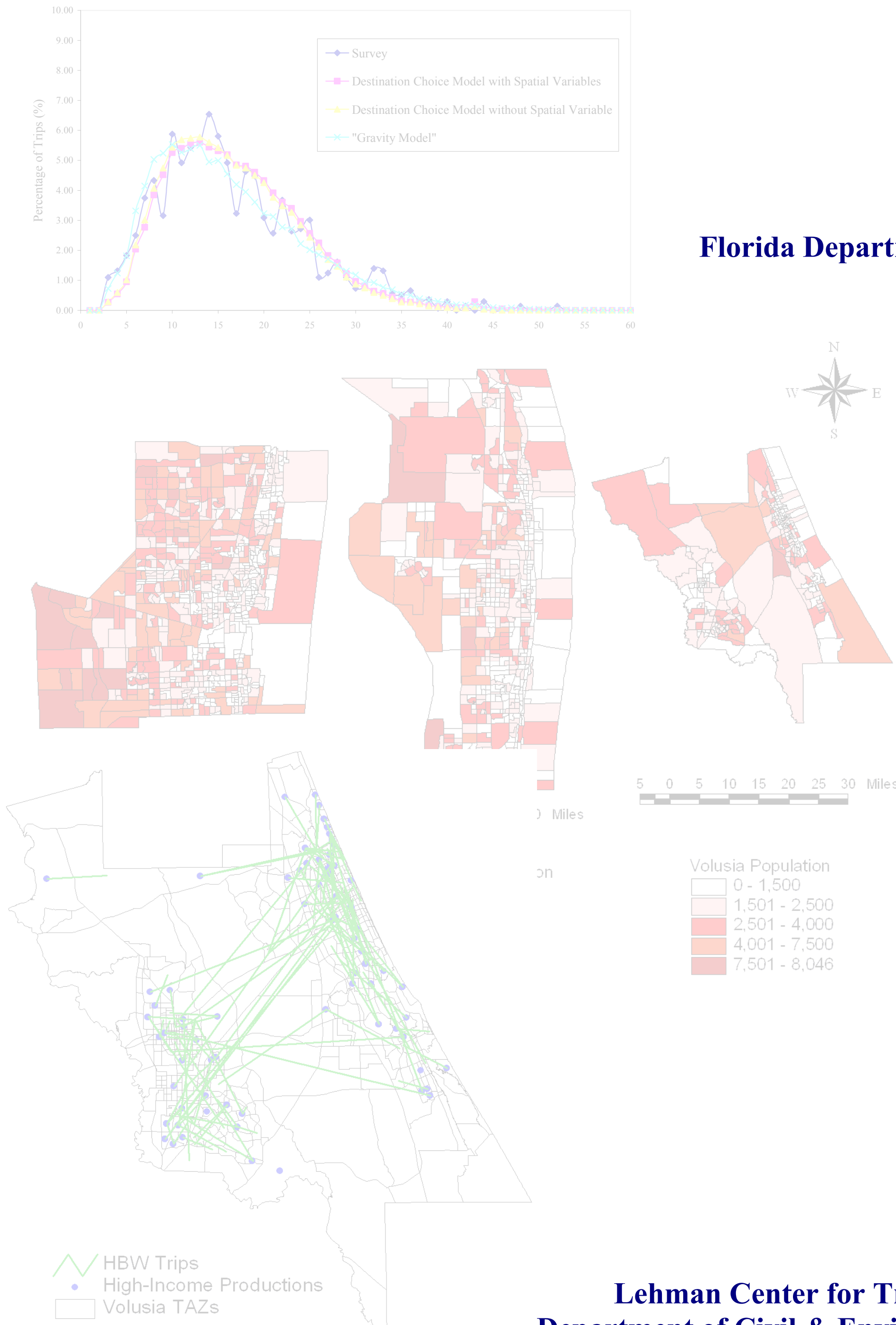
REFINEMENT OF FSUTMS TRIP DISTRIBUTION METHODOLOGY

Final Report
Contract No. BB942

Prepared for

Research Office
Florida Department of Transportation



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16. Abstract

In this report, alternative trip distribution models are investigated with the purpose of improving the current trip distribution methodology in FSUTMS. Three types of models are studied: intervening opportunity models, enhanced gravity models, and destination choice models. The performance of the models was compared against travel survey data and that of traditional gravity models. The evaluation criteria included average trip length, trip length distribution, intrazonal trips, and spatial accuracy measured by different statistical tests. The findings from the project indicate that intervening opportunity models and enhanced gravity models did not produce noteworthy improvements, although the intervening opportunity models were handicapped by the lack of suitable software for model calibration therefore no definite conclusions may be drawn regarding their potentials. Aggregate destination choice models were developed for Broward, Palm Beach, and Volusia counties for Home-Based Work (HBW) trip purpose. Although the three counties are different in their demographics, socioeconomics, and urban structures, improvements are seen in the trip distribution results produced by all the destination choice models, although the improvements for Broward and Volusia counties are more significant than those for Palm Beach County. Results from destination choice models for other trips purposes also indicate improvements.

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EXECUTIVE SUMMARY

INTRODUCTION

FSUTMS is a four-step based travel demand forecasting modeling program. As a major step in the four-step travel demand forecasting process, trip distribution distributes zonal trip ends predicted by the trip generation model to predict the flow of trips from each production zone to each attraction zone. Various trip distribution models have been developed over the past decades. These models generally share the principle that travel between any two points will increase with attractions for such travel, but decrease as the resistance to travel increases. The model used in FSUTMS for distributing trip is the gravity model, which is being used by most metropolitan planning organizations (MPOs) in the U.S.

While gravity models have the advantages of being simple, easy to understand, and easy to calibrate, they are incapable of providing explanations of travel behavior beyond travel cost and aggregate attraction, the latter measured mainly by employment in a few categories such as commercial, service, and industrial. There is also evidence that the trip length distribution is a function of land use (Ewing et al. 1995), but there has been little success in incorporating the land use patterns into the modeling process. Moreover, in Florida, gravity models have been found to be insufficient for modeling longitudinally shaped areas, such as the Palm Beach Urbanized Area, and modeling urbanized areas separated by rural areas like Volusia County. To remedy the problem, K factors (special zone-to-zone adjustment factors) or multiple sets of friction factors are sometimes used in model validation to force the distribution model to behave more closely to the observed trip making patterns. The practice of applying K factors is highly undesirable because K factors' applicability to the future conditions is uncertain. The FSUTMS modeling package is unable to accommodate the use of multiple sets of friction factors. The use of multiple sets of friction factors depicts aggregated human travel as discrete patterns, rather than a continuous pattern. As with K factors, multiple sets of friction factors are theoretically flawed and their applicability for future forecasts is debatable.

The Florida Department of Transportation (FDOT) began to standardize the structure of UTPS models for urban transportation studies throughout the state in 1978. This "model update" process was undertaken in phases over several years, culminating in 1985 with the development of a microcomputer program called Florida Standard Urban Transportation Model Structure (FSUTMS) that interfaced with the TRANPLAN travel demand software system. The FSUTMS system has been enhanced over the years to include evolving modeling techniques (FDOT 1997). Finding new techniques to enhance the trip distribution methodology in the current version of FSUTMS is the subject of this project. The objectives of this research include:

1. Reviewing current practices in trip distribution modeling;
2. Identifying potential ways to improve the performance of the existing FSUTMS trip distribution models;
3. Investigating modeling techniques that have the potential to improve trip distribution processes; and
4. Identifying future research directions.

LITERATURE REVIEW

This literature review aims at exploring current practices and research in trip distribution methodologies. The goal is to identify potential methodologies that may be adapted to improve the trip distribution methodology employed in FSUTMS. Since FSUTMS is a four-step based model and has been applied in practice for transportation plan developments and site impact studies throughout the State of Florida for more than a decade, this review emphasizes methodologies that satisfy the following criteria based on practical considerations:

1. Data required for model calibration and application are either already available or may be obtained within reasonable cost and time constraints.

2. The methodologies fit into the existing FSUTMS model structure without major modifications to other components of the structure.

3. The methodologies are not overly complex to the extent that they cannot be understood by practitioners.

Common Trip Distribution Methods

Trip distribution is most often accomplished through the use of a gravity model. However, other approaches to trip distribution have included growth-factor method, destination choice models, and opportunity models.

<u>Growth Factor Methods</u>

Growth factor methods use zonal growth rates together with existing trip patterns to forecast future interzonal trips. The methods assume that future trips between each pair of zones will be proportional to the present trips, and to some function of the growth factors for each zone pair. The growth factor methods are easily understood and applied. However, there are several problems with this approach. For example, any zones that have no trips in the base year will have no trips in the future, and the methods do not explicitly consider travel impedance therefore are not sensitive to changes in the transportation systems.

<u>Gravity Models</u>

Gravity models are the most common form of trip distribution models currently in use. They are based on the assumption that the trip interchange between zones is directly proportional to the relative attractiveness of each zone, while inversely proportional to some function of the spatial separation between the zones. Gravity models have a number of theoretical advantages. However, they also have shortcomings. The most significant may be that they lack the ability to explain many behavioral aspects of destination choices, as travel costs and attraction are the only factors that solely determine the trip interchange patterns. Another difficulty in gravity models is the *K* factor, an optional input to gravity models that is used when a gravity model fails to produce observed trip interchanges. The need for K factors has been a particular source of concern with gravity models. Although *K* factors have been justified as representing socioeconomic factors that affect trip making but are not accounted for in the gravity model, such socioeconomic factors must be assumed to remain constant throughout the forecast period. This is a questionable assumption, which may be a significant source of error in predicting future trip distributions (Stopher 1975).

Opportunity Models

Opportunity models are derived from postulates regarding destination choice that are different from those of the general discrete choice models. The most commonly known opportunity model is the intervening opportunity model. The basic idea behind this model is that the probability of choice of a particular destination is proportional to the opportunities for trip purpose satisfaction at the destination and inversely proportional to all such opportunities that are closer to the trip maker's origin, which are called the intervening opportunities. Although opportunity models are based on somewhat sophisticated principles, they are not often used in practice for reasons that their theoretical basis is less well known, that they are more difficult to understand to practitioners, and that they are not easily calibrated or applied as gravity models.

Destination Choice Models

Destination choice models belong to the family of discrete choice models and are derived from the principle of utility-maximizing choice. Destination choices of individual travelers are described by a function of the attractiveness of destinations, origin-destination travel conditions, and personal characteristics that influence the response to the attractiveness and travel conditions. The attractiveness of each destination may be described in terms of total employment, employment by job category, square footage by land use category, number of establishments by type, etc. Travel conditions between an origin and a destination may be measured by travel time and cost for one or more modes available to the traveler. Personal characteristics that influence the choices made may include household or personal income, age, sex, household structure, auto availability, etc. The main advantage of destination choice models over gravity models is their ability to explain the effects of land use and socioeconomic and demographic characteristics on travel behavior. Currently, destination choice models are widely accepted as having the potential to better explain travel behavior, and a number of metropolitan areas are either already using or are exploring destination choice models.

FSUTMS Trip Distribution

In FSUTMS, gravity models are used to distribute internal-internal and internal-external trips for seven trip purposes: Home-Based Work (HBW), Home-Based Shopping (HBS), Home-Based Social/Recreational (HBSR), Home-Based Other (HBO), NonHome-Based (NHB), Truck-Taxi, and Internal-External. Friction factors used in the gravity model are defined based on travel impedance, which includes free-flow highway travel time, intrazonal and terminal times, and the time equivalent costs such as tolls and parking. External-external trips are distributed using a growth factor method. The user may supply a growth factor for each origin and destination zone. In the absence of destination growth factors, these are assumed to be the same as origin growth factors.

Modeling Practices in Other Urban Areas

Most urban areas are still using gravity models to distribute trips. Table E.1 summarizes the trip distribution models used in selected metropolitan areas. In the table, DCM indicates a destination choice model. Logsum means travel impedance that combines travel time of different modes, including transit modes. Composite impedance combines travel time of different time of day. "Congested" impedance is the impedance resulted from a loaded network after trip distribution and traffic assignment. Most gravity models use an exponential function to represent impedance. However, Gamma and Bessel functions are also used in some models. Destination choice models have replaced gravity models in a number of urban areas in the U.S. Furthermore, journey-based models and activity-based models have also been developed and applied.

Table E.1 Trip Distribution Models Used in Various Metropolitan Areas

Urban Area	Type of Model	Trips Stratified by Income	Impedance	K factors
Atlanta	Gravity	yes	Composite, Logsum	–
Baltimore	Gravity	–	–	Use barrier penalty
Boston	3D Trip Balancing	–	Composite, Gamma function	–
Dallas-Fort Worth	Gravity	–	Bessel function	–
Denver	Gravity/DCM[1]	yes	–	–
Detroit	Gravity	–	Composite	yes
Huston-Galveston	Gravity	yes (and auto)	Logsum, composite	–
New York	Journey based DCM	yes (and auto/worker)	–	–
Phoenix	Gravity	yes (and auto)	Logsum	–
Seattle	Gravity/DCM[1]	–	–	–
St. Louis	Gravity	–	"Congested"	For crossing Mississippi River
Washington, D.C.	Gravity	yes	Incorporate penalties for river crossing	–
Portland	DCM	yes	Logsum	Dummy variables for river crossing
San Diego	Gravity	–	Composite	–
San Francisco Bay	Gravity	yes	–	–
Sacramento	DCM[2]	–	–	–

Notes: [1] Existing model is gravity and new model will be destination choice model
2 Part of an activity-based model

Potential Trip Distribution Enhancements

Ewing *et al*. (1996) categorize potential FSUTMS model enhancements based on a three-level hierarchy. Level I enhancements aim at fine-tuning the existing FSUTMS models. These enhancements do not change the structure of the traditional four-step process and the relationships among the steps. Use of composite impedance and replacing gravity models with destination choice models are examples of improvements in this category. Level II enhancements would make basic changes to the four-step process while still keeping the process sequential. These enhancements may include new steps, modified relationships among the steps, output feedback, etc. Level III enhancements require a paradigm shift from the four-step process to a completely new process. Combined (or equilibrium) and activity-based models are two such examples.

Based on findings from this review, further research was concentrated in the following three areas to enhance the current FSUTMS trip distribution methodologies:

1. Explore intervening opportunity models;

2. Enhance gravity models with variables that are identified as influential to trip length; and

3. Develop destination choice models to incorporation of socioeconomic, travel, and zonal attractiveness data in trip distribution.

MODEL EVALUATION CRITERIA

To determine if any of the models developed in this study actually improved trip distribution results, traditional gravity models were also calibrated for comparison purposes. All the models were evaluated using a fixed set of criteria, based on which the model outputs for the same study area was compared to each other as well as to survey data. These evaluation criteria include:

- Average trip length. The average trip length obtained from a model should be as close as that from the travel survey.
- Trip length distribution. The trip length frequency distribution from a model is compared to that from the survey. If the two distributions are similar, the coincidence ratio, which reflects the similarity of two distributions, should be close to 1.0.
- Intrazonal trips. The percentage of intrazonal trips from a model should be close to that from the survey.
- Spatial distribution accuracy. A set of criteria are applied to determine if a model replicate the spatial patterns of trip distribution observed from the survey data. For this purpose, an urban area is divided into a number of districts, and trip interchanges between pairs of districts are compared to those observed. Multiple test statistics are applied to evaluate the performance of the models developed in terms of interdistrict trips. These test statistics included (Sen 1995): Chi-square statistic, Neyman's modified Chi-square statistic, Simplified Freeman-Tukey statistic, Scaled deviance statistic, Sum of Errors Squared, and Mean Errors Squared. A model with a better spatial accuracy is indicated by a smaller value of the above statistics.

DEVELOPMENT OF INTERVENING OPPORTUNITY MODELS

To evaluate the potential of intervening opportunity models to replace the gravity models currently used in FSUTMS, intervening opportunity models were calibrated with Palm Beach County as the study area.

Intervening opportunity models have been proven to be a member of the gravity model family. Therefore, an intervening model may be formulated as a gravity model and calibrated as such. Calibrating an intervening opportunity model involves ranking the traffic analysis zones (TAZs) in ascending order by travel impedance and determining the probability of a traveler choosing a particular zone as the destination and not zones with smaller travel impedance. Because of a lack of suitable software for model calibration, intervening opportunity models were reformulated as gravity models and calibrated using TRANPLAN.

Models were calibrated for six trip purposes. Table E.2 presents a comparison of the average trip lengths from the survey data and those produced by the intervening opportunity models and corresponding gravity models. The coincidence ratios from the intervening opportunity models and gravity models are also compared. It may be seen that only the NHBW model had an average trip length closer to that from the survey data. In general, the intervening opportunity model overestimated the trip lengths. For most of the trip purposes, the coincidence ratios for the two models are similar, with gravity models having higher ratios for almost every trip purpose except NHBO.

Table E.2 Comparison of Average Trip Lengths and Coincidence Ratios from Intervening Opportunity and Gravity Models

Trip Purpose	Average Trip Length in Minutes			Coincidence Ratio	
	Surveyed Data	IOM*	Gravity Model	IOM	Gravity Model
HBW	16.19	17.53	15.70	0.826	0.831
HBS	12.00	13.73	11.73	0.680	0.859
HBSR	10.97	14.52	11.31	0.635	0.760
HBO	12.49	14.90	12.45	0.717	0.797
NHBW	13.08	13.07	12.66	0.778	0.789
NHBO	11.55	12.52	10.95	0.784	0.780

* IOM – intervening opportunity model

Table E.3 compares the performance of the two models in terms of the intrazonal trips produced as percentages of the total internal trips by purpose. While both types of models under-predicted intrazonal trips in general, it is more pronounced for the intervening opportunity models.

Table E.3 Percentages of Intrazonal Trips from Survey and Intervening Opportunity and Gravity Models

Trip Purpose	Surveyed Data	IOM	Gravity Model
	%	%	%
HBW	2.84	0.63	2.53
HBS	3.22	1.42	5.41
HBSR	17.70	2.07	9.65
HBO	6.64	1.84	2.42
NHBW	7.22	3.72	6.97
NHBO	11.98	3.63	6.55

Table E.4 provides results from statistical tests on model spatial accuracy. These statistics indicate that gravity models were more accurate in trip distribution for all purposes except NHBW.

Table E.4 Statistical Comparison of Spatial Accuracy of Intervening Opportunity and Gravity Models

Trip Purpose	Model	Chi-Square*	Neyman's Modified Chi-Square	Simplified Freeman-Tukey	Scale Deviance	Sum of Errors Squared	Mean Errors Squared
HBW	IOM	6.41	6.27	5.99	2.63	38.53	2.41
	Gravity	5.61	4.10	4.62	2.12	31.96	2.00
HBS	IOM	12.54	13.71	11.90	5.15	73.36	4.59
	Gravity	10.27	6.93	7.64	3.57	47.93	3.00
HBSR	IOM	23.56	25.33	21.49	9.36	196.23	12.26
	Gravity	12.45	10.78	10.96	4.89	136.31	8.52
HBO	IOM	10.09	17.30	11.63	4.72	85.98	5.37
	Gravity	4.93	5.16	4.94	2.13	48.92	3.06
NHBW	IOM	5.30	5.40	4.88	2.12	37.86	2.37
	Gravity	9.12	6.55	7.28	3.36	49.97	3.12
NHBO	IOM	5.46	4.73	4.78	2.14	25.06	1.57
	Gravity	2.59	2.18	2.34	1.05	20.60	1.29

* Degrees of freedom = 15

It needs to be mentioned that using TRANPLAN to calibrate intervening opportunity models may have compromised the model performance because TRANPLAN is not designed for such purposes and thus is unable to allow an implementation of the intervening opportunity models true to the original formulation.

DEVELOPMENT OF ENHANCED GRAVITY MODELS

After an analysis of the travel survey data (see Appendix A), a number of variables concerning density, jobs-housing balance, and regional accessibility were found to be influential to trip lengths. Therefore, a HBW gravity model was developed with these variables incorporated in hope of improving the model performance. This was achieved by replacing the travel impedance in a gravity model with the utility function in a destination choice model. In other words, the additional land use and accessibility variables were incorporated into the gravity model by calibrating a utility function expressed in these and other variables for a choice model, which is then used as the travel impedance in the gravity model.

The variables incorporated into the enhanced gravity model included travel time, attractions, census travel level population density, employment density, total (population plus employment) density, job-housing balance, and TAZ level highway network accessibility. The significance of the variables was tested during the calibration of the destination choice model utility functions, and census tract level employment density and regional accessibility were found to be significant. Table E.5 shows the results of calibrating the utility functions for the destination choice models.

Table E.5 Results of Logit Model Calibration Incorporating Additional Variables for HBW Trip Distribution

<table>
<tr><th>Additional Variable</th><th>Variable</th><th>Coefficient</th><th>Standard Error</th><th>b/St.Er.</th><th>P[|Z|>z]</th></tr>
<tr><td rowspan="6">Employee Density by Census Tract</td><td>Travel Impedance</td><td>− 0.1193</td><td>0.5062E-02</td><td>−23.566</td><td>0.0000</td></tr>
<tr><td>Log of Attractions</td><td>1.000</td><td colspan="3">------- (Fixed Parameter) --------</td></tr>
<tr><td>Interaction Effects with Travel Impedance
Employee Density</td><td>− 0.00632</td><td>0.2262E-02</td><td>− 2.794</td><td>0.0052</td></tr>
<tr><td rowspan="2">Log likelihood function
No coefficients</td><td colspan="4">− 2976.863</td></tr>
<tr><td colspan="4">− 4280.5057</td></tr>
<tr><td>ρ^2</td><td colspan="4">0.3046</td></tr>
<tr><td rowspan="7">Regional Accessibility by TAZ</td><td>Variable</td><td>Coefficient</td><td>Standard Error</td><td>b/St.Er.</td><td>P[|Z|>z]</td></tr>
<tr><td>Travel Impedance</td><td>− 0.1065</td><td>0.1007E-01</td><td>−10.583</td><td>0.0000</td></tr>
<tr><td>Log of Attractions</td><td>1.000</td><td colspan="3">------- (Fixed Parameter) --------</td></tr>
<tr><td>Interaction Effects with Travel Impedance
Accessibility</td><td>− 0.05856</td><td>0.2449E-01</td><td>− 2.391</td><td>0.0168</td></tr>
<tr><td rowspan="2">Log likelihood function
No coefficients</td><td colspan="4">− 2978.382</td></tr>
<tr><td colspan="4">− 4280.5057</td></tr>
<tr><td>ρ^2</td><td colspan="4">0.3042</td></tr>
<tr><td rowspan="2">Both models</td><td>Iterations completed</td><td colspan="4">6</td></tr>
<tr><td>Number of observations</td><td colspan="4">1859</td></tr>
</table>

The coefficients of travel impedance, log of attractions, and the variables that represent the interaction effects of employment density and accessibility with travel impedance were used to calculate the values of generalized impedance, which was then used to calibrate enhanced gravity models. Two enhanced gravity models were calibrated, one incorporating the employment density variable and the other the accessibility variable. Table E.6 compares the average trip lengths from the two enhanced gravity models and the traditional gravity model with that from the survey data. It may be seen that the average trip lengths from the enhanced gravity models were closer to that from the survey data than the traditional gravity model. Between the two enhanced gravity models, the one incorporating the accessibility variable produced better results. The enhanced gravity model with the accessibility variable also had higher coincidence ratio than the gravity model for the HBW trips.

Table E.6 Comparison of Average Trip Lengths and Trip Length Distributions for HBW Enhanced Gravity Models

	Surveyed Data	Enhanced Model		Gravity Model
		Accessibility	Employment Density	
Average Trip Length (Minutes)	16.19	16.03	15.77	15.70
Coincidence Ratio		0.836	0.831	0.831

Table E.7 compares the intrazonal trips from the enhanced gravity models and the traditional gravity model against the survey data. It may be seen that the enhanced gravity model with employment density produced better results in terms of intrazonal trips. Intrazonal trips from the enhanced gravity model with the accessibility variable were 2.35% compared to 2.53% from the traditional gravity model.

Table E.7 Percentages of Intrazonal HBW Trips from the Enhanced Gravity Models

Surveyed Data		2.85%
Enhanced Gravity	Accessibility	2.35%
	Employment Density	2.81%
Gravity		2.53%

To further investigate the performance of the models in terms of their spatial accuracy, that is whether they distributed trips to the correct destinations, the trip interchanges between different areas were examined. Table E.8 shows the statistics measuring the spatial accuracy of trip distribution. It may be seen that the model enhanced with regional accessibility was the best among the three models compared.

Table E.8 Statistical Comparison of Spatial Accuracy for HBW Trip Purpose

Additional Variable in Impedance Function	Average Trip Length	Chi-Square*	Neyman's Modified Chi-Square	Simplified Freeman-Tukey	Scale Deviance	Sum of Errors Squared	Mean Errors Squared
Survey Data	16.19						
Regional Accessibility	16.03	4.82	3.73	4.12	1.87	29.2	1.83
Employment Density	15.77	5.50	4.12	4.61	2.11	32.12	2.01
Traditional Model	15.70	5.61	4.10	4.62	2.12	31.96	2.00

* Degrees of freedom = 15

DEVELOPMENT OF DESTINATION CHOICE MODELS

Destination choice models were developed for Broward, Palm Beach, and Volusia counties for the HBW trip purpose. HBS models were developed for Broward and Volusia counties. A HBSR model and a HBO model were calibrated for Broward County.

Destination Choice Models for HBW Trip Purpose

Three sets of Home-Based Work (HBW) models, each including three models for low-, middle-, and high-income households, were calibrated for Broward, Palm Beach, and Volusia counties. Tables E.9 through E.11 give the calibrated destination choice models.

In Tables E.9, *TRPL* represents trip length in minutes, *RetSer* is the total retail and service employment, *CIG* is the total commercial, industrial, and government employment, *Prof* is the total zonal professional employment, and *BDFlag* is a flag indicating a central business district (CBD) with parking cost. *NonRetSer*, *NonCIG*, and *NonProf* are the total zonal employments that are not represented by *RetSer*, *CIG*, and *Prof,* respectively. $\mathcal{L}(0)$ is the value of the log likelihood function when all of the parameters are zero; $\mathcal{L}(\hat{\beta})$ is the value of the likelihood at its maximum; and ρ^2 is a goodness-of-fit measure defined as $1 - \mathcal{L}(\hat{\beta})/\mathcal{L}(0)$. A value of $\mathcal{L}(\hat{\beta})$ closer to 0 and a ρ^2 closer to 1.0 are indications of a better model.

Table E.9 Results of HBW Destination Choice Model Calibration for Broward County

Income Level		$\mathcal{L}(\hat{\beta})$	$\mathcal{L}(0)$	ρ^2	# of Observations
Low-Income	Statistics	– 280.0273	– 368.4136	0.2399	160
	Model	U = exp[– 0.1246 × *TRPL* + 0.4938 × ln(1.0244 × *RetSer* + *NonRetSer*)]			
Middle-Income	Statistics	– 711.4775	– 1043.0710	0.3179	453
	Model	U = exp[– 0.1506 × *TRPL* + 0.4769 × *BdFlag* + 0.7418 ×ln(1.0721 × *CIG* + *NonCIG*)]			
High-Income	Statistics	– 1140.3460	– 1581.8760	0.2791	687
	Model	U = exp[– 0.1124 × *TRPL* + 0.6201 × *BdFlag* + 0.7357 × ln(2.2303 ×*Prof* + *NonProf*)]			

Table E.10 presents the Palm Beach County models. The variables in the models have the same definitions as those in the Broward County models. Table E.11 gives the Volusia County models. The employment size variables were based on the ZDATA2 definition from the 1997 validated model. Detailed employment data similar to those in the Broward and Palm Beach models were not used because of large discrepancies found at the TAZ level.

Table E.10 Results of HBW Destination Choice Model Calibration for Palm Beach County

Income Level		$\mathcal{L}(\hat{\beta})$	$\mathcal{L}(0)$	ρ^2	Number of Observations
Low-Income	Statistics	– 283.1444	– 393.7421	0.2809	171
	Model	U = exp[– 0.1020 × *TRPL* + 0.5908 × ln(2.1828 × *RetSer* + *NonRetSer*)]			
Middle-Income	Statistics	– 851.2302	– 1284.8425	0.3375	558
	Model	U = exp[– 0.1278 × *TRPL* + 0.6057×ln(1.0068 × *CIG* + *NonCIG*)]			
High-Income	Statistics	– 828.5384	– 1307.8683	0.3665	568
	Model	U = exp[– 0.1177 × *TRPL* + 0.7632 × *BdFlag* + 0.6982 × ln(1.9916 × *Prof* + *NonProf*)]			

Table E.11 Results of Destination Choice Model Calibration for Volusia County

Income Level		$\mathcal{L}(\hat{\beta})$	$\mathcal{L}(0)$	ρ^2	Number of Observations
Low-Income	Statistics	– 151.9706	– 87.8671	0.4218	66
	Model	U = exp[– 0.1460 × *TRPL* + 0.4070 × ln(1.2970 × *Industrial* + *NonIndustrial*)]			
Middle-Income	Statistics	–162.7798	– 322.3619	0.4950	140
	Model	U = exp[– 0.1295 × *TRPL* + 0.7608 × ln(6.8833 × *Commercial* + *Non Commercial*)]			
High-Income	Statistics	– 291.3353	– 469.7274	0.3800	204
	Model	U = exp[– 0.1125 × *TRPL* + 0.5419 × ln(1.0029 × *Service* + *NonService*)]			

The variables in the final specifications were in the expected direction. For all three income levels, larger travel impedance between production zone and a candidate attraction-end zone made the candidate attraction-end zone less likely to be chosen for a HBW trip. The coefficients of the employment size variables were smaller than one, indicating that there were unobserved zonal attributes affecting the utility of working destinations within the zone (Bhat 1998). For the low-income households, the coefficient for retail plus service employment in the low-income model was greater than 1, which indicated that retail plus service employment would contribute more to the attractiveness of a zone in comparison with non-retail or non-service employment to the low-income households. For middle-income households, workers were likely to travel to areas with more commercial, industrial, and governmental employments. For the high-income households, the parameter on the professional employment is larger than the parameter on the nonprofessional employment, which meant that people with higher income would tend to work in areas with more professional jobs. The downtown variable (*BdFlag*) was significant with positive coefficients in the Broward middle- and high-income models. This means that trip makers from middle- and high-income households in Broward County were likely to go to TAZs within the business districts to work.

The performance of the HBW destination choice models were compared with those obtained from the traditional gravity models in terms of average trip length, trip length distribution, intrazonal trips, and spatial accuracy of trip distribution. Table E.12 provides statistics on the average trip lengths and trip length frequency distributions, Table E.13 the percentages of intrazonal trip distribution, and Table E.14 on the spatial accuracy of distribution.

Table E.12 Average Trip Lengths and Trip Length Distributions from Destination Choice Models and Gravity Models for HBW Trips

County	MOE	Survey	Choice	Gravity
Broward	Average Trip Length	16.61	16.78	14.36
	Coincidence Ratio	-	0.829	0.734
Palm Beach	Average Trip Length	16.19	16.05	14.67
	Coincidence Ratio	-	0.817	0.783
Volusia	Average Trip Length	12.61	13.44	14.58
	Coincidence Ratio	-	0.646	0.645

Table E.13 Percentages of Intrazonal Trips from Surveys, Destination Choice Models and gravity Models for HBW Trips

County	Survey	Choice	Gravity
Broward	4.08	1.01	2.83
Palm Beach	2.85	1.2	2.53
Volusia	12.12	2.38	4.04

Table E.14 Statistical Comparison of Spatial Accuracy from Surveys, Destination Choice Models and gravity Models for HBW Trips

County	Model	Chi-square*	Neyman's Modified Chi-Square	Simplified Freeman-Tukey	Scale Deviance	Sum of Errors Squared	Mean Errors Squared
Broward	Choice[2]	8.08	7.33	7.35	2.66	25.95	0.72
	Gravity	30.16	13.34	16.84	8.45	48.60	1.35
Palm Beach	Choice	5.58	6.41	5.69	2.43	32.79	2.05
	Gravity	5.61	4.10	4.62	2.12	31.96	2.00
Volusia	Choice	3.13	3.30	3.15	0.97	34.66	3.85
	Gravity	13.88	16.28	13.43	5.13	123.78	13.75

* Degree of freedom: Broward = 35, Palm Beach = 15, Volusia = 8

It may be seen from Table E.12 that destination choice models were able to replicate average trip lengths much closer to the data from the household surveys. With regards to trip length distribution, the performance of destination choice models was better than gravity models in terms of coincidence ratios for larger urban areas such as Broward and Palm Beach counties. For Volusia County, the coincidence ratios from these two models were nearly identical. Note that the coincidence ratios for Volusia County were lower than those from the other two counties.

Table E.13 indicates that destination choice models tended to underestimate intrazonal trips, more so than the gravity models. From Table E.14, it may be seen that for Palm Beach County both the gravity model and destination choice model fitted the spatial interchanges between survey districts well, and the difference was insignificant. Destination choice models appeared to perform significantly better in allocating trips into TADs for Broward County as well as for Volusia County. For Broward County, the destination choice models with the spatial variables performed slightly better in spatial accuracy than the destination choice models without spatial variable.

Destination Choice Models for HBS Trip Purpose

Table E.15 provides the calibrated utilities for the Broward and Volusia county destination choice models. In Tables E.15, *TRPL* represents the travel time, *RANKLS10* indicates that a destination TAZ is ranked (based impedance) ten or under, *RANKGT50* indicates that a destination TAZ is ranked above 50, *RetEmp* is the total retail employment, *SerEmp* is the total service employment, and *ComEmp* is the total zonal commercial employment.

Table E.15 Broward County HBS Destination Choice Models

County		$\mathcal{L}(\hat{\beta})$	$\mathcal{L}(0)$	ρ^2	Number of Observations
Broward	Statistic	-982.7242	-2390.0833	0.5888	1,038
	Model	U = exp[– 0.1582 × *TRPL* + 0.6524 × *RANKLS10* – 1.3770 × *RANKGT50* + 0.8009 × ln(6.7229 × *RetEmp* + *SerEmp*)]			
Volusia	Statistic	-379.7752	-971.6909	0.6092	422
	Model	U = exp[– 0.2021 × *TRPL* + 0.5814 × ln(1.6048 × *ComEmp* + *SerEmp*)]			

Table E.16 provides the statistics regarding the average trip lengths and trip length distributions from the models. The destination choice models better replicated the average trip lengths from the survey data than the gravity models for both counties.

Table E.16 Average Trip Lengths and Trip Length Distributions for HBS Trips from Surveys and Destination Choice and Gravity Models

County	MOE	Survey	Choice	Gravity
Broward	Average Trip Length	10.91	11.72	9.66
	Coincidence Ratio	–	0.773	0.808
Volusia	Average Trip Length	9.24	11.74	13.41
	Coincidence Ratio	–	0.637	0.640

Table E.17 provides the intrazonal trips and percentages from the survey, destination choice model, and gravity model for Broward and Volusia counties. The destination choice model performed better in the estimation of intrazonal trips for Broward County, although both models still underestimated intrazonal trips, particularly in Volusia County.

Table E.17 Percentages of HBS Intrazonal Trips from Surveys and Destination Choice and Gravity Models

County	Survey	Choice	Gravity
Broward	5.78	3.78	12.08
Volusia	13.51	3.72	5.07

The spatial accuracy of the trip distribution models in allocating HBS trips between traffic analysis districts was measured with the six statistics given in Table E.18 for Broward and Volusia counties. The results show that destination choice models performed better than the gravity models according to most of the statistics

Table E.18 Statistical Comparison of Spatial Accuracy of Destination Choice Models for HBS Trips

County	Model	Chi-square*	Neyman's Modified Chi-Square	Simplified Freeman-Tukey	Scale Deviance	Sum of Errors Squared	Mean Errors Squared
Broward	Choice	16.05	15.46	13.84	8.27	72.24	4.01
	Gravity	72.49	14.44	19.00	10.27	63.53	3.53
Volusia	Choice	45.11	14.27	17.33	15.96	199.81	28.54
	Gravity	89.56	70.85	38.17	23.95	367.56	52.51

* Degrees of freedom: Broward = 17, Volusia = 5

Destination Choice Models for HBSR Trip Purpose

Table E.19 describes the destination choice model for HBSR trips for Broward County, where *TRPL* represents the travel time, *Intralzonal* is a dummy variable to indicate whether a trip is an intrazonal trip, *HHs* represents the total households, *RetailEmp* is the total retail employment, and *ParkAcreage* indicates the park acreage in a destination zone.

Table E.19 HBSR Destination Choice Model Calibration for Broward County

	$\mathcal{L}(\hat{\beta})$	$\mathcal{L}(0)$	ρ^2	# of Observations
Statistics	– 874.6158	– 1667.0716	0.475	724
Model	U = exp[– 0.1920 × *TRPL* + 2.0410 × *Intralzonal* + 0.4787 × ln(0.2438 × *HHs* + 3.0348*RetailEmp* + *ParkAcreage*)]			

Table E.20 gives the average trip lengths and coincidence ratios from the destination choice model and the gravity model. It may be seen that the destination choice model better replicated the average trip length for the HBSR trips from the survey data than the gravity model. The coincidence ratio from the destination choice model was, however, lower than that from the gravity model.

Table E.20 Average Trip Lengths and Trip Length Distributions for HBSR Trips from Survey and Destination Choice and Gravity Models for Broward County

	Surveyed Data	Destination Choice Model	Gravity Model
Average Trip Length	12.03	12.11	9.686
Coincidence Ratio		0.645	0.735

Table E.21 presents the intrazonal trips percentages as the total HBSR trips from survey, destination choice model, and gravity model, respectively. The results indicate that gravity model produced better result then destination choice model in the estimation of intrazonal HBSR trips.

Table E.21 Percentages of HBSR Intrazonal Trips from Survey and Destination Choice and Gravity Models for Broward County

Surveyed Data	17.27
Destination Choice Model	14.24
Gravity Model	16.05

Test statistics that reflect the spatial accuracy of the HBSR destination choice model are provided in Table E.22. The results show that the destination choice models performed better than the gravity model.

Although the destination choice model performed better than the gravity model, in general, both destination choice model and gravity model did not predict HBSR trips well. A possible reason may be that the travel choices for social recreation trips are also determined by the characteristics of trip makers such as age, gender, and family structure, which may interact with the attributes of destinations.

Table E.22 Statistics Comparison of Spatial Accuracy of HBSR Destination Choice Model for Broward County

	Chi-square*	Neyman's Modified Chi-Square	Simplified Freeman-Tukey	Scale Deviance	Sum of Errors Squared	Mean Errors Squared
Destination Choice Model	17.87	13.89	14.81	11.40	158.49	9.91
Gravity Model	38.90	24.36	24.73	12.08	210.45	13.15

* Degrees of freedom = 15

Destination Choice Models for HBO Trip Purpose

Table E.23 gives the destination choice model for HBO trips for Broward County, where *TRPL* represents the travel time, *SchoolIndex* is a dummy variable to indicate whether there are public schools in a destination zone, *SerProfEmp* is the size of service and professional employment, and *NoneSerProfEmp* is size of the remaining employment in a TAZ.

Table E.23 Results of HBO Destination Choice Model Calibration for Broward County

	$\mathcal{L}(\hat{\beta})$	$\mathcal{L}(0)$	ρ^2	# of Observations
Statistics	-4830.8235	-2499.2662	0.483	2,098
Model	$U = \exp[-0.2823 \times TRPL + 0.2880 \times SchoolIndex + 0.4375 \times \ln(1.1225 \times SerProfEmp + NoneSerProfEmp)]$			

The average trip lengths and coincidence ratios from the survey data, destination choice model, and gravity model are provided in Table E.24. The destination choice model better replicated the average HBO trip length from the survey data than the gravity model. The coincidence ratio from the gravity model, however, was slightly better.

Table E.24 Average Trip Lengths and Trip Length Distributions for HBO Trips from Survey, Destination Choice Model, and Gravity Model for Broward County

	Surveyed Data	Destination Choice Model	Gravity Model
Average Trip Length	11.67	12.27	10.34
Coincidence Ratio		0.732	0.799

Table E.25 shows the number and percentages of the intrazonal trips from the survey, destination choice model, and gravity model. The results indicate that destination choice model did not perform as well as gravity model in the estimation of intrazonal HBO trips.

Table E.25 Percentages of HBSR Intrazonal Trips from Survey and Destination Choice and Gravity Models for Broward County

Surveyed Data	8.48%
Destination Choice Model	4.36%
Gravity Model	10.42%

The spatial accuracy of the HBO destination choice model in allocating HBO trips among TADs was compared to the gravity model based on six statistics in Table E.26. It may be seen that all statistics indicate that the destination choice model consistently performed better than the gravity model. Destination choice model was shown to perform better in replicating average trip length and percentages of trip interchanges among traffic analysis districts. However, gravity model replicated the trip length distribution and percentage of intrazonal trips better than destination choice model.

Table E.26 Statistics Comparison of Spatial Accuracy of the HBO Destination Choice Model for Broward County

	Chi-square*	Neyman's Modified Chi-Square	Simplified Freeman-Tukey	Scale Deviance	Sum of Errors Squared	Mean Errors Squared
Destination Choice Model	36.16	16.92	17.53	8.89	64.91	2.24
Gravity Model	99.62	18.86	25.52	14.54	71.01	2.45

* Degrees of freedom = 28

CONCLUSIONS

This report summarizes the results and findings of a research project aimed at improving the current trip distribution modeling practice in FSUTMS. The study investigated intervening opportunity models, enhanced gravity models, and aggregate destination choice models as potential alternatives to the existing gravity models in FSUTMS. The results show that the intervening opportunity model calibrated for Palm Beach County performed slightly better than the gravity model for NHBW trips in terms of average trip length, but not for the other purposes. Factors that may influence the performance of the model include:

- A lack of functions that are specifically designed to calibrate an intervening opportunity model in FSUTMS.
- A lack of optimal market segmentation of travel demand in terms of the attributes of trip makers and treating all destinations as equally attractive if they have the same number of attractions.
- Sensitivity of the intervening opportunity model to attractions and reliability of the attraction data.

In summary, the results from this study do not provide conclusive evidence as whether the performance of intervening opportunity models may be significantly improved, which is necessary for any possible applications.

The enhanced gravity models replace the typical travel time based impedance with a combination of travel time, land use, accessibility, and/or income variables at the production zones. There were some improvements in average trip length and trip length distribution, especially in the case when regional accessibility was considered. However, the benefits were offset by the extra cost of data preparation because accessibility to employment in adjacent counties/urban areas must be considered, increasing the need for data processing.

The destination choice models with income segmentation and aggregate alternatives at the TAZ level produced noticeable improvements for HBW trip distribution in terms of average trip lengths for the Broward and Palm Beach County models. Improvements in spatial accuracy of trip distribution as measured by inter-district trip interchanges were also observed from the Broward and Volusia county models. Although spatial barrier variables were statistically significant and did result in better performance over models without them, the improvements were not significant enough to justify their inclusion because of the difficulty in their forecast. Therefore, spatial variables should not be used or only used with extreme caution.

One weakness of the destination choice models is that they underestimated intrazonal trips in all selected urban areas. Neither the introduction of an intrazonal dummy variable nor the reduction in travel impedance effectively remedied the problem. Consequently, urban areas with high percentages of intrazonal trips may benefit less from implementing destination choice models.

The spatial transferability of destination choice models was evaluated by applying Broward's models to Palm Beach County. The results suggest that model transferability is possible. However, more studies will be needed to reach more definite conclusions.

For HBS, HBSR and HBO trips, the destination choice models were shown to perform better in replicating average trip lengths and percentages of trip interchanges among traffic analysis districts. However, gravity model replicated the trip length distribution and percentage of intrazonal trips better than the destination choice models. The improvements brought by destination choice models for home-based non-work trips were generally not as significant as those for home-based work trips.

RECOMMENDATIONS

Based on the findings from this research and many discussions among and feedback from the Florida Model Task Force members, future research on improving FSUTMS trip distribution may be directed at a number of efforts:

- A better match of income and jobs. In this research, a match between income and job was attempted based on an empirical analysis of the distribution of the reported personal income of the trip makers by job sector when calibrating destination choice models. However, because personal income information is not available for all households, census household income was used in place of personal income when destination choice models were applied. The CTPP Part 2 stratifies household income of workers at attraction zones, which allows a better match of the production and attraction zones for workers on the basis of their household income. One potential problem with trying to relate household income with occupation type is that household income may not reflect the actual salaries of workers. For example, a household income of $60,000 may be from the salary of one worker with a professional job or from the salaries of three family members, each holding a low-paying job. While it is difficult to obtain information on salaries, information on salary distribution by certain industry type would be helpful and is worth investigation. However, this will require that either personal income be estimated at the production end, or somehow be related to household income.

- Better segmentation of trips from different income groups. In this research, trips at the production end were proportioned into the three income groups based on the percentage of households in each income group. Because the characteristics of households in different income groups likely vary in terms of number of workers, presence of children, number of cars owned, and household size, households of different income groups may not produce the same number of trips. According to 200 census, low-income households had relatively fewer workers and high-income households more workers. Low-income households also tended to be smaller. Therefore, even when the percentages of households in different income groups are the same, they will produce different numbers of HBW trips. To estimate the effect of differences in household characteristics on numbers of trips produced by the three income groups, special census tabulation will be needed to further segment households by income level.

- Consideration of income effect on trip productions. While the household characteristics of households of different income groups will affect the HBW trip productions, it is also possible that households of different income will have different trip production rates. The current FSUTMS trip generation models do not consider the possible effect of income on trip rates. Some regional models such as those of the Atlanta Regional Commission, Puget Sound Regional Council, Dallas-Fort Worth, and Phoenix Maricopa Association of Governments estimate trip productions for different income groups. This alternative may be considered in the future by the Florida Model Task Force Trip Generation Committee to improve our ability to better model the influence of income on travel behavior.

- Improvement in intrazonal trip distribution. More studies are needed to improve the performance of destination choice models in distributing intrazonal trips.

- CUBE add-in module. A CUBE add-in module would need to be developed to apply destination choice models in the modeling process for different urban areas in Florida, since different modeling structures are applied for travel demand analysis in Florida.

- Investigation of destination choice models for other Florida urban areas. Destination choice models for other urban areas in Florida may be developed and evaluated, and the possibility of developing a few "standard" models for urban areas of different types need to be studied.

- Development of a statewide model. A statewide destination choice model may need to be investigated for inclusion into the statewide model.

- Possible development of a journey based model that distributes journeys using a destination choice model or a combine destination and mode choice model. This will allow chained trips to be modeled. However, this is a rather significant move that will require the first three submodels of FSUTMS, trip generation, trip distribution, and mode choice, to be revamped.

1. INTRODUCTION

FSUTMS is a four-step based travel demand forecasting modeling program. As a major step in the four-step travel demand forecasting process, trip distribution distributes zonal trip ends predicted by the trip generation model in order to predict the flow of trips from each production zone to each attraction zone. Various trip distribution models have been developed over the past decades. These models generally share the principle that travel between any two points will increase with attraction for such travel, but decrease as the resistance to travel increases. The model used in FSUTMS for distributing trip is the gravity model, which is being used by most metropolitan planning organizations (MPOs) in the U.S.

While gravity models have the advantages of being simple, easy to understand, and easy to calibrate, they are incapable of providing explanations of travel behavior beyond travel cost and aggregate attraction, the latter measured mainly by employment in a few categories such as commercial, service, and industrial. There is also evidence that the trip length distribution is a function of land use (Ewing et al. 1995), but there has been little success in incorporating the land use patterns into the modeling process. Moreover, in Florida, gravity models have been found to be insufficient for modeling longitudinally shaped areas, such as the Palm Beach Urbanized Area, and modeling urbanized areas separated by rural areas like Volusia County. To remedy the problem, K factors (special zone-to-zone adjustment factors) or multiple sets of friction factors are sometimes used in model validation to force the distribution model to behave more closely to the observed trip making patterns. The practice of applying K factors is highly undesirable because K factors' applicability to the future conditions is uncertain. The FSUTMS modeling package is unable to accommodate the use of multiple sets of friction factors. The use of multiple sets of friction factors depicts aggregated human travel as discrete patterns, rather than a continuous pattern. As with K factors, multiple sets of friction factors are theoretically flawed and their applicability for future forecasts is debatable.

The Florida Department of Transportation (FDOT) began to standardize the structure of UTPS models for urban transportation studies throughout the state in 1978. This "model update" process was undertaken in phases over several years, culminating in 1985 with the development of a microcomputer program called Florida Standard Urban Transportation Model Structure (FSUTMS) that interfaced with the TRANPLAN travel demand software system. The FSUTMS system has been enhanced over the years to include evolving modeling techniques (FDOT 1997). Finding new techniques to enhance the trip distribution methodology in the current version of FSUTMS is the subject of this project. The objectives of this research include:

1. Reviewing current practices in trip distribution modeling;
2. Identifying potential ways to improve the performance of the existing FSUTMS trip distribution models;
3. Investigating modeling techniques that have the potential to improve trip distribution processes; and
4. Identifying future research directions;

In the remainder of this report, Chapter 2 surveys the literature on trip distribution methodologies, which provides an overview of the common methods for trip distribution, followed by a description of the existing FSUTMS trip distribution model and model enhancements as identified in previous studies sponsored by FDOT. Trip distribution models used in various urban areas in the U.S. are also reviewed. The chapter ends with a discussion of various types of possible enhancements and recommendations on the focus of this research.

In Chapter 3, model evaluation criteria are defined. These criteria include different statistical tests based on which new models developed in this study are compared to trip distribution models based on the current FSUTMS methodology to determine if a proposed model improves trip distribution results.

Chapters 4, 5, and 6 describe alternative trip distribution methods investigated in this research. Chapter 4 presents the results from the development of an intervening opportunity model. Chapter 5 explores the possibility of enhancing the existing gravity models for home-based work trips by incorporating new variables that have bearing on trip length distribution. Chapter 6 describes the development of aggregate destination choice models. Finally, conclusions are provided in Chapter 7 and recommendations regarding future effort to improve trip distribution models are given in Chapter 8.

2. LITERATURE REVIEW

This literature review aims at exploring current practices and research in trip distribution methodologies. The goal is to identify potential methodologies that may be adapted to improve the trip distribution methodology employed in FSUTMS. Since FSUTMS is a four-step based model and has been applied in practice for transportation plan developments and site impact studies throughout the State of Florida for more than a decade, this review emphasizes methodologies that satisfy the following criteria based on practical considerations:

1. Data required for model calibration and application are either already available or may be obtained within reasonable cost and time constraints.

2. The methodologies fit into the existing FSUTMS model structure without major modifications to other components of the structure.

3. The methodologies are not overly complex to the extent that they cannot be understood by practitioners.

In this chapter, four types of trip distribution models are first briefly described in Sections 2.1 through 2.4. They are growth factor methods, gravity models, intervening opportunity models, and destination choice models. Section 2.5 provides a brief description of the existing trip distribution methodology used in FSUTMS. It also summarizes potential model enhancements suggested in the FSUTMS technical report for trip distribution (FDOT 1997). A review of current trip distribution practices is presented in Section 2.6. The purpose is to identify state-of-the-practice approaches that may be adapted for FSUTMS. Section 2.7 describes various potential enhancements for trip distribution. They include those that may or may not be suitable for the FSUTMS model structure. Consistent with the aforementioned practical considerations, emphases are placed on those practices and recommendations that may be incorporated into FSUTMS in the foreseeable future. Finally, the last section presents three recommendations for further research based on findings of this review.

Trip distribution is most often accomplished through the use of a growth-factor method or a gravity model. However, other approaches to trip distribution have included destination choice models and opportunity models. The following subsections introduce the basic concept and methodology of each of these models.

2.1 Growth Factor Methods

Growth factor methods use zonal growth rates together with existing trip patterns to forecast future interzonal trips. The methods assume that future trips between each pair of zones will be proportional to the present trips, and to some function of the growth factors for each zone pair. The main advantage associated with growth factor methods are that they are easily understood and applied. However, the formulation may result in certain peculiarities. Firstly, for urban areas divided into a large number of zones, it is expensive to establish an origin-destination (OD) table based entirely on observed data. Secondly, any zones that have no trips in the base year will have no trips in the future. Thirdly, since no travel impedance is explicitly considered, the methods are not sensitive to changes in the transportation systems. Finally, since the growth factor methods predict future trip interchanges based on the current trip interchange patterns, errors in the current trip interchanges will propagate into the future trips.

2.2 Gravity Models

Gravity models are the most common form of trip distribution models currently in use. They are based on the assumption that the trip interchange between zones is directly proportional to the relative attractiveness of each zone, while inversely proportional to some function of the spatial separation between the zones. Gravity models generally take the following form:

$$T_{ij} = P_i \left[\frac{A_j F_{ij} K_{ij}}{\sum_{k=1}^{N} A_k F_{ik} K_{ik}} \right]$$

where

T_{ij} = number of trips from zone i to zone j;
P_i = number of trip productions in zone i;
A_j = number of trip attractions in zone j;
F_{ij} = "friction factor" relating the spatial separation between zone i and zone j;
K_{ij} = optional adjustment factor for interchanges between zone i and zone j; and
n = total number of zones.

The friction factor in the above equation is the inverse function of the travel impendence between zones i and j. In areas with minimal transit service, travel impedances are typically based on highway travel times. For regions with extensive transit service, a "composite impedance" may be more appropriate to allow for the inclusion of multiple modes serving the trips. A composite impedance may be derived based on weighted impedances. For example, Levinson and Kumar (1994) developed a composite impedance function using mode shares from a feedback process as weights.

Gravity models have a number of theoretical advantages and there is no lack of suitable software to calibrate and apply them. However, they also have shortcomings. As mentioned before, gravity models lack the ability to explain many behavioral aspects of destination choices, as travel costs and attraction are the only factors that solely determine the trip interchange patterns.

Another difficulty in gravity models is the *K* factor, an optional input to gravity models and often referred to as socioeconomic adjustment factors. *K* factors are used when a gravity model fails to produce observed trip interchanges. The need for K factors has been a particular source of concern with gravity models. Many analysts interpret the need for use of extensive *K* factors as a sign that the data, the modeling procedure, or the gravity model itself may be problematic.

Although *K* factors have been justified as representing socioeconomic factors that affect trip making but are not accounted for in the gravity model, such socioeconomic factors must be assumed to remain constant throughout the forecast period. This is a questionable assumption, which may be a significant source of error in predicting future trip distributions (Stopher 1975). Duffus *et al*. (1987) investigated the merit of including *K* factors in a gravity model using peak-hour trip data obtained for four study-year periods (1962, 1971, 1976 and 1981) for the City of Winnipeg, Canada. They found that, while the friction factors for the 20-year period were relatively stable, *K* factors were inconsistent from one prediction period to the next. When used in forecasting trips, *K* factors resulted in larger errors than without them. It was concluded that they were not appropriate for use in predicting trip tables based on the method by which they are currently estimated.

2.3 Opportunity Models

Opportunity models are derived from postulates regarding destination choice that are different from those of the general discrete choice models. The most commonly known opportunity model is the intervening opportunity model. The basic idea behind this model is that the probability of choice of a particular destination is proportional to the opportunities for trip purpose satisfaction at the destination and inversely proportional to all such opportunities that are closer to the trip maker's origin, which are called the intervening opportunities. The model explicitly considers the opportunities available to satisfy a trip purpose at increased distance or travel time from the origin. Accordingly, for an origin zone, its possible destinations are ranked in order of increasing distance or travel impedance from the origin zone. A common intervening opportunity model for trip distribution between zones *i* and *j* takes the following form (Kanafani 1983, Ortuzar 1994):

$$T_{ij} = P_i \left[\frac{\exp(-LV(j-1)) - \exp(-LV(j))}{1 - \exp(-LV(J))} \right]$$

where

- T_{ij} = number of trips from zone *i* to zone *j*;
- P_i = number of trip productions in origin zone *i*;
- L = probability of accepting a destination opportunity;
- $V(J)$ = total destination opportunities in all *J* destinations;
- $V(j)$ = total destination opportunities from origin zone *i* to the *j*th ranked destination; and
- $V(j\text{-}1)$ = total destination opportunities from origin zone *i* to the (*j*-*1*)th ranked destination.

Although opportunity models are based on somewhat sophisticated principles, they are not often used in practice for possibly the following reasons (Ortuzar 1994):

1. The theoretical basis is less well known and more difficult to understand to practitioners.

2. The matrices with destinations ranked by distance from the origin cannot be handled easily in practice.

3. The theoretical and practical advantages of opportunity models over gravity models are not so significant as to warrant their replacing gravity models.

4. There is a lack of suitable software to calibrate and use them.

Other opportunity models of trip distribution include the competing opportunities model, which considers the competition between destination opportunities within the same travel time and cost from the origin; and the impedance-dependent opportunity model, which modifies the destination choice probability depending on the distance to the next available destination (Kanafani 1983).

2.4 Destination Choice Models

Up to now, most urban areas in the U.S. still use gravity models for distributing trips in the four-step travel demand models. Gravity models are easy to understand and calibrate, do not require hard-to-collect data, and provide reasonable results. However, a drawback of gravity models is that they are unable to model why a particular decision on the destination choice is made by trip makers other than considering travel time and opportunities at the destination, the latter usually represented by employment size. Consequently, gravity models are limited in their abilities to evaluate many policy issues for long-range planning. In recent years, discrete choice modeling techniques have been used to simultaneously model the effects of land use and socioeconomic and demographic characteristics on travel behavior. Some previous studies on discrete choice models have examined demographic and policy-sensitive explanatory variables to show that they influence the spatial interaction in human behavior. For instance, Levinson and Kumar (1994) used statistical evidence to show that destination choice was influenced by time of day, activity duration, and home location. Bhat et al. (1998) included zonal location indicator, zonal spatial structure measure, and socio-demographic variables in addition to travel impedance to estimate an attraction-end choice model for home-based work and shopping trips. The Portland MPO (Metro 2001) used a multinomial logit estimation procedure to calibrate a destination choice model that is stratified by household income and includes land use, accessibility, and topography variables. Currently, destination choice models are widely accepted as having the potential to better explain travel behavior, and a number of metropolitan areas are either already using or are exploring destination choice models.

Destination choice models belong to the family of discrete choice models and are derived from the principle of utility-maximizing choice. In destination choice models, a traveler originating at place i is assumed to choose among N destinations. The probability of the traveler choosing destination j, denoted by P_{ij}, is commonly formulated as a multinomial logit model as follows (Harvey 1993):

$$P_{ij} = \frac{\exp(V_{ij})}{\sum_{k=1}^{N} \exp(V_{ik})}$$

where V_{ij} is the utility (or attractiveness) of place j to the traveler originating in place i. The trip distribution between zones i and j is obtained as follows:

$$T_{ij} = P_{ij} P_i$$

where P_i is the number of trip makers in zone i.

Destination choices of individual travelers may be specified as a function of the attractiveness of destinations, origin-destination travel conditions, and personal characteristics that influence the response to the attractiveness and travel conditions. The attractiveness of each destination may be described in terms of total employment, employment by job category, square footage by land use category, number of establishments by type, etc. Travel conditions between an origin and a destination may be measured by travel time and cost for one or more modes available to the traveler. Personal characteristics that influence the choices made may include household or personal income, age, sex, household structure, auto availability, etc.

Destination choice models have been widely accepted as a possible alternative to gravity models. Destination choice models are disaggregate in the sense that they are concerned with the choice behaviors of individual travelers. In contrast, gravity models are aggregate because they model total trip interchanges between a pair of origin and destination zones. Aside from the disaggregate-versus-aggregate distinction, the two models actually share more similarities than differences. In terms of functional forms, the logit model, into which destination choice models are frequently formulated, actually belong to the gravity model family. A production-constrained gravity model with an exponential impedance function is identical, up to a constant multiplier, to a logit destination choice model with a utility function. The only difference is that disaggregate logit models of destination choice include attributes of the individual or household, and aggregate gravity models include zonal demographic and socioeconomic measures. Although the production-end of destination choice models are disaggregate, the attraction-end counterpart is usually aggregate. This is because disaggregate destination alternatives would lead to an excessive number of alternatives, unless there are only a few destination alternatives in a zone, such as the case of shopping malls in a metropolitan area (Kitamura 1998).

Formulating the trip distribution model as a multinomial logit model has several advantages. First, a high-quality data set of several thousand observations should be adequate to support model estimation. Second, the data and computational aspects of setting up the destination choice model are relatively simple. The most important advantage, however, lies in the fact that the utility function formulation facilitates the inclusion of a wide variety of variables that influence destination choice, including those that may be accounted for in a gravity model only through the extensive use of *K* factors and other adjustments (Harvey 1993). The disadvantages of destination choice models are that they require more information to estimate and take more computational time to process (Levinson 1994).

2.5 FSUTMS Trip Distribution

This section provides a brief summary of the trip distribution methodology currently used in FSUTMS. Recent refinements and some suggested refinements are also included. Most of the materials in this section are summarized from a technical report on trip distribution in FSUTMS (FDOT 1997).

2.5.1 Existing Methodology

In FSUTMS, gravity models are used to distribute internal-internal and internal-external trips. The process is implemented in a module called "DISTRIB." The DISTRIB module builds a trip table containing the number of person-trips between each zone pair for each of the following seven standard trip purposes:

1. Home-based work (HBW)
2. Home-based shopping (HBS)
3. Home-based social/recreational (HBSR)
4. Home-based other (HBO)
5. Non-Home-based (NHB)
6. Truck-Taxi
7. Internal-External

The existing FSUTMS DISTRIB module was originally developed directly from UTPS procedures. The execution of the DISTRIB module is usually preceded by highway network path building (HPATH) and followed by auto occupancy/mode choice (MODE). The DISTRIB module accomplishes the following five specific tasks in building the standard seven-purpose person-trip table:

1. Building intrazonal impedances in the highway network for all zones.
2. Building terminal times for all zones.
3. Augmenting the highway skims to include intrazonal impedances and terminal times.
4. Reporting revised highway skims for the highway paths including impedance summaries for distance and travel time.
5. Executing a trip distribution gravity model to produce a seven-purpose person-trip table.

The DISTRIB module uses highway network information described in terms of links, nodes, zones, and increments of travel time. Information on highway impedance skims is described in terms of network links and nodes. Trip productions and attractions input to the gravity model are defined based on TAZ. Finally, friction factors used in the gravity model are defined based on travel time.

During execution of the DISTRIB module, free-flow highway skims are revised to include intrazonal and terminal times prior to being input into the TRANPLAN gravity model for trip distribution. Terminal time refers to the walk time required to travel from trip origin to vehicle and from vehicle to final destination. Intrazonal time is an estimate of the time required to travel across a given TAZ

In FSUTMS, external-external trips are distributed using a growth factor method and is implemented in the EXT module. The user may supply a growth factor for each origin and destination zone. In the absence of destination growth factors, these are assumed to be the same as origin growth factors.

2.5.2 Recent Model Enhancements

Although there have been no direct enhancements to DISTRIB, it has benefited significantly from some of the recent enhancements to other FSUTMS modules. In particular, the incorporation of the toll facilities model into HPATH has resulted in the development of more accurate travel time skims that account for the unique nature of toll facilities. This enhancement has, in turn, improved the accuracy of the subsequent DISTRIB module.

Currently, most FSUTMS models use free-flow highway skims as input to trip distribution. However, the Southeast Regional Planning Model (SERPM) and the Tampa Bay Regional Transportation Analysis Model have implemented composite impedances, which combine restrained highway and free-flow transit skims, for input into the gravity model for trip distribution. Using this approach, an initial trip distribution is first performed based on the free-flow highway skims. Trip assignment is then performed to develop congested skims. A second and final distribution is then conducted based on a combination of congested and uncongested travel time for each trip purpose. The combinations of travel time were derived from an overall temporal distribution of traffic counts and a purpose-specific temporal distribution of surveyed trips. The use of temporal distribution also takes care of the need of some Florida areas that have unusual temporal distribution of traffic, such as high noon-hour peaks (Saha 1999).

Another enhancement implemented in SERPM is to divide school trips into public school trips and private school trips. Public school trips are distributed based on enrollments and district boundaries and private school trips are distributed based on the usual friction factors (Saha 1999).

FSUTMS Final Technical Report No. 6 (FDOT 1997) suggests the following enhancements to the DISTRIB module:

1. Allow a further stratification of trips for distribution beyond trip purpose. This may become necessary if a time-of-day modeling approach is adopted. It will also allow seasonal and permanent resident trips to be separated prior to trip distribution, as recommended in the Lee County Travel Characteristics Study.

2. Develop default procedures for estimating terminal and intrazonal times in the building of highway impedances and consider separating terminal times from driving times in the computation of trip lengths.

2.6 Modeling Practices in Other Urban Areas

This section reviews a number of trip distribution modeling methodologies used by other metropolitan areas in the U.S. The objective is to learn about the state-of-the-practice of trip distribution methodologies with the hope that some of them may be adapted as enhancements to FSUTMS.

2.6.1 Metropolitan Atlanta Region

In the Atlanta Regional Commission (ARC) travel demand model, households of different income and size are first estimated using a land use model (ARC 2002). Workers per household by household income and size are obtained by cross-tabulating data from the Public Use Microdata Sample (PUMS), which is a census product. A choice model determines the auto ownership for each type of households (by income, household size, and number of workers). The HBW trip generation model is a cross-classification model with variables being the number of workers and auto ownership in a household. The productions are then summarized for the four income groups.

For HBW attractions, results from a 1998 business establishment survey, which surveyed over 14,000 visitors and more than 10,000 employees, were used to develop a two-way cross-classification matrix of trip rates per employee by area types (from the highest to the lowest density: CBD, urban commercial, urban residential, suburban commercial, suburban residential, exurban, and rural) and by eight employment categories used in the employment size forecasting model, DRAM/EPAL.

Corresponding to the stratification of HBW trips by income group at the production end, the HBW trip attractions are also grouped based on the four income groups to allow trip distribution by income groups. As stated in (ARC 2002), there is not sufficient information to allow the separation of attractions by income. However, a previous analysis of the 1990 census data showed that variations in the proportion of work attractions by income groups were not substantial by zone. Therefore, it was decided to apply the average zonal proportion for each income group to "split" the home-based work attractions into four groups based on income.

HBW trip distribution is accomplished using four standard gravity models, one for each income group. The generalized cost used in the work trip models is the composite impedance represented by a "logsum" variable derived from the mode choice model. It was commented that the distribution models, as calibrated, ensured that the average composite impedance value was the same or very similar for the observed and estimated trips. However, there was no guarantee that the average trip length, measured over the highway network, would be the same. Therefore, a rigorous test of the model is needed to compare the observed and estimated travel times and distances over the highway network.

Each of the five types of non-work trips (HBO, HBS, HB Grade School, HB University, and Non-home Based) is modeled separately. The non-work distribution models are calibrated in the same manner as the work trip models but uncongested (off-peak) highway travel times are used rather than congested travel times.

2.6.2 Metropolitan Baltimore Region

The Metropolitan Baltimore Region (BMC 2004) uses a gravity model to distribute trips. Travel impedances are based on interzonal travel times that include terminal and intrazonal times. *K* factors are not used. Barrier penalties are included in the network to produce a better distribution. HBW, HBO, HBSCH, and work-based other trips are redistributed after completing trip pre-assignment. Following distribution, trips for the home-based purposes are stratified by income.

2.6.3 Metropolitan Boston Region

There is currently no off-the-shelf documentation on the Central Transportation Planning Staff (CTPS) Region Travel Forecasting Model. The information provided here was provided by the Boston MPO in the form of a summary of the model. The trip distribution model implements a three-dimensional trip balancing strategy without the use of friction factors or *K* factors. Provided in the EMME/2 transportation planning software, the three-dimensional trip balancing procedure distributes productions and attractions, subject to a third constraint that combines composite impedances of trip utilities from mode choice models and the total trip interchanges between districts resulted form a 1991 transportation demand survey. The trip distribution procedure estimates 60 gamma functions of scaled composite impedances from the three-dimensional balancing for trip purpose combinations, time period, and trip interchange category. For future years, these gamma functions are used to compute the seed values for the two-dimensional balancing of productions and attractions.

2.6.4 Dallas-Fort Worth Metropolitan Area

The trip distribution model in Dallas-Fort Worth Regional Travel Model **(**DFWRTM) is a standard gravity model (NCTCG 2000). However, instead of the typically used exponential function, DFWRTM uses the Bessel function as the decay function for the impedance variable. It is stated that based on comparison of performances of the Bessel function and the negative exponential function, the Bessel function was able to better simulate short trips.

2.6.5 Metropolitan Denver Region

The Metropolitan Denver Region is undergoing a multi-phase Integrated Regional Model (IRM) Project, of which the ultimate purpose is to replace the regional model with a state-of-the-art modeling system, including comprehensive upgrades to both the travel and socioeconomic elements. The efforts of the recently completed first phase were to refresh the existing model system by updating basic travel model parameters and shift the software platform from MINUTP to TransCAD. The newly released Denver Regional Model, Compass (DRCOG 2004), uses a gravity model for trip distribution. The home-based work trips are segmented into low-income, middle-income, and high-income. Separate friction factors are used for each income group for work trips. The second phase of IRM, or the Vision Phase, is currently being conducted. Possible upgrades for trip distribution include converting the gravity model into a destination choice model, probably in conjunction with activities-based models.

2.6.6 Metropolitan Detroit Region

The regional travel demand forecasting model (TDFM) of Southeast Michigan Council of Governments (SEMCOG 2004) is run on a personal computer using TransCAD, and is calibrated based on information collected in the 1994 SEMCOG Household-Based Person Trip Survey, 1995 DDOT On-Board Survey, 1996 Regional Commercial Vehicle Survey, and 2002 SEMCOG

Regional Transit On-Board Survey. The TDFM utilizes a gravity model to distribute trips of all purposes except external/external trips, for which a growth factor model is used. Travel impedances are based on network travel time weighted by four periods: morning peak, midday, afternoon peak, and off-peak. *K* factors are used as special socio-economic adjustment factors.

2.6.7 Huston-Galveston Region

The Houston-Galveston Area Council (HGAC) Travel Model is in the process of being developed. The trip-based models are being developed as the second track of a multi-track model development effort. Upon completion of calibrating the "Track2" models, Track3 work, which involves development of tour-based micro-simulation models, will begin. The HGAC trip distribution models are 'atomistic' gravity-based models (PB 2002). The model assumes that production and attraction trips within a zone are distributed uniformly throughout the zone. As a result, inter-zonal trips between two zones may be assigned different travel impedance within a range instead of the zonal centroid-to-centroid impedance. Otherwise, it is similar to more traditional forms of the gravity model. The Track2 models take advantage of market segmentation techniques to distribute trips separately by household income as well as auto ownership. The travel impedances are calculated using a logsum measure to consider all travel modes including toll roads, HOV, local bus, express bus, and rail transit.

2.6.8 New York Metropolitan

The New York Metropolitan Transportation Council (NYMTC) Travel Demand Model is a journey-based model rather than a trip-based model (PB 2001). The concepts in the first few sub-models are still similar to those in trip-based models. The journey frequency model estimates the number of work journey pairs (to and from work) for nine socio-economic groups, which are combinations of three income groups (lowest 15%, middle 70%, and highest 15% income groups) and three auto/worker strata (households with no automobiles, households with fewer automobiles than workers, and households with the same number or greater automobiles than workers). Given the number of work journey pairs, employment by type (retail, office, industrial, and other), and a set of utilities for each of the socio-economic groups, the joint distribution-mode choice model estimates the number of journeys between zones stratified by the socio-economic stratification of income and cars/workers.

Journeys are distributed using a destination choice model, after which the stop frequency and stop location selection sub-models are applied to determine the intermediate stops for each journey.

2.6.9 Metropolitan Phoenix Region

In the Phoenix Maricopa Association of Governments (MAG) Travel Demand Model, the trip distribution model is a gravity model with composite impedance (MAG 2002). There are seven distribution models for the home-based work trips, one for each combination of auto ownership and household income groups. The generalized cost used in the work trip models is the composite impedance with logsum variable derived from the mode choice model. The composite impedance include: drive mode travel time, drive mode distance, total unweighted transit time (in-vehicle time + total wait + auxiliary transit), and transit fare.

2.6.10 Metropolitan Seattle Region

A series of documents were developed for the Puget Sound Regional Council's Travel Demand Forecasting Models in 2001 (Cambridge Systematics 2001b). The full series of reports include current model and new model documentations. The current model is a traditional four-step planning model (Cambridge Systematics 2001a). HBW trip production in the current model is stratified by household size and number of workers.

The documentation on the new model describes two primary components that have been updated in recent years: the trip distribution and mode choice models. Gravity models are used for all purposes except HBW trip purpose. For HBW trips, a combined nested logit destination and mode choice model is applied. The destination choice model is in the upper nest, and the mode choice is in the lower nest.

2.6.11 Metropolitan St. Louis Region

The St. Louis regional travel demand model maintained by the East-West Gateway Coordinating Council is a modified version of the travel demand model software MINUTP (EWGCC 1997). The MINUTP distribution model uses a gravity model to distribute HBW, HBO, NHB, commercial, and external trips. Friction factors for the gravity models are based on travel time impedances from the 1965/66 survey and the 1979 supplementary survey. In addition to friction factors, *K* factors are used as attraction inhibitors for trip interchanges across the Mississippi River. The *K* factors are not used for trips crossing the Missouri River because the needed adjustment is small. To avoid inconsistent travel times between trip distribution and trip assignment, the output of the assignment is used to create new "congested" times as an input to a repeated cycle of trip distribution and mode split, leading to a new assignment output. This cyclical process is repeated until the travel times converge.

2.6.12 Metropolitan Washington, D.C. Region

The Metropolitan Washington Region uses a gravity model to distribute its trip tables (MWCOG 2004). The model employs income stratification as well as facility type stratification within the six trip purposes. The distribution involves separate gravity model runs for a total of 25 travel markets. Travel impedances are based on a composite time function that represents a blending of transit and highway travel times. Geographic bias time penalties on crossing physical barriers are imbedded in the travel impedances between twelve superdistricts.

2.6.13 Metropolitan Portland Area

In the Portland model, HBW trip are generated based solely on number of workers (Metro 2001). The HBW productions by household income level are obtained by applying a HBW trip generation model using the number of households stratified by household income quartile level.

Except college trips, trip attraction rates are no longer computed since destination choice models were adopted for trip distribution.

HBW trips are distributed separately by income groups with destination choice models developed using a multinomial logit estimation procedure. The variables include accessibility measure represented by the logsum from the mode choice model, employment data in the attraction zones, and dummy variables such as that indicating if a trip crosses Columbia River from Washington to Oregon or that if a trip's attraction end is in a business district with parking charges. The destination choice set for each origin zone consists of 30 randomly selected TAZs. The non-work destination choice models are calibrated in a similar manner as the work trip model, but are not stratified by income.

2.6.14 Metropolitan San Diego Region

The San Diego Association of Government, which recently switched transportation modeling software from TRANPLAN to TransCAD, uses gravity models for distribution of each individual trip purposes (SANDAG 2004). The "first stage" distribution model relies on off-peak travel impedance with terminal times and parking costs. The double-constrained program takes ten iterations to bring attraction estimates in line with trip generation estimates. A composite impedance that combines peak and off-peak travel times with distance is then used for the "second stage" distribution model.

2.6.15 San Francisco Bay Area

In BAYCAST, the HBW generation model is a simple regression model on HBW trips per employed resident that is stratified by household income level and applied at the zonal level (Purvis 1997). The number of workers by household income level is determined by applying the Workers in Household Nested Choice Model (a pre-generation model) using the number of households stratified by household income quartile level. The HBW attraction model is a simple regression model and is applied without stratification. The attractions are then split by household income quartile based on the 1990 census commuter data.

Although the previous version of the San Francisco Bay Area travel demand model used logit destination choice with logsum from the mode choice model, the new Bay Area trip distribution models are gravity in form (MTC 2001). The problem with the destination choice models is the need for additional gravity model-style "friction factors" to correct the overall trip length frequency distribution, which is considered a time-consuming and generally non-rewarding effort.

The home-based work trip distribution model is actually four sets of friction factors applied to HBW trip ends stratified by household income quartile level. Data from the 1990 census-based "observed" home-based work trip tables were used in calibrating these friction factors.

2.6.16 Sacramento Area Council of Governments

Sacramento employs an activity-based travel model, which is quite different from trip-based models, and there is no market segmentation involved (SACG 2001). The tour generation model in the activity-based travel model is based on a disaggregate day pattern choice approach. Rather than treating the average number of trips per household for each purpose as an independent choice, trips were derived from a multi-dimensional choice of the number of tours made during the day for each purpose and the number of intermediate stops made on the tours. Hierarchical discrete choice models were applied to predict the probability of various day-long activity patterns for a person, including the purpose and type of the primary activity of the day, the number of secondary home-based tours made for each specific purpose, and the number of intermediate stops made on each half of a tour. When applying the probability using a stochastic Monte Carlo approach, the model generates a set of predicted tours for each person-day. These are then used as inputs into the destination choice model.

The destination choice model is the disaggregate equivalence of distribution models used in the traditional four-step process. The composite utility across all modes is used as the main impedance measure, which is calculated as the logsum form the mode choice model.

2.7 Potential Trip Distribution Enhancements

Ewing *et al*. (1996) categorize potential FSUTMS model enhancements based on a three-level hierarchy. Level I enhancements aim at fine-tuning the existing FSUTMS models. These enhancements do not change the structure of the traditional four-step process and the relationships among the steps. Level II enhancements would make basic changes to the four-step process while still keeping the process sequential. These enhancements may include new steps, modified relationships among the steps, output feedback, etc. Level III enhancements require a paradigm shift from the four-step process to a completely new process. Combined (or equilibrium) and activity-based models are two such examples. These recommended enhancements are described in the following subsections.

2.7.1 Level I Enhancements

Level I enhancements include:

1. Use composite impedances or generalized cost for calibrating friction factors, rather than just highway travel times.

2. Develop separate friction factors for other variables, such as income levels, in addition to trip purposes.

3. Utilize other functions such as the Gamma and Bassel functions for describing trip length distributions.

4. Develop separate peak-hour and non-peak travel impedances for work and non-work trips.

5. Allow special friction factors to override "common" friction factors for zones warranting special considerations.

6. Include barrier penalties in friction factors in place of *K* factors.

7. Use composite impedances for transit-dependent zones and highway-only impedances for non-transit-dependent zones.

8. Employ logit destination choice models.

9. Develop logit combined destination/mode choice models.

Harvey *et al*. (1993) suggest the following Level I enhancements for trip distribution:

1. Assess the reasons that *K* factors historically have been so important in calibrating trip distribution models, and evaluate approaches that might improve model fit with less dependence on these factors.

2. Assess the performance and tractability of formal nested models through destination choice (e.g., with the expected mode choice utilities forming the accessibility variables).

3. Develop models that utilize the improved land use and employment databases that are becoming available to planning agencies due to census innovations and advances in Geographic Information Systems (GIS).

2.7.2 Level II Enhancements

Existing literature reveals a number of Level II enhancements that may be adapted for FSUTMS. Specifically, they include feedback modeling and time-of-day modeling.

A well-known problem inherent in the sequential four-step process is that travel impedances used in trip distribution, mode split, and traffic assignment are often inconsistent. The problem arises because travel impedances are a function of network congestion but the level of congestion is unknown during the trip distribution step. To provide internal consistency, i.e., to assure that the travel impedances at network equilibrium are compatible with the travel impedances used in earlier model steps, a modeling process may involve iterations, called feedback loops. It has been demonstrated that feedback may significantly affect the results of a model. A research project on incorporating feedback was sponsored by the FDOT System Planning Office and completed in 2003 (Lan et al. 2003). The results from the research do not provide sufficient evidence that supports conclusions from previous studies that feedback provides significant benefits, which has been attributed, at least partially, to the fact that the feedback model was not fully calibrated for the pre-assignment steps. However, feedback has been successfully applied in other urban models.

The purpose of time-of-day travel demand models is to produce traffic assignment results that more accurately reflect the capacity restraining impact of the highway network on the traffic volumes. Most existing modeling programs contain a single CONFAC parameter to adjust for daily capacity restraint assignments. Although FSUTMS versions higher than 5.3 have been updated to allow CONFAC parameters that vary with facility type, it still does not account for the differences in peaking characteristics among different locations in the network, nor does it consider the directional imbalance of traffic volumes during the morning and afternoon peak periods. This issue has been investigated in (Gan et al. 2003) and the results are mixed.

Most time-of-day models are post-distribution. To account for time-of-day impact, some travel models use peak-period travel impedances for home-based work trips and off-peak travel impedances for non-work trips in trip distribution and modal split. It is recognized, however, that there are trips of all purposes during each of these periods. In models developed for the Metropolitan Transportation Authority's Red Line East Side Extension project in Los Angeles, California, a pre-distribution time-of-day model was developed. In this model, trip ends are split by time period for each trip purpose. Initially, a set of factors is used to calculate trip ends for each trip purpose by time of day, usually for multi-hour peak and off-peak periods. The factors are based on peaking characteristics such as trip purpose, jurisdiction, area type, and socioeconomic stratification. These factors are applied to the trip ends from the trip generation model and produce trip ends by peak and off-peak periods for each of the trip purposes. The peak and off-peak trip ends by trip purpose are used in the trip distribution and mode choice models. This model was also used in the Dulles Corridor Alternatives Studies (Cambridge Systematics 1994, PB 1994). Pendyala (2002) reviewed the state-of-the-art in time-of-day modeling and developed default time-of-day factors for use in FSUTMS, which convert daily trips to trips by time of day for each trip purpose.

2.7.3 Level III Enhancements

This section provides a brief review of Level III enhancements, including combined (equilibrium) models, activity-based models, and trip chaining modeling.

2.7.3.1 Combined Models

Rather than using the feedback loop in the context of the sequential four-step approach, combined travel forecasting models aim at generating consistent estimates (such as network speeds) among the four components by embedding the components within a market equilibrium principle. The simultaneous nature of these models also avoids the problem of compounded prediction errors from one component to another. The available network equilibrium principles include (Miller 1997):

1. User optimal-strict: At network equilibrium, no traveler can reduce his or her travel costs by unilaterally changing routes (i.e., changing routes independently without other users' route changes).
2. User optimal-general: Travelers change routes in the next time period in a manner that reduces total cost based on the current route costs.
3. Dynamic user optimal: At network equilibrium, no traveler who has departed during the same time interval can reduce his or her travel costs by unilaterally changing routes.

4. Stochastic user optimal: At network equilibrium, no traveler can reduce his or her perceived travel costs by unilaterally changing routes.

A number of combined models based on these equilibrium principles have been developed. Models that include the trip distribution step include combined distribution/assignment models (Florian 1975, Evans 1976, Chu 1989, Chu 1990, Lam 1992, Oppenheim 1993, among others), combined distribution/split/assignment models (Florian 1978, Boyce 1997, among others), and combined generation/distribution/split/assignment models (Defermos 1982, Safwat 1988, among others). A review of the various combined models may be found in (Miller 1997). Additionally, a comprehensive treatment of combined models may be found in (Oppenheim 1995).

2.7.3.2 Activity-Based Models

Activity-based models aim at supporting policy actions that four-step based models are unable to address. Pas (1997) considered the activity-based approach to travel demand forecasting to be the only paradigm shift in the history of the development of travel demand forecasting models. He considered the shift from aggregate to disaggregate models in the 1970's as a shift in statistical technique rather than a shift in paradigm.

First proposed more than 20 years ago, activity-based models are founded on the idea that travel is a demand that arises through people's needs and desires to participate in activities that are dispersed in time and space. Accordingly, activity-based models use socio-demographic information of travelers and land use information as inputs to create schedules supposedly followed by people in their everyday life and provide as output, for a given day, detailed lists of activities pursued, times spent for each activity, and information on their travel between activities, including travel time, mode used, etc. (Goulias 1997, Kitamura 1997). These models recognize the inter-dependency among decisions about a series of trips made by an individual, as well as the interactions among members of the household when household members allocate resources such as household vehicles, assign and share tasks, and jointly engage in activities (RDC 1995).

A fundamental challenge faced by activity-based models is the combinatorial nature of these models, created by a decision process that has many feasible outcomes in many dimensions. Some of these dimensions, notably activity timing and location, are continuous. Even after transforming these dimensions into discrete categories, the number of combinations is still too large for today's most powerful computers. Bowman *et al*. (1997) provided an example that showed a typical individual being modeled could face 10^{17} daily activity schedule alternatives.

Although activity-based models have been under development for the past 20 years, actual applications of activity-based models are essentially non-existent (Goulias 1997, Kitamura 1997). Shiftan (1998) indicated that the main reason for the lack of applications was due to the complexity of the model and applications. Horowitz (1985) contended that limited understanding of non-work related travel behavior was a particular barrier to the development of activity models. Strathman *et al*. (1994) predicted that activity-based models were still fairly far from the point of generating estimates that could replace those of the four-step models.

However, activity-based models has taken the center stage in travel demand research and development since the beginning of this decade in response to the requirements created by the 1990 Clean Air Act Amendments (CAAA) and the 1991 Intermodal Surface Transportation Efficiency Act (ISTEA). To meet the requirements, the U.S. Department of Transportation, in collaboration with the U.S. Environmental Protection Agency and the U.S. Department of Energy, embarked on a research program known as the Travel Model Improvement Program (TMIP). This program aims at addressing the linkage of transportation to air quality, energy, economic growth, land use, and the overall quality of life. It addresses both analytical tools and the integration of these tools into the planning process to better support decision makers (Pas 1997). This program has provided a major impetus for the active research and development of activity-based models. A major undertaking of this program is the development of the activity-based Transportation Analysis and Simulation System, or TRANSIMS.

TRANSIMS is a microsimulation-based travel forecasting system developed by the Los Alamos National Laboratory. It is designed to provide information on traffic impacts, congestion, and pollution. TRANSIMS starts with data about people's activities and the trips they take to carry out those activities and builds a model of household activity demand. It then simulates the movement of individuals across the transportation network, including their use of vehicles such as cars or buses, on a second-by-second basis. The interactions of individual vehicles produce traffic dynamics from which analysts may estimate vehicle emissions and judge the overall performance of the transportation system. TRANSIMS has been tested in a number of studies including Albuquerque and a 25-square mile area in Dallas (FHWA 1998). A TRANSIMS model has also been implemented for metropolitan Portland, which is focused on travel forecast. In the last few years, IBM Business Consulting has been developing a commercial version of TRANSIM and has released TRANSIM-DOT, which has been deployed in Portland (Bridges 2004).

In summary, current research in activity-based models is still largely at the stage of model development and testing. The main issues are the need for household activity surveys, complexity of network coding, and computing resources. Several more years may be expected before TRANSIM is accepted for travel forecast, and many more years will likely be needed to conduct comparative analyses and for the models to become accepted by the general travel forecasting community. Currently, the only known activity-based model in use is the Sacramento model (see Section 2.6.17).

2.7.3.3 Trip Chaining

One of the travel behaviors that conventional travel models fail to reflect is the fact that people often combine travel to several destinations into a single trip circuit. Rather than making separate trips for different purposes, people often "chain" trips. The conventional four-step process analyzes home-based work, home-based non-work, and non-home-based trips as separate independent trips. In reality, the trip generation, destination choice, and mode choice of each trip in a chain are related to the other trips in the chain (Cambridge Systematics 1994).
The inclusion of trip chaining analyses in travel models may help improve the overall quality of non-work models. Non-work travel accounts for the largest share of urban area travel. Studies have shown that in large urban areas, over one-half of the person trips in the morning peak and

over two-thirds of the person trips in the afternoon peak are made for non-work purposes. Non-work trips, particularly non-home-based trips, have proven to be quite difficult to model. Generally speaking, non-work travel models perform far worse than the work models that have been developed for urban areas. Many researchers believe that the decisions leading to the formation of trip chains are essential elements of activity-based models (Cambridge Systematics 1994).

Recent research in trip chain modeling falls into three categories: (1) descriptive research, (2) development of trip generation models that incorporate trip chains, and (3) development of non-home-based destination choice models which incorporate trip chaining behavior (Cambridge Systematics 1994).

(a) Descriptive Research

Descriptive research studies are valuable because they shed light on how trip chains are formed and why. A number of researchers and planners have studied the basic characteristics of people's trip chains, including:

- Distribution of the number of links in trip chains;
- Combinations of trip purposes which are being chained;
- Household characteristics that affect the types of trip chains formed;
- Travel modes used for various types of trip chains; and
- Time-of-day characteristics of trip chains.

Lockwood *et al*. (1994) investigated characteristics of suburban non-work trips through a self-reporting household daily travel survey. Trip chaining was found to be a significant travel pattern, with the majority of trip chains made on the work-to-home trips during the afternoon peak hour. They also found that longer travel times provided incentives to chaining trips together, which suggested that increases in other travel costs might motivate efficient arrangement of trips. Clarke *et al*. (1981) found that households composed of young working adults without children developed chains around the work trips to satisfy a greater proportion of their travel utility needs.

Pas (1984) performed a multi-way contingency analysis to determine whether trip chain types might be associated with various individual and household attributes. They found that life-cycle stage, marital status, gender, employment status, education, income, presence of children, and residential density are significant discriminators for trip chain types.

Strathman *et al*. (1994) developed two descriptive trip chaining models based on data from the Portland metropolitan area. The first model addresses the propensity of households to add non-work trips to the work commute. The second model focuses on household allocation of non-work trips to alternative trip chaining options, which include the work commute, multi-stop non-work journeys, and unlinked trips. They found that the probability of forming simple work chains was significantly greater when individuals scheduled their journey to work in peak congestion periods. They also found that a travel-time based indicator of congestion did not influence the distribution of non-work trips among alternative types of trip chains.

(b) Trip Generation Models Incorporating Trip Chaining

A great deal of trip-chaining research has been conducted by researchers who are studying activity-based modeling. These researchers attempt to develop models that make use of the fact that transportation is a derived demand. They believe that models of household activities, rather than simple travel models, will ultimately prove to describe travel behavior more accurately (Goulias 1990).

(c) Trip Chaining and Destination Choice

Ewing *et al*. (1995) proposed a method based on a simple adjustment to the concept of “linked-trip accessibility” by Richardson and Young (1981). It is speculated that travelers will be more likely to choose destinations that are accessible to other destinations, as this permits efficient trip chaining.
A non-home-based model developed by Cambridge Systematics (1980) addresses the trip chaining phenomenon in its destination choice model. The model estimates the probability that a traveler at a trip end that is not his or her home will make a trip to a destination other than his or her home. If the traveler is not returning to home, the probability that the trip will be made to each particular zone is then estimated. For each traveler, this estimation for each intermediate stop is repeated until the traveler reaches home. The model assumes that each traveler's destination choice decision is independent of previous decisions. This assumption obviates the need to represent several alternative trip chains as explicit choice alternatives. The model also assumes that no mode switching occurs. In other words, the mode used for the non-home-based trip is the same as the mode used in the home-based trip to get to or from the trip end location.

A tour-based model has been developed and deployed in New York City, in which the probability of stops during a tour is estimated by a logit model, and stops are determined jointly with mode choice after trip distribution (see Section 2.6.9).

2.8 Summary

This chapter has provided an overview of the existing literature on trip distribution methodologies and practices. Presently, most MPOs are still using the traditional four step models, with gravity models for trip distribution. However, a few MPOs including Portland, New York, and Sacramento have moved to employ discrete destination choice models, tour-based models, and even activity-based models. Activity-based models are gaining more attentions, and operational TRANSIM models for simulating base year conditions have been tested for a few metropolitan areas including Dallas-Fort Worth and Portland. However, the wide acceptance of activity models by MPOs across the nation will take some time due to the need for full evaluation of these models, greater efforts required for data collection, and computational efficiency issues.

Based on findings from this review and recommendations by the Florida Model Task Force Trip Distribution Committee, further research was concentrated in the following three areas to enhance the current FSUTMS trip distribution methodologies:

1. Explore intervening opportunity models;
2. Enhance gravity models with variables that are identified as influential to trip length; and
3. Develop destination choice models to incorporation of socioeconomic, travel and zonal attractiveness data in trip distribution.

All the models will be evaluated using the same set of criteria, which will be described in the next chapter, followed by the chapters that describe each individual model development effort.

3. MODEL EVALUATION CRITERIA

To determine if any of the models developed in this study actually improved trip distribution results, traditional gravity models were also calibrated for comparison purposes. All the models were evaluated using a fixed set of criteria, based on which the model outputs for the same study area was compared to each other as well as to survey data. These evaluation criteria include:

- Average trip length
- Trip length distribution
- Intrazonal trips
- Spatial distribution accuracy

The average trip length from a model should be as close as possible to that from the survey data. However, the average trip length alone is inadequate to determine a distribution model's performance. Therefore, a coincidence ratio was also calculated to compare the shapes of the trip length distributions from the survey data and from the distribution models of interest. The coincidence ratio, defined below, lies between zero and one, with zero indicating two disjoint distributions and one indicating identical distributions.

$$coincidence\ ratio = \frac{\sum_{t=1}^{T} \min\left\{\frac{f^m(t)}{F^m}, \frac{f^0(t)}{F^0}\right\}}{\sum_{t=1}^{T} \max\left\{\frac{f^m(t)}{F^m}, \frac{f^0(t)}{F^0}\right\}} \tag{2}$$

where

$f^m(t)$ = frequency of trips in time interval *t* from model;

$f^0(t)$ = frequency of trips in time interval *t* from survey data;

$F^m(t)$ = total trips distributed from model;

$F^0(t)$ = total trips from survey data; and

T = number of time intervals.

Intrazonal trip percentages were calculated for each model developed and compared to those from the corresponding gravity models and from the travel survey data. A model that has a better performance in terms of intrazonal trip distribution should produce intrazonal trip percentages closer to those from the survey.

Because two different spatial travel patterns (as defined by intrazonal and interzonal trip interchanges) could potentially exhibit similar average trip lengths and trip length distributions, these two criteria are insufficient to determine the goodness-of-fit of a distribution model. For this reason, model outputs were further evaluated for spatial accuracy. Spatial accuracy was determined based on the degree of similarity in interzonal trip interchanges. Because the sample size of household travel surveys was not large enough to give a reliable depiction of trip interchanges at the TAZ level, TAZs in an urban area were grouped based on the definition of survey districts or traffic analysis districts (TADs). Trip interchanges between pairs of TADs were then determined and examined.

A number of statistical tests were calculated to determine if a particular spatial pattern of trip interchanges between TADs better matched that from the survey data. It is known that the use of different goodness-of-fit statistics may lead to different conclusions regarding model performance (Fotheringham 1989). Consequently, multiple test statistics were applied to evaluate the performance of the models developed in terms of interdistrict trips. These test statistics include (Sen 1995):

- Chi-square statistic
- Neyman's modified Chi-square statistic
- Simplified Freeman-Tukey statistic
- Scaled deviance statistic
- Sum of Errors Squared
- Mean Errors Squared.

These test statistics are defined below, where N_{ij} and $\hat{T}_{ij}$ represent the observed and estimated flows between spatial units i and j, respectively.

<u>Chi-Square Statistics</u>

$$\chi^2 = \sum \frac{(\text{Observed} - \text{Estimated})^2}{\text{Estimated}} = \sum_{ij} \frac{\left(N_{ij} - \hat{T}_{ij}\right)^2}{\hat{T}_{ij}} \tag{3}$$

<u>Neyman's Modified Chi-Square Statistics</u>

$$\chi^2 = \sum \frac{(\text{Observed} - \text{Estimated})^2}{\text{Observed}} = \sum_{ij} \frac{\left(N_{ij} - \hat{T}_{ij}\right)^2}{N_{ij}} \tag{4}$$

<u>Simplified Freeman-Tukey Statistics</u>

$$\sum_{ij} 4\left[\sqrt{N_{ij}} - \sqrt{\hat{T}_{ij}}\right]^2 \tag{5}$$

<u>Scale Deviance Statistics</u>

$$2\sum_{i\,j}\left[N_{ij} \log\left(\frac{N_{ij}}{\hat{T}_{ij}}\right)\right] \tag{6}$$

Sum of Errors Squared

$$\sum_{ij} \left(N_{ij} - \hat{T}_{ij} \right)^2 \tag{7}$$

Mean Error Squared

$$\frac{\sum_{ij} \left(N_{ij} - \hat{T}_{ij} \right)^2}{n} \tag{8}$$

A model with a better spatial accuracy is indicated by a smaller value of the above statistics. It is possible that these statistics may give different indications of whether a model is an improvement over another, thus making it more important to use multiple criteria.

4. DEVELOPMENT OF INTERVENING OPPORTUNITY MODELS

This chapter describes the development of intervening opportunity models for Palm Beach County. Intervening opportunity models are investigated as an alternative to the gravity models currently used as the trip distribution model in FSUTMS. This effort has been motivated mainly by two reasons. First, Palm Beach County, like some other counties in Florida, has developed in a long, narrow corridor along the coast, with multiple city cores spatially separated. The gravity models tend to over-predict short trips in such cases. When the traditional gravity models do not perform well, *K* factors sometimes have to be used. The Florida Statewide Model Task Force had suggested that intervening opportunity models might be able to better handle such urban development patterns.

Another appeal of an intervening opportunity model is that it does not depend on a trip length frequency distribution. In a gravity model, this trip length frequency distribution, typically obtained from a base year household survey, is assumed to remain unchanged for future model updates and forecasts. This assumption is unlikely to hold in reality if there will be significant changes in future land uses. An intervening opportunity model uses attractions instead as the basis in model calibration, which may be updated when land uses change, thus making the model more adaptive to changes in trip patterns.

To evaluate the potential of intervening opportunity models to replace the gravity models currently used in FSUTMS, intervening opportunity models were calibrated with Palm Beach County as the study area. Gravity models were also calibrated based on the survey data to be compared to the intervening opportunity models.

Intervening opportunity models have been proven to be a member of the gravity model family. Therefore, an intervening model may be formulated as a gravity model and calibrated as such. In the next section, the gravity model form of an intervening opportunity model is first presented. The procedure used to calibrate the intervening opportunity model is then described in Section 4.2. Section 4.3 compares the intervening opportunity model to the gravity model. Finally, a summary and discussions are provided in Section 4.4.

4.1 Intervening Opportunity Model Formulation

An intervening opportunity model assumes that trip makers consider potential destinations sequentially, in order of their impedance (commonly a linear combination of time and distance on non-toll links or time and toll on toll links) away from the origin (Rogerson 1993). The probability that a trip will terminate at one of a group of destinations is equal to the product of two probabilities: (1) the probability that an acceptable destination closer to the origin has not been chosen and (2) the probability that an acceptable destination exists in this group of destinations. The probability of a trip ending in a zone *j* may be expressed as (Eash 1980):

$$P(A_j) = \{1 - P(V_{j-1})\} L A_j$$

where

V_j	=	sum of the destination opportunities available from an origin zone to the jth zone, ranked by travel impedance from the origin zone;
A_j	=	number of destination opportunities considered in zone j;
$P(V_j)$	=	probability of finding an acceptable destination from V_j opportunities;
$P(A_j)$	=	probability of finding an acceptable destination among the A_j opportunities of zone j; and
L	=	constant probability of accepting a destination if it is considered.

Since the two probabilities, $P(V_j)$ and $P(A_j)$, may vary with location, the problem therefore may be stated in terms of limitingly small quantities assuming $P(A_j)$ to be a continuous function and zones and A_j to be small. Thus, the above equation may be written as differentials:

$$\mathrm{d}P(V_j) = \{1 - P(V_j)\}L\,\mathrm{d}V_j$$

The following relationship may then be derived by substituting V_j and $P(V_j)$ with x and $\mathrm{f}(x)$, i.e.,

$$1 - P(V_j) = 1 - f(x) = \mathrm{g}(x)$$
$$\rightarrow \mathrm{dg}(x) = -\,\mathrm{df}(x)$$
$$\mathrm{d}P(V_j) = \{1 - P(V_j)\}\,L\,\mathrm{d}V_j$$
$$\rightarrow \mathrm{df}(x) = [1 - \mathrm{f}(x)]\,L\,dx$$
$$\rightarrow -\,\mathrm{dg}(x) = \mathrm{g}(x)\,L\,\mathrm{d}x$$
$$\rightarrow -\,\mathrm{dg}(x)/\mathrm{g}(x) = L\,\mathrm{d}x$$
$$\rightarrow -\int \mathrm{dg}(x)/\mathrm{g}(x) = \int L\,\mathrm{d}x$$
$$\rightarrow \ln \mathrm{g}(x) = -\,(Lx + c)$$

Let k be a constant. The above equation may then be expressed as follows:

$$\rightarrow \mathrm{g}(x) = \exp[-\,(Lx + c)] = \exp(-\,c)\,\exp(-\,Lx) = k\,\exp(-\,Lx)$$
$$\rightarrow \mathrm{f}(x) = 1 - k\,\exp(-\,Lx)$$
$$\rightarrow P(V_j) = 1 - k\,\exp(-\,Lx)$$
$$\because P(0) = 1 - k\,\exp(0) = 1 - k = 0 \quad \therefore\ k = 1$$
$$\rightarrow P(V_j) = 1 - \exp(-\,LV_j)$$

The number of trip movements between an origin zone i and a destination zone j equals the probability of finding an acceptable destination opportunity in zone j times the number of trips from zone i, P_i:

$$T_{ij} = P_i\{P(V_j) - P(V_{j-1})\}$$
$$\rightarrow T_{ij} = P_i\{\exp(-\,LV_{j-1}) - \exp(-\,LV_j)\}$$
$$\rightarrow T_{ij} = P_i\{\exp(-\,LV_{j-1}) - \exp[-\,L(V_{j-1} + A_j)]\}$$
$$\rightarrow T_{ij} = P_i[1 - \exp(-\,LA_j)]\,\exp(-\,LV_{j-1})$$

where A_j is the number of trip attractions in zone j. If L is small, that is it is on the order of 0.1 or less, $[1 - \exp(-LA_j)]$ is nearly equal to LA_j. Therefore,

$$T_{ij} \approx P_i A_j L \exp(-LV_{j-1}) \quad (1)$$

A trip distribution model is constrained to distribute the same number of trips from a zone as there are trips originating from that zone, that is, $\sum_j T_{ij} = P_i$. The above equation may be rewritten as

$$T_{ij} = f_i P_i A_j L \exp(-LV_{j-1})$$

where f_i is a factor to force all origin trips to be distributed. Summing all the trips originating from zone i and forcing the sum to be the total production of zone i, f_i may be solved:

$$\sum_j T_{ij} = \sum_j f_i P_i A_j L \exp(-LV_{j-1}) = f_i P_i \sum_j A_j L \exp(-LV_{j-1}) = P_i$$
$$\rightarrow f_i = 1/\{\sum_j A_j L \exp(-LV_{j-1})\}$$

Therefore,

$$T_{ij} = P_i \frac{A_j e^{-LT^*_{j-1}}}{\sum_k A_k e^{-LT^*_{k-1}}}$$

Replacing $\exp(-LV_{j-1})$ with F_{ij} gives the intervening opportunity model in the form that gravity models generally take (Eash 1980):

$$T_{ij} = P_i \frac{A_j F_{ij}}{\sum_k A_k F_{ik}}$$

where F_{ij} is the “friction factor” representing the spatial separation between zone i and zone j.

The most often used expression to determine the standard gravity model friction F_{ij} is usually assumed to be a gamma function with some type of impedance between zones as an independent variable (α, β, and γ are calibration coefficients):

$$F_{ij} = \alpha d_{ij} \beta \exp(-\gamma d_{ij})$$

By setting $d_{ij} = V_{j-1}$, $\alpha = 1$, $\beta = 0$ and $\gamma = L$, the “friction factors” in an intervening opportunity model are:

$$\rightarrow F_{ij} = 1 \times (V_{j-1})^0 \exp(-LV_{j-1}) = \exp(-LV_{j-1})$$

By replacing the distance impedance in the standard gravity model with V_{j-1}, the L value may then be calibrated in the same manner as gamma in the standard gravity model software.

4.2 Intervening Opportunity Model Calibration

The TRANPLAN (TRANsportation PLANning) program may be use to calibrate parameter L since the friction factor in TRANPLAN is formulated as $f_{ij} = \exp(-\theta d_{ij})$, where θ is a coefficient and d_{ij} is the minimum travel impedance between zones i and j. Replacing d_{ij} in TRANPLAN with $V_j - 1$ converts a gravity model to an intervening opportunity model. The following five steps explain the procedure of calibrating an intervening opportunity model using TRANPLAN:

(1) Run FSUTMS with 1999 Palm Beach County data to obtain free-flow travel time impedance skim and productions and attractions for HBW, HBS, HBSR, HBO, NHBW (Non-home-based work), and NHBO (non-home-based other) purposes, respectively.

(2) Convert the binary file of the impedance skim to a database file.

(3) Construct opportunity matrices for different trip purposes. Since there are 1,172 zones in Palm Beach County, the matrices are 1,172 by 1,172. The content in the matrix cell (i, j) represents the cumulative attractions in zones i to $j - 1$. These zones are ranked by travel impedance from zone i. The procedure involves selecting zone i and sorting all other zones in an ascending order based on the travel time t_{ij}. For each given zone, e.g., zone k in the sorted list, the attractions in zone i through zone $k - 1$ ($k = i, ..., j - 1$) are summed up and the sum is stored in the opportunity matrix cell (i, k). Note that every 1,000 cumulative attraction trips are aggregated as one unit of opportunity. This factor of 1,000 was applied for the following reasons:

    (a) In practice, travel times as well as other impedance measurements are usually rounded up to the nearest integer to obtain the trip length frequency distribution.
    (b) In TRANPLAN, the maximum number that a matrix file is able to store or that the F factors may assume during the calibration process is $2^{31} - 1$, i.e., 2,147,483,647. This number is based on four-byte integer type, which until recently was the largest integer permitted on a PC. Run-time errors occurred when a factor smaller than 800 was applied in the calibration using the Palm Beach County data. After examining the TRANPLAN output, it was suspected that variables reached their upper limits during the iterations of model calibration. Note that TRANPLAN was not originally designed to calibrate intervening opportunity models thus such large values were not anticipated.

(4) Replace the travel time impedance skim with the opportunity matrix for each trip purpose using the UPDATE MATRIX command in TRANPLAN. Because the home zones of trips are origins, they will have zero intervening opportunity. However, since zero impedance cannot be specified in the GT record (i.e., trip length frequency data) for the TRANPLAN's *Calibrate Gravity Model* function, 1 is used to represent zero opportunity. Subsequently, all the non-zero opportunities obtained in Step 3 are increased by 1.

(5) Calibrate intervening opportunity model and obtain OD matrix:
   (a) Using the 1999 SEFRTCS survey data and the opportunity matrices, find the frequency distribution for the destination opportunities, which replaces the impedance in the GT record, i.e., the trip length frequency record in data specifications, for each trip purpose.
   (b) The *F* FACTOR CLOSURE is set to 5% as the default so that the TRANPLAN program, as originally designed, will iterate one more time before termination if the ratio of the average destination opportunity to the surveyed average opportunity is within 5%.
   (c) Set the friction factors in the GF records, i.e., the friction factor records in the data specifications, to 1 for initialization.
   (d) *F* FACTOR ITERATIONS, or the maximum number of iterations to be executed during the calibration run, is set to 20.

Note that the output matrix file created by the Highway Selected Summation function in TRANPLAN, which originally contains the interzonal skim impedance, is now used to store the accumulated opportunity matrix. Therefore, instead of calibrating the model to the surveyed trip length distribution as in the case of a gravity model calibration, the intervening opportunity model is calibrated to the surveyed opportunity distribution. The surveyed opportunity distribution is obtained as follows:

(1) For a particular trip purpose, the production and attraction zones of each sampled trip are identified.

(2) The total number of attractions from zones with free-flow travel times less than that between the observed zone pair is calculated (as described in Step 3 of the calibration procedure). These attractions represent the intervening opportunities that meet the trip maker's purpose but are not utilized.

(3) The opportunities are divided by 1,000 as in the case of the opportunity matrix stored in the summation file. The nearest integer of the new impedance unit is then recorded with one frequency. Again, zero opportunity is substituted by 1 and non-zero opportunities are increased by 1.

(4) The same procedure is performed for every surveyed trip to obtain the total "intervening opportunities" frequency. The distribution of these opportunities for all surveyed trips is stored in a TRANPLAN input file, TRANPLAN.IN.

4.3 Evaluation of Intervening Opportunity Models

This section discusses the results of the calibration and the performance of the intervening opportunity models for different trip purposes for Palm Beach County. Figure 4.1 shows the convergence of parameter *L* during model calibration for HBW trips. It may be seen that *L* converged at the end of the 4th iteration.

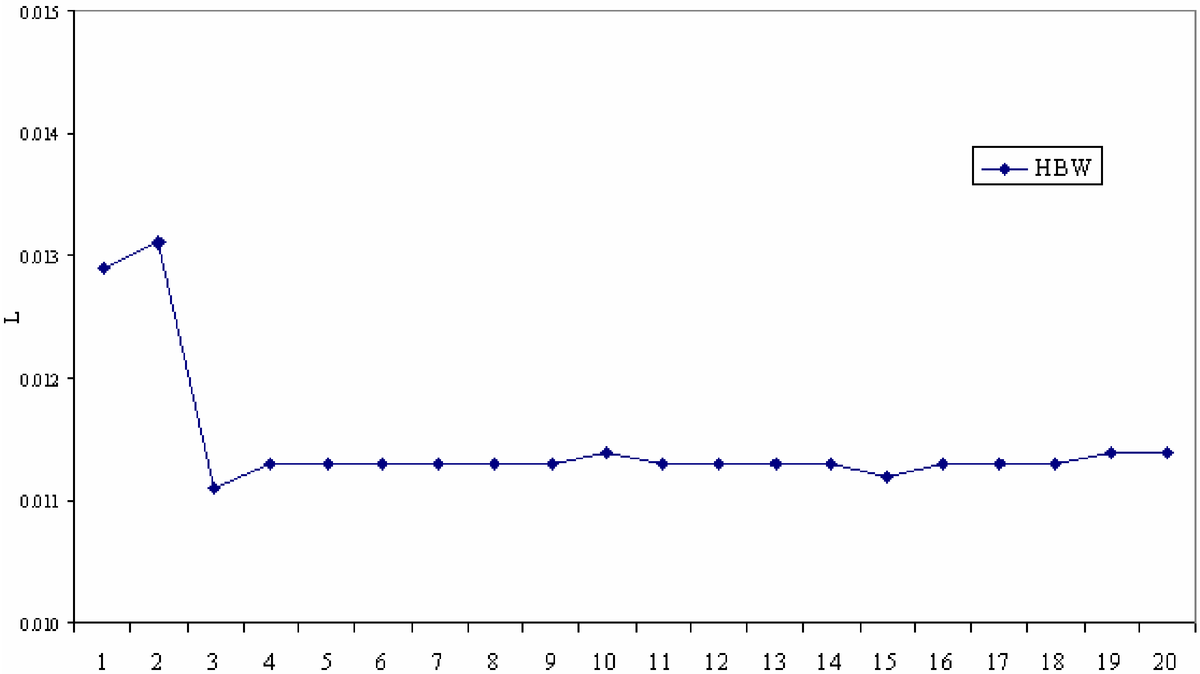

Figure 4.1 Convergence of *L* during HBW Trip Model Calibration

In Figure 4.2, the calibrated HBW friction factors (the curve with blue label points) are compared with their theoretical values (the fitted curve) for different impedance values (or attractions). The theoretical curve was obtained by fitting an exponential curve based on the calibrated friction factors. The best fitting curve has an *L* value of 0.0114. It may be seen that the calibrated friction factors are initially smaller than the theoretical values. However, they became larger than the theoretical values after impedance exceeds approximately 240. Compared to the theoretical values, the actual calibrated values of the friction factors produced more long trips. In other words, if friction factors obtained from the theoretical curve had been used, there would have been be fewer long trips and more short trips.

To evaluate the performance of the intervening opportunity models, the distributed trip length frequencies for different purposes were calculated based on the OD matrices and travel time impedance from the gravity models. The trip length frequencies from the survey data were compared with the results from the intervening opportunity models and gravity models. The performance of the intervening opportunity models was evaluated using the six criteria described in Chapter 3.

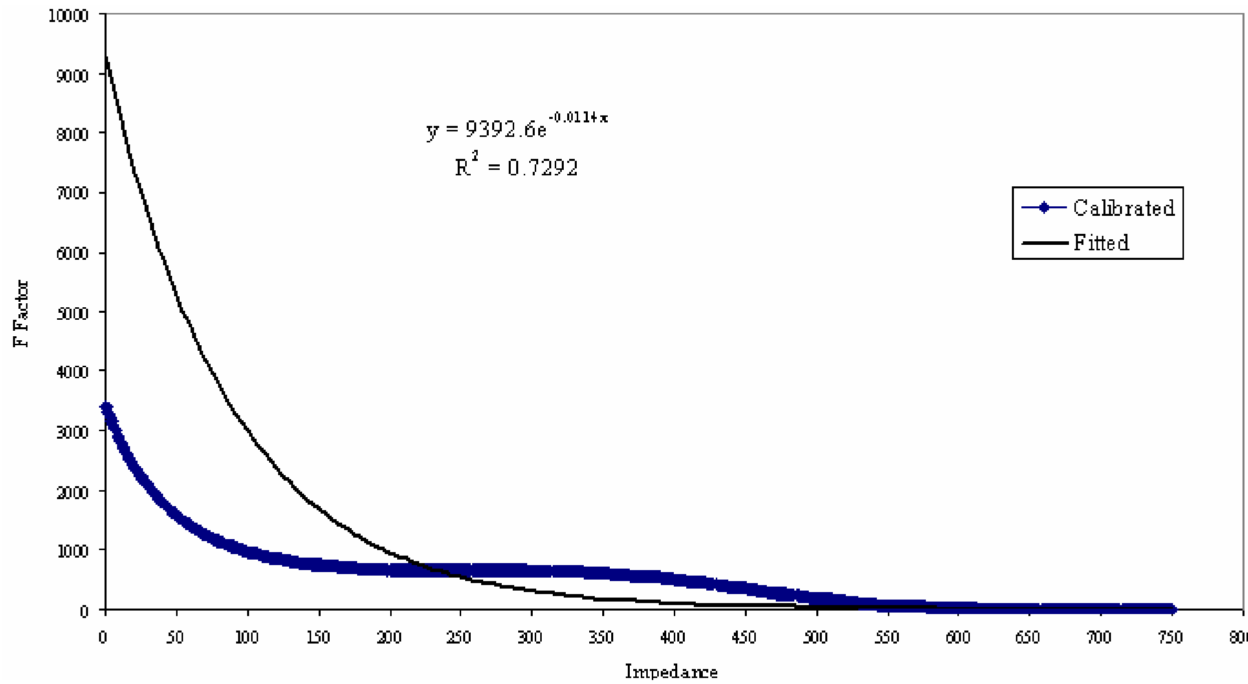

Figure 4.2 Friction Factor versus Impedance for the HBW Model

Table 4.1 compares the average trip lengths from the intervening opportunity models and the gravity models for different trip purposes. The gravity models were calibrated by Corradino, Inc. The first column in Table 4.1 shows the trip purposes, the second column the average trip lengths from the 1999 survey data, the third column the average trip lengths from the intervening opportunity models, and the fourth column those from the gravity models. The results from the intervening opportunity models show that only the NHBW trips were calibrated with an average trip length closer to that from the survey data. In general, the intervening opportunity model overestimated the trip lengths.

Table 4.1 Comparison of Average Trip Lengths from Survey and Intervening Opportunity and Gravity Models

Trip Purpose	Average Trip Length in Minutes		
	Surveyed Data	IOM*	Gravity Model
HBW	16.19	17.53	15.70
HBS	12.00	13.73	11.73
HBSR	10.97	14.52	11.31
HBO	12.49	14.90	12.45
NHBW	13.08	13.07	12.66
NHBO	11.55	12.52	10.95

* Intervening opportunity model

To further compare the gravity models and the intervening opportunity models, the shapes of the trip length distributions from the gravity and intervening opportunity models were compared and the coincidence ratios for different trip purposes are given in Table 4.2. It may be seen that, for most of the trip purposes, the coincidence ratios for the two models were similar, with gravity models having a higher ratios for almost every trip purpose except NHBO. Table 4.3 compares the performance of the two models in terms of the intrazonal trips produced as percentages of the total internal trips by purpose. While both types of models under-predicted intrazonal trips in general, it was more pronounced for the intervening opportunity models.

Table 4.2 Comparison of Coincidence Ratios of the Intervening Opportunity and Gravity Models

Trip Purpose	Coincidence Ratio	
	IOM	Gravity Model
HBW	0.826	0.831
HBS	0.680	0.859
HBSR	0.635	0.760
HBO	0.717	0.797
NHBW	0.778	0.789
NHBO	0.784	0.780

Table 4.3 Percentages of Intrazonal Trips from Survey and Intervening Opportunity and Gravity Models

Trip Purpose	Surveyed Data			IOM			Gravity Model		
	I-I* Trips	Intrazonal Trips	%	I-I* Trips	Intrazonal Trips	%	I-I* Trips	Intrazonal Trips	%
HBW	1,869	53	2.84	684,688	4,280	0.63	684,698	17,354	2.53
HBS	1,273	41	3.22	599,234	8,539	1.42	600,051	32,445	5.41
HBSR	955	169	17.70	429,186	8,882	2.07	429,482	41,466	9.65
HBO	2,394	159	6.64	841,558	15,491	1.84	842,403	20,381	2.42
NHBW	776	56	7.22	348,284	12,941	3.72	348,305	24,290	6.97
NHBO	1,844	221	11.98	682,165	24,740	3.63	682,199	44,701	6.55

Figures 4.3 through 4.8 compare the trip length distribution by purpose from the two types of models against the survey data. It may be seen that the intervening opportunity models produced longer trips, and the curves did not decay as fast as the survey data and the gravity models for trip lengths over 15 minutes.

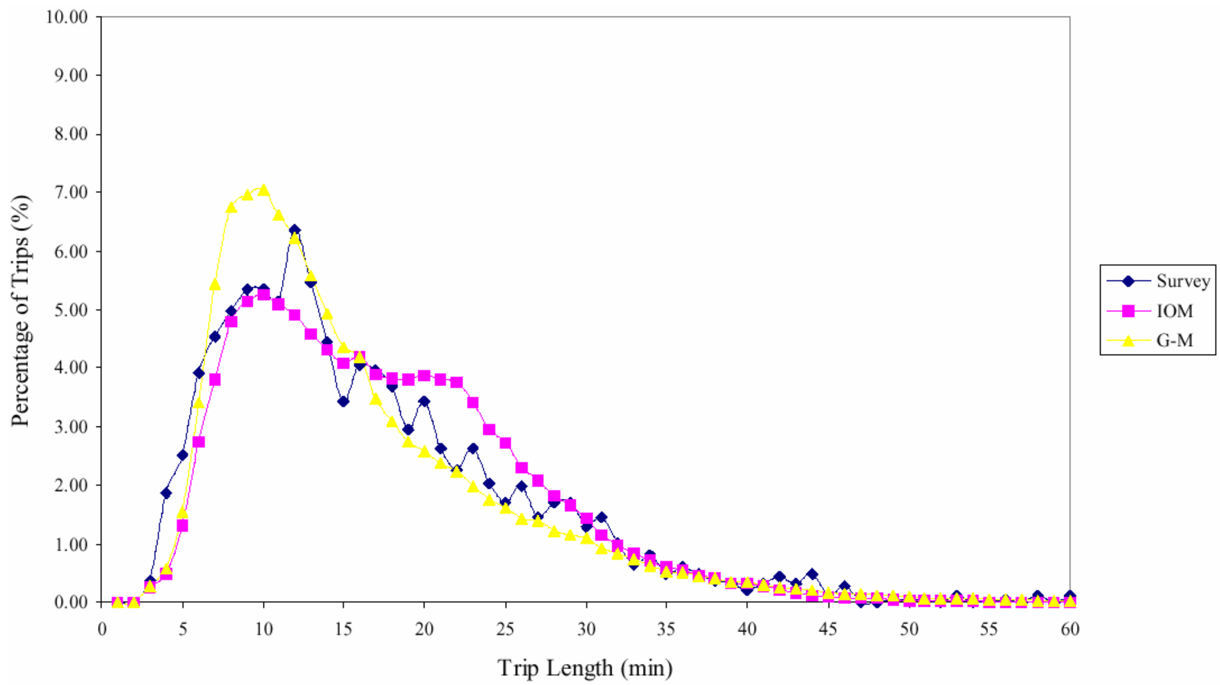

Figure 4.3 HBW Trip Length Distributions from Survey and Intervening Opportunity and Gravity Models

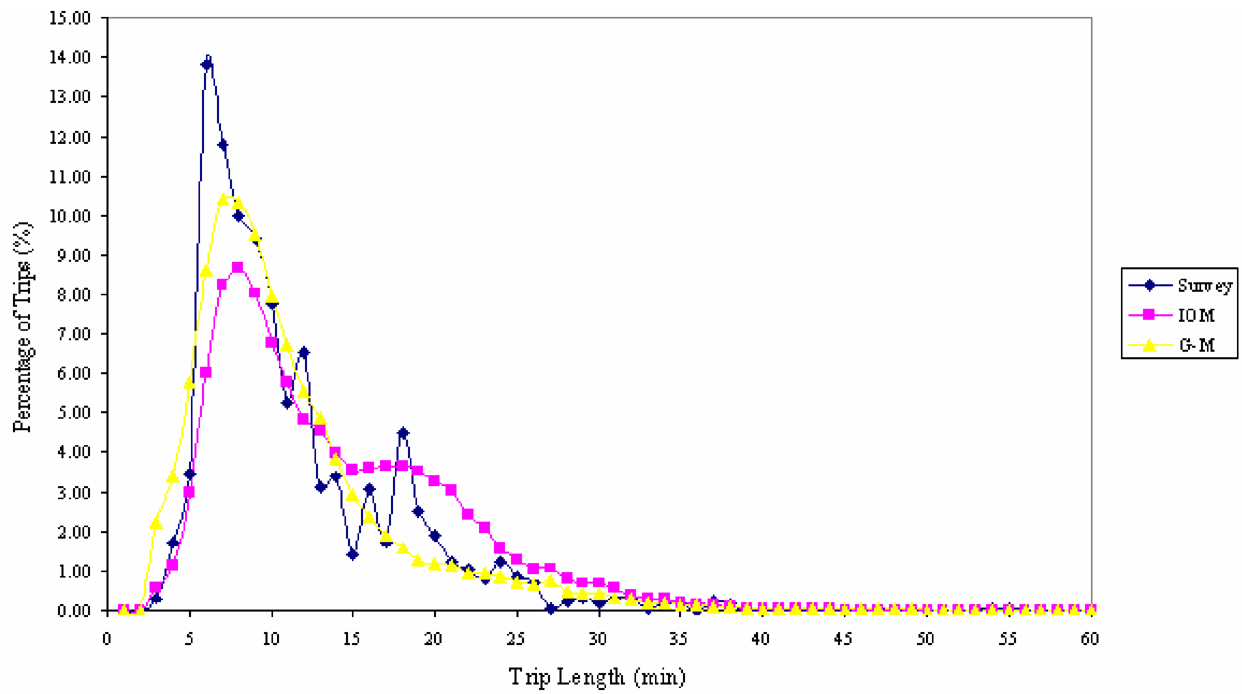

Figure 4.4 HBS Trip Length Distributions from Survey and Intervening Opportunity and Gravity Models

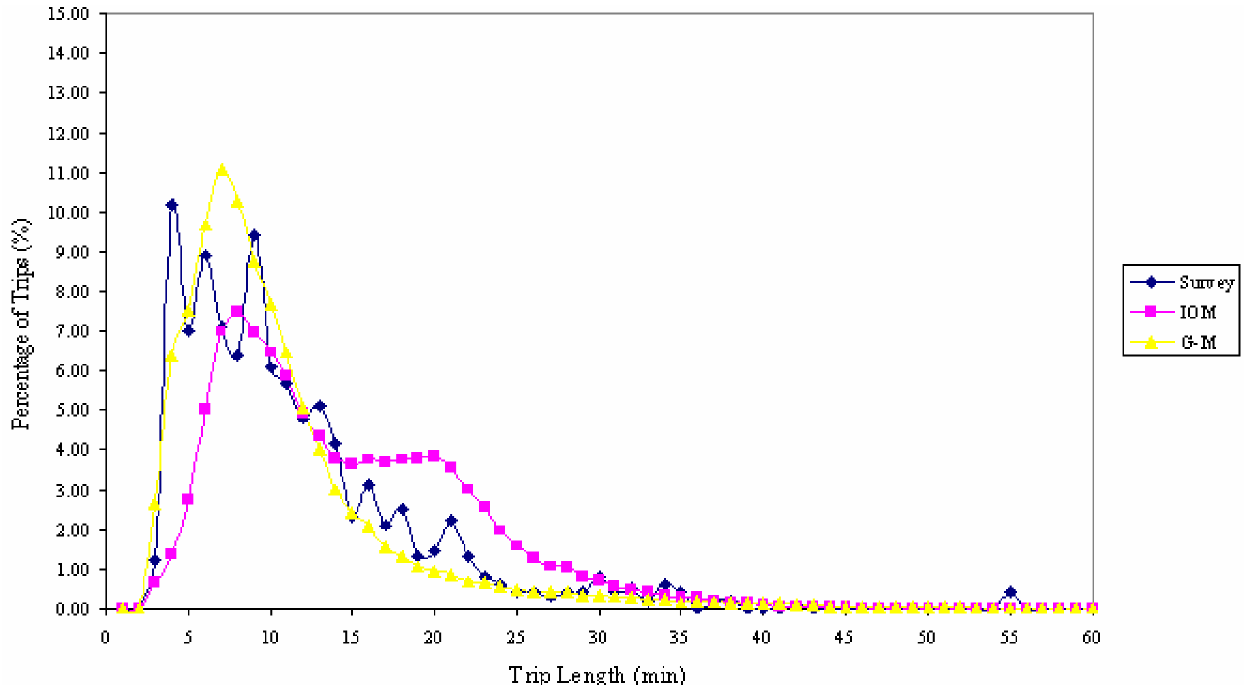

Figure 4.5 HBSR Trip Length Distributions from Survey and Intervening Opportunity and Gravity Models

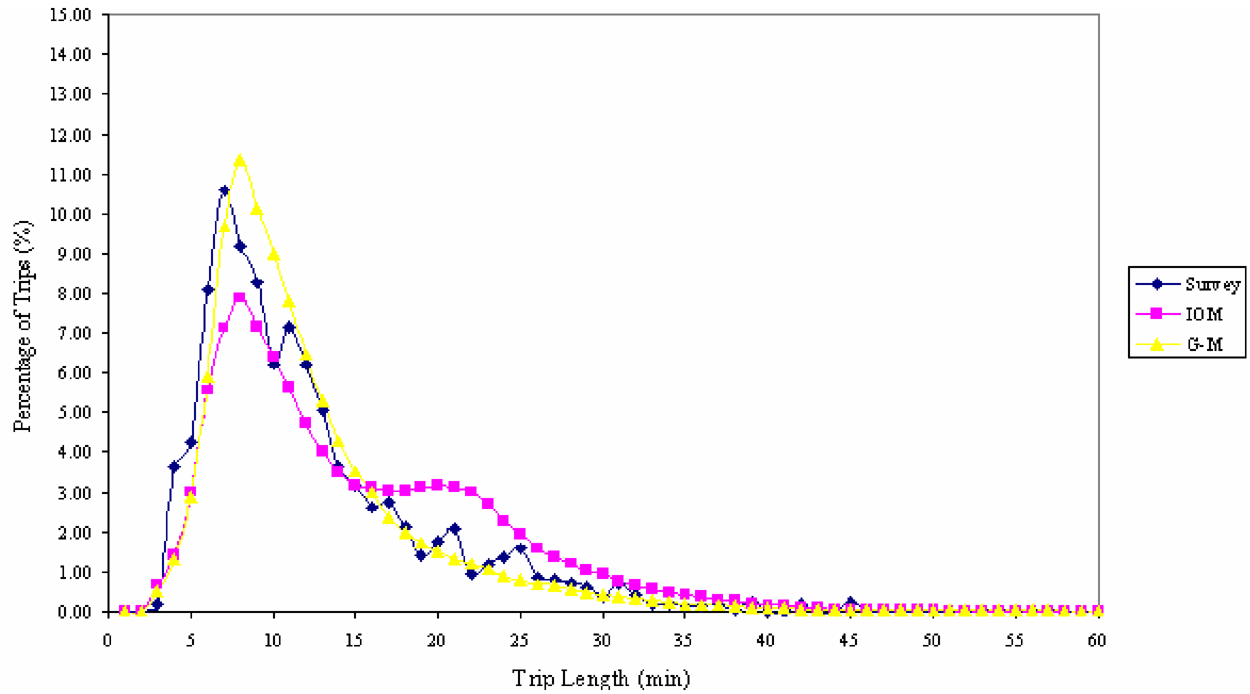

Figure 4.6 HBO Trip Length Distributions from Survey and Intervening Opportunity and Gravity Models

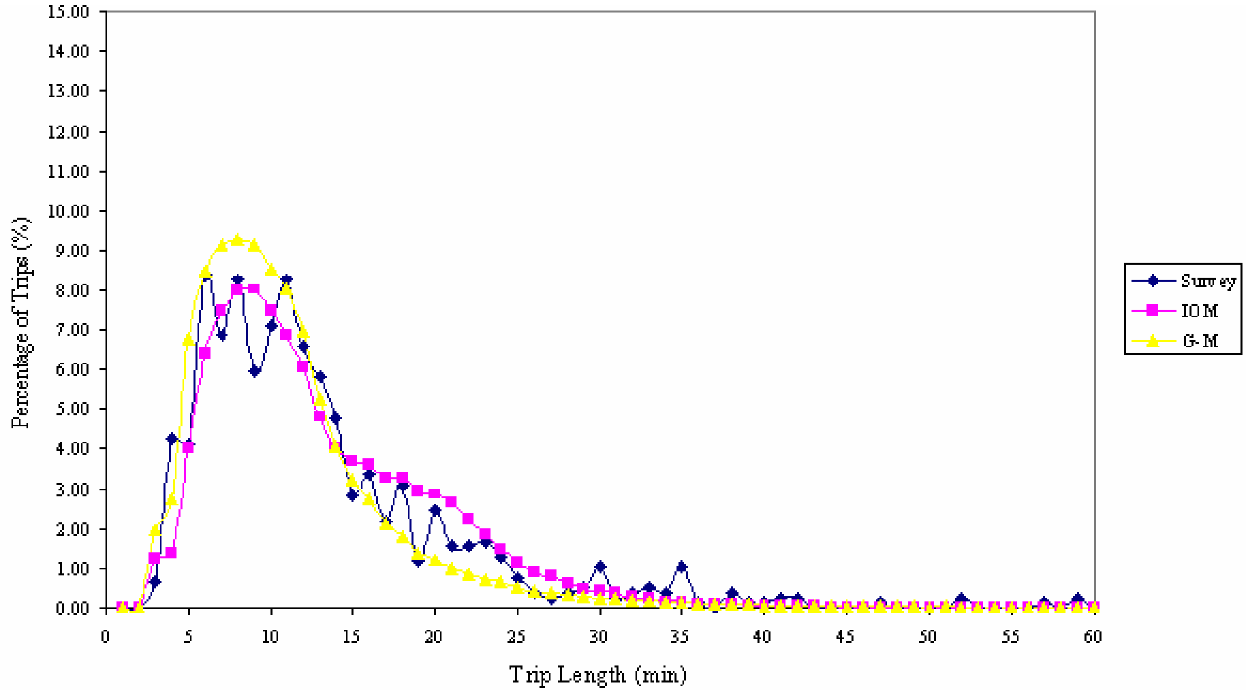

Figure 4.7 NHBW Trip Length Distributions from Survey and Intervening Opportunity and Gravity Models

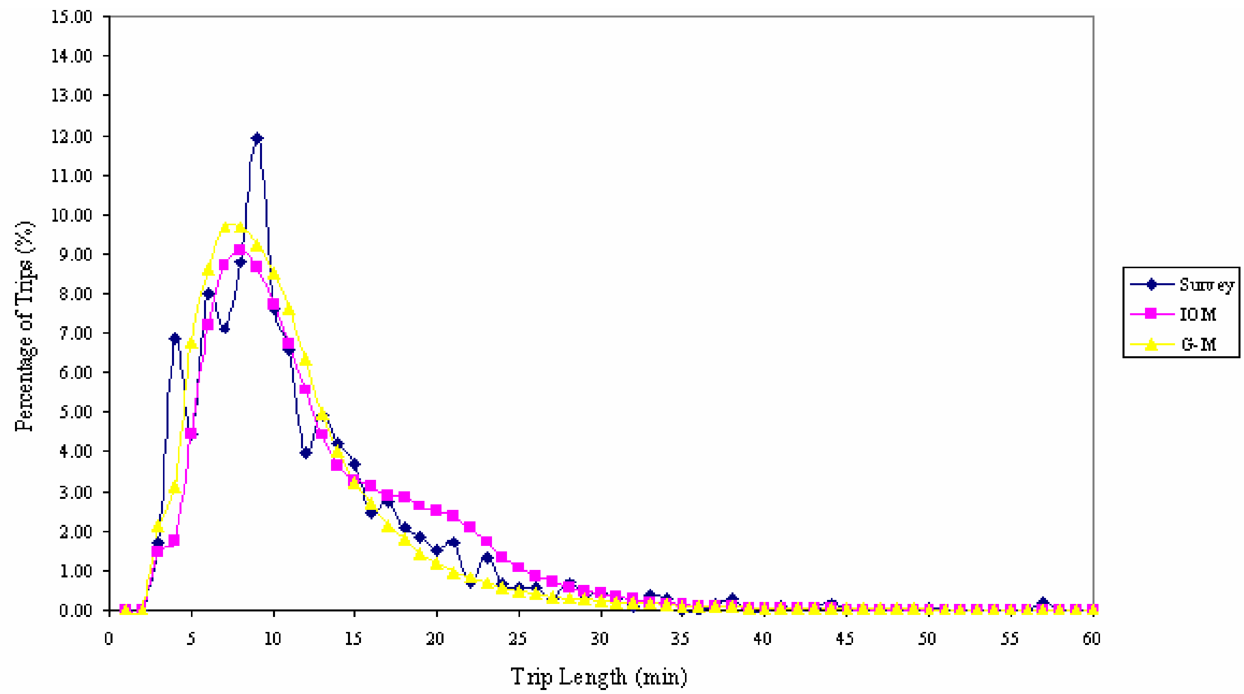

Figure 4.8 NHBO Trip Length Distributions from Survey and Intervening Opportunity and Gravity Models

To further investigate the performance of the two models in terms of their spatial accuracy, the trip interchanges between different areas were examined. For survey purposes, Palm Beach County was divided into five traffic analysis districts (TADs). However, most of the trips originated in survey district 4 ended in the same district and only a few surveyed trips ended in the other four districts, resulting in small samples of inter-district trips for some pairs of TADs. This led to large goodness-of-fit statistics due to division of close-to-zero percentage of trips. Therefore, survey district 4 was combined with district 3. Figure 4.9 shows the four TADs (districts 3 and 4 combined) in Palm Beach County. The trip interchanges as percentages of the total internal trips between these four TADs were computed. Tables 4.4 through 4.9 provide the results in terms of percentages of the total internal trips for different trip purposes. In the tables, "IOM" stands for intervening opportunity model and "GRAV" for gravity model. The shaded cells in the tables indicate that the results from the intervening opportunity models are better than those from the gravity models. It may be seen from Table 4.4 that among the 16 district pairs, the percentages of HBW trip interchanges between seven district pairs from the intervening opportunity model have smaller errors when compared to the gravity model results. For the remaining nine pairs of the districts, the percentages predicted by the gravity model are closer to the survey data. Table 4.10 provides a summary of the results, illustrating how many estimates are close to survey data for both of the intervening opportunity models and gravity models.

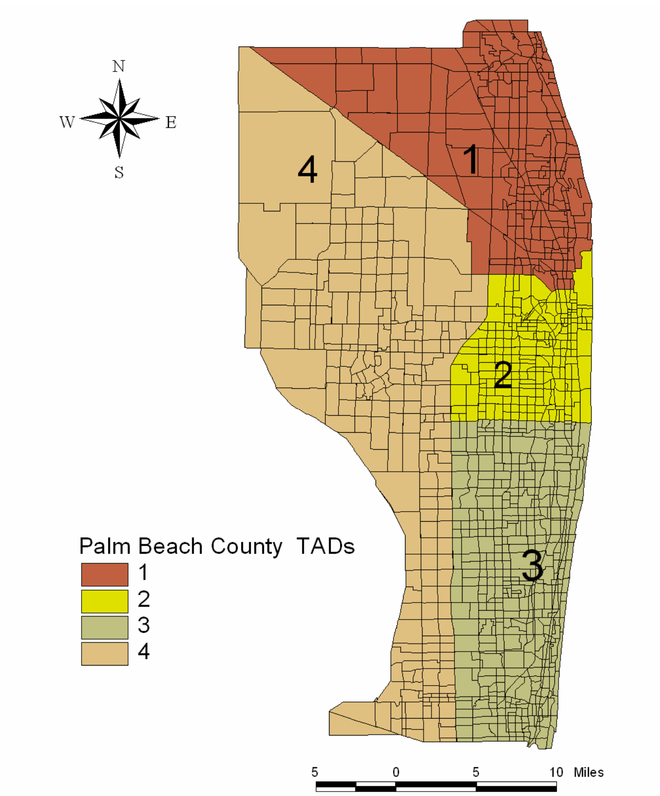

Figure 4.9 Palm Beach County Survey Districts

Table 4.4 Comparison of HBW Trip Interchanges between TADs from Survey and Intervening Opportunity and Gravity Models

District		1	2	3	4
1	SURV	15.76	5.65	1.24	0.91
	IOM	13.86	5.18	1.81	1.95
	GRAV	17.08	3.81	0.85	1.03
2	SURV	4.79	15.44	4.57	1.13
	IOM	5.32	10.90	5.31	1.52
	GRAV	3.21	14.31	4.25	0.96
3	SURV	2.26	3.44	24.53	1.78
	IOM	0.96	5.73	26.08	2.18
	GRAV	0.94	4.50	28.52	1.56
4	SURV	3.23	4.95	4.95	5.38
	IOM	3.54	4.67	6.23	4.76
	GRAV	2.40	4.15	5.52	6.90

Table 4.5 Comparison of HBS Trip Interchanges between TADs from Survey and Intervening Opportunity and Gravity Models

District		1	2	3	4
1	SURV	17.06	2.45	0.39	0.32
	IOM	17.00	3.64	0.50	0.38
	GRAV	19.38	1.95	0.13	0.05
2	SURV	1.90	14.14	1.97	1.26
	IOM	3.32	13.52	4.39	0.87
	GRAV	1.78	16.90	2.83	0.43
3	SURV	0.39	2.21	34.04	2.05
	IOM	0.22	3.74	31.89	1.76
	GRAV	0.22	2.80	34.04	0.98
4	SURV	0.95	3.00	3.79	14.06
	IOM	2.69	3.89	5.24	6.95
	GRAV	2.19	3.59	4.10	8.62

Table 4.6 Comparison of HBSR Trip Interchanges between TADs from Survey and Intervening Opportunity and Gravity Models

District		1	2	3	4
1	SURV	14.75	2.41	0.73	0.63
	IOM	16.69	4.66	1.16	0.73
	GRAV	20.21	2.41	0.52	0.16
2	SURV	1.46	12.13	2.20	0.73
	IOM	3.92	13.35	5.33	1.12
	GRAV	1.59	17.88	3.45	0.45
3	SURV	0.52	2.51	38.18	1.78
	IOM	0.35	4.47	29.41	2.24
	GRAV	0.27	3.03	32.88	0.93
4	SURV	0.52	2.20	3.66	15.59
	IOM	1.87	3.61	4.65	6.43
	GRAV	1.01	2.93	3.14	9.16

Note: IOM – intervening opportunity model
GRAV – gravity model

Table 4.7 Comparison of HBO Trip Interchanges between TADs from Survey and Intervening Opportunity and Gravity Models

District		1	2	3	4
1	SURV	17.63	3.64	0.29	0.13
	IOM	15.78	4.16	1.46	0.68
	GRAV	18.46	3.00	0.39	0.13
2	SURV	2.80	11.83	2.30	0.84
	IOM	3.52	13.27	4.78	0.93
	GRAV	2.29	15.92	3.59	0.51
3	SURV	0.38	2.97	34.98	2.01
	IOM	0.56	4.62	28.71	1.89
	GRAV	0.31	3.85	31.05	1.22
4	SURV	1.30	2.76	3.89	12.29
	IOM	2.66	4.24	5.32	7.42
	GRAV	1.76	3.92	4.50	9.09

Note: IOM – intervening opportunity model
GRAV – gravity model

Table 4.8 Comparison of NHBW Trip Interchanges between TADs from Survey and Intervening Opportunity and Gravity Models

District		1	2	3	4
1	SURV	17.57	2.66	0.43	0.49
	IOM	17.02	3.45	0.77	0.94
	GRAV	18.53	2.94	0.41	0.35
2	SURV	3.09	15.51	3.20	1.63
	IOM	4.09	16.94	3.96	1.64
	GRAV	2.83	18.69	3.56	1.25
3	SURV	0.65	3.58	34.44	2.60
	IOM	0.26	4.05	33.59	2.47
	GRAV	0.37	3.29	34.82	2.04
4	SURV	0.33	1.08	2.71	10.03
	IOM	0.78	1.72	2.58	5.74
	GRAV	0.38	1.24	2.09	7.19

Table 4.9 Comparison of NHBO Trip Interchanges between TADs from Survey and Intervening Opportunity and Gravity Models

District		1	2	3	4
1	SURV	14.75	2.41	0.73	0.63
	IOM	16.69	4.66	1.16	0.73
	GRAV	20.21	2.41	0.52	0.16
2	SURV	1.46	12.13	2.20	0.73
	IOM	3.92	13.35	5.33	1.12
	GRAV	1.59	17.88	3.45	0.45
3	SURV	0.52	2.51	38.18	1.78
	IOM	0.35	4.47	29.41	2.24
	GRAV	0.27	3.03	32.88	0.93
4	SURV	0.52	2.20	3.66	15.59
	IOM	1.87	3.61	4.65	6.43
	GRAV	1.01	2.93	3.14	9.16

Table 4.10 Comparison of the Predicted Inter-District Trips by Intervening Opportunity and Gravity Models (Total 16 District Pairs)

	HBW	HBS	HBSR	HBO	NHBW	NHBO
IOM closer	7	6	5	4	5	5
GRAV closer	9	9	11	12	11	11
Tie	0	1	0	0	0	0

Table 4.11 provides results from statistical tests on model spatial accuracy. These statistical tests have been described in Chapter 3. These statistics indicate that gravity models are more accurate in trip distribution for all purposes except NHBW.

Table 4.11 Statistical Comparison of Spatial Accuracy of Intervening Opportunity and Gravity Models

Trip Purpose	Model	Chi-Square*	Neyman's Modified Chi-Square	Simplified Freeman-Tukey	Scale Deviance	Sum of Errors Squared	Mean Errors Squared
HBW	IOM	6.41	6.27	5.99	2.63	38.53	2.41
	Gravity	5.61	4.10	4.62	2.12	31.96	2.00
HBS	IOM	12.54	13.71	11.90	5.15	73.36	4.59
	Gravity	10.27	6.93	7.64	3.57	47.93	3.00
HBSR	IOM	23.56	25.33	21.49	9.36	196.23	12.26
	Gravity	12.45	10.78	10.96	4.89	136.31	8.52
HBO	IOM	10.09	17.30	11.63	4.72	85.98	5.37
	Gravity	4.93	5.16	4.94	2.13	48.92	3.06
NHBW	IOM	5.30	5.40	4.88	2.12	37.86	2.37
	Gravity	9.12	6.55	7.28	3.36	49.97	3.12
NHBO	IOM	5.46	4.73	4.78	2.14	25.06	1.57
	Gravity	2.59	2.18	2.34	1.05	20.60	1.29

* Degrees of freedom = 15

4.4 Summary and Discussions

Based on the analyses presented in Section 4.3, it appears that the intervening opportunity models tend to over-assign long trips and thus producing longer average trip lengths. Only for NHBW trips did the intervening opportunity model produced better average trip length and had better spatial accuracy as measured by statistics in Table 4.11. There are several possible causes that may have led to this problem.

First, during the calibration of the intervening opportunity model, the selected summation file, which originally contained the interzonal skim impedance, was used to store the accumulated opportunity matrix. As mentioned in Section 4.3, TRANPLAN is not designed for intervening opportunity models therefore is unable to handle the large numbers of cumulative opportunities. For this reason, the cumulative attractions were scaled down by a factor of 1,000 in order to utilize the current calibration procedure in TRANPLAN. As a result, large variations in the survey data were not modeled as the travel times within the first impedo varied greatly. Figure 4.10 illustrates the variations in travel times within the second impedo, i.e., accumulative opportunities between 1 and 1,000. This has resulted in the model becoming insensitive to the ordering of zones for this group of zones, thus affecting the model accuracy. Additionally, it has been observed that the calibrated model parameters and subsequently the model performance varied with the factor applied, since different scaling factors would result in different distribution of trips versus opportunities. This raises the question of the appropriateness of the factor applied, as well as the stability of the solutions. Further study will be necessary to determine the sensitivity of intervening opportunity models to scaling factors.

A second problem is that if cumulative opportunities were used without cutting off at a certain value, the resulted trip length distribution curve would decrease much slowly and have a long tail, causing over-assignment of long trips. To alleviate this problem, the distribution of surveyed trip frequency versus opportunity impedance for each trip purpose was examined to locate the value at which the number of observations nearly vanished. Subsequently, the observations with an impedance value larger than the "vanishing point" were not considered in the calibration. The vanishing points for HBW, HBS, HBSR, HBO, NHBW, and NHBO trips were 400, 300, 250, 550, 200, and 400, respectively. Experiments with the use of different upper limits during the intervening opportunity model calibration did not produce noticeable improvements. It appears that the opportunity frequencies for different trip purposes sampled from Palm Beach County are not exponentially distributed. Therefore, other procedures to calibrate intervening opportunity models may need to be investigated if the model performance is to be improved.

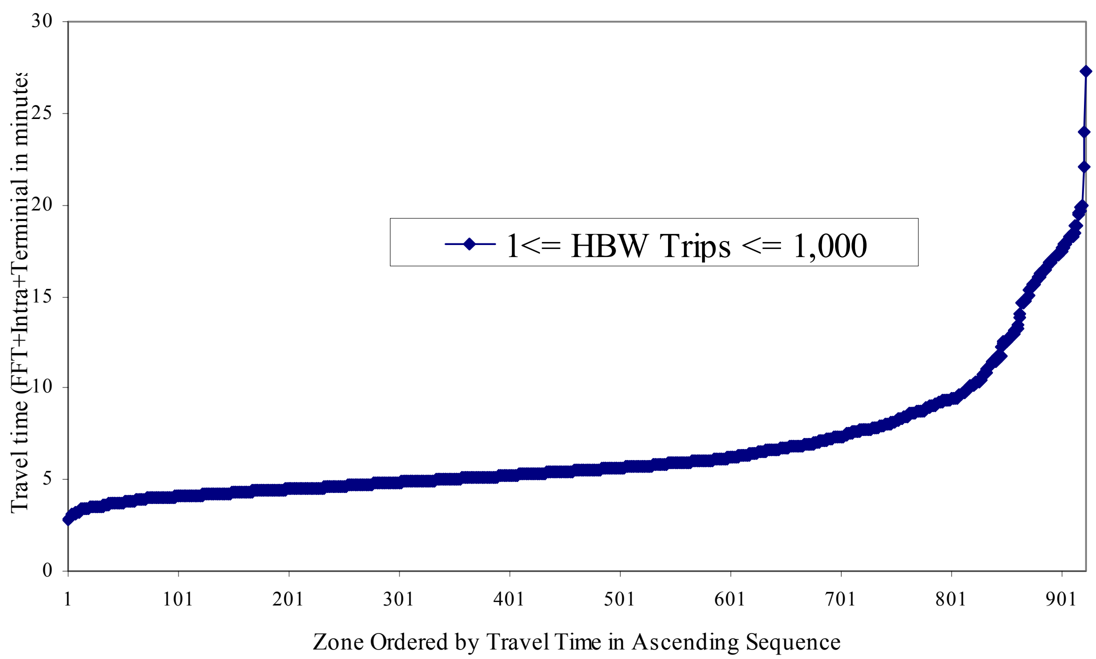

Figure 4.10 Travel Time Distribution

Another weakness of the intervening opportunity model is the underestimation of intrazonal trips as compared to the gravity model and the survey data. According to Equation (1), which specifies zonal trip interchanges using the intervening opportunity model, intrazonal trips may be calculated by setting j to equal i and the accumulative opportunities to 0 (since there are no opportunities before the first zone being considered). This means that the diagonal elements of the opportunity matrix, which are stored in the summation file, should have a value of 0. This is, however, not permitted in the calibration of gravity model in TRANPLAN since zero impedance cannot be specified using the trip length frequency record (GT). As a result, during the calibration, the diagonal elements of the opportunity matrix were set to 1 (i.e., impedance = 1). Assuming a nonzero cumulative opportunity sum for intrazonal trip distribution resulted in a smaller number of intrazonal trips assigned, since based on Equation (1), intrazonal trips would be

$$T_{ii} \approx P_i\, A_i\, L \exp(-L)$$

while theoretically it should be:

$$T_{ii} = P_i A_i L \exp(- L \times 0) = P_i A_j L$$

The difference between the two is $\exp(-L)$. Therefore the intrazonal trips have been underestimated by at least by $1/\exp(-L)$. Intrazonal trips, T_{ii}, increase monotonically with L. Therefore, the inability to properly treat the intrazonal trips will result in a smaller calibrated L value.

Other problems include inaccuracy in the estimation of attractions, the assumption of L as a constant for all attractions, and the wide range of trip lengths for any given impedance. Attractions in terms of opportunities are much more critical for an intervening opportunity model than for a gravity model due to the fact that they are used in place of travel time as a representation of travel patterns, which are to be replicated by the calibrated model. In general, there is a concern about the accuracy of attraction estimates because information on attractions as well on their estimates is lacking. Compared with travel time, attraction data may be considered less reliable. Therefore, calibrating a model based on less reliable data also raises concerns about model accuracy.

A problematic assumption of the intervening opportunity model is that L, the probability that an opportunity will be accepted, is a constant. In reality, this probability will vary even when the opportunities are of the same type. For instance, a supermarket may be more likely to be chosen than a small grocery store. Stopher and Meyburg (1975) have suggested that a L_i may be estimated for each zone i, or different L values may be estimated for different groups of trips. Estimating a L_i for each zone i will require an excessive amount of survey data, which is not cost feasible. Estimating different L values for different groups of trips has already been implemented in this model calibration effort as the trips have been segmented by trip purposes. Calibrating a model for groups of trips with different ranges of trip lengths is another possible solution. For instance, the Chicago Area Transportation Study (CATS) was reported to have calibrated separate L values for short trips, long residential trips, and long nonresidential trips (Stopher and Meyburg 1975). This approach may help reduce the problem of the wide range of trip lengths for any given impedance value. Although further segmenting the trips by trip lengths will add to model complexity, the additional complexity may be handled entirely by the program automatically without increasing the burden on the modeler.

Despite the problems inherent in the model, it is possible that an intervening opportunity model's expected advantage of better performance for elongated areas becomes more obvious if applied to the SERPM model that covers the tri-county area including Miami-Dade, Broward, and Palm Beach counties.

In summary, the intervening opportunity models calibrated for the Palm Beach County using the 1999 survey data, network, and socioeconomic data performed slightly better than the gravity model for NHBW trips in terms of average trip length, but not for the other purposes. Some of the problems that may have affected the performance of the model have been discussed. To remove or alleviate these problems requires:

1. Modifications of the existing TRANPLAN program to accommodate the needs of intervening opportunity models;
2. Development of a specialized program to calibrate intervening opportunity models; and
3. Consideration of further dividing trips into different groups based on their trip lengths and calibrating different *L* parameters for each group.

Additionally, studies are needed to determine how attraction data may be improved for intervening opportunity models. The results in this report do not provide strong evidence as whether the performance of intervening opportunity models may be significantly improved, which is necessary for any possible applications.

5. DEVELOPMENT OF ENHANCED GRAVITY MODELS

After reviews and discussions of the results from intervening opportunity model development for Palm Beach County, the Florida Model Task Force (MTF) Trip Distribution Committee recommended the discontinuation of the investigation of intervening opportunity models and directed the research toward studying the feasibility of enhancing traditional gravity models with additional variables that had been found to affect trip length distribution (Zhao et al. 2001) and destination choice models.

This chapter presents the results from an effort to develop a methodology that utilizes discrete choice techniques to produce a generalized impedance function that incorporates variables other than those in the traditional gravity model disutility functions. A number of variables including land use and accessibility that had been identified as influential to travel patterns were investigated. GIS was utilized as a tool to explore the attributes and patterns of travel. The result was an enhanced gravity model for Palm Beach County for HBW trip purpose that improved the accuracy of trip distribution procedure.

In this chapter, Section 5.1 provides a summary of the analyses on the variables that possibly affect trip lengths. Section 5.2 presents the formulation of gravity models in a form similar to discrete choice models, and Section 5.3 the calibration of the generalized impedance function using a destination choice model. The performance of the enhanced gravity model using the generalized impedance is evaluated in Section 5.4. A summary are provided in Section 5.5 at the end of this chapter.

5.1 Empirical Analysis of Trip Lengths

Trip distribution aims at duplicating the spatial distribution patterns resulting from a decision process by road users. The decision making process is influenced by a variety of factors. Socioeconomic and demographic factors are known to have impacts on road users' travel behavior. Accessibility is also important in determining travel behavior. Some believe that land-use patterns influence travel behavior to a certain degree, since it may directly contribute to congestion (e.g., Kockelman 1997, Sun *et al.* 1998, Kiefer and Mehndiratta 1998, Heanue 1998, Barr 2000, Abelson and Hensher 2001). Therefore, it is crucial to understand how people's travel behaviors are affected by socioeconomic conditions, land use patterns, and accessibility. Because the purpose was to develop aggregate models, this study was focused on aggregate measures of potential relationships between land use variables and trip patterns instead of on individuals' decision processes as in activity-based models.

Various analyses were performed, including determining the significance of land use, demographic, and socioeconomic variables to trip lengths, the relationship between income and shopping destination choices, and trip chains. These analyses are briefly described here and the conclusions drawn from these analyses are provided. For a detailed description, readers are referred to Appendix A.

One way to examine travel behavior is to investigate the trip length frequency distribution. While information on origins and destinations is more useful to understand trip distribution, samples collected from household surveys are usually not sufficiently large to accurately reflect zonal interchange patterns. In fact, zero sampling is common in an observed origin-destination (OD) table. Consequently, trip length frequency distributions, not the observed trip tables from an origin-destination survey, are used in the model calibration for the gravity model.

To identify possible variables that were related to trip lengths, the household survey data from the 1999 SEFRTCS were analyzed. These variables included population density, dwelling unit density, employment density, combined population and employment density, auto ownership, income, accessibility, and lifestyle variables. ANOVA tests were conducted to determine the significance of these variables except lifestyle variables with respect to trip lengths. A description of these variables is given below.

Population density was calculated by dividing the 1999 zonal population in the ZDATA1(A) files with the zonal area in square miles. The surveyed trip lengths were then sorted by population densities of the home zones. The density median was used to divide the sample into two low- and high-density groups of approximately equal size. ANOVA tests were then conducted to determine if the group means were statistically different thus population density had any effect on the trip lengths for different trip purposes including HBW, HBS, HBSR, HBSCH, HBO, and NHB. Similarly, population density at the census tract level was also calculated based on the 2000 census and the data were analyzed with ANOVA.

Dwelling unit density was calculated for each TAZ and a census tract by dividing the number of dwelling units in a zone by the zonal area in square miles. The dwelling units in TAZs were obtained from the 1999 ZDATA1(A) files and those in census tracts from the 2000 census. In this analysis of dwelling unit density versus trip length, the surveyed trip lengths were sorted by their associated dwelling unit densities at the home zones. The density median was used to divide the sample into two groups of equal size and ANOVA tests were conducted for all trip purpose as well as each trip purpose.

Employment density was calculated by dividing the employment size from the 1999 ZDATA2 files by the zonal area in square mile for each zone. The surveyed trip lengths were then sorted by their employment densities at the home zones. The median value divided the sample into two groups of equal size and ANOVA tests were performed to determine if employment density was significant to the trip lengths. Employment density was also aggregated to census tract level and analyzed with ANOVA.

Total density was the density of population and employment and was calculated at both TAZ and census tract levels. It was calculated for each zone by dividing the sum of population and employment with the area of that zone.

Jobs-housing balance index was a land use mix indicator, considered to have some influence on travel behavior related to work trips. For instance, since travel from home to work is a derived need to reach one’s workplace, it might be inferred that, compared to a purely residential neighborhood, a neighborhood that provides employment opportunities offers the residents the possibility of working close to their homes. The jobs-housing balance index used in this analysis was calculated using the following formula (Ewing 1995):

$$JOBS - HH = 1 - \frac{|E - 1.5H|}{E + H}$$

where

JOBS-HH = jobs-housing balance index for a zone;
E = total employment size; and
H = number of occupied households in a zone.

The formula results in a value that falls between zero and one. Zero indicates a perfectly homogenous area, either residential or non-residential, and one indicates a perfectly balanced area. The data used to calculate employment and housing data at the TAZ level were obtained from the 1999 ZDATA1(A) and ZDATA2 files. At the tract level, jobs-housing balance indices were calculated using the tract dwelling unit from 2000 census and employment data aggregated to the tract level.

Auto ownership groups were defined as households that owned no cars, households that had more workers than cars, and others. The data were obtained from the SEFRTCS household survey.

Income groups were defined based on the annual household income information from 3,135 households sampled in SEFRTCS household survey that provided the income information. These households were first sorted by their income levels into the 25th, 50th, and 75th percentiles (known as the lower, middle, and upper quartiles). These quartiles were then applied to divide households into four income groups to assure approximately equal number of cases in each group.

Accessibility has been recognized as one of the most influential factors affecting both land use and travel behavior. Accessibility was measured by an accessibility index (AI), defined as the sum of zonal attractions weighted by friction terms that reflected the ease of travel between a given zone and other zones in the region. The friction term or impedance function, $f(t_{ij})$, was assumed to have an exponential form with coefficients estimated by fitting the highway travel times from the SEFRTCS household survey data based on Levinson and Kumar's method (Levinson and Kumar 1995). The formula for calculating the highway accessibility index, a relative index expressed as a number between zero and one, for HBW trips is defined as follows:

$$AI_i = \frac{1}{RA_{\max}} \sum_{j=1}^{N} A_j \exp\left(-0.087 \times t_{ij} + 0.6611\right)$$

where

AI_i = index of regional accessibility to employment by highway travel for zone *i*;
RA_{max} = maximum regional accessibility by highway travel in a given network;
A_j = total trip attractions in zone *j*;
t_{ij} = highway travel time plus toll equivalent from zone *i* to zone *j*; and
N = total number of zones in a given network.

Note that in the definition of accessibility, zonal attractions instead of employment were used to better reflect the opportunities in different zones as two zones may have the same total employment but attract a different number of trips due to differences in employment types. Additionally, the use of attractions allows for trip-purpose specific AIs to be calculated, thus their effects on trips of different purposes could be studied.

The 1999 Palm-Beach Model data were used to investigate the significance of highway network accessibility on the HBW trip length. To consider the effects of employment in nearby counties on accessibility indices in Palm Beach County, mainly Broward County to the south and Martin County to the north, the highway networks of Palm-Beach and Broward counties were joined together and the employment in Broward County were included in the calculation of the AI; and zones within five miles of Martin County were excluded from the analysis. Based on the zonal AIs, trips were divided into two groups of low and high accessibility.

Table 5.1 summarizes the analysis results. Census tract level population density, dwelling unit density, employment density, total (population plus employment) density, job-housing balance, and TAZ level highway network accessibility were identified as potential factors to be included in the generalized impedance functions. The rest of the variables were not found to be promising. There were several reasons why a given variable was not identified as an influential factor of trip length:

1. It was not significant to trip lengths of the two groups.
2. It was significant but the mean trip lengths of the two groups were not significantly different.
3. It was found significant, but the trend was incorrect. As an example, dwelling unit density was found significant for Miami-Dade County. However, the trend was opposite to what was expected. Instead of a longer mean trip length for the low density group, the mean trip length for this group was shorter than that for the high density group.
4. It was significant for each county but the trend was inconsistent for all three counties. For instance, for the HBS trips, the average trip lengths for both population density groups in all three counties are significantly different. However, Palm Beach County had a different trip length pattern from those of the other two counties, i.e., a longer average trip length for the lower population density group.

In addition to the density variables, potential influence of lifestyle variables on trip length was also investigated. The purpose of the lifestyle variable analysis is to evaluate the differences in trip lengths for each classification of the lifestyle trip production model that has been implemented in southeast Florida. If the trip lengths appear to be significantly different among the cells, multiple sets of *F* factors, each calibrated with the data in each model cell, may improve the performance of traditional gravity models.

Detailed description of the analysis procedure and results may be found in Appendix A. A challenge to segmenting trips by lifestyle groups is the current attraction models. Although productions may be easily calculated for each aggregate lifestyle group, the trip attraction models in FSUTMS do not currently incorporate lifestyle variables, preventing gravity models to be calibrated for individual lifestyle groups. If the attraction models are able to account for the lifestyle variables, the trip distribution process may be enhanced by incorporating these variables.

Table 5.1 ANOVA Results of Impacts of Land Use Variables on HBW Trip Lengths

Factors	Summary
TAZ Level Density (population, dwelling unit employment, population plus employment)	Not consistent in significance.
Census Tract Level Density (population, dwelling unit employment, population plus employment)	Most of them were significant but Miami-Dade County data exhibited unexpected trend, e.g., the lower the density, the shorter trip lengths.
TAZ Level Jobs-Housing Balance	Not consistent in significance.
Census Tract Level Jobs-Housing Balance	Significant. The higher the jobs-housing balance, the shorter HBW trip lengths.
Auto Ownership	Significant differences in trip lengths among three groups (0, 1, 2+ autos) for all counties. However, the first two groups have small samples.
Household Income Level	Significant differences in HBW trip lengths among quartiles for all counties. However, there is no consistent relationship between income levels and trip lengths.
Lifestyle Variables	Significant differences in trip lengths in lifestyle strata. Some strata with no difference in trip length may be grouped together.
Highway Network Accessibility (AI)	(Palm Beach County only) People living in areas with a higher AI tended to make shorter work, shop, and other trips.

Table 5.2 presents the results by trip purpose in more detail. The third column indicates for which counties the variables were significant. The fourth column shows whether the trend of the trip lengths was as expected if a variable was significant. For instance, the expected trend of trip lengths with respect to population density was that low density was associated with longer trips. The fifth column indicates if trip lengths for the different tested groups were significantly different. For instance, trips were divided into low and high population density groups at the TAZ level. For each of the two density groups the mean trip length was calculated. For HBW purpose, the mean trip lengths for the two groups were significantly different. Finally, the last column indicates whether the trends of the trip lengths versus the variable under consideration were consistent across all three counties as well as in the tri-county region.

Table 5.2 ANOVA Results for Impacts of Land Use Variables on Trip Length by Purpose

Variable	Trip Purpose	Individual Counties			Trend Consistent Cross Counties
		Significant to Trip Length	Trend Correct	Trip Lengths Significantly Different	
TAZ Level Population Density	HBW	Miami-Dade, Palm Beach	Yes	Yes	No
	HBS	All	Yes (Palm Beach only)	Yes	No
	HBSR	Palm Beach	Yes	Yes	No
	HBSCH	None	No	No	No
	HBO	Broward, Region	No	No	Yes
	NHB	Miami-Dade, Region	No	Yes	Yes
TAZ Level Dwelling Unit Density	HBW	Miami-Dade, Palm Beach	Yes	Yes	Yes
	HBS	Miami-Dade, Palm Beach	Yes (Palm Beach only)	Yes	No
	HBSR	None	No	No	No
	HBSCH	Miami-Dade, Palm Beach	Yes (Palm Beach only)	Yes (Palm Beach only)	No
	HBO	None	No	No	No
	NHB	Miami-Dade	No	No	No
TAZ Level Employment Density	HBW	Miami-Dade, Palm Beach, Region	Yes	Yes	Yes
	HBS	Broward	Yes	Yes	No
	HBSR	Region	No	Yes	No
	HBSCH	Broward	No	No	No
	HBO	Palm Beach	Yes	Yes	No
	NHB	None	N/A	No	No
TAZ Level Total Density	HBW	Miami-Dade	Yes	Yes	No
	HBS	Miami-Dade	No	No	No
	HBSR	Broward	No	Yes	No
	HBSCH	Region	No	Yes	No
	HBO	Miami-Dade	No	Yes	No
	NHB	Miami-Dade, Region	No	Yes	No
Tract Level Population Density	All Purposes	All counties and region	Yes (except Miami-Dade)	Yes	No
Tract Level DU Density	All Purposes	All counties but region	Yes (except Miami-Dade)	Yes	No
Tract Level Employment Density	All Purposes	Broward, Palm Beach	Yes	Yes	Yes

Tract Level Total Density	All Purposes	All counties and region	Yes (except Miami-Dade)	Yes	No
Job-Housing Balance	HBW	Broward, Palm Beach, Region	Yes	Yes	Yes
Auto Ownership	All Purposes	All counties and region	Yes	Yes	Yes
Income Level	HBW	Broward, Miami-Dade, Region	No	No	No
	NHBW	Miami-Dade, Region	No	No	No
Accessibility	HBW	Palm Beach	Yes	Yes	N/A
	HBS	Palm Beach	Yes	Yes	N/A
	HBSR	None	Yes	Yes	N/A
	HBO	Palm Beach	Yes	Yes	N/A

5.2 Formulation of Gravity Models with a Generalized Disutility Function

In this section, the formulations of a traditional gravity model and a discrete choice model are first introduced. The two models are then related to each other to demonstrate that the utility function in a discrete choice model may be used in a gravity model as the exponential friction factor.

5.2.1 Gravity Models and Destination Choice Models

Based on the assumption that trip interchange between zones is directly proportional to the relative attractiveness of each zone, while inversely proportional to some function of the spatial separation between the zones, gravity models generally take the following form:

$$T_{ij} = P_i \left(\frac{A_j F_{ij} K_{ij}}{\sum_{k=1}^{N} A_k F_{ik} K_{ik}} \right)$$

where

- T_{ij} = number of trips from zone i to zone j;
- P_i = number of trip productions in zone i;
- A_j = number of trip attractions in zone j;
- F_{ij} = "friction factor" relating the spatial separation between zones i and j;
- K_{ij} = an optional adjustment factor for interchanges between zones i and j; and
- N = total number of zones.

The friction factor in the above equation is a decreasing function of travel impendence, which is largely dominated by the highway travel time between zones i and j. The K factors are used when a gravity model fails to produce observed trip interchanges. Many analysts believe that including variables other than travel time in the gravity model and eliminating the K factors may improve the prediction of travel behaviors.

In destination choice models, a traveler traveling from place i is assumed to choose among N destinations. The probability of the traveler choosing destination j, denoted by p_{ij}, is commonly formulated as a multinomial logit model as follows (Harvey and Deakin 1993):

$$p_{ij} = \frac{\exp(V_{ij})}{\sum_{k=1}^{N} \exp(V_{ik})}$$

where V_{ij} is the utility (or attractiveness) of place j to the traveler originating at place i. The trip distribution between zones i and j is obtained as follows:

$$T_{ij} = p_{ij} P_i$$

where P_i is the number of trip makers in zone i that have been aggregated for the analysis.

To avoid the computational burden of estimating a logit model with a large number of choices, destination alternatives at the attraction ends are aggregated zones instead of individual attractions. Using aggregated geographical zones as the destination alternatives, the utility U_{ij} for trip makers of a particular type in zone i choosing attraction-end zone j may be derived as (Ben-Akiva and Lerman 1985):

$$U_{ijn} = \beta' X_{ijn} + \frac{1}{\mu} \ln M_j + \varepsilon_{ij}$$

where

- X_{ijn} = vector of exogenous variables influencing the choice of zone j by an individual n in zone i;
- M_j = number of elemental attractions in attraction-end zone j;
- ε_{ij} = random term distributing IID Gumbel across zonal alternatives;
- β = vector to be estimated; and
- μ = scalar to be estimated.

If the characteristics of individuals in a zone are ignored, the utility for the zone becomes:

$$U_{ij} = \beta' X_{ij} + \frac{1}{\mu} \ln M_j + \varepsilon_{ij}$$

where X_{ij} is a vector of exogenous variables influencing the choice of zone j for travelers in zone i.

5.2.2 Relationship between Logit and Gravity Models

The logit model and gravity model have been shown by Wilson (1967) to be of essentially the same form, as used in statistical mechanics, as an entropy maximization model. The destination choice utility of a trip from origin zone *i* to destination zone *j* may be expressed as:

$$V_{ij} = \ln(A_j) - \theta t_{ij}$$

where

A_j = trip attractions at destination *j*;
t_{ij} = travel impedance from origin zone *i* to destination zone *j*; and
θ = model parameter to be estimated.

Substituting the above equation into the multinomial logit equation yields:

$$p_{ij} = \frac{A_j \exp\left(-\theta t_{ij}\right)}{\sum_{k=1}^{N} A_k \exp\left(-\theta\, t_{ik}\right)}$$

Thus, the share of trips produced in zone *i* and travel to zone *j* is:

$$T_{ij} = P_i \times p_{ij} = P_i \times \frac{A_j \exp\left(-\theta\, t_{ij}\right)}{\sum_{k=1}^{N} A_k \exp\left(-\theta\, t_{ij}\right)}$$

This formulation is the same as a gravity model with an exponential friction factor.

The applications of logit and gravity models differ in concept in that traditional gravity models use impedance measured by travel time in determining the probability of trip making, while a choice approach brings the socioeconomic and other contributing variables into the utility function. However, if the parameters of the exponential friction factor of the gravity model may be calibrated using a logit estimation with the parameter of $ln(A_j)$ fixed at 1, generalized impedances, rather than just highway travel times, may be used as friction factors.

5.3 Calibration of Enhanced Gravity Models for HBW Trips with Generalized Impedance Functions

This section describes the calibration of generalized impedance functions using discrete choice model techniques and the calibration of enhanced gravity models based on the generalized impedance functions. Variables considered for inclusion in the generalized impedance function are first described. Because the destination choice set is usually large, resulting in computational complexity, the determination of a reduced choice set of possible destinations and the required data processing and formatting are discussed. The calibration of two generalized impedance functions and the enhanced gravity models based on these impedance functions are then described.

5.3.1 Variables Considered in the Composite Impedances

Based on the analyses presented in Section 5.1, census tract level population density, dwelling unit density, employment density, total (population plus employment) density, job-housing balance, and TAZ level highway network accessibility were identified as potential variables to be included in the generalized impedance functions. The significance of these variables was tested during the destination choice model calibration.

Since a gravity model considers zonal characteristics rather than those of individual trip makers, auto ownership, household income level, and lifestyle variables, all describing individual trip maker's characteristics, were excluded from the generalized impedance functions. To consider them in a gravity model requires stratification of trip generation, which is not currently supported in FSUTMS.

5.3.2 Selection of a Destination Choice Set

To calibrate a destination choice model, the choice set for each origin zone must be determined. The choice set would be too large if all zones were to be included. One way to reduce the size of the destination choice sets was through sampling destination zones. Sampling destination zones only maximizes a conditional likelihood function rather than the true likelihood. However, it has been proven that under normal regularity conditions, maximization of the conditional log likelihood function yields consistent estimates of the unknown parameters (Ben-Akiva and Lerman 1985).

There are several ways to sample destination choices. For example, stratified sampling with uniform sampling probabilities within each stratum was used in the San Francisco models. Portland models used importance sampling, where the probability of sampling each zone was assumed to be a function of a size variable (the most suitable land use variable for each tour purpose, e.g., attractions) divided by an impedance measure (a function of the distance from the tour origin). The importance sampling method is more efficient but requires more intensive computation and may result in choice sets with varying numbers of unique alternatives (DKS Associates 2001). In this study, a simplest approach was used to sample a subset of the universal choice set, which consisted of randomly selected non-chosen and unique alternatives form the universal choice set and the chosen alternatives (Bhat 1998).

5.3.3 Formatting of Calibration Data Set and Software Requirements

Fictitious numbers are used here to illustrate the formatting of the data set for model calibration. Suppose that there are 1,700 sampled HBW trips in Palm Beach County. Each HBW trip in the sample is assumed to have ten destination choices, which are made up by the chosen destination zone and nine non-chosen zones that are sampled. The data matrix would now consist of 1,700 blocks of ten rows, or 17,000 rows. Each block represents the choice set for a particular trip in the survey data. The zonal attributes within a 10-row block will be the same. A dummy variable

Y will be added to indicate if a trip within a 10-row block is a trip with the chosen destination (Y = 1) or if it is a trip with a non-chosen destination (Y = 0). Therefore, within each block, Y will be 1 once and only once.

The logit model software to be used for estimating the enhanced gravity model not only should have the ability to fix any of the parameters in the model at specific values (i.e., the parameter of term $\ln(A_j)$ should be fixed at 1 as mentioned in section 2.3), but also allow each observation in the survey sample to have its own choice set, i.e., an unique set of destination zones. Consequently, the software adopted in the model calibration must be able to handle cases in which neither is the number of choices fixed nor is there a universal choice set.

5.3.4 Alternative Specification

Discrete choice models are also referred to as disaggregate models, meaning that decision-makers are assumed to be individuals. The "individual" decision-making entity depends on the particular application. For instance, we may consider a group of persons (a household or an organization, for example) as the decision-maker. In this study, the decision-maker is the group of people who live in the same TAZ because in current FSUTMS structure trip distribution is zone based. A shift toward disaggregate procedures would require a change in the fundamental specification of gravity models in practice and is not within the scope of this study.

In Section 5.1, it has been concluded that census tract level population density, job-housing balance, and TAZ level accessibility at the production-end may affected trip length. Therefore, these variables were chosen to be tested to determine how these factors affected the travel impedance and then to include the effects into the utility functions in gravity models. Since these factors were associated with the production-ends, they were identical in each block of records (each sample trip was expanded to 10 records with the same production zone but different attraction zones). A requirement of the independent variables in logit models is that they do not take identical values for all alternatives. This may be demonstrated in a simple example where a choice set consists of three alternatives. Suppose the utility function for any alternative j for a decision-maker i is

$$U_{ij} = \$_0' X_i + \$ X_{ij}$$

where

- $\$_0$ = a constant;
- X_i = characteristics of decision-maker i;
- X_{ij} = characteristics of alternative j (for illustration purpose, $j = 1, 2, 3$) for decision-maker i;
- $\$$ = parameters of X_{ij}.

Note that $\$_0 X_i$ remains the same for all alternatives (for all j). The probability of any alternative being selected will be as follows:

$$p_{ij} = \frac{e^{U_{ij}}}{\sum e^{U_{ij}}} = \frac{e^{\beta_0' X_i + \beta' X_{ij}}}{e^{\beta_0' X_i}\left(e^{\beta' X_{i1}} + e^{\beta' X_{i2}} + e^{\beta' X_{i3}}\right)} = \frac{e^{\beta' X_{ij}}}{e^{\beta' X_{i1}} + e^{\beta' X_{i2}} + e^{\beta' X_{i3}}}$$

Thus, if a socioeconomic characteristic of a decision maker i takes the same value for every alternative and is entered into every utility function with the same coefficient, it will have no effect on choice probability p_{ij}. In other words, the differences in preferences of alternatives are canceled out. For this reason, such variables must be defined as "alternative-specific." Two methods may be applied to handle alternative specification. Assuming J alternatives in total, the first method is to create as many as J-1 alternative-specific variables in each alternative's utility function for a particular socioeconomic variable. Among the J alternatives, an alternative is arbitrarily selected as the reference and its alternative-specific variable is omitted to reduce the efforts to estimate the corresponding coefficient because it is the difference between utilities that is of interest. One may interpret this type of alternative-specific variables as dummy variables. However, instead of taking the value of zero or one, the true values of the variables are used in the model (Ben-Akiva 1985).

The second method is to interact socioeconomic characteristics with a generic variable associated with each alternative. The coefficient for a generic variable is the same for every utility function. The interaction effect is incorporated in the utility function as the product of a socioeconomic attribute and a generic variable (Ben-Akiva 1985). In this study, the alternatives were destination zones. It was not unusual for the number of destination zones to be in the hundreds. Since only 10 candidate destinations were sampled and there was no universal choice set, it was impossible that every alternative had their own set of interaction terms. To deal with the "alternative specification" in this study, the production-end attributes were interacted with the travel impedance. That is, the travel impedance was multiplied with the production-end attributes to incorporate their effects on trip allocation in the modeling process to test if people living at different locations had different sensitivity to the travel impedance (Bhat et al. 1998). For example, people living in areas with better accessibility might be more sensitive to the travel distance when making a destination choice.

5.3.5 Calibration of Logit Destination Choice Models

The home-based working trip data from Palm Beach County were used to calibrate the destination choice models. The following were the steps for data preparation.

1. A total of 1,869 HBW trips were selected from the Palm Beach County survey data (SEFRTCS).
2. Origin-destination zones for each sampled trip were converted to production-attraction zones. Find the number of attractions for each attraction zone from the 1999 FSUTMS model. Samples with zero number of estimated attractions at their attraction zones were excluded.
3. Jobs-housing balance index and population density at the census tract level were calculated for the production zones.
4. Zonal accessibility index for each production zone was calculated.
5. Nine attraction TAZs (beside the actual chosen destination zone) were randomly selected for each HBW trip and a trip record for each of the selected attraction TAZ was added to

the data set. A dummy variable *Y* was created for every record. Its value was set to one for the record with the actual selected attraction zone and zero otherwise. The final data set had 1,859 blocks of records, 10 records per block. The total number of records became 18,590.

6. For the appended records, the estimated number of attractions for each randomly selected attraction zone was obtained.
7. For each of the 18,590 records, the travel time between the origin and destination was calculated using the Time2 (free flow plus toll equivalent) skims from the FSUTMS model.
8. The production-end attributes were interacted with the travel impedance.

NLOGIT, a maximum likelihood program in the software package LIMDEP, was used to estimate the HBW attraction-end choice model with the coefficient for the logarithm of attractions fixed at 1. The results indicated that population density, dwelling density, total density, and jobs-housing balance had no significant interaction with travel impedance, while employment density and regional accessibility did with expected negative signs. This means that people residing in areas with better accessibility or higher employment density tended to make shorter work trips.

The final models for the HBW attraction-end choice model are presented in Table 5.3. The log-likelihood value with no variables in the model was -3649.5974. The log-likelihood value at convergence was -2976.863 for the model including employment density and -2978.382 for the model including regional accessibility. While employment density and regional accessibility had similar statistics, their effectiveness in improving gravity models was different. This is discussed in detail in the next section.

Table 5.3 Calibrated Logit Model for Incorporating Additional Variables for HBW Trips

<table>
<tr><th>Additional Variable</th><th>Variable</th><th>Coefficient</th><th>Standard Error</th><th>b/St.Er.</th><th>P[|Z|>z]</th></tr>
<tr><td rowspan="6">Employee Density by Census Tract</td><td>Travel Impedance</td><td>-0.1193</td><td>0.5062E-02</td><td>-23.566</td><td>0.0000</td></tr>
<tr><td>Log of Attractions</td><td>1.000</td><td colspan="3">------- (Fixed Parameter) --------</td></tr>
<tr><td>Interaction Effects with Travel Impedance
Employee Density</td><td>-0.00632</td><td>0.2262E-02</td><td>-2.794</td><td>0.0052</td></tr>
<tr><td rowspan="2">Log likelihood function
No coefficients</td><td colspan="4">-2976.863</td></tr>
<tr><td colspan="4">-4280.5057</td></tr>
<tr><td>ρ^2</td><td colspan="4">0.3046</td></tr>
<tr><td rowspan="7">Regional Accessibility by TAZ</td><td>Variable</td><td>Coefficient</td><td>Standard Error</td><td>b/St.Er.</td><td>P[|Z|>z]</td></tr>
<tr><td>Travel Impedance</td><td>-0.1065</td><td>.1007E-01</td><td>-10.583</td><td>0.0000</td></tr>
<tr><td>Log of Attractions</td><td>1.000</td><td colspan="3">------- (Fixed Parameter) --------</td></tr>
<tr><td>Interaction Effects with Travel Impedance
Accessibility</td><td>-0.05856</td><td>.2449E-01</td><td>-2.391</td><td>0.0168</td></tr>
<tr><td rowspan="2">Log likelihood function
No coefficients</td><td colspan="4">-2978.382</td></tr>
<tr><td colspan="4">-4280.5057</td></tr>
<tr><td>ρ^2</td><td colspan="4">0.3042</td></tr>
<tr><td rowspan="2">Both models</td><td>Iterations completed</td><td colspan="4">6</td></tr>
<tr><td>Number of observations</td><td colspan="4">1859</td></tr>
</table>

5.3.6 Calibration of Enhanced Gravity Models

The complete, doubly constrained gravity model is:

$$T_{ij} = P_i \, A_j \, B_i \, C_j \, F_{ij}$$

where

$B_i = 1/[\ \sum A_j \, C_j \, F_{ij}\ ]$ (constraint associated with the production)

$C_j = 1/[\ \sum A_j \, B_i \, F_{ij}]$ (constraint associated with the attraction)

However, the estimation of the doubly constrained gravity model requires a fairly high level of sophistication in statistics. The conventional approach is to relax the second trip conservation rule, by setting $C_j = 1$. The result is the singly constrained gravity model as shown in Section 5.2.

The practical method employed in TRNAPLAN to solve F_{ij} is to assign trial values to the F factors initially, calculate the T_{ij} using these trial values, and compute the A_j. A_j obtained from this first approximation is then compared to the original A_j (P_i is constrained to the original value by the form of the gravity model). If the estimations of the A_j is not acceptably close to the estimated A_j and the user-specified maximum number of iterations has not been reached, the F factors are adjusted and another iteration is performed. To adjust the F factors, the trip length distribution from the survey is compared with the length distribution predicted by the model. To seek the closest possible correspondence between predicted and observed values, the number of trips for each trip length increment is divided by the total number of trips to yield the percentage of trips in each increment. This is done for both the observed and estimated trips. The ratio of the observed percentage over estimate percentage is calculated for each trip length increment and multiplied by the current F factor to produce the F factor for the new iteration.

The HBW destination choice model calibrated in this section was the disaggregate equivalent of the production-constrained gravity model (Harvey and Deakin 1993). Therefore, to balance the attractions of the singly constrained logit destination choice model, the generalized travel impedance, which took into account the interaction effects between travel time and the attributes of the production zones, was used to replace the traditional travel impedance in the traditional gravity model, and FSUTMS was used to re-calibrate the new friction factors for the generalized travel impedance. The procedure involves the following steps:

(1) Using the UPDATE MATRIX command in TRANPLAN to replace the travel impedance skim with the generalized travel impedance, which is a function of the employment density or accessibility of the production zone.

(2) Obtaining the frequency distribution for the generalized travel impedance. Because the response times from survey data showed 5-minute spikes, a proper use of this observed data would be to smooth the data using a suitable statistical distribution. In this study, the frequency distribution for the generalized travel impedance was obtained by interacting

the network travel time from the free-flow skim of the 1999 FSUTMS models for Palm Beach County with the production-end attributes.

(3) Calibrating the destination choice model using the frequency distribution based on the generalized travel impedance, which replaces the frequency distribution of the traditional travel impedance in the GT record, i.e., the trip length frequency record in data specifications.

5.4 Comparison of Traditional Gravity Model and Gravity Models with Generalized Impedance Functions

Two enhanced gravity models were calibrated using TRANPLAN, one with accessibility and the other with employment density incorporated into the generalized impedance. The productions and attractions as well as the travel time impedance skim were obtained from the validated 1999 Palm Beach County travel model. The enhanced gravity models were compared to a traditional gravity model. Figure 5.1 shows the trip length distributions retrieved from the free-flow skims for the Palm Beach County's freeway network and the results from the gravity model and the enhanced gravity model incorporating the regional accessibility variable. Figure 5.2 is similar to Figure 5.1 except that the enhanced gravity model incorporated employment density instead of regional accessibility.

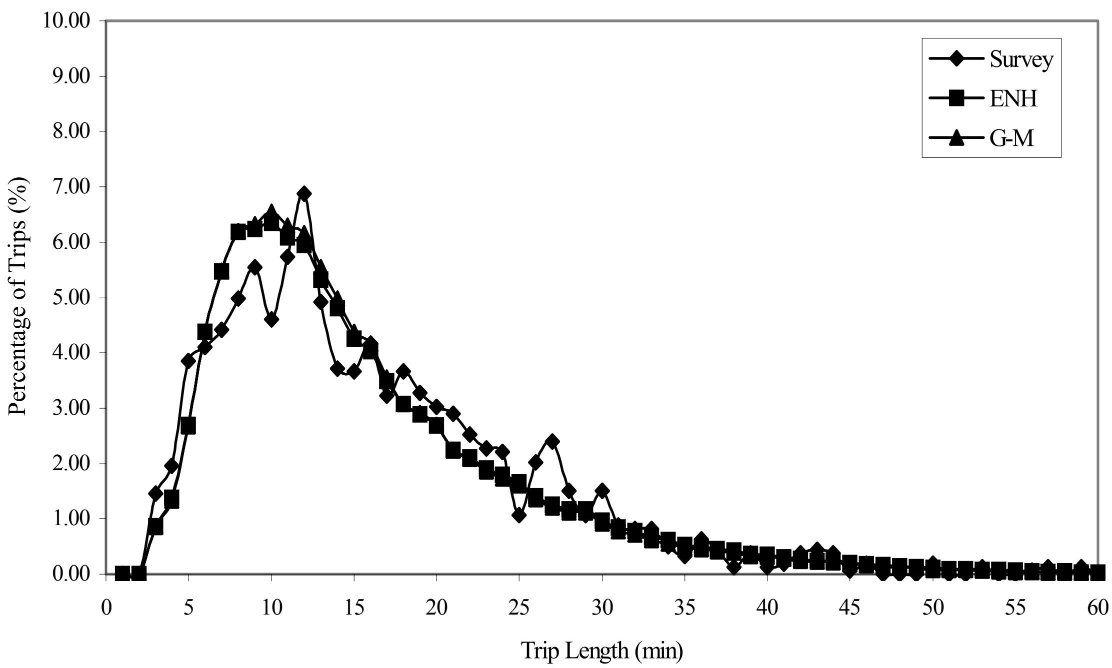

Figure 5.1 HBW Trip Length Distributions from Survey, Enhanced Gravity Model with Accessibility, and Gravity Model

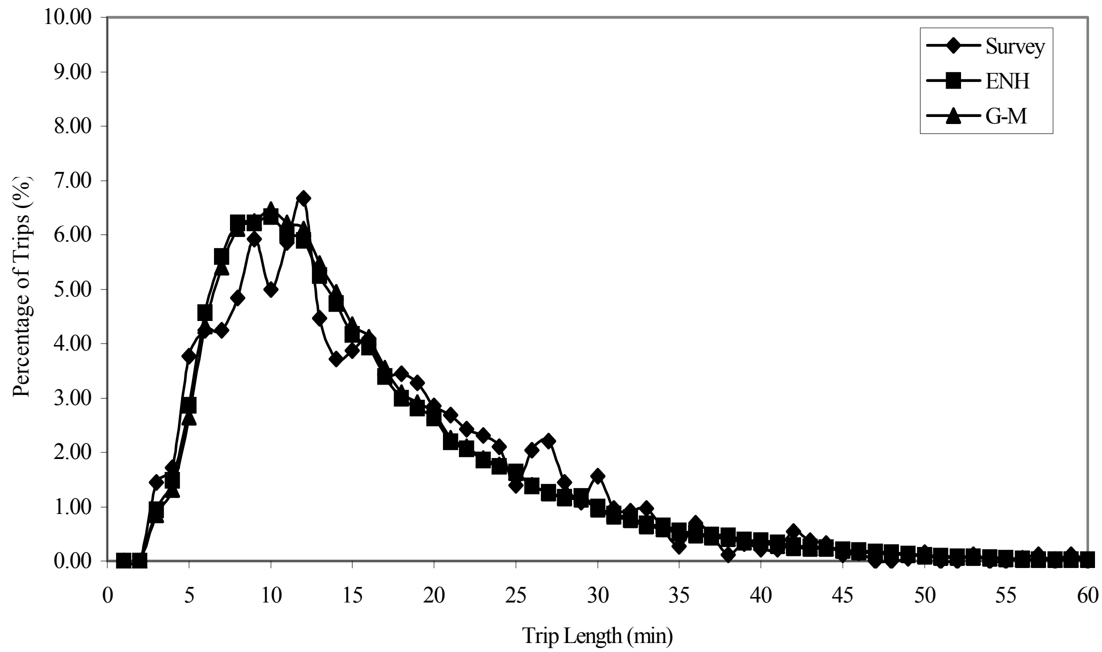

Figure 5.2 HBW Trip Length Distributions from Survey, Enhanced Gravity Model with Employment Density, and Gravity Model

Table 5.4 compares the average trip lengths from the two enhanced gravity models and the traditional gravity model with that from the survey data. It may be seen that the average trip lengths from the enhanced gravity models were closer to that from the survey data than the traditional gravity model. Between the two enhanced gravity models, the one incorporating the accessibility variable produced better results. The enhanced gravity model with the accessibility variable also had higher coincidence ratio than the gravity model for the HBW trips.

Table 5.4 Comparison of Average Trip Lengths and Trip Length Distributions for HBW Trips from Survey, Enhanced Gravity Models, and Gravity Model

	Surveyed Data	Enhanced Model		Gravity Model
		Accessibility	Employment Density	
Average Trip Length (Minutes)	16.19	16.03	15.77	15.70
Coincidence Ratio		0.836	0.831	0.831

Table 5.5 compares the intrazonal trips from the enhanced gravity models and the traditional gravity model against the survey data. It may be seen that the enhanced gravity model with employment density produced better results in terms of intrazonal trips. Intrazonal trips from the enhanced gravity model with the accessibility variable were 2.35% compared to 2.53% from the traditional gravity model.

Table 5.5 Percentages of Intrazonal HBW Trips from Survey, Enhanced Gravity Models, and Gravity Model

		I-I Trips	Intrazonal Trips	%
Surveyed Data		1,859	53	2.85
Enhanced Gravity	Accessibility	684,690	16,120	2.35
	Employment Density	684,690	19,242	2.81
Gravity		684,698	17,354	2.53

To further investigate the performance of the models in terms of their spatial accuracy, that is whether they distributed trips to the correct destinations, the trip interchanges between the four TADs (Figure 4.9) were examined. The trip interchanges between the districts as percentages of the total internal trips in Palm Beach County are given in Table 5.6. The "shaded cells" in Table 5.6 indicate that the results from the enhanced gravity models were better than those from the traditional gravity model. It may be seen that for the gravity model enhanced with the accessibility variable, among the 16 pairs of districts, the percentages of HBW trip interchanges between 11 district pairs had smaller errors when compared to the gravity model results.

Table 5.6 Comparison of HBW Trip Interchanges between TADs from Survey, Enhanced Gravity Models, and Gravity Model

District		1	2	3	4
1	SUR	15.76	5.65	1.24	0.91
	ENHA	16.82	3.90	0.98	1.07
	ENHE	17.08	3.75	0.93	1.03
	GRA	17.08	3.81	0.85	1.03
2	SUR	4.79	15.44	4.57	1.13
	ENHA	3.33	14.12	4.26	1.04
	ENHE	3.13	14.44	4.16	0.99
	GRA	3.21	14.31	4.25	0.96
3	SUR	2.26	3.44	24.53	1.78
	ENHA	1.03	4.61	28.31	1.62
	ENHE	1.00	4.50	28.49	1.57
	GRA	0.94	4.50	28.52	1.56
4	SUR	3.23	4.95	4.95	5.38
	ENHA	2.44	4.08	5.65	6.75
	ENHE	2.40	4.04	5.59	6.91
	GRA	2.40	4.15	5.52	6.90

Note: ENHA - enhanced gravity model with the accessibility variable
ENHE - enhanced gravity model with the employment density variable
GRAV - gravity model

For the gravity model enhanced by the employment density variable, six out of the 16 pairs of districts had smaller errors in the percentages of HBW trip interchanges when compared to the gravity model results. The trip percentages predicted by the gravity model were closer to the survey data for six pairs of the districts. Both models had the same percentages of trip interchanges for the remaining four pairs of districts. Therefore, the gravity model enhanced by the employment density variable did not perform as well as the gravity model enhanced by the accessibility variable and did not outperform the traditional gravity model as measured by interdistrict trips.

Table 5.7 shows the statistics measuring the spatial accuracy of trip distribution. It may be seen that the model enhanced with regional accessibility was the best among the three models compared.

Table 5.7 Statistical Comparison of Spatial Accuracy of Enhanced Gravity Models, and Gravity Model for HBW Trips

Additional Variable in Impedance Function	Average Trip Length	Chi-Square*	Neyman's Modified Chi-Square	Simplified Freeman-Tukey	Scale Deviance	Sum of Errors Squared	Mean Errors Squared
Survey Data	16.19						
Regional Accessibility	16.03	4.82	3.73	4.12	1.87	29.2	1.83
Employment Density	15.77	5.50	4.12	4.61	2.11	32.12	2.01
Traditional Model	15.70	5.61	4.10	4.62	2.12	31.96	2.00

* Degrees of freedom = 15

5.5 Summary

In this chapter, a methodology that replaced the typical travel time based impedance with a combination of travel time and additional land use, accessibility, or income variables was described. The purpose was to enhance the performance of traditional gravity models by incorporating into the impedance functions additional variables including accessibility and employment density at the production zone. The results showed there were some improvements in average trip length and trip length distribution, especially in the case when regional accessibility was considered. However, the benefits were offset by the extra cost of data preparation because accessibility to employment in adjacent counties/urban areas must be considered, thus increasing the need for data processing. This problem may become of a lesser concern in the future when FSUTMS models become more seamless across MPO jurisdictions because of common data standards regarding base maps, projections and coordinates, coding conventions, etc.

Additional variables including other density variables and jobs-housing balance were also found to be significant factors affecting trip lengths based on the ANOVA tests. However, they did not prove to be significant factors in the destination choice models. Additional work was performed to develop destination choice models, which is described in the next chapter.

6. DEVELOPMENT OF AGGREGATE DESTINATIONS CHOICE MODELS

This chapter describes the development of aggregate destination choice models. The main goal is to determine whether aggregate destination choice models are advantageous to traditional gravity models. For this purpose, three sets of HBW models with aggregate alternatives at the TAZ level were calibrated for Broward, Palm Beach, and Volusia counties, HBS models were calibrated for Broward and Volusia counties, and HBSR and HBO models were calibrated for Broward County. The performance of the destination choice models was evaluated by comparing them to the corresponding gravity models.

In the remainder of this chapter, the characteristics of the study areas are first overviewed in Section 6.1, followed by a brief introduction of the background of destination choice models with aggregate alternatives in Section 6.2. The development, calibration, and evaluation of destination choice models for HBW and HB non-work purposes are described in Sections 6.3 and 6.4. Finally, a summary is provided in Section 6.5.

6.1 Characteristics of the Study Areas

It is of interest to note that Broward, Palm Beach, and Volusia counties differ in size, demographics, urban structure, and transportation system, which may have implications in the structure and effectiveness of destination choice models. Therefore, one objective of this research was to determine whether the improvements, if any, from destination choice models varied with urban area size and if it was feasible to maintain a somewhat "standard" model structure.

To illustrate the differences between the three counties, statistics of population, households, medium household income, percentage of seasonal households, and percentage of retired population, which are from the 2000 census, are given in Table 6.1. Employment totals are also given in the table. Broward County was the largest in terms of population, households, and employment. Palm Beach County had the highest medium house income and percentage of seasonal households. All three counties also had a significant percentage of retired households.

Table 6.1 Demographic and Socioeconomic Statistics for Broward, Palm Beach and Volusia Counties

Statistics	Broward County	Palm Beach County	Volusia County
Population	1,623,018	1,131,184	443,343
Households	654,445	474,175	184,723
Mediam Household Income	$41,691	$45,062	$35,219
% of Seasonal Households	7.6%	11.6%	9.1%
% of Retired Households*	28.8%	37.6%	36.2%
Employment	654,951	452,563	161,309

* Households with householder aged 65 and over

Figures 6.1 through 6.4 show the spatial distributions of population, employment, income, and principal arterial network, respectively, in the three counties. It may be seen from Figure 6.2 that in Broward County the employment was more or less spread over most parts of the county. In

Palm Beach County, with the exception of the large employment in the northwest corner of the county, there was a tendency that employment was distributed around two urban centers, one in West Palm Beach to the north and the other in Boca Raton to the south. Employment in Volusia was concentrated in the east and west parts of the county, separated by about 15 miles. The spatial distribution of income was also different between the three counties.

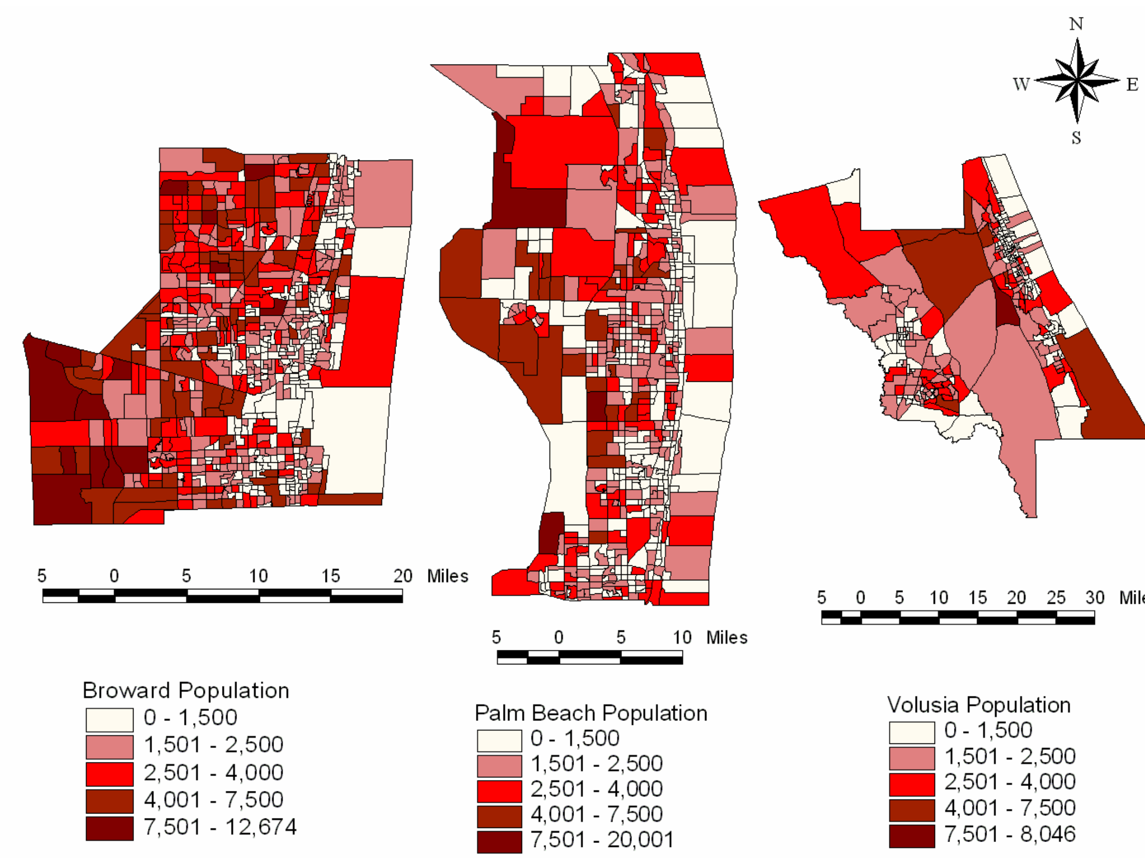

Figure 6.1 Population Distributions in the Three Counties by Census Block Group

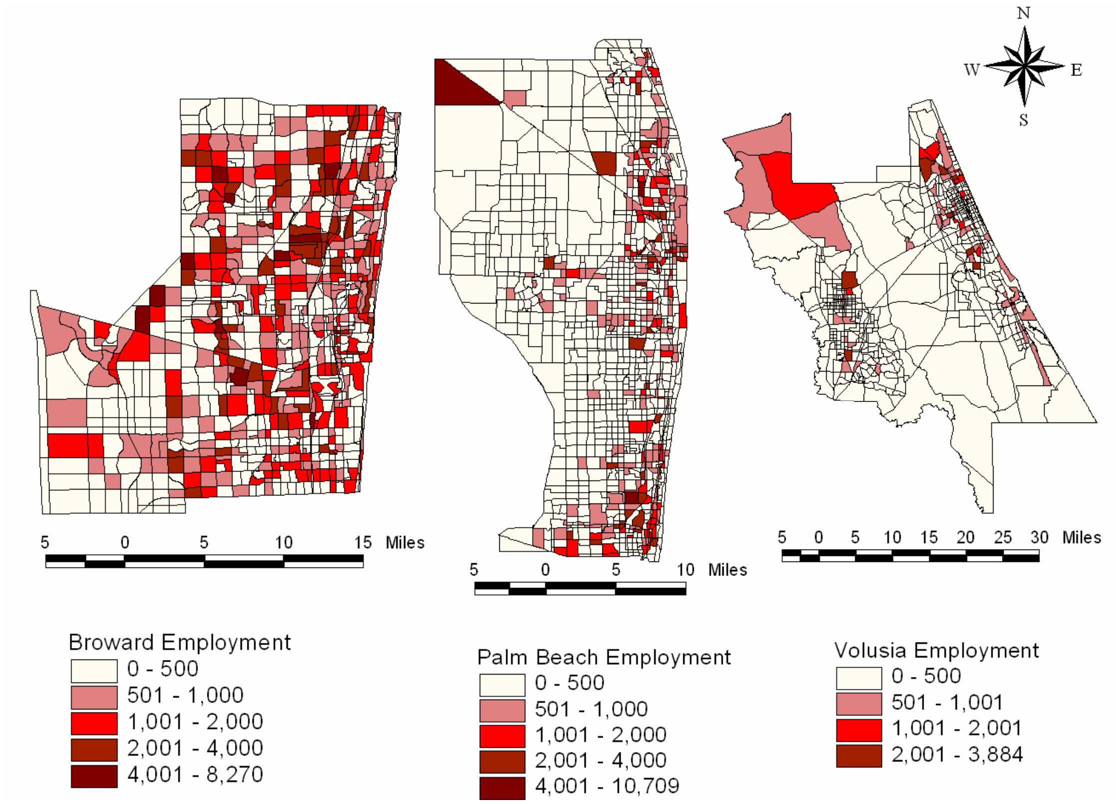

Figure 6.2 Employment Distributions in the Three Counties by TAZ

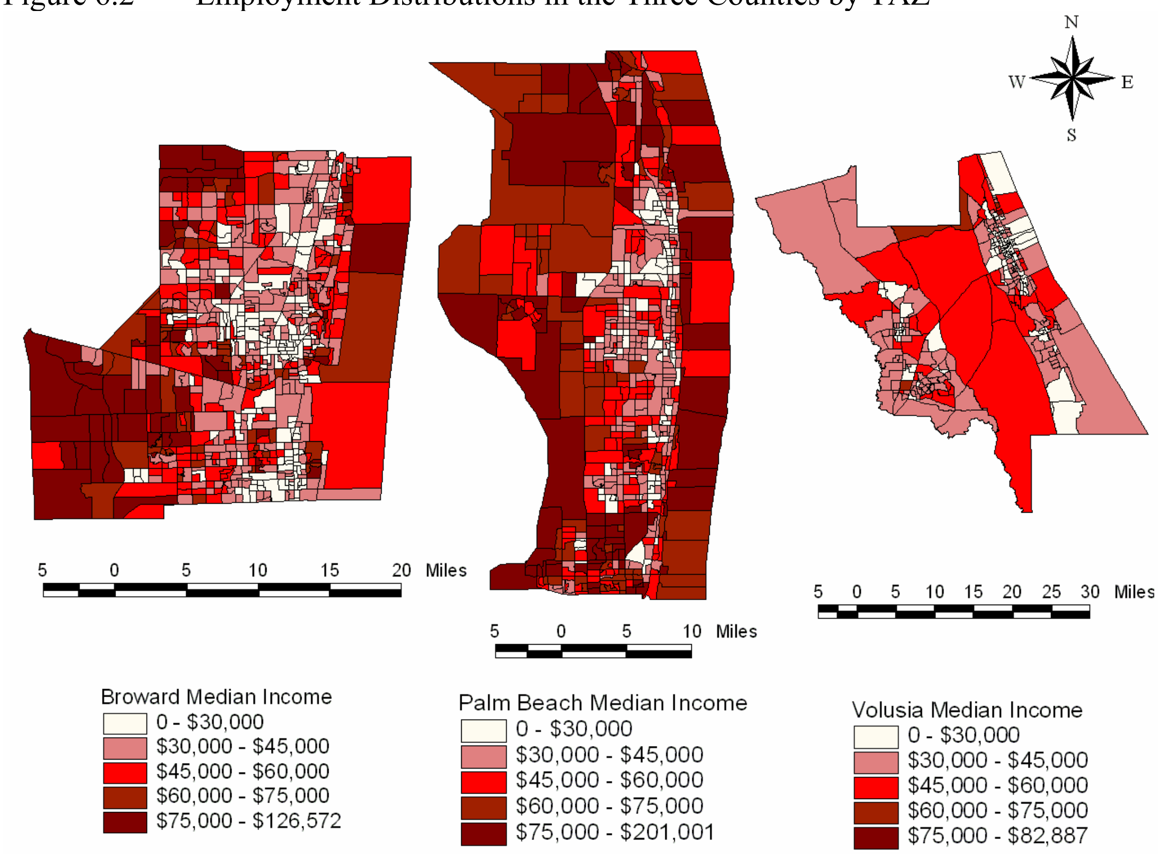

Figure 6.3 Income Distributions in the Three Counties by Census Block Group

Figure 6.4 Principal Arterial Networks in the Three Counties

6.2 Destination Choice Models With Aggregate Alternatives

Because of the difficulty to define precisely what constitutes an alternative and the computational burden of estimating a logit model with large number of alternatives, a destination choice model is calibrated based on aggregate alternatives. In other words, a trip maker would select a TAZ that generally contains a large number of elemental alternatives as his or her destination. The probability ($\pi_n(i|\mathbf{D})$) of a trip maker n selecting TAZ i as the destination zone under the condition that choice set **D** is given as follows (Ben-Akiva and Lerman 1985):

$$\pi_n(i\,|\,\mathbf{D}) = \frac{e^{\left\{\sum_{k=1}^{K'} \beta_k x_{ink} + \mu' \ln M_i + \ln \pi_n(\mathbf{D}|i)\right\}}}{\sum_{j=1}^{J} e^{\left\{\sum_{k=1}^{K'} \beta_k x_{jnk} + \mu' \ln M_j + \ln \pi_n(\mathbf{D}|j)\right\}}}, \qquad i = 1,\ldots,J, \tag{6}$$

where

$\pi_n(i\|\mathbf{D})$	=	probability of selecting TAZ i as the destination zone under the condition that choice set **D** is given;
β_k	=	coefficient of the kth attribute;
x_{ink}	=	value of the kth attribute for TAZ i and decision maker n;
M_i	=	number of elemental alternatives in TAZ i, generally a composition of multiple observable variables known as the size variables;
μ'	=	model coefficient associated with number of alternatives;
ln	=	natural log operator;

D	=	choice set which contains the destination alternatives for trip maker *n*;
K'	=	number of attribute variables; and
J	=	total number of TAZs in a study area **C**.

When alternative TAZs in choice set **D** are selected by simple random sampling, the selection probability $\pi_n(\mathbf{D}|i)$ in Equation (6) are canceled out. In this study, a simple random sampling approach was adopted to sample alternatives TAZs from a given study area, with the sample size restricted to ten. Consequently, the choice set for a trip maker contained nine randomly selected TAZs plus the one that was actually chosen.

6.3 HBW Destination Choice Models

In this section, a description of the data compiled to calibrate destination choice models stratified by income is first introduced, following by model application and performance evaluation. Attempts to improve intrazonal trip distribution are discussed, and the spatial transferability of models is investigated.

6.3.1 Study Data

In order to calibrate destination choice models for Broward, Palm Beach, and Volusia counties, data in the following categories were compiled using GIS: income, HBW trip data, network skim tables, zonal employment data, and spatial barrier variables. The HBW trip data were from two household surveys, i.e., the Southeast Florida Regional Travel Characteristics Study (SEFRTCS) for Broward and Palm Beach counties and the 2001 Home Based Travel Survey for Volusia County. The study data in each category are described in more detail in the following subsections.

6.3.1.1 Income Data

One common belief in the modeling community is that we need to improve our ability to link workers with their jobs and that the basis of such linkage is income. Although it is the personal income that is the direct link between a worker and a job, such information is difficult to obtain. Therefore, as a common practice household income is often used as a proxy since this information is readily available from the census.

In the current practice, many models either consider household income for market segmentation (same trip rates are applied for different income levels while trips are distributed separately for different income groups) or use income as an additional variable in the trip generation model (different trip rates for different income groups) for the HBW trip purpose. In this study, households in a TAZ were classified into low-, medium-, and high-income groups. Three destination choice models, one for each income group, were calibrated and used to distribute the HBW trips generated from these households.

The first step in preparing the data for model calibration was to segment the surveyed households into three income groups since the distributions of jobs taken by workers in households at different income levels might be different. The distributions of annual household income from

2000 census in the study areas as given in Table 6.2 were examined. Table 6.3 shows the income range and number of sampled HBW trips by income group by county. The dividing points to classify the households were selected such that the three income categories in each county had approximately the same number of households. For Volusia County, the trips recorded on the first day of the two-day survey were utilized since the first day data were more complete than the second day.

Table 6.2 Census Income Distribution for Broward, Palm Beach and Volusia Counties

HH Income	Broward County		Palm Beach County		Volusia County	
	Number of HHs	Cumulative %	Number of HHs	Cumulative %	Number of HHs	Cumulative %
Less than $10,000	59,064	9.0	36,110	7.61	17,264	9.35
$10,000 to $14,999	42,974	15.6	27,150	13.34	14,126	16.99
$15,000 to $19,999	42,331	22.1	28,278	19.30	15,040	25.14
$20,000 to $24,999	43,757	28.7	31,136	25.86	16,023	33.81
$25,000 to $29,999	43,454	35.4	30,539	32.30	15,146	42.01
$30,000 to $34,999	42,132	41.8	29,741	38.57	14,143	49.67
$35,000 to $39,999	38,293	47.7	27,680	44.41	12,735	56.56
$40,000 to $44,999	37,871	53.4	26,196	49.93	11,298	62.68
$45,000 to $49,999	30,938	58.2	22,985	54.78	9,775	67.97
$50,000 to $59,999	57,604	67.0	42,511	63.74	16,793	77.06
$60,000 to $74,999	66,383	77.1	47,222	73.70	16,139	85.80
$75,000 to $99,999	66,201	87.2	47,767	83.77	13,165	92.92
$100,000 to $124,999	35,475	92.6	27,234	89.51	5,655	95.98
$125,000 to $149,999	16,610	95.2	13,823	92.43	2,480	97.33
$150,000 to $199,999	15,056	97.5	14,025	95.38	2,417	98.63
$200,000 or more	16,644	100.0	21,898	100.00	2,522	100.00
Total	654,787		474,295		184,721	

Table 6.3 HBW Trips by Income Group by County

County	Income Level	HH Income	HBW Trips	Total
Broward	Low	< 30 k	160	1,361
	Middle	30 k – 60 k	514	
	High	≥ 60 k	687	
Palm Beach	Low	< 30 k	171	1,297
	Middle	30 k – 65 k	558	
	High	≥ 65 k	568	
Volusia	Low	< 25 k	66	410
	Middle	25 k – 50 k	140	
	High	≥ 50 k	204	

6.3.1.2 HBW Trip Data

The origin-destination zones for each of the sampled trips from the household surveys were converted to production-attraction zones. For each of the actually chosen attraction TAZ, nine additional alternative attraction TAZs were randomly selected and added to the choice set. A dummy variable *Y* was created for every record, with 1 indicating the TAZ that was actually chosen as the destination and 0 otherwise. The new data set consisted of 1,361; 1,297; and 410 record blocks, each with ten records for Broward, Palm Beach, and Volusia counties, respectively.

6.3.1.3 Network Skim Tables

In the Portland model, the generalized cost is the composite impedance, which is a logsum variable derived from the mode choice model and computed as the logarithm of the sum of the mode choice logit model utilities. The composite impedance represents the weighted congested travel time and travel cost for all modes. For Broward County, both highway travel impedance based on free-flow travel time and composite travel impedance were tested as the generalized cost in the destination choice models.

To build the composite impedance, the attributes of the mode choice model were extracted from the FSTUMS skim tables. Impedance skims, e.g., transit walk time, transit auto access time, transit fare, highway parking costs, etc., were obtained using the FSUTMS scripts in the Southeast Regional Planning Model V (SERPM-V). The SERPM-V mode choice model has a four-level nested structure. In the primary nest, total person trips are divided into "Auto" trips and "Transit" trips. In the secondary nest, the auto trips are split into "Drive Alone" trips and "Shared Ride" trips, and the transit trips are split into "Walk Access" trips and "Auto Access" trips. In the third nest, shared ride trips are split into "One Passenger" and "2+ Passengers". On the transit side, the walk access trips are split into "Local Bus" trips and "Premium Modes" trips, while the auto access trips are split into "Park-and-Ride" trips and "Kiss-and-Ride" trips. In the fourth nest, premium transit trips are further divided into Express Bus, Metrorail (a heavy rail system in Miami), and Tri-Rail. The utility of a mode is assumed to be a function of the attributes that define the level of service (LOS) provided by the mode (known as coefficients), and a mode specific constant. The set of LOS coefficients and mode specific constants are presented in Tables 6.4 through 6.6 (Corradino Groups 2003).

The transit skim data retrieved from the "tskimxx.r99" files included walk time, auto access time, in-vehicle time, transfer time, first wait time, and second wait time. The fare values were retrieved from the "tfarexx.r99" file. Highway skim files, i.e., HSKIMS.r99 and HVSIMS.r99, contained impedance, distance, and toll information for drive-alone and shared-ride modes, respectively. These three highway variables were used to calculate highway network travel time and operating cost with equations extracted from the SERPM-V model.

Table 6.4 LOS Coefficients for HBW Trips (Source: Corradino Groups 2003)

Variables	Coefficient
Transit Walk Time	-0.0450
Transit Auto Access Time	-0.0200
Transit Run Time	-0.0200
Transit First Wait Time < 7 Min	-0.0450
Transit First Wait Time > 7 Min	-0.0230
Transit Transfer (2nd Wait) Time	-0.0450
Transit Number of Transfers	-0.0450
Transit Fare	-0.0032
Highway Terminal Time	-0.0450
Highway Run Time	-0.0200
Auto Operating Costs	-0.0025
Highway Parking Costs	-0.0032
HOV Time Difference	-0.0180

Table 6.5 Mode Specific Constants for HBW Trips (Source: Corradino Groups, 2003)

Mode	Constant
Walk to Local Transit	
- for Zero Car Households	3.1521
- for One Car Households	-0.0215
- for Two+ Car Households	-2.5692
- for Downtown Attractions	0.2700
Walk to Express Bus Transit	
- for Zero Car Households	2.4182
- for One Car Households	-0.1243
- for Two+ Car Households	-2.7734
- for Downtown Attractions	0.2700
Walk to Metro Rail Transit	
- for Zero Car Households	3.3848
- for One Car Households	0.2767
- for Two+ Car Households	-2.2709
- for Downtown Attractions	0.2700
Walk to Tri Rail Transit	
- for Zero Car Households	1.6337
- for One Car Households	0.1238
- for Two+ Car Households	-2.2024
- for Downtown Attractions	0.2700
Park-Ride to Express Bus Transit	
- for Zero Car Households	-2.9942
- for One Car Households	-1.4733
- for Two+ Car Households	-3.3934
- for Downtown Attractions	0.9000

Park-Ride to Metro Rail Transit	
- for Zero Car Households	-3.9992
- for One Car Households	-0.2055
- for Two+ Car Households	-2.2321
- for Downtown Attractions	0.9000
Park-Ride to Tri Rail Transit	
- for Zero Car Households	-4.0071
- for One Car Households	-0.6662
- for Two+ Car Households	-2.1578
- for Downtown Attractions	0.9000
Kiss-Ride to Express Bus Transit	
- for Zero Car Households	-2.9992
- for One Car Households	-1.5020
- for Two+ Car Households	-3.5411
- for Downtown Attractions	0.9000
Kiss-Ride to Metro Rail Transit	
- for Zero Car Households	-3.0019
- for One Car Households	-0.4929
- for Two+ Car Households	-2.6556
- for Downtown Attractions	0.9000
Kiss-Ride to Tri Rail Transit	
- for Zero Car Households	-4.0071
- for One Car Households	-0.7525
- for Two+ Car Households	-2.4074
- for Downtown Attractions	0.9000

Table 6.6 Nesting Constants for HBW Trips (Source: Corradino Groups 2003)

Nest	Constant
Transit Nesting	0.30
Walk Access Local Bus Nesting	0.50
Walk Access Premium Nesting	0.50
Auto Access Nesting	0.50
Park-n-Ride	0.50
Kiss-n-Ride	0.50
Highway Nesting	0.80
Shared Ride Nesting	0.20

In addition to travel time and cost, the data for two other variables were compiled: parking cost and highway terminal time. Information on the highway parking costs was obtained from the ZDATA2 file. There are two types of parking costs: short-term and long-term. The long-term parking costs were used for home-based work trips. Terminal times were determined based on the area type. The area type of a TAZ may be determined from the LINKS file. The values of terminal time were then retrieved from PROFILE.MAS using the area types.

The logsums of modal utilities at different levels are given below:

$$LogSum_{WPM} = \ln[e^{U_{WEB}} + e^{U_{WMR}} + e^{U_{TMR}}]$$

$$LogSum_{PR} = \ln[e^{U_{PREB}} + e^{U_{PRWMR}} + e^{U_{PRTMR}}]$$

$$LogSum_{KR} = \ln[e^{U_{KREB}} + e^{U_{KRWMR}} + e^{U_{KRTMR}}]$$

$$LogSum_{WalkAccess} = \ln[e^{0.5*LogSum_{WPM}} + e^{U_{LB}}]$$

$$LogSum_{AutoAccess} = \ln[e^{0.5*LogSum_{PR}} + e^{0.5*LogSum_{KR}}]$$

$$LogSum_{Transit} = \ln[e^{0.5*LogSum_{WalkAcess}} + e^{0.5*LogSum_{AutoAccess}}]$$

$$LogSum_{ShareRide} = \ln[e^{U_{Auto2}} + e^{U_{Auto3+}}]$$

$$LogSum_{Auto} = \ln[e^{0.2*LogSum_{ShareRide}} + e^{U_{DriveAlone}}]$$

The logsum of all modal utilities was a key input to the destination choice model. It was generated as follows for HBW trips (by auto ownership):

$$LogSum_{\mathrm{mod}e} = \ln[e^{0.8*LogSum_{Auto}} + e^{0.3*LogSum_{Transit}}]$$

Highway travel times were also used in the calibration process as zonal impedance for Broward County. The logsum composite impedance was tested and the results showed that the destination choice models based on the composite impedance did not perform as well as when highway impedance was used (see Section 6.3.2). Consequently, highway travel time was used for calibrating the destination choice models. The travel time impedance skim table was obtained from the latest validated transportation models. For Broward and Palm Beach counties, the 1999 transportation models were used. For Volusia County, the most recent validated model was the 1997 transportation model, which was used to obtain the skim table. In this study, variable *TRPL* was used to represent the travel time between a given zone pair.

6.3.1.4 Zonal-Level Land Use Characteristics

For Broward and Palm Beach counties, the data from the SEFRTCS household survey were first closely examined to identify possible relationship between income and employment type. In the survey, personal annual income was determined at an increment of $5,000, which resulted in a total of 21 income levels. Employment types were classified into eleven categories. In the tri-county area, 5,114 of the 11,426 personal records had valid income information.

Table 6.7 shows the distribution of job types for the 5,114 useful personal records. It may be seen that the majority of jobs fell into the first six categories. The personal annual income distributions for these six categories are illustrated in Figures 6.5 through 6.10. Figure 6.5 shows the percentage of persons having a job in the retail trade category by income level. The corresponding average personal income was $31,281. Figure 6.6 shows the same statistics for the service employment category, which had an average income of $31,637. Figures 6.7 to 6.9 illustrate the percentage of persons by income level for the industrial, governmental, and commercial employment categories, respectively. The corresponding average incomes were $41,422, $39,205, and $40,923, respectively. Figure 6.10 shows the statistics for the professional employment category, with an average income of $47,945. The data suggested three income categories based on job sectors, i.e., low income for retail and service workers; medium income for industrial, government, and commercial workers; and high income for professional workers. This means that people with lower income were more likely to travel to destinations with more retail and service employment for work. Similarly, people with medium income would travel to areas with more industry, government, and industry employment. Finally, people with higher income would tend to work in areas with more professional jobs.

Table 6.7 Surveyed Persons by Job Type in Tri-County

Type of Work	Persons
Retail Trade	361
Service Industry	1,055
Commercial Business	348
Industry	195
Government	260
Professional	1,471
Self Employed	17
Church	3
Home Maker	1
College work study	1
Farming	1
No data	1,401
Total	5,114

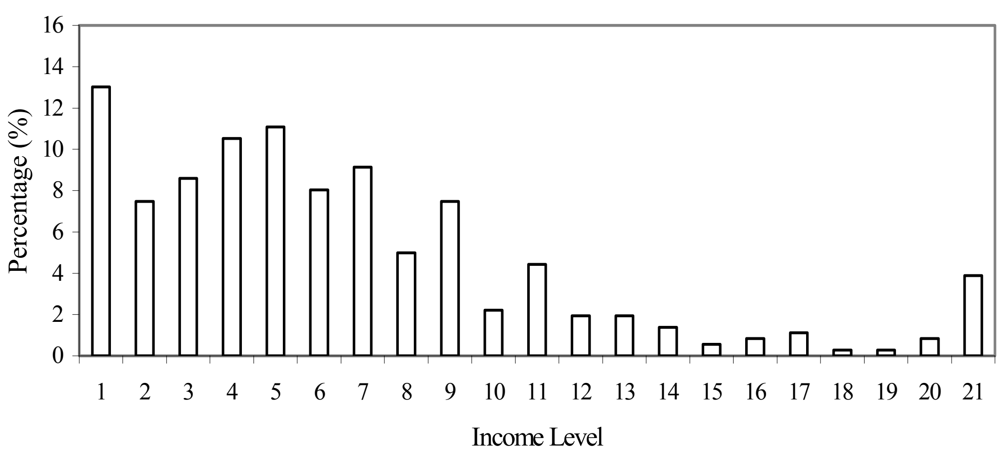

Figure 6.5 Income Distribution of Persons with Retail Trade Jobs

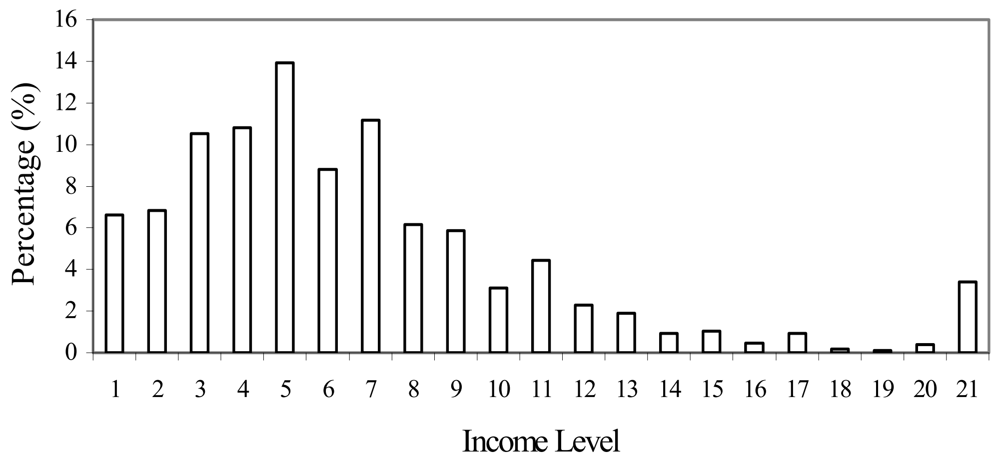

Figure 6.6 Income Distribution of Persons with Service Jobs

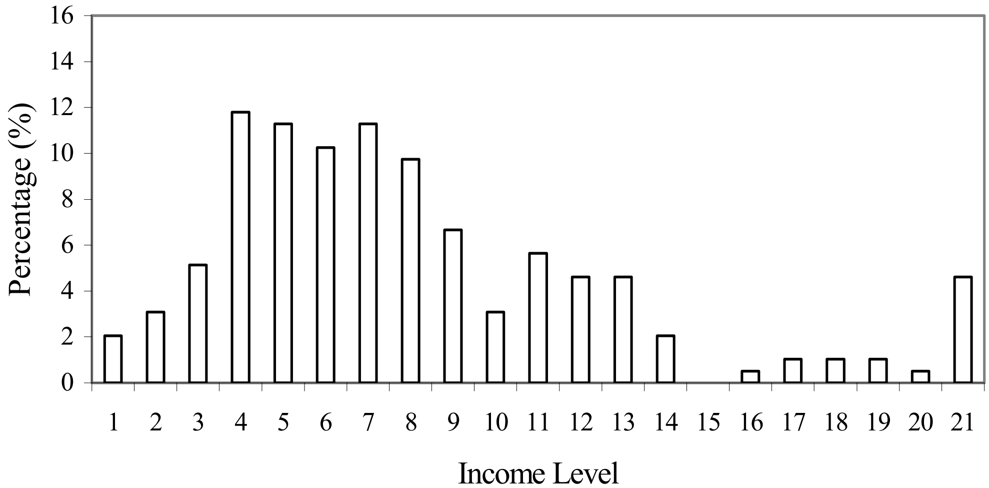

Figure 6.7 Income Distribution of Persons with Industrial Jobs

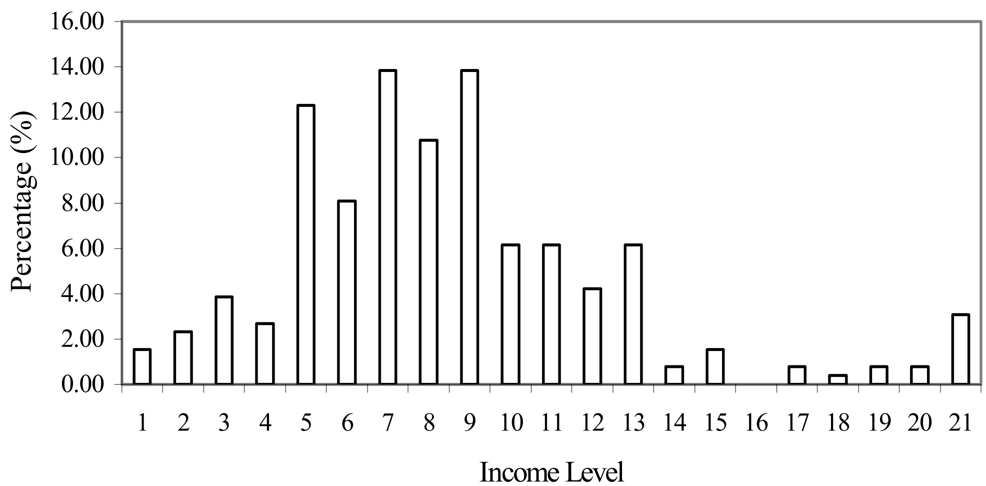

Figure 6.8 Income Distribution of Persons with Government Jobs

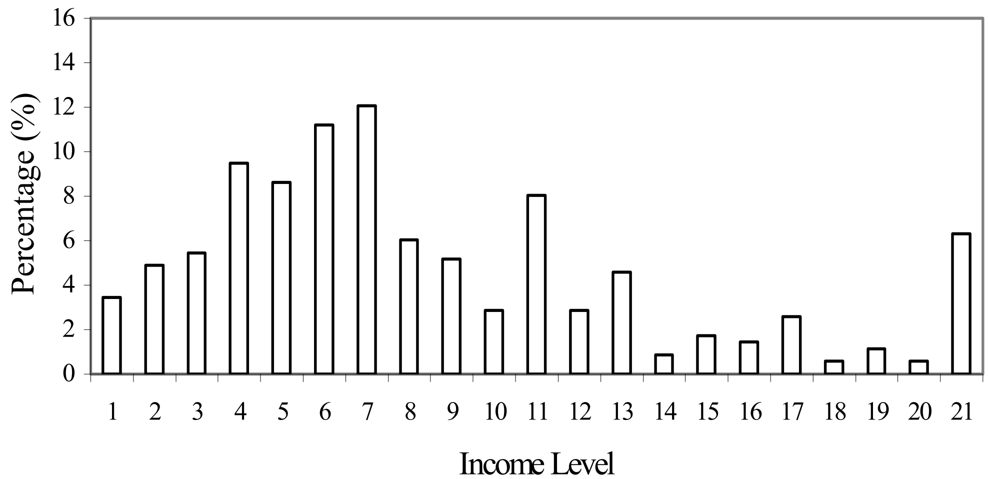

Figure 6.9 Income Distribution of Persons with Commercial Jobs

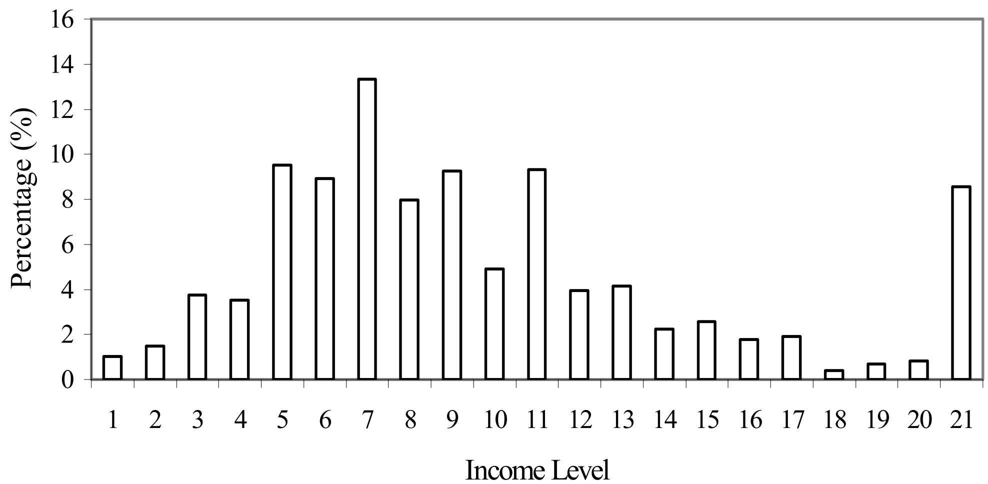

Figure 6.10 Income Distribution of Persons with Professional Jobs

The employment variables used for model development were defined based on the above categories. Table 6.8 illustrates the employment classifications based on the Standard Industry Classification (SIC) and the corresponding employment types. The percentage of employment by type of the total employment for Broward and Palm Beach counties are also provided.

Table 6.8 Employment Classifications

SIC	Description	Broward Employment %	Palm Beach Employment %	Employment Type	Broward %	Palm Beach %
52	Building Materials & Hardware	0.81	0.80	Retail	23.14	23.36
53	General Merchandise Stores	1.82	1.87			
54	Food Stores	3.70	3.98			
55	Automotive Dealers & Service Station	2.49	1.92			
56	Apparel & Accessory Stores	1.21	1.23			
57	Home Furniture & Furnishings Stores	1.73	1.54			

58	Eating & Drinking Places	8.29	8.88			
59	Miscellaneous Retail	3.09	3.04			
40	Railroad Transportation	0.00	0.01	Service	31.53	31.37
41	Local/Suburban Transit & Hwy Passenger	0.45	0.26			
42	Motor Freight Transportation/Warehouse	0.71	0.56			
44	Water Transportation	0.39	0.34			
46	Pipelines Except Natural Gas	0.00	0.00			
47	Transportation Services	1.42	0.45			
49	Electric Gas & Sanitary Services	0.45	0.67			
70	Hotels Rooming Houses & Camps	1.72	1.40			
73	Business Services	6.13	4.60			
75	Auto Repair Services & Parking	1.19	0.83			
78	Motion Pictures	0.24	0.08			
79	Amusement & Recreation Services	1.83	2.28			
80	Health Services	8.77	10.71			
82	Educational Services	5.45	5.34			
83	Social Services	1.43	2.01			
84	Museums Art Galleries & Gardens	0.01	0.02			
86	Membership Organizations	1.26	1.77			
88	Private Households	0.00	0.00			
89	Miscellaneous Services	0.08	0.04			
1	Agricultural Production-Crops	0.01	0.29	Commercial & Industrial	24.11	23.69
2	Agricultural Production-Livestock	0.02	0.02			
7	Agricultural Services	0.88	1.68			
8	Forestry	0.01	0.00			
9	Fishing Hunting & Trapping	0.01	0.00			
10	Metal Mining	0.00	0.00			
12	Coal Mining	0.00	0.00			
13	Oil & Gas Extraction	0.01	0.02			
14	Mining & Quarrying-Nonmetallic Miner	0.04	0.06			
15	Building Construction-Gen Contractor	1.51	1.98			
16	Building Construction-Gen Contractor	0.92	0.83			
17	Construction-Special Trade Contractor	3.75	4.01			
20	Food & Kindred Products Manufactures	0.62	0.48			
21	Tobacco Products Manufactures	0.01	0.00			
22	Textile Mill Products Manufactures	0.14	0.05			
23	Apparel & Other Finished Products Manufactures	0.29	0.14			
24	Lumber & Wood Prods Except Furniture Manufactures	0.36	0.22			
25	Furniture & Fixtures Manufactures	0.31	0.11			
26	Paper & Allied Products Manufactures	0.94	0.06			

27	Printing Publishing & Allied Industry	1.25	1.33			
28	Chemicals & Allied Products Manufactures	0.35	0.32			
29	Petroleum Refining & Related Industries Manufactures	0.06	0.02			
30	Rubber & Miscellaneous Plastics Manufactures	0.29	0.21			
31	Leather & Leather Products Manufactures	0.02	0.01			
32	Stone Clay Glass & Concrete Products Manufactures	0.21	0.19			
33	Primary Metal Industries Manufactures	0.24	0.17			
34	Fabricated Metal Products Manufactures	0.69	0.35			
35	Industrial & Commercial Machinery Manufactures	0.74	0.53			
36	Electronic & Other Electrical Equipment Manufactures	1.10	0.87			
37	Transportation Equipment Manufactures	0.45	1.32			
38	Measuring & Analyzing Instruments Manufactures	0.58	0.41			
39	Miscellaneous Manufacturing Industries Manufactures	0.47	0.32			
48	Communications	1.02	0.86			
50	Wholesale Trade-Durable Goods	5.54	5.33			
51	Wholesale Trade-Nondurable Goods	1.27	1.50			
43	United States Postal Service	0.19	0.23	Government	3.63	5.23
91	Executive Legislative & General Government	1.63	2.12			
92	Justice Public Order & Safety	1.24	1.80			
93	Public Finance & Taxation Policy	0.10	0.06			
94	Administration-Human Resource Programs	0.11	0.33			
95	Admin-Environmental Quality Programs	0.06	0.29			
96	Administration Of Economic Programs	0.28	0.30			
97	National Security & International Affair	0.02	0.10			
45	Transportation By Air	0.51	0.21	Professional	15.13	16.47
60	Depository Institutions	1.33	1.04			
61	Non-depository Credit Institutions	0.92	0.62			
62	Security & Commodity Brokers	0.79	1.52			
63	Insurance Carriers	0.25	0.26			
64	Insurance Agents Brokers & Service	1.59	1.50			
65	Real Estate	3.48	4.14			
67	Holding & Other Investment Offices	0.13	0.32			
72	Personal Services	2.37	2.73			
81	Legal Services	1.58	1.69			

87	Engineering & Accounting & Management Services	2.18	2.44			

Based on the results from this analysis, the following variables were created based on the two-digit SIC code:

RetSer = retail plus service employment (SIC: 40-42, 44, 47-47, 49, 52-59, 70, 73, 75, 78-80, 82-84, 86, 88-89);
CIG = commercial, industrial and government employment (SIC: 1-2, 7-10, 12-17, 20-39, 43, 48, 50-51, 91-97);
Prof = professional employment (SIC: 45, 60-65, 67, 72, 81, 87);
NonRetSer = all employment other than retail and service employment;
NonCIG = all employment other than commercial, industrial, and government employment; and
NonProf = all employment other than professional employment.

For Volusia County, the employment from the business database did not match the employment data from the 1997 transportation model at the TAZ level although the employment totals were close. In an extreme case, the business database indicated that there were only 200 employees in a particular TAZ, which had 3,000 employees according to the 1997 model. Since the detailed employment data might not be reliable, the employment categories of industrial (*Industrial*), commercial (*Commercial*) and service (*Service*) in the 1997 transportation model were used to compile the size variables for Volusia County. Similar to the data compiled for Broward and Palm Beach counties, *NonIndustrial*, *NonCommercial,* and *NonService* refer to the total employment other than *Industrial*, *Commercial,* and *Service*, respectively.

In addition to the land use characteristics, a *BdFlag* variable was used to indicate if there was a parking cost associated with an attraction TAZ. Parking costs were determined based on the data from the transportation models. For Volusia County, according to the 1997 travel model, no TAZ was associated with either short-term or long-term parking costs. Subsequently, the *BdFlag* variable was used to indicate if an attraction zone was in urban area in the Volusia destination choice model. The urban areas, as shown in Figure 6.11, were based on the 2000 census urban area definition.

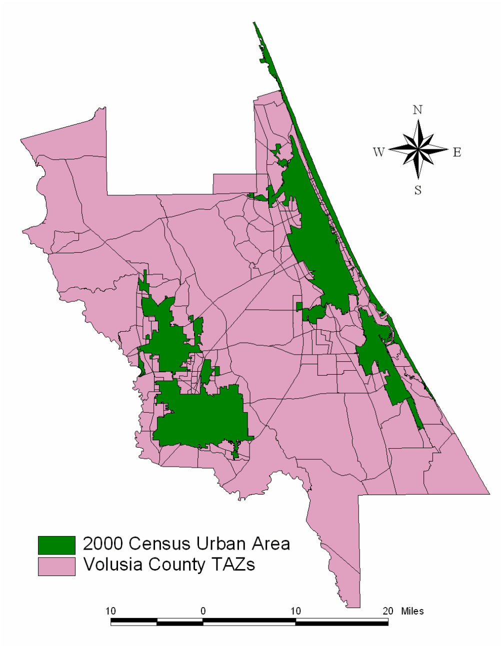

Figure 6.11 Urban Areas in Volusia County

6.3.1.5 Spatial/Physical Barrier Variables

Physical barriers make travel across the barriers impossible or difficult even though the air distance may be short. Examples of physical barriers may include rivers or valleys that have no or few bridges that link the two sides, or mountains that have no roads or are difficult to cross. Spatial barriers are "imagery" barriers that, even though not physical, impede travel that crosses them. They reflect urban structure and spatial distribution of demographics and socioeconomics and are difficult to represent in a model. When barriers cannot be adequately modeled based on travel impedance alone, *K* factors are sometimes employed to represent the additional impedance caused by the barriers. For instance, *K* factors have been applied in some models to prevent the over-distribution of trips from low-income households to central business district (CBD) where many high-paying jobs are located (Cambridge Systematics 1997).

In this study, the effects of physical/spatial barriers on HBW destination choices were investigated using the geocoded trip data from the SEFRTCS for Broward County. Initially, it was suspected that the inter-coastal waterway that separates the barrier islands from the mainland might be a physical barrier that impeded trips crossing the inter-coastal waterway. After some investigation, it was found the Florida Turnpike was a more appropriate spatial object to be considered in the calibration process. To illustrate, Figure 6.12 shows the HBW trip distribution for low-income households located east of the Florida Turnpike. Most of these HBW trips were attracted to the TAZs east of the Florida Turnpike, with only four out of 47 trips crossing the Turnpike. For the other two income groups, a possible spatial barrier was US-1 because US-1 separates inland and the coastal area where many high-income households were located. Therefore, the following four spatial variables were created and tested during calibration:

TPKEW	=	1 if trip crosses the Turnpike from east to west;
TPKWE	=	1 if trip crosses the Turnpike from west to east;
US1EW	=	1 if trip crosses US1 from east to east;
US1WE	=	1 if trip crosses US1 from west to east.

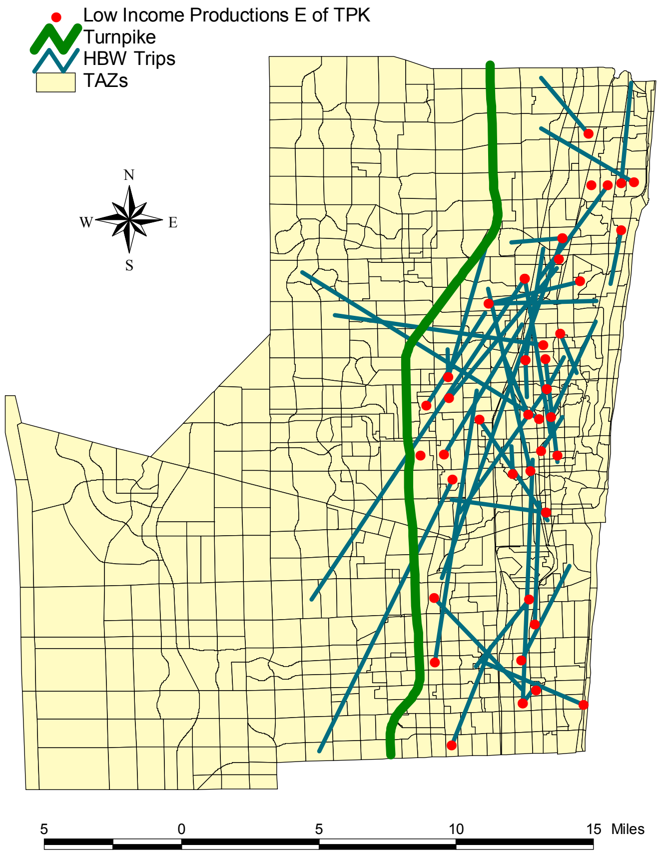

Figure 6.12 HBW Trip Distribution for Low-Income Households East of the Turnpike in Broward County

The Florida Turnpike and US-1 also appeared as barriers for Palm Beach County. Therefore, the above four variables were complied according to the locations of the productions and attractions to calibrate the Broward and Palm Beach models. The spatial barrier variables were determined simply according to the location of each zone relative to the spatial barriers.

For Volusia County, no variable was created to model spatial separation because no apparent spatial barriers were found. Although the large space (over 10 miles) between the east and west parts of the county (commonly referred to as the "Palmetto Curtain" because the area is covered by palmetto trees) appears a significant spatial barrier, test results indicated that this barrier was not significant, possibly because the reduction in trip interchanges between these two parts were already accounted for by the long travel time (up to 40 minutes according to the household survey). Consequently, adjustments to the travel times were redundant. Figures 6.13 through 6.15 illustrate the spatial distribution of trip ends from the survey data. It may be seen from Figure 6.13 that few trips from the low-income households crossed the "Palmetto Curtain". The number of trips crossing the "Palmetto Curtain" increased with the income level as shown in

Figure 6.14 and 6.15, indicating that there was at least some correlation between trip length and income.

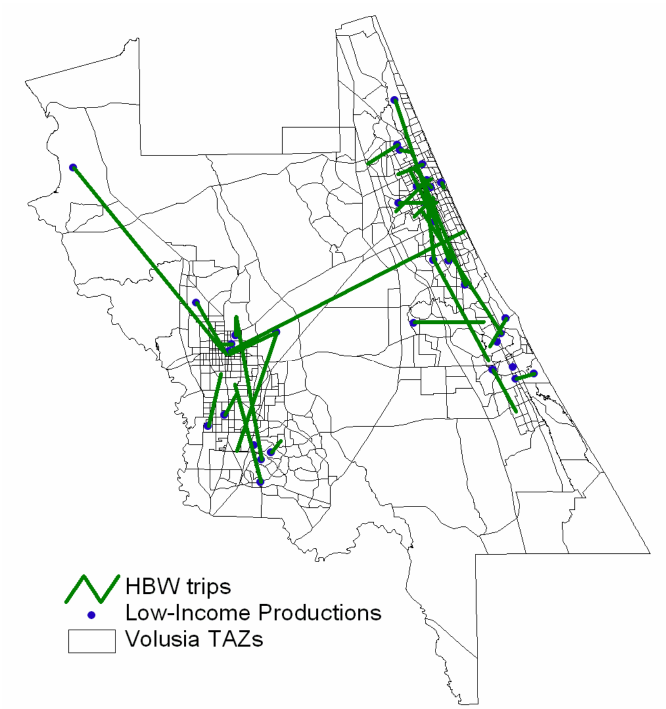

Figure 6.13 Spatial Distribution of Trips from Low-Income Households in Volusia County

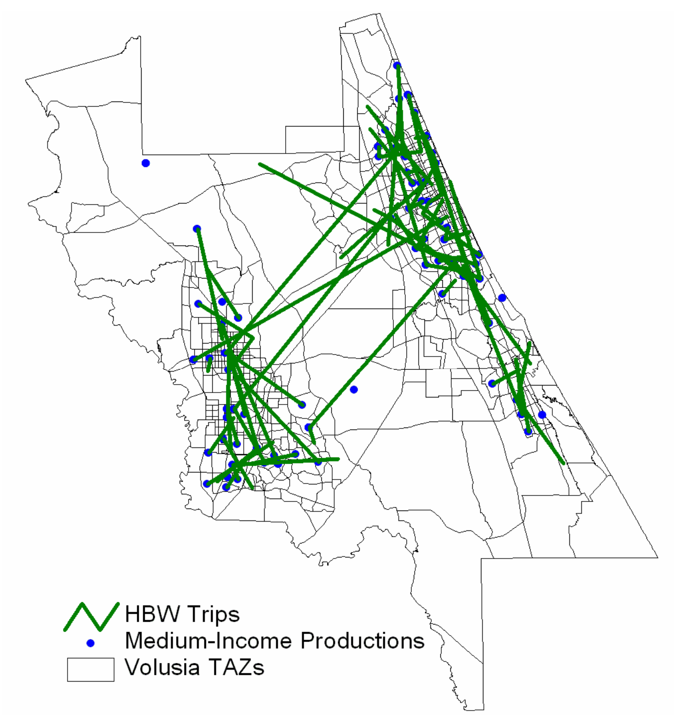

Figure 6.14 Spatial Distribution of Trips from Medium-Income Households in Volusia County

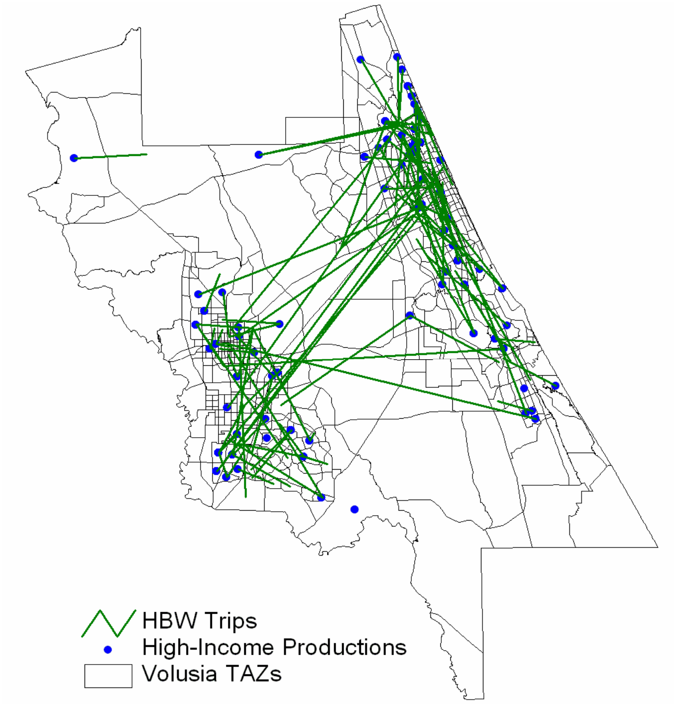

Figure 6.15 Spatial Distribution of Trips for High-Income Households in Volusia County

6.3.2 Calibration of HBW Destination Choice Models

NLOGIT version 3.0 (Econometric 2002), an extension of LIMDEP, was used to calibrate the destination choice models. NLOGIT is for estimating discrete choice models. It allows up to 100 alternatives, but is limited to 15 parameters in model calibrations.

Table 6.9 lists the calibrated destination choice models based on composite travel impedance for Broward County. $\mathcal{L}(0)$ is the value of the log likelihood function when all the parameters are zero; $\mathcal{L}(\hat{\beta})$ is the value of the log likelihood at its maximum; and ρ^2 is a goodness-of-fit measure defined as $1 - \mathcal{L}(\hat{\beta})/\mathcal{L}(0)$. Because a choice model is estimated by maximizing the log likelihood, a perfect model would have a possible maximum value of zero for $\mathcal{L}(\hat{\beta})$ and one for ρ^2.

As may be seen from Table 6.9, ρ^2 for the models were not significant. Because Broward County did not have a significant transit ridership and the logsum travel impedance was relatively complicated to calculate, the composite impedance was replaced with highway travel time in calibrating the new models.

Table 6.9 Results of HBW Destination Choice Model Calibration Using Composite Travel Impedance for Broward County

Income Level		$L(\hat{\beta})$	L(0)	ρ^2	Number of Observations
Low-Income	Statistics	-300.1273	-368.4136	0.1854	160
	Model	$U = \exp[0.3526 \times LowLogSum - 1.3880 \times TPKEW - 0.7556 \times TPKWE + 0.5649 \times \ln(2.4754 \times RetSer + NonRetSer)]$			
Middle-Income	Statistics	– 969.1043	– 1183.5287	0.1812	514
	Model	$U = \exp[2.3983 \times LowLogSum + 0.5201 \times BdFlag - 0.5093 \times TPKWE + 0.5604 \times \ln(2.4747 \times CIG + NonCIG)]$			
High-Income	Statistics	– 1309.6072	– 1581.8760	0.1721	687
	Model	$U = \exp[1.9962 \times LowLogSum + 0.9651 \times BdFlag - 0.5405 \times TPKWE - 0.823680 \times US1EW - 0.3369 \times US1WE + 0.5568 \times \ln(2.5582 \times Prof + NonProf)]$			

Table 6.10 gives the new destination choice models with an improved ρ^2. The signs of the coefficients were as expected. For all three income levels, larger travel impedance between a production zone and a candidate attraction-end zone made the candidate attraction-end zone less likely to be chosen for a HBW trip. The coefficients of the size variables were smaller than one, indicating that there were unobserved zonal attributes affecting the utility of working destinations within zones (Bhat 1998). For the low-income households, the coefficient for retail-service employment in the low-income model was greater than 1, which indicated that retail-service employment contributed more to the attractiveness of a zone to the low-income households in comparison with non-retail or non-service employment. For middle-income households, workers were more likely to travel to areas with more commercial, industrial, and governmental jobs. For the high-income households, the parameter on the professional employment was larger than the parameter on the nonprofessional employment, which means that people with higher income tended to work in areas with more professional jobs.

Table 6.10 Results of Destination Choice Model Calibration for HBW Using Highway Travel Time as Travel Impedance for Broward County

Income Level		$L(\hat{\beta})$	L(0)	ρ^2	Number of Observations
Low-Income	Statistics	-279.5734	-368.4136	0.2411	160
	Model	$U = \exp[-0.1199 \times TRPL - 0.3632 \times TPKEW + 0.4919 \times \ln(1.3404 \times RetSer + NonRetSer)]$			
Middle-Income	Statistics	-862.4219	-1183.5287	0.2713	514
	Model	$U = \exp[-0.1339 \times TRPL + 0.3055 \times BdFlag + 0.5948 \times TPKEW + 0.7286 \times \ln(1.3318 \times CIG + NonCIG)]$			
High-Income	Statistics	-1138.566	-1581.8760	0.2802	687
	Model	$U = \exp[-0.1173 \times TRPL + 0.6466 \times BdFlag + 0.2411 \times TPKWE - 0.1149 \times US1WE + 0.7336 \times \ln(1.8014 \times Prof + NonProf)]$			

The negative parameters for the spatial barrier variables in the model for the low-income households indicate that workers were less likely to cross the Turnpike from east to west to go to work. However, for the middle-income households east of the Turnpike, workers tended to cross the Turnpike to go to work. For the high-income households, which were usually located in communities west of the Turnpike, workers were more likely to cross the Turnpike to the east where the business districts were located. The other spatial variable that represented US-1 as a spatial barrier was significant in the high-income model and indicated that HBW trips were less likely to cross US-1 from west to east. This might have been caused by the type of jobs east of US-1, where most hotels were located along the coastline.

The downtown variable (*BdFlag*) was significant with positive coefficients in the Broward middle- and high-income models. This means that trip makers from middle- and high-income households in Broward County were more likely to travel to TAZs within the business districts to work.

The models calibrated for Palm Beach are given in Table 6.11. The coefficients for employment support the same conclusions drawn from the Broward models. However, none of the spatial barrier variables were significant, and *BdFlag* was statistically significant only for high-income households.

Table 6.11 Results of Destination Choice Model Calibration for Palm Beach County

Income Level		$L(\hat{\beta})$	L(0)	ρ^2	Number of Observations
Low-Income	Statistics	-283.1444	-393.7421	0.2809	171
	Model	U = exp[– 0.1020 × *TRPL* + 0.5908 × ln(2.1828 × *RetSer* + *NonRetSer*)]			
Middle-Income	Statistics	-851.2302	-1284.8425	0.3375	558
	Model	U = exp[– 0.1278 × *TRPL* + 0.6057 × ln(1.0068 × *CIG* + *NonCIG*)]			
High-Income	Statistics	-828.5384	-1307.8683	0.3665	568
	Model	U = exp[– 0.1177 × *TRPL* + 0.7632 × *BdFlag* + 0.6982 × ln(1.9916 × *Prof* + *NonProf*)]			

The calibrated models for Volusia County are described in Table 6.12. For the low-income households, the coefficient for industrial employment was greater than 1, which indicates that industrial jobs contributed more to the attractiveness of a zone in comparison with non-industrial jobs for low-income households. Similar to Broward and Palm Beach counties, commercial employment was a significant factor in determining the preference for a trip maker from a middle-income household to choose a TAZ as the HBW trip destination. For the high-income households, people with higher income tended to work in areas with more service jobs. The urban area variable (*BdFlag*) was not significant in the Volusia models.

Table 6.12 Results of Destination Choice Model Calibration for Volusia County

Income Level		$L(\hat{\beta})$	L(0)	ρ^2	Number of Observations
Low-Income	Statistics	– 151.9706	– 87.8671	0.4218	66
	Model	U = exp[– 0.1460×*TRPL* + 0.4070 × ln(1.2970 × *Industrial* + *NonIndustrial*)]			
Middle-Income	Statistics	– 162.7798	– 322.3619	0.4950	140
	Model	U = exp[– 0.1295 × *TRPL* + 0.7608 × ln(6.8833× *Commercial* + *NonCommercial*)]			
High-Income	Statistics	– 291.3353	– 469.7274	0.3800	204
	Model	U = exp[– 0.1125 × *TRPL* + 0.5419 × ln(1.0029 × *Service* + *NonService*)]			

The spatial barrier variables were found to be significant only in the Broward model. Since these variables are difficult to forecast for future years, destination choice models without spatial variables were also calibrated for Broward County. The effect of excluding the spatial barriers was then investigated in model evaluation, as described in Section 6.3.4. Table 6.13 gives the models without spatial variables. For the low- and high-come groups, the ρ^2 decreased from 0.2411 and 0.2892 in the models with the spatial variables to 0.2399 and 0.2791 in the models without the spatial variables respectively. The reductions in ρ^2, however, were not significant. For the middle-income group, it increased from 0.2713 to 0.3179.

Before the evaluation of the performance of the destination choice models for the HBW purpose, the models, two for Broward County with one including the spatial barrier variables and one excluding them and one each for Palm Beach and Volusia counties, were applied to produce the

O-D matrices. The next section explains the model applications. Evaluation of the models based on the distribution results is discussed in section 6.3.4.

Table 6.13 Destination Choice Model for HBW without Spatial Variable for Broward County

Income Level		$L(\hat{\beta})$	L(0)	ρ^2	Number of Observations
Low-Income	Statistics	– 280.0273	– 368.4136	0.2399	160
	Model	U = exp[– 0.1246 × *TRPL* + 0.4938 × ln(1.0244 × *RetSer* + *NonRetSer*)]			
Middle-Income	Statistics	– 711.4775	– 1043.0710	0.3179	453
	Model	U = exp[–0.1506 × *TRPL* + 0.4769 × *BdFlag* + 0.7418 × ln(1.0721 × *CIG* + *NonCIG*)]			
High-Income	Statistics	– 1140.3460	– 1581.8760	0.2791	687
	Model	U = exp[– 0.1124 × *TRPL* + 0.6201 × *BdFlag* + 0.7357 × ln(2.2303 × *Prof* + *NonProf*)]			

6.3.3 HBW Model Application

To apply the destination choice models, a program was written to distribute the production trips, obtained from the validated transportation models, based on the probability given by the destination choice models. However, before the trips are distributed, the data must be prepared for the model applications. The models generally include the following attributes: travel impedance, employment size for different types of employment, CBD or urban area indicator, and spatial barriers in some models. Travel impedance was obtained from the validated transportation models. The employment size variables were calculated either based on the proprietary business databases, in the case of Broward and Palm Beach counties, or the ZDATA2 file in the case of Volusia County. The value of the CBD indicator for a TAZ was determined based on the ZDATA2 file. The values of the urban area indicator and the spatial barrier variables for a TAZ were determined based on the location of the TAZ.

In addition to the above model attributes, the productions were divided into three income levels as defined in Section 6.3.1.1. The 2000 Census Transportation Planning Package (CTPP) was used to obtain the percentage of households of each income level in a TAZ. Because the 2000 census TAZ structure was slightly different from the TAZ structure used in the transportation models, a conversion was made between the census and model TAZ structures. The productions for each TAZ were then proportioned into three groups based on the percentage of households of each income level.

For external zones in the Broward County and Palm Beach County models, the proportion of the productions for a given income level was determined based on the average percentage of households of that income level for all the internal TAZs. The travel impedance for external zones was obtained from the transportation models. The spatial barrier variables were determined according to the location of the external zones. The CBD indicator was set to zero for external zones. For zonal land-use data, the estimated HBW attractions included in the ZDATA4 for the external zones were converted to employment based on the ratio of total internal HBW attractions and total employment in the internal zones. The converted employment of each external zone was then split into different job types using the average percentage of each job sector.

For Volusia County, the 1997 Transportation Model is a standard FSUTMS model, in which I-E trip is one trip purpose. The HBW productions were for internal trips only. Therefore, the destination choice models did not need to distribute I-E trips like the Broward or Palm Beach County models.

The destination choice models were then used to distribute the HBW trip productions using the following procedure based on Monte-Carlo simulation:

1. Using the logit model estimate the probability that a HBW trip will be made from each of the origin zones to each of the destination zones for each income level. The result is three matrix tables, with each cell containing the probability of a trip made between the given pair of O-D as indicated by the table row number and column number for a given income level.
2. Select a HBW production trip (from trips of all income levels and origins) randomly.
3. For the selected trip, determine the appropriate probability table from Step 1 to use based on income level and origin zone. Choose the destination zone based on the probability table.
4. Remove the trip production from the production table so that the number of remaining trips to be distributed is reduced by 1.
5. Subtract one trip from the attraction table for the selected destination zone and check if any trip attractions are left for this destination zone. This is to constrain the destination choice model at the attraction side to ensure that no excessive trips are allocated to a zone beyond the available attractions. The trip attractions from the validated FSUTMS transportation model are used. If all attractions in a destination zone are used up, remove this zone from the probability table so no more trips may be distributed to this zone.
6. Repeat Steps 2 through 5 until all trips are distributed.

The final O-D table was then compared with the O-D results from the gravity model, which is described next.

6.3.4 Evaluation of HBW Destination Choice Models

To determine if the destination choice models performed better than the traditional gravity models, the distribution tables from the destination choice models for Broward, Palm Beach, and Volusia counties were compared with the O-D results from the gravity models and survey data.

As in the evaluation of the intervening opportunity model and enhanced gravity models, the TAZs in each county were aggregated into TADs. The TAZs in Broward County and Palm Beach County were aggregated into six and four districts, respectively. Tables 6.14 and 6.15 provide the number of sampled HBW trips (including trips without income information) between districts for Broward and Palm Beach counties, respectively.

Table 6.14 Surveyed HBW Trip Interchanges for Broward County

District	1	2	3	4	5	6	Total
1	139	22	20	63	17	11	272
2	107	121	47	26	20	14	335
3	62	19	88	67	39	23	298
4	90	12	52	185	29	13	381
5	17	6	22	43	102	30	220
6	43	5	62	50	75	194	429
Total	458	185	291	434	282	285	1,935

Table 6.15 Surveyed HBW Trip Interchanges for Palm Beach County

District	1	2	3	4	Total
1	293	105	23	17	438
2	89	287	85	21	482
3	42	64	456	33	595
4	60	92	92	100	344
Total	484	548	656	171	1859

In the household survey, Volusia County was divided into six geographic regions: northeast, southeast, center, northwest, center-west, and southwest. Table 6.16 gives the number of sampled HBW trips between these six regions. It may be seen that the center and northwest regions had few samples or work trips into these two regions. Because the regions were not easily and logically combined due to their spatial locations, the goodness-of-fit statistic tests were not conducted for the cells with small samples to avoid division of close-to-zero percentage of trips. The bold numbers in Table 6.16 indicate the cells that were used to calculate the goodness-of-fit statistics. Figure 6.16 shows the TADs for the three counties.

Table 6.16 Surveyed HBW Trip Interchanges for Volusia County

District	Region	1	2	3	4	5	6	Total
1	Northeast	**200**	7	8	0	2	0	217
2	Southeast	**14**	**53**	0	0	4	0	71
3	Center	**11**	2	2	0	0	1	16
4	Northwest	0	0	0	6	6	2	14
5	Center-West	8	1	0	0	**59**	**10**	78
6	Southwest	**12**	0	0	0	**27**	**93**	132
Total		245	63	10	6	98	106	528

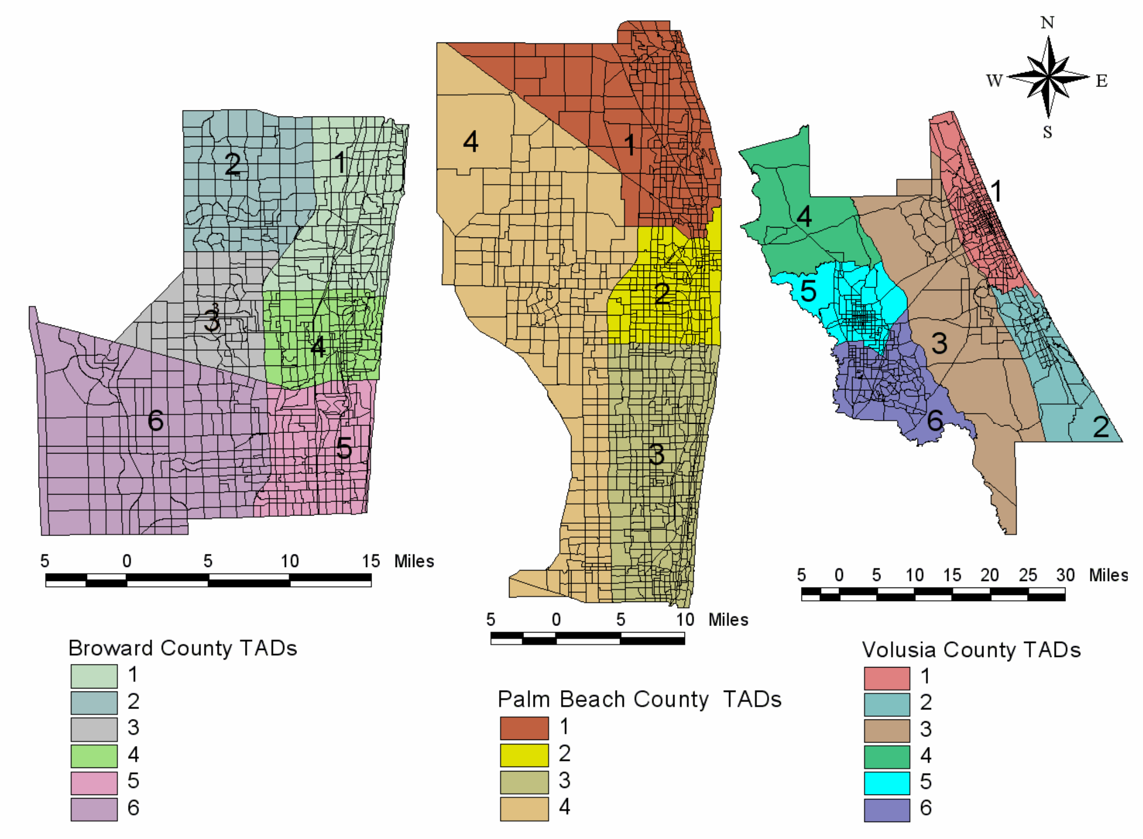

Figure 6.16 TAZs in Broward, Palm Beach, and Volusia Counties

6.3.4.1 Average Trip Lengths

The trip length distributions for the three county models are plotted in Figures 6.17 through 6.19, which are retrieved from the travel time impedance skims based on the O-D tables of survey data, the gravity models, and destination choice models.

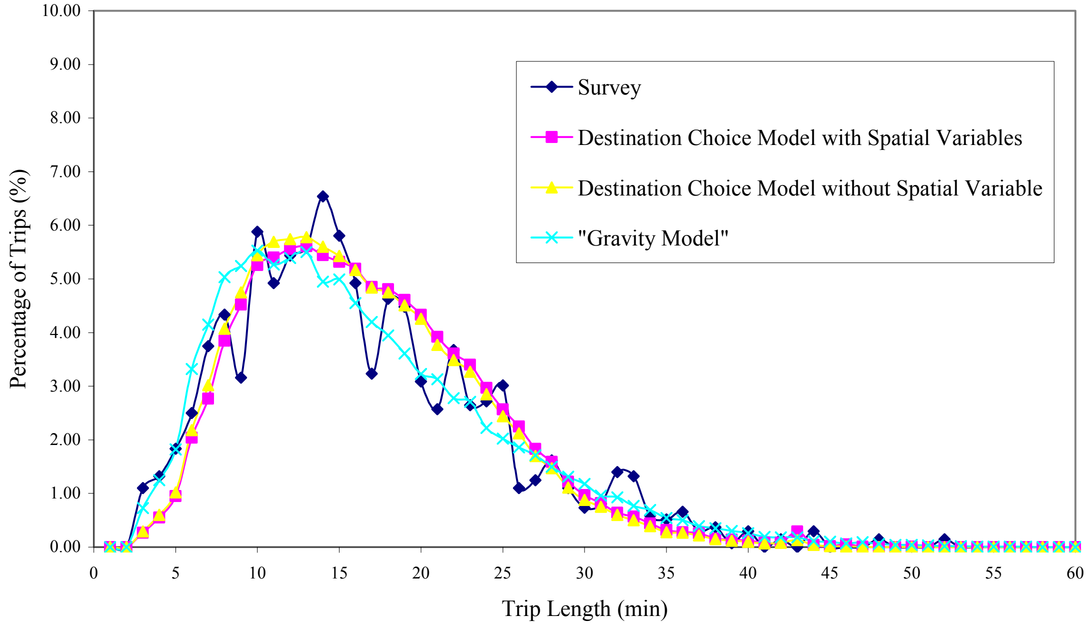

Figure 6.17 HBW Trip Length Distributions from Survey, Destination Choice Model, and Gravity Model for Broward County

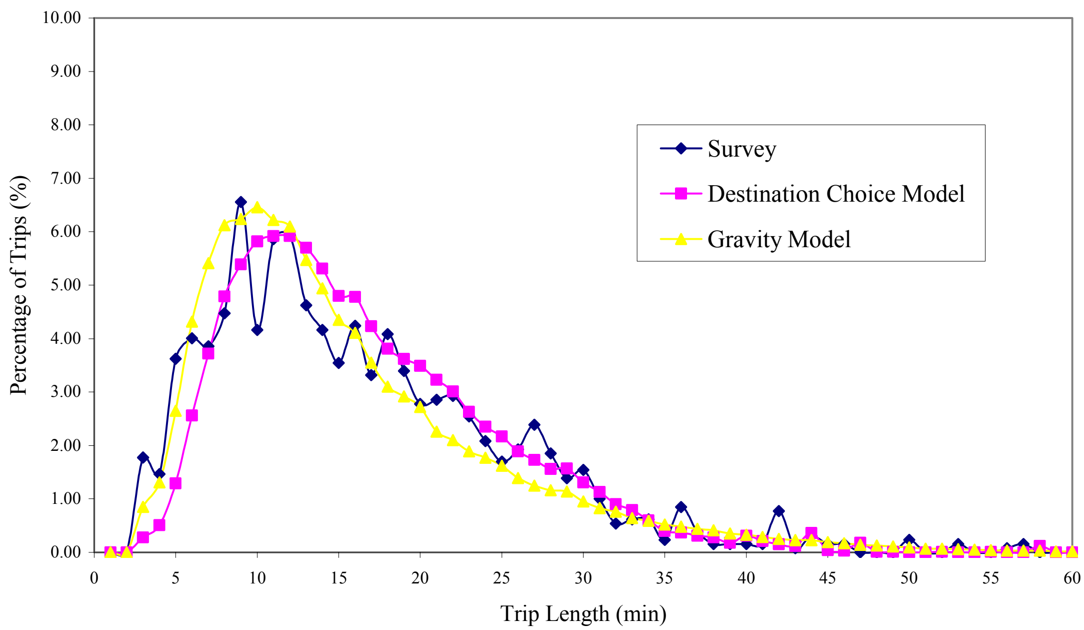

Figure 6.18 HBW Trip Length Distributions from Survey, Destination Choice Model, and Gravity Model for Palm Beach County

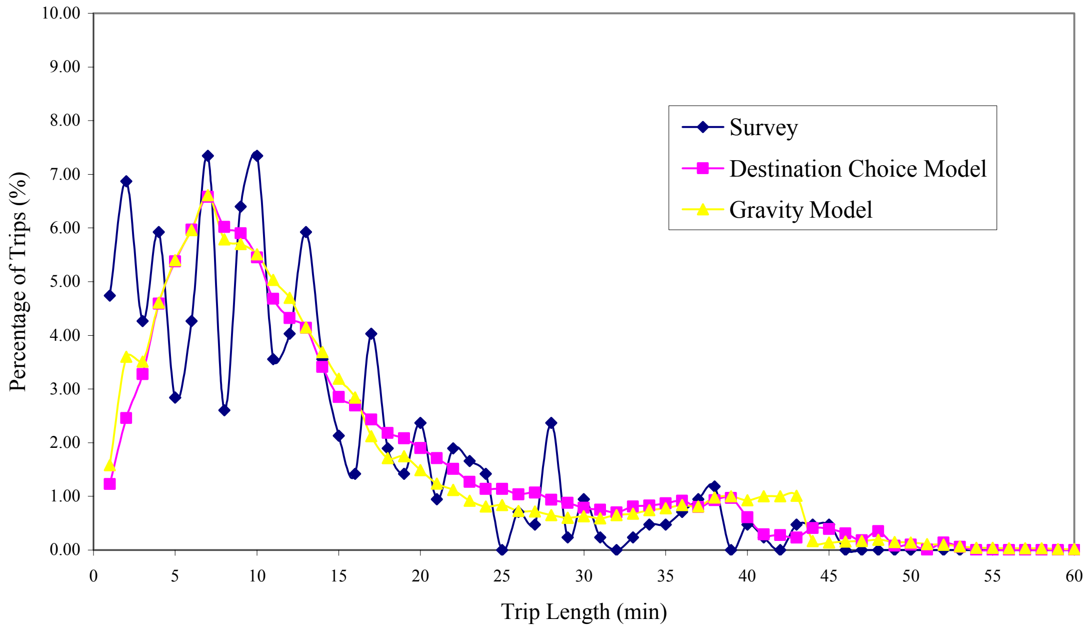

Figure 6.19 HBW Trip Length Distributions from Survey, Destination Choice Model, and Gravity Model for Volusia County

The average trip length (in minutes) from the survey data was compared with those from the destination choice and gravity models in each study area. As shown in Table 6.17, the destination choice models appear to be able to better replicate the average trip lengths from the household surveys. The destination choice models also performed better than the gravity models in terms of coincidence ratios for larger urban areas such as Broward and Palm Beach counties. In other words, the trip length distributions from the destination choice models matched closer with those from the survey data. For Volusia County, the coincidence ratios from the two models were close. Note that the coincidence ratios for Volusia County were much lower than those from the other two counties. One possible explanation is that a much smaller number of households were sampled from Volusia. Consequently, significantly higher variations existed in the data and could not be modeled well.

Table 6.17 Comparison of Average Trip Lengths and Trip Length Distributions for HBW Trips from Survey, Destination Choice Models, and Gravity Model

County	MOE	Survey	Choice		Gravity
Broward	Average Trip Length	16.61	16.89[1]	16.52[2]	14.36
	Coincidence Ratio	-	0.812	0.820	0.734
Palm Beach	Average Trip Length	16.32	16.79		14.67
	Coincidence Ratio	-	0.801		0.758
Volusia	Average Trip Length	12.61	14.53		14.58
	Coincidence Ratio	-	0.655		0.645

Note: 1 - Destination Choice Model with Spatial Variables
2 - Destination Choice Model without Spatial Variable

6.3.4.2 Intrazonal Trips

Table 6.18 compares the intrazonal trips from the gravity models and the destination choice model against the survey data. The results show that while both destination choice and conventional gravity models underestimated the percentage of intrazonal trips, regardless of the study areas, the gravity models performed better than the destination choice models. For the two larger counties, the discrepancy in intrazonal trips may be negligible since the proportions of intrazonal trips were relatively insignificant in comparison with the total trips. However, since significantly more intrazonal trips were observed from the household survey data in Volusia County than in the other two counties, intrazonal trips need to be carefully considered in smaller urban areas.

Table 6.18 Percentages of HBW Intrazonal Trips from Survey, Destination Choice Models, and Gravity Model

County	MOE	Survey	Choice		Gravity
Broward	Intrazonal Trip	79	9,969[1]	10,779[2]	30,428
	I-I Trips	1,935	1,121,608	1,122,018	1,074,159
	%	4.08	0.89	0.96	2.83
Palm Beach	Intrazonal Trip	53	13,769		17354
	I-I Trips	1,859	705,431		684,698
	%	2.85	1.95		2.53
Volusia	Intrazonal Trip	64	9,764		12,748
	I-I Trips	528	315,133		315,227
	%	12.12	3.10		4.04

Note: 1 - Destination Choice Model with Spatial Variables
2 - Destination Choice Model without Spatial Variable

In an effort to increase the percentage of the intrazonal trips from the destination models, a dummy variable was added into the Broward models to indicate intrazonal trips. Table 6.19 shows that the dummy variable increased the percentage of intrazonal trips to 6.65%, which was 2.57% higher than the expected value of 4.08%. A possible reason is that the dummy variable and trip length were correlated since intrazonal trips had short trip lengths. Therefore, more intrazonal trips were distributed by both the dummy variable and the variable of trip length.

Table 6.19 Percentages of Intrazonal Trips from Destination Choice Models with or without Dummy Variable

	I-I Trips	Intrazonal Trips	%
Surveyed Data	1,935	79	4.08
Destination Choice Model (without Spatial Variable) with dummy Variable for Intrazonal Trips	1,160,678	77,201	6.65
Destination Choice Model (without Spatial Variable)	1,162,211	11,755	1.01
Gravity Model	1,074,159	30,428	2.83

Intrazonal trips may be increased if intrazonal impedances are reduced. In FSUTMS, the intrazonal time is defined as an estimate of the time required to travel across a given traffic analysis zone. It is included in the free-flow highway skims with terminal time, which is the time required to travel from a trip origin to a car and from the car to a final destination. The intrazonal impedance is generated for each zone by halving the average impedances to a user-specified number of adjacent zones. In the validated 1999 Broward County travel model, the intrazonal impedance of each zone was determined by the impedance to the two nearest zones. To increase the percentages of the intrazonal trips, intrazonal impedance was reduced by halving the impedances to the nearest zone. The destination choice models were recalibrated with the new travel impedance skim. Table 6.20 shows the resulted intrazonal trip percentage was still lower than the expected percentage.

Table 6.20 Percentages of Intrazonal Trips for Destination Choice Model with Reduced Intrazonal Impedances

	I-I Trips	Intrazonal Trips	%
Surveyed Data	1,935	79	4.08
Destination Choice Model with Reduced Intrazonal Impedances	1,159,059	13,329	1.15
Gravity Model	1,074,159	30,428	2.83

As another attempt to increase intrazonal trip percentages, terminal times ranging between 1 and 9 minutes were excluded from the intrazonal impedance to further reduce the intrazonal impedance. However, even after the intrazonal impedance was reduced to the possible minimum value, the recalibrated destination choice model still could not distribute enough intrazonal trips as shown in Table 6.21.

Table 6.21 Percentages of Intrazonal Trips for Destination Choice Model with Minimum Intrazonal Impedances

	I-I Trips	Intrazonal Trips	%
Surveyed Data	1,935	79	4.08
Destination Choice Model with Minimum Intrazonal Impedances	1,160,326	15,818	1.36
Gravity Model	1,074,159	30,428	2.83

6.3.4.3 Spatial Accuracy

To measure the spatial accuracy of the destination choice models, the trip interchanges between TADs from the destination choice models, gravity models, and the survey data were calculated as a percentage of the total zonal trips. The statistical tests described in Chapter 3 were then conducted to evaluate the goodness-of-fit for trip interchanges between TADs.

Table 6.22 gives the percentages of trip interchanges between pairs of TADs in Broward County, which were obtained from the survey data, the destination choice models with and without the spatial variables, and the gravity model. The highlighted cells in Table 6.22 indicate that the models closely replicated the percentage of trip interchanges observed from the survey. The destination choice models, regardless whether spatial variables were included or not, yielded trip interchange percentages that better matched the observed values for two thirds of the 36 (6 × 6) TAD pairs in Table 6.22. For the remaining TAD pairs of which the trip interchanges were estimated more closely by the gravity model, the differences among the estimates from the three models were relatively insignificant. Moreover, incorporating spatial variables into the choice models did not seem to produce significantly better estimates of trip interchanges.

Table 6.22 Comparison of HBW Trip Interchanges between TADs from Survey, Destination Choice Models, and Gravity Model for Broward County

District		1	2	3	4	5	6
1	SUR	7.18	1.14	1.03	3.26	0.88	0.57
	DCM	9.33	1.43	0.74	3.16	0.98	0.15
	DCM1	9.63	1.27	0.65	3.24	0.91	0.11
	GRA	11.72	0.48	0.23	2.46	0.40	0.06
2	SUR	5.53	6.25	2.43	1.34	1.03	0.72
	DCM	7.61	6.44	2.05	1.81	0.45	0.31
	DCM1	7.46	6.70	2.08	1.70	0.38	0.32
	GRA	6.62	8.55	1.60	1.35	0.32	0.18
3	SUR	3.20	0.98	4.55	3.46	2.02	1.19
	DCM	3.18	1.49	4.12	2.96	1.65	1.57
	DCM1	3.12	1.49	4.36	2.90	1.54	1.57
	GRA	2.67	1.12	6.49	3.11	1.17	1.16
4	SUR	4.65	0.62	2.69	9.56	1.50	0.67
	DCM	4.13	0.51	1.44	5.82	2.61	0.74
	DCM1	4.15	0.45	1.29	6.14	2.60	0.64
	GRA	3.88	0.21	0.78	8.72	1.91	0.30
5	SUR	0.88	0.31	1.14	2.22	5.27	1.55
	DCM	1.26	0.05	0.53	2.35	5.64	1.65
	DCM1	1.19	0.05	0.48	2.38	5.93	1.49
	GRA	0.86	0.04	0.24	1.97	6.85	0.71
6	SUR	2.22	0.26	3.20	2.58	3.88	10.03
	DCM	1.83	0.44	3.30	3.58	5.83	8.85
	DCM1	1.63	0.43	3.34	3.22	5.71	9.42
	GRA	1.41	0.31	3.23	2.86	5.33	10.69

Note: SUR - Survey Data
DCM - Destination Choice Model with Spatial Variables
DCM1 - Destination Choice Model without Spatial Variable
GRA - Gravity Model

Tables 6.23 and 6.24 provide the same information for Palm Beach and Volusia counties, respectively. The results for Palm Beach County show that destination choice models yielded closer estimates for trip interchanges in nine of the 16 (4 × 4) TADs. For Volusia County, the choice models performed better for six out of the nine TAD pairs that had a significant number of survey samples.

Table 6.23 Comparison of HBW Trip Interchanges between TADs from Survey, Destination Choice Model, and Gravity Model for Palm Beach County

District		1	2	3	4
1	SUR	15.76	5.65	1.24	0.91
	DCM	14.48	5.08	1.34	1.06
	GRA	17.08	3.81	0.85	1.03
2	SUR	4.79	15.44	4.57	1.13
	DCM	4.51	11.01	5.47	1.35
	GRA	3.21	14.31	4.25	0.96
3	SUR	2.26	3.44	24.53	1.78
	DCM	1.21	5.71	27.27	2.49
	GRA	0.94	4.50	28.52	1.56
4	SUR	3.23	4.95	4.95	5.38
	DCM	2.72	4.36	6.33	5.63
	GRA	2.40	4.15	5.52	6.90

Note: SUR - Survey Data
DCM - Destination Choice Model
GRA - Gravity Model

Table 6.24 Comparison of HBW Trip Interchanges between TADs from Survey, Destination Choice Model, and Gravity Model for Volusia County

District		1	2	3	4	5	6
1	SUR	37.88	–	–	–	–	–
	DCM	43.21					
	GRA	43.90					
2	SUR	2.65	10.04	–	–	–	–
	DCM	4.47	8.39				
	GRA	4.42	8.41				
3	SUR	2.08	–	–	–	–	–
	DCM	3.19					
	GRA	3.56					
4	SUR	–	–	–	–	–	–
	DCM						
	GRA						
5	SUR	–	–	–	–	11.17	1.89
	DCM					7.54	1.51
	GRA					7.62	0.62
6	SUR	2.27	–	–	–	5.11	17.61
	DCM	6.39				4.80	12.44
	GRA	6.59				5.55	10.79

Note: SUR - Survey Data
DCM - Destination Choice Model
GRA - Gravity Model

Table 6.25 summarizes the goodness-of-fit statistical tests for the destination choice models and gravity models. The results show that for Palm Beach County both the gravity model and destination choice models fitted the spatial interchanges between survey districts well, and that the difference was insignificant. Destination choice models appear to perform significantly better in allocating trips into TADs for Broward County as well as for Volusia County. However, it needs to be pointed out that since significantly fewer samples were used to calibrate the gravity and destination choice models for Volusia County, the reliability of the models may be uncertain. For Broward County, there was no significant difference in the spatial accuracy of the two types of destination choice models with and without the spatial variables.

Table 6.25 Statistical Comparison of Spatial Accuracy of Destination Choice Models, and Gravity Model for HBW Trips

County	Model	Chi-Square*	Neyman's Modified Chi-Square	Simplified Freeman-Tukey	Scale Deviance	Sum of Errors Squared	Mean Errors Squared
Broward	Choice[1]	11.74	8.66	9.29	4.27	35.38	0.98
	Choice[2]	13.30	8.47	9.50	4.47	32.83	0.91
	Gravity	30.16	13.34	16.84	8.45	48.60	1.35
Palm Beach	Choice	4.96	4.82	4.74	2.08	39.37	2.46
	Gravity	5.61	4.10	4.62	2.12	31.96	2.00
Volusia	Choice	8.79	13.11	9.90	3.01	92.91	10.32
	Gravity	13.88	16.28	13.43	5.13	123.78	13.75

* Degrees of freedom: Broward = 35, Palm Beach = 15, Volusia = 8

Note: 1 Destination Choice Model with Spatial Variables
2 Destination Choice Model without Spatial Variable

6.3.5 Constraining Attractions Using Fratar Process

In Section 6.3.3, HBW trip productions were distributed using a Monte Carlo procedure in which trips were distributed one by one while keeping track of the remaining trip attractions. The procedure makes sure the destination choice model will not under- or over-distribute trips at zonal level. However, the Monte Carlo procedure requires a long processing time since the trips were processed one at a time. For Broward County, it took 12 hours for a PC with a 3.2 GHz CPU and 1.25 GB RAM to distribute a total of 1,390,661 HBW trips. Therefore, the less time-consuming Fratar process was investigated. After the productions were proportionally distributed based on the probability derived form the destination choice models, the FRATAR model in TRANPLAN was use to balance the attractions of the O-D table. The results were compared with the output from the Monte Carlo procedure. Tables 6.26 through 6.28 compare the results for the three counties.

From Tables 6.26 through 6.28, it may be seen that for Broward and Palm Beach counties, the Monte Carlo procedure performed better in terms of average trip length and percentage of intrazonal trips and slightly worse in percentages of trip interchanges among traffic analysis districts and trip length distribution. It seems that the Fratar method may be used to restrict the number of trips at attraction ends when applying the destination choice models directly based on the probabilities. For Volusia County, however, Fratar method yielded much worse results than the Monte Carlo Procedure. Therefore, the Mote Carlo simulation should be the preferable procedure when processing time and computer memory are not a concern.

Table 6.26 Comparison of Average Trip Lengths and Trip Length Distributions for HBW Trips Using Monte Carlo and Fratar Procedures

County	MOE	Survey	Monte Carlo	Fratar
Broward	Average Trip Length	16.61	16.52	17.14
	Coincidence Ratio	-	0.820	0.822
Palm Beach	Average Trip Length	16.32	16.79	17.19
	Coincidence Ratio	-	0.801	0.801
Volusia	Average Trip Length	12.61	14.53	15.99
	Coincidence Ratio	-	0.655	0.630

Table 6.27 Comparison of Percentages of HBW Intrazonal Trips Using Monte Carlo and Fratar Procedures

County	MOE	Survey	Monte Carlo	Fratar
Broward	Intrazonal Trip	79	10,779[2]	10,568
	I-I Trips	1,935	1,122,018	1,112,628
	%	4.08	0.96	0.95
Palm Beach	Intrazonal Trip	53	13,769	5,414
	I-I Trips	1,859	705,431	696,416
	%	2.85	1.95	0.78
Volusia	Intrazonal Trip	64	9,764	8,653
	I-I Trips	528	315,133	314,381
	%	12.12	3.10	2.75

Table 6.28 Statistical Comparison of Spatial Accuracy of Monte Carlo and Fratar Procedures for HBW Trips

County	Model	Chi-Square*	Neyman's Modified Chi-Square	Simplified Freeman-Tukey	Scale Deviance	Sum of Errors Squared	Mean Errors Squared
Broward	Monte Carlo	13.30	8.47	9.50	4.47	32.83	0.91
	Fratar	9.78	8.55	8.61	3.85	31.90	0.89
Palm Beach	Monte Carlo	4.96	4.82	4.74	2.08	39.37	2.46
	Fratar	4.38	4.66	4.40	1.90	34.68	2.17
Volusia	Monte Carlo	8.79	13.11	9.90	3.01	92.91	10.32
	Fratar	21.67	23.98	20.05	9.91	178.64	19.85

* Degrees of freedom: Broward = 35, Palm Beach =15, Volusia = 8

6.3.6 Spatial Transferability

It is desirable that destination choice models in different urban areas share the same structure and similar model parameters. This would allow an urban area without household travel survey to borrow a destination choice model from a similar urban area. This section discusses such possibilities, that is whether there exists spatial transferability in destination choice models.

If a model is spatially transferable, it may be applied to another area different from the area for which it is calibrated and still be able to produce satisfactory results. To test the spatial transferability of the destination choice model, both Broward County models with and without the spatial variables were applied to Palm Beach County. The results were then compared with those from the Palm Beach destination choice models. Table 6.29 shows that both the Palm Beach models and Broward models performed comparably well in terms of average trip length and trip length distribution.

Table 6.29 Average HBW Trip Lengths and Trip Length Distributions from Broward Model and Palm Beach Model for Palm Beach County

Model	Average Trip Length	Coincidence Ratio
Surveyed Data	16.32	-
Broward Model with Spatial Variables	16.43	0.799
Broward Model without Spatial Variable	16.18	0.801
Palm Beach Model	16.79	0.801
Gravity Model	14.67	0.758

Table 6.30 compares the intrazonal trips from the Palm Beach and Broward models. Although all destination choice models underestimated the intrazonal trips, the Broward Beach model distributed slightly more intrazonal trips than the Palm models**.**

Table 6.30 Percentages of HBW Intrazonal Trips Distributed by Broward Models and Palm Beach Model for Palm Beach County

Model	I-I Trips	Intrazonal Trips	%
Surveyed Data	1,859	53	2.85
Broward Model with Spatial Variables	705,744	14,079	1.99
Broward Model without Spatial Variable	705,952	15,370	2.18
Palm Beach Model	705,431	13,769	1.95
Gravity Model	684,698	17354	2.53

Table 6.31 summarized the statistical tests for spatial accuracy, which showed that the trip interchanges between TADs predicted by the Palm Beach models were closer to the survey data. However, the differences between the Broward and Palm Beach models were insignificant.

Table 6.31 Spatial Accuracy of Broward and Palm Beach HBW Models Applied to Palm Beach County

Model	Chi-square*	Neyman's Modified Chi-Square	Simplified Freeman-Tukey	Scale Deviance	Sum of Errors Squared	Mean Errors Squared
Broward Model with Spatial Variables	5.38	4.71	4.81	2.15	36.20	2.26
Broward Model without Spatial Variable	5.33	4.22	4.51	2.04	36.22	2.26
Palm Beach Model	4.96	4.82	4.74	2.08	39.37	2.46
Gravity	5.61	4.10	4.62	2.12	31.96	2.00

* Degrees of freedom = 15

6.4 HB Non-Work Destination Models

Following the same calibration procedure for HBW trips, destination choice models were developed for HBS, HBSR, and HBO trip purposes. As previously described, HBW trips are segmented into different groups by income level to better link a trip maker's home place with his/her job location. For other home-based trips, however, most metropolitan areas do not segment trips by income level. In this study, the destination choice models for trip purposes other than HBW trips were not stratified by income level. The results are described in the following subsections.

6.4.1 HBS Destination Choice Models

To develop HBS destination choice models for Broward County, a total of 1,038 valid HBS trips were retrieved from the SEFRTCS database. The final data set for model calibration consisted of 1,038 blocks of records, each containing 10 records. For Volusia County, a total of 1,652 out of the 13,408 sampled trips were HBS trips. Among these HBS trips, 901 and 751 trips were made on days 1 and 2, respectively. For the day 1 trips, only 422 trips had valid internal origin and destination TAZs. As a result, the final data set for Volusia County model calibration consisted of 422 blocks of records, or a total of 4,220 records.

After reviewing the Portland model and the regression models for HBS attraction trips in the Broward and Volusia transportation models, numerous employment combinations were tested as the size variables. For Broward County, the retail and service employment size appeared to be a reasonable measurement for the amount of shopping opportunities within a given TAZ. For Volusia County, however, the commercial and service employment size appeared to be more appropriate as the size variable. The non-size variables included in the HBW destination choice models were also tested but were found insignificant.

Figure 6.20 shows the trip length distributions from the Broward County survey data, the gravity model, and the destination choice model that incorporated only the trip length and size variables. The sharp peak of short trips in Figure 6.20 indicates that most trip makers shopped at locations near their homes during weekdays. To improve the performance of the destination choice model, the spatial variables included in the HBW model were subsequently added in the HBS model.

The spatial variables were found to be statistically significant. However, they did not improve the model performance in terms of trip length distribution, i.e., the destination choice model distributed more long trips than that were revealed by the survey data.

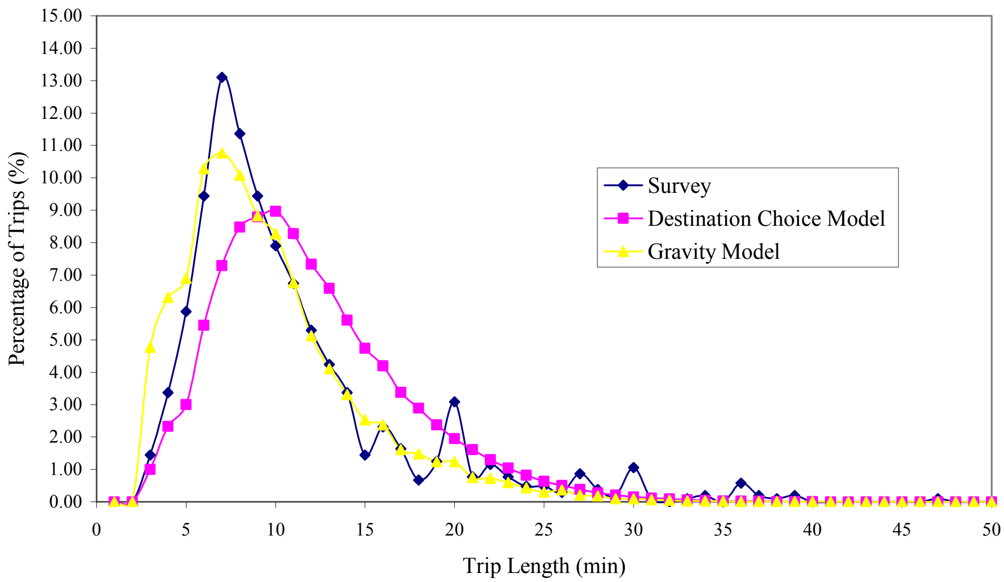

Figure 6.20 Preliminary HBS Trip Length Distributions from Survey, Destination Choice Model, and Gravity Model for Broward County

Although the trip length is the dominant factor in the model, the linear relationship in the utility function may not completely explain the travelers' behavior. The effect of trip length on the choice of shopping destinations may vary with distance. For example, trip length utility for shopping areas within five miles from homes might be different from that for shopping at locations 30 miles away. For each HBS trip from the survey data, the zones other than the home zone were ranked based the travel time from the home zone. Table 6.32 shows the ranks of the destination zones from the survey and the number of HBS trips that ended in zones of a given rank. Cumulative percentages for each rank of zones are also provided. One third of the travelers shopped in the ten nearest TAZs from their homes. The second one-third of the travelers shopped in TAZs ranked eleven to fifty away from their homes. The last one-third of the travelers shopped in the remaining TAZs. Based on this observation, two dummy variables were created and added into the destination choice model for Broward County. The first dummy variable indicated weather a traveler shopped in the first ten nearest TAZs, and the other whether the traveler shopped farther than the fiftieth TAZs close to his or her home. These variables were not used for Volusia County because the trip length distribution frequency (see Figure 6.22) did not have a sharp peak like Broward County.

Table 6.32 Surveyed Destination Zones Ranked by Travel Time

Rank	Number of Trips	Cumulated %
1	60	5.78
2	47	10.31
3	29	13.10
4	43	17.24
5	29	20.04
6	44	24.28
7	32	27.36
8	27	29.96
9	17	31.60
10	**15**	**33.04**
11-20	148	47.30
21-30	85	55.49
31-40	62	61.46
41-50	**52**	**66.47**
51-100	129	78.90
101-200	70	85.65
201-500	117	96.92
501-892	32	100.00
Total	1,038	

Table 6.33 presents the calibrated models for HBS trips for Broward and Volusia counties. The coefficient of the retail employment variable was larger than that of the service employment variable in the Broward County model, indicating that retail employment would attract more HBS trips than service employment. The travel time dummy variables determined based on the ranks of impedance were statistically significant. The coefficient for *RANKLS10*, which indicates the destination TAZs were ranked ten or under, was positive. The results were consistent with the survey data from Broward County that HBS trips were more likely to take place in adjacent TAZs. On the other hand, the coefficient of *RANKGT50*, which indicates that the destination TAZs were ranked above 50, was negative. This means that, in addition to the trip length effect, trip makers from a given origin zone were less likely to choose TAZs that were far away.

In the HBS destination choice model calibrated for Volusia County, the coefficient of the commercial employment variable was larger than that of the service employment variable, indicating that commercial employment would attract more HBS trips than service employment.

Table 6.33 Destination Choice Models for HBS Trips

County		$\mathcal{L}(\hat{\beta})$	$\mathcal{L}(0)$	ρ^2	Number of Observations
Broward	Statistic	– 982.7242	– 2390.0833	0.5888	1,038
	Model	U = exp[– 0.1582 × *TRPL* + 0.6524 × *RANKLS10* – 1.3770 × *RANKGT50* + 0.8009 × ln(6.7229 × *RetEmp* + *SerEmp*)]			
Volusia	Statistic	– 379.7752	– 971.6909	0.6092	422
	Model	U = exp[– 0.2021 × *TRPL* + 0.5814 × ln(1.6048 × *ComEmp* + *SerEmp*)]			

Table 6.34 provides statistics regarding the average trip lengths and trip length distributions from the survey data, destination choice models, and gravity models. The destination choice models better replicated the average trip lengths from the survey data than the gravity models for both counties. However, the coincidence ratios from the destination choice models were slightly worse than those of the gravity models. The trip length frequency distributions for Broward County and Volusia County are illustrated in Figures 6.21 and 6.22, respectively.

Table 6.34 Comparison of Average Trip Lengths and Trip Length Distributions for HBS Trips from Survey, Destination Choice Model, and Gravity Model

County	MOE	Survey	Choice	Gravity
Broward	Average Trip Length	10.91	11.72	9.66
	Coincidence Ratio	–	0.773	0.808
Volusia	Average Trip Length	9.24	11.74	13.41
	Coincidence Ratio	–	0.637	0.640

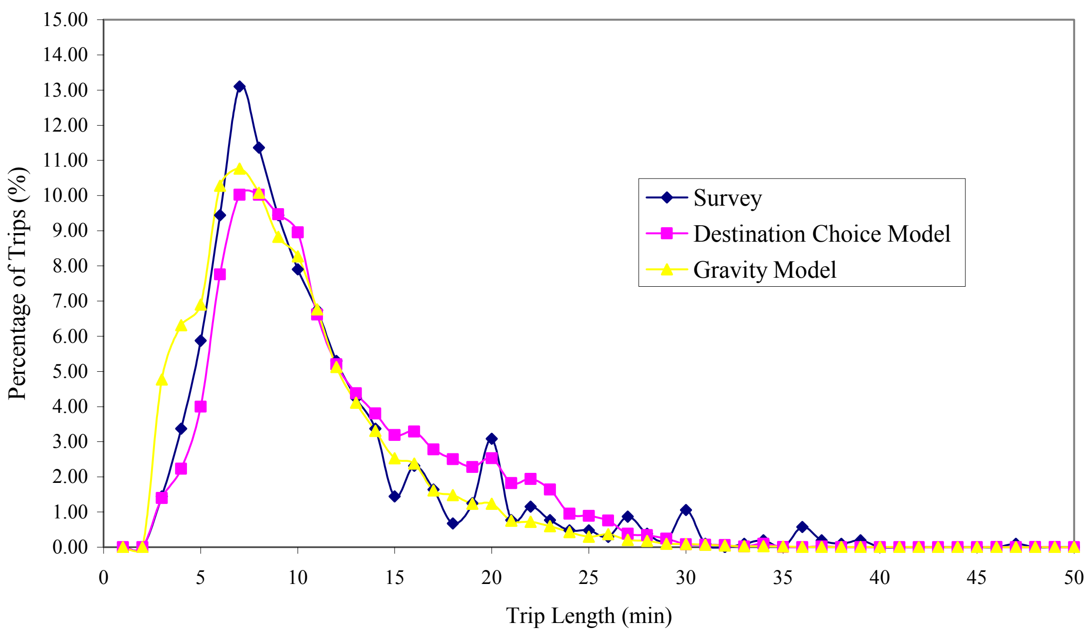

Figure 6.21 HBS Trip Length Distributions from Survey, Destination Choice Model with Travel Time Rank Dummy Variable, and Gravity Model for Broward County

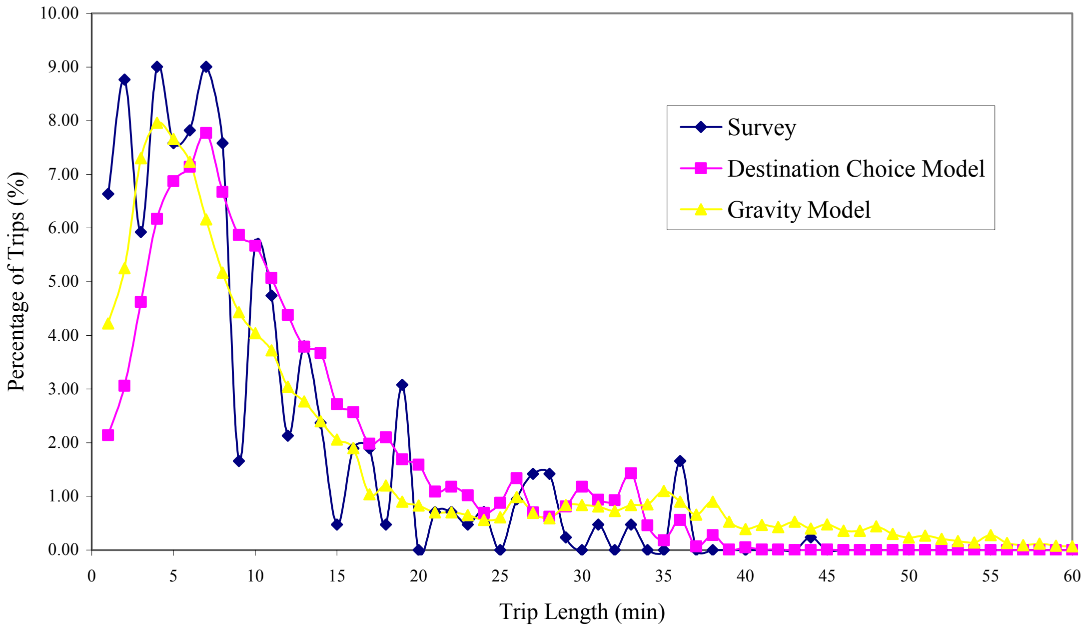

Figure 6.22 HBS Trip Length Distributions from Survey, Destination Choice Model, and Gravity Model for Volusia County

Table 6.35 gives the intrazonal trips and percentages from the survey, destination choice model, and gravity model for Broward and Volusia counties. The Broward County destination choice model performed better in estimating intrazonal trips. Both Volusia County models still significantly underestimated intrazonal trips.

Table 6.35 Percentages of HBS Intrazonal Trips from Survey, Destination Choice Model, and Gravity Model

County	MOE	Survey	Choice	Gravity
Broward	Intrazonal Trip	60	22,033	68,081
	I-I Trips	1,038	582,850	563,646
	%	5.78	3.78	12.08
Volusia	Intrazonal Trip	57	9,721	13,236
	I-I Trips	422	261,261	260,996
	%	13.51	3.72	5.07

Table 6.36 presents the number of sampled HBS trip interchanges between the six TADs in Broward County as a measure of the spatial accuracy of the destination choice model. Several district pairs were excluded due to the small numbers of trips sampled. The pairs that were included in the comparison were highlighted in bold in Table 6.36. Table 6.37 provides the sampled HBS trip interchanges between each pair of TADs for Volusia County, with the bold faced numbers being used in the model spatial accuracy evaluation.

Table 6.36 Sampled HBS Trips Interchanging between TADs in Broward County

District	1	2	3	4	5	6	Total
1	**148**	**17**	0	**15**	2	2	184
2	**32**	**135**	**14**	1	0	5	187
3	**10**	7	**111**	8	4	**21**	161
4	**11**	0	**15**	**95**	3	**12**	136
5	2	0	3	9	**97**	**15**	126
6	2	0	**32**	8	**17**	**185**	244
Total	205	159	175	136	123	240	1,038

Table 6.37 Sampled HBS Trips Interchanging between TADs in Volusia County

District	1	2	3	4	5	6	Total
1	**173**	0	**11**	0	1	0	185
2	**20**	**44**	0	0	0	1	65
3	5	1	4	0	0	0	10
4	0	0	0	0	0	0	0
5	0	0	0	0	**41**	7	48
6	4	0	0	0	4	**106**	114
Total	202	45	15	0	46	114	422

Table 6.38 shows the percentages of HBS trips between the TADs after excluding the district pairs with less than 10 sampled trips for Broward County. As indicated by shaded cells in the table, the destination choice model performed better in nine out of 18 selected district pairs.

Table 6.38 Comparison of HBS Trip Interchanges between TADs in Broward County from Survey, Destination Choice Model, and Gravity Model

District		1	2	3	4	5	6
1	SUR	14.26	1.64	–	1.45	–	–
	DCM	13.81	0.50	–	2.03	–	–
	GRA	14.74	0.07	–	1.33	–	–
2	SUR	3.08	13.01	1.35	–	–	–
	DCM	5.00	10.19	2.17	–	–	–
	GRA	4.49	11.49	1.50	–	–	–
3	SUR	0.96	–	10.69	–	–	2.02
	DCM	1.31	–	10.39	–	–	0.77
	GRA	1.00	–	12.88	–	–	0.30
4	SUR	1.06	–	1.45	9.15	–	1.16
	DCM	2.72	–	1.24	9.93	–	0.30
	GRA	2.31	–	0.95	12.30	–	0.08
5	SUR	–	–	–	–	9.34	1.45
	DCM	–	–	–	–	9.34	0.91
	GRA	–	–	–	–	9.62	0.29
6	SUR	–	–	3.08	–	1.64	17.82
	DCM	–	–	7.13	–	2.46	11.92
	GRA	–	–	6.66	–	2.09	13.19

Note: SUR - Survey Data
DCM - Destination Choice Model
GRA - Gravity Model

Table 6.39 presents the percentages of HBS trips between the selected TADs after excluding those with less than 10 sampled trips for Volusia County. The destination choice model performed better in three out of six selected district pairs.

Table 6.39 Comparison of HBS Trip Interchanges between TADs in Volusia County from Survey, Destination Choice Model, and Gravity Model

District		1	2	3	4	5	6
1	SUR	41.00	–	2.61	–	–	–
	DCM	48.78	–	0.18	–	–	–
	GRA	49.00	–	0.11	–	–	–
2	SUR	4.74	10.43	–	–	–	–
	DCM	6.25	6.58	–	–	–	–
	GRA	5.99	6.73	–	–	–	–
3	SUR	–	–	–	–	–	–
	DCM	–	–	–	–	–	–
	GRA	–	–	–	–	–	–
4	SUR	–	–	–	–	–	–
	DCM	–	–	–	–	–	–
	GRA	–	–	–	–	–	–
5	SUR	–	–	–	–	9.72	–
	DCM	–	–	–	–	7.28	–
	GRA	–	–	–	–	7.57	–
6	SUR	–	–	–	–	–	25.12
	DCM	–	–	–	–	–	14.78
	GRA	–	–	–	–	–	10.13

Note: SUR - Survey Data
DCM - Destination Choice Model
GRA - Gravity Model

The spatial accuracy of the trip distribution models in allocating HBS trips between traffic analysis districts was measured with the six statistics given in Table 6.40 for Broward and Volusia counties. The results show that destination choice models performed better than the gravity models according to most of the statistics.

Table 6.40 Statistical Comparison of Spatial Accuracy of the HBS Destination Choice and Gravity Models

County	Model	Chi-square*	Neyman's Modified Chi-Square	Simplified Freeman-Tukey	Scale Deviance	Sum of Errors Squared	Mean Errors Squared
Broward	Choice	16.05	15.46	13.84	8.27	72.24	4.01
	Gravity	72.49	14.44	19.00	10.27	63.53	3.53
Volusia	Choice	45.11	14.27	17.33	15.96	199.81	28.54
	Gravity	89.56	70.85	38.17	23.95	367.56	52.51

* Degrees of freedom: Broward = 17, Volusia = 5

6.4.2 HBSR Destination Choice Model

In SEFRTCS, HBSR trips made up only 7.41% of the surveyed trips. A total of 724 valid HBSR trips were selected from the Broward County survey data. The social recreation and entertainment activities include going to movies, visiting friends, eating meals, etc. After reviewing the Portland model and the regression model for HBSR attractions in the Broward transportation model, total household, park acreage, and retail employment of the destination zones were used as the size variables. The shape files of state, county, and city parks were downloaded from the Broward County Planning Department web site (http://gis.broward.org/gisdata/default.htm). Other possible size variables such as restaurant employment and park employments were also tested. In addition to travel impedance, non-size variables associated with the attraction zones such as household density, various types of employment density and socioeconomic characteristics were also tested. However, none of these variables proved significant. Preliminary calibration results showed that the destination choice model produced far more long trips and far fewer intrazonal trips than the gravity model. A possible reason is that the total households of the destination zones as a size variable might have overestimated the social and recreation opportunities within a zone. To shorten the trip length and increase the intrazonal trips, a dummy variable was added to indicate whether a trip was intrazonal trip. Table 6.41 describes the destination choice model for HBSR trips for Broward County

Table 6.41 HBSR Destination Choice Model for Broward County

	$\mathcal{L}(\hat{\beta})$	$\mathcal{L}(0)$	ρ^2	# of Observations
Statistics	-874.6158	-1667.0716	0.475	724
Model	$U = \exp[-0.1920 \times TRPL + 2.0410 \times Intralzonal + 0.4787 \times \ln(0.2438 \times HHs + 3.0348 RetailEmp + ParkAcreage)]$			

Table 6.42 gives the average trip lengths and coincidence ratios from the destination choice model and the gravity model. It may be seen that the destination choice model better replicated the average trip length for the HBSR trips from the survey data than the gravity model. The coincidence ratio from the destination choice model was, however, lower than that from the gravity model. As shown in Figure 6.23, gravity model performed better for trip lengths less than 15 min, and destination choice model, on the other hand, underestimated short trips and overestimate long trips.

Table 6.42 Comparison of Average Trip Lengths and Trip Length Distributions for HBSR Trips in Broward County from Survey, Destination Choice Model, and Gravity Model

	Surveyed Data	Destination Choice Model	Gravity Model
Average Trip Length	12.03	12.11	9.686
Coincidence Ratio		0.645	0.735

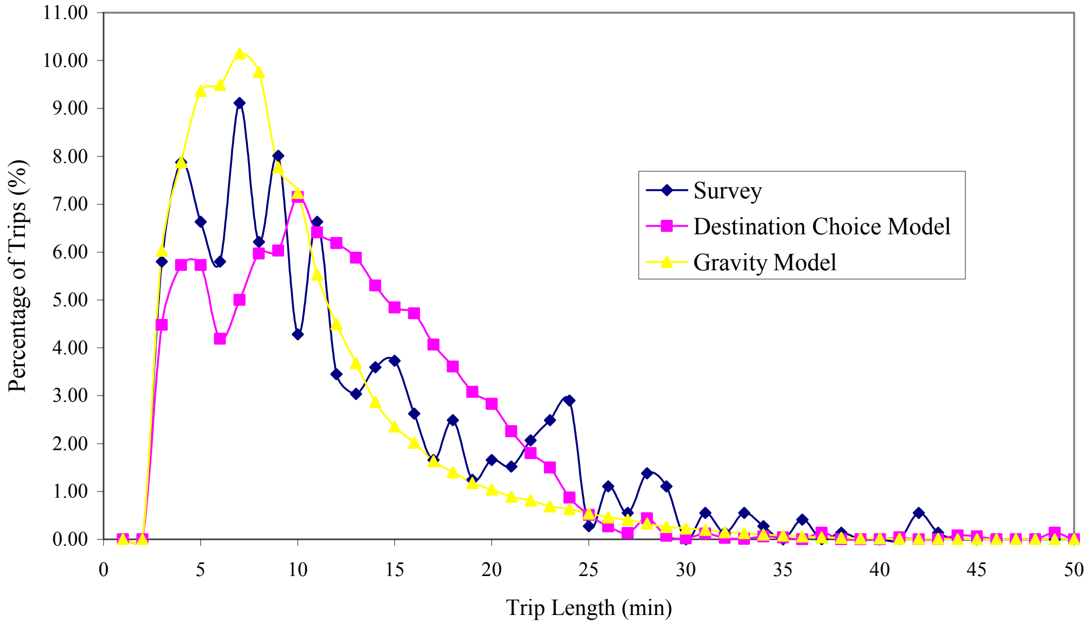

Figure 6.23 HBSR Trip Length Distributions from Survey, Destination Choice Model, and Gravity Model for Broward County

Table 6.43 shows the intrazonal trips and their percentages as the total HBSR trips from the survey, destination choice model, and gravity model, respectively. The results indicate that gravity model produced better result then destination choice model in the estimation of intrazonal HBSR trips.

Table 6.43 Percentages of HBSR Intrazonal Trips from Survey, Destination Choice Model, and Gravity Model for Broward County

	I-I Trips	Intrazonal Trips	%
Surveyed Data	724	125	17.27
Destination Choice Model	582,718	82,976	14.24
Gravity Model	549,327	88,181	16.05

Table 6.44 shows the number of sampled HBSR trip interchanges between the six TADs in Broward County. The highlighted numbers were used in evaluating the model spatial accuracy. Table 6.45 provides the percentages of HBSR trips between the TADs. The destination choice model performed better in 11 out of 16 selected district pairs, as indicated by the shaded cells.

Table 6.44 Surveyed HBSR Trip Interchanges for Broward County

District	1	2	3	4	5	6	Total
1	**90**	**10**	6	**16**	0	5	127
2	**22**	**87**	**12**	3	0	0	124
3	**11**	**11**	**56**	9	6	**15**	108
4	**15**	0	4	**53**	1	5	78
5	1	1	1	7	**51**	**25**	86
6	2	2	**14**	9	8	**166**	201
Total	141	111	93	97	66	216	724

Table 6.45 Comparison of HBSR Trip Interchanges between TADs from Survey, Destination Choice Model, and Gravity Model for Broward County

District		1	2	3	4	5	6
1	SUR	12.43	1.38	–	2.21	–	–
	DCM	13.00	1.09	–	2.93	–	–
	GRA	14.58	0.36	–	2.10	–	–
2	SUR	3.04	12.02	1.66	–	–	–
	DCM	3.55	9.65	1.56	–	–	–
	GRA	2.21	11.38	1.02	–	–	–
3	SUR	1.52	1.52	7.73	–	–	2.07
	DCM	1.40	1.28	6.59	–	–	1.03
	GRA	0.87	0.70	9.21	–	–	0.65
4	SUR	2.07	–	–	7.32	–	–
	DCM	3.55	–	–	12.44	–	–
	GRA	2.50	–	–	16.54	–	–
5	SUR	–	–	–	–	7.04	3.45
	DCM	–	–	–	–	10.29	1.33
	GRA	–	–	–	–	11.53	0.51
6	SUR	–	–	1.93	–	–	22.93
	DCM	–	–	2.61	–	–	12.67
	GRA	–	–	2.00	–	–	13.77

Note: SUR - Survey Data
DCM - Destination Choice Model
GRA - Gravity Model

The spatial accuracy of the HBSR destination choice model was measured by six test statistics, as provided in Table 6.46. The results show that the destination choice models performed better than the gravity model.

Although the destination choice model performed better than the gravity model, in general, both destination choice model and gravity model did not predict HBSR trips well. A possible reason may be that the travel choices for social recreation trips are also determined by the characteristics of trip makers such as age, gender, and family structure, which may interact with the attributes of destinations.

Table 6.46 Statistics Comparison of Spatial Accuracy of the HBSR Destination Choice and Gravity Models for Broward County

	Chi-square*	Neyman's Modified Chi-Square	Simplified Freeman-Tukey	Scale Deviance	Sum of Errors Squared	Mean Errors Squared
Destination Choice Model	17.87	13.89	14.81	11.40	158.49	9.91
Gravity Model	38.90	24.36	24.73	12.08	210.45	13.15

* Degrees of freedom = 15

6.4.3 HBO Destination Choice Model

A total of 2,098 valid HBO trips were selected from the Broward County survey data (SEFRTCS) to develop the destination choice model. The activities associated with the HBO trips were first investigated for possible size variables. Table 6.47 listed the activities for HBO trips in Tri-County survey.

Table 6.47 Activities for HBO Tips in Tri-County Survey

Activities	Trips	%
Personal Business (visits to banks, doctors, etc.)	3,429	45.57
Eat Meal	1,003	13.33
Drop Off/Pick Up Passenger	2,716	36.10
Change Travel Mode	78	1.04
Daycare/Babysitter	298	3.96
Total	7,524	100.00

From Table 6.47, it may be seen that 36.10% of the HBO trips involved dropping-off or picking-up passengers. Since most drop-off and pick-up trips were for school purposes, school enrollment (obtained from SCHOOL.99B in the Broward transportation model) in addition to possible employment in the destination zones were tested as the size variables. The results indicate that service plus professional employment and non-service and non-professional employments may be considered as measures of the amount of opportunities of HBO trips within a zone. However, school enrollment was later found insignificant as size variable. A dummy variable was then created to indicate whether there were public schools in a destination zone. The public school shape files were downloaded from Broward County's web site. This school indicator was significant in the destination choice model and had the expected sign.

In addition to travel impedance, non-size variables associated with the attraction zones, such as household density, employment density, and socioeconomic characteristics, were also tested. However, none of these non-size variables considered in the calibration were significant. Table 6.48 gives the destination choice model for HBO trips.

Table 6.48 Results of HBO Destination Choice Model Calibration for Broward County

Statistics	$\mathcal{L}(\hat{\beta})$	$\mathcal{L}(0)$	ρ^2	# of Observations
	– 4830.8235	– 2499.2662	0.483	2,098
Model	U = exp[– 0.2823 × *TRPL* + 0.2880 × *SchoolIndex* + 0.4375 × ln(1.1225 × *SerProfEmp* + *NoneSerProfEmp*)]			

The average trip lengths and coincidence ratios from the survey data, destination choice model, and gravity model are provided in Table 6.49. The destination choice model better replicated the average HBO trip length from the survey data than the gravity model. The coincidence ratio from the gravity model, however, was slightly better. As shown in Figure 6.24, the destination choice model underestimated short trips and overestimated long trips.

Table 6.49 Comparison of Average Trip Lengths and Trip Length Distributions for HBO Trips in Broward County from Survey, Destination Choice Model, and Gravity Model

	Surveyed Data	Destination Choice Model	Gravity Model
Average Trip Length	11.67	12.27	10.34
Coincidence Ratio		0.732	0.799

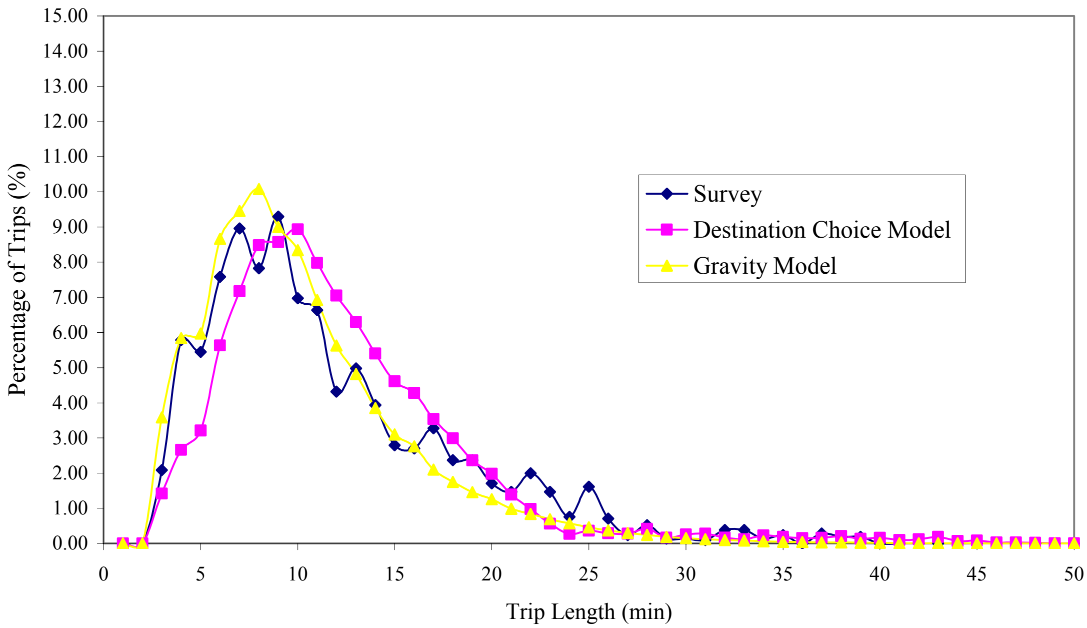

Figure 6.24 HBO Trip Length Distributions from Survey, Destination Choice Model, and Gravity Model for Broward County

Table 6.50 shows the number and percentages of the intrazonal trips from the survey, destination choice model, and gravity model. The results indicate that destination choice model did not perform as well as gravity model in the estimation of intrazonal HBO trips.

Table 6.50 Percentages of HBO Intrazonal Trips in Broward County from Survey, Destination Choice Model, and Gravity Model

	I-I Trips	Intrazonal Trips	%
Surveyed Data	2,098	178	8.48
Destination Choice Model	1,232,793	53,713	4.36
Gravity Model	1,151,402	119,983	10.42

Table 6.51 gives the number of HBO trip interchanges between the six TADs in Broward County, with the pairs that were used in the comparison highlighted. Table 6.52 provides the percentages of HBO trips between the TADs, with the district pairs with less than 10 sampled trips excluded. The cells for which the destination choice model better replicated the observed percentages than those from the gravity model were highlighted. The destination choice model performed better in 18 out of 29 selected district pairs.

Table 6.51 Surveyed HBO Trip Interchanges in Broward County

District	1	2	3	4	5	6	Total
1	**247**	**38**	**18**	**45**	**11**	0	359
2	**63**	**251**	**39**	**11**	0	**11**	375
3	**17**	**21**	**200**	**42**	**23**	**21**	324
4	**52**	**16**	**40**	**132**	**10**	**10**	260
5	1	0	2	**11**	**203**	**38**	255
6	7	8	**43**	**25**	**61**	**381**	525
Total	387	334	342	266	308	461	2,098

Table 6.52 Comparison of HBO Trip Interchanges between TADs in Broward County from Survey, Destination Choice Model, and Gravity Model

District		1	2	3	4	5	6
1	SUR	12.14	0.78	0.28	2.29	0.21	–
	DCM	13.38	0.62	0.18	2.09	0.05	–
	GRA	13.64	0.13	0.05	1.70	0.04	–
2	SUR	3.01	13.17	1.71	0.54	–	0.05
	DCM	5.01	10.46	1.60	1.23	–	0.02
	GRA	4.72	11.92	1.25	0.52	–	0.01
3	SUR	0.88	1.24	8.30	2.12	0.47	1.29
	DCM	1.79	0.94	7.46	3.36	0.39	0.93
	GRA	1.57	0.64	9.93	2.72	0.34	0.60
4	SUR	2.44	0.19	1.06	9.12	1.59	0.32
	DCM	2.75	0.11	1.00	9.86	1.43	0.20
	GRA	2.55	0.04	0.38	12.38	0.89	0.06
5	SUR	–	–	–	1.36	9.57	1.34
	DCM	–	–	–	1.32	10.28	1.11
	GRA	–	–	–	1.34	9.39	0.32
6	SUR	–	–	1.94	0.89	3.32	17.76
	DCM	–	–	3.02	1.60	3.66	12.93
	GRA	–	–	2.48	1.54	3.76	14.47

Note: SUR - Survey Data
DCM - Destination Choice Model
GRA - Gravity Model

The spatial accuracy of the HBO destination choice model in allocating HBO trips among TADs was compared to the gravity model based on six statistics given in Table 6.53. It may be seen that al statistics indicate that the destination choice model consistently performed better than the gravity model.

Table 6.53 Statistical Comparison of Spatial Accuracy of Destination Choice Model and Gravity Model for HBO Trips for Broward County

	Chi-square*	Neyman's Modified Chi-Square	Simplified Freeman-Tukey	Scale Deviance	Sum of Errors Squared	Mean Errors Squared
Destination Choice Model	36.16	16.92	17.53	8.89	64.91	2.24
Gravity Model	99.62	18.86	25.52	14.54	71.01	2.45

* Degrees of freedom = 28

6.5 Summary

In this chapter, the development of destination choice models with aggregate alternatives at the TAZ level was described and their performance evaluated. Three sets of HBW models stratified by income were calibrated for Broward, Palm Beach, and Volusia counties. The spatial distribution patterns from the models were compared with those obtained from the traditional gravity models in terms of average trip length, trip length distribution, intrazonal trips, and spatial accuracy of trip distribution.

The results indicated that destination choice models produced noticeable improvements for HBW trip distribution in terms of average trip lengths for the Broward and Palm Beach County model. Improvements in spatial accuracy of trip distribution as measured by inter-district trip interchanges were also seen from the Broward and Volusia county models, although the Volusia models might have been handicapped by a smaller number of samples and a lack of more detailed employment data, preventing a better match between income and jobs in the models. Spatial barrier variables introduced slight but insignificant improvements in destination choice models, and therefore do not appear to be worthwhile considering the difficulty in their forecasts. All destination choice models underestimated intrazonal trips, although the differences may not be serious due to their small percentages. The introduction of an intrazonal dummy variable did not prove to be effective.

The Broward HBW destination choice models may be applied to Palm Beach County without introducing significant errors. This is, of course, not sufficient to conclude that destination choice models are spatially transferable. More studies will need to be conducted to reach more definite conclusions.

Destination choice models were also developed for HBS, HBSR, and HBO trips without segmenting the trips by income level. Numerous employment combinations were tested as the size variables and land use and socioeconomic attributes were investigated as non-size variables. The destination choice models performed better in replicating average trip length and percentages of trip interchanges among traffic analysis districts. However, gravity model replicated the trip length distribution and percentage of intrazonal trips better than the destination choice models. In general, destination choice model did not produce as significant improvements for home-based non-work trips as for home-based work trips.

7. CONCLUSIONS

This report summarizes the results and findings of a research project aimed at improving the current trip distribution modeling practice in FSUTMS. The study investigated intervening opportunity models, enhanced gravity models, and aggregate destination choice models as potential alternatives to the existing gravity models in FSUTMS. The results show that the intervening opportunity model calibrated for Palm Beach County performed slightly better than the gravity model for NHBW trips in terms of average trip length, but not for the other purposes. Factors that may influence the performance of the model include:

- A lack of functions that are specifically designed to calibrate an intervening opportunity model in FSUTMS. This has forced this study to make some deviations from the original formulation in order to utilize TRANPLAN to calibrate the models, which has introduced inaccuracy into the models.
- A lack of optimal market segmentation of travel demand in terms of the attributes of trip makers. In this study, a constant *L* parameter was calibrated for each trip purpose. The possible differences in the attractiveness of different destination zones to different trip makers were ignored. When trip makers are segmented into more virtually exclusive groups, the unique attributes of each group may be appropriately quantified and their possibly different effects on trip distribution may be better considered in the modeling process.
- Sensitivity of the intervening opportunity model to attractions and reliability of the attraction data. An appeal of an intervening opportunity model is that it does not depend on a trip length frequency distribution, which a gravity model calibration relies on and assumes to remain unchanged for future model updates and forecasts while this assumption is unlikely to hold in reality if there will be significant changes in future land uses. An intervening opportunity model uses attractions instead as the basis in model calibration, which may be updated when land uses have changed, thus making the model more adaptive to changes in trip patterns. However, attraction data are also unreliable even for the base year.

In summary, the results from this study do not provide conclusive evidence as whether the performance of intervening opportunity models may be significantly improved, which is necessary for any possible applications.

The enhanced gravity models replace the typical travel time based impedance with a combination of travel time, land use, accessibility, and/or income variables at the production zones. There were some improvements in average trip length and trip length distribution, especially in the case when regional accessibility was considered. However, the benefits were offset by the extra cost of data preparation because accessibility to employment in adjacent counties/urban areas must be considered, increasing the need for data processing.

The destination choice models with income segmentation and aggregate alternatives at the TAZ level produced noticeable improvements for HBW trip distribution in terms of average trip lengths for the Broward and Palm Beach County models. Improvements in spatial accuracy of trip distribution as measured by inter-district trip interchanges were also observed from the

Broward and Volusia county models. Although spatial barrier variables were statistically significant and did result in better performance over models without them, the improvements were not significant enough to justify their inclusion because of the difficulty in their forecast. Therefore, spatial variables should not be used or only used with extreme caution.

One weakness of the destination choice models is that they underestimated intrazonal trips in all selected urban areas. Neither the introduction of an intrazonal dummy variable nor the reduction in travel impedance effectively remedied the problem. Consequently, urban areas with high percentages of intrazonal trips may benefit less from implementing destination choice models.

The spatial transferability of destination choice models was evaluated by applying Broward's models to Palm Beach County. The results suggest that model transferability is possible. However, more studies will be needed to reach more definite conclusions.

For HBS, HBSR and HBO trips, the destination choice models were shown to perform better in replicating average trip lengths and percentages of trip interchanges among traffic analysis districts. However, gravity model replicated the trip length distribution and percentage of intrazonal trips better than the destination choice models. The improvements brought by destination choice models for home-based non-work trips were generally not as significant as those for home-based work trips.

8. RECOMMENDATIONS

Based on the findings from this research and many discussions among and feedback from the Florida Model Task Force members, future research on improving FSUTMS trip distribution may be directed at a number of efforts:

- A better match of income and jobs. In this research, a match between income and job was attempted based on an empirical analysis of the distribution of the reported personal income of the trip makers by job sector when calibrating destination choice models. However, because personal income information is not available for all households, census household income was used in place of personal income when destination choice models were applied. The CTPP Part 2 stratifies household income of workers at attraction zones, which allows a better match of the production and attraction zones for workers on the basis of their household income. One potential problem with trying to relate household income with occupation type is that household income may not reflect the actual salaries of workers. For example, a household income of $60,000 may be from the salary of one worker with a professional job or from the salaries of three family members, each holding a low-paying job. While it is difficult to obtain information on salaries, information on salary distribution by certain industry type would be helpful and is worth investigation. However, this will require that either personal income be estimated at the production end, or somehow be related to household income.

- Better segmentation of trips from different income groups. In this research, trips at the production end were proportioned into the three income groups based on the percentage of households in each income group. Because the characteristics of households in different income groups likely vary in terms of number of workers, presence of children, number of cars owned, and household size, households of different income groups may not produce the same number of trips. For the three income groups, Table 8.1 gives the distribution of households by number of workers and Table 8.2 the distribution of households by household size. The data were from the 2000 census. It may be seen that low-income households had relatively fewer workers and high-income households more workers. Low-income households also tended to be smaller. Therefore, even when the percentages of households in different income groups are the same, they will produce different numbers of HBW trips. To estimate the effect of differences in household characteristics on numbers of trips produced by the three income groups, special census tabulation will be needed to further segment households by income level.

Table 8.1 Distribution of Households by Number of Workers for Three Income Groups

Total			Low Income		Medium Income		High Income	
Worker	HHs	%	HHs	%	HHs	%	HHs	%
0	193,430	30	124,025	54	44,455	21	24,955	12
1	237,465	36	87,125	38	90,470	44	59,865	28
2	183,310	28	18,330	8	61,560	30	103,420	48
3	32,025	5	1,875	1	8,725	4	21,425	10
4+	8,560	1	223	0	1,615	1	6,715	3
Total	654,790	100	231,578	100	206,825	100	216,380	100

Table 8.2 Distribution of Households by Household Size for Three Income Groups

Total			Low Income		Medium Income		High Income	
HH Size	HHs	%	HHs	%	HHs	%	HHs	%
1	193,590	30	118,195	51	54,610	26	20,785	10
2	215,400	33	61,465	27	74,405	36	79,530	37
3	99,825	15	22,965	10	32,735	16	44,125	20
4+	145,950	22	28,930	12	45,090	22	71,930	33
Total	654,765	100	231,555	100	206,840	100	216,370	100

- Consideration of income effect on trip productions. While the household characteristics of households of different income groups will affect the HBW trip productions, it is also possible that households of different income will have different trip production rates. The current FSUTMS trip generation models do not consider the possible effect of income on trip rates. Some regional models such as those of the Atlanta Regional Commission, Puget Sound Regional Council, Dallas-Fort Worth, and Phoenix Maricopa Association of Governments estimate trip productions for different income groups. This alternative may be considered in the future by the Florida Model Task Force Trip Generation Committee to improve our ability to better model the influence of income on travel behavior.

- Improvement in intrazonal trip distribution. More studies are needed to improve the performance of destination choice models in distributing intrazonal trips.

- CUBE add-in module. A CUBE add-in module would need to be developed to apply destination choice models in the modeling process for different urban areas in Florida, since different modeling structures are applied for travel demand analysis in Florida.

- Investigation of destination choice models for other Florida urban areas. Destination choice models for other urban areas in Florida may be developed and evaluated, and the possibility of developing a few “standard” models for urban areas of different types need to be studied.

- Development of a statewide model. A statewide destination choice model may need to be investigated for inclusion into the statewide model.

- Possible development of a journey based model that distributes journeys using a destination choice model or a combine destination and mode choice model. This will allow chained trips to be modeled. However, this is a rather significant move that will require the first three submodels of FSUTMS, trip generation, trip distribution, and mode choice, to be revamped.

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APPENDIX TRIP LENGTH AND TRIP PATTERN ANALYSIS

This appendix describes in detail the analyses of trip lengths and patterns, which has been briefly summarized in Chapter 5. The data were from the 2000 SEFTCS, which included household travel survey in three counties: Broward, Miami-Dade, and Palm Beach. The variables analyzed as potentially influential to trip lengths included population density, dwelling unit density, employment density, total density, jobs-housing balance, auto ownership, household income, highway network accessibility, and lifestyle variables. The analysis of these variables is described in Section A.1. Section A.2 discusses the possible influence of income on destination choice for HBS trips. Finally, Section A.3 analyzes trip chaining.

A.1 Trip Length Analysis

The longest average trip length for all purposes was observed in Miami-Dade County, followed by Broward and Palm Beach counties, which reflects the size of the counties as well as the spatial extents of population and employment distribution.

In the original database of the trip logs, 15.2 percent of the recorded trips (or 5,012 out of 33,082), did not have trip length information. Additionally, 889 trips (2.7%) had a trip length longer than 100 minutes. Table A.1 shows the trip log statistics for different trip purposes after excluding those records with a trip length greater than 100 minutes and those for which the trip length information was missing, and compares the recorded trip time with the trip time calculated from the 1990 FSUTMS regional model.

Table A.1 Trip Length Statistics of Filtered Data

Trip Purpose	Number of Trips	Average Reported Trip Length (min)	Average Free Flow Skims (min)
HBW	6,201	28.3	14.7
HBS	3,028	15.9	7.4
HBSR	2,069	18.4	10.1
HBSCH	2,681	20.7	8.8
HBO	6,151	18.1	9.3
NHB	6,934	18.6	9.3
All	27,064	20.6	10.3

The average free flow skims in Table A.1 represent the average travel times for each trip purpose. The skims were obtained from the 1990 validated regional network of SERPM-IV by first converting the LINK.90A file to GIS using GIS-TM, followed by running HNET and HTP2DBF to convert the HNET.A90 file to the HNETA90.DBF file. The shortest paths between geocoded sampled trip ends were then calculated using the Network Analyst extension in ArcView. As shown in Table A.1, the average free flow skims were nearly twice of the average reported trip lengths from the survey. Therefore, trip impedances were apparently underestimated when only the free flow times are considered in the trip distribution process, especially for HBSCH trips. The impedance for HBSR was relatively low compared to other trip purposes since most of the HBSR trips occurred during the off-peak period. The composite travel time took into account the variation of the level of traffic by hour and by purpose. For this reason, the composite travel time concept was applied in the trip distribution processes in both the 1996 validation of Palm Beach and Broward County Travel Models, as well as the 2000 Treasure Coast Regional Planning Model. The trip distribution formula uses the following equation to calculate the composite travel time:

$$Composite\ Travel\ Time = LTF_i \times Congested\ Time + (1 - LTF_i) \times Free\ Flow\ Time$$

Here, LTF_i represents the level of traffic for trip purpose i and is estimated from hourly traffic counts and temporal distribution of trips by purpose. Calculation of LTF_i has been documented in detail in Carr Smith Corradino (1998), and Carr Smith Corradino (2000). Briefly, to calculate LTF_i, the hourly traffic count data in a given urban area are first collected and consolidated to obtain a temporal distribution of traffic, which has a familiar "M" shaped distribution. The systemwide level of traffic by hour, defined as the ratio of the traffic during a given hour to the maximum hourly traffic, is then calculated. The data from the household survey are used to develop the hourly trip percentages based on their trip start time and purpose. These are then weighted by the systemwide level of traffic and summed to obtain the level of traffic by purpose. Congested times are obtained after a highway-only assignment is performed. The trip purposes in the 2000 Treasure Coast Regional Planning Model, sorted by *LTF* values in descending order, are as follows: NHB, HBS, HBO, HBW, HBSCH, and HBSR.

In order to investigate the significance of commonly encountered socioeconomic variables on travel, the following analyses to the SEFRTCS survey data were performed:

- Significance of land use variables on trip length;
- Significance of socioeconomic variables on trip length; and
- Significance of highway accessibility on trip length.

ANOVA procedures were performed to test the significance of individual land use variables on the response trip length at each trip's production end, i.e., home zone. The variables include population density, household density, employment density, population plus employment density, jobs-housing balance, auto ownership, income level, lifestyle variables, and highway accessibility. The following sections describe the statistical analysis results in detail.

A.1.1 Population Density

The population density was first calculated by dividing the 1999 zonal population in the ZDATA1(A) file with the zonal area in square miles. The surveyed trip lengths were then sorted by population densities of the home zones. The density median was used to divide the sample into two groups of approximately equal size.

Table A.2 presents the results of the test on the significance of population density at each trip's home zone on trip length for trips of all purposes. Due to missing trip end information, a total of 881 trips were excluded from the analysis, and the total numbers of trips for the tri-county region shown in Tables A.1 and A.2 are different. According to Table A.2, the longest average trip length was observed in Miami-Dade County, followed by Browad and Palm Beach counties. Although the average trip length of the high population density group was greater than that of the low density group in Broward County, the trip lengths were not significantly different at the 5% significance level. Additionally, even though trip lengths in the high and low population density groups were significantly different in Miami-Dade and Palm Beach counties as well as for the tri-county area, the average trip length for one population density group was not consistently higher than that for the other group among the different urban areas. Thus, it cannot be concluded from the SEFRTCS survey data that population density had any effects on the response trip lengths.

Table A.2 Significance of Population Density on Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 5,710	4,571	19.80	0.148
	High	> 5,710	4,571	20.27	
Miami-Dade	Low	≤ 7,400	3,846	22.57	0.024*
	High	> 7,400	3,851	23.48	
Palm Beach	Low	≤ 3,915	4,691	19.40	0.027*
	High	> 3,915	4,653	18.71	
Region	Low	≤ 5,400	13,114	19.87	0.000*
	High	> 5,400	13,069	21.26	

* Significant at the 0.05 level

Tables A.3 through A.8 summarize the results of statistical tests on the significance of population density on trip lengths for HBW, HBS, HBSR, HBSCH, HBO, and NHB trip purposes, respectively. As shown in Table A.3, the HBW trip lengths for the low population density groups are longer than those for the high density groups in Miami-Dade and Palm Beach counties at the 5% significant level. Nevertheless, the average trip lengths from the two groups in Broward County and the tri-county area are not significantly different.

Table A.3 Significance of Population Density on HBW Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 5,725	1,094	28.00	0.477
	High	> 5,725	1,090	27.50	
Miami-Dade	Low	≤ 7,600	965	32.48	0.002*
	High	> 7,600	970	29.82	
Palm Beach	Low	≤ 4,255	891	27.07	0.006*
	High	> 4,255	888	24.80	
Region	Low	≤ 5,698	2,949	28.03	0.209
	High	> 5,698	2,949	28.60	

* Significant at the 0.05 level

For the HBS trips, the average trip lengths for both groups in all three counties are significantly different (see Table A.4). However, Palm Beach County had a different trip length pattern from those of the other two counties, i.e., a longer average trip length for the lower population density group. For the HBSR trips (Table A.5), trip lengths are only significantly different in Palm Beach County, i.e., longer trip lengths for the lower population density group.

Table A.4 Significance of Population Density on HBS Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 5,805	469	13.71	0.011*
	High	> 5,805	468	15.66	
Miami-Dade	Low	≤ 7,149	402	15.79	0.000*
	High	> 7,149	398	19.22	
Palm Beach	Low	≤ 3,942	591	16.53	0.011*
	High	> 3,942	590	14.72	
Region	Low	≤ 5,330	1,459	15.31	0.025*
	High	> 5,330	1,459	16.36	

* Significant at the 0.05 level

Table A.5 Significance of Population Density on HBSR Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 5,374	351	17.52	0.771
	High	> 5,374	346	17.83	
Miami-Dade	Low	≤ 7,292	216	22.06	0.749
	High	> 7,292	215	21.53	
Palm Beach	Low	≤ 3,915	445	18.21	0.031*
	High	> 3,915	437	16.28	
Region	Low	≤ 5,095	1,009	17.91	0.149
	High	> 5,095	1,001	18.84	

* Significant at the 0.05 level

The lengths of the HBSCH trips do not differ significantly in all three counties (Table A.6). For the HBO trips, as shown in Table A.7, people living in lower population density areas in Broward County tended to make shorter trips. However, the HBO trip lengths for the other two counties are not significant with respect to population density as for Broward County.

Table A.6 Significance of Population Density on HBSCH Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 5,821	453	19.91	0.707
	High	> 5,821	446	20.27	
Miami-Dade	Low	≤ 7,492	505	21.11	0.225
	High	> 7,492	498	22.35	
Palm Beach	Low	≤ 3,915	349	19.95	0.708
	High	> 3,915	346	19.55	
Region	Low	≤ 5,769	1,302	20.21	0.160
	High	> 5,769	1,295	21.04	

* Significant at the 0.05 level

Table A.7 Significance of Population Density on HBO Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 5,709	1,013	16.30	0.036*
	High	> 5,709	1,009	17.54	
Miami-Dade	Low	≤ 7,170	880	19.35	0.496
	High	> 7,170	868	19.87	
Palm Beach	Low	≤ 3,915	1,114	17.49	0.843
	High	> 3,915	1,082	17.60	
Region	Low	≤ 5,330	2,984	17.40	0.004*
	High	> 5,330	2,984	17.40	

* Significant at the 0.05 level

Regionally, the NHB trip lengths in the lower population density areas tended to be shorter, as illustrated in Table A.8. However, the county data did not support the same conclusion.

Table A.8 Significance of Population Density on NHB Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 5,709	1,193	18.18	0.995
	High	> 5,709	1,166	18.17	
Miami-Dade	Low	≤ 6,752	873	19.97	0.050*
	High	> 6,752	872	21.57	
Palm Beach	Low	≤ 3,841	1,304	17.36	0.724
	High	> 3,841	1,273	17.57	
Region	Low	≤ 5,157	3,342	17.85	0.000*
	High	> 5.157	3,339	19.31	

* Significant at the 0.05 level

Based on the results from the above trip length analyses for different trip purposes, population density was either significant in only one county or, if it was significant in all three counties, the trip length patterns were inconsistent.

A.1.2 Dwelling Unit Density

Dwelling unit (DU) density was calculated for each TAZ by dividing the DU value in a zone with the zonal area in square miles. The DU values were obtained from the 1999 ZDATA1(A) file. In this analysis of DU density versus trip length, the surveyed trip lengths were sorted by their associated DU densities at the home zones. The density median was used to divide the sample into two groups of equal size. The significance of DU density on trip lengths was first tested for all trips of all purposes in each of the three counties. Table A.9 shows the results of the test. As in the case of population density, there exists no significant difference in trip lengths between the low and high density groups in Broward County. Although DU density is significant in Miami-Dade County, Palm Beach County, and the tri-county areas, the relationship between DU density and average trip length is inconsistent for Miami-Dade and Palm Beach counties. The low DU density group has a shorter average trip length than the high DU density group in Miami-Dade County and a longer average trip length in Palm Beach County.

Table A.9 Significance of Dwelling Unit Density on Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 2,264	4,569	20.13	0.562
	High	> 2,264	4,573	19.94	
Miami-Dade	Low	≤ 2,410	3,826	22.39	0.002*
	High	> 2,410	3,871	23.65	
Palm Beach	Low	≤ 1,600	4,704	19.49	0.019*
	High	> 1,600	4,640	18.61	
Region	Low	≤ 2,035	13,075	20.23	0.001*
	High	> 2,035	13,108	20.90	

* Significant at the 0.05 level

Tables A.10 to A.15 provide the results of statistical tests on the significance of DU density on trip lengths for different trip purposes including HBW, HBS, HBSR, HBSCH, HBO, and NHB. As shown in Table A.10, the HBW trip lengths in the low DU density areas are longer than those in the high density areas in Miami-Dade and Palm Beach counties at the 5% significant level but not in Broward County and the tri-county area. Similar to the HBW trips, the results given in Tables A.11 and A.13 reveal that DU density is also significant for the HBS and HBSCH trip lengths in Miami-Dade and Palm Beach counties. However, the average trip length for one density group is not consistently longer than that for the other group for these two trip purposes. For the HBSR and HBO trips described in Tables A.12 and A.14, respectively, trip lengths are not significantly different in any county areas. For the NHB trips (Table A.15), DU density is only significant for Miami-Dade County, where people living in the low DU density areas tend to make significantly shorter trips. .

Table A.10 Significance of Dwelling Unit Density on HBW Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 2,230	1,095	28.16	0.245
	High	> 2,230	1,089	27.34	
Miami-Dade	Low	≤ 2,523	969	32.15	0.018*
	High	> 2,523	966	30.14	
Palm Beach	Low	≤ 1,629	894	27.05	0.006*
	High	> 1,629	885	24.81	
Region	Low	≤ 2,109	2,958	28.49	0.433
	High	> 2,109	2,958	28.14	

* Significant at the 0.05 level

Table A.11 Significance of Dwelling Unit Density on HBS Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 2,348	469	14.52	0.660
	High	> 2,348	468	14.85	
Miami-Dade	Low	≤ 2,455	401	15.77	0.000*
	High	> 2,455	399	19.23	
Palm Beach	Low	≤ 1,615	592	16.68	0.003*
	High	> 1,615	589	14.57	
Region	Low	≤ 2,053	1,461	15.48	0.122
	High	> 2,053	1,457	16.20	

* Significant at the 0.05 level

Table A.12 Significance of Dwelling Unit Density on HBSR Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 2,218	351	17.13	0.300
	High	> 2,218	346	18.22	
Miami-Dade	Low	≤ 2,507	221	21.49	0.703
	High	> 2,507	210	22.12	
Palm Beach	Low	≤ 1,660	447	17.93	0.129
	High	> 1,660	435	16.57	
Region	Low	≤ 2,000	1,011	18.16	0.503
	High	> 2,000	999	18.59	

* Significant at the 0.05 level

Table A.13 Significance of Dwelling Unit Density on HBSCH Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 2,172	451	20.02	0.892
	High	> 2,172	448	20.15	
Miami-Dade	Low	≤ 2,398	503	20.72	0.048*
	High	> 2,398	500	22.74	
Palm Beach	Low	≤ 1,528	349	20.82	0.045*
	High	> 1,528	346	18.67	
Region	Low	≤ 2,057	1,301	20.32	0.290
	High	> 2,057	1,296	20.94	

* Significant at the 0.05 level

Table A.14 Significance of Dwelling Unit Density on HBO Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 2,315	1,013	16.42	0.095
	High	> 2,315	1,009	17.41	
Miami-Dade	Low	≤ 2,350	874	19.20	0.286
	High	> 2,350	874	20.02	
Palm Beach	Low	≤ 1,611	1,109	17.68	0.626
	High	> 1,611	1,087	17.40	
Region	Low	≤ 2,035	2,994	17.60	0.071
	High	> 2,035	2,972	18.27	

* Significant at the 0.05 level

Table A.15 Significance of Dwelling Unit Density on NHB Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 2,275	1,184	18.15	0.927
	High	> 2,275	1,175	18.21	
Miami-Dade	Low	≤ 2,330	875	19.40	0.001*
	High	> 2,330	870	22.16	
Palm Beach	Low	≤ 1,541	1,313	17.51	0.861
	High	> 1,541	1,264	17.41	
Region	Low	≤ 1,979	3,347	18.21	0.060
	High	> 1,979	3,334	18.95	

* Significant at the 0.05 level

A.1.3 Employment Density

In the analysis of employment density versus trip length, the employment density was calculated by dividing the total number of employees from the 1999 ZDATA2 file with the zonal area in square mile for each zone. The surveyed trip lengths were then sorted by their associated employment densities at the home zones. The median value divides the sample into two groups of equal size. Table A.16 summarizes the results of the significance test of employment density at each trip's home zone on trip lengths for all trip purposes. The results presented in Table A.16 show that trip lengths were significantly different in Palm Beach County, i.e., the lower the employment density, the longer trip lengths. Trip lengths are not significantly different for the two groups in Broward and Miami-Dade counties. At the regional level, employment density is significant but the trip lengths do not reveal the same trip length pattern of Palm Beach County since lower employment densities are associated with shorter trips.

Table A.16 Significance of Employment Density on Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 852	4,581	19.87	0.311
	High	> 852	4,561	20.20	
Miami-Dade	Low	≤ 1,050	3,873	22.97	0.793
	High	> 1,050	3,824	23.08	
Palm Beach	Low	≤ 400	4,614	19.54	0.002*
	High	> 400	4,730	18.58	
Region	Low	≤ 735	13,094	20.36	0.044*
	High	> 735	13,089	20.77	

* Significant at the 0.05 level

Tables A.17 to A.22 show the statistical results of tests on the significance of employment density on trip length for different trip purposes. As indicated in Table A.17, the HBW trip lengths in the low employment density areas are significantly longer than those in the high density areas in Miami-Dade and Palm Beach counties and the tri-county region. For the HBS trips (Table A.18), only the trip lengths in Broward County are significantly different, i.e., the lower the employment density, the longer the trip lengths. For HBSR trips (Table A.19), only the regional data reveal a significant difference in trip lengths, i.e., the lower the employment density, the shorter the trip lengths. For HBSCH trips in Table A.20, it is Broward County again that shows a significantly shorter average trip length at lower employment density. For HBO trips described in Table A.21, the data from Palm Beach County reveal longer trip lengths in lower employment density areas. For NHB trips (Table A.22), none of the average trip lengths in different counties are statistically significant different between the low and high employment density groups.

Table A.17 Significance of Employment Density on HBW Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 918	1,093	27.80	0.871
	High	> 918	1,091	27.69	
Miami-Dade	Low	≤ 1,129	969	32.50	0.001*
	High	> 1,129	966	29.78	
Palm Beach	Low	≤ 483	891	27.10	0.004*
	High	> 483	888	24.76	
Region	Low	≤ 811	2,957	28.89	0.011*
	High	> 811	2,941	27.73	

* Significant at the 0.05 level

Table A.18 Significance of Employment Density on HBS Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 1,023	471	15.55	0.024*
	High	> 1,023	466	13.82	
Miami-Dade	Low	≤ 1,219	401	16.57	0.058
	High	> 1,219	399	18.43	
Palm Beach	Low	≤ 394	593	15.59	0.909
	High	> 394	588	15.67	
Region	Low	≤ 761	1,462	15.85	0.974
	High	> 761	1,456	15.83	

* Significant at the 0.05 level

Table A.19 Significance of Employment Density on HBSR Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 775	349	17.07	0.251
	High	> 775	348	18.28	
Miami-Dade	Low	≤ 1,121	219	20.62	0.151
	High	> 1,121	212	23.01	
Palm Beach	Low	≤ 364	442	16.56	0.121
	High	> 364	440	17.59	
Region	Low	≤ 614	1,005	17.13	0.000*
	High	> 614	1,005	19.62	

* Significant at the 0.05 level

Table A.20 Significance of Employment Density on HBSCH Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 852	450	18.89	0.013*
	High	> 852	449	21.28	
Miami-Dade	Low	≤ 963	505	21.07	0.193
	High	> 963	498	22.39	
Palm Beach	Low	≤ 440	353	19.95	0.708
	High	> 440	342	19.54	
Region	Low	≤ 762	1,299	20.26	0.210
	High	> 762	1,298	21.00	

* Significant at the 0.05 level

Table A.21 Significance of Employment Density on HBO Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 784	1,024	17.06	0.625
	High	> 784	998	16.77	
Miami-Dade	Low	≤ 1,014	881	19.43	0.636
	High	> 1,014	867	19.79	
Palm Beach	Low	≤ 440	1,100	18.77	0.000*
	High	> 440	1,096	16.32	
Region	Low	≤ 711	2,987	17.97	0.858
	High	> 711	2,979	17.90	

* Significant at the 0.05 level

Table A.22 Significance of Employment Density on NHB Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 784	1,186	17.84	0.313
	High	> 784	1,173	18.52	
Miami-Dade	Low	≤ 963	876	20.09	0.091
	High	> 963	869	21.47	
Palm Beach	Low	≤ 372	1,294	17.81	0.238
	High	> 372	1,283	17.11	
Region	Low	≤ 686	3,342	18.23	0.073
	High	> 686	3,339	18.93	

* Significant at the 0.05 level

A.1.4 Total (Population plus Employment) Density

The total density is the summation of population and employment densities. It is calculated for each zone by dividing the sum of population and employment with the area of that zone. Table A.23 shows the results of the significance tests on total density at each trip's home zone on trip length. It illustrates that trip lengths are significantly different between the low and high total density groups for Miami-Dade County, Palm Beach County, and the Region as a whole. However, no consistent trip length patterns among the low and high total density groups can be found.

Table A.23 Significance of Total Density on Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 7,300	4,576	19.78	0.122
	High	> 7,300	4,566	20.29	
Miami-Dade	Low	≤ 8,650	3,857	22.46	0.004*
	High	>8,650	3,840	23.60	
Palm Beach	Low	≤ 4,950	4,703	19.33	0.017*
	High	> 4,950	4,641	18.78	
Region	Low	≤ 6,785	13,104	19.97	0.000*
	High	> 6,785	13,079	21.16	

* Significant at the 0.05 level

The results of statistical tests on the significance of total density on trip lengths for different trip purposes are provided in Tables A.24 to A.29. For the HBW trips (Table A.24), only Miami-Dade County reveals significant longer trip lengths at the low density areas. For the HBS trips in Table A.25, trip lengths are significantly shorter in the low density areas of Miami-Dade County. For the HBSR trips in Table A.26, people living in lower population plus employment density areas tend to make shorter trips in Broward county. For HBSCH trips in Table A.27, only the regional data reveal the significant difference in trip lengths, i.e., the lower the density, the shorter the trip lengths. For HBO trips in Table A.28, the data from Miami-Dade County reveal significantly shorter trip lengths at lower density areas. For NHB trips in Table A.29, the trip lengths in Miami-Dade and the tri-county areas tend to be shorter in the lower density areas.

Table A.24 Significance of Total Density on HBW Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 7,328	1,093	27.89	0.690
	High	> 7,328	1,091	27.61	
Miami-Dade	Low	≤ 9,229	961	32.30	0.007*
	High	> 9,229	974	30.01	
Palm Beach	Low	≤ 5,440	899	26.69	0.066
	High	> 5,440	880	25.17	
Region	Low	≤ 7,189	2,958	28.23	0.718
	High	> 7,189	2,940	28.40	

* Significant at the 0.05 level

Table A.25 Significance of Total Density on HBS Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 7,484	470	14.63	0.878
	High	> 7,484	467	14.75	
Miami-Dade	Low	≤ 8,676	405	15.67	0.000*
	High	> 8,676	395	19.36	
Palm Beach	Low	≤ 4,977	594	16.26	0.076
	High	> 4,977	587	14.99	
Region	Low	≤ 6,879	1,459	15.51	0.162
	High	> 6,879	1,459	16.16	

* Significant at the 0.05 level

Table A.26 Significance of Total Density on HBSR Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 6,788	355	16.31	0.008*
	High	> 6,788	342	19.09	
Miami-Dade	Low	≤ 8,372	214	21.36	0.602
	High	> 8,372	217	22.23	
Palm Beach	Low	≤ 5,164	450	17.97	0.104
	High	> 5,164	432	16.51	
Region	Low	≤ 6,254	1,006	17.76	0.059
	High	> 6,254	1,004	18.99	

* Significant at the 0.05 level

Table A.27 Significance of Total Density on HBSCH Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 7,333	452	19.25	0.084
	High	> 7,333	447	20.93	
Miami-Dade	Low	≤ 8,752	497	21.33	0.440
	High	> 8,752	506	22.11	
Palm Beach	Low	≤ 5,114	348	19.86	0.828
	High	> 5,114	347	19.63	
Region	Low	≤ 7,212	1,303	19.72	0.002*
	High	> 7,212	1,294	21.55	

* Significant at the 0.05 level

Table A.28 Significance of Total Density on HBO Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 7,280	1,012	16.70	0.462
	High	> 7,280	1,010	17.13	
Miami-Dade	Low	≤ 8,372	874	18.64	0.011*
	High	> 8,372	874	20.58	
Palm Beach	Low	≤ 4,875	1,100	17.60	0.848
	High	> 4,875	1,096	17.49	
Region	Low	≤ 6,622	2,990	17.60	0.070
	High	> 6,622	2,976	18.27	

* Significant at the 0.05 level

Table A.29 Significance of Total Density on NHB Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 7,280	1,180	18.00	0.606
	High	> 7,280	1,179	18.35	
Miami-Dade	Low	≤ 8,141	874	19.66	0.006*
	High	> 8,141	871	21.90	
Palm Beach	Low	≤ 4,509	1,291	17.68	0.452
	High	> 4,509	1,286	17.24	
Region	Low	≤ 6,548	3,341	18.14	0.027*
	High	> 6,548	3,340	19.01	

* Significant at the 0.05 level

A.1.5 Jobs-Housing Balance

The Jobs-housing balance index is a land use mix indicator considered to have some influence over travel behavior related to work trips. For instance, since travel from home to work is a derived need to reach one's workplace, it might be inferred that, compared to a purely residential neighborhood, a neighborhood that provides employment opportunities offers the residents the possibility of working close to their homes. The jobs-housing balance index used in this analysis is calculated using the following formula (Ewing, 1995):

$$JOBS-HH = 1 - \frac{|E - 1.5H|}{E + H}$$

where

- *JOBS-HH* = jobs-housing balance index for a zone;
- *E* = total employment size; and
- *H* = number of occupied households in a zone.

The formula calculates a value that falls between zero and one, with zero indicating a perfectly homogenous area, either residential or non-residential, and one indicating a perfectly balanced area. The data used to calculate employment and housing data were obtained from the 1999 ZDATA1(A) and ZDATA2 files. Table A.30 shows the statistics for the effects of job/housing balance on trip length for all trip purposes. The ANOVA tests show that people living inside the more balanced land-use TAZs do not produce significantly different trip lengths than those living in the less balanced areas.

Table A.30 Significance of Zonal Jobs-Housing Index on Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	≤ 0.38	4,560	20.04	0.996
	High	> 0.38	4,582	20.04	
Miami-Dade	Low	≤ 0.40	3,887	23.39	0.069
	High	> 0.40	3,810	22.66	
Palm Beach	Low	≤ 0.28	4,698	19.09	0.838
	High	> 0.28	4,646	19.02	
Region	Low	≤ 0.36	13,266	20.43	0.180
	High	> 0.36	12,917	20.70	

* Significant at the 0.05 level

It may be noticed that the median indices given in Table A.30 are relatively low. This was a result of the fact that TAZs were defined in such a way that the number of different land uses was reduced. Therefore, many TAZs were of small size and single use, even though they might be adjacent to other TAZs that had different land uses. For this reason, the analysis was performed again at the census tract level. Jobs-housing balance indices were calculated using the census tract dwelling unit from census 2000 and employment data aggregated to the tract level. The resulting statistics are presented in Table A.31. Note that due to missing trip end information, the total numbers of trips shown in Tables A.30 and A.31 are slightly different. Table A.31 shows that the trip lengths for the high and low job housing balance were significantly different in Broward and Miami-Dade counties, as well as the aggregated tri-county area. The data from Palm Beach County, however, did not confirm such relationship.

Table A.31 Significance of Census Tract Level Jobs-Housing Index on Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	# 0.53	4,645	20.61	0.0006*
	High	> 0.53	4,558	19.48	
Miami-Dade	Low	# 0.56	3,901	23.54	0.0124*
	High	> 0.56	3,939	22.55	
Palm Beach	Low	# 0.44	4,688	19.31	0.1463
	High	> 0.44	4,719	18.85	
Region	Low	# 0.52	13,198	20.92	0.0010*
	High	> 0.52	13,252	20.27	

* Significant at the 0.05 level

Since jobs-housing balance is considered to mainly impact work trips, the above analysis (at the tract level) was performed for HBW trips. The results are given in Table A.32. A better jobs-housing balance seems to indicate shorter trip lengths in Broward and Palm Beach counties, as well as in the tri-county region. However, it was not a significant factor in determining the trip length in Miami-Dade County, even though the average trip length for the high jobs-housing balance group is shorter than that for the low jobs-housing balance group.

Table A.32 Significance of Census Tract Level Jobs-Housing Index on HBW Trip Length

County	Density	Density Division (persons/mile2)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	# 0.52	1,111	28.63	0.0120*
	High	> 0.52	1,090	26.86	
Miami-Dade	Low	# 0.56	1,006	31.75	0.1477
	High	> 0.56	977	30.54	
Palm Beach	Low	# 0.49	888	27.22	0.0022*
	High	> 0.49	909	24.72	
Region	Low	# 0.52	2,955	29.19	0.0002*
	High	> 0.52	3,026	27.51	

* Significant at the 0.05 level

A.1.6 Census Tract Level Density

Since the jobs-housing balance became significant on trip length after expanding the index from TAZ level to census tract level, the analysis was performed again at the census tract level for the density variables. Tables A.33 to A.36 show the results of the significance tests on population density, dwelling unit density, employment density and total density at census tract level, respectively

Table A.33 Significance of Population Density on Trip Length (Tract Level)

County	Density	Density Division (persons/acre)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	# 8	4,525	20.46	0.011*
	High	> 8	4,617	19.62	
Miami-Dade	Low	# 10	3,862	22.35	0.001*
	High	> 10	3,835	23.71	
Palm Beach	Low	# 4.85	4,728	19.54	0.002*
	High	> 4.85	4,616	18.56	
Region	Low	# 7.2	13,086	20.00	0.000*
	High	> 7.2	13,097	21.13	

* Significant at the 0.05 level

Table A.34 Significance of Dwelling Unit Density on Trip Length (Tract Level)

County	Density	Density Division (persons/acre)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	# 3.25	4,603	20.38	0.035*
	High	> 3.25	4,539	19.69	
Miami-Dade	Low	# 3.25	3,828	22.58	0.027*
	High	> 3.25	3,869	23.47	
Palm Beach	Low	# 2	4,698	19.51	0.001*
	High	> 2	4,646	18.59	
Region	Low	# 2.8	13,078	20.42	0.143
	High	> 2.8	13,105	20.71	

* Significant at the 0.05 level

Table A.35 Significance of Employment Density on Trip Length (Tract Level)

County	Density	Density Division (persons/acre)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	# 1.85	4,513	20.82	0.000*
	High	> 1.85	4,629	19.28	
Miami-Dade	Low	# 2.25	3,818	22.88	0.482
	High	> 2.25	3,879	23.17	
Palm Beach	Low	# 0.95	4,722	19.94	0.000*
	High	> 0.95	4,622	18.15	
Region	Low	# 1.6	13,044	20.65	0.414
	High	> 1.6	13,139	20.48	

* Significant at the 0.05 level

Table A.36 Significance of Total Density on Trip Length (Tract Level)

County	Density	Density Division (persons/acre)	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Low	# 10.75	4,560	20.44	0.015*
	High	> 10.75	4,582	19.64	
Miami-Dade	Low	# 13.5	3,824	22.40	
	High	> 13.5	3,873	23.64	0.002*
Palm Beach	Low	# 7	4,681	19.81	0.000*
	High	> 7	4,663	18.30	
Region	Low	# 9.7	13,101	20.21	0.004*
	High	> 9.7	13,082	20.92	

* Significant at the 0.05 level

A.1.7 Auto Ownership

To analyze the effect of auto ownership on trip lengths, three groups were defined: households that own no auto, households in which the number of workers is greater than the number of autos, and other. The data were obtained from the SEFRTCS household survey. Several ANOVA tests were performed to investigate if the trips made by households in the three groups were significantly different in terms of their trip lengths.

The results summarized in Table A.37 reveal significant differences in trip lengths among these three groups in all counties and at the regional level, i.e., the more cars per worker, the shorter the trip lengths for a household. Although auto ownership has been shown with significant effects on trip length, the numbers of trips in the first two groups of auto ownership are much smaller than that in the last group. This raises concerns about the reliability of the data as well as the structure of the categories.

Table A.37 Significance of Household Auto Ownership on Response Trip Length

County	Group	Number of Trips	Average Trip Length (min)	Significance (p-value)
Broward	Zero Auto	119	27.48	0.0001*
	# of worker > # of Auto	794	23.88	
	other	8,496	19.72	
Miami-Dade	Zero Auto	169	30.21	0.0001*
	# of worker > # of Auto	1,168	23.92	
	other	6,710	22.67	
Palm Beach	Zero Auto	84	25.96	0.0001*
	# of worker > # of Auto	795	20.26	
	other	8,801	18.95	
Region	Zero Auto	372	28.38	0.0001*
	# of worker > # of Auto	2,757	22.86	
	other	24,007	20.27	

* Significant at the 0.05 level

A.1.8 Household Income Level

Of the 5,168 households sampled in SEFRTCS household survey, 3,135 households provided their annual household income information. This questionnaire used a total of 21 annual household income categories in $5,000 increments, from “less than $5,000” to “greater than $100,000.” To perform analysis of household income level versus trip lengths, the households with income information were first sorted by their income levels into the 25th, 50th, and 75th percentiles (known as the lower, middle, and upper quartiles). These quartiles were then applied to divide households into four income groups to assure approximately equal number of cases in each group. Table A.38 provides the number of households per income range category in each group. The trips recorded in the trip log for each household were then classified into two categories: HBW and NHBW trips. ANOVA tests were performed to determine if income level had any effects on the trip lengths for the HBW and NHBW trips.

Table A.38 Number of Households in Each Income Group

County	Income Group	Number of Households	# of HBW Trips	Average Trip Length (min)	Significance (p-value)
Broward	< $35,000	266	234	27.25	0.001*
	$35,000 – $54,999	284	411	25.58	
	$55,000 – $79,999	249	446	27.60	
	≥ $80,000	287	525	29.89	
Miami-Dade	< $25,000	230	171	29.10	0.001*
	$25,000 – $44,999	248	300	29.35	
	$45,000 – $69,999	261	422	34.38	
	≥ $70,000	238	371	31.75	
Palm Beach	< $35,000	298	259	23.45	0.076
	$35,000 – $54,999	280	373	25.25	
	$55,000 – $74,999	243	353	24.58	
	≥ $85,000	251	340	26.97	
Regional	< $30,000	708	569	26.74	0.003*
	$30,000 – $49,999	702	896	27.12	
	$50,000 – $69,999	837	1,386	28.11	
	≥ $70,000	888	1,354	29.41	

The significance of income levels on trip lengths was also tested for the NHBW trip purpose (Table A.39). Trip lengths for income groups in Miami-Dade County and the tri-county areas were significantly different. However, as before, the data did not reveal consistent relationship between income levels and trip lengths. Therefore, household income level did not appear to be a factor in determining the length of individual trips.

Table A.39 Significance of Household Income Level on NHBW Trip Length

County	Income Group	Number of Households	# of NHBW Trips	Average Trip Length (min)	Significance (p-value)
Broward	< $35,000	266	917	18.01	0.47
	$35,000 – $54,999	284	1,353	17.12	
	$55,000 – $79,999	249	1,261	17.79	
	≥ $80,000	287	1,690	17.91	
Miami-Dade	< $25,000	230	680	21.40	0.000*
	$25,000 – $44,999	248	868	20.19	
	$45,000 – $69,999	261	1,046	21.48	
	≥ $70,000	238	1,377	18.10	
Palm Beach	< $35,000	298	1,074	17.19	0.345
	$35,000 – $54,999	280	1,357	17.36	
	$55,000 – $74,999	243	1,441	18.05	
	≥ $85,000	251	1,595	17.25	
Regional	< $30,000	708	2,298	19.00	0.003*
	$30,000 – $49,999	702	3,002	18.04	
	$50,000 – $69,999	837	4,155	18.58	
	≥ $70,000	888	5,204	17.74	

A.1.9 Highway Network Accessibility

Accessibility has been recognized as one of the most influential factors affecting both land use and travel behavior. An application of a gravity model accessibility measure to a travel behavior study is described in Kockelman (1997). Kockelman applied the accessibility index (AI), defined as the sum of zonal employment weighted by friction terms that reflect the ease of travel between a location and activity centers, to estimate network-wide accessibility. Zonal employment may be total employment or commercial and service employment. The friction term or impedance function, $f(t_{ij})$, was assumed as an exponential form with coefficients estimated by Levinson and Kumar (1995). These authors used ordinary least squares regression (OLS) to estimates the impedance function for an application in a gravity model with the dependent variable being the number of trips per unit area in each 5-minute time band, travel time served as the independent variable.

In this study, the coefficients of the impedance function for each trip purpose were calibrated by fitting the highway travel times from the SEFRTCS household survey data based on Levinson and Kumar's method. The formula for calculating the highway accessibility index, a relative index expressed as a number between 0 and 1, for HBW trips was defined as follows:

$$AI_i = \frac{1}{RA_{\max}} \sum_{j=1}^{N} A_j \exp(-0.087 t_{ij} + 0.6611)$$

where

AI_i = index of regional accessibility to employment by highway travel for zone i;
RA_{max} = maximum regional accessibility by highway travel in a given network;
A_j = total trip attractions in zone j;
t_{ij} = highway travel time plus toll equivalent from zone i to zone j; and
N = total number of zones in a given network.

Note that in the definition of accessibility we used zonal attractions instead of employment to better reflect the opportunities that exist in different zones, which may have the same total employment but attract a different number of trips due to the difference in employment types. Additionally, the use of attractions allows for trip-purpose specific AIs to be calculated, thus their effects on trips of different purposes may be studied.

The 1999 Palm-Beach Model data were used to investigate the significance of highway network accessibility on the HBW trip length. However, not considering the employment in the bordering counties (in this case Broward and Martin counties), the zonal AIs near the county boundaries will be underestimated. To solve this problem, at the southern border of Palm Beach County, the highway networks of Palm-Beach and Broward counties were joined together, and the employment in Broward County were included in the calculation of the AI. Close to the northern boundary of the county, zones that were within five miles of the county line were excluded from the analysis. The highway networks of Palm Beach County and Martin County were not jointed due to the fact that creating a regional network required a significant effort and that the spatial interactions between these two counties were considered less significant than those between Palm Beach County and Broward County. The zones that were included in the calculations of the accessibility index for Palm Beach County are highlighted in Figure A.1.

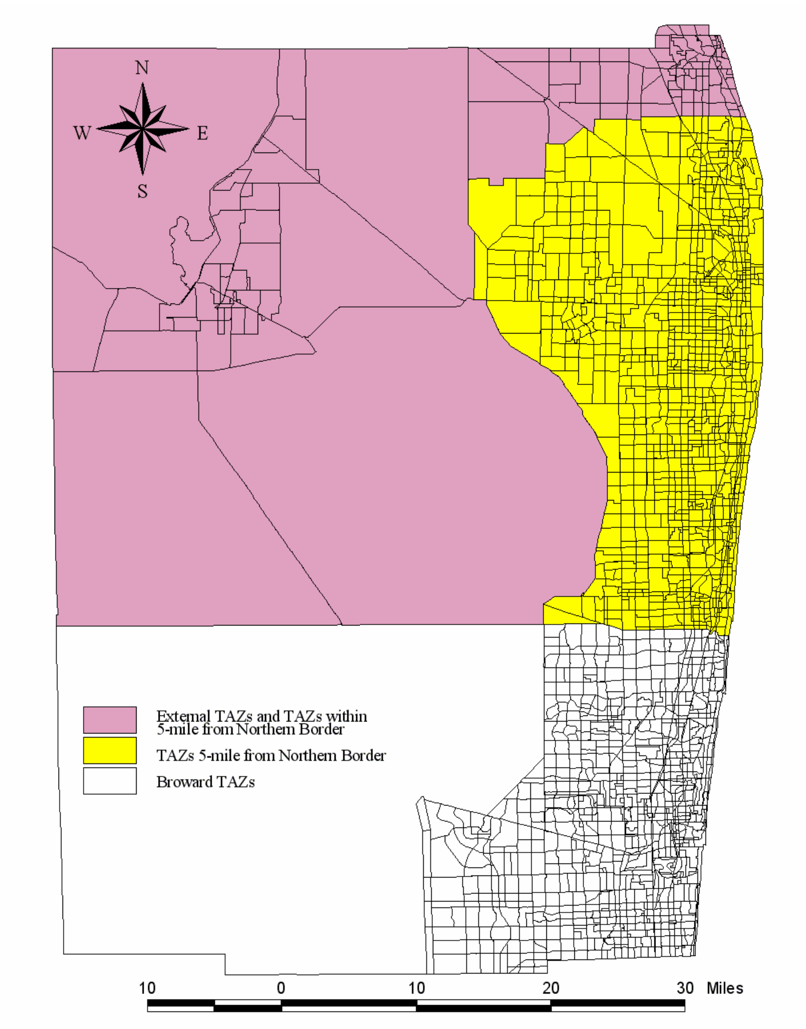

Figure A.1 Palm Beach County Traffic Analysis Zones

An ANOVA test was performed to evaluate the impacts of AI on HBW trip lengths. Observations from the 1999 SERTCS household survey were first categorized into the low and high AI groups using the median (0.454) as the break point. Table A.40 provides the statistics for these two AI groups for the HBW trips. The trip lengths from the two AI groups were then tested by ANOVA and were shown to be significant at the 0.05 significance level. In other words, people living in higher AI areas tend to make shorter work trips.

The above procedures were repeated to test the impacts of AI on trip length for the other home-based trip purposes. The calibrated impedance functions for HBS, HBSR, and HBO trips are as follows:

HBS: $\exp(-0.1192\, t_{ij} + 0.9767)$

HBSR: $\exp(-0.1237\, t_{ij} + 0.8613)$

HBO: $\exp(-0.1156\, t_{ij} + 1.5006)$

Table A.40 Descriptive Statistics for HBW Trips in Low and High AI Groups

Statistics	Number of Samples	Mean (min)	P-Value
Low	813	27.36	0.0001*
High	815	24.03	0.0001*

* Significant at the 0.05 level

Other statistics are summarized in Table A.41. The same conclusion from the HBW trips may be drawn for the HBS and HBO trips. However, accessibility did not have a significant impact on HBSR trip lengths.

Table A.41 Statistics for Low and High AI Groups for Other Home-Based Trips

Purpose	AI Median	Category	Number of Samples	Mean	P-Value
HBS	0.576	Low	534	16.74	0.0346*
		High	543	15.13	
HBSR	0.423	Low	410	17.71	0.2718
		High	411	16.71	
HBO	0.413	Low	1,007	18.88	0.0002*
		High	1,003	16.65	

* Significant at the 0.05 level

A.1.10 Lifestyle Variables

The purpose of the lifestyle variable analysis is to evaluate the differences in trip lengths for each classification of the lifestyle trip production model that is currently implemented in counties within FDOT District 4. If the trip lengths appear to be significantly different among the cells, multiple sets of *F* factors, each calibrated with the data in each model cell, may improve the performance of traditional gravity models.

The analyses were performed to two kinds of trips: the HBW trips and all other trips. Table A.42 shows the numbering scheme applied in the analyses of HBW trips for the lifestyle model categories. The sampled households in the SEFRTCS survey are first classified into the sixteen groups based on the combination of values of the lifestyle variables. The HBW trip lengths for the households in each lifestyle category were then compared with those in each of the other 15 categories using the Kruskal_Wallis (KW) test. The purpose this test was to combine trips among different lifestyle groups to reduce the number of distinct groups. The KW test is a nonparametric technique that does not assume normality for the shape of the distributions being compared. It is probably the most used nonparametric technique for testing whether several samples have been drawn from the same population (the null hypothesis).

Table A.42 Cell Numbers for HBW Trips by Lifestyle Variables

		Number of Total Workers in Household		
Presence of Children	Vehicles/Household	0	1	2+
Without Children	0 1 2 3+		1 2 3 4	9 10 11 12
With Children	0 1 2 3+		5 6 7 8	13 14 15 16

Table A.43 gives the *p*-values for the trip length comparisons between each lifestyle cell and the rest of the cells in Table 37. The highlighted cells indicate that the trip lengths between the pair of cells are significantly different. Based on the results as shown in Table A.43, trip length data from the same population, i.e., trips from groups that are not significantly different, were merged to form a new lifestyle group, which results in seven new aggregated lifestyle groups:

1. HHs without vehicle (1, 5, 9, 13).
2. HHs with 1 vehicle (2, 6, 10, 14).
3. HHs with 1 worker, no children, and more than 1 vehicle (3, 4).
4. HHs with 1 worker, children, and more than 1 vehicle (7, 8).
5. HHs with 2 + workers, no children, and more than 1 vehicle (11, 12).
6. HHs with 2 + workers, children, and 2 vehicles (15).
7 HHs with 2 + workers, children, and 3+ vehicles (16).

Table A.43 Significance of Lifestyle Variables on HBW Trip Lengths

	1*	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	31 (37.9)	0.007	0.025	0.140	0.640	0.024	0.230	0.790	0.939	0.011	0.091	0.087	0.095	0.047	0.166	0.036
2	582 (24.84)		0.234	0.147	0.086	0.247	0.000	0.003	0.017	0.754	0.000	0.000	0.902	0.114	0.000	0.025
3	308 (26.38)			0.459	0.166	0.973	0.005	0.018	0.050	0.256	0.026	0.033	0.673	0.649	0.001	0.574
4	46 (26.22)				0.302	0.490	0.364	0.192	0.125	0.174	0.746	0.725	0.516	0.642	0.348	0.598
5	21 (34.71)					0.168	0.617	0.924	0.847	0.100	0.370	0.380	0.224	0.237	0.526	0.229
6	244 (26.18)						0.009	0.023	0.057	0.284	0.045	0.057	0.673	0.701	0.002	0.605
7	301 (30.72)							0.352	0.353	0.001	0.161	0.192	0.239	0.038	0.778	0.006
8	46 (34.39)								0.755	0.006	0.130	0.123	0.170	0.044	0.301	0.028
9	17 (33.53)									0.027	0.166	0.172	0.131	0.080	0.301	0.069
10	206 (26.0)										0.002	0.003	0.922	0.167	0.000	0.085
11	1,241 (28.79)											0.973	0.363	0.174	0.048	0.026
12	751 (28.46)												0.357	0.202	0.096	0.050
13	13 (24.23)													0.594	0.235	0.568
14	214 (27.20)														0.017	0.945
15	1,326 (29.86)															0.000
16	747 (27.34)															
Total	6,094 (28.24)															

* Number of samples (average trip length) in the category

The trip lengths from the seven new lifestyle groups were analyzed again using the KW statistical tests to assure that no further aggregation could be achieved. Table A.44 presents the results of the KW tests on merged trip length data. Table A.44 indicates that 15 out of the 21 pairs of comparisons are significantly different. Therefore, no further aggregation is necessary.

Table A.44 Significance of Aggregated Lifestyle Variables on HBW Trip Lengths

	I[1] (1, 5, 9, 13)[8]	II[2] (2, 6, 10, 14)	III[3] (3, 4)	IV[4] (7, 8)	V[5] (11, 12)	VI[6] (15)	VII[7] (16)
I	82 (34.01)[9]	0.000	0.001	0.262	0.007	0.043	0.002
II	1,246 (25.70)		0.514	0.000	0.000	0.000	0.038
III	354 (26.36)			0.000	0.020	0.001	0.376
IV	347 (31.21)				0.013	0.216	0.001
V	1,992 (28.66)					0.053	0.076
VI	1,326 (29.86)						0.002
VII	747 (27.34)						
Total	6,094 (28.24)						

[1] HHs without vehicle.
[2] HHs with 1 vehicle.
[3] HHs with 1 worker, no children, and more than 1 vehicle.
[4] HHs with 1 worker, children, and more than 1 vehicle.
[5] HHs with 2 + workers, no children, and more than 1 vehicle.
[6] HHs with 2 + workers, children, and 2 vehicles.
[7] HHs with 2 + workers, children, and 3+ vehicles.
[8] Cell numbers in the lifestyle model for HBW trips that are aggregated in the category.
[9] Number of households/average trip length in the category.

Another test procedure was performed on trip data of which the trip purposes are not HBW. Table 40 shows the lifestyle model structure and the numbering scheme applied in the analyses of this second group of trips. There are 28 lifestyle categories. The trip lengths for the households in each lifestyle category as defined in Table A.45 were then compared with those in the other 27 categories using the Kruskal_Wallis (KW) test. The *p*-values for the trip length comparisons between each pair of lifestyle cells in Table A.45 are given in Table A.46. A highlighted cell indicates that the trip lengths between that pair of cells are significantly different. Based on the results shown in Table A.46, trip length data from the same population (or not significantly different) were merged to form a new lifestyle group. A total of 12 aggregated lifestyle groups were consequently defined:

Table A.45 Cell Numbers for NHBW Trips by Lifestyle Variables

		Number of Persons in Household			
Presence of Children	Vehicles/Household	1	2	3	4+
Without Children	0 1 2 3+	1 2 3 4	5 6 7 8	13 14 15 16	21 22 23 24
With Children	0 1 2 3+		9 10 11 12	17 18 19 20	25 26 27 28

1. HHs with 1 or 2 persons, 0 car, and no children (1, 5)
2. HHs with 1 person, 1+ vehicles, and no children (2, 3, 4)
3. HHs with 2 persons, 1+ vehicles, and no children (6, 7, 8)
4. HHs with 2 persons and children (9, 10, 11, 12)
5. HHs with 3 persons and no children (13, 14, 15, 16)
6. HHs with 3 persons, no more than 2 vehicles, and children (17, 18, 19)
7. HHs with 3 or 4+ persons, 3+ vehicles, and children (20, 28)
8. HHs with 4+ persons, 0 or 1 vehicle, and no children (21, 22)
9. HHs with 4+ persons, 2 or 3+ vehicles, and no children (23, 24)
10. HHs with 4+ persons, 0 vehicle, and children (25)
11. HHs with 4+ persons, 1 vehicle, and children (26)
12. HHs with 4+ persons, 2 vehicle, and children (27)

No further KW tests were performed to verify the differences in trip lengths between these 12 aggregated lifestyle groups since the total number of aggregated groups for HBW and NHBW trips exceeded the maximum number of tables allowed in TRANPLAN for a trip table file, which is 15. Complex manipulating and updating trip matrices is needed if the total of 19 trip tables are distributed via the gravity model, each with its own set of *F* factors.

Although the production trips can be easily calculated for each aggregated group, the trip attraction models in FSUTMS do not currently incorporate lifestyle variables. Consequently, the calibration of the gravity model used the lifestyle groups as described above cannot be performed. Carr Smith Corradino, Inc., is currently in the process of developing new trip attraction equations to enhance the trip attraction estimation in FSUTMS, which are expected to incorporate lifestyle variables. If the attraction models are able to account for the lifestyle variables, the trip distribution process may be enhanced by incorporating these variables.

Table A.46 Significance of Lifestyle Variables on NHBW Trip Lengths

	1*	2	3	4	5	6	7	8	9	10	11	12	13	14
1	127 (25.34)	0	0.018	0.072	0.079	0	0	0.003	0.555	0	0.113	0.085	0.659	0.024
2	1,550 (17.61)		0.297	0.805	0	0.442	0.489	0.223	0.650	0.656	0.034	0.784	0.778	0.187
3	178 (19.53)			0.557	0	0.440	0.416	0.797	0.866	0.263	0.396	0.559	0.978	0.901
4	23 (16.52)				0.002	0.685	0.719	0.531	0.677	0.917	0.257	0.857	0.683	0.439
5	37 (29.38)					0	0	0	0.162	0	0.001	0.006	0.242	0
6	1,804 (17.97)						0.861	0.449	0.684	0.348	0.062	0.731	0.813	0.320
7	3,439 (17.96)							0.395	0.706	0.393	0.054	0.705	0.827	0.281
8	355 (18.21)								0.746	0.202	0.182	0.610	0.846	0.672
9	10 (21.20)									0.664	0.967	0.595	0.823	0.864
10	384 (17.83)										0.036	0.836	0.773	0.153
11	114 (19.18)											0.300	0.831	0.420
12	17 (15.71)												0.893	0.496
13	2 (15.00)													0.920
14	172 (19.74)													
15	408 (20.07)													
16	678 (20.28)													
17	43 (23.07)													
18	608 (19.12)													
19	1,688 (18.05)													
20	304 (17.09)													
21	11 (10.82)													
22	29 (13.48)													
23	187 (18.94)													
24	413 (20.22)													
25	53 (30.08)													
26	1,033 (20.03)													
27	5,110 (17.13)													
28	2,313 (18.55)													
Total	21,090 (18.23)													

* Number of samples/average trip length in the category

Table A.46 Significance of Lifestyle Variables on NHBW Trip Lengths (Cont.)

	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1	0.024	0.055	0.412	0.009	0	0	0.017	0.001	0.036	0.040	0.148	0.029	0	0.002
2	0.007	0	0.178	0.005	0.095	0.656	0.183	0.038	0.035	0.002	0	0	0.359	0.003
3	0.521	0.181	0.489	0.666	0.668	0.319	0.107	0.034	0.595	0.366	0.001	0.248	0.142	0.973
4	0.340	0.213	0.278	0.366	0.590	0.799	0.386	0.240	0.296	0.295	0.010	0.225	0.887	0.480
5	0	0.001	0.030	0	0	0	0	0	0	0.001	0.722	0	0	0
6	0.023	0	0.242	0.018	0.320	0.623	0.153	0.022	0.070	0.006	0	0	0.052	0.024
7	0.015	0	0.227	0.010	0.217	0.658	0.149	0.028	0.064	0.004	0	0	0.030	0.006
8	0.263	0.024	0.366	0.293	0.899	0.327	0.104	0.012	0.281	0.133	0	0.028	0.075	0.602
9	0.921	0.959	0.900	0.874	0.727	0.590	0.230	0.304	0.879	0.988	0.220	0.957	0.586	0.812
10	0.016	0	0.160	0.015	0.147	0.767	0.238	0.068	0.039	0.007	0	0	0.990	0.034
11	0.623	0.922	0.852	0.503	0.127	0.046	0.033	0.004	0.668	0.831	0.005	0.939	0.012	0.247
12	0.404	0.276	0.391	0.436	0.620	0.846	0.280	0.401	0.427	0.334	0.014	0.308	0.865	0.517
13	0.966	0.873	0.956	0.990	0.897	0.764	0.190	0.250	0.989	0.948	0.296	0.897	0.745	0.955
14	0.652	0.229	0.537	0.726	0.573	0.245	0.093	0.012	0.585	0.461	0.001	0.258	0.090	0.892
15		0.339	0.672	0.797	0.100	0.037	0.068	0.005	0.913	0.715	0.001	0.428	0.001	0.313
16			0.917	0.155	0.001	0.001	0.030	0.002	0.461	0.602	0.001	0.714	0	0.007
17				0.600	0.326	0.198	0.111	0.017	0.737	0.777	0.067	0.868	0.133	0.429
18					0.106	0.039	0.058	0.006	0.776	0.476	0	0.215	0	0.391
19						0.277	0.102	0.017	0.191	0.031	0	0	0.002	0.239
20							0.178	0.034	0.060	0.014	0	0.001	0.705	0.085
21								0.757	0.043	0.050	0.001	0.030	0.200	0.076
22									0.004	0.005	0	0.002	0.045	0.009
23										0.790	0.001	0.589	0.009	0.422
24											0.001	0.792	0	0.127
25												0.001	0	0
26													0	0.007
27														0
28														
Total														

A.2 Income Data at HBS Trip Ends

Income levels have long been suspected as an important factor influencing people's decisions on where to shop. In this section, we investigate if people tended to shop at destinations with household income level similar to their own. The income data at zonal level in the tri-county area were first retrieved from the 1990 Census using the 1990 Census Transportation Planning Package (CTPP). In the SEFRTCS survey, 1,040 zones were either the origins or destinations of HBS trips. Table A.47 provides the number of zones with reported HBS trips in each county by number of households in each zone. Only the income data at sampled HBS trip ends were prepared. However, some zones did not have household income information because there were no households in these zones. Other zones did have households in the zone but their number was small for the household income data to be reliable. For such zones, i.e., zones with no households or with fewer than 100 households, the average income data from the immediately adjacent zones, excluding those separated by physical barriers such as freeways, canals, railroads, lacks, etc., were derived and used to represent the income level of these zones.

Table A.47 Number of TAZs with Reported HBS Trips

County	Number of Households		
	> 100	= 0	< 100
Broward	266	29	15
Miami-Dade	291	32	19
Palm-Beach	308	54	26
Total	865	115	60

Once the zonal income data were obtained, the income intervals for different areas were determined using the 25, 50, and 75 percentiles to ensure an equal number of cases in each group. Figure A.2 illustrates the relationships between the income levels of the two ends of the shopping trips in Broward County. Along the horizontal axis, four income ranges for the origin zones of the HBS trips are identified. For each of the four income ranges for the origin zones, the numbers of HBS trips ending in zones with one of the four income ranges are plotted. Figure A.2 illustrates the tendency for people to shop at destinations with the same or similar income levels. This is true for all four groups. The Chi-square test was used to examine the independence of income levels at the home and attraction zones in Broward County, which resulted in a 0.001 p-value, rejecting the null hypothesis that income levels at the two trip ends are independent.

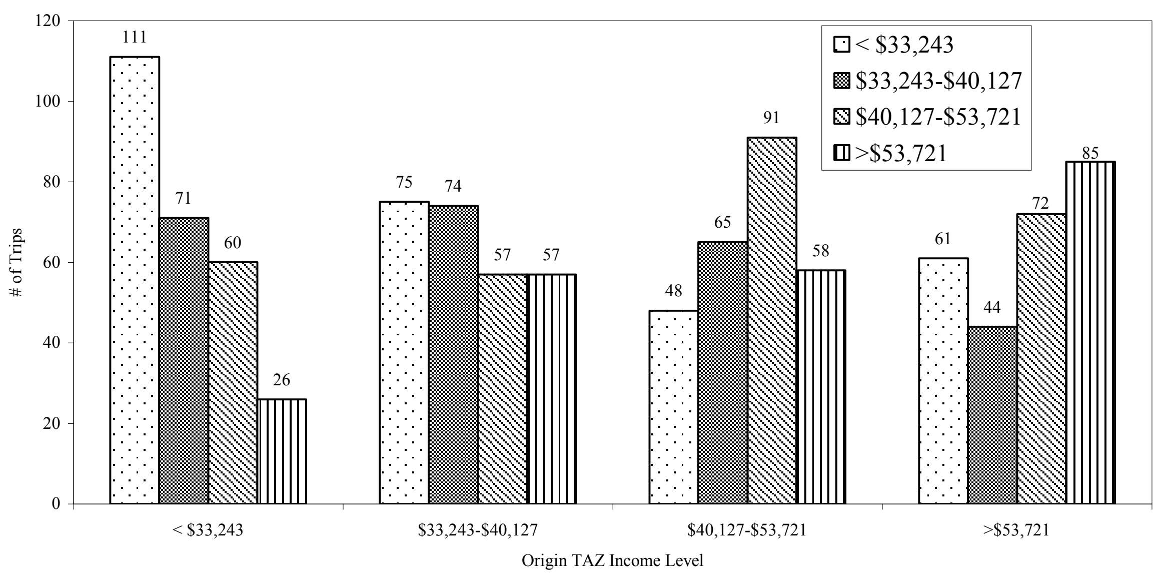

Figure A.2 Number of Home-Based Shopping Trips between TAZs at Different Income Levels in Broward County

Using data for Miami-Dade County in a similar fashion as above, Figure A.3 shows even more obviously that people tended to shop at destinations with the same or similar income levels. Again, a Chi-square test showed a 0.001 p-value which assures that the income level at the two ends of shopping trips in Miami-Dade are related.

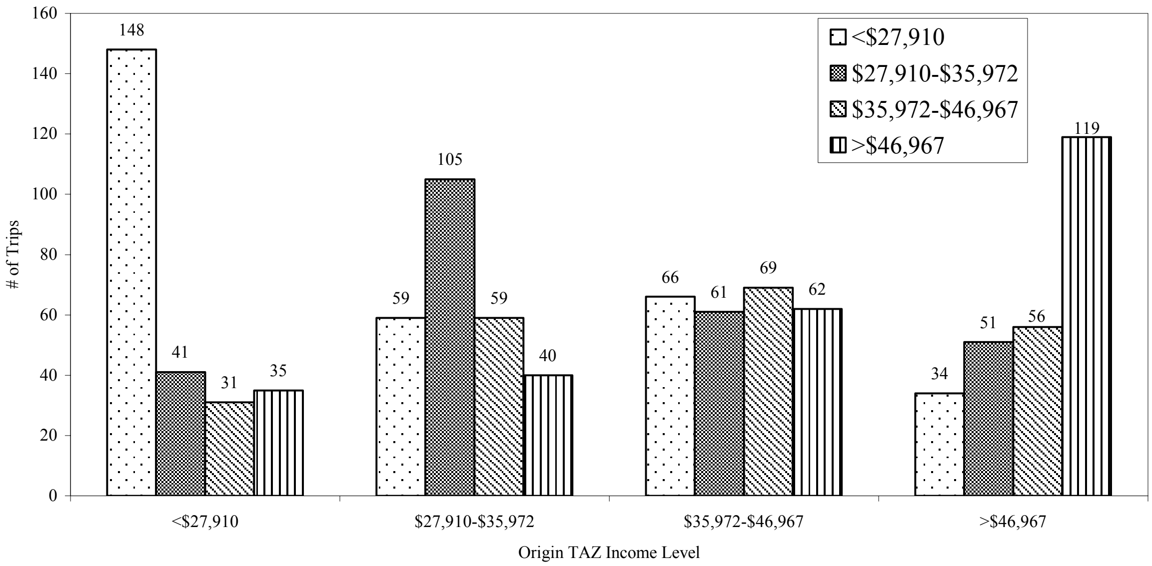

Figure A.3 Number of Home-Based Shopping Trips between TAZs at Different Income Levels in Miami-Dade County

The Palm Beach County data analyzed similarly to that Broward and Miami-Dade counties, and the distributions of HBS trips are plotted in Figure A.4. The dividing points are $34,000, $45,600, and $63,400 for income intervals at HBS origin ends, and the numbers of samples are 321, 334, 325, and 329, respectively. The tendency of people shopping at destinations with the same or similar income levels is also obvious. Since the p-value from the Chi-square test is 0.001, the income levels at the HBS trip ends in Palm Beach County are related.

Figure A.5 illustrates the relationship between income levels at HBS trip origin and destination ends using the region-wide data. It shows that the dividing points are $32,200, $40,600, and $54,700 for income intervals at HBS origin ends and the numbers of samples are 844, 846, 864, and 846, respectively. Like in the individual counties, region-wide data demonstrate the similar relationship between income levels at HBS trip ends. In addition, the Chi-square test on region-wide data also revealed a significant relationship between the income levels at HBS trip ends. Therefore, from the results presented in Figures A.2 through A.5, income levels appear to be a factor in influencing where people tend to shop. While the above analyses have demonstrated that income level is a factor in trip makers' choice of shopping destinations, it is also possible that the phenomenon is simply a result of the dependent nature of retail services on the socioeconomic and demographic characteristics of the areas they intend to serve, since merchants typically research the market in the intended service areas to tailor their services and products to the population. For this reason, we further tested our hypothesis that income levels do affect the choice of destinations by considering only shopping trips longer than 10 minutes since such trips will be well away from a shopper's own neighborhood. We refer to these longer trips as "preference" shopping trips and the shorter ones as "convenience" shopping trips. Of all the HBS trips from the SEFRTCS survey, 48.3% are convenience shopping trips and the other 51.7% are preference shopping trips.

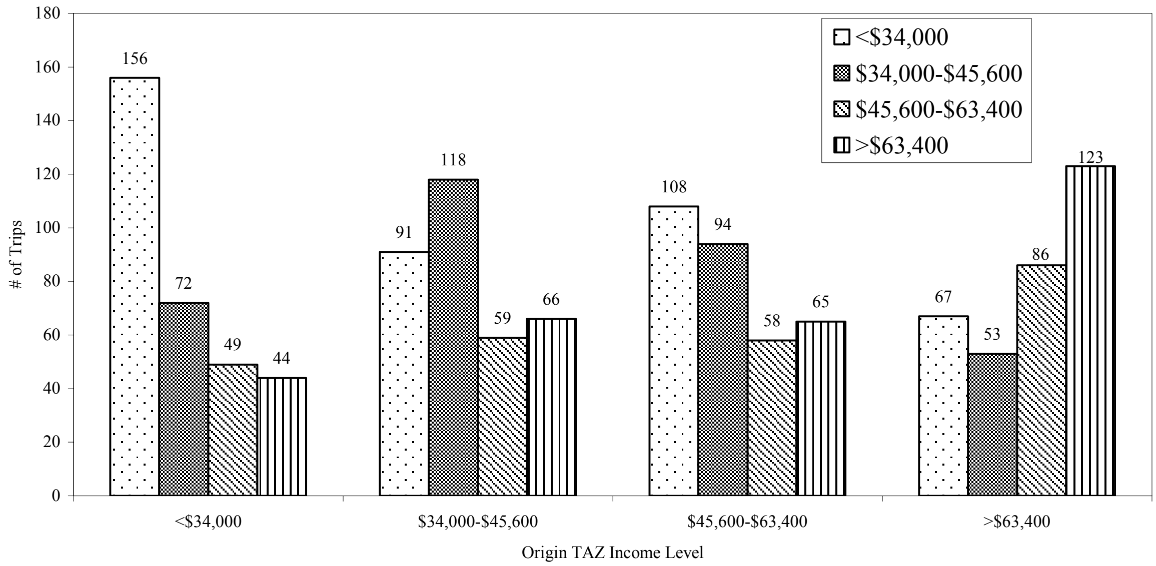

Figure A.4 Number of Home-Based Shopping Trips between TAZs with Different Income Levels in Palm Beach County

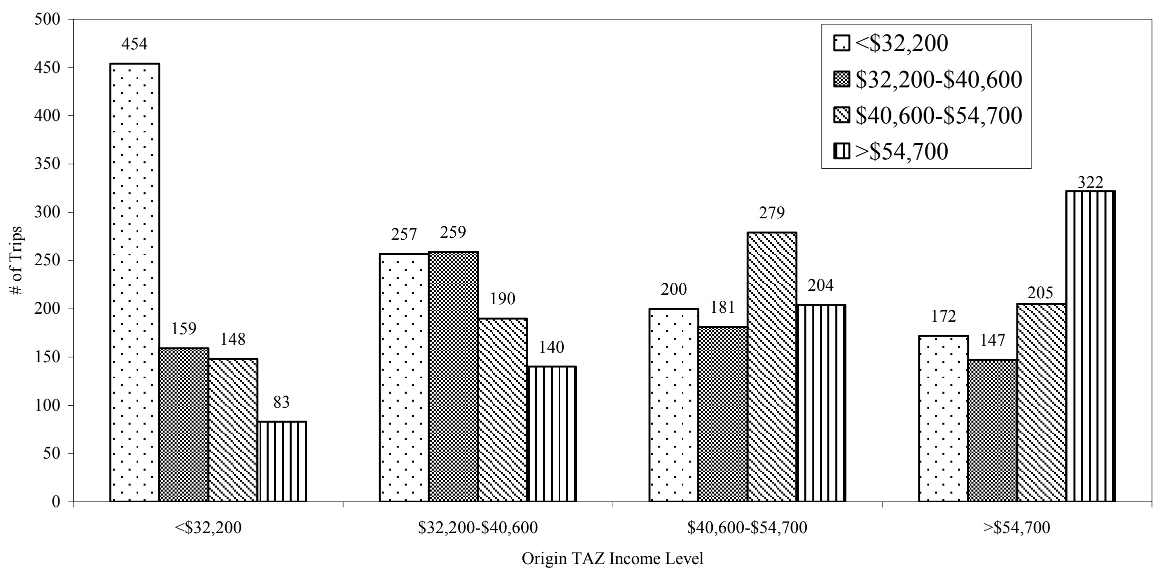

Figure A.5 Number of Home-Based Shopping Trips between TAZs with Different Income Levels in Tri-County Area

Figures A.6 through A.9 again illustrate the relationship between the income levels at the origin and destination ends of the "preference" shopping trips for Broward, Miami-Dade and Palm Beach counties, and the tri-county area. For most trips, there appears to be a link between the origin and destination income levels. The Chi-square tests for all four data sets provided a 0.001

p-value. Therefore, it may be concluded that income levels at the origin and destination ends are indeed related. This finding offers the possibility of further improving the trip distribution model for shopping trips by considering the different zonal income levels.

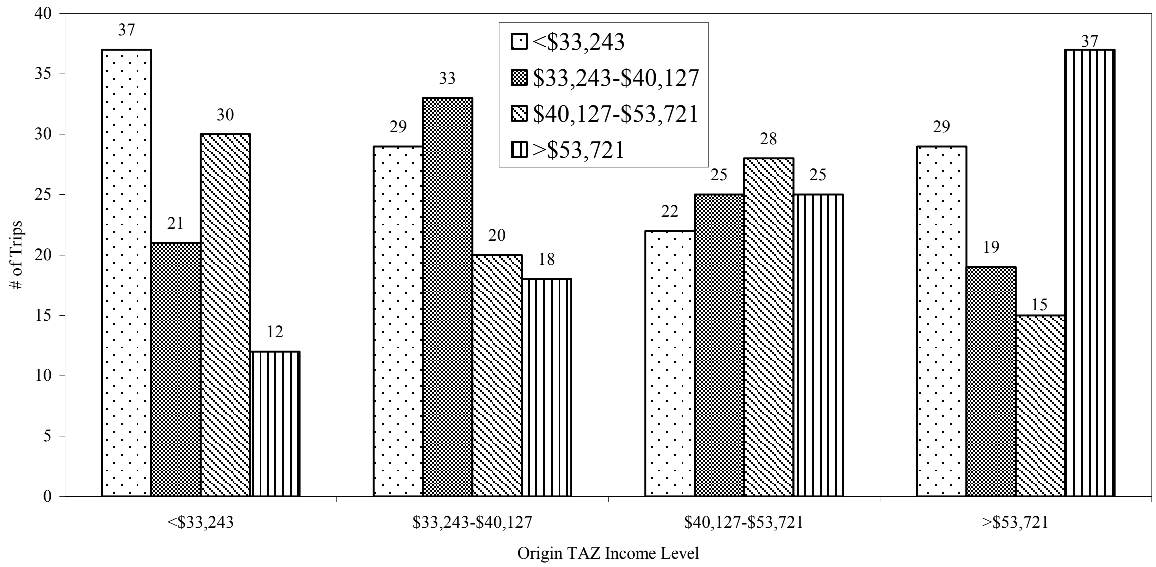

Figure A.6 Percentages of Long Home-Based Shopping Trips between TAZs with Different Income Levels in Broward County

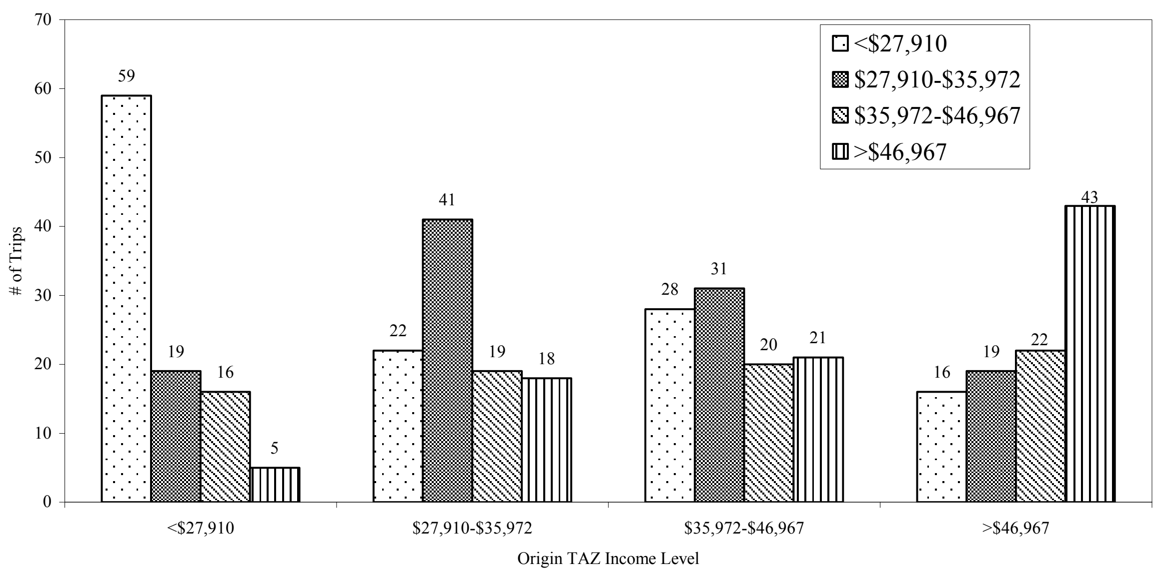

Figure A.7 Percentages of Long Home-Based Shopping Trips between TAZs with Different Income Levels in Miami-Dade County

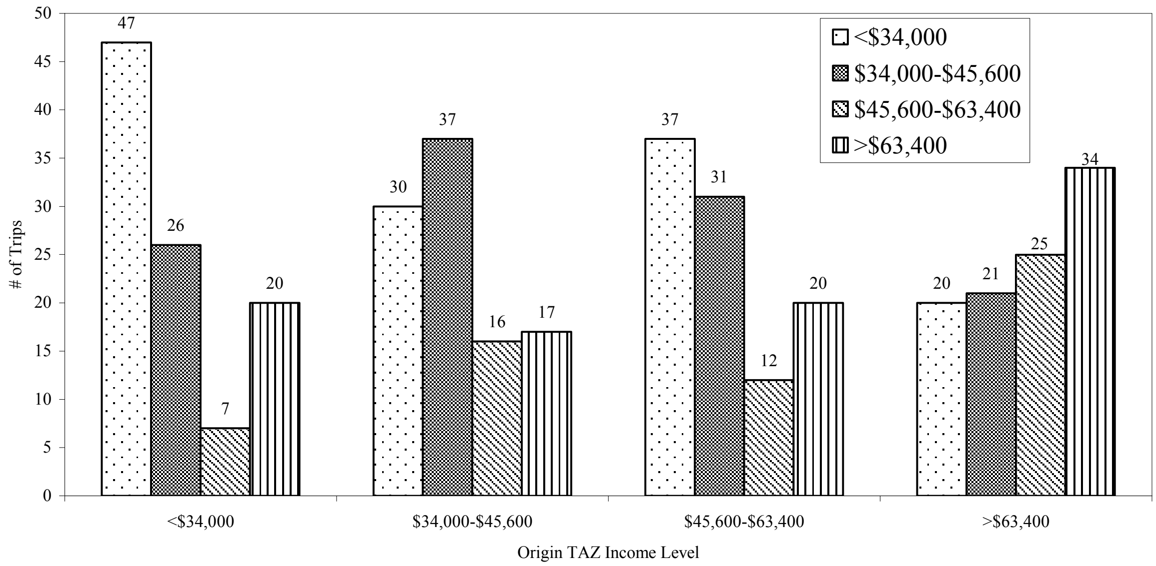

Figure A.8 Percentages of Long Home-Based Shopping Trips between TAZs with Different Income Levels in Palm Beach County

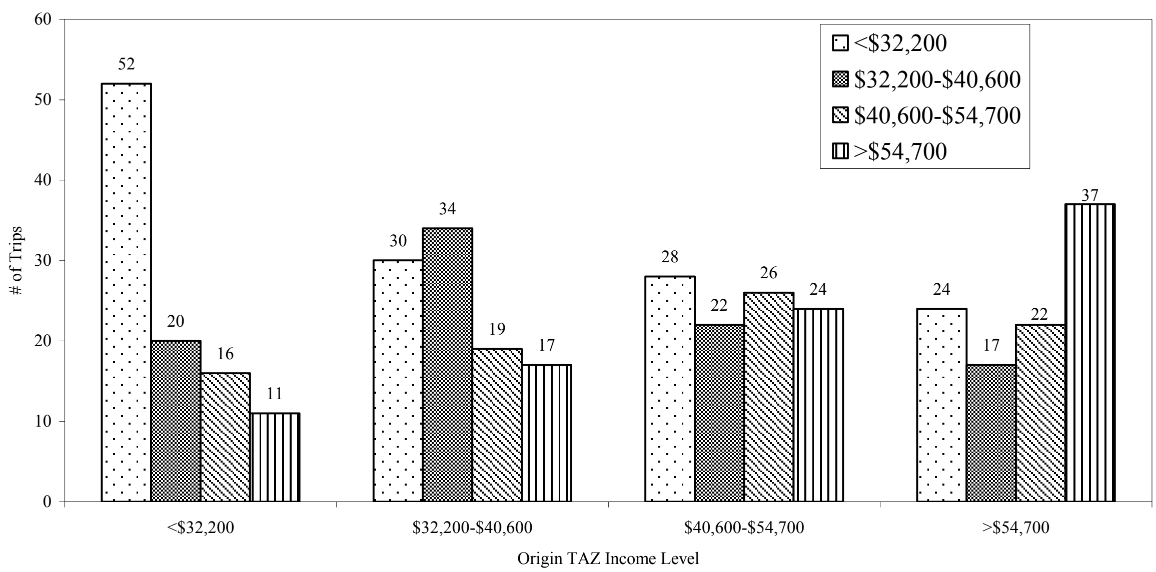

Figure A.9 Percentages of Long Home-Based Shopping Trips between TAZs with Different Income Levels in Tri-County Area

A.3 Analysis of Non-Home Based Trips and Trip Chaining

Non-home-based (NHB) trips account for 24% of the 33,082 total trips. To better understand the characteristics of NHB trips and trip chaining patterns, the following NHB tour-based trip chain categories were adopted:

- Journey to work: non-home-based trips made while a person is going to work;
- Journey from work: non-home-based trips made when a person leaves from work;
- At work: non-home-based trips made while a person is at work; and
- Non-work-related: non-home-based trips made with no connection to work.

A trip is defined as a single travel movement from an origin to a destination, while a sequence of connected trips that start and end at home is referred to as a "tour." The above tour-based categories are different from the categories developed by Corradino for the 1999 Broward County FSUTMS Model, which divides the NHB trips into NHB work trips (NHB trips with one end at work places) and NHB other trips (NHB trips without work places at trip ends). Figure A.10 illustrates the hierarchical decomposition of the 1999 SEFRTCS survey data based on the adopted NHB tour-based categories and number of samples in each subgroup.

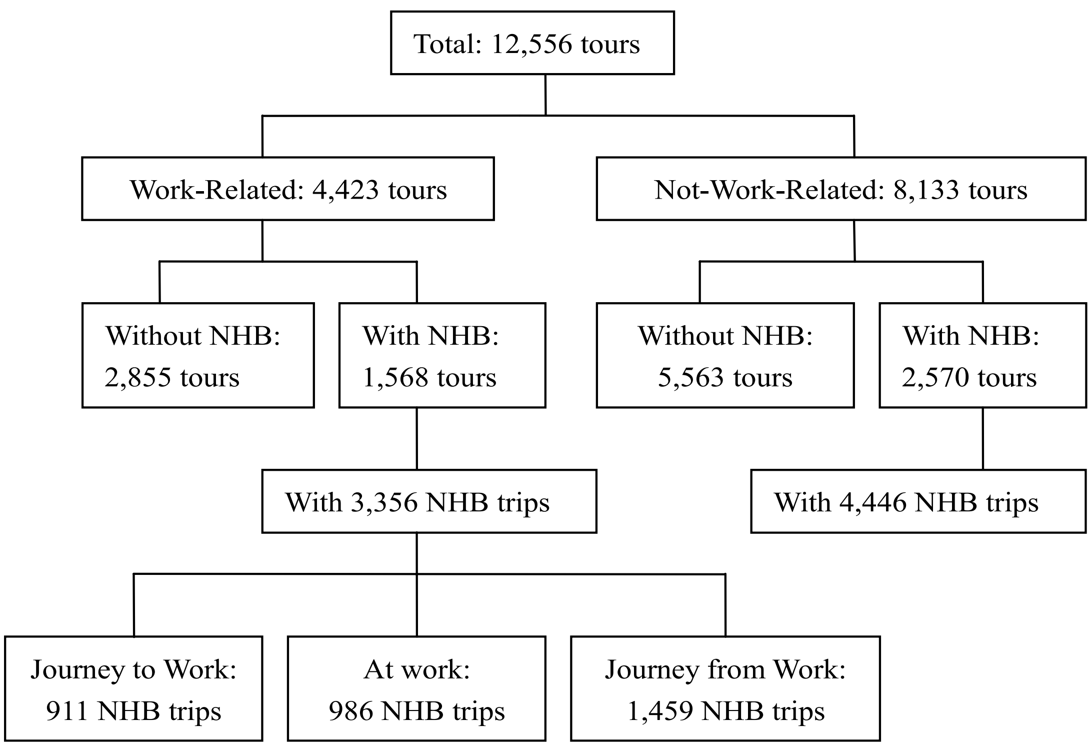

Figure A.10 Statistics for NHB Trips Summarized from the SEFRTCS Survey

A total of 12,556 tour samples were collected in the 1999 SEFRTCS survey. Among these tours, 4,423 are work-related and 8,133 are non-work-related. A tour that is work-related means that at least one trip in the tour has a trip end at a work place. Thus, in the hierarchical tree shown in

Figure A.10, the "without NHB" node under the "work-related" node simply represents those tours with the work place as the intermediate stop and home as the two tour ends. A total of 1,568 work-related tours (i.e., 3,356 NHB trips) were classified into the "with NHB" node. These NHB trips are further classified into journey to work (NHB trips occur on the way to work), at work (NHB trips begin and end at the work place), and journey from work (NHB trips occur on the way to home) groups, each with 911, 986, and 1,459 NHB trips, respectively. By grouping work-related NHB trips into the journey to work and journey from work categories, different travel behaviors may be observed since different types of activities are expected to occur on the way to and from work. Figure A.11 shows a typical scenario of a journey to work or journey from work tour. It is made by two trips: from home to an intermediate stop for a particular activity, and then from the activity to work for a journey to work tour, and the opposite for a journey from work tour. It is of interest to find out what types of activities were carried out on tours, how far people traveled to carry out other activities either before or after work, and how much people deviated from their home-work or work-home routes to perform these activities. In Figure A.11, d_1 is the Euclidian distance d_1 between home and the intermediate stop, d_2 the distance between the intermediate stop and work, and d_3 between home and work.

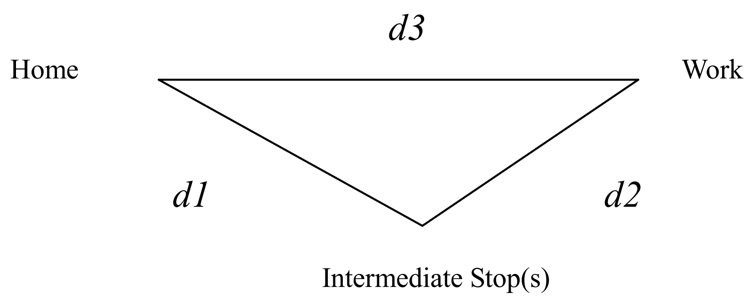

Figure A.11 Distances between Trip Ends in a Journey to Work or a Journey from Work Tour

Tables A.48 through A.50 provide the statistics for the NHB trips in the journey to work, at work, journey from work, and not-work-related categories, respectively. Table A.48 describes the trip segment between the intermediate stop and the work in a journey to work tour. The first column describes the type of activities carried out at the intermediate stop, or the non-work end(s) of a trip. The number of sampled trips that shares the same kind of activities is given in the second column. The third column gives the average surveyed trip length in minutes for the second trip segment of a journey to work tour (the segment indicated by d_2 in Figure A.11). The fourth column is the network trip length the shortest travel times computed from free flow speeds using the1990 SERPM regional network for the same trip segment. Only those trips recorded with trip lengths between 1 and 100 minutes are included in the summary. The fifth through the tenth columns provide the average Euclidian and network distances for d_1, d_2, and d_3, respectively. The Euclidian distance was calculated as the air distance between two geocoded trip stops factored by $\sqrt{2}$ as an estimate of the network travel distance assuming a grided street network. Table A.49 describes the at work journeys in terms of their purposes, number of trips of each purpose, the trip distance in miles, the average surveyed trip length in minutes, and the average network trip length in minutes. Table A.50 is similar to Table A.48, except that the tours described are work-to-home journeys. As expected, the results presented in Tables A.48

through A.41 for work-related NHB trips indicate that more NHB work-related trips occur during the journey-from-work because there is less time pressure. Journey-at-work NHB trips appear to have the shortest spatial trip distances while nearly equal trip distances were observed for NHB trips in the other two categories. The results related to the survey trip length indicate that journey from work trips are the longest, followed by journey to work, and the at-work trips. Additionally, most of the NHB trips occurring on the way to work were to drop off/pick up passengers (e.g., sending children to school). The activity type changes to "eat meal" in the at-work category. Other activities (e.g., personal business, shopping, and social/recreational) become significant for the journey from work category. As a result, although the NHB trips in the journey to and from work categories appear to have similar trip lengths and trip distances, their activity types are different and may need to be modeled separately for trip distribution.

Tables A.48 through A.50 also give the average spatial distance and the network trip length between the activity and work, as well as between home and work. The purpose of providing such information is to examine how far people would detour for specific activities on their way either to or from work. The sum of the average distances between work and activity and between activity and home ($d_1 + d_2$) was compared with the distance between home and work (d_3) for journey to work NHB trips. For instance, the average network trip distances in Table 5.39 for home to shopping and from shopping to work are 5.66 and 7.34 miles, respectively. The sum of these two distances is 13.00 miles, which is 3.35 miles longer than the average network trip distance between work and home (i.e., 9.45 miles).

Table A.48 Statistics for the NHB Trips in Journey to Work Tours

Activity Type	No. of Trips	Survey Trip Length (min)	Network Trip Length (min)	Avg. Distance d_1 (mile)		Avg. Distance d_2 (mile)		Avg. Distance d_3 (mile)	
				Euclidian	Network	Euclidian	Network	Euclidian	Network
Business Trip	48	22.1	12.2	12.26	10.50	12.26	10.33	11.09	9.59
Shop	100	17.5	9.9	6.56	5.66	9.26	7.34	11.92	9.65
School	63	23.2	10.4	6.84	6.10	9.43	7.99	10.85	9.97
Social/Recreation	36	19.4	11.2	5.66	5.10	10.85	9.05	10.18	8.82
Personal Business	171	22.2	11.2	7.68	6.31	9.53	7.90	10.88	8.96
Eat Meal	74	17.5	10.1	9.96	8.32	9.89	8.05	15.88	13.07
Drop Off /Pick Up Passenger	376	21.7	12.2	6.42	5.65	11.75	8.87	13.28	10.26
Change Travel Mode	22	18.8	15.0	9.04	7.27	13.32	10.59	19.93	15.75
Unknown	21	20.5	11.9	5.12	3.67	9.22	7.77	10.86	8.82
Total	911	20.9	11.5	7.28	6.25	10.73	8.50	12.59	10.16

Table A.49 Statistics for At-Work NHB Trips

Activity Type	No. of Trips	Avg. Trip Distance (mile)	Survey Trip Length (min)	Network Trip Length (min)
Go Back to Work	493	5.52	16.7	8.0
Business Trip	70	6.18	20.8	10.1
Shop	35	3.03	10.5	5.5
School	4	2.92	11.7	6.5
Social/Recreation	13	4.97	21.3	10.7
Personal Business	81	3.60	12.4	6.9
Eat Meal	256	2.99	10.2	5.4
Drop Off /Pick Up Passenger	21	4.56	20.6	8.9
Change Travel Mode	0	-	-	-
Refused/Don't Know/Missing	13	6.3	-	10.7
Total	986	4.67	14.8	7.9

Table A.50 Statistics for Journey from Work NHB Trips

Activity Type	No. of Trips	Survey Trip Length (min)	Network Trip Length (min)	Avg. Distance d_1 (mile)		Avg. Distance d_2 (mile)		Avg. Distance d_3 (mile)	
				Euclidian	Network	Euclidian	Network	Euclidian	Network
Other Work	94	23.3	11.6	14.48	12.22	7.78	6.45	12.69	10.66
Business Trip	81	21.6	13.0	14.93	12.82	11.87	9.68	16.63	13.43
Shop	314	20.7	10.6	5.44	4.78	9.74	7.66	10.75	8.84
School	51	33.0	16.1	13.85	11.59	13.55	11.18	14.00	12.03
Social/Recreation	117	25.9	11.2	9.25	7.27	9.01	7.59	11.09	8.67
Personal Business	286	22.0	10.3	8.60	7.23	10.89	8.44	11.29	9.35
Eat Meal	115	22.1	8.9	10.66	8.52	9.69	7.41	13.27	11.17
Drop Off/Pick Up Passenger	274	24.2	12.3	7.03	6.17	10.83	8.35	11.85	9.25
Change Travel Mode	14	16.4	8.9	16.60	13.54	6.80	5.52	20.93	16.69
Unknown	113	25.9	9.7	9.79	8.32	8.13	6.56	12.18	10.09
Total	1,459	22.9	11.1	8.87	7.50	10.11	7.99	12.05	9.82

To have a rough measure of the additional distance traveled or travel time spent for carrying out other activities, a detour distance is defined as $d_1 + d_2 - d_3$. The NHB activity that incurred the longest detour measured by network trip length for the home to work journeys was therefore business trips (11.24 miles), followed by social/recreation (5.33 miles), personal business (5.25 miles), drop off/pick up passenger (4.26 miles), school (4.12 miles), shop (3.35 miles), eat meal (3.3 miles), and change travel mode (2.11 miles). These results are provided in Table A.51.

Table A.51 Activities and Detour Distance (Network) During Journey to/from Work

Journey to Work		Journey from Work	
Activity	Detour ($d_1 + d_2 - d_3$) (miles)	Activity	Detour ($d_1 + d_2 - d_3$) (miles)
Business Trip	11.24	School	10.74
Social Recreation	5.33	Business Trip	9.07
Personal Business	5.25	Other Work	8.01
Drop Off /Pick Up Passenger	4.26	Personal Business	6.32
School	4.12	Social Recreation	6.19
Shop	3.35	Drop Off/Pick Up Passenger	5.27
Eat Meal	3.30	Eat Meal	4.76
Change Travel Mode	2.11	Shop	3.60
		Change Travel Mode	2.37

Table A.51 also compares the detours measured by the network trip lengths occurred during journey from work. The longest detour was school (10.74 miles), followed by business trip (9.07 miles), other work (8.01 miles), personal business (6.32 miles), social/recreation (6.19 miles), drop off/pick up passenger (5.27 miles), eat meal (4.76 miles), shop (3.6 miles) and finally change travel mode (2.37 miles). By comparing the above detour trip distances between the activities in the two trip chaining categories (i.e., home-to-work and work-to-home), people tend to travel farther on their way to work for business trip, social recreational, personal business, drop off/pick up passenger, school, shop, and change travel mode activities. On their way back from work, people tend to travel farther for school, business, and other work activities. The results presented in Table A.52 show that significantly more non-work-related NHB trips are related to personal business and shopping activities. Moreover, shopping trips have the shortest average spatial trip distance, survey trip length, and network trip length. This is an indication that people selected nearby locations to meet their shopping needs. Although not as obvious as shopping activities, the same pattern may be observed for personal business trips.

Table A.52 Statistics for Non-Work-Related NHB Trips

Activity Type	No. of Trips	Avg. Trip Distance (mile)	Survey Trip Length (min)	Network Trip Length (min)
Business Trip	151	6.27	25.2	9.1
Shop	947	4.26	15.6	6.9
School	324	4.63	20.0	8.3
Social/ Recreation	501	4.48	17.7	8.2
Personal Business	1,160	4.77	18.1	8.3
Eat Meal	330	5.41	17.6	7.4
Drop Off/Pick Up Passenger	632	5.30	18.4	9.4
Change Travel Mode	44	9.62	24.8	10.9
Unknown	357	5.48	16.1	8.7
Total	4,446	4.89	17.9	8.2