_{ij}\,, \tag{4}$$

where $c(t_{ij})$ is the measure of impedance between TAZs i and j, u_i is an indicator of the origin i being urban (takes a value of one if the origin TAZ is an urban TAZ, and zero otherwise), r_i is another indicator of the origin i being rural (takes a value of one if the origin TAZ is a suburban TAZ, and zero otherwise; the origin being suburban is treated as the base), n_{ij} is an indicator to denote i and j being neighbors (takes a value of 1 if the boundary of TAZ i touches the boundary of TAZ j), and s_{ij} indicates whether or not a destination TAZ j is the same as the origin TAZ i. β_1 captures the effect of impedance on utility if the origin TAZ is in a suburban area. $(\beta_1 + \beta_2)$ and $(\beta_1 + \beta_3)$ would be the effect of impedance on utility if the origin TAZ is in an urban area and rural area, respectively. We expect the quantities β_1, $(\beta_1 + \beta_2)$ and $(\beta_1 + \beta_3)$ to be negative as drivers should be less likely to pick-up passengers from TAZs that are further away. In the final specification, the impedance measure is introduced into the size independent component (the $\boldsymbol{x}_{ij}$ vector in Equation (2)).

4.4.2 Accessibility measure

The retail and service accessibility of the destination zone is included in the model specification. This measure indicates the degree to which a candidate destination zone for a deadhead trip is close to other candidate destination locations with high retail and service opportunities. In the current analysis, the retail and service accessibility of a candidate destination zone j is computed using the Hansen-type accessibility measure:

$$M_j = \frac{1}{N}\sum_{l=1}^{N} \frac{R_l + S_l}{t_{jl}^{\alpha}}\,, \tag{5}$$

where N is the total number of TAZs, R_l and S_l are, respectively, the number of retail and service employment opportunities in TAZ l, t_{jl} is the travel time from TAZ j to TAZ l, and α is a constant parameter (α>0). α controls the extent to which travel time controls the effect of proximity to retail and service opportunities. As α increases in magnitude, it implies that the relative

[5] The travel time from a TAZ to itself (intra-zonal travel time) is assumed to be half the travel time to the nearest TAZ (Venigalla *et al*., 1999).

positioning of retail and service opportunities in space has a lesser and lesser impact on the attractiveness of any specific candidate destination zone. In our final model specification, we use an α value of 1.2 to compute accessibility. This value was arrived at by systematically comparing several specifications with the accessibility measures calculated using different values of α ranging from 0.6 to 3. Overall, large values of the accessibility variable M_j indicate more retail/service opportunities in close proximity of zone j, and small values indicate zones that are spatially isolated from other retail/service opportunities.

The coefficient of the accessibility measure (say λ, on the accessibility measure M_j) captures the effect of the retail and service opportunities in nearby zones. A negative coefficient ($\lambda < 0$) would imply that the retail and service opportunities in nearby zones have a competing effect on the retail and service locations within the zone. That is, a TAZ that is not close to other TAZs with a high number of retail/service opportunities attracts more deadheading trips. Equivalently, a TAZ that is close to other TAZs with a high number of retail/service opportunities would attract fewer deadheading trips (this "competition" situation can happen because the lack of retail/service opportunities in close proximity to a specific zone can attract considerable shopping/retail activity of individuals who then want to be picked up from the zone after their activity there). On the other hand, a positive coefficient ($\lambda > 0$) suggests that the agglomeration pattern of retail and service opportunities enhances the attractiveness of individual locations for activity participation. That is, a zone that is close to other zones with a high number of retail/service opportunities attracts a number of deadheading trips. The effect of competition versus agglomeration of shopping locations was explored previously by Bhat *et al*. (1998), who find that the effect of having other shopping locations nearby is primarily competitive.

4.4.3 Conditions for identification and validity of the likelihood function

As mentioned in Section 4.2, one of the coefficients of the variables used in size term ($\boldsymbol{\delta}$) must be normalized to a constant (a value of one is adopted here) to allow for the identification of all coefficients. The variable that is normalized must have a statistically significant effect on the size term, because we are pre-specifying it to have an impact on the size term. Experimentation with preliminary specifications revealed that the number of retail employment opportunities had a significant impact for all time-of-day periods. Therefore, this variable was used for normalization.

Another issue to be considered when building the specification is that the size term must always be strictly positive. It is possible that there are TAZs for which $\boldsymbol{z}_j$ is a zero vector (it cannot be negative because of the nature of variables in $\boldsymbol{z}_j$). This would make the utility of those TAZs undefined. To avoid this issue, the area of the TAZ is retained as one of the variables in the size term even when it is statistically insignificant. The presence of this variable ensures that the size term is positive.

5 EMPIRICAL RESULTS

Deadheading trips were identified for the time periods of AM peak, mid-day, PM peak, and weekend night using the approach described in Section 4.1. Two-thirds of the trips were used for estimation, while the other one-third were set aside for validation. The destination TAZs for each time period were modeled separately. Section 5.1 presents the estimation results for the NPMNL model and inferences are drawn from the estimated coefficients. Section 5.2 presents a comparison of the goodness-of-fit between the NPMNL model and a simple Multinomial Logit (MNL) model.

5.1 NPMNL Model Estimation

For the estimation of the NPMNL model, all of the variables provided in Table 1 and the variables discussed in Section 4.4 were considered. Additionally, indicator variables denoting the area type of TAZs (urban, suburban, or rural), whether an urban TAZ belongs to the Central Business District (CBD), and TAZs corresponding to the airport (ABIA) and the University of Texas campus were included in the specification. The final specification was arrived at by sequentially dropping explanatory variables that were found to be insignificant. Table 2 shows the coefficients estimated using the NPMNL model for different time periods in a day. The table also provides the t-stats of the estimated coefficients. The t-stat is the ratio of the deviation of the estimated coefficient from a hypothesized value (the numerator) and the standard error of the estimated coefficient (the denominator). The hypothesized value is set to zero for computing the t-stat for all coefficients except that of the logarithm of the size term. A high value of the t-stat for these coefficients (say greater than 1.96) indicates that the departure of the estimated coefficient from zero was not simply a fluke because of the sample used (to be precise, if the t-stat is higher than 1.96, there is a 95% probability that we can reject the hypothesis that the coefficient is actually zero in the population; that is, the coefficient is statistically significant, or, equivalently, that the corresponding variable does play a role in affecting the destination of deadheading trips). For the coefficient of the logarithm of the size term, the t-stat is computed with respect to a hypothesized value of one. As explained in Section 4.2, a value of one for this coefficient would indicate that there is no competing influence between elementary destinations within the same TAZ.

5.1.1 Influence of impedance

The model allows for the effect of impedance on deadheading trip destination to be different for different area types of the origin TAZ. In our model specification we considered the suburban and rural area types to be the base area type for estimating the effect of impedance. Therefore, the coefficient of "Travel Time^{½}" denotes the effect of impedance for trips originating from suburban or rural areas. The coefficients of the interaction terms between the area type of the origin and the impedance capture the differential effect of impedance of trips starting from the other area types when compared to the trips starting from suburban or rural areas. Also note that since TAZs inside the CBD are all urban, the coefficient of the interaction between the origin being inside the CBD and the impedance term gives the differential impact of impedance of trips starting in the CBD when compared to that of trips originating in urban areas. To illustrate, the effect of impedance for deadheading trips originating from suburban/rural, urban and CBD areas in the Weekend Night period are -1.4249, -1.4249 – 0.5621 = -1.987 and -1.4249 – 0.5621 + 0.2787 = -1.7083 respectively. The effect of impedance is negative for all area types indicating that passenger pick-ups are more likely to be made closer to the origin of the deadheading trip. The relative magnitudes of these impedance coefficients indicate that deadheading trips originating in urban areas are likely to be shorter than those originating in suburban or rural areas. This is likely due to higher demand for ride-hailing in denser urban areas, leading to shorter distances between drop-off and pick-up locations. The effect of impedance on deadheading trips originating within CBD zones in comparison to the effect on trips originating in urban areas outside the CBD is not consistent across time periods. Deadheading trips originating in the CBD are shorter in the PM peak period, but longer in the mid-day and weekend night period. This may be due to a larger number of work-based ride-hailing trips occurring in the PM peak period, consistent with what Lavieri and Bhat (2019) found for the Dallas-Fort Worth region. Since the CBD has a relatively high employment density (the highest ratio of average total number of employment to average TAZ area according to Table 1), the higher demand for ride-hailing in the CBD region in the PM peak period will result in lower deadheading distances. The effect of impedance is further nuanced by the intrazonal and neighboring zone indicators. These variables help capture the possible non-linearities in the effect of impedance on the utility of a TAZ. These indicators depict differential effects by time-of-day. It appears that deadheading trips in the peak periods (which are more likely to be associated with work-based passenger trips) are less likely to be within the same zone or in neighboring zones. On the other hand, weekend night deadheading trips are more likely to have origins and destinations within the same vicinity of one another. Interestingly, for the mid-day period, deadheading trips seem to be less likely to be within the same zone but more likely to be between adjacent zones. Further exploration of ride-hailing passenger trip patterns and characteristics would provide additional insights on the reasons for these findings.

5.1.2 Influence of built environment attributes

The area types of destination alternatives were included in the specification. The suburban area type was treated as the base by assuming its coefficient to be zero. The estimation results indicate that deadheading destinations (that is, passenger pick-ups) are more likely to be in urban areas than in CBD and suburban areas. Similarly, deadheading destinations (passenger pick-ups) are more likely to occur in suburban areas than in the rural areas. Urban areas are the most likely destinations for deadheading trips (markets for ride-hailing passenger pick-ups). This could be because urban areas have a higher population density relative to other areas (the average population density of the urban TAZs outside the CBD is 5002.7 while that of the CBD TAZs is 4780.7). Previous studies have also found ride-hailing passenger demand to be higher in urban areas (Clewlow and Mishra, 2017). Lavieri *et al.* (2018) has shown that ride-hailing demand tends to be more in densely populated areas.

There is a higher propensity for deadheading trip destinations to be in the TAZ that houses the airport (ABIA). Previous studies have already established that ride-hailing is a popular mode for airport access/egress passenger trips (Lavieri *et al*., 2018; Rayle *et al*., 2016). Also, the likelihood of a deadheading trip destination in the TAZ housing the University of Texas campus is higher than from other TAZs during the mid-day and PM peak periods, and lower than from other TAZs during the AM peak and weekend night periods. The last result is not surprising, because passenger pick-ups are unlikely to happen at the University of Texas campus on weekend nights (the campus itself is not the hub of activity over the weekend nights).

Table 2 Estimation Results for NPMNL Model of Deadheading Trip Destination (Next Passenger Pick-up Location)

Variable	AM Peak		Mid-day		PM Peak		Weekend Night	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
TAZ Size Independent Attributes								
Impedance ($mi^{1/2}$) measures								
Travel Time$^{1/2}$	-1.6436	-64.89	-1.5137	-90.25	-1.5947	-79.39	-1.4249	-72.79
Travel Time$^{1/2}$ × Origin is urban[a]	-0.2974	-10.73	-0.2473	-13.74	-0.3289	-15.52	-0.5621	-27.56
Travel Time$^{1/2}$ × Origin is in CBD[a]	--	--	0.1731	12.56	-0.1021	-4.12	0.2787	22.31
Destination same as origin	-0.7931	-15.14	-0.1145	-3.75	-0.5169	-15.54	0.3193	13.65
Destination is a neighbor of origin	-0.2977	-11.23	0.0357	2.15	-0.0773	-4.35	0.0814	6.30
Built environment attributes								
Rural[b]	-1.5254	-6.24	-0.8879	-7.55	-0.5101	-4.50	--	--
Urban[b]	1.0448	29.62	0.7437	31.71	0.4323	17.11	0.9780	41.90
Central business district (CBD) [b]	-0.6734	-23.62	-0.1636	-9.52	-0.5067	-27.10	-0.4683	-46.86
Presence of ABIA	1.6627	15.22	3.4996	72.31	3.9906	69.63	5.5956	147.52
Presence of UT main campus	-0.6007	-10.54	0.5594	20.44	0.5589	16.21	-0.0420	-1.68
Transit frequency at PM peak ($mi^{-2}h^{-1}$) (/1000)	0.5893	12.21	0.6132	19.68	0.2608	6.74	0.9708	39.64
TAZ Accessibility/Size Attributes								
Retail and service accessibility ($/10^4$)	0.3774	47.70	0.4547	80.70	0.4865	71.00	0.7570	184.28
Size measures								
Employment variables								
Retail employment	1.0000	(fixed)	1.0000	(fixed)	1.0000	(fixed)	1.0000	(fixed)
Basic employment	--	--	--	--	0.0530	3.40	--	--
Service employment	0.5704	8.06	0.2330	22.85	0.2231	23.35	--	--
Education employment	--	--	--	--	--	--	--	--
Demographic variables								
No. HHs with income ≥ $150K (/1000)	16.5283	8.96	4.0955	23.75	5.2876	28.29	1.4854	37.33
No. of people aged 18-35 years (/1000)	2.9941	9.00	0.7078	24.53	0.4230	20.41	0.1205	26.80
No. HHs without vehicles (/1000)	--	--	0.2080	1.70	--	--	--	--
No. of Single person HHs (/1000)	5.6403	7.54	0.6052	7.78	0.6940	10.4940	--	--
Area (mi^2)	0.0067	0.11	0.0001	0.01	0.0001	0.01	0.0002	0.18
Log of composite zonal size measure[c]	0.7038	81.41	0.7057	120.90	0.8046	118.51	0.6482	136.13

[a] Base area type is Suburban/Rural
[b] Base area type is Suburban
[c] t-stats for coefficient being different from 1
-- Not statistically significantly different from zero at the 90% level of confidence and removed from the specification

The hourly frequency of transit per square mile of the TAZ (during PM peak) is used as a proxy for the transit connectivity of TAZs. In all the time periods, there is a higher likelihood for deadheading destinations (passenger pick-ups) to be in TAZs that are better served by transit. To some degree, this may be indicative of a competitive substitution effect between ride-hailing and transit, as has been reported in previous studies (Dias *et al*., 2017; Schaller, 2018). TAZs with better transit service are also likely to be locations with more attractions, employment and population concentrations, and destination opportunities. Therefore, these locations are likely to see higher levels of ride-hailing demand, thus increasing the probability that they will be destinations of deadheading trips.

5.1.3 Influence of TAZ accessibility/size attributes

The positive sign on the retail and service accessibility variables shows that the spatial clustering of retail and service opportunities is associated with a higher frequency of deadheading trip destinations (passenger pick-ups), suggesting an agglomeration effect (see Section 4.4.2). This could be because such areas constitute "attraction-sheds" for consumers who perceive a large variety of service and retail opportunities, and seek ride-hailing pick-ups at the end of their shopping/dining pursuits. Another reason for this finding may be that higher retail and service accessibility renders it easier for ride-hailing drivers to pick-up passengers from nearby TAZs. Ride-hailing drivers may prefer to cruise in search of passengers in and around TAZs that have high accessibility. Previous research has indicated that individuals use ride-hailing services to avoid driving under the influence and the hassle of finding and paying for parking (Clewlow and Mishra, 2017; Lahkar, 2018). Indeed, the coefficient for retail and service accessibility is higher in the weekend night period, suggesting that popular drinking locations in Austin lie within close proximity to each other and depict a high propensity for passenger pick-ups.

In addition to the relative positioning of TAZs in terms of retail and service opportunities, there is a pure size effect of retail and service employment, as captured by the number of employment opportunities (note that the coefficient on retail employment is normalized to one for identification). Interestingly, basic employment, as part of the size measure, impacts deadheading trip destination attractiveness only for the PM peak, a finding that certainly deserves additional investigation. The number of employment opportunities in education was found to be insignificant for predicting ride-hailing demand. However, this insignificance manifested only after including the indicator variable for the presence of the University of Texas at Austin (UT) main campus. This implies that once the effect of the UT main campus is captured, other locations with education employment opportunities do not contribute significantly to deadheading destination attractiveness. The relative magnitudes of the size measures clearly indicates that retail employment is the primary driver of deadheading trip attractiveness (passenger pick-up propensity) relative to employment in other sectors. As indicated earlier, the area of a zone does not contribute much to the zone attractiveness as a deadheading destination, but is included to ensure that the size measure does not take a value of zero for any TAZ. Finally, under the size measures, the coefficient for the log of the zonal size measure η is estimated to be less than 1, indicating that there is some degree of cannibalization of prospective passengers by the different elemental attraction locations within a zone. Indeed, earlier studies on shopping trips and work trips have also found competing effects between elemental locations within the same TAZ in attracting individuals (Bhat *et al*., 1998).

In terms of the effects of demographic attributes within the size measure, in all of the time periods, deadheading trip destinations are more likely (that is, passenger pick-ups are higher) in locations with a larger presence of high-income households, and also in areas with a higher number of individuals aged between 18 and 35 years. This is consistent with previous studies that have repeatedly identified the demographic group of wealthy younger adults to be the most frequent users of ride-hailing services (Alemi *et al*., 2018; Clewlow and Mishra, 2017; Rayle *et al*., 2016). Interestingly, TAZs with a higher number of zero-vehicle households attract more deadheading trips only in the mid-day period. Several past studies have found that areas with lower vehicle ownership rates are associated with higher ride-hailing passenger pick-up demand (Lavieri *et al*., 2018; Clewlow and Mishra, 2017). The results also indicate that deadheading trip destinations (passenger pick-up demand) are likely to be observed in areas with a large presence of single person households, consistent with previous findings (*e.g.*, Henao and Marshall, 2019) that ride-hailing users are more likely to be single and unmarried. The coefficients associated with the race-related variables were all insignificant and therefore do not appear in Table 2. This is different from the studies of Lavieri *et al*. (2018) and Lavieri and Bhat (2019), both of which noted a lower propensity to use ride-hailing among non-Hispanic whites.

5.2 Measures of Fit

In this section, the goodness-of-fit of the NPMNL models is compared with that of simpler MNL models. All variables in the category of "TAZ Size independent attributes" in Table 2 are used in the MNL model specification. Since the MNL model does not allow for the nonlinear-in-parameter structure, the effect of TAZ size (in Equation (1)) must be captured by a single proxy variable for size that is strictly positive. In the specification for the MNL model, the TAZ area is used for this purpose.

The metrics used for measuring the goodness-of-fit are log-likelihood, adjusted likelihood ratio index (ALRI), and average probability of correct prediction. To measure the model goodness-of-fit for the estimation datasets, the adjusted likelihood ratio index (ALRI; Windmeijer, 1995) is calculated as:

$$\bar{\rho}^2 = 1 - \frac{L(\hat{\beta}) - Q}{L(c)}, \tag{6}$$

where, $L(\hat{\beta})$ is the likelihood of the model at convergence, $L(c)$ is the likelihood at convergence of a naïve model, and Q is the difference in number of parameters between the naïve model and the estimated model. The naïve model refers to selecting a TAZ from the choice set at random, corresponding to a model where all estimated parameters are zero. Similarly, the predictive ALRI is calculated, with the likelihoods computed with respect to the validation sample instead of the estimation sample. The log-likelihoods and ALRIs are computed using the sampled choice sets that have 30 TAZs (including the destination). The average probability of correct prediction is computed using the full choice set containing all TAZs within 15 miles of the origin. The likelihood ratio test is used to statistically compare the goodness-of-fits of the NPMNL models and the MNL models for all time periods.

The goodness-of-fit statistics are presented in Table 3. An average probability of correct prediction in the order of 0.01 is quite reasonable considering that the average choice set size is 865.41 (note that a random TAZ selection would provide an average probability of correct prediction of only 0.0012; see third row of Table 3). The NPMNL model outperforms the MNL model in every metric for all time periods. The likelihood ratio test statistic between the NPMNL and the MNL models clearly illustrates the statistical superiority of the NPMNL model (the figures in Table 3 for the test statistic are far larger than the corresponding table chi-squared value with the appropriate degrees of freedom at even the 0.0001 significance level for all the time-of-day models). Similar results are found in the validation sample, providing clear evidence that the superior data fit of the NPMNL in the estimation sample is not simply an artifact of overfitting.

Table 3 Goodness-of-Fit and Validation Statistics for the NPMNL and MNL Models

Summary Statistic	**AM Peak**	**Mid-day**	**PM Peak**	**Weekend Night**
Estimation Sample				
No. observations	31003	72858	59261	127899
Log-likelihood at zero	-105447.32	-247804.44	-201558.36	-435009.74
Probability of correct prediction (random selection)	0.0012	0.0012	0.0012	0.0012
NPMNL				
Number of parameters	17	19	19	15
Log-likelihood at convergence	-67575.69	-156952.16	-112213.67	-241202.17
ADLRI	0.3590	0.3666	0.4432	0.4455
Probability of correct prediction	0.0110	0.0195	0.0290	0.0150
MNL				
Number of parameters	12	13	13	12
Log-likelihood at convergence	-70344.57	-163140.72	-117388.93	-254079.04
ADLRI	0.3328	0.3416	0.4175	0.4159
Probability of correct prediction	0.0094	0.0178	0.0259	0.0127
Likelihood ratio test statistic	5537.76	12377.12	10350.53	25822.81
Chi-square table value at the 0.0001 significance level	$\chi_5^2 = 25.74$	$\chi_6^2 = 27.86$	$\chi_6^2 = 27.86$	$\chi_3^2 = 21.11$
Validation Sample				
No. observations	15502	36429	29621	63950
Log-likelihood at zero	-52725.36	-123902.22	-100746.87	-217506.57
Probability of correct prediction (random selection)	0.0012	0.0012	0.0012	0.0012
NPMNL				
Number of parameters	17	19	19	15
Predictive Log-likelihood	-33790.79	-77944.95	-56543.28	-120449.76
Predictive ADLRI	0.3588	0.3708	0.4386	0.4462
Probability of correct prediction	0.0108	0.0194	0.0280	0.0147
MNL				
Number of parameters	12	13	13	12
Predictive Log-likelihood	-35175.59	-81212.28	-59242.70	-126816.17
Predictive ADLRI	0.3326	0.3444	0.4118	0.4169
Probability of correct prediction	0.0097	0.0171	0.0251	0.0128

6 IMPLICATIONS AND APPLICATIONS OF MODEL SYSTEM

The models developed in this paper provide key insights into the nature of deadheading trips and can be used to guide the development of policies related to ride-hailing services. Additionally, the modeling framework of this study can be incorporated in travel demand forecasting models, which do not currently take into account the impacts of deadheading trips. This section offers a discussion of the implications and applications of the model system developed in this study. Section 6.1 provides some of the direct implications of the model results presented in Section 5.1. A useful metric for policy makers and TNCs interested in reducing deadheading is the expected deadheading distance at various locations. Section 6.2 illustrates how this metric may be computed. Section 6.3 presents a discussion on how the number of deadheading trip interchanges may be computed from the model results.

6.1 Planning and Policy Implications

The distance traveled per deadheading trip seems to be higher if the deadheading trip originates (or if the previous passenger was dropped off) in a suburban or rural area. This may be because it is relatively more difficult to find a new passenger in these areas and hence the driver needs to travel a farther distance for the next passenger pick-up. This may suggest that it would be prudent to discourage ride-hailing in suburban and rural areas so that the amount of deadheading mileage can be minimized. However, if policies that penalize or discourage ride-hailing services to operate in suburban and rural areas are implemented, the consequences of such policies need to be considered carefully. It is generally difficult to serve these areas with conventional transit (due to lower densities) and ride-hailing services constitute a convenient mobility option, especially for the transportation disadvantaged in these locations. The fact is that ride-hailing services fill an important mobility gap in areas that are not well served by other modes of travel. The question then arises as to how ride-hailing services in these areas can be deployed and priced in such a way that deadheading is minimized while fully realizing the mobility benefits that ride-hailing provide.

The model results suggest that ride-hailing caters to individuals who engage in social and entertainment activities in the weekend night period. The use of ride-hailing for these activities has merit because it leads to a reduction in the incidence of driving under the influence or using transit while intoxicated. In fact, several cities have witnessed a drop in driving under the influence after ride-hailing services became popular (Rabin, 2018; Richards, 2018). Also, ride-hailing demand is higher in zones well served by transit, particularly in the mid-day and PM peak periods when people are more likely to be engaging in out-of-home activities. Whether this is indicative of a competitive effect on transit usage remains to be determined, although recent evidence suggests that ride-hailing is likely to be substituting transit trips (Schaller, 2018), but complementing transit in some markets (Hall *et al.*, 2018). However, when coupled with the finding that ride-hailing demand is higher in areas with higher retail and service accessibility and in urban areas, it is entirely possible that ride-hailing pick-ups are occurring in activity centers which have traditionally been better served by transit in the first place. In addition, it is likely that ride-hailing drivers prefer to search these areas for passenger pick-ups. Ride-hailing drivers searching specific areas for passengers can reduce waiting times and bolster ride-hailing demand in these areas.

It appears that ride-hailing is still primarily used by the niche demographics of young adults and wealthy households. If TNCs or urban planners wish to increase the use of ride-hailing in the city to reduce vehicle ownership, reduce need for parking, and promote Mobility-as-a-Service (MaaS), targeted efforts must be made to encourage the use of ride-hailing among other demographic groups. A reduction in space allocated to parking would allow cities to convert existing parking land to other valuable uses.

6.2 Computation of Expected Deadheading Distance

It is in the best interest of city planners, TNC operators, and society at large to minimize deadheading. The model developed in this paper can be used to compute expected deadheading distance for various locations. Once areas associated with higher expected deadheading distances are identified, policies and pricing schemes can be enacted to discourage individuals from making ride-hailing trips to these areas. However, the potential deadheading reductions associated with such strategies should be weighed against the potential adverse impacts on mobility enhancements that ride-hailing could provide such areas. The expected deadheading distance originating from a TAZ can be computed as shown in Equation (7) using the probability mass function of TAZs being selected as the destination:

$$E(d_i) = \sum_{j=1}^{N} d_{ij} P_{ij} , \tag{7}$$

where P_{ij} is the probability that a deadheading trip originating at TAZ *i* ends at TAZ *j* as computed by Equation (3) and d_{ij} is the network distance between the TAZs. The average deadheading distance in the PM peak period is mapped in Figure 4. To measure the accuracy of the expected deadheading distances predicted by the model, the predicted value is compared against the empirically calculated value of the expected deadheading distance for each TAZ. The expected deadheading distances are calculated empirically only for the 698 TAZs that have at least 10 deadheading trips originating within their boundaries. The mean absolute percentage error in the predicted expected deadheading distance across all of the TAZs is 16.66%, which is on the high side, but not completely uncommon in such models (for example, see Section 5.1.4 of Ferdous *et al.*, 2011). As expected, deadhead distances are smaller in higher density urban areas and larger in outlying suburban and rural areas.

6.3 Incorporation into Travel Demand Forecasting Models

It is relatively easy to forecast ride-hailing passenger trips in travel demand forecasting models. The mode choice model can be updated based on information gathered from travel surveys to reflect the use of ride-hailing options. The end points of passenger trips form the origins of deadheading trips. Once the origin of a deadheading trip is known, the destination of the trip can be determined based on the probability function given in Equation (3). If B_{ij} is the number of passenger trips that go from TAZ *i* to TAZ *j*, then the number of deadheading trips M_{od} between an origin TAZ *o* and a destination TAZ *d* can be expressed as:

$$M_{od} = \sum_{i} B_{io} P_{od} , \tag{8}$$

where P_{od} is the probability that a deadheading trip originating at TAZ *o* ends at TAZ *d* as computed by Equation (3). The above expression assumes that all ride-hailing vehicles that drop a passenger at TAZ *o* will make only one trip to pick up the next passenger. In other words, it is assumed that all deadheading trips belong to the first category as defined in Section 4.1. In reality, some drivers may end the ride-hailing session and return home or proceed to perform other personal activities. The deadheading trips resulting from the pursuit of these other personal activities are not modeled in this study. However, accounting for these deadheading trips in at least some manner is likely to be better than completely ignoring them.

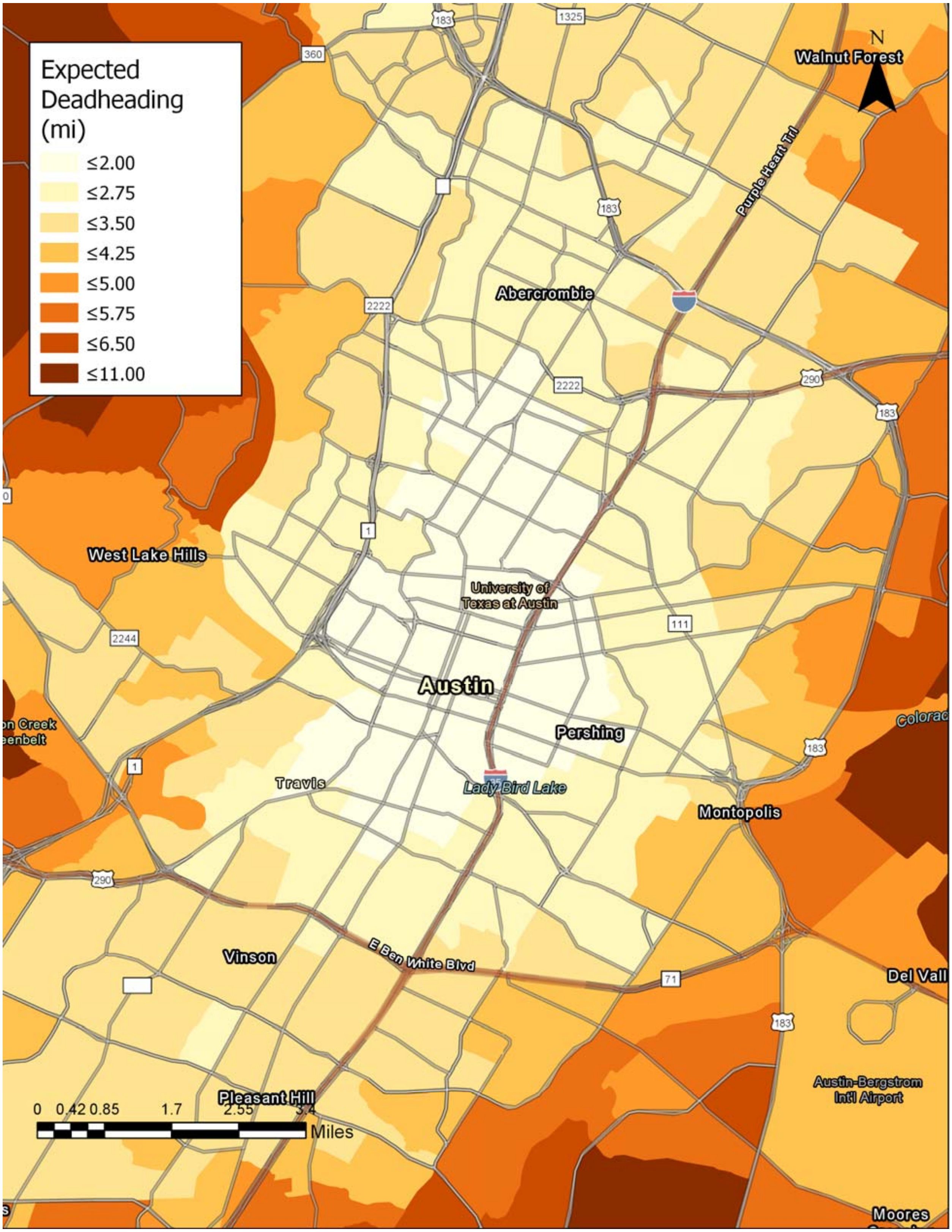

Figure 4 Expected Deadheading Distance from TAZs in the PM Peak Period

7 CONCLUSIONS

The research in this paper is motivated by the rapidly increasing use of ride-hailing options in cities around the world. The use of ride-hailing services leads to empty vehicle mileage because ride-hailing service drivers (often) need to travel some finite distance to pick-up their next passenger after dropping off a prior passenger. These trips, referred to as deadheading trips, have important implications for vehicle miles of travel (VMT), traffic congestion, and carbon footprint of auto travel. Although there is considerable research dedicated to studying ride-hailing passenger trips and their characteristics, there is very little research on deadheading trips thus rendering it challenging to formulate strategies to reduce deadheading mileage and to account for such trips in travel demand forecasting models.

This paper presents a model for forecasting the destinations of deadheading trips. A dataset of deadheading trips was generated by imputing such trips from a dataset on ride-hailing passenger trips released by the TNC, Ride Austin. The model provides valuable insights on the factors that affect deadheading trip patterns at different time periods in a day and at different locations. The model is sensitive to location specific characteristics related to the built environment, employment opportunities, and socio-demographic characteristics. The goodness-of-fit of the nonlinear-in-parameters multinomial logit (NPMNL) model developed in this paper is found to be significantly better than that of a simple multinomial logit (MNL) model. The paper presents a detailed discussion of possible applications of the model for transportation planning and travel demand forecasting.

A shortcoming of this study is that the model only accounts for deadheading trips that occur when the driver is searching for a new passenger after dropping off the previous passenger. There is another category of deadheading trips that involve the driver stopping the ride-hailing session and traveling to perform other activities. The dataset used in this study was not suitable for modeling this category of deadheading trips. Also, the results in this paper do not apply to shared ride-hailing services where unrelated passengers can share rides. Because the Ride Austin platform did not provide this service at the time when the data was collected, this mode of ride-hailing could not be considered. Also, when incorporating the deadheading trip model into a travel demand forecasting model, it is important to recognize that most of the conventional travel demand forecasting models assume that all trips occur along the path with the lowest impedance. Since at least a part of the deadheading trip may be utilized to search for new passengers, the resulting path to the next pick-up location may not be along the path with the lowest impedance. The model presented in this paper only identifies the destination of the deadheading trip and not the path taken to reach that destination. Modeling the actual path taken in the search for new passengers would be a worthwhile endeavor for future research in terms of obtaining more accurate VMT implications of deadheading trips.

Another limitation of our study is that the model developed in this paper is not sensitive to the supply-side characteristics of ride-hailing such as vehicle availability, wait times, and pricing. These characteristics could potentially affect deadheading. When the number of vehicles searching for passengers (vehicle availability) is low, it is more likely that drivers would be matched to passengers that are far away. This phenomenon is referred to as "Wild Goose Chase (WGC)" by Castillo *et al*. (2018). WGCs can result in higher wait times for passengers and longer deadheading for drivers. Ride-hailing companies have identified surge pricing as an effective mechanism for managing ride-hailing supply and demand to ensure that WGCs do not occur (Castillo *et al*., 2018). Our model does not capture the intricate relationships between the supply, demand and price and its potential impact on deadheading. The reader is referred to studies by Bai *et al*. (2018), Castillo *et al*. (2018), Nourinejad and Ramezani (2020) and Zha *et al*. (2016) for recent attempts at developing theoretical frameworks for modeling the relationships between characteristics related to supply, demand and price. The relation between supply and demand would also depend on the specific algorithms used by the ride-hailing companies for matching drivers with passengers. Using theoretical frameworks and numerical experiments, Xu *et al*. (2019) and Yang *et al*. (2020) explore the effectiveness of different matching strategies for optimizing the performance of ride-hailing systems. In all the aforementioned studies, supply and demand side characteristics are modeled in the aggregate. They do not consider the heterogeneity of these characteristics over space because of different socio-demographic and built-environment characteristics. Just as there are limitations in our study, these other studies are also substantially limited because they ignore the heterogeneity in ride-hailing demand over space. Doing so invites what has long been referred to as the "ecological fallacy" in analysis methodology (see Robinson, 1950, Duncan *et al*., 1961), and will, in general, result in inaccurate estimates and results due to aggregation bias (see also Koppelman, 1974). Besides, wait times and surge pricing considerations are intricately tied with demand patterns, not simply supply issues (after all, wait times will be high for a given supply when demand is high, and surge pricing is related to demand not just supply). In addition, many of these studies are based on numerical experiments, rather than actual empirical data. In contrast, we model the ride-hailing demand-side characteristic of passenger pick-up opportunities endogenously as a function of spatio-temporally varying characteristics at the disaggregate level of trips using actual empirical data.

There have also been studies that focus exclusively on the supply-side of ride-hailing. Most of these studies are based on data collected using a ride-hailing service's publicly accessible Application Programming Interface (API). The data collected in this manner is rich in supply-side characteristics such as wait times, surge pricing and vehicle availability. Hughes and MacKenzie (2016) and Wang and Mu (2018) have used data collected in this manner to model waiting times based on socio-demographic and built-environment variables. These studies find that wait times are generally lower in areas with high population density. They also find that race and wealth of the local demography does not necessarily affect wait-times. Even though the models used in these studies make use of socio-demographic and built-environment variables to model wait-times, the effect of ride-hailing demand is not explicitly captured by these variables. In effect, these models can be viewed as "reduced-form" efforts rather than structural models that explicitly consider spatio-temporal patterns of demand. In this manner, they are unlike our study where we endogenously model the number of pick-up opportunities in different areas with the size term using actual data on passenger pick-ups.

Data collected through ride-hailing APIs have also been used to develop models for predicting surge pricing. Battifarano and Qian (2019) develop a model for making short-term predictions of surge-pricing based on past surge-pricing information, network characteristics and occurrence of special events. Since the objective of the model was only to undertake a short-term prediction, and past surge pricing was used as an explanatory variable, socio-demographic characteristics or built-environment characteristics were not used in the model. Jiao (2018) explores the characteristics of Uber's surge pricing in the city of Austin during the 4th of July weekend of 2015. They focus on modeling only the temporal variations of surge prices. They use the time of day and the other supply-side variable of expected waiting time as the independent variables for modeling surge pricing. Unfortunately, the aforementioned studies on surge pricing do not include any variable related to ride-hailing demand as explanatory variables. Surely, issues of surge pricing should technically be based on demand patterns, not on past surge-pricing information (after all, surge pricing is fundamentally based on a demand-supply imbalance!). Thus, these earlier studies can be improved by including a measure of ride-hailing demand directly or endogenously in a manner similar to what is described in this paper.

To summarize, while our demand-side study misses some important supply-side considerations, earlier supply-side studies have also missed out on important demand-side issues. A valuable avenue for further research then is to combine data on the demand-side and the supply-side to develop a more comprehensive empirical model for ride-hailing trip patterns. More ride-hailing companies have recently started sharing data on ride-hailing passenger trips. In 2018, DiDi – the TNC with the largest market share in China – made the data on all ride-hailing trips that occurred within a span of two months in the city of Chengdu, China, available to researchers.[6] More recently, the city of Chicago passed an ordinance that requires TNCs to publish anonymized and disaggregate ride-hailing trip data every quarter. The first batch of this data was made available in April 2019.[7] TNCs are still reluctant to explicitly share disaggregate data on the supply side. However, as mentioned earlier, it is possible to collect information on supply-side characteristics through the ride-hailing services Application Programming Interface (API). As such, the scope for formulation and developing comprehensive integrated demand-supply models for ride-hailing trip patterns is wide open and constitutes a ripe direction for future research.

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