



# Comparing ridership attraction of rail and bus

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## Abstract

The objective of this study is to analyze whether or not there is evidence indicating a significant preference for rail travel over bus, and, if such a preference exists, to learn about the characteristics that affect it and cause it to vary from one situation to another. After a brief review of existing literature, models of choice among alternative travel modes are estimated using revealed preference data and stated preference data. The main conclusion of the study is that there is no evident preference for rail travel over bus when quantifiable service characteristics such as travel time and cost are equal, but a bias does arise when rail travel offers a higher quality service. The investigation of the impact of different service characteristics using more advanced demand estimation techniques is suggested as a topic for future research. © 2002 Elsevier Science Ltd. All rights reserved.

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## 1. Introduction

### 1.1. The problem

Evolving technologies have added new transit options such as light-rail-transit, low-floor bus and dual-mode bus to conventional heavy rail, trams and bus. It has however, been, argued that a rail transit service is able to attract significantly more passengers than an express bus service even if both services offer similar level-of-service (LOS) characteristics such as travel time, fare, frequency and the number of transfers. This is based on the supposition that rail systems are inherently more attractive than bus systems, which means that, given the choice between seemingly equivalent systems, travelers will prefer rail to bus.

It has been postulated that this preference for rail over bus may be due to less tangible attributes such as reliability, comfort, safety and others for which rail is often perceived to be superior. At the same time, it is argued that bus systems hold an advantage over rail in that they usually have denser network and hence require less transfers.

Since new rail systems are very expensive to construct, rail should have a definite advantage over alternative systems to justify implementation. Vuchic (1991) emphasizes the strength of rail systems by listing many successful

examples of rail and disputes the criticism raised by anti-rail academicians. A recent extensive investigation on urban public transport all over the world, however, found that many of the newly developed rail-based systems have ended up with ridership which is well below the forecasted (Mackett and Edwards, 1998). They point out that there are very expensive 'image benefits' bestowed by a light rail that a bus cannot provide.

In spite of this, the problem of ridership attraction of rail versus bus has been discussed mostly in qualitative rather than quantitative terms. The only quantitative statement about this issue relates to the alternative specific constants in models of travelers' choice of modes which capture the effects of omitted factors from the model. If a model includes only easily quantifiable attributes such as travel time and cost, as is typically the case, the alternative specific constants must capture the less tangible attributes mentioned earlier.

There are, nonetheless, two difficulties in analyzing the alternative specific constants. The first problem is scarcity of travel behavior data from corridors where the two transit modes exist. Secondly, an alternative specific constant may capture various effects, such as situational constraints and taste variation, as well as the aforementioned intangible attributes. An alternative source of data is from stated preference (SP) surveys in which travelers are asked to react to hypothetical scenarios of bus and rail services. SP data may be able to provide purer information on relative preference of two modes because choice contexts can be controlled in SP experiments. However, since SP data are

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subject to biases and errors, its reliability is questionable (Ben-Akiva et al., 1992).

The principal objective of this study is to analyze whether there is evidence indicating a significant preference for rail from two case studies. Moreover, if such a preference exists, the purpose of this study is to learn about transit service characteristics that affect it and cause it to vary from one situation to another. The study methodology is to compare the ridership attraction of rail and bus by analyzing the values of alternative specific constants of choice models estimated from large scale census data and SP data. Analysis of the large scale census data is described in Section 2. The data, collected in the metropolitan Washington DC area, are used to analyze the choice among three travel modes, i.e. transit, drive alone and shared ride, for commuting trips. The SP data, collected in Boston, are associated with a restoration plan of a light rail service and provide information on preferences for rail versus the existing bus service. Methodological development of how to analyze SP data and empirical work using the Boston SP survey are presented in Section 3. Section 4 summarizes the findings of this research and suggests directions for future work.

### 1.2. Level of service factors

Mode choice models generally include only a few LOS variables such as in-vehicle travel time, out-of-vehicle travel time, travel cost and the number of transfers. The reasons are twofold: other characteristics, first, are difficult to quantify, and second, do not vary among the origins and destinations of the trips within a mode.

The following factors are considered to be important in the choice of a mode between rail and bus, yet they are usually not specified in a model due to the above reasons. Rather, the effects of these factors may be embedded in an alternative specific constant.

1. *Reliability.* Rail service has its own right-of-way and thus avoids interference from other modes. An express bus service which runs on an exclusive right-of-way can provide similar level of reliability. Bus systems, on the other hand, have the flexibility to use alternate routes when their regular ones are blocked. An entire bus system is not significantly affected by the failure of a single bus, whereas the failure of a single train can block an entire line of rail service.
2. *Information availability.* Information availability involves the ease with which passengers can obtain information about schedules, station locations, destinations served, etc. Rail service tends to have the advantage over bus service since the former operates on an easily identifiable right-of-way and at higher frequency than do most bus services. City bus routes are generally not easy to recognize and the waiting time for the next bus is highly uncertain. Recent information technologies enable the operators to provide, for instance, the optimal transit

route to the destination and real-time bus schedule. But still the off-hand information availability for rail is considered to be better than bus due to the above reasons.

3. *Comfort.* Travel comfort includes seating availability, ride quality, heating and ventilation, etc. Rail travel often holds an advantage in terms of comfort because the ride is usually smoother than on a bus, and seats can be roomier. Alternatively, express bus services usually provide rides with seats, which typical urban rail systems often have a much higher proportion of standees. As for waiting time, level of comfort at rail stations are usually higher than bus stops.
4. *Safety from accidents.* Rail service may have a perceived advantage due to its mechanical guidance, mechanized train control systems and lack of interference from competing traffic.
5. *Security from crime.* In terms of on-board crime, bus travel is perceived to hold an advantage because every vehicle has a driver. However, rail stations tend to be more heavily populated than bus stops which are often widely dispersed and hence are inherently less secure areas. Also, rail stations can employ security measures such as closed circuit television whereas typical bus stops could not feasibly be similarly equipped. In many countries, buses are mainly used by the low-income group, which may give an impression of less security for buses.
6. *Availability.* Each mode probably holds its own advantage with respect to a particular type of availability. Locationally, bus stops will generally be within walking distance of a greater number of people acting as their own feeders. Rail service is invariably more frequent as it is concentrated in one corridor, and bus service generally cannot compete with the frequency of rail service. Although availability is a key factor for mode choice models, it is often omitted because of difficulty of determining availability of a particular mode for a specific trip.

### 1.3. Empirical approaches

An early work of a comparison between rail and bus can be found in the Vuchic's study of the Lindenwold Line and the Shirley Highway (Vuchic and Stanger, 1973). In this particular example, they found that most of the attributes favored the rail service. Although this comparison of two very different types of service in different metropolitan areas does not answer the rail versus bus question, it does point to some of the ways that rail and bus may differ in practice.

Two alternative approaches are considered to empirically analyze the relative ridership attraction of rail and bus:

1. impact studies
  - analysis of data from before-and-after changes in rail and/or bus service

2. statistical analysis of cross-sectional data  
analysis of estimation results of disaggregate mode choice models.

Before-and-after analyses compare rail and bus ridership before and after the introduction of a new system (e.g. new rail). Data are obtained from passenger counts, revenue statistics, and passenger surveys. This approach is useful because actual ridership changes caused (at least partially) by the introduction of the new alternative are observed. One may also be able to observe a wide range of indirect and secondary effects such as changes in employment and population distributions.

Most impact studies concern a new rail service that replaces an existing bus service rather than creating a competitive situation between the two modes. In other words, the observed situation does not represent a choice context between rail and bus, but rather forced conversion and attraction to a new service which offers a higher level of service. This makes it difficult to quantitatively analyze the relative ridership attraction of rail and bus modes which offer the same level of service by means of before-and-after analysis because service levels are invariably different when a new rail system is introduced. It would also be difficult to use longitudinal data to answer the basic question of whether similar ridership response would have been achieved with similar qualitative service improvements generated by another mode. Finally it is difficult to distinguish the effects of the new service from confounding effects. Hence, before-and-after analyses tend to be specific to the study area and inconclusive with respect to the issue of rail versus bus attraction. Among all, the following two Boston area's before-and-after studies showed no specific preference between rail and bus.

One study evaluated the impacts of the Massachusetts Bay Transportation Authority's Red Line Extension to Braintree (March, 1980) on commuting patterns of South Shore residents. Passenger questionnaire surveys were conducted before and after the extension. According to the survey results, 17% of the morning peak period passengers (1900) are new riders. Of these, 55% did not make the trip prior to the station's opening; 26% used an automobile (18% drove alone and 8% carpooled); 10% used a private carrier bus; and 8% used some other mode or did not respond. Regular riders, defined as those who used the Red Line for their commute to Boston both before and after the extension, totaled 83% or 9000 passengers. The results indicate that a significant amount of shifting occurred after the extension (Central Transportation Planning Staff (CTPS), 1981a).

The other study examined the results of an on-board ridership survey on the Needham express bus service which replaced commuter rail service in October 1979. It shows that although some rail riders did not switch to buses, new bus riders who had not used the trains more than offset the loss. The survey revealed the comparative advantages of

the replacement bus service to be flexibility, increased frequency and adherence to schedule and showed the main disadvantage to be reduced seating comfort. Of the former Needham train riders who switched to buses, SP was almost evenly divided between train (46%) and bus (44%), with 10% indifferent (Central Transportation Planning Staff (CTPS), 1981b).

An alternative approach to find the relative ridership attraction of rail and bus is based on statistical analysis of cross-sectional data. Two types of disaggregate mode choice data can be used in this type of analysis: revealed preference (RP) and SP. RP data are based on actual traveler behavior while SP data are collected by asking travelers for their preferences under hypothetical scenarios. Although estimation of travel demand models has traditionally relied on RP data, there has been an awakening interest in the use of SP data in transportation demand analysis since early 80s (e.g. Bates, 1983; Louviere, 1988; Special issue in *Journal of Transport Economic and Policy* 22 (1), 1988; Special Issue in *Transportation*, 21, 1994; and Louviere et al., 2001).

SP data have the potential to provide valuable information which RP data cannot provide. Reliability or information availability can be varied within a mode in the SP questionnaire and could be included in the choice model. The crucial problem is the reliability of SP data. The consistency of one's SPs with one's actual market behavior is uncertain.

Early works of mode choice models with generalized cost functions have omitted mode specific constants, thus implicitly saying that there is no inherent difference between bus and rail. Vuchic and Stanger (1973), Mitric (1977) and Koppelman (1983) have criticized the generalized cost models because of this. Since the middle of 1970s most of the mode choice models have been estimated using the disaggregate random utility model with mode specific constant terms (McFadden, 1974; Ben-Akiva and Lerman, 1985; Hensher and Button, 2000). Although comparisons of rail and bus constants are made in most studies, detailed analysis such as corridor specific unobserved effects in conjunction with LOS variety has rarely been made.

## 2. Analysis of revealed preference data

This section presents an analysis of the choice of travel mode by commuters using RP survey data. The unique aspect of this analysis is the separate treatment of four different transit modes: rapid transit, commuter rail, express bus and local bus. The estimated utilities of the mode choice model are used to obtain the preference order for these transit modes under different conditions.

### 2.1. Descriptions of the data

The 1980 census journey to work data were used by the Metropolitan Washington Council of Governments to

Table 1

Estimation results (*t*-statistics in parentheses). Note: TR, transit; DA, drive alone; SR, shared ride

Variable	0 car households		1 car households		2 + car households	
Metro dummy (TR)	5.13	(17.5)	2.78	(27.7)	2.29	(18.6)
Com. rail dummy (TR)	2.21	(15.2)	0.588	(9.4)	0.107	(1.7)
Exp. bus dummy (TR)	2.60	(23.6)	0.841	(17.9)	0.323	(6.3)
Local bus dummy (TR)	2.94	(34.8)	1.39	(33.1)	1.07	(22.5)
CBD Metro dummy (TR)	-0.355	(-1.9)	-0.0386	(-0.6)	0.0784	(0.9)
CBD Com. rail dummy (TR)	-0.0727	(-0.2)	0.508	(4.9)	0.308	(4.0)
CBD Exp. bus dummy (TR)	0.283	(3.1)	0.496	(15.8)	0.299	(9.8)
Lowfrequency Metro dummy (TR)	-1.69	(-7.5)	-0.696	(-10.8)	-0.479	(-5.6)
HOV Exp. bus dummy (TR)	0.509	(4.2)	0.458	(15.1)	0.534	(19.6)
Walk time (TR)	-0.0380	(-4.6)	-0.0967	(-24.1)	-0.0973	(-20.7)
Wait time 1 (TR)	-0.0349	(-3.4)	-0.0849	(-17.5)	-0.0950	(-16.6)
Wait time 2 (TR)	-0.0746	(-13.9)	-0.103	(-40.9)	-0.0931	(-42.1)
Transfer time (TR)	-0.0310	(-9.3)	-0.0484	(-28.2)	-0.0452	(-26.1)
Transit running time (TR)	-0.00881	(-4.4)	-0.0133	(-15.6)	-0.0160	(-20.3)
Transit fare (TR)	-0.577	(-8.1)	-0.665	(-20.2)	-1.17	(-34.2)
Drive alone constant (DA)			0.934	(56.2)	1.46	(122.8)
Highway running time 1 (DA)			-0.0450	(-23.6)	-0.0391	(-20.7)
Highway running time 2 (DA)			-0.0394	(-21.6)	-0.0788	(-56.6)
Highway running time 1 (SR)	0.00013	(0.0)	-0.0317	(-15.9)	-0.0233	(-11.9)
Highway running time 2 (SR)	-0.00592	(-1.3)	-0.0238	(-12.4)	-0.0511	(-33.5)
Highway terminal time (DA, SR)	0.0164	(2.4)	-0.00477	(-1.5)	-0.0490	(-13.9)
Parking cost (DA)			-0.354	(-32.3)	-0.398	(-34.8)
Parking cost (SR)	-0.0219	(-1.0)	-0.0741	(-7.0)	-0.0688	(-6.1)
CBD dummy (DA)			-0.774	(-39.3)	-0.880	(-40.0)
CBD dummy (SR)	-0.406	(-11.2)	-0.486	(-23.1)	-0.508	(-21.6)
$L(0)$	-46664.04		-201904.08		-370483.81	
$L(\beta)$	-23205.71		-178025.92		-263917.60	
$\bar{\rho}^2$	0.5023		0.1181		0.2876	
$N$	67 329		184 043		338 227	

prepare a data set with transportation level of service attributes for the estimation of mode choice models. This data set is very extensive consisting of one out of every twelve households. The data are aggregated into traffic zones and the following three car ownership groups: no car households, one car households, and two or more car households. Models are estimated for each of the three market segments.

Travel time and cost characteristics representing the transit services and the highway system during 1980 were appended to the census data by the Metropolitan Washington Council of Government. For every origin to destination (O–D) pair the transit running time (i.e. transit in-vehicle travel time) is disaggregated into the following five modes: commuter rail, D.C. local bus, Metro, Virginia local bus, and express bus. An O–D pair is classified into one of the following types: Metro, commuter rail, express bus, local bus, and other, according to the fraction of running time by each transit mode, as follows:

1. Metro—O–D pairs of which transit running time consists exclusively of Metro running time;
2. commuter rail—O–D pairs of which transit running time consists exclusively of commuter rail running time;

3. express bus—O–D pairs of which transit running time consists exclusively of express bus running time;
4. local bus—O–D pairs of which transit running time consists exclusively of local bus running time; and
5. other—all O–D pairs that do not meet the above four criteria.

For the estimation of the mode choice models the observations that belong to the fifth corridor type were omitted. O–D pairs for which transit is not accessible by walking were also omitted. Thus, only observations from O–D pairs which are served by four ‘pure’ transit modes with walk access and egress were considered. Hence, the ‘transit’ mode corresponds to one of the four aforementioned modes (Metro, commuter rail, express bus, and local bus) which are identifiable from the component of transit running time.

## 2.2. Estimation results

Multinomial logit (MNL) models were estimated for each of the three market segments (0, 1 and 2 + car households). The full choice set consists of three primary travel modes: transit, drive alone and shared ride. Nested logit models

Table 2  
Values of transit travel times in \$/h (*t*-statistics in parentheses)

Variable	0 car households		1 car households		2 + car households	
Walk time	4.0	(4.0)	8.7	(15.2)	5.0	(17.1)
Wait time 1	3.6	(2.9)	7.7	(11.8)	4.9	(13.6)
Wait time 2	7.8	(6.7)	9.3	(17.9)	4.8	(26.8)
Transfer time	3.2	(5.4)	4.4	(15.7)	2.3	(20.8)
Transit running time	0.9	(6.0)	1.2	(13.1)	0.8	(17.1)

were tried but did not give significantly different estimation results from MNL models.

Mode availability is based on the following two assumptions:

- (i) drive alone is not available for 0 car households; and
- (ii) transit is not available if either walk, wait, or transfer time is more than 20 min or the number of transfers is greater than three.

The definitions of the explanatory variables are as follows:

- Metro dummy = 1 for Metro O–D pair; 0 otherwise;
- Com. rail dummy = 1 for commuter rail O–D pair; 0 otherwise;
- Exp. bus dummy = 1 for express bus O–D pair; 0 otherwise;
- Local bus dummy = 1 for local bus O–D pair; 0 otherwise;
- CBD dummy = 1 if either origin or destination zones are in the CBD; 0 otherwise;
- Lowfreq = 1 for Metro O–D pair where Metro service is less frequent; 0 otherwise; (During the year of the survey the Metro peak period headway was six minutes except for one line which operated with a headway of eight minutes and is defined here is the less frequency Metro service.)
- HOV = 1 if the O–D pair uses a highway with an HOV lane; 0 otherwise;
- Walk time = walking time to and from transit (minutes);
- Wait time 1 = waiting time (minutes) at the transit boarding location if the waiting time is 5 min or less; 5 if the waiting time is more than 5 min;
- Wait time 2 = 0 if the waiting time is 5 min or less; waiting time (minutes) minus 5 if the waiting time is more than 5 min;

- Transfer time = transit transfer time (minutes);
- Transit running time = transit running time (minutes);
- Transit fare = transit fare (dollars);
- Highway running time 1 = highway running time (minutes) if it is 20 min or less; 20 if it is more than 20 min;
- Highway running time 2 = 0 if highway running time is 20 min or less; highway running time (minutes) minus 20 if it is more than 20 min;
- Highway terminal time = highway terminal time at both ends (minutes);
- Parking cost = daily parking cost (dollars).

The estimation results are presented in Table 1. The model includes three utility functions for transit (TR), drive alone (DA) and shared ride (SR). For each variable, the utility functions in which it appears are indicated in parentheses following the variable name. The table includes the estimated values of the coefficients of the variables and *t*-statistics. The bottom of the table provides auxiliary statistics which can be used to measure the goodness of fit of the estimated model.

All the coefficients of the transit LOS attributes have the expected negative sign. The only LOS coefficients which are poorly estimated are in the shared ride utility for 0 car households. It appears that for these households the choice of the SR mode is not influenced by highway running and terminal times. Table 2 presents the values in \$/h of the different transit travel time components. The calculated value of time for transit running time is approximately 1 \$/h and that for walk and wait time ranges from 4 to 9 \$/h for different market segments. The value of transfer time is around 3 \$/h. Table 3 provides the equivalent minutes of transit running time per one minute of transit walk, wait and transfer times. These values indicate as expected that out-of-vehicle time is perceived to be more onerous than in-vehicle time. However, these ratios, ranging

Table 3  
Equivalent minutes per one minute of transit running time (*t*-statistics in parentheses)

Variable	0 car households		1 car households		2 + car households	
Walk time	4.3	(3.4)	7.3	(13.8)	6.1	(15.2)
Wait time 1	4.0	(2.8)	6.4	(11.5)	5.9	(12.7)
Wait time 2	8.5	(4.2)	7.7	(14.4)	5.8	(17.8)
Transfer time	3.5	(3.7)	3.6	(12.3)	2.8	(14.2)

Table 4

Preference order of transit modes (Corridor type 1: Neither origin nor destination is in the CBD; Not Metro low frequency line corridor; Not HOV lane corridor. Corridor type 2: Neither origin nor destination is in the CBD; Not Metro low frequency line corridor; HOV lane corridor. Corridor type 3: Neither origin nor destination is in the CBD; Metro low frequency line corridor; Not HOV lane corridor. Corridor type 4: Neither origin nor destination is in the CBD; Metro low frequency line corridor; HOV lane corridor. Corridor type 5: At least either origin or destination is in the CBD; Not Metro low frequency line corridor; Not HOV lane corridor. Corridor type 6: At least either origin or destination is in the CBD; Not Metro low frequency line corridor; HOV lane corridor. Corridor type 7: At least either origin or destination is in the CBD; Metro low frequency line corridor; Not HOV lane corridor. Corridor type 8: At least either origin or destination is in the CBD; Metro low frequency line corridor; HOV lane corridor)

0 car households		1 car households		2 + car households	
<i>Corridor type 1</i>					
Metro	5.13	Metro	2.78	Metro	2.29
Local bus	2.94	Local bus	1.39	Local bus	1.07
Exp. bus	2.60	Exp. Bus	0.84	Exp. bus	0.32
Com. rail	2.21	Com. rail	0.59	Com. rail	0.11
<i>Corridor type 2</i>					
Metro	5.13	Metro	2.78	Metro	2.29
Exp. bus	3.11	Local bus	1.39	Local bus	1.07
Local bus	2.94	Exp. bus	1.30	Exp. bus	0.86
Com. rail	2.21	Com. rail	0.59	Com. rail	0.11
<i>Corridor type 3</i>					
Metro	3.44	Metro	2.08	Metro	1.81
Local bus	2.94	Local bus	1.39	Local bus	1.07
Exp. bus	2.60	Exp. bus	0.84	Exp. bus	0.32
Com. rail	2.21	Com. rail	0.59	Com. rail	0.11
<i>Corridor type 4</i>					
Metro	3.44	Metro	2.08	Metro	1.81
Exp. bus	3.11	Local bus	1.39	Local bus	1.07
Local bus	2.94	Exp. bus	1.30	Exp. bus	0.86
Com. rail	2.21	Com. rail	0.59	Com. rail	0.11
<i>Corridor type 5</i>					
Metro	4.78	Metro	2.74	Metro	2.37
Local bus	2.94	Local bus	1.39	Local bus	1.07
Exp. bus	2.88	Exp. bus	1.34	Exp. bus	0.62
Com. rail	2.14	Com. rail	1.10	Com. rail	0.42
<i>Corridor type 6</i>					
Metro	4.78	Metro	2.74	Metro	2.37
Exp. bus	3.39	Exp. bus	1.80	Exp. bus	1.15
Local bus	2.94	Local bus	1.39	Local bus	1.07
Com. rail	2.14	Com. rail	1.10	Com. rail	0.42
<i>Corridor type 7</i>					
Metro	3.09	Metro	2.04	Metro	1.89
Local bus	2.94	Local bus	1.39	Local bus	1.07
Exp. bus	2.88	Exp. Bus	1.34	Exp. bus	0.62
Com. rail	2.14	Com. rail	1.10	Com. rail	0.42
<i>Corridor type 8</i>					
Exp bus	3.39	Metro	2.04	Metro	1.89
Metro	3.09	Exp. bus	1.80	Exp. bus	1.15
Local bus	2.94	Local bus	1.39	Local bus	1.07
Com. rail	2.14	Com. rail	1.10	Com. rail	0.42

from 2.8 to 8.5 are significantly greater than the usual values of 2 or 2.5 assumed in generalized cost. This may be caused by the small value of transit running time. The estimated values indicate that it may be more appropriate to assume that walk and wait times are perceived to be about six times more onerous than running time and transfer time is about three times more onerous than running time.

The model contains a number of dummy variables which serve as proxy variables for omitted LOS characteristics. The focus of this study is on the four dummy variables indicating the type of transit service: Metro, rail, express bus and local bus. Note that the values of these alternative specific constants are relative to the constant of the shared ride alternative for which it is normalized to zero. In view of the prevailing CBD orientation of transit service the model also includes CBD dummy variables for the different modes. (The local bus transit alternative serves as the base for this variable, i.e. the CBD dummy is omitted from this alternative.) The CBD dummies are, in general, significant with the exception of the Metro service alternative. However, a dummy for Metro line that operated at lower frequency (three quarters) than all the other lines proved to be negative and significant. The advantage of exclusive and congestion free highway lanes for express bus operations is represented by the HOV dummy variable for the express bus alternative.

### 2.3. Relative attraction of bus and rail

The transit level of service coefficients are the same for all transit modes. Thus, if the transit travel times and costs are held constant, the relative attraction of each transit mode relative to the car modes is measured by the coefficients of the dummy variables.

The coefficients of the dummy variables for the different transit modes for all three market segments indicate that the Metro is most preferred followed by local bus, express bus, and commuter rail, in that order. However, note that this preference order holds under the following corridor type: (i) neither origin nor destination are in the CBD; (ii) a Metro trip does not include the low frequency line; and (iii) an express bus trip does not use an HOV lane. The following analysis presented in Table 4 investigates the preference order among transit modes under different situations. The values given in Table 4 are the estimated transit mode specific constants under the corresponding corridor types. Note that the model assumes that only one transit mode is available and the constant represents the transit share in competition with drive alone and shared ride. Thus, under corridor type 5, for example, a Metro service would attract significantly more transit share than a bus service with comparable travel time and costs. However, under corridor type 8 the transit share that would be attracted by a Metro service is approximately the same to the share that would be attracted by an express bus service with the same travel times and costs. Note that the large values of some of

these alternative specific constants may simply indicate the lack of appeal of the shared ride alternative for which the constant is set to zero. Some differences between alternative specific constants are very large suggesting that factors other than omitted LOS attributes may play a role. Other omitted factors may include situational constraints, habitual behavior, general service availability in off-peak periods, and measurement errors in the included variables.

The analysis of Table 4 reveals that although Metro travel is most preferred under most corridor types, express and local bus service are almost equally preferred as Metro under some corridor types and particularly by 0 car households. Under corridor type 8, for instance, 0 car households prefer express bus to Metro. The preference bias toward Metro travel over express bus and commuter rail travel increases as the car availability increases. This may indicate that express bus and commuter rail service compete more with car than does Metro service. In other words, for the households with greater car availability, express bus and commuter rail travel is less attractive.

Express and local bus services are equally preferred in most cases. Those two bus modes have comparable attractiveness with Metro for 0 car households in the Metro low frequency O–D pair. This indicates the importance of schedule frequency of transit to increase its ridership.

When an express bus uses a highway with an HOV lane, especially when it runs to or from the CBD, its attractiveness increases substantially. This is because the relative utility of the car mode decreases under this situation due to traffic congestion and shortage of parking spaces. The same effect of the CBD can be observed for commuter rail. This observation is noteworthy because transit services and in particular rail and express bus lines are usually CBD oriented. Therefore, the most relevant corridor types for the comparison of Metro versus express bus use the CBD corridors with HOV lanes, i.e. corridor types 6 and 8.

These results show that the Metro service in the Washington DC area provides superior service to existing express bus services in 1980. However, a bus service may contain some of the desirable qualitative attributes of a Metro service as shown by the exclusive lane dummy variable.

Thus, it is possible to conclude from this analysis that Metro service in the Washington DC area attracts more ridership than a bus service with comparable travel times and costs because of its advantages along other attributes that were not quantified. However, in some situations, and in particular for express bus service operating on an exclusive lane, the preference toward Metro vanishes. Since the existing HOV lanes do not have all the features of a Metro like service it is reasonable to expect that a bus service with more Metro like features will be even more attractive. Therefore, one can conclude that a high quality express bus service with exclusive right-of-way may be equally attractive to Metro service.

### 3. Analysis of stated preference data

The transit level of service attributes included in the RP analysis in Section 2 were limited to travel times and costs. In SP analysis one can also incorporate some of the qualitative attributes discussed in Section 1. The following presents an analysis of such SP data, addressing the relative attractions of rail versus bus.

#### 3.1. Analysis of ranking type stated preference data

The following analysis explicitly considers the reliability of ranking type of SP data. The ranking data analyzed were collected for a local transit agency to study relative preferences between bus and light rail (street car) services. The estimation results of the proposed approach and those of a simplified method lead to contradictory conclusions about the relative attractiveness of rail compared with bus.

Discrete choice models can be estimated from the choice data that are reformed or ‘expanded’ from ranking data by the ‘explosion rule’ (Chapman and Staelin, 1982). More specifically, if the choice behavior underlying the ranking task follows Luce’s choice axiom (Luce, 1959), the ranking of  $J$  alternatives is equivalent to the following sequence of independent choice tasks: The alternative ranked first is chosen over all the other alternatives, the alternative ranked second is preferred to all others except the first ranked, and so on. The Luce and Suppes ranking choice theorem (Luce and Suppes, 1965) states this decomposition of the ranking task in terms of choice probabilities:

$$\begin{aligned} P(1, 2, \dots, J) &= P(1|\{1, 2, \dots, J\})P(1|\{2, 3, \dots, J\}) \cdots P(J-1|\{J-1, J\}) \\ &= \prod_{j=1}^{J-1} P(j|\{j, \dots, J\}) \end{aligned}$$

where  $P(1, 2, \dots, J)$  is the probability of observing the rank order of alternative 1 being preferred to alternative 2, alternative 2 preferred to alternative 3, and so on, and  $P(j|\{j, j+1, \dots, J\})$  is the probability of alternative  $j$  being chosen from the set of alternatives  $\{j, j+1, \dots, J\}$ . This equation is equivalent to saying that the event of  $J$  ranked alternatives is composed of  $J-1$  statistically independent choice events. The estimators of MNL models through this expanded choice data were first developed by Beggs et al. (1981) and such models are often called ‘rank logit’ or ‘exploded logit’ models.

Empirical analyses by Chapman and Staelin (1982) and Hausman and Ruud (1987) indicate that higher ranks provide more reliable information on preferences than lower ranks. In the MNL specification, different levels of ‘noise’ in the data sets are represented by different ‘scales’ of the parameter estimates. In the following empirical analysis of ranking data, rank specific scale parameters are

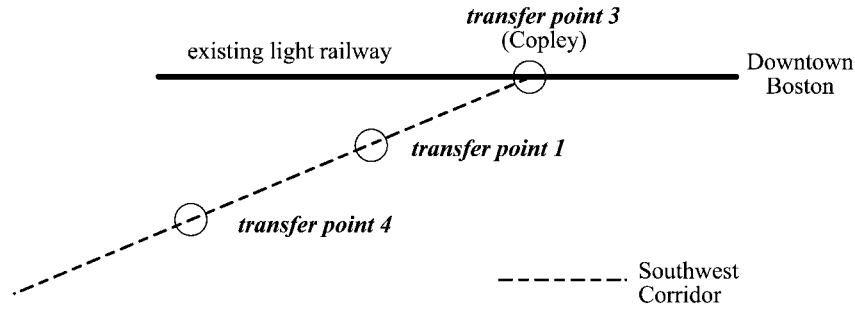


Fig. 1. Boston southwest corridor.

introduced and estimated together with coefficients of the utility functions. Also, some coefficients such as alternative specific constants are estimated in the rank-specific way. More detailed presentation of the theoretical developments for this analysis is found in Ben-Akiva et al. (1992).

3.2. Empirical analysis

The SP data were collected for a metropolitan transit agency as part of a study of the relative preferences for bus and light rail services in Boston’s southwest corridor. At the time of the survey the light rail service had been discontinued on the corridor. As exhibited in Fig. 1, they had to take a bus on the corridor and change to the light rail at Copley (later defined as transfer point 3) to go to downtown Boston. The survey was conducted to obtain users’ preferences for the existing bus service versus three alternative light rail restoration plans. The three plans differ in the bus-rail transfer points. Respondents were asked to rank

four alternatives, i.e. three restoration plans and the status quo in order of preference.

Alternative 2 is a through service to downtown by rail without a transfer, while the other three alternatives require a bus-rail transfer. The fraction of rail service between the west terminal point of the corridor and the downtown decreases in the order of alternatives 2 (all rail), 4, 1, and 3. For every alternative, numerical values were specified for three attributes: wait time, travel time reliability, and in-vehicle ride time. Six combinations of attribute values were prepared to form six versions of the questionnaire. Wait time by mode was specified for all the six versions. Three of them included values of travel time reliability (i.e. the number of trips out of 20 for which one is more than 10 min late), while in-vehicle ride time was given in the other three versions.

Alternatives 1, 3 and 4 have a distinct transfer point from bus to rail (or vice versa) while alternative 2 consists of rail service without a transfer. Hence, three constants specific to

Table 5  
Estimation results (*t*-statistics in parentheses)

Variable	Data Sets 1 and 2		Data Sets 2 and 3		Data Sets 1, 2 and 3	
Dummy 1 (Data 1)	-0.659	(-4.7)			-0.634	(-4.6)
Dummy 3 (Data 1)	-0.318	(-1.9)			-0.317	(-2.0)
Dummy 4 (Data 1)	-1.18	(-7.3)			-1.16	(-7.2)
Dummy 1 (Data 2)	-0.186	(-1.0)	0.0543	(0.3)	-0.154	(-0.9)
Dummy 3 (Data 2)	0.318	(1.4)	0.449	(2.2)	0.318	(1.4)
Dummy 4 (Data 2)	-0.586	(-2.5)	-0.311	(-1.9)	-0.555	(-2.5)
Dummy 1 (Data 3)			1.13	(2.6)	1.83	(1.8)
Dummy 3 (Data 3)			0.516	(1.7)	0.580	(1.1)
Dummy 4 (Data 3)			0.0328	(0.2)	-0.198	(-0.5)
Perceived wait time	-0.0532	(-2.3)	-0.0160	(-0.6)	-0.0448	(-2.0)
Ride time	-0.0232	(-1.9)	-0.0398	(-2.7)	-0.0267	(-2.2)
Travel time reliability	-0.127	(-4.1)	-0.0438	(-1.4)	-0.113	(-3.8)
Bus dummy	0.677	(5.3)	0.448	(3.2)	0.703	(5.5)
Rail dummy	0.574	(4.0)	0.563	(3.9)	0.583	(4.2)
$\mu_1$	0.734	(4.3)			0.749	(4.3)
$\rho_2$			0.683	(2.5)		
$\mu_1 \mu_2$					0.346	(1.8)
$L(0)$	-2040.45		-1453.76		-2598.84	
$L(\hat{\beta})$	-1896.49		-1384.27		-2430.66	
$\mu^2$	0.0706		0.0478		0.0647	
$\hat{\rho}^2$	0.0647		0.0395		0.0586	
$N$	1641		1620		2446	



alternatives 1, 3 and 4 represent dummy variables for specific transfer points.

The ranking data were expanded into three choice data sets: Data Set 1 (the first rank is chosen from all four alternatives), Data Set 2 (the second rank is chosen from the three alternatives left after eliminating the first ranked alternative), and Data Set 3 (the third rank is chosen from the two alternatives left after eliminating the first and second ranked alternatives). The number of usable observations is 828 for Data Set 1, 824 for Data Set 2, and 817 for Data Set 3.

Explanatory variables used are the following:

1. transfer point 1 dummy (specific to alternative 1)
2. transfer point 3 dummy (specific to alternative 3)
3. transfer point 4 dummy (specific to alternative 4)
4. wait time (minute)
5. ride time (minute)
6. travel time reliability

In addition to the above variables that are given as the attribute values of alternative profiles, the following dummy variables are introduced:

$$BUS_i = \begin{cases} 1 & \text{if the current trip is made solely by bus} \\ & \text{(without transfer) with alternative } i \\ 0 & \text{otherwise} \end{cases}$$

$$RAIL_i = \begin{cases} 1 & \text{if the current trip is made solely by rail} \\ & \text{(without transfer) with alternative } i \\ 0 & \text{otherwise} \end{cases}$$

These dummies are introduced in order to capture the effect of the current actual choice on the responses to the SP questions. For, it is natural for the respondents to refer to the specific origin and destination of their most typical trip when they evaluate the alternatives that were presented to them. The data set includes information on the origin and the destination of the trip made on the day of the survey and that trip seems to be the typical daily trip for most respondents because work and school trips comprise 86.3% of the total trips. This behavioral hypothesis implies that the dummy variables,  $BUS_i$  and  $RAIL_i$ , have a significant effect on choice.

The estimation results are shown in Table 5. The first column shows the parameter estimates from Data Sets 1 and 2 combined, the second column from Data Sets 2 and 3 combined, and third column from all the data sets combined.  $\mu_1$  and  $\mu_2$  are the scale parameters to adjust different noise levels contained in different data sets. These values show that the model fits Data Set 1 (1st rank) with the smallest magnitude of the error terms followed by Data Sets 2 (2nd rank) and 3 (3rd rank) in this order. The estimates appeared in the third column take into consideration the difference in scale or the degree of reliability of different ranks.

The estimated alternative specific constants from Data Set 1 show that alternative 2 (all-rail-no-transfer) is most preferable followed by alternatives 3, 1, and 4 in that order. The constants for Data Set 2 have the preference order of alternatives 3, 2, 1, and 4. Thus, for the three alternatives that require a bus-rail transfer, i.e. alternatives 1, 3, and 4, the unique preference order is: 3, 1, and 4. This preference order parallels the decreasing fractions of bus service between the two terminal points. This observation by itself indicates a preference for bus over rail. On the other hand, alternative 2 (all-rail-no-transfer) is strongly preferred to alternatives 1, 3, and 4, which may be construed as a preference for rail. These two observations seem to show contradiction about the preference between rail and bus. In addition, since there is no option of ‘all-bus-no-transfer’, we cannot conclude that people prefer ‘all-rail-no-transfer’ to ‘all-bus-no-transfer’.

The bus and rail dummies defined earlier could elicit the information about ridership attraction for rail versus bus. The estimation results show that both dummies have significant positive coefficients and have approximately the same magnitudes. The positive coefficients indicate users’ dislike of transfers, which supports the first statement postulated earlier. The similar values of the bus and rail dummy coefficients imply that there is no clear preference bias between rail and bus.

As shown earlier, the users’ underlying preference for bus and rail cannot be measured by the alternative specific constants in this analysis. On the other hand, the bus and rail dummy variables were introduced to explicitly capture this preference in the context of the survey. They indicate no preference bias between rail and bus, but a strong aversion to a bus–rail transfer.

#### 4. Conclusions

Two empirical studies have been examined in order to investigate ridership attraction of rail compared with bus. The first empirical work estimates mode choice models using RP data and finds the situations under which rail is preferred to bus. The second empirical work uses SP data which could provide purer information on preference bias.

The analysis of the RP data revealed an overall preference for Metro over other modes, e.g. commuter rail, express bus and local bus, as indicated by the coefficients of the dummy variables for the different transit modes in the mode choice models. However, some situations are identified in which these overall preferences change. For example, the preference for Metro decreases substantially if the trip requires the use of a low frequency Metro line; the preference for express bus service increases when a part of the trip takes place on an HOV lane. For a travel scenario such as ‘CBD trip using Metro low frequency and HOV lane corridor’ people not owning a car prefer express bus service to Metro.

When an express bus uses a highway with an HOV lane

(particularly when it runs to or from the CBD), its attractiveness increases substantially. This is because the relative utility of the car mode decreases under this situation due to traffic congestion and shortage of parking spaces. The same effect of the CBD can be observed for commuter rail.

The SP data analyzed are ranking, or rank-ordered, data in which four alternatives of connections of bus and light rail services are evaluated. Simply comparing alternative specific constants does not provide information on preference bias of light rail and bus services. More specifically, the significantly large constant for the rail through service alternative does not indicate a strong preference for rail but indicates strong dislike of transfers. This was verified by introducing new dummy variables, 'rail' and 'bus', which indicate the mode that the respondent's relevant trip uses. According to the estimated coefficients of these dummies, there is no evidence that the light rail service is preferred to the current bus service.

These results are reinforced by the reviews of 'before and after' studies and previous analyses. Thus, the principal conclusion of this study is that rail and bus services which provide similar service attributes have the same ridership attraction.

This conclusion implies that high performance bus service can well be a substitutive for rail service. As shown in the case studies, high performance subway systems such as the Washington, DC Metro is comparable to express bus service using HOV lanes, and low performance light rail systems such as the Boston Green Line is equally evaluated with regular local bus service.

However, if the transit service requires multiple transfers or is scheduled with low frequency, people are likely to shift to using automobiles and the public transit alternative will fail to attract potential users. Consequently, in order to increase ridership to public transit, the service should be designed to have favorable levels of passenger convenience. Whether it is rail system or bus system should not be of great importance.

The findings of this study imply that there is no justification to the introduction of a rail preference bias in a mode choice model which is employed to analyze alternative transit services including both rail and high quality express bus. A bus service with 'Metro-like' attributes should be analyzed using the same alternative specific constant used for a comparable rail service. However, if the qualitative attributes of the rail and bus services under consideration vary, it is necessary to use more advanced demand estimation techniques that attempt to quantify the effects of these intangible attributes (Morikawa et al., 2002).

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### References

- Bates, J., 1983. Stated preference technique for the analysis of transportation behavior. *Proceedings of the World Conference on Transport Research*. Hamburg, West Germany, pp. 252–265.
- Beggs, S., Cardell, S., Hausman, J., 1981. Assessing the potential demand for electric cars. *Journal of Econometrics* 17, 1–20.
- Ben-Akiva, M., Lerman, S., 1985. *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press, Cambridge, MA.
- Ben-Akiva, M., Morikawa, T., Shiroishi, F., 1992. Analysis of the reliability of preference ranking data. *Journal of Business Research* 24 (2), 149–164.
- Central Transportation Planning Staff (CTPS), (1981a). *An Impact Analyses of the Red Line Extension to Braintree*.
- Central Transportation Planning Staff (CTPS), (1981b). *Evaluation of Needham Express Bus Service and Framingham Commuter Rail Service*.
- Chapman, R.G., Staelin, R., 1982. Exploiting rank ordered choice set data within the stochastic utility model. *Journal of Marketing Research* XIX, 288–301.
- Hausman, J.A., Ruud, P.A., 1987. Specifying and testing econometric models for rank-ordered data. *Journal of Econometrics* 34, 83–104.
- Hensher, D.A., Button, K.J., 2000. *Handbook of Transport Modelling*. Pergamon Press, Oxford.
- Koppelman, F.S., 1983. Predicting transit ridership in response to transit service changes. *Journal of Transportation Engineering* 109 (4), 548–564.
- Louviere, J.J., 1988. *Analyzing Decision Making: Metric Conjoint Analysis*. Sage University Paper Series on Quantitative Applications in the Social Sciences. Sage, Beverly Hills, CA.
- Louviere, J.J., Hensher, D.A., Swait, J., 2001. *Stated Choice Methods: Analysis and Applications in Marketing, Transportation and Environmental Valuation*. Cambridge University Press, Cambridge.
- Luce, R.D., 1959. *Individual Choice Behavior: A Theoretical Analysis*. Wiley, New York.
- Luce, R.D., Suppes, P., 1965. Preference, utility, and subjective probability. In: Luce, R.D., Bush, R.R., Galanter, E. (Eds.), *Handbook of Mathematical Psychology*, vol. 3. Wiley, New York, pp. 249–410.
- Mackett, R., Edwards, M., 1998. The impact of new urban public transport systems: will the expectations be met? *Transportation Research—A* 32 (4), 231–245.
- McFadden, D., 1974. Conditional logit analysis of qualitative choice behavior. In: Zarembka, P. (Ed.), *Frontiers in Econometrics*. Academic Press, New York, pp. 105–142.
- Mitric, S., 1977. Comparing modes in urban transportation. *Transportation Research Record* 639, 19–24.
- Morikawa, T., Ben-Akiva, M., McFadden, D., 2002. Discrete choice models incorporating revealed preferences and psychometric data. *Econometric Models in Marketing* 16, 27–53.
- Vuchic, V.R., 1991. Recognizing the value of rail transit. *TR News* 156, 13–19.
- Vuchic, V.R., Stanger, R.M., 1973. Lindenwold rail line and Shirley busway: a comparison. *Highway Research Record* No. 459, 13–28.