Received: 10 June 2022 | Revised: 5 January 2023 | Accepted: 23 January 2023

DOI: 10.1002/sys.21670

REGULAR ARTICLE

WILEY

Using conjoint analysis to incorporate heterogeneous preferences into multimodal transit trip simulations

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Funding information
Toyota Mobility Foundation

Abstract

Urban transportation systems involve thousands of individuals making choices between routes with multiple modes and transfers. For transportation system simulations to produce realistic results, modelers need to incorporate these users and their choices. Choice-based conjoint surveys provide an attractive solution for obtaining flexible utility models that can be used to predict choices for a wide variety of trips. In this study, we demonstrate an example using conjoint survey data of commuter mode choice in the Washington, D.C. metro area ($N = 1651$). We sample commuters who primarily drive and those that take transit. We examine preferences for different types of multimodal trips, including those with intramodal and intermodel transfers. We find that trips involving a bus transfer are the least preferred while both drivers and transit users both value metro similarly to driving. We also find that walking during transit trips is an important barrier, with the travel time penalty for walking being 60% higher than that of time in a vehicle. Our findings highlight the significance of accounting for differences in modal transfer types in transportation system simulations. Reducing arrival time uncertainty was not a significant factor in commuter mode choice, and commuters' value of time was similar across all vehicle types, suggesting that increasing the relative speed of transit modes may only have a marginal effect on commuter substitution away from personal vehicles.

KEYWORDS
conjoint analysis, decision analysis/management, human factors, model-based systems engineering (MBSE), modeling and simulation

1 | INTRODUCTION

The majority of commuters in the United States use personal passenger vehicles, which have multiple negative externalities such as air pollution, greenhouse gas emissions, congestion, and vehicle crashes.[1] The transportation sector is the largest source of greenhouse gas emissions in the United States, and personal vehicles are responsible for approximately two thirds of those emissions.[2] Rather than attempt to further accommodate "automobility" via more roadway infrastructure, a more sustainable development path in most urban cities is to increase public transit usage.[3,4] Nonetheless, public transit has important drawbacks for some commuters. The level of service can be less than desirable depending on factors such as route scheduling, reliability, and the inconvenience of having to make transfers.[5,6] Exogenous factors such as the socio-economic backgrounds of different commuters also affects people's perspective on using public transit.[7,8]

To accurately measure the impacts of policies aimed at increasing transit ridership, it is vital to have an accurate model of commuters' decision-making processes when choosing their commute. Towards this goal, urban public transit can be modeled as a system involving a complex network of multiple mode options and travel routes, often requiring transfers between modes. Several studies have explored models of commuter mode choice, but most use single-mode trips as alternatives to driving, such as one-leg bus, metro, and bike trips,[8] ignoring the complexities of multimodal trips that require transfers.

This study contributes to this prior research by demonstrating how complex trip alternatives can be disaggregated into sets of features using a controlled conjoint survey experiment. Preferences for those features (described jointly via a utility model) can then be used to assess the impact of policies or changes in features (e.g., reducing trip transfers) on mode choice and public transit usage.[5,6] We use data collected from a controlled conjoint experiment in the Washington, D.C. metro area ($N = 1651$) to estimated discrete choice utility models and then use those models to simulate commuter choices for different types of multimodal trips, including those with intramodal and inter-model transfers. By using a conjoint experiment, we are able to answer questions about different features of commuter trip choices that are important for policy makers to consider, including:

1. What is the effect of intramodal and intermodal transfers on commuter trip choice?
2. How do commuters value time along different components of trips, including time walking, waiting, transferring, and riding in different vehicles?
3. How does reducing uncertainty in arrival time affect commuters' trip choices?
4. How do preferences for car-dependent commuters differ from those of public transit commuters?
5. Under what conditions are commuters more likely to choose a transit trip over driving a personal vehicle?

We address questions 1–4 by estimating commuter willingness-to-pay (WTP) for reduced travel time, reduced arrival time uncertainty, and different modes on one- and two-leg trips, all else being equal. We address question 4 via simulations where we compare the probability of commuters choosing a transit trip over driving a personal vehicle under different conditions. Our results serve as a case study to illustrate the significance of accounting for differences in modal transfer types in transportation system simulations.

2 | BACKGROUND

User behavior is a critical component to model in system simulations that involve individual user choice. In a transportation system model, users' preferences for different trip features will determine how they respond to a policy or design change, which can dramatically change the overall system performance as well as outcomes for different user groups.[9]

A significant body of research has studied different factors that affect commuter travel preferences. Earlier work from Bhat et al. indicates that the trip purpose and socio-economic factors of users both play an important role in commuter mode choice.[7] An individual's driving behavior can also change based on income, car ownership, and schedule flexibility; high car availability within households is positively correlated with auto usage, and higher household income is associated with less auto usage but not less metro usage.[8]

Researchers have also investigated factors related to the trip itself, such as the urban environment, trip distance, and trip complexity. For example, Frank et al.[10] studied how urban form affects travel patterns, finding that land use mix, retail density, and street connectivity near a commuter's home and workplace increase walking, cycling, and transit use. They also found that more shops near commuters' homes or work places reduced the overall complexity for home-to-work trips, leading to greater transit usage.[11] similarly found that commuters were more likely to drive as the trip chain complexity increased. They also concluded that a bidirectional causality exists between mode choice and trip complexity; auto-dependency causes the formation of more complex trip chains, and complex trip chains simultaneously cause higher auto-dependency. Finally, others have found that trip distance is another important factor, with more people choosing to drive as the distance increased.[12,13]

More recent studies have also begun unpacking the significance of having to make transfers on whether or not people will choose to use public transit. For example, Ha et al.[13] used a complex trip design survey to study the effect of transfers and walking segments on public transit use, but they only assessed the *number* of transfers in a trip rather than the type of transfer (e.g., intermodal or intramodal transfers were modeled as identical). Multiple studies have focused on the importance of transfer time between stops. Ceder et al.[14] found that commuters prefer trips with less uncertainty in out-of-vehicle time. Guo and Wilson[15] also emphasized the importance of optimizing transfer waiting time. However, time is only a portion of the penalty associated with making a transfer, and only optimizing for transfer time may not lead to an optimal transfer experience.

Others have found that simply transferring at all invokes a "pure transfer" penalty that is not associated with trip time. Hadas and Ceder,[16] for example, found that missing a transfer during a multimodel trip is one of the primary factors for unreliability in the public transit system, and missing a transfer increased commuters' mental stress, leading to a worse overall experience. Refs. 5, 17 further evaluated this pure transfer penalty and found that commuters may actually prefer a longer, one-leg trip over shorter trips that involve even one transfer.

While these prior findings have been particularly insightful for understanding barriers to public transit ridership, many are limited by their data samples or their experiment design. For example, many prior studies on transfer preferences have only elicited preferences from existing transit riders,[5,17–19] and others have collected data from only student survey responses.[4,8,20] Many of these studies lack any data on the preferences of commuters who primarily drive to work, and attracting some of the "drive-only" commuters into taking public transit is important for achieving sustainable transportation goals. Making transit policy recommendations based on only the preferences of existing transit users could produce suboptimal results[21]; for example, found that car users react to certain transportation policies differently than transit users.

Many prior studies also do not differentiate the transfer penalty by the type of transfer. One reason for this is the high dimensionality of the possible intermodal transfers that can occur in a typical transportation system. Designing a study that accounts for all transfer types could require large sample sizes to obtain precise parameter estimates, and making simplifying assumptions (e.g., all transfers are equally preferred) can substantially reduce the necessary sample size. The trade off is less information about the heterogeneity in preferences for different types of transit trips.

In this study, we build on this prior body of work on trip transfers and transit use by focusing on how different types of transfers as well as uncertainty in arrival time impact the mode choice preferences of commuters. We capture commuter preferences for different types of transfers, and we capture both current transit users and car drivers in our sample, enabling greater insights into heterogeneous commuter preference towards different types of transit trips.

3 | METHODS

We use a stated preference conjoint survey to measure and model commuter preferences for different types of commute trips. Stated preference conjoint surveys have been widely used to model choice and assess consumer stated preferences for transportation mode choice.[22] The general approach is to show survey respondents a series of randomized alternatives and then ask them to select the alternative they most prefer. These stated preference choice data can then be used to estimate discrete choice models to identify attribute preferences. Using simulated choice sets in a conjoint survey has many advantages over historical market data, such as the ability to obtain multiple observations for each respondent and the fact that the set of alternatives under consideration (and their attributes) are fully known. In addition, multicolinearities between attributes and endogeneity biases can be eliminated. Of course, one disadvantage of stated preference data is that people may choose differently in a hypothetical survey rather than an actual choice scenario. The rest of this section provides greater detail out the survey design and modeling techniques applied.

3.1 | Survey design

Respondents were asked to choose from sets of three commute trip alternatives, with trip attributes and prices chosen to reflect actual trip alternatives in the DC metro area. Most prior mode choice studies have presented trip alternatives in a tabular format where each attribute of each trip is displayed in rows and each trip is represented by columns, for example,[8,23] However, a tabular display of alternatives does not emphasize the differences between transfer and nontransfer trips, nor does it reflect how trips are typically displayed with modern navigation software such as Google Maps. Furthermore, since trip complexity has previously been found to be important for commuter mode choice,[11] we were concerned that a tabular display of trip alternatives might mask the transfer complexity of different multimodal trips.

As a result of these factors, we represented each trip using a graphical diagram of the trip modes. In our trip graphics, the length of each line was proportional to the length of time spent on each mode, and transfers were indicated with circles. An example choice question is shown in Figure 1.

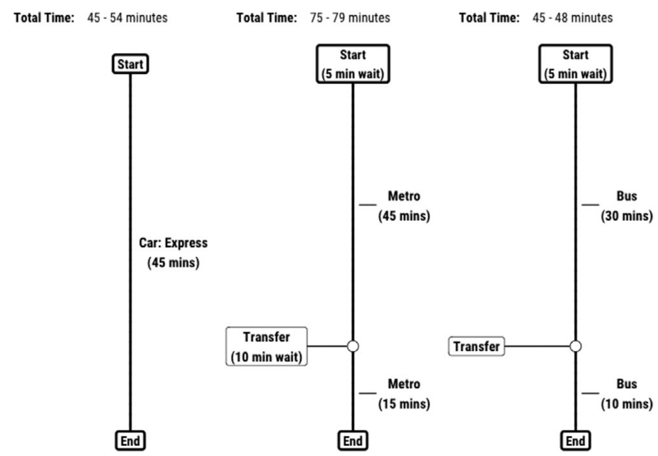

FIGURE 1 An example conjoint choice question in the survey. Each choice question contained three alternatives.

TABLE 1 Attributes used in conjoint survey.

Attribute	Level
Price	$2, $5, $10, $15
Car express fee	$0, $5, $10
Start time	0, 5, 10 min
Leg 1 time	10, 20, 30, 45 min
Transfer time	0, 5, 10 min
Leg 2 time	10, 15, 20 min
Additional time uncertainty	5%, 10%, 20%
Trip mode	Car
	Ride hailing
	Bus
	Metro
	Metro to metro
	Metro to bus
	Bus to bus
	Bus to metro
	Walk to bus
	Walk to metro

Each alternative included the trip graphic, the total trip price, the total trip time, and how much time would be spent on each leg of the trip. The total trip time was presented as a range from a lower bound (the sum of the travel time for each leg) to an upper bound that was computed as an additional 5, 10%, or 20% of the lower bound. All car trips were one-leg trips, though some included the use of an express lane, which had an additional $5 or $10 fee. The final set of conjoint choice questions used was designed and randomized using the *cbcTools* R package.[24] Table 1 shows the full set of attributes included in the randomization. To make sure the values shown were reasonable for local commuters, a pilot survey was distributed and the value sets for attributes were tuned according to the feedback from those initial participants. Each participant was shown eight separate choice questions in which they were asked to choose their most preferred trip for commuting to work.

3.2 | Data collection

The survey was hosted on formr.org, an open source online platform that uses the R programming language to define survey questions.[25] The sample was collected via Dynata, a market research firm. The sample was limited to DC commuters and was distributed between February 16, 2021 and April 22, 2021. Participants were filtered by zip code and commute pattern to ensure that the sample only captured commuters living in the DC metropolitan area.

A total of 2064 participants completed the survey. Among them, 415 participants were removed due to multiple validity check violations, including spending too little time to complete survey, failing attention check questions, and randomly answering questions (e.g., choosing the same answer for all eight choice questions). The final sample used in our analysis was 1651 participants, resulting in 13,208 choice observations.

Table 2 shows summary statistics for our final sample as well as a comparison with demographics from a previous survey (N = 16,000) conducted by the Metropolitan Washington Council of Governments,[26] which was also focused specifically on DC commuters. Our sample is consistent with that of the MWCG sample along several important demographics, including a relative balance across gender groups and a similar percentage of participants with different levels of car ownership. The majority of our participants are between 25 and 55 years old with a mean of around 40 (we do not have age demographics from the MWCG survey). While we did over-sample on home ownership, we expect that this is likely because we included surrounding counties around the DC metropolitan area where more home owners live whereas the MWCG survey did not include these residents.

TABLE 2 Summary statistics of our sample.

	$N = 1651$	MWCG
Age		
min	18	
max	93	
mean (sd)	43.35 ± 13.24	
Gender		
Male	869 (53)	49.5%
Female	767 (46)	50.5%
Other	115 (1)	
Employment		
Employed	1511 (92)	
Unemployed	33 (2)	
Student	74 (4)	
Other	33 (2)	
Car ownership		
None/Prefer not say	73 (4)	18.5%
1	738 (45)	42.9%
2	611 (37)	29.5%
3	135 (8)	9.2%[a]
4	72 (4)	
5+	22 (1)	
Home ownership		
Own	1232 (75)	59.1%
Rent	381 (23)	39.4%
Not to say	38 (2)	
Daily commute method		
Only drive	772 (47)	91%[b]
Drive transit	701 (42)	
Only transit	178 (11)	9%

The number in parenthesis is the percentage for categorical data.
[a]MWCG percentage is for car owners with three or more cars.
[b]Ninety-one percent is travelers using other modes besides transit.

3.3 | Model estimation

Using the stated choice data, commuters' choices can be modeled using a random utility framework, which assumes that individuals make choices that maximize an underlying random utility model. Specifically, the utility u_{ij} of alternative j to a consumer i is modeled based on choice observations as a function of observable attributes $v_{ij} = f_i(x_j)$ and unobserved attributes ε_{ij}, such that $u_{ij} = v_{ij} + \varepsilon_{ij}$. The unobserved component ε_{ij} is modeled as a random variable, making the utility u_{ij} also random. These models predict the probability of choice P_{ij} as the probability that the utility of one alternative j is greater than the utility of the other alternatives. Assuming the error term follows a Gumbel extreme value distribution, the probability that a consumer i will choose option j from the choice set $\mathcal{J}_c$ follows a convenient, closed form expression[27]:

$$P_{ij} = \frac{\exp(v_j)}{\sum_{k \in \mathcal{J}_c} \exp(v_k)}, \qquad \forall c \in \{1, 2, 3, \dots C\}, \quad j \in \mathcal{J}_c, \tag{1}$$

where c indexes a set of C choice sets and v_j is the observed portion of the utility model. We estimate multinomial logit (MNL) models, which assume that the parameters in v_j are fixed across all respondents, and mixed logit (MXL) models, which assume that some of those parameters vary randomly across the population according to assumed distributions. To make the results more easily interpretable, the utility models were specified in the "willingness-to-pay" (WTP) space[28,29] such that estimated model coefficients can be interpreted as the marginal WTP (with units of US dollars) for marginal changes in

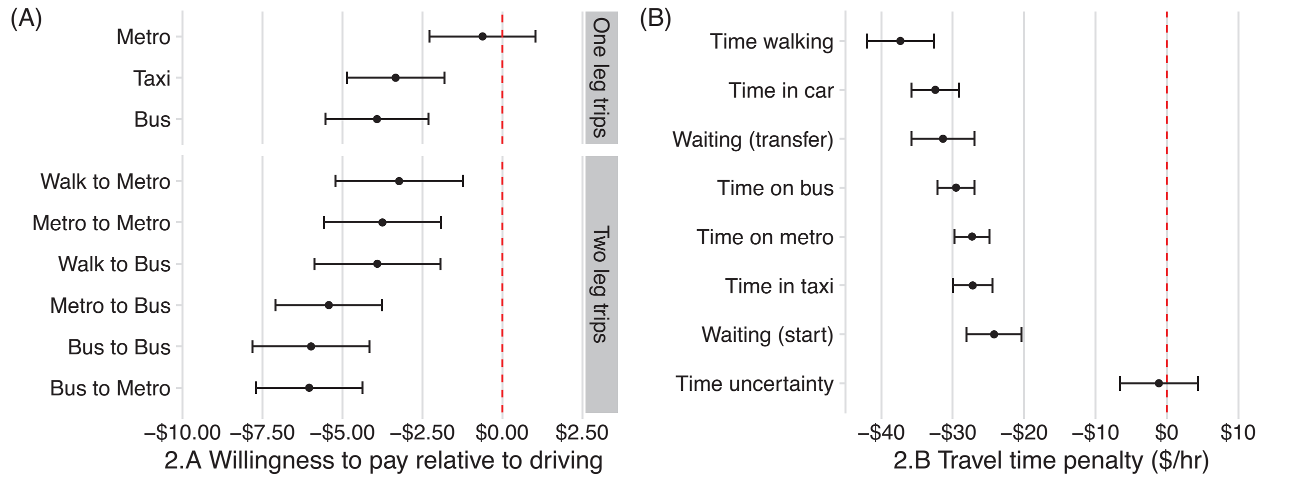

FIGURE 2 Estimates WTP coefficients from model 1. WTP, willingness-to-pay.

each attribute:

$$u_{ij} = \lambda(\boldsymbol{\omega}'\mathbf{x}_j - p_j) + \varepsilon_j, \tag{2}$$

where p_j is price and $\mathbf{x}_j$ is all nonprice attributes for alternative j. For this study, the utility model for the MXL model has the following form:

$$u_{ij} = \lambda\left(\boldsymbol{\omega}'\mathbf{x}_j^{\text{mode}} + \boldsymbol{\tau}'\mathbf{x}_j^{\text{time}} + \nu x_j^{\text{unc}} - p_j\right) + \varepsilon_j \tag{3}$$

where $\boldsymbol{\omega}$ is a vector of WTP parameters for all modes except for driving (the reference level for the mode attribute), $\mathbf{x}_j^{\text{mode}}$ is a matrix of dummy-coded variables for each mode, $\boldsymbol{\tau}$ is a vector of WTP parameters for each type of time in the trips (start, transfer, and travel times), $\mathbf{x}_j^{\text{time}}$ is a matrix of trip times, ν is the WTP parameter for additional arrival time uncertainty, x_j^{unc} is the percentage of additional travel time (due to uncertainty in arrival time), and p_j is the total price of the trip. All model estimation was conducted using the *logitr* R package, written by Professor John Paul Helveston.[30]

4 | RESULTS

4.1 | Willingness to pay

Table 3 presents the estimated coefficients from multiple models, including a MXL model for the entire respondent population (model 1) as well as MNL models comparing preferences between essential and nonessential workers (models 2 and 3), respondents with more or less flexibility in work arrival times (models 3 and 4), and respondents that primarily commute by car (model 6), transit (model 8), or a mix of both (model 7). Figure 2 plots the mean WTP coefficients for model 1, including coefficients for each trip type (relative to driving) and the travel time penalty for each component of a trip. For this model, all WTP covariates were modeled as normally distributed, with the estimated means and standard deviations presented in the first two columns of Table 3.

Figure 2A indicates that DC commuters on average are relatively indifferent between one-leg metro trips and driving, and that all other trips are less preferred than driving, all else being equal. Another important observation is the clustering of two-leg trips with the lowest WTPs: metro to bus, bus to bus, and bus to metro. All of these trips involve bus transfers, suggesting that commuters are willing to pay a substantial premium to avoid trips with bus transfers relative to driving.

Figure 2B presents the penalty associated with increasing the length of time spent on different portions of a trip. All of the in-vehicle time parameters have insignificant differences between each other, which indicates that commuters' in-vehicle value of time is relatively consistent regardless of the mode. Likewise, the value of time while waiting at the start of the trip and during a transfer in the trip is approximately equal with the in-vehicle time valuation. The only parameters that are significantly different from each other are *Time Walking* and *Time Uncertainty*. The larger penalty on *Time Walking* suggests that commuters are willing to pay about 50% more to reduce time spent while walking compared to time spent in a vehicle, which is consistent with prior research.[31] In contrast, the *Time Uncertainty* parameter is not statistically significantly different from zero, suggesting that either respondents are not willing to pay a premium to reduce the arrival time uncertainty or that they simply ignored this attribute when evaluating trip alternatives while taking the survey.

In addition to these mean estimates, the standard deviation parameters on many of the trip and time variables in the MXL model were quite large, suggesting the presence of substantial preference heterogeneity. To investigate this further, we divided the sample into different subgroups according to demographic variables and responses on other survey questions (models 2–8). Models 2 and 3 revealed the expect result that respondents that self-identified as essential workers had higher time penalties and stronger preferences for driving over any other trip type compared to nonessential workers. Outcomes were similar for respondents that self-reported as having greater flexibility in work arrival times than those that reported having less flexibility (models 4 and 5), though this outcome is also correlated with

TABLE 3 Regression results

Parameters	MXL μ	MXL σ	Essential worker	Not essential	Have flexibility	No flexibility	Pro driving	Mixed preference	Pro transit
	(0.01)	(-)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
Bus to bus	−6.48[a]	1.75	−13.23[a]	−5.06[a]	−6.95[a]	−14.23[a]	−14.03[a]	−4.43[a]	0.56
	(0.93)	(0.96)	(2.43)	(1.25)	(1.22)	(3.61)	(2.05)	(1.63)	(3.63)
Bus to metro	−6.98[a]	2.20	−12.93[a]	−6.05[a]	−7.01[a]	−15.00[a]	−13.94[a]	−4.05[a]	−3.45
	(0.87)	(0.98)	(2.14)	(1.08)	(1.06)	(3.16)	(1.79)	(1.42)	(3.30)
Metro to bus	−6.03[a]	1.17	−10.13[a]	−5.97[a]	−6.47[a]	−11.99[a]	−11.65[a]	−4.31[a]	−1.27
	(0.81)	(0.77)	(2.11)	(1.07)	(1.06)	(3.11)	(1.76)	(1.41)	(3.27)
Bus	−4.39[a]	0.23	−10.02[a]	−1.59	−3.63[a]	−9.48[a]	−9.26[a]	−2.07	4.90
	(0.83)	(1.20)	(2.06)	(1.09)	(1.05)	(3.07)	(1.73)	(1.42)	(3.32)
Metro to metro	−3.54[a]	3.03	−9.81[a]	−2.97[a]	−4.34[a]	−9.47[a]	−8.40[a]	−1.96	−2.96
	(0.93)	(0.92)	(2.40)	(1.23)	(1.21)	(3.06)	(1.97)	(1.65)	(3.58)
Metro	−0.74	2.43	−3.91[c]	1.10	0.15	−3.64	−2.44	0.53	5.61
	(0.86)	(1.27)	(2.10)	(1.11)	(1.09)	(3.06)	(1.77)	(1.45)	(3.32)
Taxi	−4.43[a]	3.55	−4.42[a]	−1.70[c]	−2.22[b]	−5.07[c]	−5.26[a]	−0.72	3.18
	(0.76)	(0.68)	(1.96)	(1.01)	(0.99)	(2.93)	(1.63)	(1.30)	(3.29)
Walk to bus	−4.29[a]	1.31	−7.97[a]	−2.33[c]	−3.81[a]	−7.68[b]	−9.17[a]	−2.18	5.42
	(1.02)	(0.88)	(2.59)	(1.35)	(1.31)	(3.85)	(2.17)	(1.75)	(4.01)
Walk to metro	−3.40[a]	0.56	−7.97[a]	−2.14	−3.48[a]	−7.44[c]	−8.02[a]	−1.31	2.32
	(1.03)	(0.93)	(2.61)	(1.37)	(1.32)	(3.94)	(2.22)	(1.76)	(3.98)
Time on walk	−36.94[a]	24.83	−55.09[a]	−40.60[a]	−41.47[a]	−66.66[a]	−54.49[a]	−39.18[a]	−44.70[a]
	(1.65)	(1.82)	(6.63)	(3.23)	(3.14)	(10.60)	(5.71)	(4.08)	(8.62)
Time in car	−33.01[a]	17.04	−38.11[a]	−21.32[a]	−23.87[a]	−43.80[a]	−33.19[a]	−24.65[a]	−16.11[a]
	(1.65)	(1.41)	(3.67)	(1.63)	(1.63)	(5.73)	(2.91)	(2.12)	(5.62)
Time in bus	−28.03[a]	15.78	−36.67[a]	−27.31[a]	−28.30[a]	−36.57[a]	−32.02[a]	−29.00[a]	−25.11[a]
	(1.27)	(0.89)	(3.41)	(1.63)	(1.61)	(5.16)	(2.81)	(2.18)	(3.86)
Time in metro	−26.25[a]	14.81	−38.35[a]	−24.51[a]	−27.26[a]	−41.58[a]	−37.11[a]	−26.99[a]	−17.75[a]
	(1.22)	(0.91)	(3.52)	(1.52)	(1.56)	(5.35)	(2.93)	(2.09)	(3.42)
Time in taxi	−27.19[a]	2.86	−40.62[a]	−26.29[a]	−29.05[a]	−41.54[a]	−36.32[a]	−28.54[a]	−26.50[a]
	(1.36)	(1.01)	(3.98)	(1.76)	(1.77)	(5.94)	(3.20)	(2.33)	(4.85)
Waiting at transfer	−30.89[a]	25.83	−38.51[a]	−29.05[a]	−33.77[a]	−25.34[a]	−34.01[a]	−37.28[a]	−5.30
	(2.26)	(4.38)	(6.33)	(3.10)	(3.11)	(8.94)	(5.22)	(4.17)	(7.84)
Waiting at start	−24.14[a]	14.03	−36.35[a]	−25.20[a]	−28.30[a]	−34.22[a]	−28.48[a]	−29.94[a]	−30.10[a]
	(2.25)	(3.81)	(5.38)	(2.61)	(2.59)	(7.88)	(4.40)	(3.47)	(6.61)
Time uncertainty	−0.39	13.62	−4.02	−3.72	−3.59	−2.90	−3.90	−5.11	5.74
	(2.96)	(7.66)	(6.60)	(3.46)	(3.36)	(9.73)	(5.67)	(4.45)	(8.64)
n	1651		839	812	1196	455	772	701	178

[a]0.001; [b]0.01; [c]0.05; [d]0.1.

income as jobs with higher salaries tend to have greater arrival time flexibility.

One of the primary variables where we saw significant differences in preferences was the respondents' commute patterns. For this variable, we asked participants about their commute patterns and created subgroups based on whether they answered that they only drive, only use transit, or use a mix of both. Understanding the preferences of commuters who primarily drive is particularly important for reducing auto dependency and promoting greater public transit use.

Figure 3 shows the MNL estimation results for the "driving only" and "mixed mode" subgroups (models 6 and 7). Except for one-leg metro trips, commuters who primarily drive have substantially lower WTPs for all other trips compared to the mixed commute pattern group. Drivers also have a statistically significantly lower WTP for bus trips

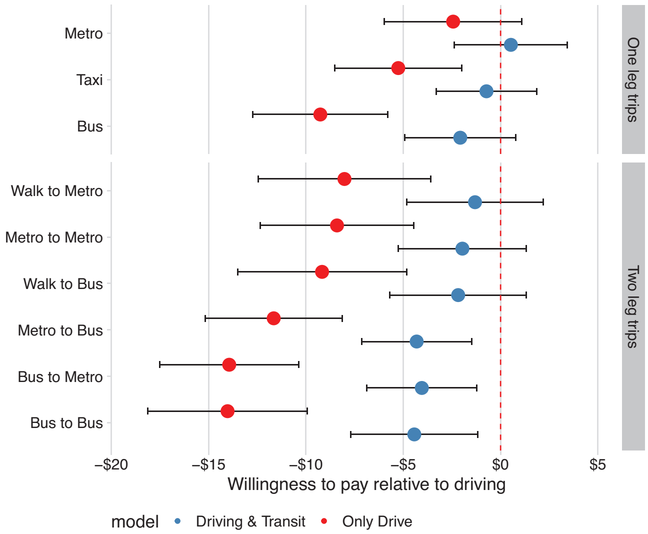

FIGURE 3 WTP comparison between drive-only and mixed mode commuters. WTP, willingness-to-pay.

compared to mixed mode commuters, including both one-leg bus trips and any two-leg trip that involves the bus. We also see that most transit modes for mixed mode commuters are only slightly negative, with only the two-leg bus trips having statistically significantly negative WTPs relative to driving.

4.2 | Policy simulation

We conduct a series of simulations comparing a transit trip with a driving trip. In each simulation, all attributes are the same except for the different mode and the travel time of each trip. Starting with equal travel times, we incrementally increase the additional travel time on the transit trip and compute the probability of choosing the transit trip in each case. The goal is to understand the probability of choosing transit over driving in different conditions.

In Figure 4, which reflects the preferences from model 1, the one-leg metro trip is the most preferred of all transit trips, with commuters being essentially indifferent between it and driving when the travel times are the same. As the additional travel time increases, the probability of choosing the metro decreases, down to approximately 30% at 15 extra minutes and 20% at 25 extra minutes. One-leg bus trips are similar to the metro curve, but the probabilities are all shifted down by approximately 10 percentage points, highlighting the preference for metro over bus. We also see a clear drop in the probability of choosing transit for trips that involve bus transfers.

For a metro-only trip, average commuters are willing to spend one more minute to be indifferent with driving. This shows that commuters on average value one-leg metro trips similarly to driving trips, holding all else equal. However, commuters are only approximately 30% likely to choose transit over driving when the trip involves a bus transfer and the travel time is equal to the driving trip. In these cases, the transit trips need to be significantly faster in order to be indifferent

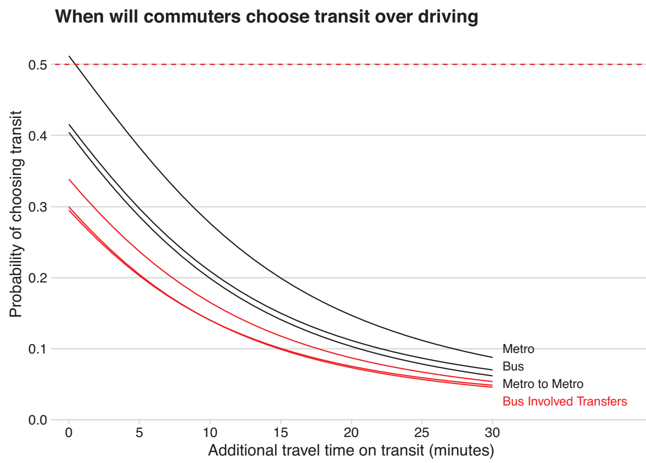

FIGURE 4 Probability of choosing the transit trip over driving.

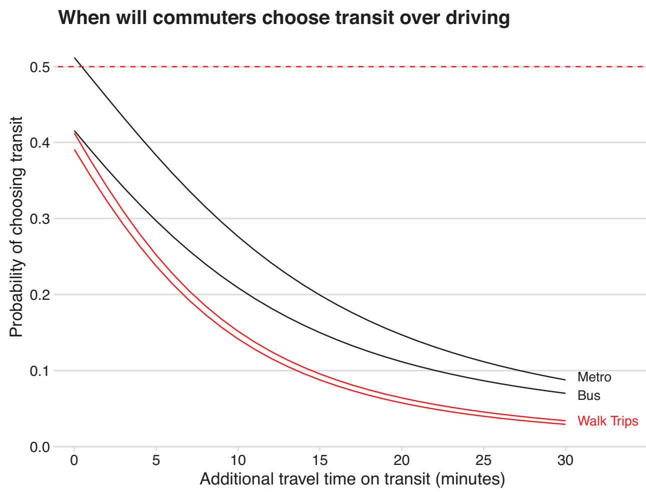

FIGURE 5 Probability of choosing the transit trip over driving. Additional travel times for the walking trips were added to the walking portion of the trip.

with choosing the driving trip. This difference in probability is consistent with Garcia's finding that commuters will choose a longer trip to avoid making a transfer.[5] This simulation also indicates that instead of reducing transit travel time, creating transit alternatives that involve fewer bus transfers may be more effective in promoting public transit use among commuters.

Another important finding is that commuters place a significantly higher penalty on walking time comparing to other time factors. In Figure 5, we include walking trips ("Walk to Metro" and "Walk to Bus") in the simulations, comparing them again to the one-leg metro and bus trips. For trips that involve walking to transit, the additional time was added to the walking portion of the trip, and thus the probability of choosing transit for those trips drops at a faster rate than those that do not involve walking since walking time is penalized at a greater rate than in-vehicle time.

In these simulations, the effect of increased walking time is dramatic—just 5 extra minutes of walking decreases the probability of

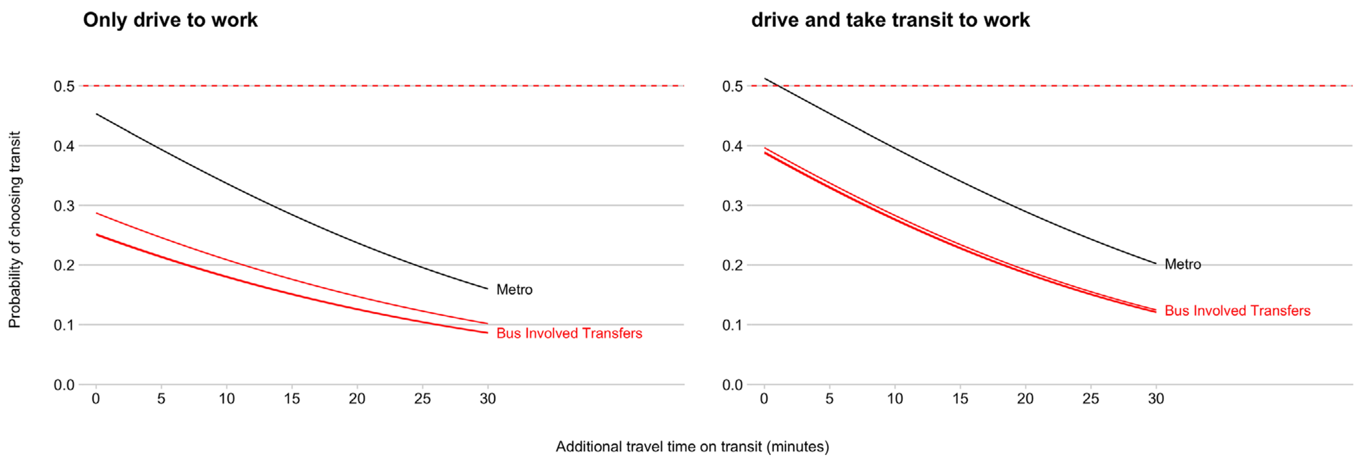

FIGURE 6 Probability of choosing transit over driving for commuters who only drive versus those who take a mixture of driving and transit.

choosing transit by approximately 15%. The higher penalty on walking time has a similar effect as intermodal transfer. When the walking time is high, commuters would rather choose a longer trip with more in-vehicle time. For example, commuters have a similar probability of choosing the transit trip across the following three trips: a 15-min walk, a 22-min bus trip, or a 27-min metro trip. These results suggest that reducing walking time is an important factor for increasing transit ridership and could be more important than reducing in-vehicle time.

It is important to emphasize that the results of the simulations in Figures 4 and 5 reflect the *average* preferences of our entire survey sample, but this sample contains substantial preference heterogeneity in terms of WTP for trip modes and time factors. Figure 6 highlights this heterogeneity by showing the results of simulations conducted using models 6 and 7, which reflect the preferences of commuters who only drive versus those that take a mixture of driving and transit.

These results show that the drive-only group has a much lower probability of choosing transit trips for nearly all trips except for one-leg metro trips. When the trip time is close to a driving trip, the drive-only group is approximately 10 and 6% less likely to choose a bus-involved trip or metro trip, respectively.

These simulations also suggest that substituting bus-involved trips with more metro trips could be an effective strategy for recruiting more drivers into taking transit. For example, a 20% increase in transit ridership could be achieved by changing a bus-to-metro transfer trip into a one-leg metro trip among drive-only commuters when the trip duration is close to a driving trip. This is a much more significant effect compared to the 11% increase in the mixed mode subgroup.

Figure 7 illustrates this substitution difference between the drive-only and mixed mode commuters. For this figure, we computed the difference in percentage points between a bus-to-metro trip and a one-leg metro trip for each group of commuters at each additional amount of time spent on transit compared to driving. When the travel times between transit and driving are similar, the substitution from an intermodal trip to a metro trip is almost twice as large for the drive-only commuters compared to the mixed mode commuters. However, as the additional transit travel time increase, both groups converge to similar gaps. This highlights the importance of sampling and measuring the

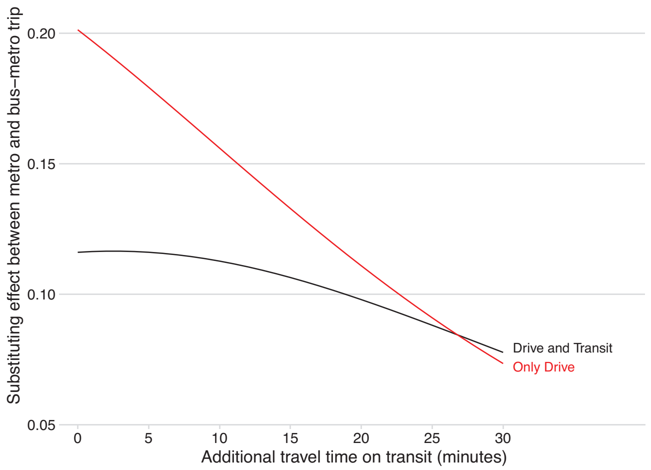

FIGURE 7 Comparison of the effect of substituting a bus-to-metro trip with a one-leg metro trip between drive-only and mixed mode commuters.

preferences of different groups of commuters when designing studies aimed at quantifying commuter preferences.

5 | LIMITATIONS

In this study, we assume that commuters make route choice decision at the very beginning of the trip instead of making separate decisions at each transfer point. We also assume the type of transfer matters to commuters based on Garcia-Martinez's finding on intermodal transfer penalties.[5] As a result, we designed 10 different trips in our conjoint survey to capture multiple different trip combinations. While this enabled greater insight into commuter preferences for different types of trips, it also led to larger standard errors on the mode coefficients in our models. This limits the precision with which we can model the preferences of different subgroups of commuters.

Another limitation is that we limited trips to only one transfer. This decision was a compromise between including multiple trip combinations while maintaining reasonable sample size requirements to identify model parameters. Even with just a single transfer, there were 10 trip combinations between the modes included in our experiment; including a second transfer would result in tens more trip combinations and several thousand more respondents. As a result, the data and models in this study are limited to only two-leg trips.

Finally, it is important to acknowledge that the sampling period (February 16 to April 22 2021) was during the COVID19 pandemic, a time during which commuting by transit was limited and many residents were still working remotely or had considerably modified commute patterns compared to pre-pandemic norms. We recognize this limitation could cause some distortions in our results. Nonetheless, we did inform respondents to answer questions according to their commute experiences before the start of the pandemic, and much of our findings are consistent with previous research on intermodal transfers and time penalties, for example, Refs. 5, 17, 31.

6 | CONCLUSION

Public transit is a complex system involving multiple modes and transfers between them. Improving our understanding of commuters' mode choice preferences and their WTP for related commute trip features via conjoint analysis is a promising approach for building system simulations for examining the potential outcomes of policies aimed at increasing public transit usage. We demonstrate this using a conjoint survey to collect stated preference data on multimodal commute choices for DC commuters, including those that only drive and those that use transit. We apply multinomial and mixed logit regression to compare respondents' WTP for trip modes and travel times, and we conduct simulations to assess the probability of choosing transit over driving in different conditions.

We find that the penalty commuters assign for increased trip time is similar across driving and transit modes but approximately 40% higher when walking, suggesting a strong preference to avoid increased walking time. Single leg metro trips were the most preferred transit trips, and most commuters are indifferent between these trips and driving, all else being equal. On average, trips that involve transfers with a bus were the least-preferred transit modes, and commuters are willing to pay on average $6–7 to avoid these trips compared to driving, all else being equal. Our results also suggest that reducing the uncertainty of arrival time was not significantly important. Policy simulations illustrate that reducing walking time and bus transfers are two important methods for potentially increasing public transit usage, in particular for commuters who currently drive. These findings are consistent with prior literature on intermodal transfers and travel time penalties, for example, Refs. 5, 17, 32.

In comparing two important subgroups (those who commute by driving versus those who drive and take transit), our WTP analyses and policy simulations both suggest that trips with bus-involved transfers have significantly higher penalties for drive-only versus mixed mode commuters. These groups both prefer one-leg metro trips for transit, and both are relatively indifferent between these trips and driving, all else being equal. These results suggest that expanding metro access and reducing bus-involved transfers could potentially attract commuters away from driving. The differences revealed in comparing these two groups highlight the importance of considering preference heterogeneity when making transportation policy decisions and building transportation simulation models. Analyses that only consider the preferences of current transit users could underestimate or overestimate the effects of specific policies on increasing or decreasing transit use.

ACKNOWLEDGMENTS

We would like to thank Zhenglin Wei for his feedback throughout the design and execution of this study. This study was supported by the Toyota Mobility Foundation.

DATA AVAILABILITY STATEMENT

All data and code used to estimate the models and charts presented will be made publicly available in a Github repository upon publication.

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How to cite this article: Zhao L, Szajnfarber Z, Broniatowski D, Helveston JP. Using conjoint analysis to incorporate heterogeneous preferences into multimodal transit trip simulations. *Systems Engineering*. 2023;1-11. https://doi.org/10.1002/sys.21670

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