Theoretical and Empirical Researches in Urban Management
Volume 6 Issue 2 / May 2011

CALIBRATING THE INTERCITY HIGH SPEED RAIL (HSR) CHOICE MODEL FOR THE RICHMOND-WASHINGTON, D.C. CORRIDOR

Xueming CHEN
Virginia Commonwealth University, 923 West Franklin Street, Richmond, VA 23284, United States of America, xchen2@vcu.edu

Abstract
This study aims to quantitatively investigate how the introduction of high-speed rail (HSR) influences traveler's choice behavior. The study focuses on recalibrating the Florida-based HSR choice model to fit the intercity travel northward from Richmond, Virginia to Washington, D.C. The model takes a nested logit formulation and includes a binary marginal choice submodel to project travel behavior between aggregate ground and individual air transportation modes, and a trinomial conditional mode choice model to examine the travel behavior patterns within three ground transportation submodes: auto, bus, and rail. The data collected is based upon the base year 2008 market conditions, and the recalibrated model is used to forecast the year 2014 HSR levels of service. Empirical results show that reduced travel cost and other impedance factors stand to increase utility for HSR, even though the auto will continue to be the dominant travel mode.
Keywords: high speed rail, nested logit model, mode choice, Richmond, Washington, D.C.

1. INTRODUCTION

Plans for the Southeast High Speed Rail (SEHSR) Corridor are being developed for the cities extending from Jacksonville, Florida to Washington, D.C. In the Commonwealth of Virginia, intercity rail enhancements are viewed as an important strategy to improve level of service and intercity travels to cities located between 100 and 500 miles apart. Potential for increased demand for high-speed rail (HSR) is especially high in the northern portion of the Commonwealth where major development and economic activities attract travelers from Richmond (the capital city of Virginia), which is about two hours away by conventional ground travel. In a region well known for high dependence on automobile and daily congestion, investment in HSR will provide an alternate travel mode for many travelers while simultaneously reducing the number of automobiles.

As the Commonwealth's No. 1 priority high-performance intercity rail corridor improvement project (Virginia High Speed Rail Development Committee, 2001), the HSR development in Northern Virginia is expected to substantially lower travel times between Richmond and Washington, D.C. At full build-out, the HSR may reduce overall travel times by more than one hour over conventional modes of travel. The reduced travel times and convenient access would attract choice-riders, address highway congestion, and make daily commutes more realistic. At this time, the Virginia Department of Rail and Public Transportation (VDRPT) just completed the Tier II Environmental Impact Statement required by the National Environmental Policy Act (NEPA) of 1969. New efforts are underway to identify capital projects and begin constructing portions of the HSR network.

Figure 1 shows the proposed HSR link planned from Richmond to Washington D.C., extending about 115 miles (184 km) from the Amtrak Staples Mill Station in Richmond to the Amtrak Union Station in Washington, D.C. This link is one of the four designated rail links serving commuters between Richmond and Washington, D.C. with urban center stations in Ashland, Fredericksburg, Woodbridge, and Alexandria in between.

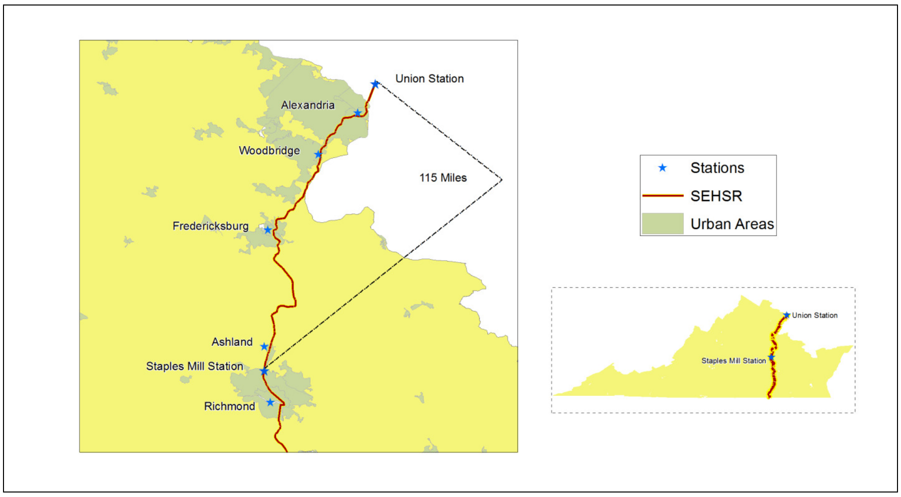

FIGURE 1 HIGH SPEED RAIL LINKS TO WASHINGTON, D.C. IN VIRGINIA

The demand for high-speed rail is perhaps greatest north of Fredericksburg where extensive highway congestion along I-95 has severely impacted daily commutes. Several reasons contributing to corridor congestion include: regional economic growth, uninterrupted suburban sprawl, and intensive intercity linkages. At the same time, capacity enhancement projects, such as construction of I-295, I-395, and I-495 beltways, have not dramatically improved traffic flowing conditions. According to VDRPT (unspecified date), improvements in the rail corridor could permit increased speeds for the corridor passenger trains, resulting in shorter train travel times, which might convince more car drivers to become train passengers.

Air travelers also demand HSR for distances greater than 100 miles (161 km) but less than 500 miles (805 km). The often-cited disadvantages with air travel are high air fare cost, check-in delays, and long access/egress times to/from airport terminals lying outside urban areas. Amtrak (2009) confirms these patterns reporting evidence of shifting mode choice behavior. Amtrak's market share for distances

Theoretical and Empirical Researches in Urban Management
Volume 6 Issue 2 / May 2011

between 100 and 500 miles has exceeded 50 percent that of air for travel routes north of Washington, D.C., including the air trips to intermediate cities.

Evidence of increased demand for rail also exists in the Richmond area. For example, during Fiscal Year 2009, the Richmond - Staples Mill station had a total boarding and alighting amounting to 256,006, which ranked No.1 in Virginia (25% of total Virginia Amtrak station usage) (Source: http://www.amtrak.com/pdf/factsheets/VIRGINIA09.pdf).

Given the fact that HSR is destined to be more and more important in the Richmond-Washington, D.C. Corridor, it is necessary and timely to conduct a preliminary choice model-based quantitative analysis on the future prospect of HSR modal share and ridership. This study will assist decision makers with promotion of the HSR in Virginia and help achieve the following three planning objectives: evaluate changes in intercity modal options over a future period; demonstrate how improvements in level of service influence mode choice; and provide a model for high-speed rail analysis to state/regional rail and public transportation agencies. Even though this study still lacks a full-blown and new intercity travel behavioral survey, the paper documents the experience and lessons learned in transferring and recalibrating the Florida HSR Choice Model to Virginia based on the limited data collected.

Following this introductory Section 1, Section 2 provides a literature review on the choice models, in particular, the logit models. Section 3 presents a nested logit formulation containing a trinomial conditional choice model and a binary marginal choice model, which will be recalibrated against the existing observed market data in the corridor. Section 4 forecasts HSR ridership based on future year assumptions with different HSR service levels assumed. Finally, Section 5 summarizes research findings and draws conclusions.

2. LITERATURE REVIEW

2.1. Choice Modeling Development

Choice modeling is based on the random utility theory, which assumes that the decisions maker's preference for a discrete alternative is captured by a value called a utility, and his/her choice is reflected in the choice set with the highest utility, or the lowest disutility. Choice modeling has many functional forms, the most common of which is the set of logit models.

The multinomial logit model is mathematically simple and widely used, but imposes the restriction that the distribution of the random error terms is independent and identical over the alternatives, causing the cross-elasticities between all pairs of alternatives to be identical, which can produce biased estimates. Furthermore, outcomes that could theoretically violate the Independence of Irrelevant Alternatives (IIA) property may make multinomial logit model unrealistic and invalid (McFadden, 1973; Ben-Akiva and Bierlaire, 2003).

The IIA property can be relaxed by specifying a hierarchical model, ranking the choice alternatives. The most popular approach of doing this is called the nested logit model. The nested logit model allows the error terms of pairs or groups of alternatives to be correlated, but the remaining restrictions on the equality of cross-elasticities may still be unrealistic (Williams, 1977).

Other logit models, which allow different cross-elasticities between pairs of alternatives, include: the paired combinatorial logit model, the cross-nested logit model, the generalized extreme value model, and the product differentiation model.

The paired combinatorial logit model allocates some alternatives in equal proportions, and allocates other alternatives and estimates dissimilarity for each nest. In this way, it captures the similarity of all possible pairs of alternatives. The random utilities of each alternative have identical variance (Chu, 1989).

The cross-nested logit model, which is derived from the generalized extreme value class, can be thought of as a generalization of the nested logit model. This model calculates the cross similarities between different pure and combined modes. The cross-nested structure allows for the introduction of the differentiated measurement of pairwise similarities among modes as opposed to the inflexible groupwise similarities permitted by the nested logit model (Vovsha, 1997).

The generalized extreme value (GEV) model has been derived from the random utility model by McFadden (1978). This general model consists of a large family of models that include the multinomial logit, the nested logit and the cross-nested logit models. The GEV model allows cross-elasticities between pairs of alternatives.

Product differentiation model allocates alternatives to nests based on pre-selected dimensions with parameters constrained equally across each choice dimension. Alternatives contained in this model are neither ordered nor categorized along dimensions (Bresnahan et al., 1997).

2.2. Choice Modeling Applications in High-Speed Rail Analysis

When modeling HSR, many professionals use multiple ways to forecast mode choice, such as choice hierarchy model, diversion model, logit model, and others (Roth, 1998).

Since the beginning of 1980s, there were different forms of disaggregate mode choice models developed for forecasting HSR ridership in the U.S. For example, Grayson (1981) employed multinomial

Theoretical and Empirical Researches in Urban Management
Volume 6 Issue 2 / May 2011

logit models. Cohen et al. (1978), Brand et al. (1992), KPMG Peat Marwick et al. (1993), Chu and Chen (1995), and Charles River Associates (2000) formulated mode choice as separate binary diversion models, in which percentages of auto, air, and bus passengers are diverted to HSR via binary models. Other transportation modelers relied on the use of nested logit models for intercity mode choice (TMS/Benesch High Speed Rail Consultants, 1991; Forinash and Koppelman, 1993). In the 1990s, Bhat (1995, 1997, 1998) experimented with different nested logit model formulations, which were widely cited.

Wen and Koppelman's 2001 generalized nested logit (GNL) study of rail ridership is perhaps the most comprehensive overview of the nested logit models. They first reassembled the data used from an earlier study (KPMG Peat Marwick and Koppelman, 1993) of the Toronto-Montreal Corridor to compare the effectiveness of a variety of logit model formulations. After that, they proposed a GNL model with a form of the general extreme value model. The model accommodates differential cross-elasticities of pairs and allocates fractions of each alternative to a set of nests that have a distinct logsum or dissimilarity parameter. Wen and Koppelman concluded that model outcomes varied and modal forecasts and investment decisions could be impacted by model selection and interpretation. They further reasoned that attribute parameters in the utility function influence the magnitude and complexity of the model structure (Wen and Koppelman, 2001).

The California High Speed Rail Authority (CHSRA) and the Metropolitan Transportation Commission (MTC) have developed a new HSR statewide model, which recognizes the unique characteristics of intraregional travel demand and interregional travel demand. Interregional travel models capture behavior important to longer distance travel, whereas intraregional travel models rely on local highway and transit characteristics and behavior associated with shorter distance trips (Outwater et al., 2010).

More recently, Li and Liu (2010) proposed a nested logit/continuous choice model to improve the demand forecast in the context of intercity travel. In addition to incorporating the interrelationship between trip generation and mode choice decisions, the simultaneous model also provided a platform for the same utility function flowing between both decision making processes. Using American Travel Survey (ATS) data supplemented by various mode parameters, the proposed model is proved to improve the forecast accuracy and confirm the significant impact of travel cost on both mode choice and trip generation.

Internationally, Hensher (1997) used a more flexible heteroskedastic extreme value 'logit' mode choice model, which relaxes the constant variance (CV) assumption of the multinomial logit model, to forecast the demand for high-speed rail service between Sydney and Canberra.

3. MODEL STRUCTURE

The original Florida HSR Choice Model, which will be transferred to the Richmond-Washington, D.C. Corridor, is a two-stage choice model:

- The first stage is a nonlinear exponential function used to estimate the total intercity travel demand, which extrapolates the existing year travel demand to the future year travel demand based on population, employment growth and intercity impedance factors. In this empirical study, the existing and future year travel demand estimates have been obtained through a professional survey of local transportation stakeholders, therefore the first stage model is not used in this paper;
- The second stage is a nested logit function used to estimate the market share among modal options: air, auto, bus, and rail (Chu and Chen, 1995; ICF Kaiser Engineers, 1993; KPMG Peat Marwick et al., 1993). The second stage nested logit model set contains a binary marginal mode choice model (composite ground transportation mode and air mode) and a trinomial conditional mode choice model (automobile, bus, and rail submodes within the ground transportation mode). For the convenience of presenting modeling equations, the trinomial conditional mode choice model is presented first.

3.1. Trinomial Conditional Mode Choice Model

The trinomial conditional mode choice model takes the following form:

$$P_{m \mid grd} = \frac{e^{V_m}}{e^{I_{grd}}}$$

The value $P_{m|grd}$ represents the probability of selecting ground mode *m* given that the composite ground (*grd*) transportation mode is selected. V_m is a linear utility function of parameters (a_m, b_m, c_m, d_m, e_m, f_m) and attributes (X_{lm}, X_{2m}, X_{3m}, X_{4m}, X_{5m}) describing ground mode *m*:

$$V_m = a_m + b_m X_{lm} + c_m X_{2m} + d_m X_{3m} + e_m X_{4m} + f_m X_{5m}$$

The five attributes in the utility function V_m are:

X_{1m} = Median Annual Income ($);

X_{2m} = Daily Frequency (number of departure trips);

X_{3m} = Total One-Way Cost ($);

X_{4m} = Total Time (minutes); and

X_{5m} = Access Time/Distance (minutes/mile).

Theoretical and Empirical Researches in Urban Management
Volume 6 Issue 2 / May 2011

In a typical mode choice model, generalized costs (travel time and cost) are the commonly used variables (Michael Baker Jr., Inc., 2004). Some more sophisticated mode choice models also include household income levels, which impact their modal sensitivities (Southern California Association of Governments, 2008). In the above V_m equation, X_{1m} variable directly affects the propensity to use high-cost transportation mode, such as air transportation. Bhat (1997) also concurred that the air mode is less accessible as an alternative mode to low income ground-mode users than high income ground-mode users. X_{2m} variable is positively related to the utility level of a public transportation mode. X_{3m}, X_{4m}, and X_{5m} variables are all negatively related to the utility levels of all transportation modes.

The composite impedance for the three ground transportation modes is I_{grd}, computed as the natural log of the sum of the exponential utility functions (V) for auto, bus and rail.

$$I_{grd} = \ln(e^{V_{auto}} + e^{V_{bus}} + e^{V_{rail}})$$

Table 1 shows the existing parameters in utility functions that were originally applied in the Florida HSR Model. KPMG Peat Marwick et al. derived these parameters based on their 1993 travel surveys conducted for the Tampa-Orlando HSR Corridor in Florida. For air mode, household income level and daily frequency make air mode more attractive. Relative access time carries a much higher penalty than total travel time and cost. For auto mode, which is a readily available private transportation mode, only travel time and cost are considered. Compared to air mode, bus and rail are much cheaper. Therefore, bus and rail modal shares are relatively insensitive to income level. Therefore, household income variable is left out from bus and rail modes. All other travel time and cost variables have the same parameters as those of air and auto modes.

TABLE 1 - EXISTING PARAMETERS IN UTILITY FUNCTIONS

Parameters	Travel Modes (m)			
	Air	Auto	Bus	Rail
a	-12.6	N/A	-4.84	-4.84
b	0.007	N/A	N/A	N/A
c	0.1881	N/A	0.1881	0.1881
d	-0.021	-0.021	-0.021	-0.021
e	-0.021	-0.021	-0.021	-0.021
f	-2.08	-2.08	-2.08	-2.08

3.2. Binary Marginal Mode Choice Model

The binary marginal mode choice model is a logit model as follows:

$$P_{air} = \frac{e^{0.47 \cdot I_{air}}}{e^{0.47 \cdot I_{air}} + e^{0.60 \cdot I_{grd}}}$$

$$P_{grd} = \frac{e^{0.60 \cdot I_{grd}}}{e^{0.47 \cdot I_{air}} + e^{0.60 \cdot I_{grd}}}$$

The parameters in the above model directly come from the Florida HSR model (KPMG Peat Marwick et al., 1993), which were recalibrated based on local travel survey data. The discrete probability of choosing an air or ground mode of travel is calculated using the above equations. In this case, $I_{air} = V_{air}$, representing the only air travel service available in the study area. The probability of choosing a ground mode of travel is shown as P_{grd}, which is the product of each ground transportation submode's conditional choice and the ground transportation mode's marginal choice. Conditional choice and marginal choice of each component of ground transportation take the following forms:

$$P_{auto} = P_{auto|grd} \cdot P_{grd}$$

$$P_{bus} = P_{bus|grd} \cdot P_{grd}$$

$$P_{rail} = P_{rail|grd} \cdot P_{grd}$$

3.3. Existing Year Input Assumptions

Data inputs for the two-stage choice model are based on real world conditions and data available to represent each mode share. Existing year attribute assumptions (2008) are aligned with the initial attribute parameters, based on the discrepancy between real world data and initial model data, the choice model has been recalibrated. Since this is the intercity travel mode split analysis rather than station-specific ridership analysis, only two terminal cities (Richmond and Washington, D.C.) are examined. The Virginia Commonwealth University represents the geographic location of Richmond, and the Amtrak Union Station in Washington represents that of Washington, D.C. This is a very limited case study, without regards to detailed transportation networks and traffic analysis zones commonly found in the four-step urban transportation modeling system.

1) Air Mode Attributes

The United Airlines has four flights from Richmond to Washington, D.C. each day. The average daily ridership for this service is 214 passengers. The existing year air mode attributes are represented in Table 2. Trip frequency, fare, and travel time are estimated using United Reservations (Source: http://travel.united.com/ube). Cost of operating and owning a car is estimated to be $0.43 per mile and average vehicle occupancy is 1.1 (Source: http://www.vtpi.org/tca/tca00.pdf).

Theoretical and Empirical Researches in Urban Management
Volume 6 Issue 2 / May 2011

TABLE 2 - EXISTING YEAR AIR MODE ATTRIBUTES

Attribute	Data	Notes
X_1	$38,385	Inflation-adjusted median household income based on 2008 American Community Survey for Richmond City (http://factfinder.census.gov).
X_2	4	Richmond International Airport (2010) (RIC) Master Plan (www.flyrichmond.com/Load.php?Content=Master_Plan).
X_3	$576.30	Driving to RIC = $4.30; RIC Daily Parking = $12; air fare RIC-IAD = $500; taxi fare IAD-Union Station = $60. X_3 = $4.30 + $12 + $500 + $60 = $576.3.
X_4	125 min	Flight time = 60 min; ground access time = 65 min. Sum = 125 min.
X_5	1.7 min/mile	Access time/distance: to RIC (auto) = 20 min/10 mile; IAD-D.C. (taxi): 45 min/28 mile. X_5 = 65 min/38 mile = 1.7 min/mile.

Note: IAD = Washington Dulles International Airport; Union Station = Amtrak Union Station in Washington, D.C.

2) Auto Mode Attributes

Average Annual Daily Traffic (AADT) estimates come from 2006 Virginia Department of Transportation (VDOT) Daily Traffic Volume Estimates - Fredericksburg Special Locality Report (chosen for its midway location between Richmond and Washington, D.C.; only I-95 North is used to represent the one-way northbound travel).

On the average, there are 59,000 vehicles that make daily trips from Richmond to Washington, D.C., including through trips. Assuming vehicle occupancy is 1.1 persons/vehicle, then there are 64,900 person trips daily. The existing year auto mode attributes are shown in Table 3. Auto mode has three modeling parameters (d, e, f) represented by attribute values X_3, X_4 and X_5. Respectively, the travel cost for a one way trip is $66.30, the total travel time averages 120 minutes, and access time is ignored.

TABLE 3 - EXISTING YEAR AUTO MODE ATTRIBUTES

Attribute	Data	Notes
X_3	$66.30	Driving to D.C.: $47.30; D.C. Parking: $19. X_3 = $47.30 + $19 = $66.30.
X_4	120 min	Normally 2 hours to drive from Richmond to Washington, D.C.
X_5	0 min/mile	Driving a private auto does not take access time.

Note: The driving distance from Richmond to Washington, D.C. is assumed to be 110 miles. Auto operating and owning cost = $0.43/mile.

3) Bus Mode Attributes

According to Greyhound (2009) estimates, on the average, about 385 passengers ride the bus to Washington, D.C. each day. The existing year bus mode attributes are shown in Table 4. Bus mode has modeling parameters (b, c, d, e) represented by attributes X_2-X_5. Respectively, the daily frequency of departures from Richmond is 11 times/day, the total travel cost for a one-way ticket is $25.76, the total travel time is 146 minutes, and access time is 1.7 minutes.

TABLE 4 - EXISTING YEAR BUS MODE ATTRIBUTES

Attribute	Data	Notes
X2	11	Greyhound terminal operator cited 11 bus trips to D.C. every day.
X3	$25.76	Driving to Greyhound Station: $1.51; Bus Fare: $24.25. X3 = $1.51 + $24.25 = $25.76.
X4	146 min	146 minutes (140 minute bus time + 6 minute access time).
X5	1.7 min/mile	To Greyhound Station: 6 minutes/3.5 miles = 1.7 minutes/mile.

4) Rail Mode Attributes

According to the estimates of Virginia Department of Rail and Public Transportation (VDRPT), approximately 396 passengers go from Richmond to Washington, D.C. by rail daily.

The existing year rail mode attributes are depicted in Table 5. Rail mode consists of parameters (b, c, d, e) represented by attributes X_2-X_5. Respectively, there are seven departures from Richmond, the cost one-way is $32.01, the total commute time is 160 minutes, and typical access time is 1.4 minutes per mile.

TABLE 5 - EXISTING YEAR RAIL MODE ATTRIBUTES

Attribute	Data	Notes
X2	7	Amtrak has 7 daily train departures to D.C.
X3	$32.01	Driving to Amtrak Staples Mill Road Station: $3.01; Train Fare: $29. X3 = $3.01 + $29 = $32.01.
X4	160 min	160 min (150 min train time + 10 min access time).
X5	1.4 min/mile	Richmond-Staples Mill Road Station (auto): 10 minutes/7miles = 1.4 minutes/mile.

5) Combined Person Trips

Combining the total one-way person trips for all travel modes, there is an average of 65,895 person trips per day from Richmond to Washington, D.C.

3.4. Existing Year Model Results

The purpose of this recalibration is to carry out checks to align the existing year model results with observed data prior to forecasting a future situation.

The first iteration calculates the existing year utility (disutility) value for air, auto, bus, and rail modes using the existing parameter assumptions described in Table 1. Table 6 shows the initial utility values for different modes.

Directly derived from Table 7, Table 8 compares real world data with initial model data. It clearly indicates that the existing Florida HSR model would generate very erroneous results for the Richmond-Washington, D.C. Corridor. The existing model parameters must be recalibrated in order to be valid.

Theoretical and Empirical Researches in Urban Management
Volume 6 Issue 2 / May 2011

TABLE 6 - INITIAL UTILITY VALUES FOR AIR, AUTO, BUS, AND RAIL MODES

Mode Utility	a	b	X_1	c	X_2	d	X_3	e	X_4	f	X_5	Value
V_{air}	-12.6	0.007	38,385	0.1881	4	-0.021	576.30	-0.021	125	-2.08	1.7	238.58
V_{auto}	-	-	-	-	-	-0.021	66.30	-0.021	120	-2.08	0.0	-3.91
V_{bus}	-4.84	-	-	0.1881	11	-0.021	25.76	-0.021	146	-2.08	1.7	-9.91
V_{rail}	-4.84	-	-	0.1881	7	-0.021	32.01	-0.021	160	-2.08	1.4	-10.47

Table 7 shows the initial results of mode choice model calculation.

TABLE 7 - INITIAL RESULTS OF MODE CHOICE MODEL CALCULATION

NOTES	VARIABLE NAMES	VALUES
IMPEDANCE FUNCTIONS FOR AIR AND COMPOSITE GROUND	L_{AIR}	238.58
	L_{GRD}	-3.91
MARKET SHARES FOR AIR AND GROUND TRANSPORTATION	P_{AIR}	1.000
	P_{GRD}	0.000
CONDITIONAL MODE CHOICE	$P_{AUTO\|GRD}$	0.996
	$P_{BUS\|GRD}$	0.002
	$P_{RAIL\|GRD}$	0.001
GROUND TRANSPORTATION MARKET SHARES	P_{AUTO}	0.0000
	P_{BUS}	0.0000
	P_{RAIL}	0.0000

TABLE 8 - MODE CHOICE MODAL TRAVEL COMPARISON

Mode	Real World Data (a)	Initial Model Data (b)	% Error (c) = (b)/(a) - 1
Air	214	65,895	30,692%
Auto	64,900	0	-100%
Bus	385	0	-100%
Rail	396	0	-100%

3.5. Model Recalibration

It is determined the original Florida HSR model is overly sensitive to the median household income parameter for air travel. As a result, air travel parameter is recalibrated first.

Trial and error to align the air mode with current real world data yields 0.000336 for parameter *b* for variable "Median Annual Income." It is noted that parameter *b* drops dramatically from 0.007 to 0.000336. The original parameter *b* of 0.007 would make the model overly sensitive to income level and thus greatly overestimate the air travel demand between Richmond and Washington, D.C. These two places (110 miles apart) are too close to fly. After determining the new parameter *b*, the bias constant *a* is adjusted for air, bus and rail to offset discrepancies in modal shares. Table 9 shows the revised parameters. Leaving most parameters unchanged, the readjusted parameters are bolded. The most significant change is parameter *b*.

TABLE 9 - REVISED PARAMETERS IN UTILITY FUNCTIONS

Mode Utility	a	b	X_1	c	X_2	d	X_3	e	X_4	f	X_5	Value
V_{air}	**-12.55**	**0.000336**	38,385	0.1881	4	-0.021	576.3	-0.021	125	-2.08	1.7	-17.16
V_{auto}	-	-	-	-	-	-0.021	66.3	-0.021	120	-2.08	0.0	-3.91
V_{bus}	**-3.97**	-	-	0.1881	11	-0.021	25.76	-0.021	146	-2.08	1.7	-9.04
V_{rail}	**-3.38**	-	-	0.1881	7	-0.021	32.01	-0.021	160	-2.08	1.4	-9.01

Table 10 shows the revised results of mode choice model calculation.

TABLE 10 - REVISED RESULTS OF MODE CHOICE MODEL CALCULATION

NOTES	VARIABLE NAMES	VALUES
IMPEDANCE FUNCTIONS FOR AIR AND COMPOSITE GROUND	L_{AIR}	-17.16
	L_{GRD}	-3.90
MARKET SHARES FOR AIR AND GROUND TRANSPORTATION	P_{AIR}	0.003
	P_{GRD}	0.997
CONDITIONAL MODE CHOICE	$P_{AUTO\|GRD}$	0.988
	$P_{BUS\|GRD}$	0.006
	$P_{RAIL\|GRD}$	0.006
GROUND TRANSPORTATION MARKET SHARES	P_{AUTO}	0.9849
	P_{BUS}	0.0058
	P_{RAIL}	0.0060

Table 11 shows the final calculated results. The parameter adjustment has totally eliminated marginal errors and matched the revised model data with real world data perfectly.

TABLE 11 RECALIBRATED MODE CHOICE MODAL TRAVEL COMPARISON

MODE	REAL WORLD DATA	REVISED MODEL DATA	% ERROR
AIR	214	214	0%
AUTO	64,900	64,900	0%
BUS	385	383	0%
RAIL	396	398	0%

4. MODEL FORECAST

4.1. Future Year Input Assumptions

1) Air Mode Attributes

Table 12 shows the future year air mode attributes.

TABLE 12 - FUTURE YEAR AIR MODE ATTRIBUTES

Attribute	Data	Notes
X_1	$45,000	The future median annual income is estimated based on an assumed 3% Consumer Price Index annual growth rate.
X_2	4	The future frequency of flights is assumed to be the same as present.
X_3	$672.30	Gasoline price is assumed to go up $0.50/gallon per year ($5.30/gallon in 2014), which will add $0.10 per mile to auto operating and owning cost and approximately $5 to take taxi. Therefore, driving to RIC: $5.30; RIC Daily Parking: $12; Air Fare from Richmond to Washington, D.C.: $590; Taxi Fare from the Washington Dulles International Airport (IAD) to the Washington Union Station: $65. X_3 = $5.30 + $12 + $590 + $65 = $672.30.
X_4	125 min	Assume 60 minutes of flight time and 65 minutes of ground access time.
X_5	1.7 min/mile	VCU-RIC (auto): 20 minutes/10 miles; IAD-D.C. (taxi): 45 minutes/28 miles. Access Time/Distance = 65 minutes/38 miles = 1.7 minutes/mile.

Note: Future year auto operating and owning cost = $0.53/mile.

2) Auto Mode Attributes

Since auto mode has three modeling parameters (d, e, f), only X_3, X_4 and X_5 data are collected, as shown in Table 13.

TABLE 13 - FUTURE YEAR AUTO MODE ATTRIBUTES

Attribute	Data	Notes
X_3	$77.30	Driving to D.C.: $58.30; D.C. Parking: $19. $58.30 + $19 = $77.30.
X_4	120 mi	It normally takes 2 hours to drive from Richmond to Washington, D.C.
X_5	0 min/mile	Driving a private auto does not take access time.

Note: Future year auto operating and owning cost = $0.53/mile.

3) Bus Mode Attributes

The future year bus mode has the following attributes, as shown in Table 14.

TABLE 14 - FUTURE YEAR BUS MODE ATTRIBUTES

Attribute	Data	Notes
X2	11	The Greyhound will continue having 11 bus trips to D.C. every day.
X3	$26.11	Driving to Greyhound Station: $1.86; Bus Fare: $24.25. $1.86 + $24.25 = $26.11.
X4	146 min	146 minutes (140 minute bus time + 6 minute access time).
X5	1.7 min/mile	Richmond-Greyhound Station: 6 minutes/3.5 miles = 1.7 minutes/mile.

4) Rail Mode Attributes

Speed is an important variable for model prediction. The Federal Railroad Administration (FRA)'s (2009) guidelines for high speed level of service set 90 – 110 miles per hour or mph (145 – 177 km/h) for distances between 100-500 miles (161 – 805 km). Based on the FRA guidelines, three levels of service

(LOS) scenarios are assumed in this paper: Level 1: 90 mph operating speed; Level 2: 100 mph operating speed; and Level 3: 110 mph operating speed.

Table 15 shows the rail mode attributes under these assumptions. Daily frequency (X_2) remains constant at 20, due to the assumption that all HSR scenarios will operate 20 trains per day. Total one-way travel cost (X_3) varies based on train fare. The price of a conventional train ticket for the base year 2008 was $0.26/mile. Considering the enormous amount of capital needed to upgrade the rail network to facilitate HSR, the new ticket price for HSR Level 1 service is estimated at $0.78/mile. For the purposes of this model, this price serves as an example of balancing construction and increased operating costs over increased ridership due to upgrades in level of service. X_3 equals driving cost to Staples Mill Station plus train fare to Washington, D.C. In addition, each upgrade in level of service (from LOS Level 1 to LOS Level 2, and LOS Level 2 to LOS Level 3) then incurs an additional $5 (Scenario #1) or $10 (Scenario #2) in ticket price. Total one-way travel time (X_4) simply depends on the speed-distance calculation for each of the operating speeds, with a constant 10-minute access time assumed for every scenario. Access time/distance (X_5) is assumed to remain constant.

TABLE 15 - FUTURE YEAR RAIL MODE ATTRIBUTES

Attribute	LOS Level 1	LOS Level 2		LOS Level 3	
		Scenario #1	Scenario #2	Scenario #1	Scenario #2
X_2	20	20	20	20	20
X_3	$89.51	$94.51	$99.51	$99.51	$109.51
X_4	84 min	76 min	76 min	70 min	70 min
X_5	1.4 min/mile	1.4 min/mile	1.4 min/mile	1.4 min/mile	1.4 min/mile

5) Combined Person Trips

Based on the professional forecasts made by local transportation stakeholders, the future year (2014) combined person trips will be around 81,947 trips from Richmond to Washington, D.C.

4.2. Future Year Model Results

The above future year input assumptions and the recalibrated parameters shown in Table 9 are applied to the HSR Mode Choice Model, which yields the following model results. In Tables 16 and 17, base year (2008) model data are shown as benchmarks against which the future year (2014) model data are compared. In Figures 2 and 3, air and bus curves are overlaid and visually indistinguishable due to their negligible and fractional modal shares.

Theoretical and Empirical Researches in Urban Management
Volume 6 Issue 2 / May 2011

Theoretical and Empirical Researches in Urban Management
Volume 6 Issue 2 / May 2011

Scenario #1: Each upgrade in HSR level of service incurs an additional $5 in ticket price.

As shown in Table 16 and Figure 2, under this scenario, air and bus modal shares will remain less than 1%, playing a very insignificant role in local transportation market. Due to the short distance between the two cities, air mode understandably does not have a comparative speed advantage over HSR mode. Bus is not competing against rail, either.

However, with a steady increase of HSR modal share, auto modal share is expected to be diminishing accordingly. Therefore, HSR will potentially relieve traffic congestion along this important corridor, even though auto mode remains dominant.

TABLE 16 - FUTURE YEAR MODEL FORECAST RESULTS / (SCENARIO #1)

MODE	BASE YEAR (2008)		HSR LEVEL 1 (2014)		HSR LEVEL 2 (2014)		HSR LEVEL 3 (2014)	
	DAILY TRIPS	% TOTAL	DAILY TRIPS	% TOTAL	DAILY TRIPS	% TOTAL	DAILY TRIPS	% TOTAL
AIR	214	0.32%	314	0.38%	312	0.38%	312	0.38%
AUTO	64,900	98.49%	71,692	87.49%	71,159	86.84%	70,976	86.61%
BUS	383	0.58%	530	0.65%	526	0.64%	524	0.64%
RAIL	398	0.60%	9,412	11.49%	9,949	12.14%	10,134	12.37%
TOTAL	65895	100.00%	81,947	100.00%	81,947	100.00%	81,947	100.00%

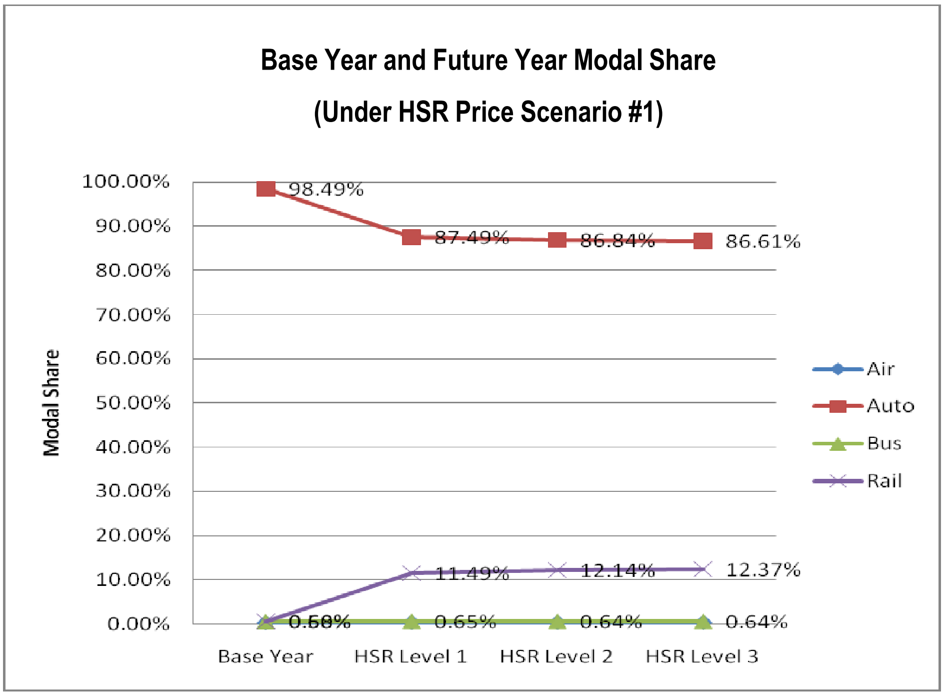

FIGURE 2 - COMPARISON OF MODEL FORECAST RESULTS UNDER SCENARIO #1

Scenario #2: Each upgrade in level of service incurs an additional $10 in ticket price.

As shown in Table 17 and Figure 3, overall, the model results under Scenario #2 are similar to those under Scenario #1. However, it is worth noting that HSR ridership actually steadily decreases with every speed upgrade. This suggests that the positive ridership effects of speed upgrade (10 mph increase from one level to another level) are more than offset by the negative ridership effects of ticket price increase ($10 more from one level to another level). Therefore, Scenario #1 seems to be more reasonable than Scenario #2 in terms of boosting HSR ridership.

TABLE 17 - FUTURE YEAR MODEL FORECAST RESULTS / (SCENARIO #2)

MODE	BASE YEAR (2008)		HSR LEVEL 1 (2014)		HSR LEVEL 2 (2014)		HSR LEVEL 3 (2014)	
	DAILY TRIPS	% TOTAL	DAILY TRIPS	% TOTAL	DAILY TRIPS	% TOTAL	DAILY TRIPS	% TOTAL
AIR	214	0.32%	314	0.38%	315	0.38%	316	0.39%
AUTO	64,900	98.49%	71,692	87.49%	72,032	87.90%	72,681	88.69%
BUS	383	0.58%	530	0.65%	532	0.65%	537	0.66%
RAIL	398	0.60%	9,412	11.49%	9,068	11.07%	8,412	10.27%
TOTAL	65895	100.00%	81947	100.00%	81947	100.00%	81947	100.00%

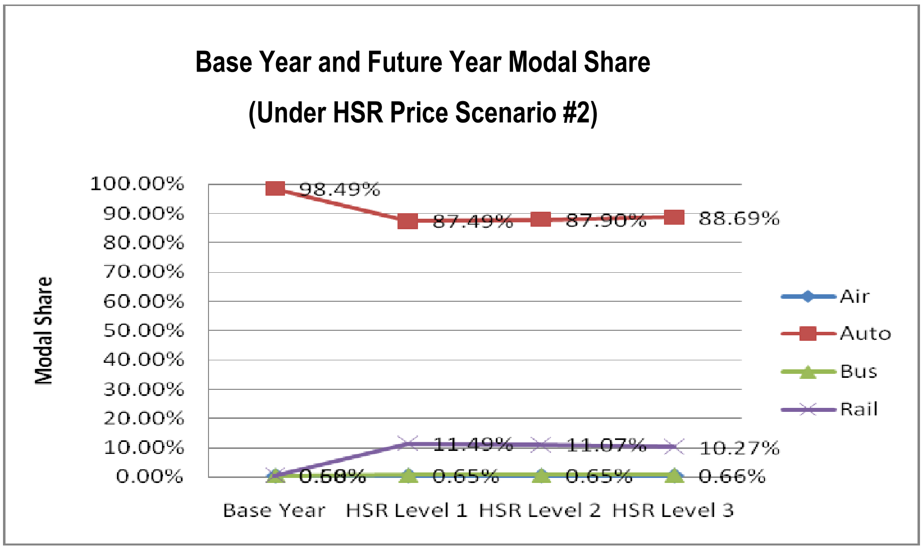

FIGURE 3 - COMPARISON OF MODEL FORECAST RESULTS UNDER SCENARIO #2

5. CONCLUSIONS

This paper documents the recalibration process of the Florida Intercity High-Speed Rail (HSR) Choice Model against the 2008 base year input assumptions of the Richmond-Washington, D.C. Corridor in Virginia and presents some preliminary model results for the year 2014.

Through this empirical study, it is found that:

1) The HSR Choice Model can be transferred from one place to another after properly readjusting its key and most sensitive parameters. In this study, the parameter for median household income, found to be most sensitive to air mode, is readjusted to fit the Virginian circumstance.

In addition, bias constants for air, bus and rail are recalibrated to fine-tune the initial model results. Through this recalibration process, the revised base year model results match the observed survey outcomes perfectly.

2) The behavior choice for HSR is forecast to increase substantially from conventional rail to high-speed rail due to its significant speed increase. HSR can potentially improve modal structures by shifting some auto users to train users, even though auto will remain as the dominant mode in the years to come.

3) There is a trade-off between HSR ridership and its price level. If the HSR price level is set too high, it will negatively impact its ridership. This case study indicates that the price upgrade of \$5/10 mph speed increase seems to be more reasonable than that of \$10/10 mph speed increase in terms of boosting ridership.

4) Mode choice is highly dependent on speed increases and time savings. An inference suggests that more attention should be given to infrastructure development for increasing levels of service to meet future demand.

It is recognized that, due to data scarcity and time constraints, this study still has limitations. First of all, this is more the HSR choice model than the actual ridership forecast model. Because of that, it cannot predict station-specific boardings and alightings along the corridor. Second, there is no inherent feedback mechanism built into the model. It can only show diverted trips from auto to HSR, but not induced trips affecting total travel demand. If more detailed data could be collected, the model would have been more refined to optimize its nesting structures with new variables and parameters to be incorporated or recalibrated. A full-blown new travel survey is needed in order to derive the behavior-based HSR model for this corridor in the future.

Acknowledgments

This author would like to thank the following individuals for their help and supports during the preparation process of this paper: Dr. Chaushie Chu of Los Angeles County Metropolitan Transportation Authority for his technical guidance and initial comments; Mr. Irving Heath Henshaw and Mr. Wallace Myers of Virginia Commonwealth University for their data collection and graphics help; and Dr. Asad Khattak and Dr. Xin Wang of Old Dominion University for their helpful comments. The potential remaining errors of this paper are mine.

REFERENCES

Amtrak. (2009). *Amtrak National Facts*. Retrieved July 20, 2010 from: www.amtrak.com/servlet/ContentServer?c=Page&pagename=am%2FLayout&cid=1246041980246.

Ben-Akiva, M. and Bierlaire, M. (2003). Discrete Choice Methods and Their Applications to Short-Term Travel Decisions. *In*: R. Hall, ed., *Handbook of Transportation Science (International Series in Operations Research & Management Science), 2nd Edition*. New York, NY: Springer.

Bhat, C.R. (1995). A Heteroscedastic Extreme Value Model of Intercity Travel Mode Choice. *Transportation Research Part B*, 29 (6), pp. 471-483.

Bhat, C.R. (1997). Covariance Heterogeneity in Nested Logit Models: Econometric Structure and Application to Intercity Travel. *Transportation Research Part B*, 31 (1), pp. 11-21.

Bhat, C.R. (1998). Accommodating Variations in Responsiveness to Level-of-Service Measures in Travel Choice Modeling. *Transportation Research Part A*, 32 (7), pp. 49-57.

Brand, D., Parody, T.E., Hsu, P.S. and Tierney, K. (1992). Forecasting High-Speed Rail Ridership. *Transportation Research Record*, 1342, pp. 12-18.

Bresnahan, T.F. et al. (1997). Market Segmentation and the Sources of Rents from Innovation: Personal Computers in the Late 1980s. *RAND Journal of Economics*, 28 (0), pp. 17-44.

Charles River Associates. (2000). *Independent Ridership and Passenger Revenue Projections for High Speed Rail Alternatives in California*. Prepared for the California High-Speed Rail Authority.

Chu, C. (1989). A Paired Combinatorial Logit Model for Travel Demand Analysis. *In*: *Proceedings of the 5th World Conference on Transportation Research*, 4, Ventura, California, pp. 295-309.

Chu, C. and Chen, X. (1995). Forecasting the Patronage of High Speed Rail in Southern California. *In: Proceedings of the 8th REAAA Conference*, Taipei.

Cohen, G., Erlbaum, N.S. and Hartgen, D.T. (1978). Intercity Rail Travel Models. *Transportation Research Record*, 673, pp. 21-25.

Federal Railroad Administration. (2009). *High-Speed and Intercity Passenger Rail: Vision of High-Speed Rail in America*. Retrieved July 21, 2010 from: http://www.fra.dot.gov/Pages/31.shtml.

Forinash, C. and Koppelman, F.S. (1993). Application and Interpretation of Nested Logit Models of Intercity Mode Choice. *Transportation Research Record*, 1413, pp. 98-106.

Grayson, A. (1981). Disaggregate Model of Mode Choice in Intercity Travel. *Transportation Research Record*, 835, pp. 36-42.

Greyhound. (2009). *Scheduling, Fares, and Ridership Data*. Retrieved November 10, 2009 from: http://www.greyhound.com.

Hensher, D.A. (1997). A Practical Approach to Identifying the Market for High Speed Rail in the Sydney-Canberra Corridor. *Transportation Research Part A*, 31(6), pp. 431-446.

ICF Kaiser Engineers. (1993). *Description of Florida Intercity Ridership Forecast, High Speed Ground Transportation Project: Terminal Station Site Assessment.* Bakersfield, CA: Kern Council of Governments.

KPMG Peat Marwick and Koppelman, F.S. (1990). *Proposal for Analysis of the Market Demand for High Speed Rail in the Quebec/Ontario Corridor*. Submitted to Ontario/Quebec Rapid Train Task Force.

KPMG Peat Marwick, in association with ICF Kaiser Engineers, Inc., Midwest System Sciences, Resource Systems Group, Comsis Corporation and Transportation Consulting Group. (1993). *Florida High Speed and Intercity Rail Market and Ridership Study: Final Report*. Submitted to the Florida Department of Transportation.

McFadden, D. (1973). Conditional Logit Analysis of Qualitative Choice Behavior. *In*: P. Zaremmbka, ed., *Frontiers in Econometrics*. New York, NY: Academic Press.

McFadden, D. (1978). Modeling the Choice of Residential Location. *In*: A. Karlqvist, F. Snickars and J. Weibull, eds., *Spatial Interaction Theory and Residential Location*. Amsterdam, Netherlands: North-Holland Publishing Company, pp. 75-96.

Michael Baker Jr., Inc. (2004). *2000 Hampton Roads Model Validation Memorandum*. Prepared for Virginia Department of Transportation.

Outwater, M., et al. (2010). California Statewide Model for High-Speed Rail. *Journal of Choice Modelling*, 3 (1), pp. 58-83.

Richmond International Airport. (2010). *Richmond International Airport Master Plan*. Retrieved July 30, 2010 from: http://www.flyrichmond.com/Load.php?Content=Master_Plan.

Roth, D.L. (1998). State of the Art Practices in High Speed Rail Ridership Forecasting. *In*: T. Lynch, ed., *High Speed Rail in the US: Super Trains for the New Millennium*. Amsterdam, Netherlands: Gordon & Breech, pp. 52-80.

Southern California Association of Governments. (2008). *Year 2003 Model Validation and Summary: Regional Transportation Model*. Los Angeles, CA: Southern California Association of Governments.

TMS/Benesch High Speed Rail Consultants. (1991). Tri-State Study of High Speed Rail Service: Chicago-Milwaukee-Twin Cities Corridor. Prepared for Illinois, Minnesota, and Wisconsin Departments of Transportation.

Virginia Department of Rail and Public Transportation, unspecified date. *Washington D.C. – Richmond Passenger Rail Study – Detailed Information*. Retrieved November 20, 2009 from: http://www.drpt.virginia.gov/studies/selectedfile.aspx?id=122.

Virginia High Speed Rail Development Committee. (2001). *Virginia Rail Plan*. Richmond, VA: Virginia High Speed Rail Development Committee.

Vovsha, P. (1997). Application of Cross-Nested Logit Model to Mode Choice in Tel Aviv, Israel, Metropolitan Area. *Transportation Research Record*, 1607, pp. 6-15.

Wen, C.-H. and Koppelman, F.S. (2001). The Generalized Nested Logit Model. *Transportation Research Part B*, 35, pp. 627-641.

Williams, H.C.W.L. (1977). On the Formation of Travel Demand Models and Economic Evaluation Measures of User Benefit. *Environment and Planning A*, 9 (3), pp. 285-344.