Impacts of Extreme Events on Intercity Passenger Travel Behavior: The September 11th Experience

José Holguín-Veras
Department of Civil and Environmental Engineering
Rensselaer Polytechnic Institute

Robert E. Paaswell
Department of Civil Engineering
City College of New York

Ann-Marie Yali
Department of Psychology
City College of New York

Introduction

The tragic events of September 11, 2001, have had a profound impact on activities in all of lower Manhattan, and the New York City metropolitan region—profound, of course, because of the huge loss of life and the continuing sense of trauma of the survivors. These events have also provided a major challenge to transportation and city planners because there are few guidelines in the technical literature on how to manage after such an event occurs.

The scale of the event was enormous: 13.4 million square feet of office space were lost in the World Trade Center, while 12.1 million square feet were rendered temporarily unusable in the adjacent properties (Holusha, 2002, p. 1). Over 100,000 jobs were displaced. Tens of thousands of additional jobs have been lost or interrupted because they serve the World Trade Center and its neighborhoods. Additional acts and threats of terror, such as the anthrax attacks, have made New Yorkers cautious about where and how they travel to participate in activities.

The changing perception of the safety of transportation modes is, in particular, affecting the way in which the traveling public makes choices concerning mode of transportation, place of work, and location of residence. On September 10, most travel analysts would have said that reliability, travel time, and cost were the primary determinants of mode choice. On September 12, personal security became, and still remains for many New Yorkers, a key concern. As a result of the September 11th disaster, businesses and individuals are making choices that will impact whether or not (1) they remain in their jobs in a new location, outside the impacted site; (2) they change jobs; (3) they change travel mode or its route; (4) they move from the New York region; among many other possibilities. While all of these choices are extremely complex, closely inter-related, and changing over time, two dimensions of choice stand out. The first is the individual's overall response to the tragedy, and his or her personal relationship to it. The second is the individual's sense of security as it applies to each mode available for a given trip. Travel choices will vary according to the individual and his or her personal response to the tragedy. Much can be learned by studying and evaluating these impacts over time.

The September 11th disaster has also affected the real estate and commerce systems in rather subtle and indirect ways. Before September 11th, the business location process was determined by variables such as transportation accessibility to markets, economies of agglomeration, and accessibility. Mathematical formulations based on such assumptions have successfully been employed to model the business location process. Figure 1 and Equation 1 show a model estimated by the research team for northern New Jersey as a function of the economic attractiveness of the markets of New York City and Philadelphia (Holguín-Veras et al., 2002). The mathematical formulation used assumes that the probability that a business chooses a given location i, is a function of the proximity to the economic poles (i.e., New York City and Philadelphia), and the corresponding market sizes. As shown in Equation 1, simple assumptions of economic rationality lead to a powerful explanatory model (t-statistics in parentheses).

$$P(i) = \sum_k \alpha_k \Pi_k e^{-\beta C_{ki}} = 0.1132\Pi_{NY} e^{-0.070 C_{NY,i}} + 0.05569\Pi_{PA} e^{-0.1303 C_{PA,i}} \quad (1)$$

(19.373) (-22.100) (6.984) (-4.255) F=361.46 R^2=0.98

Where:

Π_k = Market size at economic pole k, and *P(i)* = Probability of choosing location i, $C_{NY,i}$ and $C_{PA,i}$ are the distances to location i, from New York and Philadelphia, respectively.

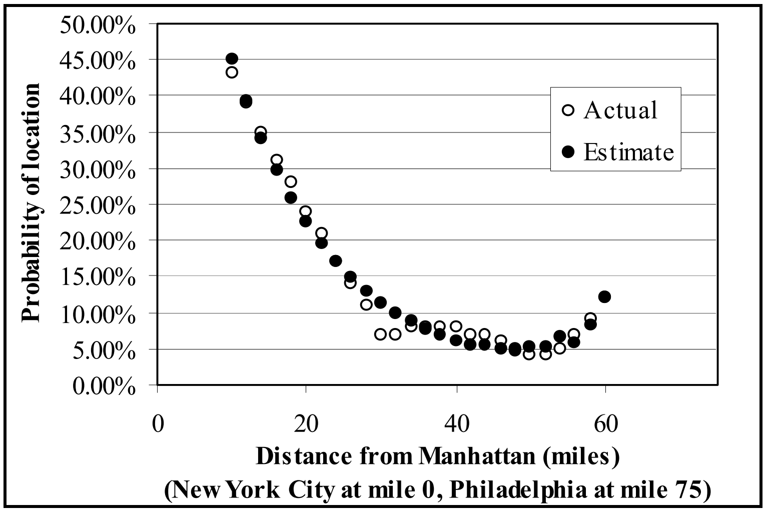

Figure 1. Actual and estimated values of business location model.

The traditional assumptions of economic rationality have been altered in the wake of September 11th. This in turn has produced some surprising phenomena. The World Trade Center events, far from leading to a tighter real estate market (to be expected after the sudden disappearance of 25% of downtown's office space), released a flood of sublet space (*New York Times*, 2002), which seems to be a reflection of the changes in business patterns and a weakening economy. Ultimately these changing business patterns are having a significant impact upon the processes of work-residential choice, as well as transportation mode and route choice. It is still too early to determine if these changes are transient or permanent. Those who survived the attacks and those who were forced to relocate because of changes in business patterns had to develop new commuting patterns.

The impacts of September 11th on travel behavior extend far beyond the New York City metropolitan area. As it was widely reported in the media, air transportation throughout the nation experienced a dramatic drop, while train alternatives such as the ones provided by Amtrak and the regional commuter lines had to deal with a significant upsurge in demand. Interestingly enough, the information provided to the authors by the technical staff of Greyhound and other regional bus operators indicated an across-the-board drop in demand, which they attributed to the fact that their customer base is formed primarily by low-income individuals who were directly affected by the weakening of the economy in the post-September 11th period.

The research reported here was conducted by faculty members of the Rensselaer Polytechnic Institute and the City College of New York as part of a project funded by the National Science Foundation to assess the changes on passenger travel behavior produced by the terrorist attacks of September 11, 2001. This paper specifically focuses on describing the behavioral changes in intercity travel. A separate component of this project—dealing with the impacts upon urban travel—could not be reported here because of the delays experienced in the corresponding data collection process. This delay was, in part, due to the inherent and understandable difficulties of coordinating work with transportation agencies directly affected by the events of September 11th and/or involved in the rescue and recovery operations in its aftermath. The regional planning organization, the New York Metropolitan Transportation Council, a research partner to this project and the lead agency in transportation data collection in the New York City metropolitan area, had its headquarters destroyed in the collapse of 1 World Trade Center, and is still in the process of reassembling the data sets lost in the attack.

Research Approach

This section provides a summary of the research approach implemented by the project team. This description, for the most part, focuses on the conceptual aspects of the work done, minimally describing the methodological formulations of the models used. This decision was taken in order to ensure that this paper is able to reach as wide an audience as possible.

The unique nature of this research project necessitated the implementation of a research approach able to capture the most significant changes in passenger travel behavior that have taken place as a consequence of the disaster of September 11th. To this effect, the research team decided to use behavioral models based on Random Utility Theory (RUT) to assess such behavioral changes. In this context, the random utility models provided the methodological framework for the assessment of behavioral changes, while the transportation surveys conducted provide the data to be used in the analyses and model estimation processes.

RUT is a behavioral/economic theory that postulates that decision makers choose the alternative that maximizes the utility derived from their choices. The distinguishing feature in RUT is the assumption that the utility function is composed of a systematic component, which depends upon the socio-economic characteristics of the decision maker and the alternatives' attributes, and a set of random terms that consider the fact that the analyst does not have full information about all relevant variables and decision processes. The latter translates into unobserved effects and measurement errors that are operationalized as observational randomness in RUT. The consideration of a random error term enables the formulation of random utility models based on probability principles. The origins of RUT can be traced to Thurstone (1927), though it was McFadden (1974, 1978) who provided the foundations for RUT and made it an operational theory that has become the standard tool for disaggregate modeling of transportation phenomena. The following section provides a brief overview of RUT. For the most part, the review follows Ben-Akiva and Lerman (2000), unless otherwise indicated.

RUT differs from the traditional (deterministic) utility theory in that the utility is assumed to have two components: (a) the systematic component, which is the one explained by the variables included in the model; and (b) the random component, which represents the unobservable factors and measurement errors that, as a rule, are not known to the analyst. The consideration of the random component enables the formulation of random utility models using probability concepts. In this context, the utility of alternative i for individual n, U_{in}, comprises the systematic (explained) component, V_{in} and a random term ε_i, as follows:

$$U_{in} = V_{in} + \varepsilon_i \tag{1}$$

As a result of the consideration of the random component, the choice process is formulated in terms of the probability that a given alternative is chosen, which is defined as the probability that its utility is higher than the maximum utility of the other alternatives. In mathematical terms:

$$P_n(i) = P[U_{in} > Max U_{jn}] = P[V_{in} + \varepsilon_i > Max(V_{jn} + \varepsilon_j)], \forall j \neq i \tag{2}$$

Different assumptions about the error terms lead to different discrete choice models. The model specification process, in short, consists of the specification of the systematic component of the utility function and the specification (assumption) of the distribution of error terms most appropriate to the problem at hand. The systematic component is, for the most part, assumed to be a linear-in-parameters combination (X_{in}) of socio-economic characteristics of the decision maker (S_n), the attributes of the alternative *i* as perceived by individual n (Z_{in}), and a vector of parameters β. Mathematically:

$$V_{in} = h(S_n, Z_{in}) = \beta' X_{in} \tag{3}$$

In general terms, the parameters of alternative models are estimated using maximum likelihood principles. In a typical application, the parameters and the model are tested for statistical significance. Depending upon the model structure, other tests such as the test for violations of the Independence of Irrelevant Alternatives may need to be conducted. In addition to the assessment of the statistical significance, the modeler is also required to analyze the conceptual validity of the model and its parameters.

Random utility models require, for calibration and forecasting purposes, disaggregate data that could represent (a) revealed preference data, i.e., actual choices; and (b) stated preference data, which is the data obtained by eliciting responses from the decision makers about choices and rankings in hypothetical choice situations. Using either revealed preference or stated preference data has advantages and disadvantages, though an increasing body of evidence indicates that discrete choice models estimated with stated preference data could be highly accurate, provided they are designed and conducted properly (Hensher, 1994). For that reason, the research team decided to rely on stated preference data to assess the changes in intercity travel behavior produced by the terrorist attacks of September 11th.

The Choice Experiment and the Survey Instrument

In order to provide a decision context for the respondents, the project team selected a choice situation that involved a compulsory trip, supposedly a business trip to another city. A business trip was selected because its compulsory nature eliminates one choice dimension, i.e., the decision to travel or not. This, in turn, presents a fairly clear choice situation that minimizes misunderstandings on the part of the respondents. Another benefit of using a compulsory trip in the choice situation is that the behavioral changes identified could be interpreted as lower bounds of the impacts, because non-compulsory trips (because of their inherent elasticity) are likely to be more impacted than compulsory trips.

Another relevant decision concerning the choice situation involved the trip distance. Since for long trip distances, air transportation may be the only practical alternative, focusing on long distances would have made it more difficult to assess behavioral changes in intercity travel because the dimension of mode choice would not have been present (which is the anticipated consequence of the decision makers' feeling "captive" of air transportation). For that reason, the project team decided to focus on the lower range of trip distances, for which the decision makers have different alternatives that effectively compete with each other. In this context, the behavioral changes would reveal themselves as components of the tradeoffs among alternatives captured by the systematic component of the utility functions.

The respondents were randomly assigned to three different trips: (a) New York–Washington, D.C., (b) New York–Boston, and (c) Boston–Washington, D.C. The percentages of respondents for each trip type were 43.47%, 28.80%, and 27.71% respectively. As shown in Table 1, the breakdown according to trip type correlates fairly well with the breakdown from the American Travel Survey (Bureau of Transportation Statistics, 1997). A similar situation happens with the mode split data. As shown in Table 2, the mode split in the sample seems to be in the appropriate order of magnitude (taking into account that the American Travel Survey includes all trip purposes). However, since there was no information available about the breakdown for business trips that could be used to further refine the sample, the project team decided to use the data as it came from the sample without using any correcting (weighting) factors. This decision was taken because, without the backing of solid statistics, using weighting factors would have introduced an unquantifiable amount of uncertainty in the estimation that did not seem justified in light of the results shown in Tables 1 and 2.

Table 1. Breakdown of number of trips (1000 trips/year) for selected trip interchanges (Bureau of Transportation Statistics, 1997).

Trip interchange	trips/year (1000)	Trip interchange	trips/year (1000)	Market breakdown	Sample breakdown
Boston-New York City	445	New York City-Boston	393	31.21%	28.80%
Boston-DC	253	DC-Boston	202	16.95%	27.71%
New York City-DC	676	DC-New York City	716	51.84%	43.47%
Totals	1,374	Totals	1,311	2,685	

Table 2. Mode split in sample and the American Travel Survey (Bureau of Transportation Statistics, 1997).

Mode split in sample			Mode split in ATS		
Mode	Trips	%	Mode	1,000 trips/year	%
Train A (Metroliner)	354	21.38%			
Train B (Acela)	202	12.20%	Other	242	18.29%
Commercial airplane	622	37.56%	Commercial airplane	396	29.93%
Personal use vehicle	478	28.86%	Personal use vehicle	685	51.78%
Total	1656	100.00%	Total	1323	100.00%

Approximately half of the respondents were told that their employer was paying for the trip, while the other half were told that they (the respondents) were paying for trip expenses. The respondents were provided with nine different choice scenarios involving four different transportation choices: two alternatives of rail service (Amtrak's Metroliner and Acela); one air transportation alternative; and a car alternative, and were asked to rank order the alternatives. Although rank order data was available, only the first choices were used in the analyses. A bus alternative was not included after consultations with the technical staff at the regional bus companies indicated that buses do not compete with these modes for business travel.

The alternatives in the choice set were characterized in terms of cost, travel time, and inspection/boarding time at the airport. Cost and time were broken down by segment of the trip (beginning of the journey, main trip, and end of the journey). Since the objective of the analysis is to assess behavioral changes, everything else being equal, the attributes of the different alternatives were—for the most part—assumed to be equal to the ones corresponding to the alternatives available in the market place. The only exceptions were the scenarios that included a "high speed" rail alternative (a variation on the current Acela service), not currently available in the market place. The attributes (factors) that were varied in the experiment were the inspection and boarding time at the airport that was assumed to have three factor levels (25, 60, and 120 minutes); and the departure and arrival times of the train alternatives and air (three factor levels each). Throughout the experiment the car alternative remained the constant option, i.e., with attributes that did not change values. The factor levels were combined in nine scenarios (treatment combinations). The scenarios were screened to eliminate those deemed to be not feasible from the technological or policy standpoint.

The questionnaire had five major sections, in addition to the stated preference section. The first section was intended to ascertain if participants had ever traveled to the target city, how frequently they travel there, the primary reason for traveling there, what mode they use and prefer, why they chose that particular mode, and the perceived level of quality of that mode. They are also asked to rate the mode of travel chosen on items such as cost, cleanliness, service, comfort, and safety. The second section contained a choice scenario in which the respondents were asked to indicate what their preference of four travel alternatives would have been before September 11th. This choice scenario was exactly the same as the base case in the stated preference section. The third section of the questionnaire included questions about the impacts of September 11th on the respondents: how much September 11th changed their travel choices on a 7-point scale (1=not at all; 7=significantly). In addition, participants indicated whether September 11th affected them in six different ways by checking the statements that apply to them: "I am more conscious of security," "I avoid traveling by plane," "I am more aware of people traveling with me," "I am more selective in choosing my travel mode," "I plan to change type of work," and "As much as I can, I avoid traveling altogether." The fourth section was aimed at gathering the socio-economic characteristics of the respondents to describe sample characteristics. Single items assessed age, gender, marital status, number of people in household, number of children in household, education, and income. The fifth section consisted of a set of four questions aimed at assessing perceived stress level. A four-item version of the Perceived Stress Scale (PSS4; Cohen and Williamson, 1988) was used to assess the degree to which respondents appraise their life as stressful. Respondents indicated how frequently they felt unable to control the important things in life, felt confident about handling personal problems, felt things were going right, and felt unable to overcome difficulties. Each of these items was rated on a 5-point scale ranging from 1 (never) to 5 (very often) with two reverse-scored items. A total stress score (PSS4) for each subject was calculated by summing item responses. The sixth section contained the stated preference scenarios described above.

The questionnaire was administered to an initial set of volunteers, graduate and undergraduate students at the City College of New York. The graduate students were asked to administer the questionnaire to three other individuals selected by them in order to maximize the variability in the socio-economic characteristics of the sample. The undergraduate students were only asked to respond to their questionnaires. Each volunteer filled out a consent form and one of four versions of the survey. The confidentiality of the responses was guaranteed, in accordance to National Science Foundation's human subject research guidelines. A total of 192 volunteers participated in the study. The questionnaires were administered between March 14, 2002, and April 4, 2002, about six months after the September 11th disaster.

It is important to highlight that the data collection and the experimental design process faced significant limitations due to the unique circumstances in which the data was collected. This translated into a rather unorthodox experimental design and data collection process. Faced with the decision either to wait for more resources to become available, or to spend resources and time in fine tuning the experimental design, the authors made a pragmatic decision regarding the scenarios to be included in the experiment and the main focus of the investigation, in order to avoid more delays in the data collection process that would have further dissipated transient behavioral effects. These decisions have proven to have advantages and disadvantages that are discussed throughout the paper.

Description of the Sample

The study sample comprised 192 participants, with 184 providing descriptive information (see Table 3). The majority were male, aged 20 to 25, and single with no children. The median income level reported was between $35,000 and $49,999, with two people in the household. Due to using a convenience sample, the majority of participants were college educated.

The sample differs from the general population of the five boroughs of New York City in a number of ways. Census data from 1990 on sociodemographic variables are included in Table 3. The sample is disproportionately male and single compared to the general population, which is 53% female, 41% married. In addition, the sample is younger, more educated, and wealthier than the general population. While household size seems to be similar to the general population, the majority of participants in this study have no children (60%), whereas only 46% in the population is without children.

Figure 2 shows the geographic distribution of the zip code of residence of the respondents (with triangles). As shown, the bulk of the respondents are residents of New York City, while there is a smaller, though significant, number of respondents that live in northern New Jersey and the rest of the New York City metropolitan area.

Results

This section is divided into two parts. The first section highlights the descriptive analyses and the second section describes the behavioral models. It is important to highlight that many of the results discussed in this section, specifically those pertaining to behavioral responses after September 11th, are highly dynamic in nature and, as a result, are likely to change with time as the respondents regain comfort in the routine nature of daily life. In this context, the results shown here are to be interpreted as a snapshot taken six months after September 11th. A second wave of panel data collected approximately a year after September 11th (not available at the moment of producing this document) is likely to provide more information about the dynamic transient behavioral effects.

The reader is asked to note that standard statistical abbreviations will be used. For example, SD is the standard deviation, α refers to Cronbach's alpha, a measure of the internal consistency of a scale (the higher the number, the better the scale's reliability), χ^2 is the chi-square statistic for differences in nonparametric data, and r is the Pearson's coefficient of correlation.

Table 3. Sample and population descriptives.

Variable	Sample* n	Sample* %	NYC Population **	NYC Population ** %
Gender (n=184)				
Male	112	61%		47%
Female	72	39%		53%
Age (n =183)				
<25	64	35%	17-24	15%
26-30	34	19%	25-29	12%
31-36	39	21%	30-34	12%
37-45	28	15%	35-44	19%
46-55	10	5%	45-54	14%
>55	8	4%	>55	28%
Size of Household (n = 162)				
1	40	25%		33%
2	46	28%		27%
3	35	22%		16%
4	21	13%		12%
>4	20	12%		12%
Number of Children (n =158)				
0	111	70%	0	54%
1	21	13%	1 or more	46%
2	17	11%		
>2	9	6%		

Variable	Sample* n	Sample* %	NYC Population **	NYC Population ** %
Marital Status (n =184)				
Single	107	58%		38%
Married	69	38%		41%
Divorced	8	4%	***	12%
Widowed	0	0%		9%
Income (n =182)				
< $24,999	42	23%		43%
$25-34,999	26	14%		14%
$35-49,999	24	13%		16%
$50-74,999	45	25%		15%
$75-99,999	21	12%		6%
$100,000+	24	13%		6%
Education (n = 179)				
			< High school	32%
High school	17	9%	High school	26%
College UG	67	37%	College UG	14%
College grad	68	38%	College grad	18%
Postgraduate	27	15%	Postgraduate	10%

Notes:
* Percentage columns may not add up to 100% due to rounding errors.
** 1990 Census data for the five boroughs of New York City.
*** Individuals reporting a divorce or separation are collapsed in this number.

Descriptive Analyses

A majority of the participants indicated that they have actually traveled from New York City to Washington, D.C. (70%) and from New York City to Boston (72%); however only 26% of those surveyed had ever made the Boston-to-Washington, D.C. trip. This makes sense given that the sample consisted of those whose primary residence was New York City and thus one would expect their trips to originate from there.

Of those who had traveled to the target cities in the past, approximately 55% made that trip over 12 months ago, 19% 6–12 months ago, 21% 1–6 months ago, and 5% made the trip less than a month ago. In addition, 83% said they visit the target city twice a year, 10% visit 3–5 times per year, 3% visit 6–8 times a year, and 2 participants reported that they visit the target city

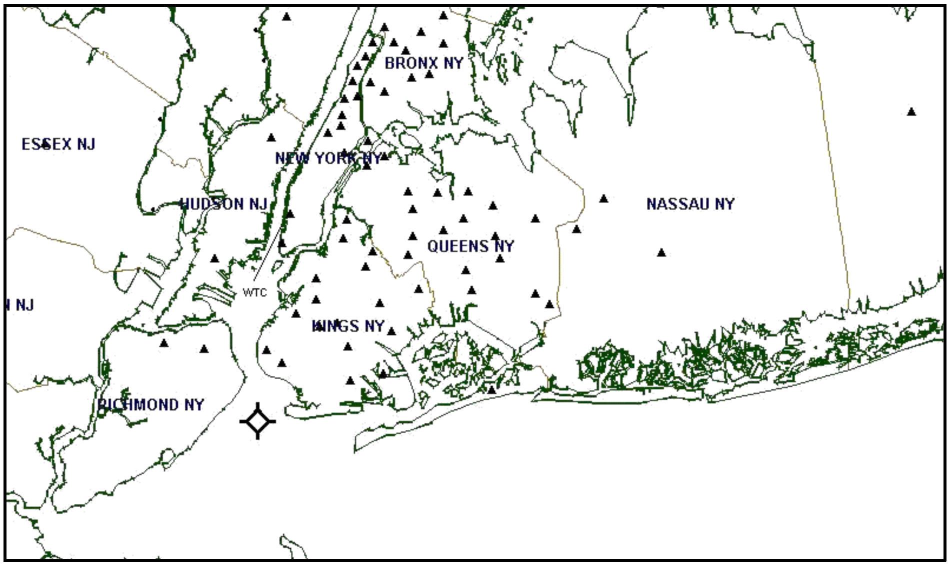

Figure 2. Geographic distribution of respondents.

more than 8 times per year (2 respondents did not answer this question). When asked to indicate the primary purpose of the trip, reasons were social (63%), work (15%), education (5%), and "other" (17%). Most traveled to the target city by car (63%), followed by air and train (14% each), and 8% said "other" (one person failed to answer this question). Participants were then asked to indicate all of the reasons that they chose the mode used on that last trip by checking off a list. Collapsing across modes, 21% marked reliability, 68% marked convenience, 53% cost, 17% safety, 12% security, 38% comfort, and 9% marked easy. On that last trip, the majority paid for the trip themselves (66%), which may explain why cost was important in mode selection. Of those who did not pay for the trip themselves, 12% had employers pay, 8% had family pay, and 9% had "other" pay for the trip.

Participants were also asked to rate the mode they selected on their last trip to the target city on various features including cost, cleanliness, service quality, reliability, security, comfort, and safety. Collapsing across modes, the mean for each feature ranged from 5.21 to 5.60 (SDs ranged from 1.3 to 1.4). A multivariate analysis of variance was conducted to assess if the mean ratings of each feature differed by mode (car, air, train, other), by trip (New York City to Washington, D.C., New York City to Boston, Boston to

Washington, D.C.), or by an interaction (mode x trip). The model indicated that there was a significant difference in ratings by mode (Wilks' lambda = 0.583, F = 1.98, p < .01). There was no significant effect for trip or the interaction term. Post hoc comparisons using the Bonferroni test (a method for adjusting for the increase in Type I error associated with running multiple unplanned comparisons) revealed which mode feature ratings were significantly different (Table 4 lists the means by mode).

Table 4. Mean values of quality ratings by mode.

	Feature						
	Cost	**Cleanliness**	**Service**	**Reliability**	**Comfort**	**Safety**	**Security**
Air	4.93	5.20	5.20	4.93	4.80	5.33	5.27
Train	4.33	5.13	4.73	5.47	4.73	5.27	5.00
Car	6.07	6.62	6.33	5.98	6.31	5.98	6.04
Other	4.89	4.55	4.11	4.44	4.33	3.88	4.33

Note: 1 = very bad, 4 = fair, and 7 = very good

For cost, cars were rated higher than air or train, but not different from "other." The only significant difference for cleanliness and service was between car and "other." Reliability was rated equally across modes. Air, train, and cars were rated equally for comfort; "other" was rated significantly lower. The only difference for safety was between car and "other," with cars rated higher. For security, cars were rated as more secure than train and "other;" air, train, and "other" were not significantly different.

Participants were then asked how much September 11th changed their choice of whether or not to travel. Scores ranged from 1 to 7, with an average change score of 3.39 (SD=2.0), which corresponds to "moderately." Analysis of variance tests revealed no significant differences on this change variable for gender, age, education, income, marital status, or number of children. However, there was a significant difference in change for household size (F = 2.11, df = 157, p < .05). Post-hoc comparisons revealed that those with two and four people in the household reported greater change than those in one-person households. No other comparisons were significant.

Participants were also asked to check off on a list how September 11th specifically affected their behavior: 74% indicated that they are now more conscious of security, 46% are more aware of other travelers, 33% are more selective in choosing their mode of travel, 22% avoid traveling by plane, 11% indicated that they now avoid traveling altogether, and 3% planned to change their jobs as a result of September 11th. Participants were asked if they would be willing to pay more to travel if those funds were used to increase security. Few participants said that they would be willing to pay more; the majority responded that they would not pay more (60%), while 23% were unsure.

Participants were then asked to indicate how often they felt overwhelmed and not in control per the perceived stress scale described above. Total stress (PSS4) scores could range from 4 to 20; the minimum and maximum total stress scores in this sample were 4 and 14, respectively. The mean was 9.56, with a standard deviation of 2.1. This corresponds to an item mean of 2.39 (SD = .5), or "almost never" having felt the way the item described. The reliability of the stress measure in this sample was acceptable (α = .60). These findings are highly similar to the published psychometrics for this scale. In a national area probability sample, the PSS4 had adequate reliability (α = .60), with a mean score (based on a 0–4 scale) of 4.49 (SD = 2.96) (Cohen and Williamson, 1988). This corresponds to "almost never" on the item response scale. Converting the current sample to a 0–4 scale yields a mean of 5.56 and a SD of 2.09. The item mean would then be 1.39, corresponding to "almost never" perceiving stress.

There were no significant differences in reported stress scores for any of the demographic variables (gender, marital status, education, income, number of people in household, number of children, age). These findings are different from the national sample on which the psychometrics for the scale were derived. In that sample, females reported greater perceived stress than males (Cohen and Williamson, 1988). Those who were divorced had greater perceived stress than those who were single, who had greater perceived stress than those who were married. In addition, stress scores decreased with age, income, and education; PSS4 scores increased with number of people in the household and number of children. The differences found in our sample may reflect the specific characteristics of the sample as described above.

Correlation analyses revealed a small but significant association between perceived stress and the degree to which respondents reported how much September 11th changed their choice of whether or not to travel ($r = .19$, $p<.02$). However, perceived stress scores were not significantly different for those who indicated having been impacted by September 11th in some particular fashion (i.e., becoming more conscious of security, more aware of others traveling, more selective in choosing travel mode, by planning to change their work, or by avoiding traveling by plane, or avoiding traveling altogether) than for those who did not report September 11th affecting them in any of these ways.

Figure 3 shows the geographic distribution of the perceived stress, while Figure 4 depicts the geographic distribution of the variable *Change*, which represents in a scale of 1 to 7 (1=not at all, 7=significantly) how much the September 11th events changed the respondents' travel choices. In both cases, the variables seem to be uniformly distributed across the geography of New York City. In the case of the variable *Change*, this seems to indicate that the September 11th events had similar impacts on the respondents, regardless of their proximity to the World Trade Center.

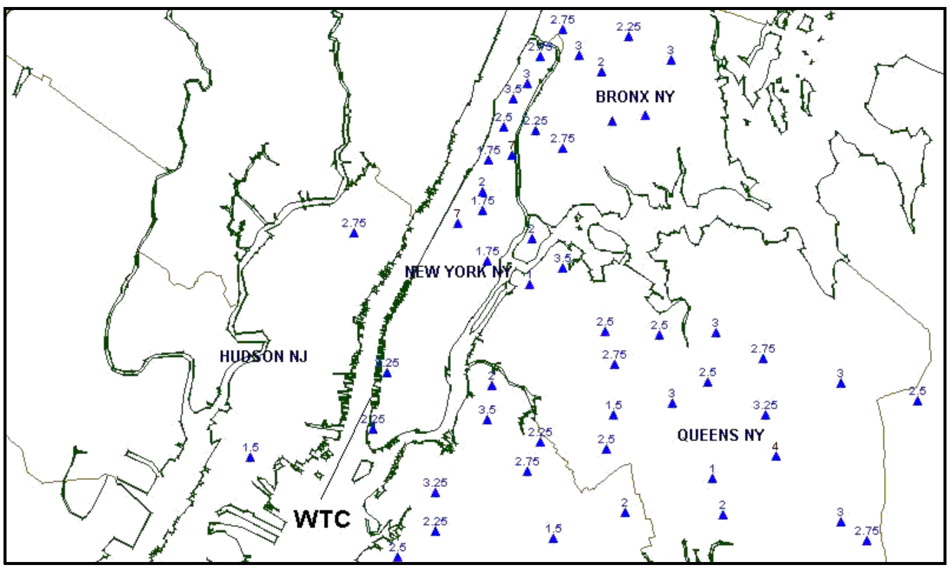

Figure 3. Geographic distribution of perceived stress.

Behavioral Analyses

This section describes the main results of the behavioral modeling conducted as part of this investigation. A number of different families of models were estimated. These families of models differ in the variables that were included in the models and in the specific type of discrete choice model used in the estimation. Two different types of discrete choice models were used: Nested Logit (NL) and Covariance-Heterogeneity Nested Logit (CHNL). The NL model is widely used in situations in which the analyst suspects a violation of the independent of irrelevant alternatives (IIA) property of the MNL model. This case arises when a subset of the alternatives is expected to share

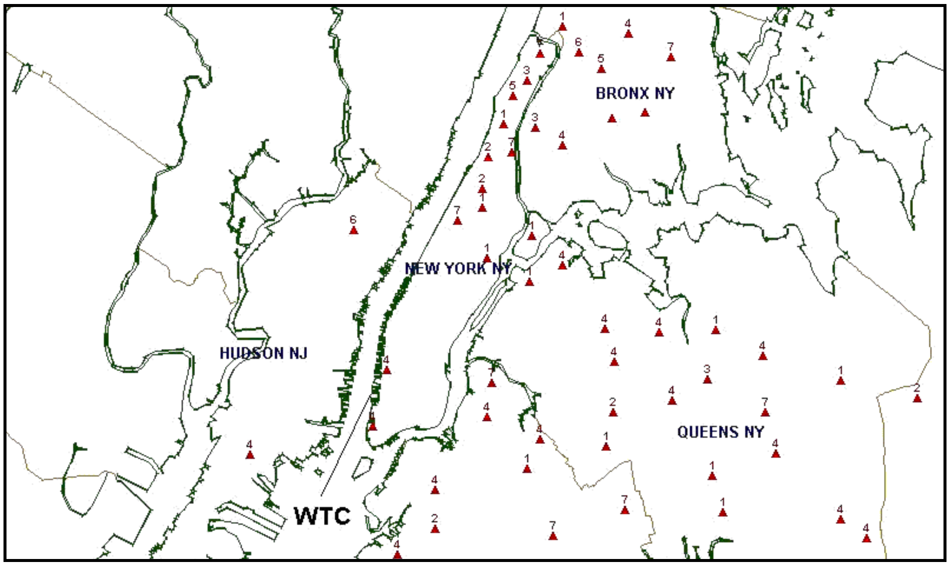

Figure 4. Geographic distribution of Change *after September 11th.*

unobserved attributes and/or measurement errors that cause the error terms to be correlated. Since the presence of the two rail alternatives (Metroliner and Acela) may introduce a violation of the IIA property for the reasons mentioned above, the NL model was selected for use in this investigation. The choice tree considered is shown in Figure 5.

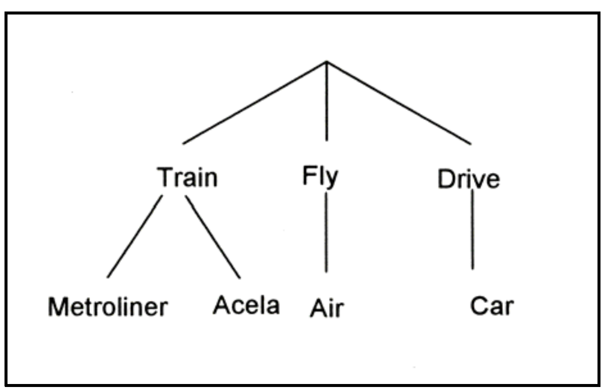

Figure 5. Choice tree.

Another issue that must be dealt with is the correlation introduced by the stated preference data. The different scenarios of stated preference are introduced in the model estimation process as different observations that share the values of the same socio-economic characteristics. The fact that the observations for the same individual are not statistically independent introduces error in the estimation process. This is usually dealt with by using discrete choice models that allow for specific consideration of population heterogeneity (e.g., Random Parameters Logit). As a compromise between ease of implementation and theoretical applicability, the project team decided to use the covariance-heterogeneity nested logit (CHNL) model available in LIMDEP (Greene, 1998), which is based on the model developed by Bhat (1997). The CHNL considers the case in which the parameters of the inclusive values exhibit a systematic relationship with some socio-economic characteristics of the decision makers. Since the coefficients of the inclusive values—related to the ratio of the scale parameters for the lower and upper levels—determine the sensitivity of choice between the alternatives in the nested branch and the others in the tree, the CHNL model enables the explicit consideration of the role that variables, such as income, may play in determining the cross elasticities of choice. Higher values of the coefficients of the inclusive value terms imply higher cross elasticities of choice. In this context, a direct relationship between the explanatory variable in the covariance heterogeneity term would lead to increased cross elasticities. A side benefit of using the CHNL model is that, since covariance heterogeneity is a particular form of population heterogeneity, using the CHNL model helps mitigate the repeated measurement problem introduced by the stated preference data.

In mathematical terms, the basic equations for the conditional and the marginal probabilities in the NL are (after Ben-Akiva and Lerman, 2000; Bhat, 1997; and Greene, 1998):

$$P_n(i/m) = \frac{\exp(\mu_m V_{in})}{\sum_{j \in C_m} \exp(\mu_m V_{jn})} = \frac{\exp(\mu_m \beta' X_{in})}{\sum_{j \in C_m} \exp(\mu_m \beta' X_{jn})} \tag{4}$$

$$P_n(m) = \frac{e^{\mu V_{mn}}}{\sum_{m'=1}^{M'} e^{\mu V_{m'n}}} = \frac{\exp(\frac{\mu}{\mu_m} I_{mn} + \alpha' X_{mn})}{\sum_{m'=1}^{M'} \exp(\frac{\mu}{\mu_m} I_{m'n} + \alpha' X_{m'n})} = \frac{\exp(\gamma I_{mn} + \alpha' X_{mn})}{\sum_{m'=1}^{M'} \exp(\gamma I_{m'n} + \alpha' X_{m'n})} \tag{5}$$

Where: μ and μ_m are the scale parameters for the upper (marginal) and lower (conditional) models; α, β are vectors of parameters; and X is the vector of attributes included in the utility functions.

In the CHNL model (Bhat, 1997; Greene, 1998), the parameter γ, which is the coefficient of the inclusive value I_{mn}, is allowed to vary across individuals as a function of a vector of parameters δ' and a set of variables Y_{mn} as shown in Equation 6.

$$\gamma_{mn} = \gamma_m \exp(\delta' Y_{mn}) \tag{6}$$

Where: $\gamma = \dfrac{\mu}{\mu_m}$ is the coefficient of the inclusive value I_{mn}; δ is a vector of parameters; and Y represents the vectors of variables explaining the covariance-heterogeneity.

Both NL and CHNL were applied to two basic cases. The first case considered utility functions in which the inspection/boarding time and the rest of the total travel time were treated as separate variables. Among other things, this specification allows the analyst to specifically assess the role of inspection/boarding time at the airport as a factor in mode choice. The second case considered utility functions in which only the total travel time was considered. The families of models considered are represented schematically in Table 5.

Table 5. Families of models considered.

Type of model:	Inspection/boarding time and the rest of total time as two variables	Total travel time as one variable
Nested Logit (NL)	Family of models A	Family of models C
Covariance Heterogeneity Nested Logit (CHNL)	Family of models B	Family of models D

The best models from each of the families described above are discussed next. The model results are shown in a table containing the variables, coefficients, and t-statistics in the traditional format of discrete choice modeling. The models were estimated using the set of variables collected in the sample. The main emphasis of the modeling work was on the attitudinal variables related to September 11th impacts.

Variables Considered in the Models

The models considered alternative specific constants, usually for the air and car alternatives. Travel costs were considered by means of two variables: "*Company costs*" and "*User costs*" (in US dollars) that represent the actual charges incurred either by the traveler or the company (depending on who pay for the trip expenses). The role of travel time was considered using three different variables: "*Inspection/boarding time*," "*Main travel time,*" and "*Total travel time*," all of them in minutes. *Inspection/boarding time* refers to the time spent at the airport checking in and going through the security check points. *Main travel time* is the time spent in door-to-door travel excluding inspection/boarding time, i.e., total travel time minus inspection and boarding. *Total travel time* is the door-to-door travel time. "*Time (1 and 2) before meeting*" are two variables comprising a piece-wise linear approximation to non-linear effects in the utility functions, as shown in Figure 6. *Time 1 before meeting* represents the time up to the cutoff value of 30 minutes, while *Time 2 before meeting* represents the time in excess of 30 minutes. A similar approach was used with the variable *Age*, which was decomposed into three pieces: *Age 1* (less than 25 years old), *Age 2* (number of years in excess of 25, up to 50 years), and *Age 3* (number of years in excess of 50). These piece-wise approximations were intended to capture effects such as the one illustrated in Figure 6, in which time available in excess of the first 30 minutes has a negative utility (for more information, see Ben-Akiva and Lerman, 2000).

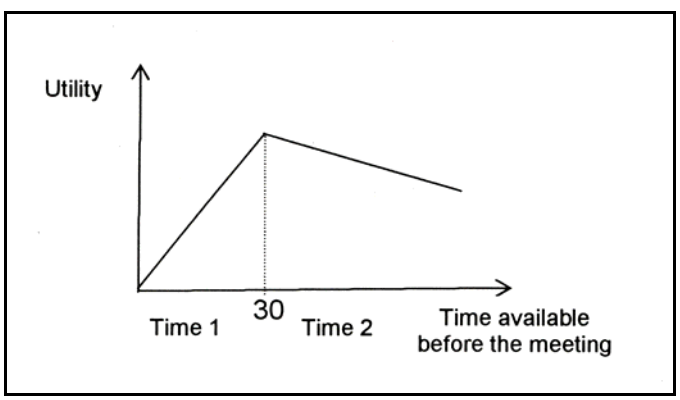

Figure 6. Piece-wise linear approximation to non-linear effects of time available before meeting.

The models included variables that measured both the stress level (*Stress*) and the stated impact produced by September 11th (*Change*). The variable *Change*, that captured their responses to the question of how much September 11th impacted them (1= not at all; 7=significantly), was used in interaction terms with travel time. It was assumed that the variables *Stress* and *Change* could be treated as if they were ratio scales (when in fact they are ordinal scales). This simplifying assumption was taken in order to expedite the model estimation process. Other socioeconomic variables that were found to be significant were income, education level (represented by a set of binary variables), and marital status (a set of binary variables).

It is also important to acknowledge the likely existence of endogeneity bias in some of the models discussed here. This would arise if the variable *Change* shares common unobserved attributes with the mode choice. Correcting for endogeneity bias, either by using instrumental variables (as in Holguín-Veras, 2002) or by explicitly modeling the econometric interactions between the error terms (as suggested in Train, 1986) could not be undertaken here because of the project constraints. This remains the subject of future research.

Models obtained using Inspection/boarding time and Main travel time as two separate variables—Tables 6 and 7 show both the NL and the CHNL versions of the models estimated treating inspection/ boarding time and main travel time as two separate variables. The results outlined in Table 6 illustrate a number of key results that are found in all models. The alternative specific constants for air and car are statistically significant and positive, which indicates bias toward the use of these modes.

In the tradition of discrete choice modeling, the role of the different explanatory variables in the choice process is assessed using the concept of marginal disutility, which represents the rate of change of disutility with respect to an explanatory variable, as shown in Equation 7. In general terms, if a linear in parameters specification is used and there are no interaction terms, the marginal utilities reduce to the coefficient of the variable. If interaction variables are used, the marginal utilities will have additional terms that correspond to the partial derivatives of the interaction variables.

$$U'_{x_{ink}} = \frac{\partial U}{\partial x_{ink}} = \beta_{ink} \tag{7}$$

The marginal disutility of company costs is approximately half the value of the marginal disutility of user costs (the reader should notice that since the coefficients are negative, these are disutilities). This indicates that when the company pays, users behave as having a valuation of travel time, which is double the valuation of their time when they are paying for the expenses. Table 6 also indicates the significance of inspection/boarding time, which has a marginal disutility higher than the marginal disutility for the main travel time (except for air).

As shown in Table 6, the main travel time interacts with the variable *Change*. For that reason, its marginal disutility must be computed taking into account this interaction. In mathematical terms:

$$U(Train\ \ A,B)'_{t_m} = \frac{\partial U(Train\ \ A,B)}{\partial t_m} = -0.010983 - 0.000486\,Change \tag{8}$$

$$U(Air)'_{t_m} = \frac{\partial U(Air)}{\partial t_m} = -0.6435 - 0.003222\,Change \tag{9}$$

$$U(Car)'_{t_m} = \frac{\partial U(Car)}{\partial t_m} = -0.01517 - 0.001221\,Change \tag{10}$$

Where: t_m is the main travel time (total travel time minus inspection/boarding) in minutes.

Equations 8, 9, and 10 indicate how onerous (in utility terms) it is to travel by each of the transportation modes considered. Equations 8, 9, and 10 show that the marginal disutilities have two components (one attributed to the main travel time and another due to the interaction term between main travel time and *Change*). As shown, the marginal disutilities for the train alternatives are much lower than the ones corresponding to air and car. Furthermore, the marginal disutility for rail is much less affected by the impacts of September 11th on the users, captured through *Change*. This can be appreciated by noting that the coefficients of *Change* in Equation 8, i.e., 0.000486, is 2.5 times smaller than the coefficient of car (0.001221), and approximately 9 times smaller than the same coefficient in the utility function of air (0.003222). As shown in Equation 9, the marginal disutilities for air are much higher than the one corresponding to the other alternatives. Equation 9 also shows that, on a per-minute basis, the impacts of September 11th have had a more noticeable effect on the utility function of air than on the others (due to magnitude of the coefficient of *Change*, i.e., 0.003222).

This indicates the mechanisms by which air demand was affected by the September 11th events, and train demand increased. As shown, the psychological impact of September 11th measured by *Change* had virtually no effect in the decision to use train alternatives. The choices of air and car, in this sample, were significantly impacted by the September 11th events.

Table 6. Nested Logit (NL) version (Model A).

Variable	Rail alternatives: Utility function of Metroliner	Rail alternatives: Utility function of Acela	Fly: Utility function of Air	Drive: Utility function of Car
Alternative specific constants			85.00947	2.66552
			(3.812)	(2.128)
Company costs ($)	-0.012631	-0.012631	-0.012631	-0.012631
	-(4.532)	-(4.532)	-(4.532)	-(4.532)
User costs ($)	-0.028119	-0.028119	-0.028119	-0.028119
	-(7.275)	-(7.275)	-(7.275)	-(7.275)
Inspection/boarding time (mins)	-0.014219	-0.014219	-0.014219	-0.014219
	-(3.919)	-(3.919)	-(3.919)	-(3.919)
Main travel time (mins)	-0.010983	-0.010983	-0.643502	-0.015174
	-(2.999)	-(2.999)	-(3.703)	-(2.478)
(Main travel time) (Change)	-0.000486	-0.000486	-0.003222	-0.001221
	-(1.154)	-(1.154)	-(2.674)	-(2.354)
Time 1 before meeting (< 30 mins)	0.031467	0.031467	0.031467	0.031467
	(3.619)	(3.619)	(3.619)	(3.619)
Time 2 before meeting (> 30 mins)	-0.015489	-0.015489	-0.015489	-0.015489
	-(2.981)	-(2.981)	-(2.981)	-(2.981)

Variable		Utility function of RAIL	Utility function of FLY	Utility function of DRIVE
Income ($ 000/year)		-0.007105		
		-(4.156)		
College Undergraduate (binary)		-0.324041		
		-(2.022)		
College Graduate (binary)		-0.181456		
		-(1.149)		
Stress (PSS4)			-0.096745	
			-(3.460)	
Age (years)			0.009479	
			(1.667)	
Single (binary)				-0.261534
				-(1.887)
High School education (binary)				-0.400265
				-(1.615)
Inclusive value parameters		0.569605	0.563207	0.553665
		(4.512)	(5.844)	(3.682)
Log likelihood function	-1665.667		R-squared	0.1906
Restricted log likelihood	-2057.806		R-squared Adj	0.1866
Chi-squared	784.2782			
Degrees of freedom	23			
Significance level	0.00000			

The perceived stress was also found to negatively affect the choice of air alternatives. As shown in the second part of Table 6, the higher the *Stress*, the less likely the decision makers to choose air. Other socio-economic variables also play a role in the choice process, though for the sake of brevity their effects are not discussed here.

Table 7 shows the CHNL version of the model. As in the NL model shown before, the alternative specific constants for air and car are positive and statistically significant. It is also worthwhile to note that the alternative specific constant for air is smaller than the one estimated from the previous model, which is more in line with what one would reasonably expect. As before, the marginal disutilities of company cost (0.0085) are much smaller than that corresponding to user cost (0.0217), which highlights the respondents' differing valuations of time depending on who pays.

A peculiar feature of Model B is that it does not include the travel time in the utility functions for train, though interaction terms involving travel times and socioeconomic characteristics are statistically significant. The interaction variable (*Main travel time*)(*Change*) was not significant and was taken out of the model. As shown in Equations 11, 12, and 13, Model B is consistent with Model A in pointing out that traveling by air has higher disutilities on a per-minute basis than all the other modes, and that it has been impacted more severely by the post-September 11th events.

$$U(Train\quad A,B)'_{t_m} = -0.017863\,\delta_{HS} - 0.003946\,\delta_{CU} - 0.010561\,\delta_{CG} \tag{11}$$

$$U(Air)'_{t_m} = -0.2645 - 0.001454\,Change - 0.0532\,\delta_{HS} - 0.006776\,\delta_{CU} - 0.0289\,\delta_{CG} \tag{12}$$

$$U(Car)'_{t_m} = -0.00395 - 0.000434\,Change - 0.01769\,\delta_{HS} - 0.00708\,\delta_{CG} \tag{13}$$

The covariance heterogeneity function considered only included *Income* as an explanatory variable. As shown in the second part of Table 6, this covariate was highly significant and positive. This indicates that individuals with higher income exhibit higher cross elasticities, which conceptually makes sense. This result is also consistent with Bhat (1997).

Models obtained using total travel time—As indicated previously, the choice situations did not contain the wide range of travel times that would have allowed proper estimation of parameters such as subjective travel time values (because in the choice situation, the travel times only changed with the corridor being considered). In order to mitigate this problem, the research

Table 7. Covariance Heterogeneity Nested Logit (CHNL) version (Model B).

	Rail alternatives		Fly	Drive
Variable	Utility function of Metroliner	Utility function of Acela	Utility function of Air	Utility function of Car
Alternative specific constants			40.28663	2.59457
			(2.922)	(3.031)
Company costs ($)	-0.008547	-0.008547	-0.008547	-0.008547
	-(5.331)	-(5.331)	-(5.331)	-(5.331)
User costs ($)	-0.021749	-0.021749	-0.021749	-0.021749
	-(8.836)	-(8.836)	-(8.836)	-(8.836)
Inspection/boarding time (mins)	-0.011175	-0.011175	-0.011175	-0.011175
	-(4.028)	-(4.028)	-(4.028)	-(4.028)
Main travel time (mins)			-0.264585	-0.003951
			-(2.459)	-(1.692)
(Main travel time) (Change)			-0.001454	-0.000434
			-(3.397)	-(2.653)
Time 1 before meeting (< 30 mins)	0.028372	0.028372	0.028372	0.028372
	(3.250)	(3.250)	(3.250)	(3.250)
Time 2 before meeting (> 30 mins)	-0.010273	-0.010273	-0.010273	-0.010273
	-(2.294)	-(2.294)	-(2.294)	-(2.294)
(Main travel time) (High School)	-0.017863	-0.017863	-0.053292	-0.017691
	-(4.601)	-(4.601)	-(4.757)	-(3.917)
(Main travel time) (College Underg)	-0.003946	-0.003946	-0.006773	
	-(3.321)	-(3.321)	-(2.499)	
(Main travel time) (College Grad)	-0.010561	-0.010561	-0.028961	-0.007085
	-(4.203)	-(4.203)	-(4.725)	-(3.324)

Variable		Utility function of RAIL	Utility function of FLY	Utility function of DRIVE
(Main travel time) (Age 1)		0.000095		
		(1.607)		
(Main travel time) (Age 3)		-0.000231		
		-(3.903)		
Stress (PSS4)			-0.146633	
			-(4.772)	
Single (binary)				-0.402543
				-(2.702)
Inclusive value parameters		0.754331	0.611342	0.705494
		(5.375)	(6.507)	(4.511)
Coefficient of the Cov-Het term				
Income ($ 000/year)	0.002896			
	(4.179)			
Log likelihood function	-1623.847		R-squared	0.2109
Restricted log likelihood	-2057.806		R-squared Adj	0.2063
Chi-squared	867.918			
Degrees of freedom	27			
Significance level	0.00000			

team decided to estimate two families of models, similar to the ones discussed above, using total travel time instead of inspection/boarding time and the main travel time. This section reports the findings of these efforts.

Table 8 shows the statistics of Model C. As shown, the alternative specific constants reduced their values significantly to more realistic levels. In both cases, these constants are positive, indicating that, in equality of conditions, users would favor these transportation modes. As in the previous models, the marginal disutilities of user costs are much higher than the ones corresponding to company costs.

The marginal disutilities for total travel time vary by mode. The estimation results indicate that traveling by air has the higher disutility of time (0.009693) followed by car (0.008083) and train (0.02527). The marginal disutilities of travel time are increased by the interaction terms between total travel time and the variable *Change*. As shown, the marginal disutilities of (*Total travel time*)(*Change*) for the air alternative (0.001105) are approximately twice the value of that corresponding to car (0.000568), while this variable plays no role whatsoever in the utility of rail.

$$U(Train\ \ A,B)'_{t_T} = -0.002527 \tag{14}$$

$$U(Air)'_{t_T} = -0.009693 - 0.001105\,Change \tag{15}$$

$$U(Car)'_{t_T} = -0.008083 - 0.000568\,Change \tag{16}$$

Where: t_T is the total travel time (door to door) in minutes.

Stress, as in the previous models, was found to have a statistically significant negative impact on the choice of air. There were other socio-economic attributes that were also found to play a role in mode choice, among them level of education and age.

The CHNL version of this model is shown in Table 9. The parameters of the model are highly consistent with the parameters of the models discussed in the previous section, in that (1) the marginal disutilities of company costs (0.00693) are much smaller than the ones corresponding to user costs (0.022031); (2) the disutilities of travel time for air (0.009781) are higher than that corresponding to car (0.008294) and train (0.002615); (3) the interaction variable (*Total travel time*)(*Change*) has a more pronounced impact upon the choice of air (0.001017) than for any other mode; (4) the amount of free time before the meeting has a positive effect on mode choice as long as it is less

Table 8. Nested Logit (NL) version (Model C).

	Rail alternatives		Fly	Drive
Variable	Utility function of Metroliner	Utility function of Acela	Utility function of Air	Utility function of Car
Alternative specific constants			3.30624	2.42130
			(3.920)	(2.683)
Company costs ($)	-0.006787	-0.006787	-0.006787	-0.006787
	-(4.357)	-(4.357)	-(4.357)	-(4.357)
User costs ($)	-0.022127	-0.022127	-0.022127	-0.022127
	-(8.451)	-(8.451)	-(8.451)	-(8.451)
Total travel time (mins)	-0.002527	-0.002527	-0.009693	-0.008083
	-(2.180)	-(2.180)	-(3.142)	-(2.545)
(Total travel time) (Change)			-0.001105	-0.000568
			-(3.499)	-(2.879)
Time 1 before meeting (< 30 mins)	0.027873	0.027873	0.027873	0.027873
	(3.065)	(3.065)	(3.065)	(3.065)
Time 2 before meeting (> 30 mins)	-0.015641	-0.015641	-0.015641	-0.015641
	-(3.033)	-(3.033)	-(3.033)	-(3.033)
Variable		Utility function of RAIL	Utility function of FLY	Utility function of DRIVE
Income ($ 000/year)		-0.006718		
		-(4.021)		
College Undergraduate (binary)		-0.355810		
		-(2.268)		
College Graduate (binary)		-0.199004		
		-(1.291)		
Stress (PSS4)			-0.097166	
			-(3.435)	
Age (years)			0.009208	
			(1.606)	
Single (binary)				-0.243119
				-(1.772)
High School education (binary)				-0.300308
				-(1.211)
Inclusive value parameters		0.696508	0.627950	0.723297
		(4.922)	(5.907)	(4.181)
Log likelihood function	-1676.746		R-squared	0.1852
Restricted log likelihood	-2057.806		R-squared Adj	0.1815
Chi-squared	762.1207			
Degrees of freedom	21			
Significance level	0.00000			

Table 9. Covariance Heterogeneity Nested Logit (CHNL) version (Model D).

	Rail alternatives		Fly	Drive
Variable	Utility function of Metroliner	Utility function of Acela	Utility function of Air	Utility function of Car
Alternative specific constants			4.60847	3.35028
			(4.976)	(3.195)
Company costs ($)	-0.006930	-0.006930	-0.006930	-0.006930
	-(4.259)	-(4.259)	-(4.259)	-(4.259)
User costs ($)	-0.022031	-0.022031	-0.022031	-0.022031
	-(8.399)	-(8.399)	-(8.399)	-(8.399)
Total travel time (mins)	-0.002615	-0.002615	-0.009781	-0.008294
	-(2.075)	-(2.075)	-(3.026)	-(2.524)
(Total travel time) (Change)			-0.001017	-0.000590
			-(3.287)	-(2.775)
Time 1 before meeting (< 30 mins)	0.029564	0.029564	0.029564	0.029564
	(3.323)	(3.323)	(3.323)	(3.323)
Time 2 before meeting (> 30 mins)	-0.015805	-0.015805	-0.015805	-0.015805
	-(3.119)	-(3.119)	-(3.119)	-(3.119)

Variable		Utility function of RAIL	Utility function of FLY	Utility function of DRIVE
College Undergraduate (binary)		-0.155024		
		-(1.120)		
Stress (PSS4)			-0.122360	
			-(4.392)	
Age (years)			0.007727	
			(1.205)	
Single (binary)				-0.367154
				-(2.629)
High School (binary)				-0.400432
				-(1.472)
Inclusive value parameters		0.584141	0.525658	0.581367
		(4.816)	(5.880)	(4.155)
Coefficient of the Cov-Het term				
Income ($ 000/year)	0.002582			
	(2.756)			
Log likelihood function	-1683.443		R-squared	0.1819
Restricted log likelihood	-2057.806		R-squared Adj	0.1784
Chi-squared	748.726			
Degrees of freedom	20			
Significance level	0.000000			

than 30 minutes, after this threshold, it has a negative impact; and (5) the higher the *Stress* level, the less likely the users are to choose air. The marginal disutilities for total travel time are shown in Equations 17, 18, and 19.

$$U(Train\ \ A, B)'_{t_T} = -0.002615 \tag{17}$$

$$U(Air)'_{t_T} = -0.009781 - 0.001017\,Change \tag{18}$$

$$U(Car)'_{t_T} = -0.008294 - 0.000590\,Change \tag{19}$$

The modeling results confirmed previously held assumptions about the factors determining intercity mode choice. Variables such as travel costs, time, income, gender, and the like were found to be statistically significant explanatory variables in the mode choice process. These results are in complete agreement with the intercity mode choice literature (e.g., Forinash and Kopppelman, 1993; Bhat, 1997).

As indicated by the model results, the impacts of extreme events on intercity passenger travel behavior consist of modifications of the utility functions for the different modes that translate into a departure from what is normally expected. The authors' conjecture is that these impacts are dynamic in nature and, for that reason, some of them are likely to evolve over time. This suggests that further research is needed to distinguish among the transient and permanent behavioral changes produced by September 11th on intercity travel.

Conclusions

This paper summarized the research conducted on the impacts of extreme events upon intercity travel behavior. This research relied on stated preference data provided by a convenience sample of residents of the New York City metropolitan area, collected six months after September 11th, and the use of modern econometric techniques based on Random Utility Theory to assess behavioral changes. The data collected was based on stated preference techniques, by which the respondents are asked to rank order the different alternatives (air, car, Metroliner, and Acela) as part of a hypothetical choice situation.

The findings may be limited in their generality given the nature of the sample. The participants in this study were mostly young, male, and single without children. They were also highly educated and reported higher incomes than the general population of the five boroughs of New York City. Despite these specific characteristics, a majority of the participants reported having made trips to the target cities, which indicates that the sample was an appropriate one to use and that these individuals do constitute a subset of the market demand in the corridors studied.

Participants reported that before September 11th they were most likely to choose transportation mode based on convenience and cost, and the mode of preference for most was car. Indeed, trips by car were rated better on cost than air or train, and were rated as more secure than trains. While there were no other significant differences among the primary modes (air, train, car) on any of the other features assessed (cleanliness, comfort, and safety), these features may not be as important as cost when choosing mode, especially when one is paying for the trip oneself, as was the case for the majority of participants.

On average, participants reported that September 11th affected travel change "moderately" but it is important to note that the full range of the scale was endorsed by participants. The most frequently reported specific changes were that people became more conscious of security and more aware of other travelers. Participants also had average perceived stress levels that correspond to "almost never" on the response scale, which is comparable to the data from a national probability sample (Cohen and Williamson, 1988). Despite low levels of perceived stress, the general change measure was significantly associated with stress levels, such that those who reported a greater September 11th impact on travel behavior also reported greater levels of perceived stress.

In terms of behavioral modeling, two different types of random utility models were estimated: Nested Logit and Covariance-Heterogeneity Nested Logit models. These two basic types were used in the estimation process using the variables gathered during the data collection process. The estimated models are highly consistent among themselves in highlighting a set of fundamental conclusions about travel behavior in the aftermath of an extreme event.

The modeling results confirmed previously held assumptions about the factors determining intercity mode choice. Variables such as travel costs, time, income, gender, and the like were found to be statistically significant explanatory variables in the mode choice process. These results are in complete agreement with the intercity mode choice literature (e.g., Forinash and Koppelman, 1993; Bhat, 1997).

The research was successful in finding statistically significant linkages between changes in travel behavior and the impact of an extreme event, in this case September 11th. These linkages revealed themselves as additional terms in the utility functions estimated using Random Utility Theory. In all models estimated, the variable that measured the impact of the September 11th events upon the individuals that participated in the survey, i.e., *Change*, and a psychometric scale of perceived stress level, i.e., *Stress*, were found to play a statistically significant role in the mode choice process. Interestingly, *Change* and *Stress* seem to have different mechanisms.

The variable *Change* was found to have significant interactions with the travel time. This, in turn, translates into the marginal disutility of travel time being modified by *Change*, as shown in Equations 8 to 19. The magnitude of this modification is clearly related to the transportation mode. In all cases, the contribution of the interaction term between *Change* and travel time is highest for air, followed by car and then train. This may be related to the fact that the terrorist attacks involved airplanes and the effect this had on the general public's perception about the safety of the air transportation system after September 11th. The modeling results clearly indicate that the utility functions of the train alternatives are minimally affected by the interaction terms between *Change* and travel time (in some cases, the interaction term drops out of the utility functions). The latter suggests that the users perceive the train alternatives as being less taxing to them, in utility terms, after an extreme event such as September 11th.

The perceived level of stress, i.e., *Stress*, was found to have a statistically significant impact in mode choice. However, the interpretation of the impact of *Stress* and its relation to September 11th is obscured by the fact that the psychometric measure used (PSS4; Cohen and Williamson, 1988) provides a measure of overall stress level, not of the stress specifically produced by September 11th. In any case, *Stress* specifically impacted the utility function of air without interacting with any other variable or utility function. In general terms, the higher the stress level, the less likely the decision makers to choose the air alternative.

In spite of the numerous and significant limitations faced in this research, the authors are confident in the ability of this research to provide insights into the effects that extreme events have upon intercity travel behavior. This modest success should not obscure the fact that this paper is nothing more than a first step in the long march towards a better understanding of the impacts of extreme events on travel behavior.

References

Ben-Akiva, M. and S. Lerman. 2000. *Discrete Choice Analysis*. Cambridge, MA: MIT Press.

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

Bureau of Transportation Statistics. 1997. *American Travel Survey.* Publication No. BTS/ATS95–US. Washington D.C.: U.S. Department of Transportation.

Cohen, S. and G.M. Williamson. 1988. "Perceived Stress in a Probability Sample of the United States." Pp. 31–67 in S. Spacapan and S. Oskamp, eds., *The Social Psychology of Health*. Newbury Park, CA: Sage.

Forinash, C. and F. Koppelman. 1993. "Application and Interpretation of Nested Logit Models of Intercity Mode Choice." Presentation at the 72nd Annual Meeting of the Transportation Research Board, Washington, D.C.

Greene, W. 1998. *LIMDEP: User's Manual*. Plainview, NY: Econometric Software, Inc.

Hensher, D. 1994. "Stated Preference Analysis of Travel Choices: The State of the Practice." *Transportation* 21: 107–133.

Holguín-Veras, J. 2002. "Revealed Preference Analysis of the Commercial Vehicle Choice Process." *Journal of Transportation Engineering* 128(4): 336–346.

Holguín-Veras, J., R. Paaswell, and E. Marin. 2002. "Business Location Modeling Working Paper." New York: University Transportation Research Center.

Holusha, J. 2002. "In Office Market, a Time of Uncertainty." *New York Times* (January 6): Real Estate Section 1,9.

McFadden, D. 1974. "Conditional Logit Analysis of Qualitative Choice Behavior." Pp. 105–142 in P. Zarembka, ed., *Frontiers in Econometrics*. New York: Academic Press.

McFadden, D. 1978. "The Theory and Practice of Disaggregate Demand Forecasting for Various Modes of Urban Transportation." Pp. 1–27 in W. Brown, ed., *Emerging Transportation Planning Methods*. Washington, D.C.: U.S. Department of Transportation.

Thurstone, L.L. 1927. "A Law of Comparative Judgement." *Psychological Review* 34: 273–286.

Train, K. 1986. *Qualitative Choice Analysis*. Cambridge, MA: MIT Press.

Acknowledgments

The research team expresses its gratitude and admiration for the staff of the New York Metropolitan Transportation Council and the Port Authority of New York and New Jersey, who despite having suffered terrible loses in September 11th had the energy, resiliency, and motivation to collaborate in this and other research projects. The research team is also grateful to the approximately 200 volunteers who generously agreed to participate in this important investigation. The investigators also recognize the collaboration of the staff of the Bureau of Transportation Statistics, particularly Mr. John Wells, Chief Economist, for providing data crucial to this investigation. Mr. Gary Grayley, from Greyhound, provided key insights into the nature of intercity mode competition. The extraordinary work done by Ms. Eva Marin, Graduate Research Assistant at the City College of New York, in putting together the data files and supporting the analyses is to be commended. The insights provided by Professor Chandra Bhat, University of Texas at Austin, into the Covariance Heterogeneity Nested Logit model are gratefully acknowledged. The contributions of all these individuals contributed to enhancing the quality of the analyses conducted here, but do not make any one of them responsible for the shortcomings of the research.

This research was partially supported by a grant from the National Science Foundation. This support is both acknowledged and appreciated.

Correspondence should be directed to José Holguín-Veras, Ph.D., P.E., Associate Professor, Department of Civil and Environmental Engineering, Rensselaer Polytechnic Institute, 4030 Jonsson Engineering Center, 110 Eighth Street, Troy, NY 12180-3590; e-mail: jhv@ti-mail.engr.ccny.cuny.edu or to Robert E. Paaswell, Ph.D., P.E., Distinguished Professor, City College of New York, Bldg. Y-220, New York, NY 10031; e-mail: paaswellcius@ccny.cuny.edu.