WHICH STATION?
ACCESS TRIPS AND BIKE SHARE ROUTE CHOICE

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ABSTRACT

Bike share systems are an emerging technology in the United States and worldwide, but little is known about how people integrate bike share trip segments into their daily travel. Through this research, we attempt to fill this knowledge gap by studying how people navigate from place to place using the Nice Ride Minnesota bike share system in Minneapolis and St. Paul. We develop a theoretical model for bike share station choice inspired by research on transit route choice literature. We then model people's choice of origin station using a conditional logit model to evaluate their sensitivity to time spent walking, deviation from the shortest path, and a set of station amenity and neighborhood control variables.

As expected, people prefer to use stations that do not require long detours out of the way to access. However, commuters and non-work travelers differ in how they value the walking portion of their trip, and what station amenities and neighborhood features increase a station's utility. The results from this study will be important for planners who need a better understanding of bike share user behavior in order to design or optimize their system. The findings also provide a strong foundation for future study about comprehensive route choice analysis of this new bicycling technology.

INTRODUCTION AND BACKGROUND

Bicycle sharing systems are an emerging trend in the United States and worldwide. Cities are jumping on the trend in response to promises that bike share will induce mode shift, alleviate congestion, promote active and healthy lifestyles, and spawn economic development. However, as cities embrace the systems, our understanding about how people actually integrate these systems into their daily travel is limited.

Through this research, we attempt to fill some of this knowledge gap by studying how people navigate from place to place using the Nice Ride Minnesota bike share system in Minneapolis and St. Paul. First, we review parallel research about transit route choice and station access trips. In Section 4, we then develop a theoretical model for bike share station choice inspired by these examples from public transit. In Section 5, we describe the methodology used to test this theory empirically, including data sources and geographic calculations to quantify the station choice sets available to study participants.

In Section 6, we present results from two sets of conditional logit models. The first set models commute trips made by Nice Ride, and the second describes non-work trips. The models fit the data well, and several of the findings confirm expectations. People do in fact prefer to use stations that do not require long detours out of the way to access. However, commuters and non-work travelers differ in how they value the walking portion of their trip, and what station amenities and neighborhood features increase a station's utility.

Finally, in Section 7, this paper concludes with a discussion of how these results impact current practice and ongoing research, as well as areas for further development or improvement. The results from this study will be important for planners who need a better understanding of bike share user behavior in order to design or optimize their system. Understanding people's relative preferences for walking and biking within a single bike share trip provides guidance for system expansion and densification, and enriches forecasting methodology by demonstrating a distribution of typical walking distances associated with accessing a bike share station. The results also demonstrate that the surrounding location plays an important role as well. Notably, proximity to parks and the local crime rate around the station are significantly associated with the likelihood of any given station being chosen for a trip. The findings also provide a strong foundation for future study about comprehensive route choice analysis of this new bicycling technology.

BACKGROUND

Bike share and Transit route choice

Bike share is an on-demand system: bicycles are available at any time of day or night. Despite this temporal difference with transit, the spatial structure of a person's route through the system is similar.

Bike share trips, like transit, are comprised of three primary segments:

1. Station access walking trip
2. One or more on-bicycle segments between stations
3. Station egress walking trip

These segments are by definition anchored to two or more of the stations within the system. Because of this similarity, research about accessing transit stations provides some guidance bike share.

Several studies have explored mode choice for the station access and egress segments of transit trips, while assuming the station choice is fixed *(1, 2)*. Despite leaving out this station choice element, these studies provide insight into how people value travel time between several access modes to the station. Given that one component of bike share station choice is how people relatively value travel time spent walking versus biking, these findings are interesting. Chalermpong et al. found that the cumulative share of travelers arriving at a station by motorcycle taxi overtakes walking at about 0.7 kilometers from the station, and increases drastically beyond 0.9 km from the station *(1)*. Hsiao et al. reported on what share of passengers using a transit station walked from a range of distances *(2)*. Notable drop-offs occur at 0.25 miles (about 400 meters) and 0.75 miles (about 1200 meters).

Guo et al. modeled subway commuters' station egress routes of Boston subway commuters from an on-board transit survey *(3)*. They identified two possible paths for each participant: One where the traveler may avoid a transfer by having a longer walk time, and another where the traveler transfers between routes and has a shorter walk time. Because the paths originated from different transit stations, route overlap between paths was minimal, avoiding the Independence of Irrelevant Alternatives condition that challenges many route choice studies. They found that paths through Boston Common (open space/parkland) increased the utility of the trip by 2.9 minutes, while paths through hilly terrain decreased utility by 3.5 minutes. Collectively, all their pedestrian environment variables increased pedestrian utility by about 21 to 33$\%$, shifting the balance of how many people would choose the longer walking path based on travel time advantage alone.

Further underscoring the importance of relative durations of walking and bicycling is research into how transit passengers perceive time spent in different stages of their trips *(4)*. Bovy et al. address this in their study of transit route choice *(5)*. They model each segment, including the access and egress trips, station choice, and main route segment using a set of multi-nested generalized extreme value (GEV) models. The station choice component of their models focused on the caliber of service provided there: inter-city or local.

THEORETICAL MODEL OF STATION UTILITY

Unlike transit, the user has significantly greater flexibility to choose stations and routes in between that satisfy her preferences for travel time savings, minimizing (or possibly maximizing) physical exertion, or even just a pleasurable riding environment.

Figure 1 maps a hypothetical scenario with several bike share stations and several transit stations connecting the same origin (TO) and destination (TD). This illustrates the system's flexibility, and underlines how complex this makes the study of bike share user route choice. The traveler could use any of the three closest bike share stations. The closest station requires walking away from the destination for a short distance. The most direct station is also the farthest away and would require the most walking. Finally, the third nearby station demonstrates additional station amenities that may make the station more attractive. In this scenario, the bike ride along the park may be more comfortable or easier than the bike ride along the main street. As a point of comparison, only a few of the nearby transit stations are appropriate for the trip between TO and TD, as many are either connected to the wrong route or the wrong direction of the correct route.

Relative Station Position

For the station choice scenario, let us temporarily assume that utility is derived solely from travel time savings, not from station amenities or individual characteristics. These other factors will be

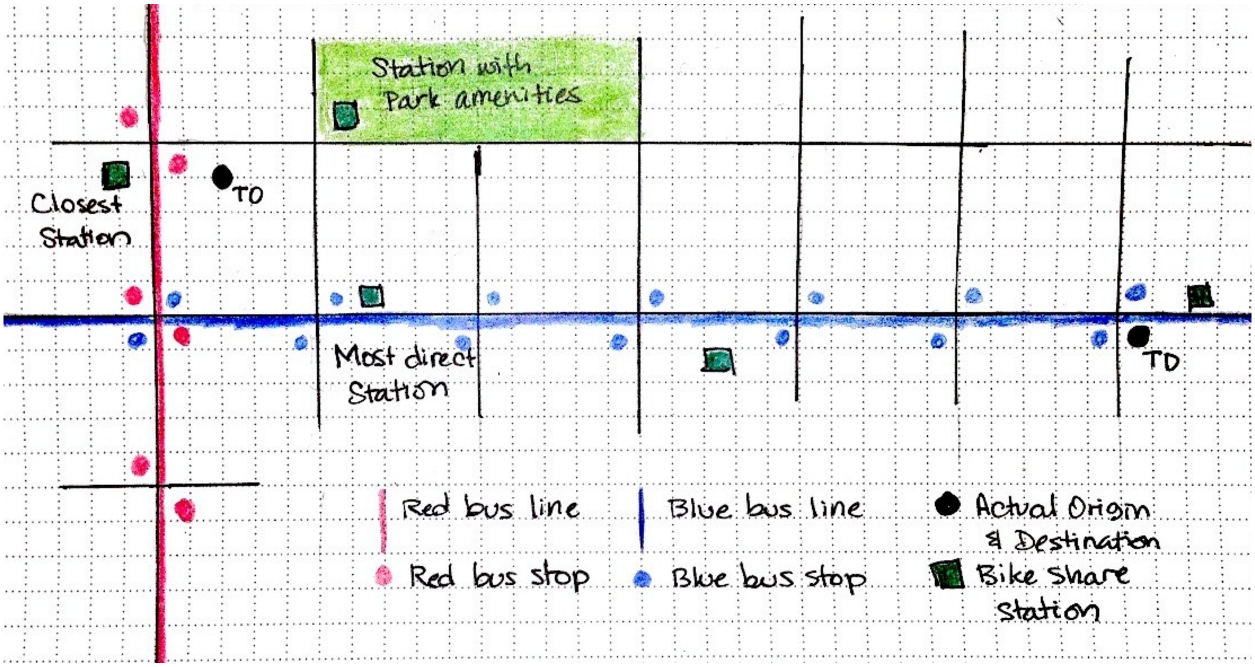

FIGURE 1 Hypothetical Transit Stations versus Bike Share Stations. Any of the bike share stations can be used to travel from TO to TD, but only a small number of bus stops are eligible.

included in the final model, but the conceptual framework is easier to visualize by focusing strictly on travel time. A trip is comprised of a walking segment from the individual's origin to their originating station, a bicycling segment from the originating station to the arriving station, and another walking segment from the arriving station to the individual's destination. Since we are focusing strictly on station origins in this paper, the second and third segments will be regarded as one.

As shown in Figure 1, when an individual starts a bike share trip, they may have several nearby stations to choose from. These stations vary in distance from the individual's origin, distance to the individual's destination, and the amount of deviation from a "shortest path" route between the origin and destination that is required to utilize that station.

Depending on the individual's relative walking and bicycling speeds and their respective preferences for each mode, they may be faced with a decision to walk to the closest station which requires detouring from the shortest path, or else walking a longer distance to use a station that minimizes overall travel distance.

Figure 2 shows three sets of equal travel time boundaries that vary with walking and bicycling speed. These boundaries show the relative value of retrieving a bicycle from the closest station versus walking farther in the direction of travel. Figure 3 shows one of these boundaries overlaid on a hypothetical grid network.

An individual starting from position TO (true origin) to position TD (true destination) with an average walking speed w and average bicycling speed b, assuming a grid-like street network, will find that they achieve equal travel time by selecting a station anywhere along one of the

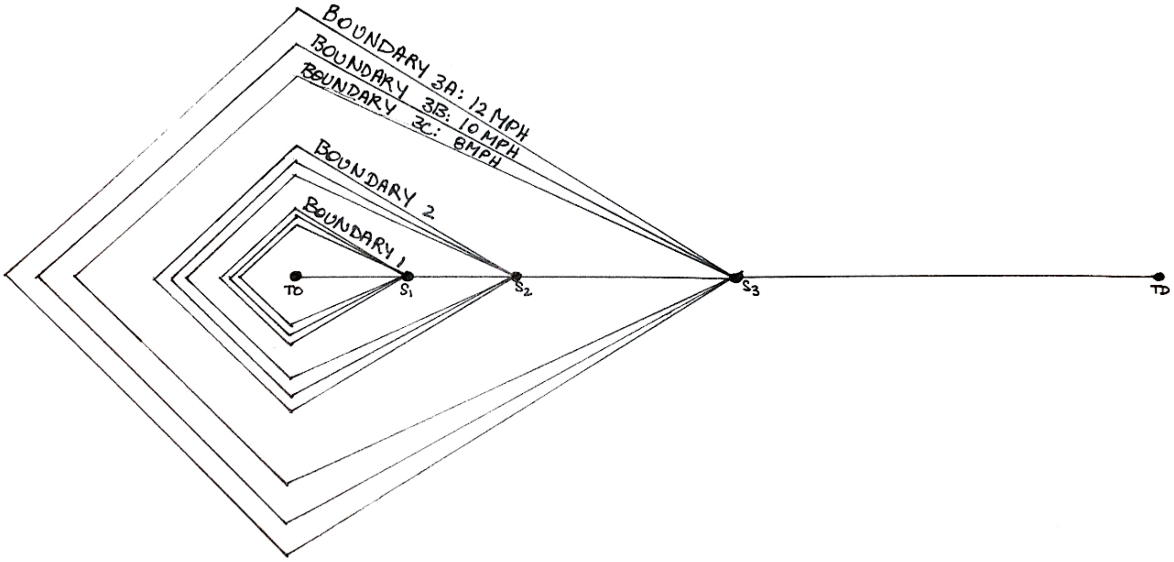

FIGURE 2 Theoretical Equal Travel Time Boundaries. A person starting at TO experiences equal travel time if they use station S_3 or any other station placed along Boundary 3A, 3B, or 3C depending on their travel speeds.

boundaries that corresponds to their travel speed.

For the 2-mile trip from TO to TD in Figure 2, consider the station located at position S_3, halfway between the origin and destination and directly along the shortest path of travel. An individual with $w = 3$ mph (about 5 kph) and $b = 12$ mph (about 19 kph) can achieve equal travel time by either walking one mile east to retrieve a bicycle and biking the remaining mile, or walking 0.6 miles west, even though the latter alternative increases their overall travel distance by more than 1/3.

Conditional Logit choice model

Given the complexity of variables potentially influencing a person's choice of station, the conditional logit model structure is a natural fit for the data. The stations available to each participant are not ordered, ranked, or labeled in a way that would be conducive to multinomial logistic regression. The choice set for each participant is unique to their origin, so the stations are identified solely by their attributes as they relate to the individual and their trip.

Conditional logit analysis is a generalized form of the binary logit formulation for modeling discrete choices *(6)*. The underlying assumption for discrete choice models is that an individual chooses the alternative that they believe will maximize their utility subject to the errors in perception. Therefore, the selection probability of any given choice is equal to the probability that the individual perceives it to have the highest utility, which is a function both of attributes describing the choice and of the individual herself. McFadden defines utility in this context using Equation 1 *(6)*:

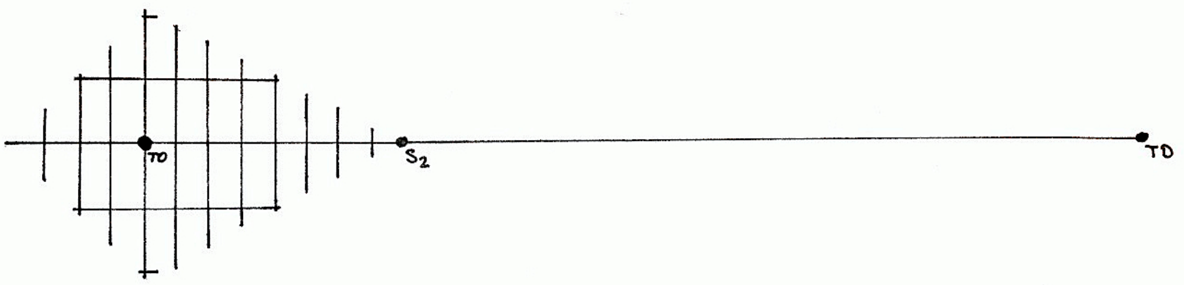

FIGURE 3 Theoretical Equal Travel Time Grid. A station placed anywhere on the grid network will provide equal or better travel time accessibility between TO and TD as station S_2.

$$U = V(s, x) + \varepsilon(s, \beta) \tag{1}$$

where s is a vector of attributes describing the individual, β is a vector of attributes describing each of the alternatives, and v and ε are functions describing typical population preference and the idiosyncratic preferences of the individual, respectively *(6)*.

In the station choice problem, each alternative has a set of defining attributes (independent variables). Random errors capture individual variation.

METHODOLOGY

Survey

The data come from an online survey of Nice Ride Minnesota bike share subscribers conducted as part of another study about economic activity around bike share stations *(7, 8)*. Nice Ride Minnesota emailed an introductory letter and survey link to 3,693 monthly and annual subscribers in May 2012. We received 1,197 valid surveys, for a response rate of 30%.

The survey focused primarily on aggregate trip behavior, such as the frequency with which the respondent visited various types of destinations via Nice Ride. The final section of the survey invited respondents to report the geographic details of specific trips they recently completed using Nice Ride bikes. These records captured the respondent's origin, the station they used at the beginning of their trip, the station at which they returned their bike, and their final destination, along with a verbal description of the route each participant rode and the purpose of the trip. A copy of the survey instrument used to collect trip records is available on pages 54 to 57 of *(7)*.

Survey Trips

597 respondents agreed to complete the final section and report one or more (up to five) trips. These records were manually geocoded using a combination of Google Maps and ESRI ArcGIS 10.1. Each trip record contained three or more segments: a station access segment between the respondent's origin and the originating station they used, one or more bicycling segments between stations, and another station access segment between the final station and the respondent's destination. Due to the open-ended questions used in the survey instrument, many trip records were

TABLE 1 Frequency of choosing the i^{th} closest station

Rank i	Not Chosen	Chosen	Pct. Chosen	Cumulative Pct.	Total
1	90	418	82.6%	82.6%	508
2	447	57	11.3%	93.9%	504
3	493	18	3.6%	97.4%	511
4	496	6	1.2%	98.6%	502
5	509	1	0.2%	98.8%	510
6 to 10	2,534	5	1.0%	99.8%	2,539
11 to 20	4,912	1	0.2%	100.0%	4,913
21 and higher	20,563	0	0.0%	100.0%	20,563
Total	30,044	506	100.0%	100.0%	30,550

incomplete or unidentifiable. The resulting dataset contained 506 complete trip records. An additional 10 were removed because their trip started and ended at the same location (round trip).

Choice Set

Each geocoded trip was matched to the specific stations that the participant used. OpenTripPlanner's batch analyst tool was used to calculate the distances between all stations and each person's origin and destination. Trips were then flagged by whether they used the closest station to their origin, or another station. Table 1 shows the frequency of people starting their trip by using the i^{th} closest station. As the table shows, the vast majority of trips (82.6%) use the station closest to the origin, and 98.8% of trips use a station ranked 5^{th} or closer. Therefore, we constrained the choice set to include only the five closest stations to each origin, measured in minutes walking at 5 kph. The dependent variable is a binary indicator of whether that particular station is the one that the traveler used as part of their trip.

Explanatory Variables

A summary of the explanatory variables is available in Table 2. A simple t-test results shows which variables have a significant difference between the stations people chose as parts of their trip and the stations that were selected to comprise each person's choice set.

Measures derived from trip length

The length and duration of each trip segment in the choice set was measured using OpenTripPlanner's Batch Analyst and street network file downloaded from OpenStreetMap. Batch Analyst uses an algorithm to identify the shortest path between sets of origins and destinations and calculates a travel time. We assumed a walking speed of 5 kilometers (3.1 miles per hour) and a bicycling speed of 16 kilometers per hour (10 miles per hour).

The travel time (in minutes) from the participant's origin to each station in their choice set was included in the model. Additionally, a ratio of walking time to total trip time (walking + biking) was included. These two variables capture people's absolute and relative preferences for time spent walking versus biking.

The straight-line distance between the true origin, stations, and true destination was calculated in meters using PostGIS. A measure of deviation from the shortest path was calculated by

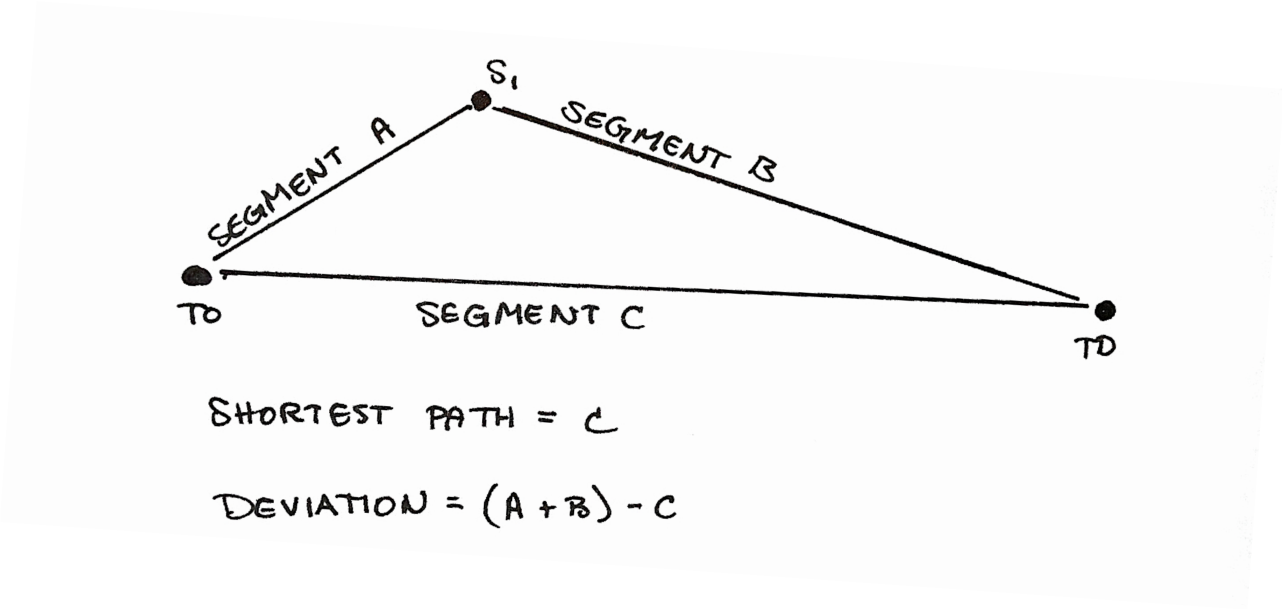

FIGURE 4 Measuring Deviation from Shortest Path

subtracting the direct distance between origin and destination (S_0) from the combined distance of origin to station (S_1) and station to destination (S_2), as shown in Equation 2. Figure 4 shows these segments on a hypothetical trip.

$$(S_1 + S_2) - S_0 \tag{2}$$

Station Area Amenities

The presence of a bike trail and proximity to parks were included in the model to identify whether station area amenities increased the utility of a particular station. Trails are measured with a dummy variable for whether a bike trail passes through a 400-meter ($\frac{1}{4}$—mile) network distance buffer around each station. Proximity to park land is measured in meters.

Neighborhood Characteristics

Crime rates and median household income were added to control for social variables that may encourage or discourage a person from using a particular station. Local crime statistics from the Minneapolis and St. Paul police departments were measured at the neighborhood level as the number of violent crimes that occurred per 10,000 people in 2010. Each station assumes the crime rate of the neighborhood that contains it. While neighborhoods are a much coarser resolution than preferred, data were not available in a more disaggregated format. To account for Downtown Minneapolis having both the highest crime rate and the largest concentration of stations and bike share activity, an interaction variable between crime rate and Downtown was created. The model includes a measure of crime rate *outside* the central business district only. Median household income is similarly measured at the neighborhood level, with the station assuming the median income of the neighborhood that contains it.

TABLE 2 Variable names, units, and summary statistics for all variables included in modeling. The final column shows the results of a t-test comparing chosen stations to stations selected to be in the choice set for each person.

			Chosen stations		Non-chosen set		Significant
	Variable Definition	Units	Mean	(S.D.)	Mean	(S.D.)	Difference
C	Chosen station (Dependent Variable)	Binary					
W	Walk Time to Station	Minutes	2.83	(2.77)	10.00	(6.09)	***
R	Ratio of Walk to Total Travel Time	Percent	25.19	(18.25)	55.00	(17.28)	***
D	Deviation from Shortest Path	Meters $*$ 100	1.31	(1.87)	5.48	(5.28)	***
T	Trail within $\frac{1}{4}$−mile of station	Binary	0.41	(0.49)	0.33	(0.47)	***
P	Distance to Park	Meters $*$ 100	2.13	(1.67)	2.26	(1.79)	*
V	Violent crime rate	Number per 10,000 people	61.39	(76.75)	56.54	(70.43)	*
M	Median Household Income	USD $*$ 1,000	$47.87	($24.63)	$46.78	($24.07)	

*** Significant at the 0.01 level

** Significant at the 0.05 level

* Significant at the 0.1 level

Trip Purpose

Trip purpose can change the priorities people have while traveling. Someone on their morning commute may prioritize travel time savings above all else, whereas someone taking a bike out on their lunch break to get some fresh air may value other characteristics. To account for this possible difference, we modeled commute trips and non-work trips separately.

Individual Characteristics

Data about each member's age and gender were available from electronic trip records provided by Nice Ride for matching with survey data. Several interaction variables between age, gender, and the walking and deviation variables were tested and ultimately excluded due to insignificance.

RESULTS

Model Fit

Table 3 shows the results from modeling station choice for commute and non-work trips. The first model, "Base Model" includes only the walking and deviation variables. The "Full Model" controls for proximity to a bike trail and parks, crime rates for stations outside the CBD, and median household income in the neighborhood containing the station. The final column shows a more parsimonious model where control variables with p-values greater than 0.1 were removed stepwise in order from highest p-value to lowest, followed by walking or deviation variables under the same criteria.

McFadden's Pseudo$-R^2$ and Bayesian Information Criterion (BIC) are reported for all models. The commute models have Pseudo$-R^2$ values ranging from 0.724 to 0.758. The non-work trips have slightly lower Pseudo$-R^2$ values, from 0.700 to 0.708, possibly because people experience greater time pressure on commute trips, and other amenities matter less in station choice. Overall, these values are high, suggesting that the fitted models are all substantial improvement over the null models. In both commute and non-work trips, most of the improvement over a null model comes from the walking and linear deviation variables. Controlling for station amenities and neighborhood characteristics provides only a marginal improvement. BIC assesses model fit with a specific emphasis on penalizing the addition of superfluous variables that marginally improve the log-likelihood without contributing any meaning. The BIC for both commute and non-work trips suggest that the additional parameters in the full model do not add significant value, and either the base model or final model are preferable.

Commute Trips

Travel time to the station, deviation from the shortest path, proximity to parks, and crime outside the CBD are all significantly associated with choosing a particular station at the beginning of a commute trip. The conditional logit regression coefficients represent the change in log-odds of choosing a station based on a 1-unit change in the independent variable, so the odds ratios are also presented for ease of interpretation. In the final model, each additional minute required to walk to a station is associated with a -0.741 decrease in the log-odds of choosing that station. Put another way, that station is 47.7% as likely to be chosen as one that is one minute closer.

Interestingly, the absolute measure of walking (minutes) is significant in the final model, but the ratio of walk time to total trip time disappears. The deviation from the shortest path variable is also significant. From this we can infer that commuters value shorter trips, and have a threshold above which they prefer not to walk. But the relative balance of walking and bicycling in any given

TABLE 3 Conditional Logit Model Results of Origin Station Choice for Commute and Non-work Trips

	Model 1				Model 2				Model 3			
Variable	Coeff	(SE)	OR	Sig	Coeff	(SE)	OR	Sig	Coeff	(SE)	OR	Sig
Work Trips												
W Walk to Station (minutes)	-0.559	(0.233)	0.572	**	-0.557	(0.263)	0.573	**	-0.741	(0.120)	0.477	***
R Ratio of walking to trip time	-0.018	(0.037)	0.982		-0.036	(0.045)	0.964					
D Deviation (meters * 100)	-0.162	(0.095)	0.850	*	-0.212	(0.107)	0.809	**	-0.201	(0.100)	0.818	**
T Trail within 400 meters					0.267	(0.550)	1.306					
P Distance to Park (meters * 100)					-0.411	(0.198)	0.663	**	-0.417	(0.185)	0.659	**
V Crime (outside CBD)					-0.007	(0.004)	0.993	*	-0.006	(0.003)	0.994	**
M Median Income ($ * 1,000)					-0.013	(0.015)	0.987					
N Chosen (Choices)	97 (485)				97 (485)				97 (485)			
McFadden's Pseudo-R^2	0.724				0.758				0.751			
Bayesian Information Criterion	104.730				118.894				102.500			
Non-work Trips												
W Walk to Station (minutes)	-0.117	(0.089)	0.890		-0.113	(0.092)	0.893					
R Ratio of walking to trip time	-0.083	(0.017)	0.920	***	-0.089	(0.018)	0.915	***	-0.108	(0.008)	0.897	***
D Deviation (meters * 100)	-0.303	(0.046)	0.738	***	-0.296	(0.047)	0.744	***	-0.327	(0.042)	0.721	***
T Trail within 400 meters					0.129	(0.272)	1.138					
P Distance to Park (meters * 100)					-0.118	(0.082)	0.888					
V Crime (outside CBD)					-0.003	(0.002)	0.997	**	-0.003	(0.002)	0.997	**
M Median Income ($ * 1,000)					-0.011	(0.007)	0.989	*	-0.013	(0.007)	0.988	*
N Chosen (Choices)	394 (1,970)				394 (1,970)				394 (1,970)			
McFadden's Pseudo-R^2	0.700				0.708				0.705			
Bayesian Information Criterion	402.622				423.060				404.387			

$* * *$ Significant at $p < 0.01$

$**$ Significant at $p < 0.05$

$*$ Significant at $p < 0.1$

trip is irrelevant, as long as the travel times meet the other criteria.

Proximity to parks appears to be an important factor, and these findings are consistent with *(9)*. For commuters, the park may increase the station's utility by making the walk to and from the station more pleasurable. Alternatively, it could simply be a function of home-based commute trips starting in residential areas that have better park access in general.

Non-work Trips

Like commute trips, deviation from the shortest path and crime rates for stations outside the CBD are significant. For non-work trips, however, the relative amount of walk time seems to be more important than an absolute threshold of minutes. People making non-work trips prefer to spend most of their travel time on the bicycle rather than walking to the station. A station for which the walk segment comprises a 1-percentage point larger share of the total trip time is only 89.7% as likely to be chosen.

The negative sign on the income variable is curious. Given the demographics of Nice Ride users - higher income, highly educated, young professionals - one would expect stations in higher income neighborhoods to have a higher utility. However, this suggests that a marginal increase in the income level of the neighborhood actually decreases the likelihood for stations within that neighborhood. This could be a function of where Nice Ride subscribers tend to live. Although their demographic profile suggests higher income, they may be more likely to live in diverse neighborhoods than exclusively wealthy areas, so stations in these areas would get more use.

A station with an increase of one violent crime per 10,000 people has a subtle disadvantage (99.7% as likely to be chosen), but rescaling the variable makes the effect more noticeable. A station in a neighborhood with 64 more violent crimes per 10,000 people (the standard deviation of crime rate in this sample) has an odds ratio of 81.9%.

CONCLUSIONS

Implications for policy

The findings from this study will be important for practitioners considering or already managing bike share systems.

Relative preferences for biking over walking

The models for commute trips and non-work trips found preference for shorter walking segments, both in absolute terms (minutes walking to the station), and relative terms (ratio of walk time to overall trip time). The relative value of walking and biking times versus distance can inform decisions about station spacing and network expansion. A strong preference for time spent biking over walking suggests that a denser network may enable people to decrease these walking segments. While spacing stations along a route would enable people to walk in the direction of their destination to pick up a bike, given the preference for time spent biking, clustering stations near where people are starting and ending their trips may make more sense.

The preference for longer biking durations relative to walking suggests that the pricing structure that discourages longer bike trips may be undermining the utility of the system somewhat. In situations where people are faced with a decision about taking a longer trip that is comprised of a larger share of biking time, the typical pricing structure that starts charging trip fees beyond 30 minutes may deter ridership.

How far people walk to access stations

More fundamentally than the tradeoffs between walking and biking time and overall distance, this study helps us learn how far people walk to stations in general. There is no control group of people who didn't make a trip to advise how far is too far, but there is at least evidence that the vast majority of people prefer to use the closest station. With future research, this may help with forecasting or anticipating demand by providing an appropriate catchment area size for each station.

Station Amenities and Neighborhood Attributes

Unlike an aggregate model of station use, such as *(7)*, this study measures how individuals choose which stations to use. The aggregate model estimates the value of station amenities and nearby businesses as trip generators and attractors. But in this study, the station choice is assumed to be to some extent independent of the trip purpose, and only dependent on the origin and destination spatially (with the exception of commute trips or other trip purposes that constrain time). The findings from the regression models in this study identified the disproportionate importance of parks for commute trips. Stations closer to parks were more likely to be chosen, all else equal. The importance of parks for commuters may ease tension within bike share system administration about planning for regular long-term members versus recreational short-term users who generate more revenue.

Limitations and Areas for Future Study

This study had several notable limitations. The data came from the Nice Ride Minnesota system, a mid-sized bike share network with well-managed station balancing efforts. Because network congestion is not an issue here, uncertainty variables such as station capacity and probability of being empty or full when a traveler needs a bicycle were not included. The results from this study will therefore be more applicable to small- and medium-sized cities with a similar operations context. Larger systems that face greater congestion challenges, such as Washington, D.C., may find that the model results are inadequate because they disregard this significant source of uncertainty for users.

Another limitation is the unit of analysis for neighborhood attribute variables. Crime reports are not available at any level finer than a neighborhood, but this means that many participants' entire choice sets may fall entirely within a single neighborhood, so that all the nearby stations have the same measure of crime rate. Median income was evaluated at the same level as crime rate for consistency, but is available at smaller levels of aggregation. Future analysis might consider removing the crime variable, measuring income levels at the block group or census tract level, and adding other neighborhood spatial variables.

This paper set up a framework for evaluating route choice in bike share trips. The empirical model focused strictly on the station access component, but future research should consider the egress segment and the bicycling route as well. Some of the examples from transit literature, such as *(5)*, provide a starting point for jointly estimating these components.

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