An Empirical Analysis of the Impact of Security Perception on Intercity Mode Choice Using a Panel Rank-Ordered Mixed-Logit Model

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ABSTRACT
In the aftermath of the terrorist attacks of September 11, 2001, individuals have become increasingly conscious about travel safety and security issues. Hence, in addition to travel times and costs, the perceptions about the security-levels can also be expected to be an important factor influencing intercity travel decisions. In the last few years, the Transportation Security Administration (TSA) has implemented several procedures including rigorous screening to improve airline security. However, these procedures have also increased the airline travel times. In this paper, we present an empirical analysis of individuals' mode choice for intercity business trips incorporating trade-offs between improved security levels and increased travel times. Stated-preference data collected in New York City are used to develop a panel rank-ordered mixed logit model.

We find that individuals who hold positive impressions about the security measures are more likely to fly, but the utility of air mode decreases with increasing inspection and boarding time. The implication of these empirical results is that the TSA should seek to both improve the public perceptions of the security arrangements as well as ensure fast and efficient screening so as to sustain/increase the demand for air travel. However, caution should be administered in generalizing these findings as these are based on a small sample and data gathered from an area directly impacted by the events of 9/11. In summary, this paper reiterates the importance of research toward understanding the role of security perceptions on intercity travel decisions and presents a first step in this direction.

1. BACKGROUND AND RESEARCH OBJECTIVES

The importance of the influence of traveler perceptions and attitudes in activity-travel decision making has been well acknowledged in transportation literature [see for example, Kuppam *et al.* (*1*)]. In particular, in the aftermath of the extreme events of September 11, 2001, the heightened security consciousness of travelers has become a significant factor in determining intercity travel behavior. For example, based on data collected in New York City within about six months after 9/11/2001, Liu and Li (*2*) find that intercity travel decisions are impacted by security considerations in addition to travel time, cost, and reliability. Such security considerations can be expected to be, in part, responsible for the overall decrease in the demand for air transportation after 9/11. In fact, Guzhva and Pagiavlas (*3*) report that the terrorist attack has had a significant negative impact on the performance of the airline industry even after controlling for the influence of macroeconomic factors.

One of the possible consequences of decreased air travel levels is a corresponding increase in highway traffic volumes. Research studies undertaken by Rossiter and Dresner (*4*) and Gigerenzer (*5*) suggest that such a diversion of air traffic to the highways could potentially lead to increased roadway fatalities. Hence, it is necessary for transportation planning agencies to undertake steps such as improvement of aviation security to minimize the diversion of air traffic to the highways and maintain the overall safety of the transportation system.

The Transportation Security Administration (TSA) was established by the Aviation and Transportation Security Act (ATSA) on November 19, 2001 as an administrative unit responsible for preventing criminal and terrorist acts in the air transportation system (see www.tsa.gov for details). The TSA has implemented several measures to make the air travelers feel safer and thereby increase the attractiveness of the air mode for long distance travel. However, these procedures have also resulted in an increase in the airline travel times because of the increased time required for passenger and baggage screening. Further, the security measures are paid for by additional fees imposed on both the commercial carriers as well as the passengers, thereby increasing travel costs for the air mode. Thus, in evaluating the response of individuals to these new policy actions, it is necessary to consider the trade-offs made by passengers between improved security levels and increased travel times/costs.

The objective of this paper is to examine the impact of security perceptions on intercity mode choice for business trips in the aftermath of the extreme event of September 11, 2001. Specifically, this study seeks to analyze travelers' trade-off between perceived security levels and increased airline inspection/boarding time due to implementation of rigorous security measures. Thus, this paper contributes to the literature on intercity mode choice analysis which, to date, has predominantly focused on impacts of level-of-service and traveler demographics [see for example, Lee *et al.* (*6*), Limtanakool *et al.* (*7*), Carlsson (*8*), Bhat (*9-11*), and Forinash and Koppelman (*12*)].

Data on mode-choice decisions of individuals can be collected using either stated-preference (SP) or revealed-preference (RP) surveys. The former methodology is attractive for this analysis as it allows for eliciting preference information for scenarios which do not exist currently in the real-world, but could potentially be realized in the future. For example, these hypothetical scenarios could reflect significant variations in airline inspection times that are currently not observed. However, unlike RP data, SP data are only self-stated preferences and not actually observed choices. This is a clear shortcoming as people may not actually do what they say they would [see for example, Train (*13*)]. Recently, there have been efforts to develop advanced econometric methods that effectively incorporate both RP and SP data [see for example, Bhat and Castelar (*14*)]. However, for the purposes of this study, we restrict ourselves to the use of only stated-preference data.

There are three common response dimensions employed in stated preference surveys [see also Hensher (*15*)]. These are (1) rating of alternatives, (2) ranking of alternatives, and (3) choice of the single most-preferred alternative. The rating of alternatives provides the richest preference data to the analyst, but it is also the most demanding to the respondent. In contrast, the single-choice response provides the least preference information for analysis, but is also least demanding to the respondent. The ranking approach may be seen as an attractive middle-ground between the rating and the single-choice approaches. This is because, in the ranking approach, the respondent provides a preference ordering of alternatives (more data than a single choice response) but not the relative degree of preferences (less data than the rating response). Consequently, the use of ranking of alternatives as the response dimension can help limit the sample size compared to surveys using single choice as the response, while at the same time not imposing substantial burden on the respondent as would a rating approach.

The econometric methodology to analyze rank-ordered data was first developed and applied by Beggs *et al.* (*16*) and Chapman and Staelin (*17*). This methodology (called the "rank logit" or "exploded logit") involves "exploding" or expanding the ranking of a set of *K* alternatives into a sequence of *K*-1 independent "implicit" choice occasions. The first implicit choice corresponds to choosing the highest ranked alternative from among all the *K* available alternatives. In the second choice occasion, the second highest ranked alternative is chosen from the remaining *K*-1 alternatives (*i.e.*, after excluding the alternative assigned the highest rank), and so on until the last or the $(K\text{-}1)^{th}$ choice occasion in which the alternative to be assigned rank *K*-1 is picked from the two remaining alternatives that have not been yet been assigned a rank. Hausman and Ruud (*18*) enhanced the rank-logit model and proposed the "heteroscedastic rank logit" specification that allows for the variance of the error term to be different for the different levels of the ranking. This modeling enhancement recognizes that individuals may pay lesser attention to assigning lower ranks compared to higher ranks, consequently decreasing the reliability (or increasing the variance) of the ranking of less preferred alternatives. Some applications of these approaches in the field of Transportation include Ben-Akiva *et al.* (*19*) Bradley and Daly (*20*), Odeck (*21*), Fridstrom and Elvik (*22*), and Hunt (*23*).

Despite the overall popularity of these methods, the validity of simply pooling "implicit" choices from different ranking levels as independent observations for modeling has also been questioned [see for example, Ben-Akiva e*t al.* (*19*), Bradley and Daly (*20*), and Hensher (*15*)]. With advances in the field of discrete-choice analysis in the area of mixed models and simulation estimation techniques, it is possible to relax the restrictive independence assumption using the mixed-logit or random-coefficient model specifications [see for example, Train (*13*)]. Such "rank-ordered mixed-logit" models can capture the correlations across the different implicit choices made by an individual and thereby model the rank-ordered data more realistically. Layton (*24*) developed a random-coefficients rank-ordered model using partial ranking data (only the first two ranks were considered) from a survey of public preferences for a hazardous-waste site cleanup. Calfee *et al.* (*25*) analyzed commuters' trade-offs between travel times and costs to determine the value of travel time. A random-coefficients rank-ordered model was estimated using stated-preference data in which the respondents ranked thirteen different scenarios. Both the above studies report that including preference data from lower ranks increases the precision of the parameter estimates after incorporating preference heterogeneity (*i.e.*, the random coefficients).

In this paper, we present a rank-ordered mixed logit model to examine the impact of security perceptions on intercity mode choice in the aftermath of the extreme event of September 11, 2001. Stated-preference data collected in New York City are used in the empirical analysis. The rest of this paper is organized as follows. Section 2 presents the econometric formulation of the panel rank-ordered mixed logit model. Section 3 describes the simulation-based technique for model estimation. Section 4 describes the survey instrument and the sample characteristics. Section 5 discusses the empirical model results. Section 6 summarizes the research and highlights the major conclusions.

2. ECONOMETRIC MODEL FORMULATION

Let q be the index for individuals and s be the index for the scenarios presented to each individual. Let k (=1,2,…,K) be the index for the set of choice alternatives (travel modes) rank ordered in each scenario. As already discussed, the rank ordering of K alternatives corresponds to K-1 implicit choice occasions. Let m (=1,2,,…,K-1) represent the index over these implicit choice occasions. The reader will note that the m^{th} implicit choice occasion corresponds to the assignment of rank m to an alternative.

The utility of mode k in the implicit choice occasion m corresponding to scenario s for an individual q is:

$$U_{qsmk} = \beta X_{qsk} + \omega_{qk} + \varepsilon_{qsmk} \tag{1}$$

In the above equation, X_{qsk} is the vector of explanatory variables for alternative k, corresponding to scenario s of an individual q, and β is the vector of coefficients on these variables. The reader will note that, based on the above utility specification, the deterministic utility for each alternative is the same for all the implicit choice occasions corresponding to a particular scenario. Thus, the model assumes that the individuals have the same protocol for "choosing" the preferred alternative at all levels of ranks.

ω_{qk} is an error term that captures the impacts of individual-specific unobserved factors on the utility of alternative k for all the implicit choice occasions corresponding to a particular ranking and for all the scenarios corresponding to an individual. Thus, this error term introduces the correlations across all the implicit choices made by an individual, thereby relaxing the independence assumption of the classical rank logit model. These error terms are assumed to be independently and normally distributed with a zero mean and variance σ_k^2 across individuals for each alternative k. Let F_k represent the corresponding cumulative distribution functions. These errors are also assumed to be independently and identically distributed across individuals.

ε_{qsmk} is the residual gumbel-distributed error term with a zero mean and unit scale. This error term is assumed to be independently and identically distributed across the choice alternatives, the implicit choice occasions, the scenarios, and the individuals.

The probability of an individual q assigning rank m to an alternative k in scenario s (or equivalently, the probability of choosing alternative k from the set of available alternatives C^m in the implicit choice occasion m) conditional on $\omega_{qk'} \forall k' \in C^m$ is given by:

$$\Pr_{qsm}[k \in C^m \mid \omega_{qk'} \forall k' \in C^m] = \frac{\exp[\beta X_{qsk} + \omega_{qk}]}{\sum_{k' \in C^m} \exp[\beta X_{qsk'} + \omega_{qk'}]} \tag{2}$$

The conditional probability (conditional on $\omega_{qk'} \forall k' \in C^1$) of an individual q assigning a rank ordering of $k^1, k^2, k^3, .., k^{K-1}$ (*i.e.*, alternative k^1 is assigned rank 1, alternative k^2 is assigned rank 2, and so on) for a scenario s is computed as the product of the conditional probability for all the implicit choice occasions:

$$\Pr_{qs}[k^1, k^2, k^3, ..k^{K-1} \mid \omega_{qk'} \forall k' \in C^1] = \prod_m \Pr_{qsm}[k^m \in C^m \mid \omega_{qk'} \forall k' \in C^m] \tag{3}$$

Finally, the unconditional probability of a ranking $k^1, k^2, k^3, .., k^{K-1}$ for a scenario s for an individual q is obtained as:

$$\Pr_{qs}[k^1, k^2, k^3, ..k^m] = \int_{\omega_{qk'} \forall k' \in C^1} \left\{ \prod_m \Pr_{qsm}[k^m \in C^m \mid \omega_{qk'} \forall k' \in C^m] \right\} d[F_1(\omega_{q1})]d[F_2(\omega_{q2})...d[F_K(\omega_{qK})] \tag{4}$$

3. MODEL ESTIMATION PROCEDURE

Define a binary variable δ_{qsmk} that equals 1 if person q assigns rank m to alternative k in scenario s and zero otherwise. The conditional likelihood of observing the reported rank ordering in a scenario s by person q is given by:

$$L_{qs} \mid (\omega_{qk'} \forall k' \in C^1) = \prod_m \left\{ \prod_{k \in C^m} \left[\Pr_{qsm}[k \in C^m \mid \omega_{qk'} \forall k' \in C^m] \right]^{\delta_{qsmk}} \right\} \tag{5}$$

The conditional likelihood of observing all the reported rank-orderings of an individual q is computed as the product of the conditional likelihoods of observing the reported rank-orderings for each of the scenarios:

$$L_q \mid (\omega_{qk'} \forall k' \in C^1) = \prod_s \left\{ L_{qs} \mid (\omega_{qk'} \forall k' \in C^1) \right\} \tag{6}$$

Therefore, the unconditional log-likelihood function for an individual q is determined as:

$$LogL_q = Ln\left[\int_{\omega_{qk'} \forall k' \in C^1} \left\{ L_q \mid (\omega_{qk'} \forall k' \in C^1) \right\} d[F_1(\omega_{q1})]d[F_2(\omega_{q2})...d[F_K(\omega_{qK})] \right] \tag{7}$$

In the model estimation, the above log-likelihood function is maximized to determine β, the vector of coefficients on the explanatory variables and the standard-deviations (*i.e.*, $\sigma_k \forall k \in C^1$) of the individual specific error terms ω_{qk}.

The estimation involves the use of simulation techniques as the log-likelihood function to be maximized (*i.e.*, equation 7) does not have a closed-form analytic solution. Specifically, the conditional likelihood function from equation (6) is computed for different realizations of ω_{qk} and appropriately drawn from their normal distribution functions (F_k) and averaged to obtain an approximation of the unconditional likelihood function value. The realizations of ω_{qk} are obtained using Quasi-Monte Carlo techniques. In this research, we use 2000[1] draws of the Halton sequence [see Bhat (*26*) for details on the Halton sequence and the QMC estimation procedures]. The parameters are estimated using the maximum (log) simulated likelihood (MSL) estimation procedure. The likelihood functions and the analytical gradients were coded in the GAUSS 6.0 (Aptech Systems, Inc.) programming language. The maximum likelihood estimations were performed using the MAXLIK library of functions.

4. DATA

The data used in this analysis were collected using a stated preference survey administered by The City College of New York. The data were collected from respondents in New York City during the months of October 2003 – May 2004 (approximately between two and two-and-a-half years after the events of 9/11/2001). This survey also represents the third wave of data collection undertaken as part of an NSF-funded research project examining the impacts of extreme events on passenger travel behavior [the reader is referred to Holguin-Veras *et al.* (*27*) for details on the first wave survey]. This section of the paper first describes the third wave survey instrument with primary focus on the elements relevant to this analysis, and subsequently presents a descriptive analysis of the data sample used in this analysis.

4.1 Survey Instrument

The primary component of the survey comprised a choice experiment in which respondents were asked to rank-order four travel modes for a business trip under different scenarios for one of six intercity corridors. These intercity corridors are (1) Boston – Washington D.C, (2) New York City – Boston, (3) New York City – Buffalo, (4) New York City – Chicago, (5) New York City – Washington D.C., and (6) New York City – Montreal. In addition, approximately one-half of the respondents were asked to respond to the choice experiment assuming that their employer was paying for the trip and the rest were asked to respond assuming that they were paying for their own trip.

The four travel modes presented to the respondents are (1) A Metroliner-type train (referred to as Train M in the rest of the paper), (2) An Acela-type train (referred to as Train A in the rest of the paper), (3) Airplane and (4) Car. These alternatives were characterized in terms of time-of-day of departure, travel time, airplane inspection and boarding (I&B) time, and travel cost. Feasible and reasonable combinations of the values of the above attributes characterizing the modes were identified to produce nine different scenarios. Specifically, in the first three scenarios, the airplane inspection/boarding times were varied as 120, 60, and 30 minutes respectively, holding all the other attributes for the air and other modes to the currently-prevailing levels. Scenarios four, five, and six were generated by changing the departure times for Train M in scenarios one, two, and three respectively. Finally, scenarios seven, eight, and nine were generated by changing the travel times and costs for Train A (travel time was decreased and cost increased to generate a high-speed high-cost alternative) in scenarios one, two, and three respectively.

Each respondent was asked to provide the preferred rank-ordering of the four travel modes for each of the nine scenarios described above for the intercity corridor assigned to them. In addition, the respondents were also asked to rank order the alternatives in the first scenario

[1] The need for a large number of Halton draws is because of the small sample size of 114 individuals.

assuming that the trip was being made prior to September 11, 2001. Thus, in the overall, the survey elicits ten rank-ordering responses from each individual.

In addition to the choice experiment, the survey also included questions on the individuals' security perceptions. Specifically, the respondents were asked to provide their opinion about prevailing security measures on a scale of 1 though 5 with 1 being "very ineffective", 2 being "ineffective", 3 being "neutral", 4 being "effective", and 5 being "very effective".

Data on individual demographic characteristics (gender, marital status, age, education level, and household income) were also collected. In addition, the degree to which individuals appraise their life as stressful was determined through the following four questions: (1) How often have you felt that you were unable to control the important things in your life?, (2) How often have you felt confident about your ability to handle personal problems?, (3) How often have you felt that things were going your way?, and (4) How often have you felt difficulties were piling up so high that you could not overcome them?. Each of these questions were rated on a five-point scale (1 = never, 2 = almost never, 3 = sometimes, 4 = fairly often, and 5 = very often).

Finally, the respondents were also asked to describe their travel characteristics in the assigned travel corridor, if they have actually traveled in that corridor. The data collected include the frequency and purpose of trips and the mode of travel during the last trip.

4.2 Sample Formation and Characteristics

A total of 124 individuals participated in the survey. With each individual providing ten mode choice rankings, a total of 1240 cases are obtained. Of these, 995 cases (80.24%) had complete ranking information (*i.e.*, all alternatives were ranked) without any ties in the ranking (*i.e.*, all ranks were assigned) and were used in the modeling exercise[2]. These 995 cases correspond to 114 individuals. 61.4% of these individuals had data for all the ten scenarios in the final sample; 14.9% had nine scenarios, 6.1% had eight scenarios, 5.3% had seven scenarios, and the rest had six or fewer scenarios in the final data sample. The split by corridors are as follows: 8.7% of the individuals were assigned the Boston-DC corridor, 23.7% were assigned the New York City – Boston Corridor, 16.7% were assigned the New York City – Buffalo corridor, 17.5% were assigned the New York City – Chicago corridor, 14% were assigned the New York City – Washington D.C. corridor, and 19.3% were assigned the New York City – Montreal corridor.

About 65% of the survey respondents are male and 40% are married. About one-third of the respondents are less than 25 years of age, one-third are between the ages of 25-30, 17.5% are between the ages of 31-35, and the rest are over 36 years of age. About 9% of the sample comprises individuals with a high school diploma, 48% have an undergraduate degree, 32% have a graduate degree and the rest have a post-graduate degree. About one-third of the respondents have a household income of less than 15,000, 27% have an income between 15,000 and 35,000, 22% have an income between 35,000 and 75,000 and the rest have household income in the excess of 75,000.

Overall, the survey sample comprises predominantly of young individuals, with at least an undergraduate degree. Thus, the sample is not very representative of the overall population. It is therefore necessary to administer caution in generalizing the results from this study. For

[2] The modeling methodology can be extended to incorporate both tied ranks and incomplete rankings. However, for the sake of simplicity, we chose to restrict ourselves to cases with complete ranking without ties.

example, the perceptions and responses of middle-aged and elderly people and low-education individuals may be different and not adequately captured in this analysis.

The responses to the four questions about the individuals' appraisal of their stress levels were used to construct a 4-item Perceived Stress Scale (PSS4) measure [see Cohen and Williamson (*28*) and Holguin-Veras *et al.* (*27*)]. The measure was computed by averaging the ratings for the four questions after reversing the ratings for the second and third questions (*i.e.*, "How often have you felt confident about your ability to handle personal problems?" and "How often have you felt that things were going your way?"). A lower value of the PSS4 score implies that the individual perceives his/her life as less stressful, while a higher value of the PSS4 score implies perception of life as being more stressful. The average value of the PSS4 score in the sample is 2.6075 with a standard deviation of 0.5044. The PSS4 score ranges from 1.25 to 3.50 for the 114 individuals in the final sample.

As already described in the previous section, data on the perceptions of individuals about security measures were also collected. Of the 114 individuals in the final sample, 5.3% felt that the security measures are "very ineffective", 18.4% felt that the measures were "ineffective", 47.4% had "neutral" opinions, 26.3% felt that the measures were "effective" and the rest (2.6%) were of the opinion that the security measures are "very effective".

40 of the 114 (35%) individuals surveyed reported that they have actually traveled in the intercity corridor assigned to them. Of these 40 individuals, 50% drove during their last trip in the assigned intercity corridor, 22.5% flew, 15% took the train, and 12.5% used other modes (predominantly the bus).

Descriptive statistics on the observed rank-ordering of the four modes in the 995 cases in the final sample is presented in Table 1. Specifically, this table presents the frequency with which each of the four ranks is assigned to each of the four alternatives. The air mode is found to be the most likely (45.33%) to be assigned the first rank whereas the train modes are found to be the least likely to be assigned the first rank. Further, the faster Acela-type train (Train A) is more likely to be assigned the first rank compared to the slower Metroliner-type (Train M) train. The two train modes are more likely to be assigned the middle ranks (*i.e.*, ranks 2 and 3) compared to the air and car modes. When Train M is more likely to be assigned the third rank (36.68%), Train A is more likely to be assigned the second rank (43.62%). Finally, we also observe that the car mode is the most likely to be assigned the last rank (42.61%) followed by Train M (28.54%). Train A is the least likely to be assigned the last rank among all the four modes.

The frequencies of the different rank-ordering combinations observed in the final sample comprising 995 cases are presented in Table 2. It is interesting to note that all the 24 different rank-orderings possible are observed in the sample. Air > Train A > Train M > Car is the most commonly observed rank-ordering (19.70% of all cases). Air > Train M > Car > Train A is the least commonly observed rank-ordering (0.2% of all the cases).

5. EMPIRICAL MODEL RESULTS

This section discusses the panel rank-ordered mixed-logit model developed for intercity mode choice using the stated preference data described in the previous section. The log-likelihood value at convergence for the panel rank-ordered mixed logit model is -2194.939 and the corresponding value for the rank-ordered MNL model (*i.e.,* the rank logit or exploded logit model discussed in Section 1) is -2910.617. The reader will note that the rank-ordered MNL is obtained by restricting the standard deviations σ_k to zero in the rank-ordered mixed logit model.

The log-likelihood values clearly indicate that the mixed model fits the data substantially better than the MNL model.

The explanatory variables included in the empirical model specification (Table 3) are broadly classified into five categories: (1) Level of service, (2) Perception about security measures, (3) Stress and demographic variables, (4) Revealed travel characteristics, and (5) Trip characteristics. Each of these is discussed in detail below.

The level of service variables included in the model specification are total travel time, travel cost (normalized by household income), and airline inspection and boarding (I&B) times. As would be expected, the empirical results indicate decreasing utility of travel modes with increasing travel times and costs. Further, the sensitivity of individuals to travel costs is found to be inversely proportional to their household income, *i.e.*, individuals from high-income households are less sensitive to the same travel cost compared to individuals from low-income households. The coefficients on the airline inspection and boarding time variables for the air mode are negative and strongly significant. This result indicates that increased I&B times due to rigorous security measures decreases the utility of the air mode for travelers, possibly as a consequence of the discomfort faced by travelers as they wait in queues for personal and baggage screenings. Hence, it is necessary for TSA to ensure that the screening procedures are not only rigorous but also speedy.

Individuals who feel more positively about the security measures (as indicated by an "effective" or "very effective" rating on the security-perception related question described in Section 4.1) have a greater utility for the air-mode compared to individuals who hold "neutral", "ineffective", or "very ineffective" opinions (see the positive coefficient on the dummy variable, "effective or very effective rating").[3] This indicates that active steps undertaken to enhance travelers' perception about the effectiveness of the security measures can help increase the share of the air mode for intercity travel. We did not find any empirical evidence to suggest differences in the impact of security perceptions on mode choice based on demographic characteristics such as gender and marital status.

The next set of variables captures the effects of stress and demographics on mode choice. Individuals with high stress levels (as indicated by a PSS4 score of 3 or higher) are found to prefer the car mode to any of the public transportation modes for intercity travel. This could be because of the desire of such individuals to interact less with others and be more "in control" during the long-distance travel. The demographic characteristics impacting mode choice decisions are the age and the marital status of travelers. Specifically, married individuals are found to be more likely to fly for long distance trips and young adults (age $\leq$ 25) are found not to prefer the car mode.

The fourth category of variables captures the impact of revealed travel behavior on the stated mode-choice decisions. In general, we observe that individuals who have actually traveled by a particular mode in the corridor assigned to them are more likely to choose the same mode in the stated-preference choice experiments. A plausible explanation of this result is the impact of familiarity acquired from actual travel by the mode in the specific corridor. The reader will note that this impact of revealed travel is very strong in the case of the air mode.

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[3] The perceptions about security measures introduced as three dummy variables: Positive perception ("effective" or "very effective" rating), neutral perception ("neutral" rating), and negative perception ("ineffective or very ineffective" rating). We did not find any significant difference between the impact of the neutral and negative perception categories. Hence, these categories are combined and constitute the base category.

The final category of explanatory variables relate to the characteristics of the trip. As already discussed in Section 4.1, approximately one-half of the respondents were asked to respond to the choice experiment assuming that their employer was paying for the trip and the rest were asked to respond assuming that they were paying for their own trip. The empirical results indicate that individuals are more likely to choose the air mode if the trip was paid for by the employer.

The last explanatory variables included in the model are the alternative specific constants. These capture the generic preference for the different modes after accommodating the impacts of the other explanatory factors and offer no substantive interpretation. For theoretical and empirical modeling considerations, the constants for both the train modes were fixed to zero.

The standard deviations, *i.e.* σ_k, of the individual-specific error terms are found to be statistically very significant (The standard deviations for the two train modes were set to be equal for empirical reasons). This indicates the strong presence of individual-specific unobserved factors that impact the individual's utility for each of the modes for all the implicit choice occasions corresponding to a particular ranking exercise and for all the scenarios. Thus, the model suggests that the different implicit choices of an individual are correlated.

6. SUMMARY AND CONCLUSIONS

Attitudes and perceptions of travelers play a significant role in determining their activity-travel patterns. In particular, the heightened security consciousness of travelers in the aftermath of the extreme events of September 9/11 are paramount in influencing the mode choice for long distance trips. The Transportation Security Administration has taken several steps to enhance aviation security, but these measures have also resulted in increased travel times and travel costs for the air mode. Thus, in evaluating these new measures, it is necessary to consider the passengers' trade-offs between travel times/costs and security levels in travel mode choice decisions. Identification of suitable measures that encourage air travel can help reduce the diversion of the corresponding trips to the highways and prevent any undue increase in highway fatalities.

In the light of these reasons, this paper examined the impacts of the security perceptions of travelers and the increased I&B times on intercity mode choice decisions for business trips. Stated preference data collected from New York City were used to estimate a panel rank-ordered mixed logit model. Prior to discussing the results, it is useful to note here that it is necessary to exercise caution in generalizing the results from this study given the size (114 individuals) and composition (young, well educated, New York City residents) of the sample used for the analysis.

The empirical model results indicate that people who feel more positively about the security measures are more likely to fly for long distance trips (after controlling for the impacts of level of service, demographic factors, and reveled travel behavior). However, the travelers' utility for the air mode is also significantly and negatively impacted by increased I&B times required as consequence of passenger and baggage screening procedures. Overall, this analysis suggests that the success of the strategies employed to improve aviation security in order to reduce the diversion of traffic to the highways depends on the passengers' perceptions of the measures implemented as well as the inspection times. Therefore, it is necessary for TSA to generate (via advertising campaigns or other means) a favorable public perception of the merits of all the implemented security measures. In addition, the airport personnel should be trained to conduct the security checks efficiently (*i.e.*, thoroughly and quickly) in order to minimize wait times at the airport.

In summary, this paper reiterates the importance of the influence of the security perceptions of people on their intercity travel decisions. The empirical analysis in this study was undertaken in the context of business trips. The analysis can be extended to leisure trips where individuals have greater flexibility in travel decisions. Further, it is useful to analyze spatial variations in the sensitivities to the security measures. The current analysis used data from New York City, a region that was directly impacted by the incidents of September 11, 2001. Consequently, it is quite possible that the survey respondents were considerably more sensitive to security issues compared to individuals from the rest of the country. In addition, temporal changes should also be examined. Specifically, the extent of the influence of security perceptions on mode choice decisions can also be expected to be the highest immediately following an extreme event and decrease over time. Finally, it is important to note that it is difficult and tricky to accurately capture subjective issues like security perceptions in surveys. In our research, the respondents provided their opinion on the effectiveness of security measures on a simple rating scale. Future research should seek to develop innovative methods to elicit and analyze data on travelers' perceptions.

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TABLE 1 Frequency With Which Each Rank is Assigned to Each of the Four Modes

Rank	Train M (Metroliner)		Train A (Acela)		Air		Car	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
1	135	13.57	177	17.79	451	45.33	232	23.32
2	211	21.21	434	43.62	177	17.79	173	17.39
3	365	36.68	296	29.75	168	16.88	166	16.68
4	284	28.54	88	8.84	199	20.00	424	42.61
Total	995	100.00	995	100.00	995	100.00	995	100.00

TABLE 2 Frequency Distribution of the Different Possible Rank-Ordering Combinations in the Final Sample

Rank 1	Rank 2	Rank 3	Rank 4	Freq.	%
Air	Train A	Train M	Car	196	19.70
Air	Train A	Car	Train M	83	8.34
Air	Car	Train A	Train M	77	7.74
Car	Air	Train A	Train M	64	6.43
Car	Train M	Train A	Air	62	6.23
Train M	Train A	Air	Car	57	5.73
Car	Train A	Train M	Air	54	5.43
Air	Train M	Train A	Car	48	4.82
Train A	Train M	Air	Car	46	4.62
Air	Car	Train M	Train A	45	4.52
Train A	Air	Train M	Car	40	4.02
Train M	Air	Train A	Car	37	3.72
Train A	Train M	Car	Air	37	3.72
Car	Train A	Air	Train M	24	2.41
Train A	Car	Air	Train M	21	2.11
Train M	Train A	Car	Air	20	2.01
Train A	Car	Train M	Air	18	1.81
Car	Train M	Air	Train A	16	1.61
Train A	Air	Car	Train M	15	1.51
Car	Air	Train M	Train A	12	1.21
Train M	Air	Car	Train A	9	0.90
Train M	Car	Train A	Air	8	0.80
Train M	Car	Air	Train A	4	0.40
Air	Train M	Car	Train A	2	0.20
				995	100

TABLE 3 Panel Rank-Ordered Mixed-Logit Model for Intercity Mode Choice

	Train M		Train A		Air		Car	
	Param.	**t stat.**	**Param.**	**t stat.**	**Param.**	**t stat.**	**Param.**	**t stat.**
Level of service								
Total travel time (hours)	-0.2509	-9.157	-0.2509	-9.157	-0.2509	-9.157	-0.2509	-9.157
Travel cost ($) / Household income (000 $)	-0.0316	-2.247	-0.0316	-2.247	-0.0316	-2.247	-0.0316	-2.247
Airline inspection and boarding time = 120 mins.	-	-	-	-	-0.8009	-4.738	-	-
Airline inspection and boarding time = 60 mins.	-	-	-	-	-0.3518	-2.208	-	-
Perception about security measures								
"Effective" or "Very Effective" rating	-	-	-	-	1.2716	2.524	-	-
Stress and demographic variables								
High stress person (PSS4 score >= 3)	-	-	-	-	-	-	1.2057	1.829
Married	-	-	-	-	1.4206	2.936	-	-
Age <= 25 years	-	-	-	-	-	-	-0.7416	-1.090
Revealed travel characteristics								
Traveled in assigned corridor by Train	1.1299	3.969	-	-	-	-	-	-
Traveled in assigned corridor by Air	-	-	-	-	4.1521	4.657	-	-
Traveled in assigned corridor by Car	-	-	-	-	-	-	1.2057	1.890
Trip characteristics								
Company-paid trip	-	-	-	-	0.8495	1.775	-	-
Constant	0	(fixed)	0	(fixed)	-0.3243	-0.724	-0.891	-1.833
SD (σ_k) of the normal error term	0.9258	3.728	0.9258	3.728	2.4265	10.335	3.2516	9.716