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Environmental Justice Ties to Electronic Travel Surveys and Transit Accessibility

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Environmental Justice Ties to Electronic Travel Surveys and Transit Accessibility

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CHAPTER 1: INTRODUCTION

BACKGROUND

Today's Environmental Justice (EJ) initiatives in transportation originate from Title VI of the Civil Rights Act of 1964. Title VI of the Civil Rights Act of 1964 (42 U.S.C. Section 2000d) states that:

"No person in the United States shall, on the ground of race, color, or national origin, be excluded from participation in, be denied the benefits of, or be subjected to discrimination under any program or activity receiving Federal financial assistance."

However, EJ initiatives generally did not become a forefront topic in transportation research until 1994 with the signing of Executive Order 12898: Federal Actions to Address Environmental Justice in Minority Populations and Low-Income Populations:

"Each Federal agency shall make achieving environmental justice part of its mission by identifying and addressing, as appropriate, disproportionately high and adverse human health or environmental effects of its programs, policies, and activities on minority populations and low-income populations."

The Department of Transportation uses this Executive Order to define their guiding Environmental Justice principles, briefly summarized as follows:

- To avoid, minimize, or mitigate disproportionately high and adverse human health and environmental effects, including social and economic effects, on minority populations and low-income populations.
- To ensure the full and fair participation by all potentially affected communities in the transportation decision making process.
- To prevent the denial of, reduction in, or significant delay in the receipt of benefits by minority and low-income populations.

While the DOT has been devoted to adopting environmental justice into its regulations many, such as Duthie et al *(1)*, believe major challenges still exist in incorporating EJ into metropolitan transportation planning. This thesis seeks to contribute to the DOT's guidance on social and economic effects of transportation planning in relation to minority populations and low-income populations.

STRUCTURE OF THESIS

Four chapters are presented in this thesis, including this first introductory chapter. The next two chapters present two separate research efforts with implications to environmental justice.

Chapter 2 is dedicated to investigating potential bias resulting from web-based implementations of electronic travel surveys, and using the special capabilities of the survey tool to reduce them. The degree of potential bias results from a person's propensity of Internet-use and could have significant impacts in planning for unemployed and low-income populations, as well as those relying on non-auto modes of travel. A paper "Analysis of a Method for Bias Reduction in Electronic Travel Surveys" is used to exemplify this chapter. This paper was presented at the Transportation Research Board 91st Annual Meeting in Washington DC.

Chapter 3 investigates the economic impacts of car ownership on low-income households. Auto dependence is a substantial economic burden for low income households, and detrimental to those who have made residential location choices in an attempt to adopt a public transit lifestyle. A relationship is then investigated between LIHCO households in the urban core and their transit access to low income jobs. A paper "Urban Core Transit Access to Low Income Jobs" is used to denote this chapter. This paper is set to be presented at the

Transportation Research Board 92nd Annual Meeting in Washington DC, and is currently being considered for publication in the Transportation Research Record.

The two research efforts outlined in Chapters 2 and 3 should be regarded in their own contexts and study objectives. Nonetheless, common ground between the two chapters is explored to develop an overall conclusion in Chapter 4 along with recommendations and suggestions for future research.

CHAPTER 2: ANALYSIS OF A METHOD FOR BIAS REDUCTION IN ELECTRONIC TRAVEL SURVEYS

ABSTRACT

Representative and up to date household travel data is crucial evidence for transportation planners and political authorities to make proper decisions on improving and maintaining our infrastructure. This research investigates the viability of Internet-based surveys to gather this information through comparing demographics and travel behavior among various levels of Internet-users. Data is gathered from an electronic, intercept-based household travel survey. Internet-use and daily number of non-auto trips are modeled with multiple regression, with employment status found to be a key indicator of each. This study finds that Internet-based surveys may come as a disadvantage for the unemployed, as their potential underrepresentation from less Internet-use may lead to inequitable transportation planning through less focus on public transit. Conclusions recommend supplemental survey methods such as those presented in this study should accompany Internet-based household travel surveys. Furthermore it is recommended demographic differences and mode choice options are included for those investigating the differences in travel behavior among ICT users.

INTRODUCTION

Effective transportation decision making requires a wide range of data. Ultimately the quality of a transportation policy decision made by political authorities and transportation engineers is dependent on the quality of that data. At the heart of these data needs is household travel data consisting of travel patterns, household characteristics, and individual personal attributes. The cost of collecting this data has risen significantly over recent years, as response rates have declined with traditional survey methods. The result is a limitation on the amount of quality data that can be put to use. Many planning agencies are forced to use older survey data that no longer applies to current travel conditions and demographic characteristics. This has a huge impact on our ability to effectively maintain our aging infrastructure.

Traditional telephone and mail-back survey methods have approached their limit of effectiveness. There has been a large public demand for increased privacy on the telephone. A significant number of households use methods such as caller-id and answering machines to screen phone calls. Even if a prospective participant in a household travel survey would normally be of interest in participating, since the general population is exceedingly jaded from telemarketing, they might mistake the survey inquiry as something else. Furthermore some households run lifestyles that leave the house vacant during times of surveying. Also the use of landlines is declining as households are making a switch to mobile devices as a main form of communication, which are not capable of being contacted by survey administrators. This leads to significant coverage error and loss of important data as households with higher levels of connectivity through cellular devices tend to be more mobile, which is important as the use of cellular devices becomes an integral element of society. Potential demographic differences between these mobile device users, or ICT (Information and Communication Technology) users, such as the employed versus the unemployed, act to compound response biases.

To make matters worse, when contact is achieved with a participant, the quality of data gathered through these means is often compromised due to recall errors that lead to underreporting, or false trip rate and trip length information due to trip chaining. A potential solution to the precluding problems is using the Internet as a means of data collection. The Internet offers the ability to create more integrated and user-friendly surveys to combat underreporting and capture information from mobile households that might otherwise be excluded. Such surveys have the ability to be sent via email or accessed on webpages, and may be completed at the convenience of the participant.

As suitable as Internet-based household data collection seems for the present and future of transportation planning, much is still to be learned about its effectiveness. New forms of coverage error emerge from those without access to the Internet such as the unemployed, or those who choose to use it infrequently. Some research suggests that even though new coverage errors would exist, they appear to be no worse, if not smaller than the coverage error presented by telephone surveys (*2*).

However, often overlooked in assessing the switch to Internet-based collection of household travel data is the potential difference in trip making behavior between internet users with different usage characteristics. For example, the unemployed, elderly or lower-income household members may not access the Internet as much as their demographic counterparts, and observed trip-making behavior may not accurately represent these populations. If significant differences exist, supplemental means of data collection must be implemented. This paper seeks to inform these issues by identifying demographic and socio-economic differences on the basis of Internet use, and analyzing trip making characteristics between them. Internet use and non-auto travel are then modeled based on demographic and socio-economic indicators. Data is gathered from an innovative electronic, intercept-based household travel survey administered at public libraries across the state of Connecticut.

This paper is organized as follows; the next section provides a brief synthesis of literature investigating Internet survey coverage and differences in travel behavior between Internet and non Internet-users. This is followed by a description of the study methodology. Then the results are presented and interpreted, showing the demographic and socio-economic indicators, along with the multiple regression models derived. The paper then concludes with a discussion of the results and their impact for future study on Internet-based household travel surveys.

LITERATURE REVIEW

Surveys are an integral part of many areas of research. Researchers in all fields have recently struggled with the increased burdens of telephone and mail back surveys, including rising unit costs, coverage error, and item non response. Alsnih (*3*) looks at Internet surveys as a combative measure to these rising unit costs, while providing a synthesis of web based surveys with applications in travel research. Adler et al (*4*) studied survey response rates and trip making non response in a household travel survey with a split sample of Internet, mail, and telephone survey methods.

Smith and Spitz (*2*) use two case studies to look into coverage error brought upon by Internet survey methods to perform travel surveys. Conclusions indicate when sampling frames are targeted to populations of drivers or transit riders, surveying by Internet methods does not introduce significant coverage error. Coverage error for Internet methods was found to be not worse than, and potentially smaller than that of telephone surveys. It is suggested research must be done in comparing travel behavior among populations with and without Internet access to test the need for supplemental survey methods.

Prior research investigating Internet (or general technology) usage and transportation has mainly focused on the relationship between the use of ICT's (Information and Communication Technologies) and travel patterns. Krizek and Johnson (*5*) define four types of interaction between ICT and travel. These four interactions include substitution, modification, complementarity (or generation), and neutrality. Substitution refers to a net decrease in travel demand through either a reduction in total number of trips or a reduction in trip duration as a result of ICT use. Modification refers to travel that is likely to be altered by a shift in timing and routing of trips through spatial and/or temporal transformations. Srinivasan and Athuru (*6*) state that this also includes how ICT users may save time and money through virtual activities, which may be used towards additional discretionary travel. Complementarity focuses on the induced trips as a result of ICT use, through better awareness of activity opportunities. Finally, neutrality simply refers to instances where ICT use has no foreseeable effect on household travel behavior. While the substitution hypothesis is one that holds great hope by many, the scale to which it is occurring is estimated to be much smaller than originally anticipated. This is first addressed by Salomon (*7*) as the importance of assessing future modifications of travel rather than focusing on the promises of substitution is shown. Mokhtarian (*8,9*), Mokhtarian and Salomon (*10*) state that while some short term studies may show cases of substitution, long term comprehensive studies are likely to show net complementarity effects brought upon by a faster growth in telecommunications than travel, but continued growth in travel in absolute terms.

Wang and Law (*11*) uses structural equations modeling to empirically investigate the complex relationships among ICT usage, activity participation, travel behavior and socio-demographics. Further evidence is provided on the complementarity and generation effects that ICT has on travel. It is found that the use of ICT led to more time for out-of-home recreation activities and more trips, which in turn increased total travel time. This study also provided more justification for the holistic and comprehensive approach to studying the interrelationships between ICT and travel and the need to analyze the indirect effects. Mosa et al (*12*) uses a simultaneous nonrecursive structural-equations model to capture the intrapersonal and interpersonal interactions in daily in-home and out-of-home physical and virtual travel decisions. The results show substantial linkages among joint and solo-activity participations patterns, household-individual characteristics and travel behavior. Virtual in-home activities had complementarity effects on out-of-home joint activities, as well as complementarity relationships between joint activity participation and the use of telecommunication. Hjorthol (*13*) conducted an analysis of daily travel and home computer use which indicated adjustment of work and family life, but no net reduction in travel activity. Mainly noted was a development of spatial and temporal flexibility brought upon by communication technology.

Srinivasan and Athuru (*6*) use travel data from the San Francisco Bay Area to model the relationship among ICT use, virtual activity participation, and travel patterns of individuals. More specifically a series of models was used to analyze ICT use and virtual activity participation patterns, the relationship between in-home and out-of-home participation in maintenance and discretionary activities, and models of travel patterns represented by the dimensions of aggregate trip frequency and trip duration in a day across all activities. The results provide considerable evidence in support of substitution and generation of trips due to

ICT (particularly Internet) use. Work-related characteristics and sociodemographic attributes strongly affected not only whether the Internet is used but also virtual activity purpose. A strong positive relationship between mobility needs and connectivity needs was suggested. This was also suggested by Viswanathan and Goulias (*14*) which reported that Internet use was correlated negatively with time spent on travel, whereas mobile phone use was positively correlated. Ren and Kwan (*15*) use multi-group structural equation modeling to examine the complex impacts of the Internet on human activity-travel patterns with a focus on gender differences. It is found Internet use for maintenance purposes has a greater impact on women's activity-travel in the physical world, while Internet use for leisure purposes affects men's physical activities and travel to a greater extent.

The studies cited provide valuable insights on various aspects of Internet survey coverage, and travel differences between ICT and non ICT users. This study seeks to combine these two issues by observing differences in Internet-use among the employed and unemployed, then modeling daily number of non-auto trips using data from various levels of Internet users to show response bias. From this, insight is gained on the ability of the Internet to function as a suitable medium to gather household travel data, and identify the need for supplemental methods of data collection

METHODOLOGY

The methodology utilizes an electronic household travel survey to obtain demographic and trip making data. The data is used to study demographic differences across Internet use and identify differences within these demographic strata in trip making behavior. An open-source survey software, LimeSurvey, was used to code the developed survey instrument and improve design flexibility and data output management (*16*). The survey was administered electronically as an intercept survey at five public libraries across the state of Connecticut.

Survey Questions

Survey questions were developed using accepted best practices in transportation survey design (*17*, *18*) and results of a pilot study performed in Connecticut testing online survey methods and question construction (*16)*. Participants were asked to report all of their own travel from the previous day. A trip was defined to the participant as anytime they left one location to go to another location. At the start of the survey an example was given of a person who made ten trips throughout a day. For each trip made the participant was asked to indicate the departure time, destination type and location, mode, and length in minutes. The participant was asked who they traveled with and whether or not they were the driver if auto was used as the mode. Transit access and egress mode was investigated as well as transit transfer information. This information was repeated for each trip using a conditional question format. An example of the conditional question format can be seen in Figure 1.

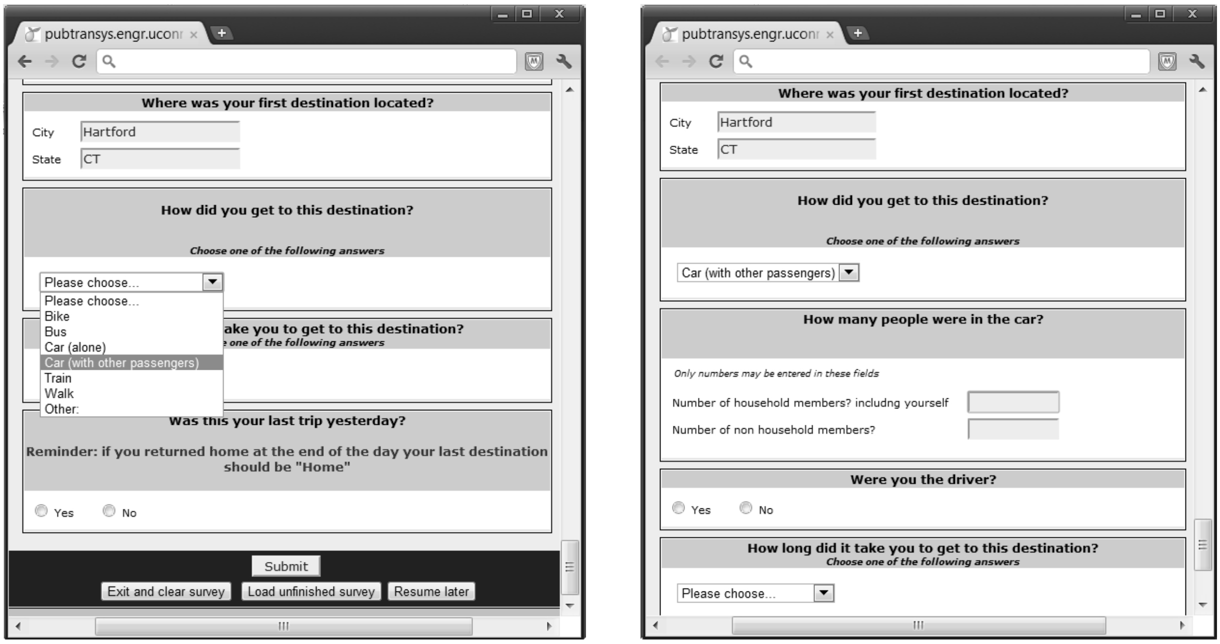

FIGURE 1 Example of conditional question formatting; Respondent chooses travel mode (left), then is prompted questions based on mode selection (right).

Remaining questions in the survey are categorized as household or personal. These questions along with their levels are summarized in Table 1.

TABLE 1 Breakdown of Survey Questions and Associated Levels

Type	Question	Levels
Household	Where is your current residence located?	City State Zipcode
	Do you own or rent your residence?	Own Rent or Lease Other: No Answer
	Do you live in a....	Single Family Home Duplex Townhouse or Rowhouse Apartment Mobile Home or Trailer Other: No Answer
	How many people live in your household?	1,2,3,4,5,6,7+
	How many people in your household are employed (including yourself)?	Full Time: Part Time:
	What is your households annual income range? (before taxes)	Less than \$20,000 \$20,001 - \$30,000 \$30,001 - \$40,000 \$40,001 - \$50,000 \$50,001 - \$60,000 \$60,001 - \$70,000 \$70,001 - \$90,000 \$90,001 - \$120,000 \$120,001 - \$150,000 More than \$150,000 No Answer
	How many motorized vehicles does your household own (or lease)? Do not include recreational vehicles (i.e. quads, dirt bikes..etc.)	0,1,2,3+
	How far is it from your home to the nearest bus stop or train station?	1 Block Less than half a mile More than half a mile No answer

<table>
<tr><td rowspan="10">Personal</td><td>Gender?</td><td>Female
Male</td></tr>
<tr><td>What is your race?</td><td>White
African American
Asian
Other:
No Answer</td></tr>
<tr><td>To which age group do you belong?</td><td>Under 15
15-21
22-35
36-59
60-75
75+
Other:</td></tr>
<tr><td>Are you currently employed?</td><td>Yes
No
No Answer</td></tr>
<tr><td>Are you a Student?</td><td>No
Yes, Full Time
Yes, Part Time</td></tr>
<tr><td>Approximately how often do you use a bicycle?</td><td rowspan="3">Every Day
More than THREE times a WEEK
TWICE a WEEK
ONCE a WEEK
TWICE a MONTH
ONCE a MONTH
less than ONCE a MONTH
NEVER</td></tr>
<tr><td>Approximately how often do you use public transit?</td></tr>
<tr><td>On average how often do you access the internet?</td></tr>
<tr><td>Do you have access to an internet connection?</td><td>No
Yes, At Home
Yes, At Work
Yes, At School
Yes, on my phone or mobile device
Yes, but only at public places
Other:</td></tr>
</table>

Survey Delivery

The survey was administered as an electronic intercept survey at five public libraries (Putnam, Norwich, Winsted, Simsbury, Hartford) across the state of Connecticut. Public libraries were sought as a place where a higher rate of respondents would be found to have limited Internet access/use, a demographic which needed to be well represented. 41% of respondents who took the survey were unemployed, which turned out to be a key demographic for analysis.

Public libraries also function as a means to gather information in geographic areas that might be underrepresented in an on-line survey. In the pilot study (*16*) there were significant demographic (age, income, employment) and geographic (rural) underrepresentation identified that benefit from the targeting displayed in Figure 2. As seen in Figure 2, a relatively broad geographic spread was achieved during this first intercept survey phase, as areas in the center, NW, NE, and SE areas were targeted. The survey was administered on laptop computers with survey teams in groups of one to three. To increase response efficiency the survey was administered at each location for a maximum of six hours per day over a period of two days.

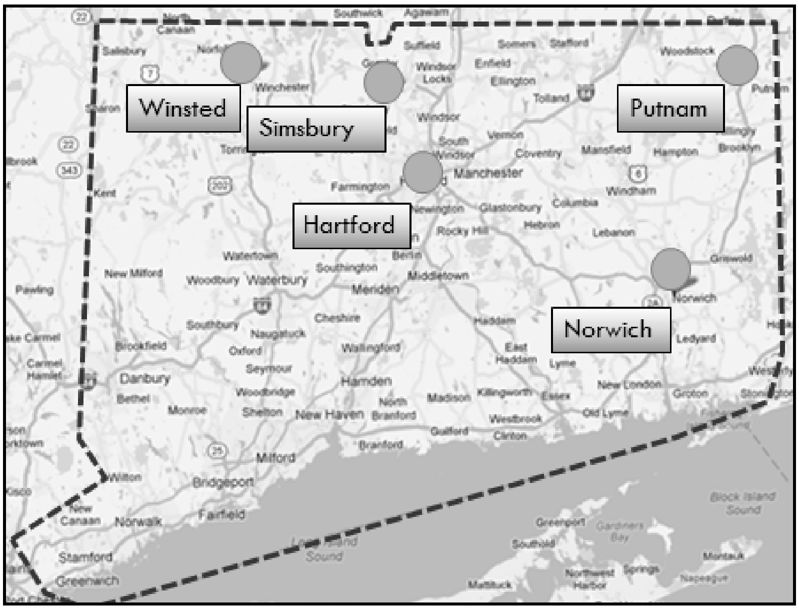

FIGURE 2: Geographic Location of Survey Sites

Modeling

Hypothesis testing was performed to find differences in Internet use and the number of non-auto trips made within the demographics to select appropriate variables for multiple regression models. A Student's t-distribution was assumed since the population standard deviation is unknown. Sample sizes were unequal and the population variances were assumed to be different for each variable being tested, therefore a Welch's t-test was performed. Unlike in Student's t-test, the denominator is not based on a pooled variance estimate. The t statistic to test for a difference in population means is calculated as follows:

$$t = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

Where:

$\overline{X}_i$	=	i^{th} sample mean
s_i^2	=	i^{th} sample variance
n_i	=	i^{th} sample size

Multiple regression models were then estimated using variables suggested from the t-tests: one model for Internet use and one model for number of daily non-auto trips. A multiple regression model has a sample of n items, and on each item a measured dependent variable and p independent variables $x_1, \ldots, x_p$. The i^{th} sample item gives rise to the ordered set $(y_i, x_{1i}, \ldots, x_{pi})$. The multiple regression model takes the form:

$$y_i = \beta_0 + \beta_1 x_{1i} + \ldots + \beta_p x_{pi} + \varepsilon_i$$

Where:

β_p	=	p^{th} regression coefficient
ε_i	=	i^{th} error term

There are four assumptions made. The errors $\varepsilon_1,\ldots,\varepsilon_n$:
are random and independent.
all have mean of zero.
all have the same variance.
are normally distributed.

These assumptions imply that the observations y_i are independent random variables, each with its own normal distribution. These assumptions have been tested using standard statistical processes (*19*) and the evidence suggest they are valid for this dataset. The following table displays the breakdown of the independent variables.

TABLE 2 Breakdown of Variables

Variable	Value	Description (Abbreviation)
Employment	0	Unemployed (UE)
	1	Employed (E)
Gender	0	Male (M)
	1	Female (F)
Age	0	Over 60 years (O60)
	1	Under 60 years (U60)
Race	0	Non White (NW)
	1	White (W)

Notes: 0 = Baseline Value

To maintain focus on employment status in the models, the income variable was eliminated due to a strong correlation observed between it and unemployment. It was found that low-income households in general were associated with much higher unemployment rates. This is observed in Figure 2 where it can be seen that majority of the unemployed had an income less than $30,000.

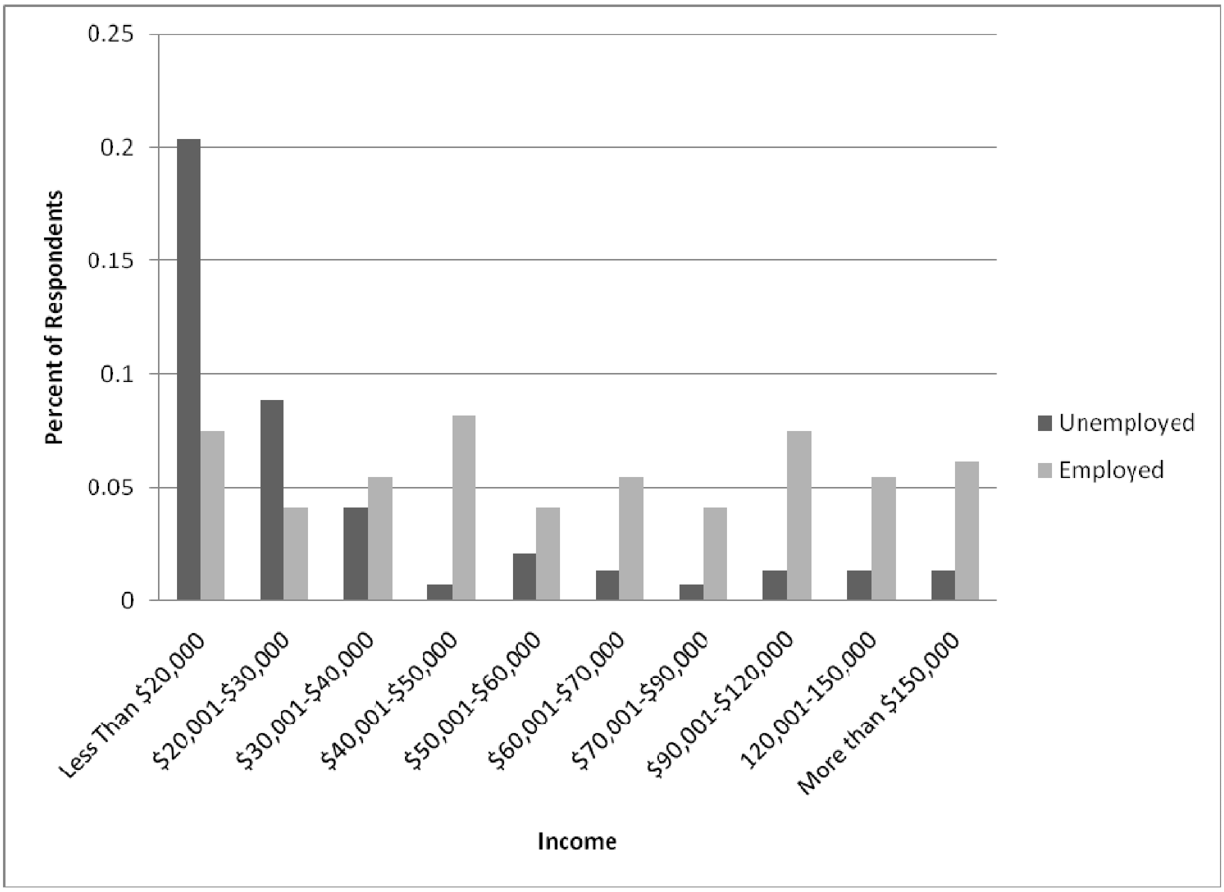

FIGURE 3 Histogram Comparing Income of the Employed and Unemployed

Other adjustments made for the model occurred within the Internet-use variable. When responding to the question on Internet-use, respondents chose their answer from a dropdown menu containing categorical values (See Table 1). When performing analysis, variables ranging ONCE a WEEK to less than ONCE a MONTH were combined to a single category due to small representation within each. For the model, these categorical variables had to be converted to continuous variables. Categories were converted to number of days Internet is accessed per month, represented by; 30, 16, 8, 3, and 0 respectively.

RESULTS

Internet-Use Model

Hypothesis testing results for difference in means among Internet-use is shown in Table 3. In particular, hypothesis tests were conducted to compare the internet usage characteristics of:

- The unemployed vs. the employed
- Low-income households vs. other
- Males vs. Females
- Non-white respondents vs. white respondents
- Respondents 60 and over vs. those under 60

In each test, the original hypothesis being tested was that the former category (unemployed, low-income, males, non-white, elderly) would have lower internet usage characteristics that their counterpart.

TABLE 3 Internet-Use t-tests

Variable	μ_1	μ_2	t-stat
Employment Variable 1: Unemployed Variable 2: Employed $H_o = \mu_1 \leq \mu_2$	18.12987	23.5	-2.949 **
Income Variable 1: Under 30k Variable 2: Over 30k $H_o = \mu_1 \leq \mu_2$	18.92647	23.79348	-2.567 **
Gender Variable 1: Male Variable 2: Female $H_o = \mu_1 \leq \mu_2$	19.26957	23.35135	-2.338 *
Race Variable 1: Non White Variable 2: White $H_o = \mu_1 \leq \mu_2$	18.65854	22.56075	-2.180 *
Age Variable 1: 60 and over Variable 2: Under 60 $H_o = \mu_1 \leq \mu_2$	21.57143	20.82353	0.322

*Notes: * significant at 5% level, ** significant at 1% level, no asterisk indicates insignificant at 5%*

From these tests it can be seen that employment and income are significant at a 1% level, and gender and race are significant at a 5% level. Age was shown to be insignificant. This provides evidence that Internet-use is strongly influenced by employment and income, while also being influenced by gender and race. As stated in the methodology, employment and income were expected to hold similar influences due to their correlation. Therefore when variables were chosen for the regression model income was eliminated to emphasize the focus on employment and reduce any confounding in the estimated model. The results of the multiple regression estimation of Internet-use are presented in Table 4 and correspond to the form:

$$I_i = \beta_0 + \beta_E E_i + \beta_R R_i + \beta_G G_i + \varepsilon_i$$

Where I = Internet-Use

TABLE 4 Regression Model Parameter Estimates for Internet Use

Variable	Abbreviation	Coefficient (β)	t-stat	P-value
Employment	E	4.4340	2.434	0.0160
Race	R	3.2898	1.823	0.0700
Gender	G	2.3892	1.291	0.1983
Intercept		15.8237	9.634	0.0000
R Square	0.0804			
Observations	175			

Of the variables within the Internet-use model developed, only employment was significant at the 5% level. In this analysis, race and gender are included as control variables as evidence from the t-tests suggests that they play a role in Internet use. It is suspected that a larger sample size would provide the observations needed for improved statistical significance to be reported.

This suggests that certain demographic strata, especially employment status would be underrepresented in an Internet-based household travel survey. This can be expected as the unemployed will tend to have a lower annual household income. Under these circumstances Internet becomes less accessible due to the cost of subscribing and owning a computer, or an inability to operate a computer and/or the Internet. Without the representation of the unemployed, the data obtained may lead to transportation models that are overly commuter-based. This could place unnecessary emphasis on automobile and freeway trips, which would reduce equity in the provision of transportation by excluding captive transit users and non-auto users. Of those surveyed, the employed (56% of respondents) had a household average of 1.88 motorized vehicles, with only 12% of households owning zero. This is compared to those surveyed who were unemployed (41% of respondents) which had a household average of 0.86 motorized vehicles and 49% of households owning zero (A t-test performed for difference in means of number of vehicles was found to be significant at the 1% level). Unemployed households averaged a full vehicle less than the employed, and over four times the percentage of households with zero motorized vehicles. As significant users of non-auto modes, the unemployed must be represented to support the need for more efficient and accessible public transit and walkable urban areas, which in turn may open doors to new job opportunities.

Daily Non-Auto Trips Model

As with Internet-use, hypothesis testing was performed for differences in means among trip-making variables. These variables included; daily number of trips, daily total travel time, daily number of auto trips, and daily number of non-auto trips. Of these four dependent variables, only daily number of auto trips and daily number of non-auto trips were found to have statistically significant variables within them. The lack of relationships within total number of trips and daily total travel time support the theory that substitution effects of Internet-use are negligible, since no relationship between Internet-use and travel time were observed. Modification and complementarity appear to be more likely phenomenon as the ability to model different modes can show differences in spatial and temporal flexibility. Auto trips would be more flexible in this regard than non-auto trips since non-auto trips generally involve public transit, which is limited in its spatial and temporal capabilities. This increased flexibility among Internet-users was observed by Hjorthol (13). The fact that employed households own on average an entire car more than the unemployed, and are also more likely to use the Internet, helps explain one of the reasons for modification among Internet users vs non Internet-users. It is important to note based on this explanation that modification observed by Internet-users may not simply be a result of their online activities.

To emphasize employment status impacts on travel characteristics, a model for daily non-auto trips was chosen, as the unemployed would be expected to play a strong role. Hypothesis testing for difference in means among number of daily non-auto trips is summarized in Table 5.

TABLE 5: Number of Daily Non-Auto Trips t-test

Variable	μ_1	μ_2	t-stat
Employment Variable 1: Unemployed Variable 2: Employed $H_o = \mu_2 \leq \mu_1$	1.220779	0.683673	-2.465 **
Income Variable 1: Under 30k Variable 2: Over 30k $H_o = \mu_2 \leq \mu_1$	1.323529	0.684783	-2.799 **
Gender Variable 1: Male Variable 2: Female $H_o = \mu_2 \leq \mu_1$	1.130435	0.608108	-2.601 **
Race Variable 1: Non White Variable 2: White $H_o = \mu_2 \leq \mu_1$	0.987805	0.878505	-0.536
Age Variable 1: Over 60 Variable 2: Under 60 $H_o = \mu_1 \leq \mu_2$	0.371429	1.058824	-3.639 **

*Notes: ** significant at 1% level, no asterisk indicates insignificant within 5%*

From these tests evidence is gathered that the number of daily non-auto trips can be explained by employment, income, gender, and age. Employment, income, and gender variables overlap as predictor variables for both Internet-use and non-auto trips. Therefore from the t-tests it is suspected that there is some relation between Internet-use and daily number of non-auto trips. Statistically significant variables established from the t-tests were used to inform multiple regression models predicting non-auto trips. Once again income was excluded from the model. To display the effects of Internet access, four different models were derived, each formed from different pools of respondents based on their Internet-use.. The first model was derived from all of the respondents, the second from those who use the Internet eight or more days per month, the third from those who use the Internet sixteen or more days per month, and the fourth from those who use the Internet everyday. This shows how the trip making model changes depending on the level of survey penetration achieved by means of Internet distribution. The results of the multiple regression output of non-auto trips are presented in Table 6 and correspond to the form:

$$T_{NA} = \beta_0 + \beta_E E_i + \beta_A A_i + \beta_G G_i + \varepsilon_i$$

Where T_{NA} = Daily Number of Non-Auto Trips

TABLE 6: Regression Model Parameter Estimates for Number of Daily Non-Auto Trips

Respondents	Variable (Abr.)	Coefficient (β)	t-stat	P-value	R Square	Obs.
All	Employment (E)	-0.5537	-2.770	0.0062		
	Age (A)	0.7276	2.866	0.0047		
	Gender (G)	-0.4344	-2.136	0.0341		
	Intercept	0.7825	3.014	0.0030	0.1265	173
Use Internet 8 or more times per month	Employment (E)	-0.5354	-2.386	0.0185		
	Age (A)	0.6717	2.347	0.0204		
	Gender (G)	-0.4182	-1.846	0.0671		
	Intercept	0.7820	2.562	0.0115	0.1275	137
Use Internet 16 or more times per month	Employment (E)	-0.4639	-1.943	0.0543		
	Age (A)	0.6368	2.190	0.0304		
	Gender (G)	-0.3800	-1.598	0.1125		
	Intercept	0.7165	2.317	0.0222	0.1075	128
Use Internet everyday	Employment (E)	-0.5503	-2.056	0.0423		
	Age (A)	0.7259	2.338	0.0213		
	Gender (G)	-0.2704	-1.045	0.2983		
	Intercept	0.6033	1.803	0.0742	0.1149	108

Note: Variables significant at 5% level except those in bold

As the sample decrease towards those with the most Internet-use and does not account for those with limited Internet-use, the significance of the gender variable in the models decrease and the models become less powerful. The model containing all users (both Internet and non Internet-users) is the strongest, containing variables that are the most significant. Output from the models are shown in Figure 4.

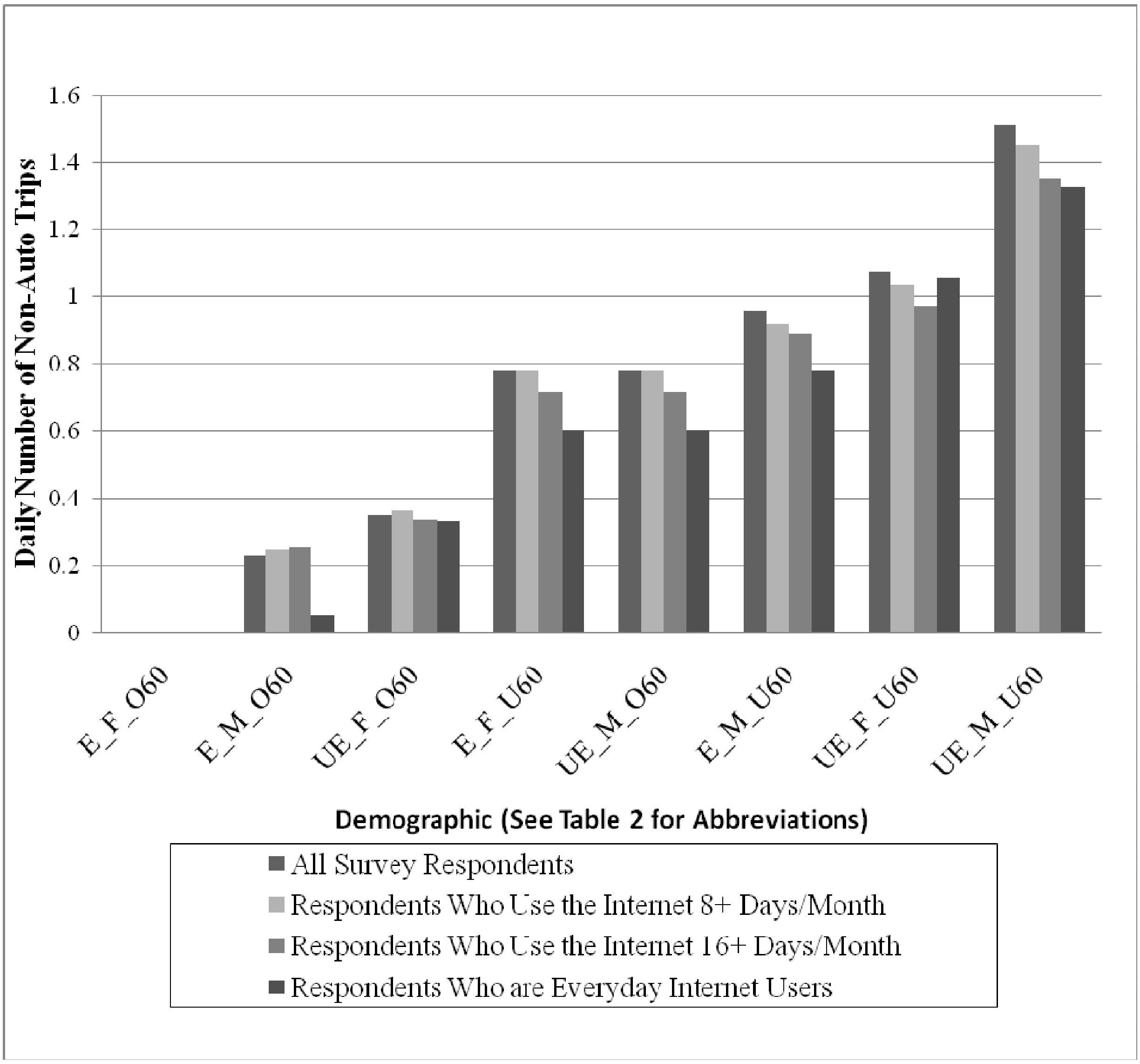

FIGURE 4 Output Results for Daily Number of Non-Auto Trip Models Varying by Internet-Usage.

Figure 4 shows non-auto daily trip rates as a function of employment, age, race and internet usage if the developed model is applied. This indicates further evidence that a response bias may occur if a travel survey is not distributed to those with less frequent Internet use. Burdens from such biases will fall on the unemployed as they account for the most daily non-auto trips from the sample; on average they make 1.22 daily non-auto trips versus 0.68 for the employed.

CONCLUSIONS

Internet survey distribution offers a means supplementing or complementing data collection methods that are either obsolete or overly labor intensive. However, this does not come without new dangers of response bias. While more research is needed to fully investigate where these biases exist and how they may impact transportation planning, this study shows how the unemployed may be underrepresented and ultimately negatively impacted by an Internet-based survey. Evidence shows the unemployed most likely access the Internet less than the employed. Not accounting for the unemployed may under represent the need for public transit in a transportation planning survey that is exclusively Internet-based.

To achieve an inclusive sampling frame, supplemental survey methods such as the electronic intercept survey implemented in this study should be performed in addition to an Internet-based administration. Of all the survey respondents, 41% were unemployed, indicating the method utilized for this project would be a strong starting point. This can be accomplished utilizing public libraries, schools, and other community centers that may be strong attractors for the unemployed or lower-income households. Another benefit of these supplemental survey methods is their ability to target specific geographic locations across the state to achieve full geographic representation, which is especially important in statewide planning survey applications in smaller states such as Connecticut with diverse and distinct urban and rural populations.

In this analysis, hypothesis testing supported the current thought that suggests substitution effects are negligible for Internet-users. Furthermore, a case can be made for modification based from spatial and temporal flexibility of auto-use by the employed, who ultimately use the Internet more than the unemployed. The unemployed, who use the Internet less and have a higher dependence on public transit, are constricted in their travel options. This provides evidence that modification is not solely impacted by activities carried out on the Internet, and research should be conducted to investigate the degree to which differences in travel behavior due to ICT use are a result of demographic differences and mode choice options.

Continuing research will take a structural equation modeling (SEM) approach to examine the casual relations between Internet-use, demographics, and travel behavior.

CHAPTER 3: URBAN CORE TRANSIT ACCESS TO LOW INCOME JOBS

ABSTRACT

In many areas around the country, low income jobs have followed patterns of suburbanization, resulting in a spatial mismatch between low income workers residing in dense urban areas and low income jobs located in suburban areas of the outlying urban periphery. This facilitates a need for auto ownership in core urban areas traditionally thought to be rich in transit supply and robust in transit accessibility. Resulting auto dependence is a substantial economic burden for low income households, and detrimental to those who have made residential location choices in an attempt to adopt a public transit lifestyle. This paper seeks to explain varying levels of Low Income and High Car Ownership (LIHCO) households in the urban core by investigating their accessibility to low income job locations. Two transit accessibility metrics geared towards low income populations are derived, and applied. The first score is based on the number of low income jobs accessible by transit from the residential location, and the second is based on late night transit frequency at the residential location. These accessibility scores are then correlated with the magnitude of LIHCO households residing in each spatial unit of analysis. The results suggest a link between transit access to low income jobs, late night transit frequency, and the number of LIHCO households in existence. It is concluded that improving transit access to low income jobs and increasing late night transit frequency may reduce auto ownership among LIHCO households, improving their economic welfare.

INTRODUCTION

A household's economic welfare can be dramatically affected by transportation expenditures. Transportation accounts for a significant portion of household expenditures, ranking as the second highest share since the 1970's (*20*). Recently, transportations costs have been rising at a faster rate than household income, which is especially troubling during recent times of increasing gas prices and increased unemployment. These impacts can be even greater for low income households who live an auto dependent lifestyle, and are magnified by the greater number of vehicles a household operates.

A simple way to reduce transportation expenditure is to reduce auto use and increase public transportation use. However, even in central areas of our most robust transit systems, many low income households choose to own and operate multiple vehicles at a large economic disadvantage, even when public transportation is available at a much cheaper cost. This suggests that contemporary transit services may not be tailored to low income households within the urban core. This study seeks to investigate auto dependence among low income households in the urban core as a function of two explicitly derived transit accessibility metrics for low income populations. The first metric is formed by transit access to high-density low income job areas, and the second from late night transit frequency. The target demographic of this study is Low Income and High Car Ownership (LIHCO) households.

This paper proceeds with a literature review of previous LIHCO studies, and highlights the role of public transportation system design in the transport options of low income members of the urban core. The Methodology section develops a transit accessibility metric based on access to low-income jobs and applies them in a case study. The results section uses the relationships between the location of LIHCO households and transit accessibility metrics to estimate a multiple regression model estimating the percentages of low-income households that fall into LIHCO categorization. The final section concludes the paper with a short discussion on what the findings suggest about current transit policy.

LITERATURE REVIEW

Currie and Senbergs (*21*) investigate "forced car ownership" in Melbourne as a relationship between income, location, car ownership, and public transport supply. Analysis found a one-to-one relationship between High Car Ownership on Low Income (HCOOLI) households and public transport supply in the urban fringe, but minimal association within the urban core, directing a majority of Currie's research to focus on the fringe and outer areas of Melbourne. The degree to which car ownership is "forced" upon HCOOLI households in the fringe is explored in Currie and Delbosc (*22*). They find that Low Income and High Car Ownership (LIHCO) households are less concerned with public transportation access than they are with home affordability and living near green spaces such as parks and open country. This is in comparison to Low Income and Non Car Owning (LINCO) households in the fringe who were able to make financially sustainable home location decisions to balance mobility and accessibility with their limited budgets. Further study in Currie et al (*23*) find even though LIHCO households in the fringe place more value in mobility and cheaper dwellings than public transport, they demonstrate numerous strategies to reduce high car costs. Many limit their travel as a result of costs, and own older/second hand cars which are more expensive to operate in the long-term (*21*).

In the urban core, it should come as no surprise that adopting a public transportation lifestyle can reduce household transportation costs. Baily (*24*) finds households that use public transportation saved an average of $6,251 annually when compared to an equivalent household with no access to public transportation. A strong majority of our most robust transit systems are designed to offer extensive accessibility in the core areas of our cities, which should intuitively result in reduced auto ownership and dependency in these areas. Despite this, reducing auto ownership among the low income in the core is more difficult in practice.

Research by Sanchez (*25*) finds it is difficult for public transportation to overcome the spatial mismatch between urban worker residence and job location, suggesting that vehicle ownership remains a key factor in job accessibility and labor participation. Sanchez finds employment levels are not positively influenced by the availability of transit service, being that most transit systems provide an insufficient level of service at off hours for entry-level, low-skill, temporary, and shift-work positions which often correlate to low-income wages. Research by Giuliano (*26*) suggests the suburbanization of low income jobs as one of the three main ways low income households in the inner city are disadvantaged by limited mobility. The other two disadvantages stem from transit fare structures and consumer captivity in goods, services, and medical care. Giuliano argues transport service costs lead low income populations to pay a higher transit fare per unit of service as low income households adapting to limited mobility resources take shorter trips. Flat fares or fares based only lightly on trip distance mean that shorter trips have a higher price per unit. Also since transit demand is generally larger in low income areas, fares from low income populations are contributing a higher percentage to fare box revenues which has become an even greater burden as many transit agencies have recently increased fares in an effort to displace operating costs as federal funding has become more competitive.

Giuliano further argues low income populations who are transport disadvantaged may become captive consumers of goods, services, or medical care. Establishments may charge higher prices when consumers are limited to local neighborhood stores and services. Consumer captivity of low income urban populations without personal auto is also explored in Coveny and O'Dwyer (*27*) who find difficulty in accessing quality food shops, even in areas undesignated as "food deserts," resulting in high financial and temporal costs. Furthermore Wallace et al (*28*) and Sipe et al (*29*) investigate missed medical appointments as a result of using public transportation. Lucas (*30*) suggests the lack of at least one car within a household considerably reduces the life chances of its members, forcing many low income families to own cars as the only means of guaranteeing their inclusion in society. Gleeson and Randolph (*31*) provide their analysis of how current land use and infrastructure policy is worsening transport poverty by making car ownership more necessary in Sydney. Recent efforts have focused on increasing the quality of transit service for the transportation disadvantaged and transit dependent relative to auto accessibility. Duthie et al (*32*) developed the transit frequency problem, which accounts for environmental justice factors to minimize the differences in accessibility between transit and auto. Mamun and Lownes (*33*) incorporate transit needs into transit accessibility indexing to evaluate existing transportation systems and their service gaps by including a variable for LIHCO households.

A metric designed to measure the link between low-income urban core dwellers – those considered transport disadvantaged in many cases and transit accessibility is presented in the next section. Following the description of the metric development is an application to a case study in New Haven, CT.

METHODOLOGY

Transport Disadvantage and Auto Ownership

Many early studies which combine low income populations with high vehicle ownership used the term “forced car ownership.” However, as in Currie and Senbergs (*21*), the authors of this paper have chosen to define analysis based on “Low Income and High Car Ownership (LIHCO)” households. To suggest that car ownership among all low income populations is “forced” is somewhat naive, as many different reasons for vehicle ownership exist for members of this demographic, especially among different residence locations. In certain low income populations vehicle ownership comes not as a burden, but rather part of a lifestyle choice. One example of this choice is those who live outside of central high density areas, who perhaps choose access to green-spaces, better schools, and cheaper housing over access to public transportation. Suggesting auto ownership is forced among these populations would be unwarranted. However, under certain conditions we come closer to observing auto ownership that may be viewed as “forced” and not a lifestyle choice. This condition may exist in areas where low income households have made a residential location choice in an effort to benefit from public transit options, which generally occur in urbanized areas. Auto ownership may be necessary if these households find that although public transit options exist, they do not outweigh the benefits offered by a personal auto, regardless of the financial burden. Under this assumption, we observe “forced car ownership” when we investigate LIHCO households in the urban core.

This study defines LIHCO as households with 2+ vehicles and \$0-20K household income, or 3+ vehicles and \$20-30K household income.

Personal Vehicle Expenditure

Transportation has been the second highest share of household expenditures since the 1970's. Many policies and studies have focused on transportation costs, although usually via reducing vehicle ownership costs and gas prices which account for only around 16% of total transportation expenditures (*20*). From 2000 to 2005 average transportation and housing costs rose 13.4% and 15.4% respectively while household income only rose 10.3% (*34*). More recently, from 2009-2010 household income dropped 0.6% and expenditures on food dropped 3.8%, but transportation costs remained about the same, increasing by 0.2% (*35*).

Baily (*24*) found that households who used public transportation saved a significant amount of money annually. A "public transportation household" (located within ¾ mile of public transportation, with two adults and one car) saved an average of $6,251 in 2006 ($7,115 in 2012 dollars) when compared to an equivalent household with two cars and no access to public transportation. To put this into perspective, the average U.S. household spent $5,781 on food in 2004 ($7,023 in 2012 dollars). Baily also estimated a scenario with a hypothetical gas price of $4.00 per gallon with taxes, and found average household expenditures on gasoline in 2006 would have equaled around $2,788 dollars per year ($3,172 in 2012 dollars). This is noteworthy as the U.S. Energy Information Administration (*36*) estimates a similar average gasoline price of $4.01 for the summer of 2012. AAA (*37*) estimated the 2010 average vehicle ownership cost to be $8,487, or 56.6 cents per mile, for a car driven 15,000 miles per year. This estimate accounts for fuel, maintenance, tires, insurance, taxes, depreciation, and finance, as seen below in Table 1. Many families cope with these high auto ownership costs by skipping routine maintenance, purchasing used or hand-me-down vehicles, or even driving uninsured. However, many times these strategies result in higher long-term costs. Historically high unemployment rates coupled with all of the above means many households nationwide have recently experienced setbacks in affording travel by personal vehicle for the very first time.

TABLE 1: Yearly Driving Costs by Vehicle Type and Total Miles Driven (2010)

Driving Costs	**Small Sedan**	**Medium Sedan**	**Large Sedan**	**Average**
Operating Costs (Cents/Mile)				
Gas	9.24	11.97	12.88	11.36
Maintenance	4.21	4.42	5.00	4.54
Tires	0.65	0.91	0.94	0.83
Cost Per Mile	14.1	17.3	18.82	16.74
Ownership Costs (Dollars/Year)				
Insurance	1,005	1,004	1,084	1,031
License, Registration, Taxes	427	583	745	585
Depreciation	2,384	3,451	4,828	3,554
Cost Per Year	4,381	5,841	7,707	5,976
Total Cost (Dollars/Year)				
10,000 Total mi/yr	5,636	7,285	9,259	7,393
15,000 Total mi/yr	6,496	8,436	10,530	8,487
20,000 Total mi/yr	7,321	9,519	11,721	9,520

Source: AAA: Your Driving Costs (18)

Transit Accessibility and Transport Disadvantage in the Urban Core

An investigation of the relationship between transit accessibility and LIHCO is now presented. This is first attempted in Currie and Senbergs (*21*) , in which a significant relationship is found between LIHCO households and transit access in the middle and outer areas of Melbourne's metropolitan area. However in these outer city areas, it is hard to justify that the magnitude of LIHCO households is a direct result of the availability of public transit, as other studies by Currie and Delbosc (*22*) show those who choose to reside in the urban fringe are generally not worried about reduced transit supply or the cost of owning a vehicle. LIHCO households residing in the Melbourne urban fringe find more utility in factors such as reduced housing costs, better schools, and being close to parks and open-county. None of the LIHCO households surveyed in the urban fringe listed distance to public transit as a top three reason for choosing their home location and were highly supportive of their auto dependent home locations. 82% said it was great to own their vehicle(s) and were happy to pay for good mobility. 65% said the benefits of living in the fringe outweighed the travel costs. 0% said it was a mistake living there because transport costs were too high. These findings suggest that policy aimed towards reducing the number of LIHCO households in urban fringe and other outside areas might be an inefficient use of resources.

As a result, transit accessibility may be more important to LIHCO households residing in the urban core. The case for improving transit access for low income households in the core is justified by Sanchez (*25*) and Giuliano (*26*). Both describe the burdens faced by low income households commuting to work from the suburbanization of low income jobs. Sanchez further argues that poor late night service levels are a burden for low income households, and Giuliano argues fare structures and consumer captivity can be a burden as well.

As stated earlier, a significant relationship was found in the middle and outer Melbourne areas between LIHCO and public transport supply in Melbourne. However the method used in the study to quantify public transport supply for the entire region was heavily influenced by overlapping transit stop buffers, which is an attribute common to most inner city areas and detrimental to observing a relationship at such a level because it results in little variability in transit access throughout the urban core. As a result inner Melbourne exhibited a much higher supply score than the middle and outer areas, and offered no variability with which to compare to levels of LIHCO. This suggests that a study of the urban core region may require supplementary case-specific methods for quantifying transit accessibility in order to establish a relation to LIHCO.

Case Study Application

The authors sought to test multiple transit accessibility metrics in the urban core of New Haven, CT and observe their relation to existing LIHCO levels at the census block group level. New Haven is the second largest city in Connecticut with a population near 130,000 and an aggregate population density of 19.68 persons/hectare, almost exactly the 20 persons/hectare criterion for urban core suggested by Newman and Kenworthy (*38*). With continuing downtown urban renewal, population density within the city is expected to keep rising. New Haven's bus system is operated by the New Haven Division of CT Transit. It is the second largest system in the state of Connecticut, with 24 routes, all of which originate from the New Haven Green, clasifying it as a hub-and-spoke network. Currently there is a flat rate fare of $1.30, with reduced fair for youths and seniors and a commuter tax incentive program which allows employess to set aside pre-tax income to pay for bus commuter costs. However, ConnDOT and the Connecticut Department of Social Services (DSS) are working together to increase transportation resources for low-income workers under Job Access and Reverse Commute (JARC). This will be accomplished by adding hours of service, days of service, or expanding routes when needed using the existing transportation network. A map of New Haven as well as its LIHCO characteristics are displayed below in Figure 1. LIHCO is represented as a percentage among low income households ($0-30K). There are a total of 1,241 LIHCO households residing within New Havens borders.

LIHCO and Existing Transit Accessibility Measures

A simple regression anlysis (results summarized in Table 2) was conducted to identify correlation between common spatial and temporal transit accessibility metrics and the percentage of low-income household in a block group belonging to the LIHCO cateogrization. Three accessiblity methods were initially tested. The Time-of-Day Tool (*39*) (TOD), the Local Index of Transit Availablility (*40*) (LITA), and theTransit Capacity and Quality of Service Manual (*41*) (TCQSM). Also presented in Table 2 are the metrics involved in each of these methods. Year 2000 data from the Census Transportation Planning Package (CTPP) (*42*) was used to identify LIHCO households as a percentage of low income ($0-30K) households at a census block group level. The Time-of-Day tool provided the best fit suggesting temporal aspects of accessibility may play an important role in reducing LIHCO. However, even in the case of the TOD tool, the explanatory power was not very compelling. This suggests that while spatial coverage and service frequency are necessary conditions for reducing auto dependency in the urban core, they are not sufficient indicators of the most important factors for LIHCO households.

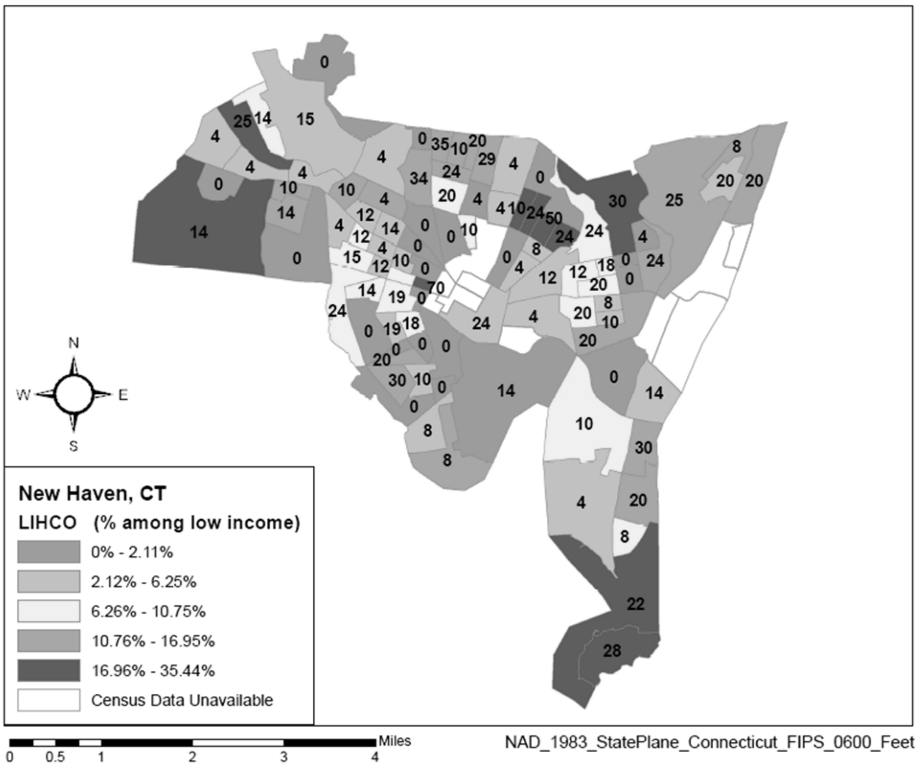

FIGURE 1: New Haven Low Income and High Car Ownership
Note: Numbers on map represent aggregate number of LIHCO households in each block group for a total of 1,241.

TABLE 2: Accessibility Metrics by Method and Regression Statistics with LIHCO

Method	Accessibility Metrics	R^2	P-value	Observations
TOD*	Service Coverage	0.042	0.046	96
	Service Frequency			
	Demographics			
	Travel Demand			
	Waiting Time			
LITA	Service Coverage	0.040	0.051	
	Service Frequency			
	Demographics			
	Capacity			
TCQSM	Service Coverage	0.003	0.574	

Note: * significant at 5% level

Investigating Supplementary Transit Accessibility Metrics to Explicate LIHCO Variance within the Urban Core

With common accessibility methods explaining only a small fraction of the correlation between transit access and LIHCO households, a different approach was needed. The approach adopted stems from the notion that one of the major factors impacting low income households is the suburbanization of low income jobs. As low income jobs have moved outside the core into the periphery, accessing work via public transit has been increasingly difficult for many low income workers, especially as many public transportation systems are designed to bring workers into, not away, from the city core. The fact that the previously tested accessibility measures do not connect any origin and destination pairs may explain their lack of correlation. It is hypothesized that finding a significant factor which leads to increased LIHCO households in the core might account for access to low income jobs.

Using the New Haven case study, the representation of access to low income jobs locates the census block groups that exist within a quarter mile of a New Haven CT Transit bus stop.

The number of low income jobs within each of the resulting block groups is then calculated as the number of workers working within the group whose yearly income is $0-30K also using year 2000 data from the Census Transportation Planning Package (*42*), which is the same income range defined for LIHCO households. Analysis was limited to the 95th percentile block groups of low income jobs which equated to block groups (based on a fitted lognormal distribution with $\mu = 1$ and $\sigma = 0.5$) with over 620 low income jobs. Narrowing this analysis window demonstrates the spatial mismatch of low income jobs and low income households in the urban core. As can be seen in Figure 2 below, only a handful of the low income hotspots fall within city limits, while a vast majority are located outside in the periphery.

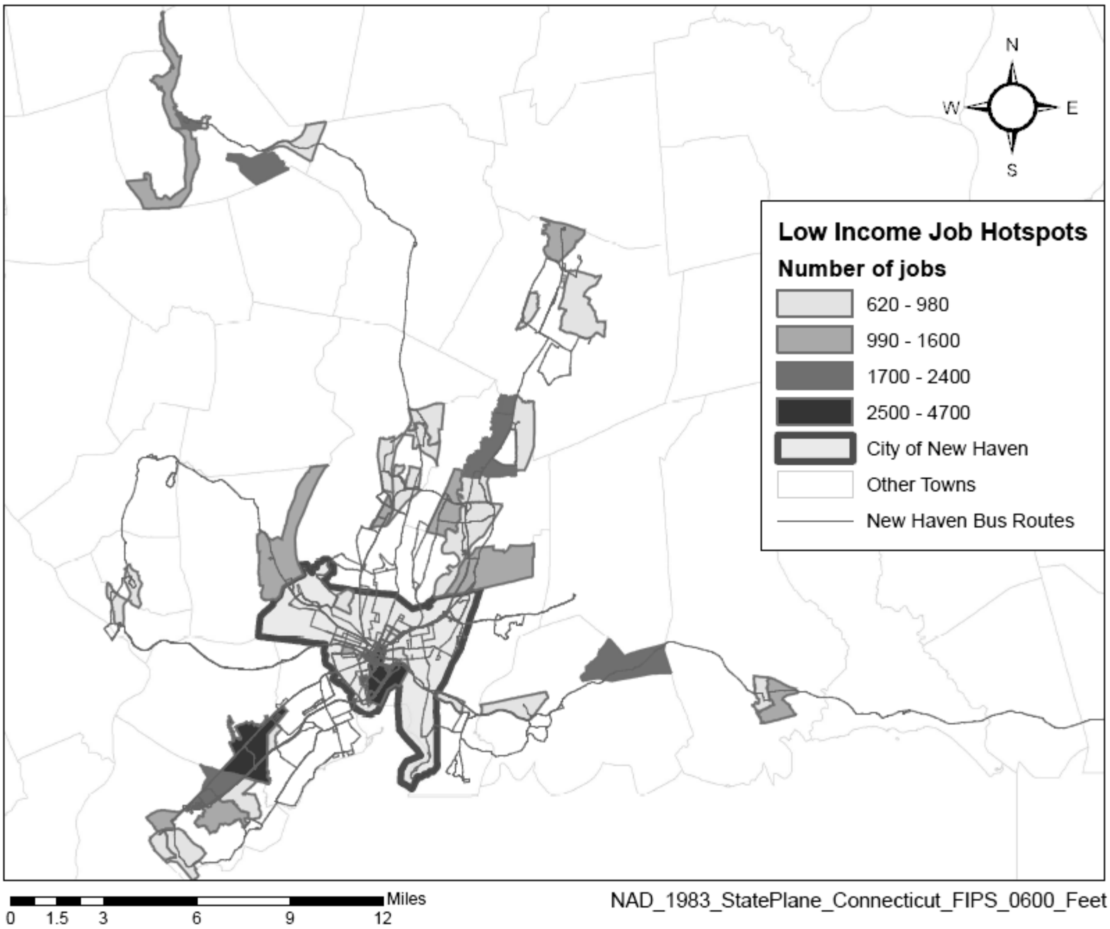

FIGURE 2: Low Income Job Hotspots Accessible Via CT Transit

In an effort to verify that low income workers from the urban core align with the jobs available in the designated hotspots, a breakdown of workers by industry was compared between the place of residence (New Haven) and the place of work (low income job hotspots). From Table 3 it is shown that worker demographics between the two areas are similar, with both areas having the greatest number of 0- 30k income workers in the same four industries. Based on this, an indirect assumption is made that a substantial amount of low income workers in New Haven are commuting to these outside areas. However this cannot be directly verified as appropriate travel data is not available.

TABLE 3: Comparison of Workers by Between Place of Work and Place of Residence

Industry	At Place of Work (Low Income Job Hotspots)			At Place of Residence (New Haven)		
	Number of Workers	Workers Earning 0-30k	Percent of Entire Working Population	Number of Workers	Workers Earning 0-30k	Percent of Entire Working Population
Agriculture, and Forestry	198	93	0.1%	147	97	0.3%
Construction	4705	1489	1.1%	1361	724	1.9%
Manufacturing	21950	7632	5.8%	4354	2332	6.2%
Wholesale Trade	4777	1700	1.3%	863	448	1.2%
Retail Trade	16533	10367	7.9%	3491	2376	6.3%
Transportation and Warehousing	5765	1701	1.3%	1488	636	1.7%
Information	6693	1996	1.5%	1535	749	2.0%
Finance, Insurance, and Real Estate	9001	3494	2.6%	1375	711	1.9%
Professional and Scientific	11040	4839	3.7%	3380	1569	4.2%
Educational, Health and Social Services	33505	14705	11.1%	13015	7254	19.3%
Arts, Accommodation and Food Services	7770	5818	4.4%	2994	2152	5.7%
Other Services	4190	2678	2.0%	1977	1262	3.4%
Public Administration	5807	1477	1.1%	1581	462	1.2%
Armed Forces	44	20	0.0%	19	15	0.0%
Total	131978	58009	44.0%	37580	20787	55.3%

Note: Highlighted areas represent industries with the highest magnitude of 0-30k workers as a percentage of the entire workforce for the respective spatial designation.

The next step taken was to investigate how many of the low income job hot spots could be reached via transit from each residential location. An urban New Haven census block group was deemed connected to a low income job hotspot if it was accessible via the bus system within a total travel time of 60 minutes or less. This stems from average travel time data obtained from the 2009 American Community Survey (*43*) which shows 93% of Connecticut commuters make their work trip in less than 60 minutes. Though it should be noted in Table 4 we can see that long commuter times are borne disproportionately by those traveling by bus in New Haven. New Haven's bus system headways vary over the course of a day and therefore a distinction was made to indicate the peak service periods, which in the case of a weekday is from 7-8. AM

TABLE 4: Commute Time to Work for Residents of New Haven

Travel Time to work			
Time	All means	Bus	Bus Share
0-5min	774	14	2%
5-10min	4002	50	1%
10-15min	7829	236	3%
15-20min	7497	373	5%
20-25min	6224	550	9%
25-30min	1827	269	15%
30-35min	3655	819	22%
35-40min	423	79	19%
40-45min	520	76	15%
45-50min	1036	328	32%
50-55min	248	58	23%
55-60min	67	24	36%
60-75min	1288	514	40%
75-90min	268	68	25%
90+min	1037	231	22%

Combining these two factors, connectivity from residence to job area existed if the destination work zone could be reached between the hours of 7-8 AM in under 60 minutes. This can be interpreted as having the means to reach an 8 AM job in under 60 minutes, while arriving in the area no sooner than an hour early. Travel times were calculated using CT Transit's Online Trip Planner (*44*), using a representative bus stop for each block group which was either geographically located closest to the center of the zone, or covered the most service area within the zone. However the analysis was not limited to the selected representative bus stops, as the Online Trip Planner accounts for the ability to walk to other nearby bus stop locations for faster routing. Once connectivity was established for each origin-destination pair, the total number of low wage jobs accessible for each census block group in New Haven was tallied.

Accounting for Temporal Aspects of Accessibility

With the constraints for low income job accessibility covering the spatial and trip aspects of morning commute connectivity, a metric accounting for temporal accessibility was needed. Early evidence from the previous testing of existing accessibility measures suggested a temporal accessibility effect on the number of LIHCO households. This is further argued by Sanchez (*25*) who finds it hard to positively influence employment levels based on the availability of transit services due to insufficient levels of service during off hours. To account for this, the cumulative transit frequency for the off-peak hours of 9pm - 12am was found for each block group in New Haven. This was calculated by summing the frequency of each bus route accessible to a particular block group between the off-peak hours.

RESULTS

A relationship was sought between LIHCO as a percentage among low income population and the low-income job accessibility metrics that were developed. With such a relationship, we can correlate aspects of transit accesibility in which improvement strategies may lead to reduced auto ownership in low income households. As seen below in Figure 3(a) and 3(b), plotting LIHCO and the low-income job accessibility metrics suggest the percentage of LIHCO households correlate with areas of lower late night service frequency and lesser low income job accessibility.

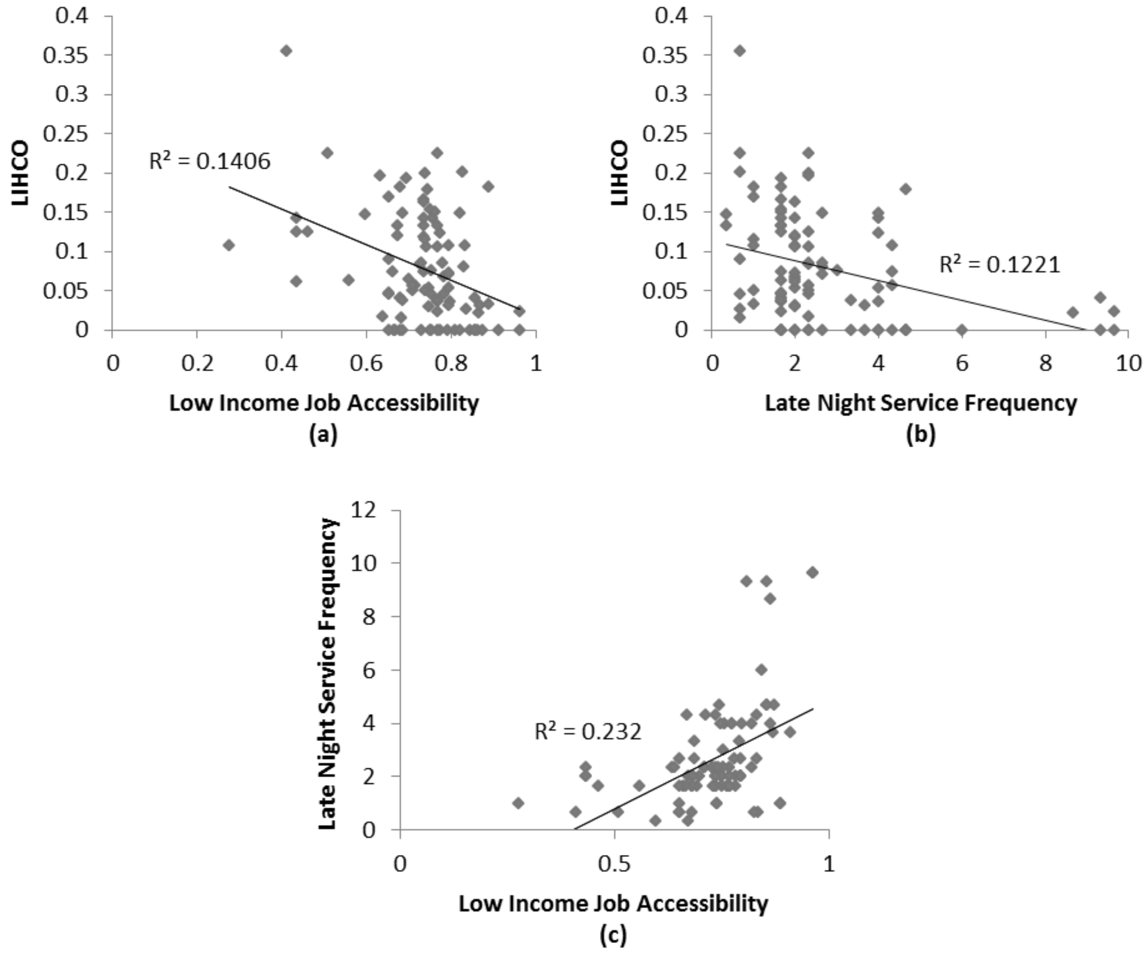

FIGURE 3: Plots and Trendlines between: (a) and (b) LIHCO and predictors, and (c) the two LIHCO predictors.

Figure 3(c) suggests that late night service frequency is correlated with access to low income jobs, suggesting the New Haven network planners have acknowledged this linkage in their service design. However, the regression results find both variables significant at the 5% level, indicating that both the spatial and temporal aspects of low-income job accessibility play a role in the existence of LIHCO households. The two LIHCO predictors were used to estimate a multiple regression model as seen in Table 5.

TABLE 5: Multiple Regression Parameter Estimates for LIHCO

Dependent Variable	**Variable**	**Coefficient**	**P-value**	**R Square**	**F Sig**	**Obs.**
LIHCO	Intercept	0.2189	0.0000	0.178	0.0001	95
	Late Night Service Frequency*	-0.0079	0.0445			
	Transit Access to Low Income Jobs*	-0.1626	0.0144			

*Notes: * significant at 5% level. LIHCO represents a LIHCO percentage of low income households.*

The multiple regression model suggests that LIHCO households correlate to areas of lower late night service frequency and lesser accessibility to low income jobs. The estimated coefficients in this case suggest that in order to decrease LIHCO households as a percentage of a block group's low income populations by 1%, either late night service frequency should be increased by 1.27 vehicles per hour between 9 pm and midnight, or low income job accessibility should be increased by 6.25%. It is difficult to generalize the results of this case study beyond New Haven, however the results do suggest late night service frequency and access to low income jobs be included in a methodology to evaluate policies designed to reduce LIHCO households and transport disadvantage.

CONCLUSIONS

This research has demonstrated that auto dependent low income households exhibit correlation to different measures of transit accessibility than the general population. This was shown by forming a multiple regression model based upon access to low income job locations and late night service frequency. This suggests that adding hours of service and expanding frequent service to low income job centers in the periphery can increase the economic stability of many low income households in the core. This supports programs such as Job Access and Reverse Commute (JARC) which can be implemented within existing transit networks. Reducing auto dependency among LIHCO households also acts towards reducing citywide congestion and air pollution, all while improving economic welfare for low income populations.

Future research should take on a stated preference surveys and household travel surveys among LIHCO households in the core to explore their attitudes towards auto dependency, public transportation, and investigate their current travel patterns. Activity-based travel demand modeling may provide proper insight into how LIHCO households interact with public transportation, as well as spatial and temporal mismatch between low income jobs and transit network design. In an attempt to discover universal trends, similar studies should be applied to other cities exhibiting various demographics, spatial composition, and transit network structures. Further research should also investigate other metrics that might prevent LIHCO households from adopting a public transportation lifestyle such as fare structures and consumer captivity due to limited goods and services available by traveling the transit network.

CHAPTER 4: CONCLUSIONS

GENERAL CONCLUSIONS

While the DOT has been devoted to adopting environmental justice into its regulations, Duthie et al *(1)* states that many major challenges still exist in incorporating EJ into metropolitan transportation planning, specifically the long range plans produced by metropolitan planning organizations. Some of the major challenges outlined were data needs and availability, as well as using proper analysis units. Both are crucial to making EJ decisions in long-term planning.

As the length of the forecast or plan is increased, so are impacts from the accuracy and completeness of the data used. Data needs for EJ involve travel data for creating trip tables to estimate EJ performance measures of accessibility to employment, medical care, food stores, and other essential destinations. Duthie et al *(1)* shows if trip tables were available by minority and income classes, much more could be done to measure accessibility. Segmented trip tables would allow for better insight in determining benefits offered to certain socio-economic groups by certain roadway or transit projects. Otherwise these accessibility measures must assume the percentage of trips between each origin and destination pair must be equal to the percentage of residents at the origin that are a member of each group, which is usually unlikely to be the case. Furthermore this data can be used in microsimulation models which track activity patterns as an effective way to account for where transport disadvantaged populations would like to travel as opposed to simply streamlining paths to where they are currently forced to travel.

Analyzing a method for bias reduction in electronic travel surveys has shed some light on solving the data needs for EJ planning in long term transportation plans. The method described offers geographic and temporal flexibility in recruiting low income and minorities for collecting household travel data. The survey tool can be strategically set up as an intercept survey where target demographics are likely to be, or passed onto groups and organizations involved in outreach and programs for protected populations. Improving the quality and quantity of data for these populations less likely to be reached by traditional survey methods leads to better representation in the planning process and a reduction in error due to long term projections. The flexibility of the survey would also allow for the collection of regional data needed to produce segmented trip tables for improved accessibility impact studies in EJ. By improving the quality of these studies through data collection, the benefits offered from public meetings and charrettes will also increase as discussions and interactions are based around more relevant and factual premises.

One major pitfall of the survey was the trip information was not transferable to activity-based modeling and microsimulation. The trip destination choices offered to the survey respondent were not well chosen, and as a result any further analysis on trip making behavior, let alone activity modeling, was virtually impractical. This supports the case for standardized question and response option wording, as suggested by the NCHRP Report 571. By asking the right questions in our surveys, proper application of the data can be implemented. In the case of EJ, collecting proper data for accessibility-based modeling and microsimulation offers state-of-the-art methods for analyzing the travel behavior and transportation impacts on minority and low income populations. This allows better insight on the ability to plan when and where populations might prefer to travel, as opposed to continuing to plan based on the travel patterns they might currently be forced into which only solidifies mobility and access issues.

The issue of using a proper analysis unit can be seen in urban core transit access to low-income jobs. Of course as with most studies, the analysis units used were a result of the data which was available. The effects of population size within each geographic unit were incorporated by displaying the total number of LIHCO households per unit in addition to the percentages which were used for analysis. Therefore these effects aren't directly accounted for in the results, but provide a visual verification for practitioners. This supports a methodology for performing analysis at a group level, which then once again reverts back to the proper data needs required for supplying quality segmented trip tables.

Overall, this shows the increasing importance of collecting a distributing quality data. It is my opinion which a majority of transportation practices have rapidly evolved to take on more and more complexity, while inclusive and proper data collection efforts needed to implement them have been neglected. Placing more emphasis on data collection and survey techniques may offer some of the most marginal effects in improving and advancing the practice of environmental justice in transportation planning.

FUTURE RESEARCH

Future efforts are underway to address these needs at the University of Connecticut known as "t-HUB." t-HUB seeks to act as a public transport data center for the State of Connecticut. Initial efforts have centered on guiding Connecticut's Regional Planning Organizations and transit operators with compliance under Title VI. Current efforts are focused on the requirements set forth by FTA Circular 4702.1B, but the long term plans of t-HUB involve guiding and improving statewide data collection, as well as developing new metrics and research insights into transit-related environmental justice practices.

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