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Joint Modeling of Access Mode and Parking Choice of Air Travelers Using Revealed Preference Data

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Abstract

Airport ground access mode choice is distinct from everyday mode choice decisions, necessitating context-specific choice model estimation. Understanding airport ground access mode choice decisions is not only important for developing infrastructure planning strategies, but also for assessing the impacts of emerging modes on airport revenues, particularly from parking. However, parking choice is an often-overlooked dimension in airport ground access choice modeling. This paper addresses this gap through the development of a joint model of airport access mode and parking option choice using a passenger survey conducted at Dallas-Fort Worth (DFW) International Airport in 2015. Compared with a traditional conditional logit model that does not consider parking options available at DFW airport, the joint model of mode and parking decisions was found to generate more realistic values of travel time and was shown to have better predictive performance, both of which are critical for obtaining better airport parking revenue estimates and identifying traveler cohorts who may respond more strongly to potential policies targeting curb congestion and parking demand.

Airports are often considered as high-volume "special generators" in regional travel demand models (*1*). Before the COVID-19 pandemic, data from several major airports in the U.S.A. indicated a 3.8% annualized growth from 2011, which means more than doubling of air travel demand every 20 years (*2*). Although travel in general (and air travel in particular) has seen a significant decrease from the pandemic, the availability of vaccines is increasing optimism for "back to normal" conditions, including a return to previously projected levels of air travel demand (*3*).

Within the past decade, transportation networking companies (TNCs) have become an attractive alternative to traditional modes (such as driving oneself, drop-off/pick-up, taxis, transit, and courtesy shuttles) to access airports (*4*). There is evidence that shift in mode share is eating into airport parking revenues (*2*) and creating congestion at the curb (*4*). This is important to recognize because parking revenues comprise about 18% of the total revenue at a typical U.S. airport (*5*) and curb space at U.S. airports is becoming scarce enough to warrant curb pricing as a solution to alleviate this traffic congestion (*6*). Thus, understanding the how and why of getting to/from airports is critical for forecasting future travel demand and airport ground infrastructure needs. Notably, airport access/egress mode choice varies from regular mode choices both in the set of available alternatives and in the factors that influence the choice. Besides the traditional modes noted above, the airport ground mode choice set comprises of alternatives such as charter bus, hotel shuttle, and airport shuttle. Moreover, airports usually offer multiple parking services with varying prices and first/last leg travel based on proximity of the parking location to the terminal. Taking Dallas-Fort Worth (DFW) International Airport as an example, in addition to the most popular terminal parking option, there is valet parking on one hand and more economical parking options on the other.

There is an abundance of literature that utilizes variants of discrete choice modeling (DCM) to study airport access mode choice (*7*). Built on the basis of random utility maximization theory, DCM assumes individuals make decisions to maximize utility specified as a linear

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weighted summation of the independent variables and an alternative specific constant (8). For the modeling of airport access mode, the general form of utility specification is defined as

$$U_{ij} = ASC_j + \theta_1 * Time_{ij} + \theta_2 * Cost_{ij} + \theta' X_i + \varepsilon_{ij} \quad (1)$$

where U_{ij} refers to the utility of alternative j of individual i, which is influenced by travel time ($Time_{ij}$), travel cost ($Cost_{ij}$), socio-demographic characteristics of the individuals, and characteristics of the trip (X_i). Time and cost are usually considered to be the most important variables for predicting mode choice. The ratio of coefficients of these two variables, defined as value of travel time (VoT), indicates the monetary amount an individual is willing to pay to save one unit of time (e.g., dollars per hour). VoT is essential for reliably estimating the impact of various infrastructure planning and demand management scenarios on the mode choice probabilities. For example, VoT can inform congestion pricing policies by estimating the amount of money people are willing to spend for better access to their destinations.

To better capture the influence of airport parking configurations on airport mode choice decisions, this research expands the existing literature on airport ground access choice through a joint airport access mode and parking product choice model. The existing literature often ignores the diversity of parking options while modeling airport ground access (9). Some studies estimated parking cost based on the price of the most popular parking option (1, 10), while some others calculated a weighted average based on the services available to consumers (7, 11). Some previous studies distinguished on- and off-airport parking in the access mode choice model (4, 12), but did not account for the parking products with completely different features and pricing schemes within those two options. These approaches likely underestimate the influence of parking cost for some consumers, which result in biased VoT estimates. By considering the diversity of the parking services available to the consumers, the nested structure proposed in this study offers a more realistic portrayal of VoT and thus better encapsulates the interaction between the mode and parking choice dimensions that are directly tied to airport revenue generation.

It is important to note that this research effort builds on a prior effort for modeling airport mode choice at DFW (10). Utilizing the same survey dataset used by Aziz et al. (10), this research specifies a model that jointly considers mode and parking product choice decisions. The results generated by this research are intended to be incorporated as a behavioral input into the infrastructure optimization model of the U.S. Department of Energy Athena project (13).

Survey and Sample

Survey Design and Data Collection

The dataset used for the analyses in this paper is from a passenger survey among air travelers flying out of DFW, that is, departing passengers. The survey was commissioned by the North Central Texas Council of Governments (NCTCOG) and the data collection was carried out from October 13, 2015 to February 3, 2016. A stratified sampling strategy based on the distributions of airlines, destination zones, and the time of day was applied to obtain a representative sample of passengers. Survey respondents were randomly approached by the interviewers while they were waiting at the airline gate and answered the questionnaire via electronic tablets (14).

The respondents were asked to provide the following categories of information: socio-demographic characteristics, information on their air travel such as the travel duration and trip purpose, and information on their airport access trip such as the origin, mode, and parking location (if applicable). After a meticulous review by the data collection agency, 84% (8,379) of the 9,942 survey responses qualified as usable because of containing necessary geospatial information (14). After further cleaning the survey data based on missing and incomplete information on mode choice and socio-demographic characteristics, 8,130 survey responses were retained for the purposes of this analysis.

Sample Description

Table 1 details the distributions of several key sample characteristics. Among respondents who were local residents that were on business trips (RB), parking was the most prevalent mode choice, followed by being dropped off by friends or family members. For residents that were on nonbusiness trips (RNB), being dropped off was the most popular option. For passengers that were not DFW area residents and were on nonbusiness trips (NRNB), about 42% were dropped off at the airport and a much smaller proportion chose to use rental cars (~27%). Unsurprisingly, hotel shuttle was popular mostly among nonresident respondents. The proportion of TNC is roughly similar for the four groups. Terminal parking had the highest market share in the RB group, but for nonbusiness trips, remote parking was the most popular choice at DFW.

Model Framework

The most common DCM structure employed in airport access model analyses is multinomial logistic regression (MNL) (4, 12, 15). Nested MNL models (NMNL) have been preferred over MNL in more recent studies (16–18)

Table 1. Description of Sample

		Resident business (RB)	Resident nonbusiness (RNB)	Nonresident business (NRB)	Nonresident nonbusiness (NRNB)
	Sample size	2217	2402	2194	1317
Mode choice (%)	Being dropped off	23.09	47.38	9.34	42.29
	Drive + park	56.16	34.55	0.73	1.52
	Rental car	6.00	1.96	42.84	27.26
	Hotel shuttle	2.80	1.17	16.04	11.31
	Transit	0.72	1.46	0.55	1.44
	Taxi	6.22	5.00	17.68	6.68
	Airport shuttle	0.72	1.96	4.38	2.28
	Transportation networking company (TNC)	4.06	6.20	7.43	6.61
	Charter bus	0.23	0.33	1.00	0.61
Parking choice (%)	Terminal	41.89	23.53	31.25	26.32
	Express	13.96	16.79	25.00	10.53
	Remote	28.97	42.16	31.25	52.63
	Valet	7.91	4.90	6.25	0.00
	Parking spot	4.44	9.19	6.25	5.26
	Park and fly	2.58	3.19	0.00	5.26
	Swift park	0.24	0.25	0.00	0.00
Household income (%)	Under $24,999	1.37	6.72	1.50	7.87
	$25,000–$49,999	3.85	14.81	3.53	17.10
	$50,000–$74,999	16.46	20.82	13.48	22.01
	$75,000–$99,999	16.46	18.20	21.01	19.38
	$100,000–$149,999	27.33	21.12	30.96	18.59
	$150,000 or more	34.53	18.32	29.51	15.05
Age (%)	16–18	0.05	0.72	0.09	0.31
	19–24	3.61	9.03	4.03	10.74
	25–34	19.37	22.97	22.85	22.10
	35–49	42.39	29.70	38.55	24.81
	50–64	30.24	26.37	31.79	29.44
	65 or older	4.34	11.21	2.69	12.60
Gender (%)	Male	70.54	42.23	72.25	45.97
	Female	29.46	57.77	27.75	54.03

to account for similarities among certain modes, and to avoid the violation of the independence from irrelevant alternatives (IIA) property, which is a primary assumption of MNL (*8*). NMNL is proven to offer better predictive performance than MNL in some airports that have multiple types of transit services, such as airports in Germany (*16*), Gimpo Airport and Daegu Airport in South Korea (*17*), and Baltimore-Washington International Airport in the U.S.A. (*18*). The ACRP Synthesis Report (*19*) also documents better-performing NMNL cases at a few other American airports, such as Atlanta Hartsfield-Jackson International Airport, Miami International Airport, Chicago Midway and O'Hare International airport, and Boston Logan Airport. However, there are exceptions; no meaningful nesting structure was observed in the access mode choice modeling work at airports in New York metropolitan area but MNLs generate more realistic estimates (*12*). For DFW, researchers found that a mixed MNL (MMNL) is preferable over NMNL (*6*). MMNL is not constrained by the IIA property and also has the capability of incorporating unobserved heterogeneity of consumer preference (*6*), therefore, it has been gaining popularity in this area in recent years (*10*, *20*).

In addition to accounting for the nesting structure of access modes, NMNL has been applied in the literature to model the joint decision of airport and mode choice at German airports (*1*) and airports in New York metropolitan area (*16*). In this research effort, NMNL is used for the joint modeling of mode choice and parking decisions. Even though NMNL has been applied before in the topic area of access mode choice modeling, it has yet to be explored in the context of joint modeling of mode and parking choice decisions.

The model structure of NMNL is essentially built on the conditional logit model (CL) framework developed by McFadden (*21*) under the assumption of random utility maximization. There are two components to an

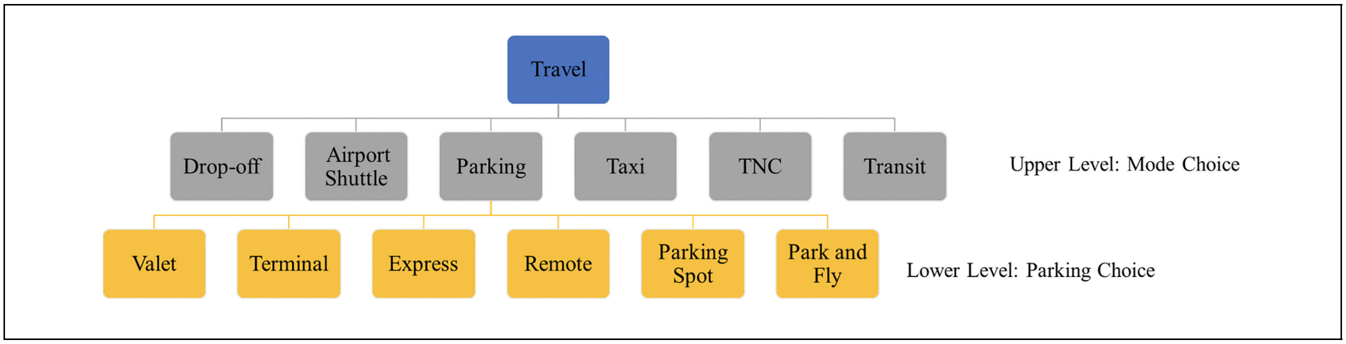

Figure 1. Model structure of the nested multinomial logistic regression (NMNL) of mode choice and parking decision.
Note: TNC = transportation networking company.

individual's utility function $U(d_i,\ X_i,\ \theta)$: a systematic component $u(d_i,\ X_i,\ \theta)$ and a random error component $\varepsilon(d_i)$ (Equation 2). The chosen alternative, denoted as d_i^*, produces the highest systematic utility value, as shown by Equation 3. Then, assuming the random error $\varepsilon(d_i)$ is independently and identically distributed across the sample and follows the extreme value distribution, expressed by the probability density function given in Equation 4, the probability of alternative j being chosen is shown as Equation 5.

$$U(d_i,\ X_i,\ \theta)\ = u(d_i,\ X_i,\ \theta) +\ \varepsilon(d_i) \tag{2}$$

$$d_i^* = argMax_{d_i \in D_i} u(d_i,\ X_i,\ \theta) \tag{3}$$

$$f(\varepsilon) = e^{-\varepsilon - e^{-\varepsilon}} \tag{4}$$

$$P(d_i = j) = \frac{e^{u(d_i = j,\ X_i,\ \theta)}}{\sum_{k=1}^{D_{it}} e^{u(d_i = k,\ X_i,\ \theta)}} \tag{5}$$

NMNL primarily differs from CL in that the random error component $\varepsilon(d_i)$ of the utility function is correlated, rather than independent, among some alternatives (*22*). This relaxation of the error term distribution assumption facilitates the modeling of the choices with a nested structure. As illustrated by Figure 1, the NMNL proposed in this study has an upper-level model on mode choice and a lower-level model on parking decisions. The upper-level mode choice decision of individual i is denoted as d_{mi} and the lower-level parking choice of individual i as d_{ip}, the probability of mode j being chosen is a function of the systematic component of the utility $u(d_{mi} = j)$, as shown by Equation 6, in which M_i is the mode choice set.

$$P(d_{mi} = j) = \frac{e^{u(d_{mi} = j)}}{\sum_{k=1}^{M_i} e^{u(d_{mi} = k,)}} \tag{6}$$

Conditional on the probability of individual i choosing parking, the probability of parking option l being chosen is shown by Equation 7, in which $v\left(d_{pi} = l,\ Z_i,\ \beta\right)$ means the systematic component of the utility of parking option l. Here, Z_i and β are respectively the independent variable matrix and the coefficient matrix for the parking choice.

$$P\left(d_{pi} = l \mid d_{mi}{}^* = parking\right) = \frac{e^{v\left(d_{pi} = l,\ Z_i,\ \beta\right)/\lambda}}{\sum_{k=1}^{P_i} e^{u\left(d_{pi} = k,\ Z_i,\ \beta\right)/\lambda}} \tag{7}$$

For mode choice alternatives that are not parking, the systematic component of the utility function is a weighted linear combination of the covariates (X_i) with weights being the coefficient matrix β, as shown by Equation 8. The systematic component of the utility of the mode option parking includes an inclusive value component entailing the log sum of the utilities of all parking options, as shown by Equation 9. Here, λ, often referred to as IV parameter, is the coefficient of the inclusive value. λ serves as an indicator for the correlation of the unobserved component $\varepsilon(d_i)$ between alternatives; $\lambda = 1$ indicates $\varepsilon(d_i)$ are independent across alternatives, which means the nesting structure is unnecessary and the simpler MNL structure is appropriate.

$$u(d_{mi} = j, X_i,\ \theta)_{j \neq parking} = \theta X_i \tag{8}$$

$$u(d_{mi} = parking, X_i,\ \theta) = \theta X_i +\ \lambda^* \ln \left(\sum_{k=1}^{P_i} e^{u\left(d_{pi} = k,\ Z_i,\ \beta\right)/\lambda}\right) \tag{9}$$

Model Specification

The proposed model specification involves determining (i) the choice set for two levels of decisions, (ii) the covariates that are included in the model utility functions, (iii) the specific format in which these variables should be included in the utility function, and (iv) how these variables are derived based on the available information. The following subsections mirror this order and describe the specification process in detail.

Choice Sets

The most common options for traveling to airports are drive and park, being dropped off by friends or family members, taxi, and transit. Charter buses, hotel shuttle, airport shuttle, rental vehicles are also available at many airports (*1*, *7*, *8*, *10*). TNC services such as Uber and Lyft are a more recent addition to this mode choice set and have diverted a considerable proportion of the taxi and transit ridership base away from those services (*6*).

Accordingly, the mode choice alternatives included in this study are drop-off, parking, taxi, TNC, transit, and airport shuttle, a shared ride service with typically larger vehicles that accepts reservation beforehand. Charter bus is typically a mode arranged for large groups like tourist groups, in which case the users likely do not consider other alternatives for their access mode; therefore, charter bus trips are deleted from the dataset. Similarly, hotel shuttle and rental cars are likely to be choices that were made for other purposes during the travel besides getting to the airport and those choices should be evaluated in a different modeling framework. For this reason, they are also excluded from this analysis. Meanwhile, the parking decision choice set includes valet parking, terminal parking, express parking, remote parking, parking spot, and park and fly. Swift Park is deleted from the dataset because of inadequate sample size.

Literature on the Effect of Time and Cost

Travel time and travel cost are widely used in modeling airport access mode choice; however, the manner in which these variables are included in the utility functions is greatly nuanced. Specifically, researchers have made different choices along the following three dimensions:

(1) *Whether to use total travel time or distinguish travel time by stage*

The most common practice in the literature is to use total travel time in the access mode choice model (*12*, *15*–*17*, *23*), but there is evidence that VoT differs at different stages of the trip. For example, transit wait time (*2*, *7*) and transit station access time (*24*) are found to have a larger influence on mode choice than in-vehicle transit time; extra travel time within the airport terminal is also shown to have larger influence on mode decision than in-vehicle travel time (*2*). In this research, the authors chose to use total travel time instead of distinguishing travel time by stage to produce a more parsimonious representation that is less reliant on assumptions made by the research team with regard to these more microscopic details.

(2) *How to distinguish VoT for individuals in different market segments: business trip (B) or nonbusiness trip (NB), resident (R) or nonresident (NR)*

Estimating separate mode choice models for individuals in different market segments is a common practice among researchers. It has been applied on many occasions to showcase the difference in VoT between business trips and nonbusiness trips (*23*, *25*, *26*). Reibach (*7*) estimated different VoT for the four segments: business resident (BR), nonbusiness resident (NBR), business nonresident (BNR), and nonbusiness nonresident (NBNR). This approach is straightforward and for some cases, has been proven to offer reasonable model performance and parameter estimates, however, it requires sufficient sample size for each segment.

An alternative to estimating one model for each market segment is to include interaction terms of these segment categories with travel cost or travel time, which generates a different VoT for each market segment. By experimenting with multiple MNL models with different specifications of statistical moderation, Kisia (*12*) presents multiple insights based on a case study for airports in the New York metropolitan area. To expound:

- Compared with estimating one mode choice model for each market segment, the pooled data approach with the interaction terms between travel cost and market segment dummy variables offer more reasonable parameter estimates.
- Individuals in different household income brackets have different VoT, and that nuance can be best captured by including interaction terms of cost with all income brackets as opposed to an interaction term between cost and the continuous income variable; and
- Contrary to the common belief that business travelers have a greater sensitivity to travel time, their sensitivity to travel cost contributes primarily to their higher VoT. Kisia speculates this could be explained by the availability of travel reimbursement privileges among business travelers (*12*).

In this paper, the authors decided to estimate cost–segment interaction terms for BR, NBR, BNR, NBNR to capture the VoT for these four groups. A model that estimates different cost coefficients for different income brackets exhibited lesser goodness-of-fit.

(3) *Generic coefficients for travel time/cost or estimate mode-specific coefficients?*

Table 2. Variables that Influence Airport Access Mode Choice in the Literature

Category	Variable	Mode	Effect	Sources
Mode-specific variables	Total travel time	Generic coefficient for all modes	−	(*12*, *16*, *17*)
		Driving (reference level: taxi)	+	(*15*)
	Transit waiting time	Transit	−	(*7*)
	Transit access/egress time	Transit	−	(*24*)
	Extra time in the terminal	Generic coefficient for all modes	−	(*2*)
	Travel cost	Generic coefficient for all modes	−	(*1*, *16*, *17*)
	Number of transfers for transit	Transit	−	(*7*)
Socio-demographic variables	Female	Shared rides	+	(*16*, *25*)
	Income	Rental car	+	(*1*, *17*)
		Taxi/Limo	+	(*1*, *17*)
	Travel frequency	Shared rides	−	(*7*)
	Attitude toward car dependency	Driving	+	(*28*)
	Foreigner	Driving	−	(*29*)
	Foreigner	Transit	+	(*29*)
Travel-specific variables	Number of travel companions	Transit (reference level: drop-off)	−	(*1*)
		Taxi (reference level: drop-off)	−	(*1*)
	Travel with children	Transit	−	(*7*)
	Number of checked bags	Transit	−	(*16*)
		Shared rides	+	(*7*)
		Rental car	+	(*7*)
	Paid by employers	Rental	+	(*7*)
		Taxi/limo	+	(*7*)
	Weekend	Transit	+	(*7*, *16*)
	Time of departure—early morning	Hotel shuttle	+	(*7*, *16*)
	Time of departure—late evening	Drop-off	+	(*7*)
	International trip	Hotel shuttle	+	(*7*)
	Duration of travel	Parking	−	(*7*)

Note: + = positive effect; – = negative effect.

Estimating generic time and cost coefficients for all mode alternatives with the assumption that VoT is the same regardless of mode is a common practice for access mode choice decision models (*4*, *12*, *24*, *27*). Some researchers, however, believe that the disutility of time and cost differs by mode, and choose to estimate mode-specific travel time and cost coefficients (*10*, *25*). As with the previous point, sufficient sample size is required for each travel mode's market share. In this research, the authors chose to use generic coefficients to achieve more robust estimates considering a limited number of respondents chose to use transit.

Literature on the Effect of Individual and Travel Characteristics

Besides time and cost, the following variables on travel characteristics have been proven to be significant predictors of access mode choice: the travel group size (*1*), whether traveling with young children (*7*), number of checked bags (*7*, *16*), whether employer pays for the trip (*7*), day of the week and the departure of the flight (*7*, *16*), whether the flight is international or domestic (*7*), and the duration of travel (*7*). Individual-specific variables such as household income (*1*, *17*), gender (*12*, *25*), employment status (*7*), age (*16*), and travel frequency at the targeted airport (*7*) also affect airport access mode choice. Attitudes toward car dependency also have been shown to be a significant predictor of ground access to the airport (*28*), but such information is not included in the dataset used in this analysis. The details of how these variables influence mode choice are listed in Table 2.

Variable Derivation and Utility Function

Time and Cost. The most important information in the survey for the calculation of travel time and cost is the ground trip origin address or nearest intersection reported by respondents. The travel distance and in-vehicle travel time variable for model estimation were generated based on automobile and transit travel skims from the 2014 NCTCOG Dallas-Fort Worth Travel Model for the Expanded Area (DFX). The DFX model, which is a sequential four-step model, serves as the source for forecasting vehicle miles of travel and other travel characteristics for the North Central Texas nonattainment area (*30*). To obtain distance and time values, each trip's origin and destination locations were geocoded to latitude and longitude (*14*), and the trips were then matched to one of the 5,386 traffic survey zones (TSZs) used in DFX (*30*). For travel distance, the automobile driving distances were assigned to trips originating within the metropolitan area for all available modes based on the origin TSZ (transit distances are not available). The in-vehicle travel time was estimated by matching the origin TSZ, access mode, and the time-of-day information from survey data with travel skims from DFX results. For origin TSZs with multiple transit options, the fastest alternative is selected for estimating transit/shuttle travel time.

Time. The following assumptions are made about travel time for each mode:

- Drop-off: the total travel time is assumed to be equal to the in-vehicle travel time as the individuals will be dropped off at the curb.
- Taxi and TNC: the total travel time is the in-vehicle time plus the waiting, which is assumed to be 10 min. This value is chosen based on "expert judgment" because of the lack of data sources for TNC/taxi waiting time in the year 2015. Future efforts will explore the impact of using variable wait times (based on population as well as built environment density) on airport access mode and parking choice.
- Airport shuttle: the total travel time is assumed to be in-vehicle time plus terminal travel time, which is assumed to be 20 min.
- Transit: the total travel time by transit, including waiting time, station access time, and in-vehicle travel time, is directly pulled from the transit travel skims generated by the DFX model.
- Parking: The total travel time from origin to parking location for the mode of parking is assigned based on the DFX model automobile travel skims. The extra time required to arrive at the curb from the different parking options is calculated using Google Maps based on the locations of the parking lots.
- Terminal parking: it is assumed that 10 min is needed to park the car and walk to the terminal.
- Valet parking: the terminal time is assumed to be zero.
- Express parking: the time from parking location to the terminal is assumed to be 20 min based on the circular bus schedule at DFW airport.
- Remote parking: the time from remote parking location to terminal is assumed to be 29 min, with 7.5 min being the waiting time (15 min headway) and 16.5 min being the average time in the airport circular bus to the terminals, according to Google Maps, and 5 min for parking the car and transferring to the bus.
- Parking spot and park and fly: the additional terminal time is assumed to be 39 min as they are roughly 10 min away by driving from the remote parking lots.

Cost. The travel cost was estimated for each available mode by calculating the potential out-of-pocket cost in 2015 USD for specific origin-destination pairs:

1. **Dropped off by friends or family:** Overall cost is comprised of toll costs and energy costs. Toll costs are estimated by the travel time skim of the DFX model that is sensitive to time of day and group size. Gasoline cost is calculated based on the trip distance (*d*), the fuel economy (*mpg*) of the vehicle that is assumed to be 30 mpg, and local gasoline price ($2.58 per gallon). The cost is doubled to account for the round trip to and from the airport for the driver.

$$C_{dropped\ off} = 2 \times Toll\ cost + 2 \times \frac{d}{mpg} \times gas\ price \quad (10)$$

2. **Parking:** the cost includes the cost of operation and cost of parking. The former, similar to drop-off, includes toll cost and gasoline cost. The cost of vehicle parking varies by parking services and travel duration, and it is halved because the parked car serves both the trip to the airport and the egress trip for leaving the airport when the traveler returns to DFW from their journey.

$$C_{parking} = Toll\ cost + \frac{d}{mpg} \times gas\ price + \frac{P_{parking} \times duration}{2} \quad (11)$$

The price of the parking options is based on parking schemes available on the official websites of these services:

Terminal: $24/day on average
Express: $13.5/day on average
Remote: $10/day on average
Parking Spot: $9.75/day on average
Park and Fly: $8.5/day on average
Valet: $31/day on average

3. **Taxi and limousine:** the cost is estimated using the travel distance multiplied by the lowest possible fare rate available at the airport, which is $1.7 per mile with a minimum $2.1 charge (*31*). The airport area toll cost ($2) is also added. A factor of 1.2 is applied to account for the tip.

Table 3. Distributions of Individual and Travel Related Variables

Variables	Type	Mean	Minimum	Maximum
Time of day: arrive at airport before 10:00 a.m.	Dummy	0.305	0	1
Time of day: arrive at airport after 8:00 p.m.	Dummy	0.047	0	1
Day of week: Monday	Dummy	0.211	0	1
Day of week: Tuesday	Dummy	0.192	0	1
Day of week: Wednesday	Dummy	0.194	0	1
Day of week: Thursday	Dummy	0.230	0	1
Day of week: Friday	Dummy	0.173	0	1
Business trip	Dummy	0.489	0	1
There are well wishers	Dummy	0.071	0	1
Travel party size	Continuous	1.360	1	4
Domestic travel	Dummy	0.890	0	1
Travel distance (miles)	Continuous	20.920	0.5	82.02
Resident	Dummy	0.710	0	1
Female	Dummy	0.441	0	1
Under 25 years old	Dummy	0.072	0	1
Above 65 years old	Dummy	0.078	0	1
Household income between \$50,000 and \$100,000	Dummy	0.250	0	1
Household income >\$100,000	Dummy	0.360	0	1
Race is white	Dummy	0.690	0	1
Working full time	Dummy	0.740	0	1

$$C_{taxi} = (\max(2.1, \quad 1.7 \times d) + 2) \times 1.2 \qquad (12)$$

4. **TNC:** the cost is estimated using the fare structure from Uber, using a combination of a base fee (\$1), a \$2.85 booking fee, a mileage-based fee (\$ 0.8/mile), and a time-based fee (\$ 0.16/minute). The minimum cost is \$6.65 and the airport area toll cost (\$2) is added to the estimated cost to get the final expense (*32*).

$$C_{TNC} = \max(6.65, \quad 1 + 2.85 + 0.8 \times d + \ 0.16 \times t) + 2 \qquad (13)$$

5. **Transit:** the cost per trip is \$3 based on DART fare rate (*33*).
6. **Airport shuttle:** the travel cost is assumed to be \$30 per trip based on average airport shuttle costs from multiple operators (*34–36*).

Although these assumptions encapsulate the best information available, estimation bias is still possible because of inaccuracies.

Individual and Travel Characteristics. Other potential covariates are directly taken from the survey data. Table 3 provides descriptive analyses of key candidate variables to be tested in the model. For the dummy variables, the mean value shows the share of the variable being 1.

Results

First, an all-encompassing nested multinomial logit regression (NMNL) was estimated by including all the individual and travel related variables listed in Table 3 for each mode and parking option. The model was then refined in a stepwise manner by removing variables with low statistical significance (i.e., *t*-values lower than 1.5). A baseline CL model with the terminal parking price assumed for the mode of driving was also estimated for the purpose of comparison. The results of the models are presented in Tables 4 and 5.

VoT Estimates and Goodness-of-Fit

The comparison of the VoT estimates and goodness-of-fit measures between the final NMNL and the baseline CL are presented in Table 4. VoT is calculated based on the coefficient estimates of the time and cost variables. For example, the VoT of nonresident business travelers (BNR) is $VoT_{BNR} = \frac{\beta_t}{\beta_{c} + \beta_{c\_BNR}} \times 60$. The VoT estimates for nonresident business travelers (BNR), resident business travelers (BR), resident travelers on nonbusiness trips (NBR) and nonresident travelers on nonbusiness trips (NBNR) are respectively \$72.5/h, \$31.0/h, \$21.7/h and \$17.8/h. The magnitude of VoT estimates among various market segments is consistent with intuition. For business trips, nonresidents tend to be less sensitive to costs, as their mode and parking choices are typically governed by official business schedules rather than opting for the most economical choice. Thus, this segment is

Table 4. Value of Travel Time (VoT) Estimates and Goodness-of-Fit Comparison

Category	Variable	Nested multinomial logistic		Conditional logit	
		Coefficients	*t*-Value	Coefficients	*t*-Value
Generic	Time (β_t)	−0.0133	−1.9933	−0.037	−5.4637
	Cost (β_c)	−0.0448	−7.4162	−0.0485	−7.5625
	Cost-BNR (β_{c_BNR})	0.0338	7.1174	0.0365	7.6849
	Cost-NBR (β_{c_NBR})	0.0081	1.5841	0.0179	2.8815
	Cost-BR (β_{c_BR})	0.0209	3.5526	0.0295	4.4472
Inclusive value parameter		0.5404	8.8465	na	
N (mode choice)		5676		5676	
N (parking choice)		1908		na	
Degree of freedom (mode choice)		5625		5626	
Log-likelihood (mode choice)		−5498.14		−5544.82	
Log-likelihood (parking choice)		−2354.67		na	
Akaike information criterion (AIC) (mode choice)		11088		11180	
Bayesian information criterion (BIC) (mode choice)		11169		11258	
McFadden ρ^2 (mode choice)		0.296		0.290	
VoT—BNR ($/h)		72.5		185.0	
VoT—BR ($/h)		31.0		116.8	
VoT—NBR ($/h)		21.7		72.5	
VoT—NBNR ($/h)		17.8		45.8	

na=not applicable.

expected to have the highest VoT, followed by residents on business travel, who have some control over their schedule as they are starting their trips from their home base. For nonbusiness travel, it can be conjectured that residents will prefer to travel comfortably to the airport as they are commencing their nonbusiness (i.e., leisure/pleasure) trip, whereas nonresidents who are concluding their trip will be inclined to prefer cost effective options over convenience for accessing the airport. Based on the sample size and the VoT estimates of the four market segments (Table 1), the VoT for those on business trips and nonbusiness trips are $51.6 and $20.3 respectively, which are on the lower end of the spectrum compared with VoT estimates for New York metropolitan area based on a stated preference survey ($63 for business and $42 for nonbusiness travelers) (*1*). The variation between this study and the New York metropolitan area-based study can be attributed to income differences as well as traffic condition variation between the two regions. Compared with the VoT estimates of the NMNL, CL estimates VoT to be unreasonably high within each market segment, particularly for nonresidents on business trips ($185/h).

Log-likelihood is calculated respectively for the mode choice and parking decisions for the NMNL, as shown in Table 4. CL does not have log-likelihood for parking choice as it does not model parking product choice. For the mode choice decision, besides the log-likelihood, the McFadden ρ^2, Akaike information criterion (AIC) and Bayesian information criterion (BIC) are also reported as goodness-of-fit indicators for the two models. From the goodness-of-fit measures, it can be observed that NMNL has higher log-likelihood, lower AIC and BIC values, and higher pseudo R-squared, which indicates NMNL model has slightly higher explanatory power for mode choice. The log-likelihood ratio test is performed to test whether the goodness-of-fit difference of the two models is statistically significant. The χ^2 statistic is calculated as $-2*[LL_{NMNL} - LL_{CL}] = 93.6$, larger than $\chi^2_{2,\ 99\%}$ (6.63), which shows that NMNL has statistically better performance than CL. These comparisons show the nesting structure that incorporates the characteristics of all parking options provides a better model fit compared with the CL based on the parking price of the most popular parking alternative.

Socio-demographic Variables and Travel Characteristics

The estimates of the socio-demographic and travel specific variables of NMNL and CL are presented in Table 5. For model estimation, being dropped off is considered as the base alternative, so all the coefficient estimates represent an alternative's performance with respect to being dropped off. For example, travelers reaching the airport before 10:00 a.m. prefer drive and park over being dropped off. Individuals traveling to the airport with other family (or non-family) members choose to drive and park instead of being dropped off. This finding is intuitive in that individuals traveling in large parties (purportedly with family members) will prefer to travel in their own vehicles for the sake of convenience as well as cost. Compared with males, females are less likely to choose drive and park instead of being dropped off. For the

Table 5. Socio-demographic Variables and Travel Characteristics

Category	Variable	Nested multinomial logistic		Conditional logit	
		Coefficients	*t*-Value	Coefficients	*t*-Value
Parking	Time of day: arrive at airport before 10:00 a.m.	0.4777	5.8318	0.3977	5.0812
	Business trip	0.4569	4.5645	0.2099	1.4872
	There are well wishers	−3.0512	−10.1235	−3.101	−10.6729
	Travel party size	0.6864	10.0309	0.5359	8.0551
	Travel distance	0.017	3.6638	0.0188	4.3212
	Resident	3.1223	14.4517	2.9035	10.9819
	Female	−0.4916	−5.6684	−0.4657	−5.6382
	Under 25 years old	−0.4901	−2.8752	−0.4593	−2.6908
	Household income >$100,000	0.5404	5.8673	0.2337	2.7807
	Working full time	0.3945	3.594	0.5557	5.3907
	ASC	−3.9523	−13.6658	−2.8266	−8.7465
Transit	There are well wishers	−2.2658	−3.0038	−1.4902	−1.9777
	Travel party size	0.3711	1.9838	−0.8015	−4.2969
	Travel distance	−0.013	−0.9305	−0.0748	−5.3939
	Household income: $50,000 and $100,000	−0.694	−2.1607	−0.8849	−2.7577
	Household income >$100,000	−0.5618	−1.8363	−0.7497	−2.4522
	ASC	−2.9963	−7.756	−2.3472	−6.0959
Airport shuttle	There are well wishers	−3.2626	−4.4262	−3.1573	−4.2812
	Travel party size	0.6923	6.1045	0.5657	4.9782
	Travel distance	−0.0689	−6.5463	−0.0756	−7.1605
	Resident	−1.302	−5.8087	−1.5249	−6.4782
	Female	−0.3799	−2.1727	−0.4203	−2.4014
	Household income: $50,000 and $100,000	0.86	3.7767	0.9281	4.0866
	Household income >$100,000	0.9394	4.2949	0.9299	4.2547
	ASC	−0.8162	−2.3126	−1.6559	−4.6134
Taxi	Business trip	0.6097	4.5372	0.4678	3.3084
	There are well wishers	−2.9003	−7.518	−2.7666	−7.169
	Travel party size	0.633	7.7897	0.405	4.9828
	Travel distance	0.0349	4.0408	0.0144	1.7166
	Resident	−1.2324	−6.7013	−1.5321	−7.6217
	Female	−0.2936	−2.7933	−0.4395	−4.184
	Household income: $50,000 and $100,000	0.2701	2.1042	0.2737	2.15
	Household income >$100,000	0.4713	3.9078	0.4083	3.4057
	Working full time	0.3273	2.5071	0.1214	0.9325
	ASC	−1.3151	−5.5204	−1.8282	−7.4782
Transportation networking company (TNC)	Time of day: arrive at airport after 8:00 p.m.	0.7788	4.3576	0.7013	3.9243
	There are well wishers	−2.7035	−6.6953	−2.5134	−6.2223
	Travel party size	0.3413	3.7822	0.0737	0.8161
	Travel distance	0.0068	1.0502	−0.0131	−2.0651
	Resident	−0.839	−6.4583	−1.0142	−7.5234
	Female	−0.3675	−3.2733	−0.5267	−4.6882
	Household income: $50,000 and $100,000	0.4563	3.3717	0.4414	3.2891
	Household income >$100,000	0.5349	4.0612	0.4349	3.3177
	Working full time	0.5413	4.0825	0.2382	1.799
	ASC	−1.3971	−5.9507	−1.1735	−4.9552
Express parking	Business trip	0.0441	0.5858	na	na
	Travel distance	0.0023	0.6951	na	na
	Household income: $50,000 and $100,000	0.3085	3.4302	na	na
	ASC	−1.0253	−6.3507	na	na
Remote parking	Time of day: arrive at airport before 10:00 a.m.	−0.3186	−4.2338	na	na
	There are well wishers	−0.5118	−1.3355	na	na
	Travel party size	−0.1143	−2.4043	na	na
	Travel distance	0.0061	2.0487	na	na
	Female	0.1679	2.4417	na	na
	Household income: $50,000 and $100,000	−0.9368	−7.6	na	na
	Household income >$100,000	−1.2064	−8.19	na	na
	Working full time	0.7788	6.0877	na	na
	ASC	−0.5861	−3.1919	na	na

(continued)

Table 5. (continued)

Category	Variable	Nested multinomial logistic		Conditional logit	
		Coefficients	*t*-Value	Coefficients	*t*-Value
Valet parking	Time of day: arrive at airport after 8:00 p.m.	0.3599	1.3182	na	na
	Travel distance	0.0051	1.1185	na	na
	Female	0.3515	3.1298	na	na
	Household income >$100,000	0.544	4.0291	na	na
	ASC	−1.3672	−5.9421	na	na
Parking spot	Time of day: arrive at airport before 10:00 a.m.	0.2247	2.023	na	na
	Travel distance	0.0041	0.8807	na	na
	ASC	−1.6613	−6.1445	na	na
Park and fly	There are well wishers	−6.4245	−0.0344	na	na
	Travel distance	0.0153	2.6583	na	na
	Household income >$100,000	−0.312	−1.9342	na	na
	ASC	−2.2008	−6.5975	na	na

Note: ASC = alternative specific constant; na= not applicable.
Reference level of mode choice model = being dropped of.
Parking product choice = terminal parking.

younger cohort (under 25 years old), drive + park is less preferable to being dropped off.

The presence of well-wishers on the airport trip corresponds to a higher probability of being dropped off at the airport over choosing any other mode, consistent with expectation. Larger travel party size is negatively correlated with the probability of being dropped off at the airport (based on the positive sign for this variable in all modes in Table 5). Households with annual income >$50,000 are less likely to prefer transit over being dropped off, which implies that individuals from households with lower income (i.e., annual income <$50,000) are more likely to use transit over being dropped off at the airport. A straightforward explanation for this is that lower income households in general tend to own fewer vehicles, making it difficult for a household member or a well wisher to drop them off at the airport. Individuals from high income households tend to prefer airport shuttles, as they can trade the higher cost of the shuttle for convenient access to the airport.

Several socio-demographic variables and travel characteristics have similar effects on the preference of TNCs and taxi for airport access, as these modes have very similar characteristics. Longer travel distances, visitors, male travelers, those in higher income group, and full-time workers prefer TNCs or taxi instead of being dropped off. An interesting finding here is that having a flight later in the evening (Time of day: arrive at airport after 8:00 p.m.) motivates the usage of TNC over being dropped off whereas this variable did not show any significance for choosing taxis for airport access. This speaks to one of the primary factors that differentiate TNCs from taxis—the ease of requesting a ride, which has helped TNCs seize market share from taxis.

With respect to the lower nest (for parking product choice), higher income is correlated with the choice of more expensive parking options. On trips where well-wishers accompanied a traveler to see them off, terminal parking was preferred over remote parking or park and fly, which could be to facilitate social interactions that can be made possible by parking at the terminal. Females, compared with their male counterparts, are found to prefer valet parking (to a higher degree) and remote parking (to a lower degree) over terminal parking. Travelers accessing the airport in large travel parties are found to prefer terminal parking over remote parking. Travel distance does seem to have an impact on parking product choice though the significance of that variable needs further investigation.

Though most of the results presented here are consistent with findings from previous studies, the directions of some effects do differ from existing literature on the topic. For example, late evening departures result in a higher probability of parking instead of being dropped off. Also, compared with male travelers, female travelers have a decreased tendency to use shared services (i.e., airport shuttle, TNC, and taxi) to access airports.

Sensitivity Analysis

Compared with independent models for airport access mode and parking choice, these findings show that a joint mode choice and parking decision (NMNL) model captures the interaction of the two choices much better. For example, change of price of a parking product (say, terminal parking) not only influences the parking choice but can also influence the choice of access mode. To demonstrate this capability of the model, an illustrative example is presented with a fictitious individual named Jane, who

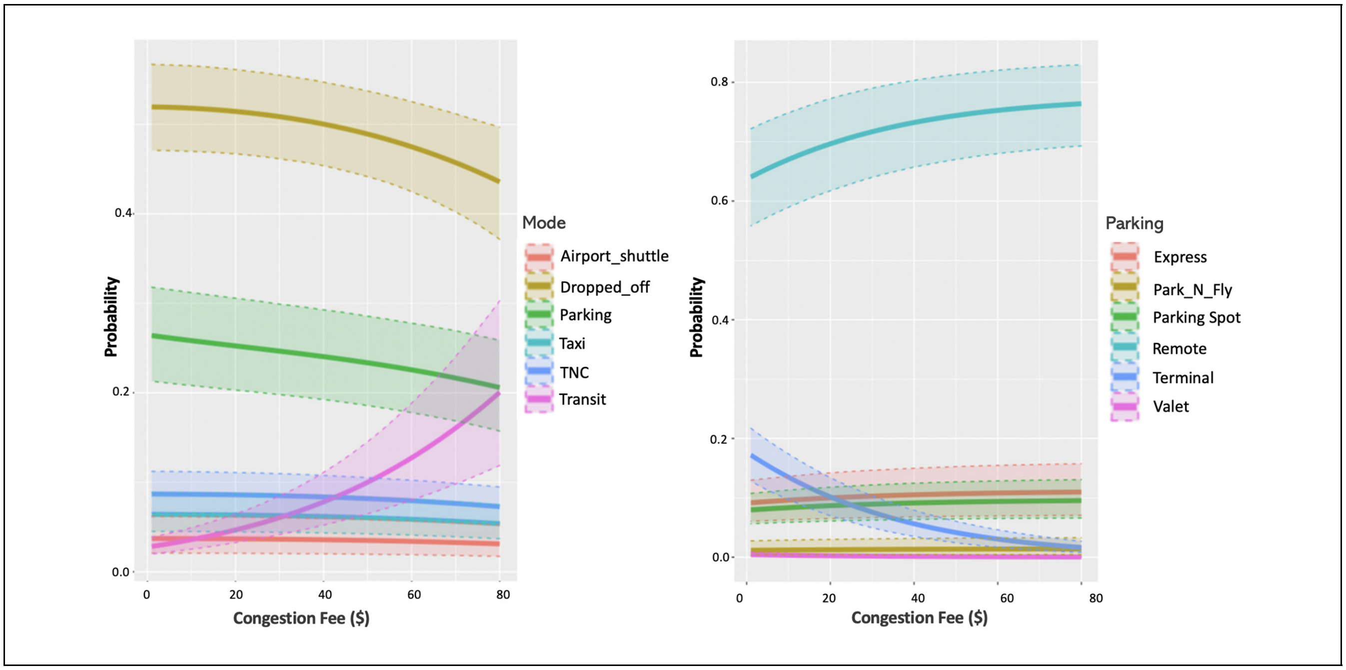

Figure 2. Mode choice and parking choice probability for Jane with the introduction of congestion fee in Dallas-Fort Worth area (solid lines represent the estimates of the probabilities, shaded area represents the 95% confidence interval): (*a*) mode choice and (*b*) parking choice.
Note: TNC = transportation networking company.

is a middle-aged DFW resident, resides 5 mi away from the airport, and has an upcoming leisure trip. Plugging Jane's individual and trip characteristics in the model, it can be seen that Jane has a higher probability of being dropped off or parking at the airport. If parking, Jane's top preferences are either to park at the airport's remote parking lots or at the terminal. Let us consider a set of scenarios where a congestion fee is introduced in the DFW region and is increased up to a maximum of $80. The congestion fee is reflected in the travel cost for various modes, particularly the car modes. It can be observed from Figure 2 that, with increasing congestion fee, Jane's likelihood of being dropped off or driving herself (i.e., parking), gradually decrease, whereas her likelihood of taking transit increases exponentially. Even in parking choices, Jane's likelihood of choosing remote parking increases with congestion fee, consistent with expectations.

Similarly, when terminal parking price is increased, Jane's likelihood of parking decreases whereas her likelihood of being dropped off or using TNC improves. Unsurprisingly, with the increase of terminal parking price, Jane's likelihood of parking at the terminal decreases exponentially, coupled with a complementary increase in remote parking (Figure 3).

Conclusion

While the basic construct of mode choice is similar between general travel and airport ground access, the contexts are differentiated by a few important facets, including the set of alternatives and the contributing factors. Additionally, the numbers of parking products offered by an airport far exceed the types of parking configurations experienced in the context of day-to-day travel. While joint choice of airport and access mode has been studied well in the literature, choice of airport ground access mode in conjunction with parking product choice has not been examined in great detail. The importance of this topic is amplified by emerging modes (such as TNCs) gaining market share in airport mode choice, which in turn influences airport parking revenues as well as curb space availability.

This research extends the literature on airport ground access choice by developing a joint model of access mode and parking product choice using data from a 2015 passenger survey conducted at DFW airport. The proposed NMNL model is compared with a baseline CL model. Since the NMNL model structure is more context-specific, its results are found to provide realistic VoT estimates for travel cohorts, compared with the CL model. The efficacy of the NMNL model is reinforced by the greater goodness-of-fit of the nested structure compared with the CL model. The NMNL model results were found to be consistent with findings from existing studies. From the model results, it was found that individuals from higher income households tend to prefer costlier modes and expensive parking options (as a tradeoff for higher convenience), and that the presence of well

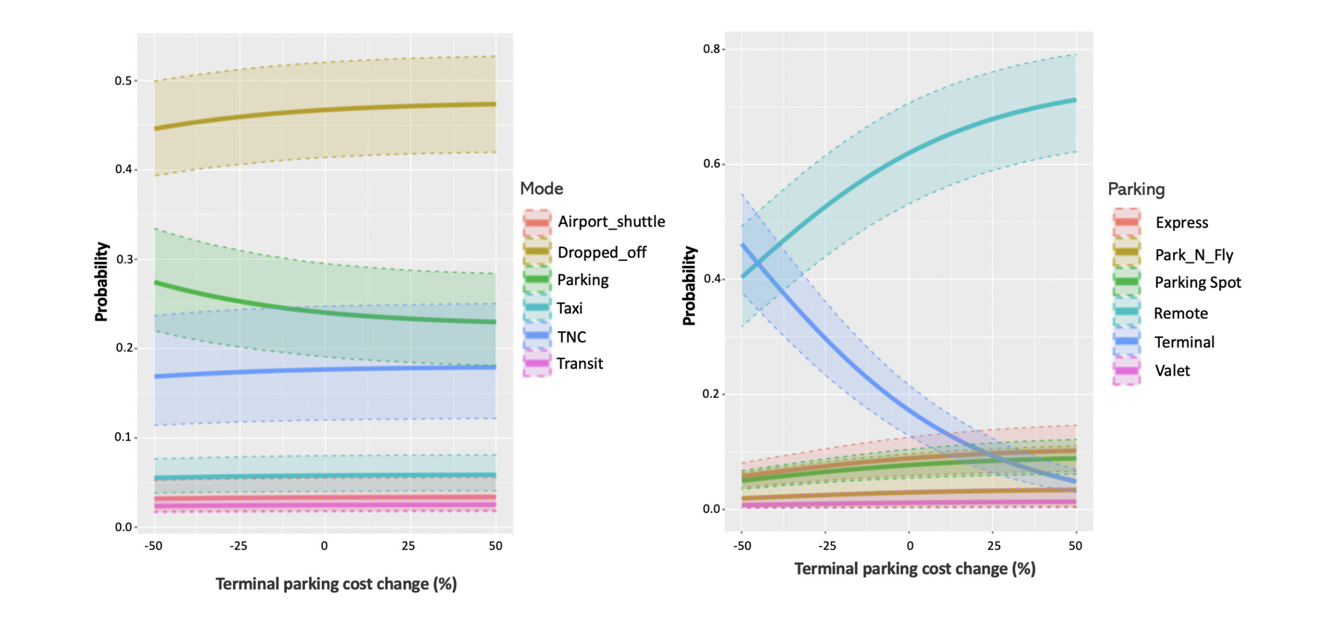

Figure 3. Mode choice and parking choice probability for Jane when terminal parking price changes (solid lines represent the estimates of the probabilities, shaded area represents the 95% confidence interval): (*a*) mode choice and (*b*) parking choice.
Note: TNC = transportation networking company.

wishers on an airport trip is associated with higher probability of being dropped off. The study also uncovered a few interesting insights that are different than findings from the existing literature. For example, at DFW airport, female travelers have a lower tendency to use services such as airport shuttle, TNC, and taxi, and a late flight motivates higher probability of using TNC instead of being dropped off. Sensitivity analyses were conducted to showcase the capability of the joint model structure to illustrate the influence of parking price on mode choice, and the impact of a regional congestion fee on airport terminal parking. The model structure proposed in this study can provide a more accurate understanding of airport access travel behaviors for policy makers or airport authorities that (desire to) utilize choice models to inform decision-making processes.

Future modeling efforts on airport access mode decisions can benefit from the exploration of a few behavioral elements that are not covered in this paper because of data limitations. Notably, rental car is excluded from this modeling effort as the decision to rent a car is likely influenced more by visit-level characteristics, such as the frequency, distances, and purposes of the planned trips throughout the duration of the stay in the DFW area, as opposed to merely the ground trip to/from the airport. Future research should delve into the decision mechanisms and external factors motivating car rentals in parallel to other mode alternatives. Similarly, the current study did not explore visitors' destination choice, which could have an impact on their access/egress mode choice. Visit-level characteristics noted above can also inform visitor destination choice. Finally, a next step of this research effort is to incorporate the findings from the mode choice model presented here in airport infrastructure and planning decisions.

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