AN ASSESSMENT OF THE IMPACTS OF INSPECTION TIME ON THE AIRLINE INDUSTRY'S MARKET SHARE AFTER 9/11

Ning Xu
Senior Analyst, Ph.D.
Northwest Airlines, Inc.
2700 Lone Oak Parkway, Eagan, MN 55121
Tel: +1 612 727 4748, Fax: +1 612 727 7110, Email: xun12180@gmail.com

Jose Holguin-Veras
Professor and Acting Department Head, Ph.D., P.E.
Department of Civil and Environmental Engineering, Rensselaer Polytechnic Institute,
110 Eighth Street, 4030 Jonsson Engineering Center, Troy, NY 12180-3590, USA
Tel: +1 518 276 6221, Fax: +1 518 276 4833, Email: jhv@rpi.edu

Chandra Bhat
Professor, Ph.D.
Department of Civil, Architectural & Environmental Engineering,
The University of Texas at Austin, 1 University Station C1761, Austin, Texas 78712, USA
Tel: +1 512 471 4535, Fax: +1 512 475 8744, Email: bhat@mail.utexas.edu

Abstract

The main objective of this paper is to examine the impacts of inspection times on the airline, as well as the overall economic optimality of current goals in terms of inspection times. The analyses are conducted by means of the combined use of discrete choice models to quantify passenger behavior after 9/11, a discrete event simulation of security screening operations to quantify the performance of alternative screening procedures, and an economic formulation to compute welfare. The behavioral modeling results indicate that inspection time, travel cost and travel time play critical roles in mode choice. The simulation results show that reducing inspection times had a noticeable effect on the airline market share: for an average inspection time of about two hours (the situation immediately after 9/11), the market share would have been about 32% for the corridors considered in the paper, while reducing inspection times to ten minutes leads to a market share of 49%. The results of economic welfare indicate that an inspection time of ten minutes is not much better than twenty minutes. This suggests that a relaxation of the ten minutes goal recommended by the Transportation Security Administration may be in order.

Keywords: Airport Security Screening; Behavioral Impacts; Discrete Choice Modeling; Extreme Events; Mixed Logit

1. INTRODUCTION

Immediately after the 9/11 attack, the North American airspace completely shut down for four days leading to an unprecedented decline in demand for air travel. It has been estimated that, just in the first week after 9/11, the U.S. airline industry lost $1-2 billion in sales revenue (*1*). Some of these impacts lingered. Although passenger surveys show that most travelers feel as safe flying now as they did before 9/11, a significant number of travelers still avoid traveling by air, either out of fear or because of the increased security and the uncertainty of passenger processing times at the airport (*2*).

This paper is concerned with the study of two interrelated aspects of intercity travel. The first one is associated with the behavioral changes produced by 9/11 on passengers' mode choice, some of which have been reported elsewhere (*3*). Of great interest is the role played by inspection time, which was found to be an important variable in the mode choice models. The second aspect is related to the study of the economic impacts of the security investment made after 9/11, which drove down inspection times from a peak of more than two hours to 10-20 minutes. The paper focuses on these two aspects because they obviously interact.

The development of an optimal policy concerning inspection times requires finding the proper balance between the airline industry's interest and that of the rest of society. On the one hand, from the standpoint of the airline industry, the ideal situation is to have the lowest values of inspection times possible to ensure an "appropriate" level of security, because short inspection times help the airline industry maintain a competitive advantage. However, short inspection times require substantial amounts of public funds in terms of security personnel and equipment. On the other hand, homeland security agencies do not have a natural incentive to minimize inspection times–other than avoiding complaints from politicians and passengers–as their main mission is to ensure the maximum level of security possible given their budget constraint. However, the long inspection times may have a detrimental effect on the profitability of the airline industry and consumer welfare.

The obvious policy question based on the above discussion related to what the ideal value of inspection time is, i.e., the one that maximizes collective welfare. The primary objective of this paper is to shed light on this issue using behavioral models to quantify the role of inspection times, a discrete event simulation to quantify inspection times for a variety of security screening configurations, and an economic model to assess economic welfare. A secondary objective of this research is to provide estimates of the impact of transportation security policies on helping restore the market share of the airline industry after 9/11. Among other things, this knowledge will enable transportation and city planners to evaluate and implement alternative strategies to help a city recover after extreme events.

The paper has six sections, including this introduction. Section 2 describes the overall methodology. Sections 3, 4, and 5 discuss the procedures used to estimate the behavioral models, to develop and perform the discrete event simulations, and to conduct the economic analyses, respectively. Section 6 summarizes the key findings.

2. OVERALL METHODOLOGY

As outlined in the introduction, the paper uses three different models to develop a comprehensive picture of the subject under study. The discrete choice model is intended to capture the passengers' decision making process regarding intercity travel mode. The discrete event simulation is aimed at estimating the inspection times associated with alternative security screening setups, which are ultimately provided to the discrete choice model as an input for estimation of air market shares. The third model uses the output of both the discrete choice model and the discrete event simulation to compute economic welfare.

Taken together, these models assess the performance of alternative security screening procedures, and the impact that resulting inspection times have on airline industry's market share and economic welfare. In doing so, the paper integrates state of the art behavioral models, discrete event simulations, and an economic model to support policy making.

3. ESTIMATION OF BEHAVIORAL MODELS

The data used for estimation of the behavioral models are drawn from a survey conducted for a project sponsored by the National Science Foundation to assess the changes produced by 9/11 on intercity passenger travel behavior. Preliminary analyses of the data can be found in 3. The data consist of a sample of 214 individuals providing Stated Preference (SP) responses on hypothetical intercity travel choice situations. The survey was conducted from March to May of 2002, approximately six months after 9/11. Using the SP data collected from the survey, the research undertaken here focuses on (1) estimating behavioral models based on the Random Utility Theory (RUT), (2) analyzing the modeling results, and (3) assessing the impacts of 9/11 on intercity passenger travel behavior.

Choice Situation

The survey used a choice situation involving a hypothetical business trip. A business trip was used because it (1) eliminates the choice of not to travel that is available for non-compulsory trips, and (2) presents a fairly clear choice situation that minimizes misunderstandings on the part of the respondents. Another benefit of using a business trip is that the behavioral changes identified could be interpreted as lower bounds of impacts, because non-business trips are likely to be more impacted than business trips.

Another relevant decision concerning the choice situation is trip distance. For long trip distances, air transportation may be the only practical alternative and so respondents may feel captive to air transportation. At the other extreme, short trips may not be suitable for air transportation, and therefore respondents may feel captive to the ground alternatives. For these reasons, the focus here is on the mid 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.

Survey Instrument

The survey focused on three different intercity corridors in the northeast part of the U.S.: (a) New York City-Washington D.C., (b) New York City-Boston, and (c) Boston-Washington D.C. The respondents were asked to choose a preferred mode for nine hypothetical scenarios of travel in one of the three assigned corridors, presented in randomized order. About half of the respondents were told that their employer would pay for the trip, while the other half were asked to assume they would pay by themselves. The choice set included four alternatives: two train alternatives (Metroliner and Acela), air, and car. The two train alternatives differed in travel time and cost in the choice scenarios to reflect the fact that trips by Acela take less time and cost more than Metroliner. The alternatives in the choice set were characterized in terms of (a) travel time, (b) inspection/boarding time at the airport (assumed to have three factor levels of 25, 60 and 120 minutes), (c) cost of travel time, and (d) the departure and arrival times of the train and air alternatives (three factor levels each). A full factorial design was used and non-feasible combinations were removed. Throughout the experiment, the attributes of the car alternative remained constant.

Descriptive Analyses

The majority of respondents were male (61.2%), college educated (88.8%), single (56.1%), and with no children (57.0%). A typical respondent is about 32 years old, with 2.8 individuals in the household. The questionnaire collected data about whether or not the respondents had made the trip in the intercity corridor they were assigned to in the SP experiments, the trip purposes of the trips made in the corridor, the reasons why they chose the mode they used for the last trip in the corridor, and who paid for the last trip. For a complete analysis, the reader is referred to a previous study (*3*).

The survey also collected information about the psychological impacts of 9/11 on intercity travel. This was based on two sets of variables derived from the questionnaire: the stated impact produced by 9/11 (*Change*) and respondents' stress level (Stress). The variable *Change* was estimated using a seven point ordinal scale using the question: "How much did 9/11 change your travel choice of whether to travel or not" (1 = not at all, and 7 = significantly). The survey results showed that the average *Change* score is 3.4 (standard deviation=2.0), which corresponds to moderate *Change*. Respondents were then asked how 9/11 affected their choice of travel (they were allowed to check all that apply). It was found that the majority of respondents (73.4%) mentioned *they are more conscious of security*, followed by *more aware of people traveling with them* (45.3%), *more selective in choosing travel mode* (33.6%), *avoid traveling by air* (21.0%), and *avoid traveling altogether as much as they can* (11.2%).

Stress was estimated using a 4-item version of the Perceived Stress Scale (PSS4) (*4*), which assessed 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 unable to overcome difficulties, felt confident about handling personal problems, and felt things were going right. The first two items were rated on a 5-point scale ranging from 1 (never) to 5 (often) and the last two were reversely scored. A total stress score (PSS4) for each respondent was calculated by summing item responses. PSS4 scores could range from 4 to 20; the lowest and highest total stress scores in this sample were 4 and 14, respectively. The mean was 9.6, with a standard deviation of 2.1. This translates into a mean of 2.4 for each item, corresponding to "almost never" for the first two items, and "fairly often" for the last two.

3.1 Methodology

The methodology relies on the use of discrete choice models (DCM). The DCMs used here are based on the concept of random utility maximization (RUM), which is a behavioral/economic theory that postulates that decision makers choose the alternative that maximizes the utility derived from their choices. RUM assumes that utility has two components: (a) a systematic component, which depends upon the socio-economic characteristics of the decision maker and the alternative attributes, and (b) a random component, which recognizes that the analyst does not have full information about all relevant variables and the decision process. Different assumptions of the distribution of the random terms lead to different models. In the case that the random terms are assumed to be independent and identically distributed Gumbel across alternatives, one obtains the familiar multinomial logit (MNL) (*5*).

However, in spite of its usefulness, the MNL model is not suited for modeling of the problem described in this paper. First, the MNL assumes that the coefficients of the variables in the utility functions are constant across individuals. Although this assumption can be relaxed using market segmentation techniques, it is likely that there will be a significant degree of random taste heterogeneity across individuals in choice experiments that involve subjective valuations of complex dynamics. Second, one important characteristic of the MNL model is the independence from irrelevant alternatives (IIA) property, which arises from assuming that the disturbances are mutually independent. However, this is not likely to be the case in this study because there are two train alternatives, i.e., Metroliner and Acela, that may share unobserved train characteristics. Third, the MNL model assumes that repeated choices made by the same respondent are independent (*6*). Since in this study, each respondent provided attitudinal data for nine different scenarios, using responses from the same individuals is likely to introduce correlation in the data set (this is known as the repeated measurement problem, which is related to random taste heterogeneity).

On the other hand, the mixed logit (ML) model relaxes all three restrictions of the MNL model, and constitutes a more realistic and flexible formulation. ML allows coefficients to vary in the population, does not exhibit the IIA property, and allows correlation in unobserved utility over alternatives and repeated choices.

In the paper, 200 draws per individual of the Halton sequence are used in a maximum simulated likelihood (MSL) estimation approach (*7*). The results were tested with different numbers of Halton draws, though the results clearly stabilized at 200 draws. In addition, an individual-specific error term was introduced in the utility functions of Metroliner and Acela. This error component induces higher levels of sensitivity between the two rail modes.

3.2 Modeling Results

The inter-city mode choice models were estimated using car as the base alternative for introducing alternative specific constants. Two travel cost variables were considered: *Company Costs* and *User Costs* (in U.S. dollars) that represent the actual charges incurred either by the company or the traveler (depending on who pays for the trip expenses).

The role of time was considered using four different variables. *Inspection 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 time, i.e., total travel time minus inspection. Respondents were told that they had an important meeting at a certain time. Depending on the mode they chose, they arrived at the destination some time before the meeting, which varied from 5-80 minutes. *Extra Time 1 before Meeting* represents the extra time before the meeting up to the cutoff value of 30 minutes, while *Extra Time 2 before Meeting* represents the extra time in excess of 30 minutes. *Extra Time 1 and 2* create a piecewise linear approximation to nonlinear effects.

A set of binary variables were created to indicate different levels of *Change* and *Stress*, and used as interaction terms with main travel time. For the variable *Change*, three binary variables were created to indicate if respondents reveal small, moderate, or significant *Change*: if the *Change* score is 1 or 2, the binary variable *Change 1* (small *Change*) is equal to 1; if the *Change* score is from 3 to 5, the binary variable *Change 2* (moderate *Change*) is equal to 1; if the *Change* score is 6 or 7, the binary variable *Change 3* (significant *Change*) is equal to 1. Similarly, three binary variables were created for *Stress*: if the *Stress* score is from 4 to 8, the binary variable *Stress 1* (small *Stress* level) is equal to 1; if the *Stress* score is from 9 to 11, the binary variable *Stress 2* (medium *Stress* level) is equal to 1; if the *Stress* score is greater than 11 (from 12 to 14 in this case), the binary variable *Stress 3* (high *Stress* level) is equal to 1.

Table 1 presents the best estimation results for the ML model. Several different error components structures (to generate correlation and heteroscedasticity across alternatives at the individual level) as well as varying sensitivities across individuals to the time and cost variables were considered. The final specification in Table 1 was the result of retaining only the statistically significant effects. In this final specification, the standard deviation of the individual specific error term generating the higher sensitivity between the two rail modes does not appear because it turned out to be statistically insignificant. The model includes variables of trip attributes such as main travel time (total travel time minus inspection time), inspection time, extra time before meeting, interaction term between main travel time and the binary variable indicating how individuals changed their decision of travel after 9/11, as well as demographic variables indicating if the respondent is married.

In this model, the coefficient of the main travel time is random, with a mean that is about the same as the one for inspection time. The coefficients of *CC* (travel cost if company pays/household income) and *UC* (travel cost if user pays/household income) are both negative, indicating that the utility function decreases with travel cost. However, the effect of cost reduces as income increases. The absolute value of the coefficient for *CC* is about three times the value of that of *UC,* indicating that when company pays, users behave as having a much higher valuation of travel time than when they are paying for the expenses. Using $45,000 as the household income (the household median income of these respondents is about $44,058), and the mean of the main travel time, the implied money values of travel time are about $343.3/hr if company pays and $122.3/hr if traveler pays. The travel time values are relatively high. This might be due to the inclusion of the cost divided by income variable, which is consistent with the findings from a previous study, which found that discrete choice models using a cost over income variable yielded average travel time value up to ten times larger than the linear in cost models for the same population data (*8*). The coefficient of *ET1* (extra time before meeting up to 30 minutes) is positive, while that of *ET2* (extra time before meeting in excess of 30 minutes) is negative, suggesting that individuals prefer to have some time before meeting, but not too much as this would be a waste of their time.

The term *TT2CH23* captures the interaction between main travel time and the binary variable for moderate or significant *Change* (this variable takes the value of 1 if the *Change* score is from 3 to 7). The variable *Change 1* did not exhibit a significant effect when interacted with travel time, and thus is not included in the model. This is reasonable because these respondents said that 9/11 did not have much of an impact of their choice of whether or not to travel. The binary variables *Change 2* and *Change 3* were combined here because, when treated separately, the coefficients of these two interaction terms were statistically the same, indicating that the impacts on choice of travel are about the same for respondents reporting moderate and significant *Change*. The coefficients of *TT2CH23* were only significant for air and car, and the absolute value of the coefficient for air is about three times the value of that of car, indicating that the impact on air travel is much larger than the other alternatives, which is reasonable due to the 9/11 events. The only demographic variable included in this model is *MARRIED*, whose coefficient is positive and significant for train and car.

Overall, travel costs, travel time, inspection time at the airport security checkpoint, income, and marital status were found to be statistically significant explanatory variables in the mode choice process. The results indicate that air travel is much more adversely affected by 9/11 compared to the other three alternatives, which is consistent with the fact that, after 9/11, people avoid traveling by air either out of fear or because of the increasing security and the uncertainty of passenger processing times at the airport. This suggests that the massive security investment post 9/11 – by significantly reducing inspection time – has had a significant impact in restoring the airline industry's market share.

4. DISCRETE EVENT SIMULATION OF SECURITY SCREENING PROCEDURES

This section assesses the performance of alternative security screening procedures in terms of inspection times, which refers to the time spent to clear security screening including the time spent in queue. This is accomplished by means of the combined use of discrete event simulation to estimate inspection times for various configurations, and the discrete choice models estimated in the previous section to estimate the corresponding market shares.

In undertaking the analyses, it would have been ideal to have access to data for a real life airport immediately after 9/11, when passengers experienced huge delays at the security checkpoints. Unfortunately, no publicly available data were found. Instead, the authors decided to simulate an idealized airport checkpoint operation—a composite of different airports—with passenger traffic and checkpoint configurations similar to the ones post-9/11.

The hypothetical airport used in the simulations is a hybrid of two real life airports: the Hartsfield-Jackson Atlanta International Airport (ATL) and the Tampa International Airport (TPA). The arrival patterns in the simulations correspond to the ones for ATL (*9*, *10*), while the service time distributions come from TPA. In essence, this is equivalent to assuming that the security checkpoint process in ATL follows the same statistical distributions as the ones observed in TPA. Given the data constraint, this seems a reasonable assumption. The data on the security screening process at TPA comes from *11* and *12*.

Discrete event simulation techniques were used to simulate the process at the security checkpoint. Figure 1 shows the flow chart of the screening process used in the simulation. The security screening procedures start when passengers arrive at the checkpoint and join the line where a security guard checks IDs and passports (at left side of the figure). As passengers approach the screening lanes, passengers remove metal items, take off their coats and shoes, and load them on trays to put them to the X-ray machines. Then the carry-on baggage screening process starts, at the same time the passenger screening process begins. If an alarm is set off, a secondary screening process starts, in which the baggage or the passenger will be searched. Once the passenger and bags successfully pass the security check, passengers pick up their belongings, and go to the gates.

The simulation focuses on a typical one hour period. The simulation program stops when the last passenger is processed. It was assumed that 80% of passengers would pass the primary security screening and go to gates directly, another 10% would need to go through the secondary screening then go to gates, the rest 10% cannot pass the security screening and their entries are denied, which is consistent with the guidelines of Transportation Security Administration (TSA) that the average number of cleared passengers be more than 90% of passenger arrivals.

As mentioned earlier, the objective of this part of the analysis is to assess how security infrastructure impacts inspection time. For that reason, inspection times were estimated for various configurations of security screening procedures. For each of these configurations, the present value of costs (PVC) were computed assuming an economic life of 10 years and an opportunity cost of the capital of 6%. It was assumed that a new screening lane costs $2 million, which corresponds to the average cost reported for the Washington National Airport (*13*). The salary of the security personnel was assumed to be $15 per hour with 100% overhead and 36% fringe benefits. The labor costs were estimated assuming that there are five security guards at each security lane and all lanes are open for 12 hours everyday. These assumptions are approximately equivalent to a typical profile of lane usage at a large airport throughout the weekdays (*14*).

Table 2 shows the results from different simulation runs together with the PVCs. As shown, when there are only 10 inspection lanes, the average inspection time is close to two hours, which is what was observed at major airports immediately after 9/11. As expected, as more inspection lanes become available, the inspection times become shorter and total cost becomes larger.

Table 3 shows the market shares of the four modes under different configurations, which were estimated using results from the best ML model, using the average inspection time obtained from the simulation models. The results show that if the number of screening lanes increased from 10 to 36, the inspection time would decrease from about two hours to only 10 minutes, and the percentage traveling by air would increase from 32.11% to 49.32%; also, if the number of screening lanes increased from 16 to 36, the inspection time would decrease from about one hour to 10 minutes, and the percentage traveling by air would increase from 40.76% to 49.32%. As shown in Table 3, further reductions in inspection time require significant increases in the number of screening lanes, e.g., to reduce inspection times from 9.8 to 4.5 minutes, an additional six lanes are needed. For reference purposes, the market shares for the case with no inspection times are also shown. Figure 2 shows the change of air market share and inspection time for different configurations, with the PVCs (rounded to the closest integer) shown as labels on top the curve of inspection time. This analysis suggests that the higher investment in security has a significant impact on increasing the airline industry's market share, but there are diminishing returns to scale in terms of air market share, as we discuss further in the next section.

5. ECONOMIC IMPLICATIONS

The estimates produced in the previous section suggest that the security investment made after 9/11 provided a significant boost to the airline industry's market share. However, some important questions remain: Was this investment justified from an economic point of view? What is the optimal amount of investment in security screening procedures? These are important questions not only because of the economic implications, but because they help shape the public image of the security agencies involved.

It should be noted that two months after the attack, the Transportation Security Administration (TSA) announced as a service goal that 95% of passengers will wait no more than ten minutes to go through security screening (*15*). However, this has proven to be a difficult goal to meet: "On average, air travelers faced lines of more than 10 minutes about 6% of the time. At major airports during peak morning travel times, security lines exceeded 10 minutes 14% of the time…" (*16*). TSA says it has reduced the passenger waiting times in 2004 and is meeting a goal of having an average wait of ten minutes at each airport each day (*16*). It was found that, the impacts of the attack were not temporary: as long as passengers need to arrive at the airport earlier (relative to their scheduled flight departure times) compared to the pre-9/11 period (due to the enhanced airport security measures, which increases the opportunity cost of air travel), revenue passenger miles will be expected to be lower than that would have been in the absence of 9/11 (*17*).

This section describes an economic formulation used to estimate the economic welfare associated with alternative security screening procedures. This formulation considers the passengers' consumer surplus (C_S) and the government expenses (G) associated with security screening. In this context, the total welfare (W) is equal to:

$$W = C_S + G \tag{1}$$

For analytic procedures that use a discrete choice model, the consumer surplus must be evaluated using the expressions derived by (*18*). In the case of a discrete choice model, as shown elsewhere (*18*), the expected utility associated with the intercity mode choice context is given by:

$$\overline{U} = \frac{1}{\mu} \ln \sum_i \exp(\mu V_i) \tag{2}$$

Where: μ is the scale parameter of the discrete choice model and V_i is the systematic utility associated with alternative i.

The expected consumer surplus, $\overline{C_S}$, could then be obtained by dividing the expected utility by the marginal utility of income, θ, which is equal to the negative of the marginal utility of cost from the discrete choice models (*19*):

$$\overline{C_S} = \frac{1}{\theta\mu} \ln \sum_i \exp(\mu V_i) \tag{3}$$

Assuming that there are Q^T observationally identical individuals, and that $\mu = 1$, it follows that the collective consumer welfare is equal to:

$$C_S = \frac{Q^T}{\theta} \ln \sum_i \exp(V_i) \tag{4}$$

Finally, the welfare is:

$$W = \frac{Q^T}{\theta} \ln \sum_i \exp(V_i) + G \tag{5}$$

Equation (5) is used in this paper to estimate welfare. The consumer surplus was projected for a planning horizon of ten years to compute a Present Value of Benefits (PVB) and combined with the Present Value of Costs (PVC) from Table 2, to estimate Net Present Values (NPV) for the different screening configurations. The results are shown in Table 4.

As shown in Table 4, adding screening lanes significantly reduces the inspection times and increases economic welfare. At some point, however, adding more lanes only has a minor effect on inspection times and, consequently, on the present value of benefits (PVB). The estimates show that the NPV increases with reductions in inspection time and then stabilizes in the range of $120 million, which corresponds to inspection times in the range of ten to twenty minutes. The maximum value of NPV seems to be at about an inspection time of fourteen minutes, though, because of the inherent uncertainty in welfare computations, it is not advisable to interpret this estimate as a definitive optimal value.

It should be noted that, from the standpoint of overall economic impacts, an inspection time of twenty minutes is not significantly different than the goal of ten minutes suggested by the Transportation Security Administration. As shown in Table 4, the NPV for 9.8 minutes ($120.05 million) is only 0.05% higher than the one for 20.4 minutes ($119.47 million), though it costs 29% more. This suggests that a relaxation of the TSA goal is in order.

6. CONCLUSIONS

This paper uses a state-of-the-art discrete choice model, a discrete event simulation, and an economic formulation to assess behavioral changes produced by 9/11, examine the role played by the massive investment in security screening in restoring the airline industry’s market shares, and estimate the overall economic optimality of security screening investments. The discrete choice models show that the users’ valuation of travel time depends on who is paying for the trip, i.e., when the traveler’s company pays, users have a higher valuation of travel time (about three times higher) than when respondents are paying for the expenses themselves. In general, the modeling results are quite intuitive, and indicate that air travel has been much more adversely affected by 9/11 compared to the other three alternatives of car, Acela, and Metroliner. This is consistent with the fact that, after 9/11, people avoided traveling by air either out of fear or because of the increased security and uncertainty of inspection times at airports.

The discrete event simulations considered the case of a hypothetical commercial airport to estimate the inspection times for alternative screening procedures. Construction, labor costs and present value of costs (PVCs) for different configurations of the security checkpoint were estimated, as well as the market shares of the four transportation modes considered in the paper. The latter were estimated using the discrete choice model described before. The computations indicate that the reduction of inspection times significantly increased the market share of the airline industry. The results show that reducing inspection times from two hours to 10 minutes is estimated to have increased the airline’s market share from 32% to 49% for the intercity corridors considered.

The computation of economic welfare suggests that the Net Present Values (NPV) increase with reductions in inspection times. However, the NPV stabilizes in the range of $120 million, which corresponds to inspection times in the range of ten to twenty minutes. The maximum value of NPV ($122.65 million) seems to take place in the vicinity of an inspection time of fourteen minutes, though because of the inherent uncertainty in welfare computations, it is advisable not to interpret this estimate as a definitive optimal value. The welfare results also indicate that, from the standpoint of overall economic impacts, an inspection time of twenty minutes is not significantly different than the goal of ten minutes suggested by the Transportation Security Administration. As shown in the paper, the NPV for 9.8 minutes ($120.05 million) is only 0.05% higher than the one for 20.4 minutes ($119.47 million), though it costs 29% more. From the economic point of view, this indicates that attempting to ensure inspection times in the range of ten minutes is not optimal, as it will require additional expenses that are not compensated by the marginal benefits.

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Table 1: Best Discrete Choice Model

Variable	Rail alternatives		Fly	Drive
	Metroliner	Acela	Air	Car
Alternative specific constants	-1.6221	-2.7621	-2.2633	0.0000
	(-5.949)	(-3.969)	(-2.327)	(--)
Standard deviations for alternative specific	--	2.4165	--	--
constants	(--)	(3.082)	(--)	(--)
Main travel time	-0.0367	-0.0367	-0.0367	-0.0367
	(-5.271)	(-5.271)	(-5.271)	(-5.271)
Standard deviations for main travel time	0.0422	0.0422	0.0422	0.0422
	(5.164)	(5.164)	(5.164)	(5.164)
IT	--	--	-0.0347	--
(inspection time)	(--)	(--)	(-4.521)	(--)
CC	-0.2826	-0.2826	-0.2826	-0.2826
(company cost/income in thousands)	(-4.484)	(-4.484)	(-4.484)	(-4.484)
UC	-0.7932	-0.7932	-0.7932	-0.7932
(user cost/income in thousands)	(-7.249)	(-7.249)	(-7.249)	(-7.249)
ET1	0.0533	0.0533	0.0533	0.0533
(extra time before meeting < = 30 mins)	(3.719)	(3.719)	(3.719)	(3.719)
ET2	-0.0075	-0.0075	-0.0075	-0.0075
(extra time after meeting > 30 mins)	(-1.249)	(-1.249)	(-1.249)	(-1.249)
TT2CH23	--	--	-0.0106	-0.0039
(Main travel time* Change 2 or 3)	(--)	(--)	(-3.091)	(-5.228)
MARRIED	1.8609	1.5599	--	2.1982
(1 if married)	(3.609)	(3.237)	(--)	(3.602)
Mean Log likelihood function		-1.37377		
Number of Cases		1755		
Adjusted rho-squared bar with respect to constants		0.112		

Table 2: Estimation of Costs Based on Simulation Results

Screening Lanes	Average Inspection Time (min)	Construction Cost ($ million)	Labor Cost ($ million/yr)	Present value of cost ($ million)
14	69.96	28	10.85	73.47
16	56.86	32	12.40	83.97
18	48.22	36	13.95	94.46
20	39.05	40	15.51	104.96
22	33.71	44	17.06	115.45
24	28.86	48	18.61	125.95
26	24.25	52	20.16	136.44
28	20.37	56	21.71	146.94
30	18.27	60	23.26	157.44
32	14.11	64	24.81	167.93
34	12.18	68	26.36	178.43
36	9.60	72	27.91	188.92
38	8.50	76	29.460	199.42
40	6.30	80	31.010	209.91
42	4.48	84	32.561	220.41
44	3.50	88	34.111	230.91
46	2.23	92	35.662	241.40
48	2.15	96	37.212	251.90
50	2.14	100	38.763	262.39

Table 3: Estimation of Market Shares Based on Simulation Results

Screening Lanes	**Average Inspection Time (min)**	**Market Share**			
		Metroliner	**Acela**	**Air**	**Car**
10	111.26	20.81%	17.10%	32.11%	29.98%
12	87.90	19.43%	15.61%	35.62%	29.34%
14	69.96	18.31%	14.42%	38.53%	28.75%
16	56.86	17.45%	13.53%	40.76%	28.27%
18	48.22	16.87%	12.93%	42.28%	27.92%
20	39.05	16.24%	12.30%	43.93%	27.53%
22	33.71	15.88%	11.93%	44.89%	27.30%
24	28.86	15.55%	11.60%	45.77%	27.08%
26	24.25	15.23%	11.28%	46.61%	26.87%
28	20.37	14.81%	10.87%	47.73%	26.58%
30	18.27	14.52%	10.59%	48.51%	26.38%
32	14.11	14.52%	10.59%	48.51%	26.38%
34	12.18	14.39%	10.46%	48.87%	26.28%
36	9.60	14.22%	10.30%	49.32%	26.16%
38	8.50	14.13%	10.21%	49.56%	26.10%
40	6.30	13.98%	10.06%	49.98%	25.98%
42	4.48	13.85%	9.94%	50.32%	25.89%
44	3.50	13.78%	9.87%	50.51%	25.84%
46	2.23	13.69%	9.79%	50.75%	25.77%
48	2.15	13.69%	9.79%	50.75%	25.77%
50	2.14	13.69%	9.78%	50.76%	25.77%
n/a	0.00	13.54%	9.64%	51.17%	25.65%

Table 4: Economic Indicators

Number of Screening Lanes	Average Insp. Time (min)	Construction Cost ($ million)	Labor Cost ($ million/yr)	Present Value of Cost ($ million)	Present Value of Benefits ($ million)	Net Present Value ($ million)
10	111.26	20	7.75	52.48	27.06	-25.42
12	87.90	24	9.30	62.97	77.68	14.70
14	69.96	28	10.85	73.47	119.58	46.11
16	56.86	32	12.40	83.97	152.86	68.89
18	48.22	36	13.95	94.46	176.75	82.28
20	39.05	40	15.51	104.96	203.35	98.39
22	33.71	44	17.06	115.45	220.34	104.89
24	28.86	48	18.61	125.95	236.47	110.52
26	24.25	52	20.16	136.44	252.36	115.91
28	20.37	56	21.71	146.94	266.41	119.47
30	18.27	60	23.26	157.44	275.04	117.60
32	14.11	64	24.81	167.93	290.58	122.65
34	12.18	68	26.36	178.43	298.95	120.52
36	9.80	72	27.91	188.92	308.97	120.05
38	8.50	76	29.46	199.42	315.32	115.91
40	6.30	80	31.01	209.91	324.92	115.00
42	4.48	84	32.56	220.41	333.26	112.85
44	3.50	88	34.11	230.91	338.69	107.78
46	2.23	92	35.66	241.40	345.23	103.83
48	2.15	96	37.21	251.90	347.39	95.50
50	2.14	100	38.76	262.39	349.49	87.10

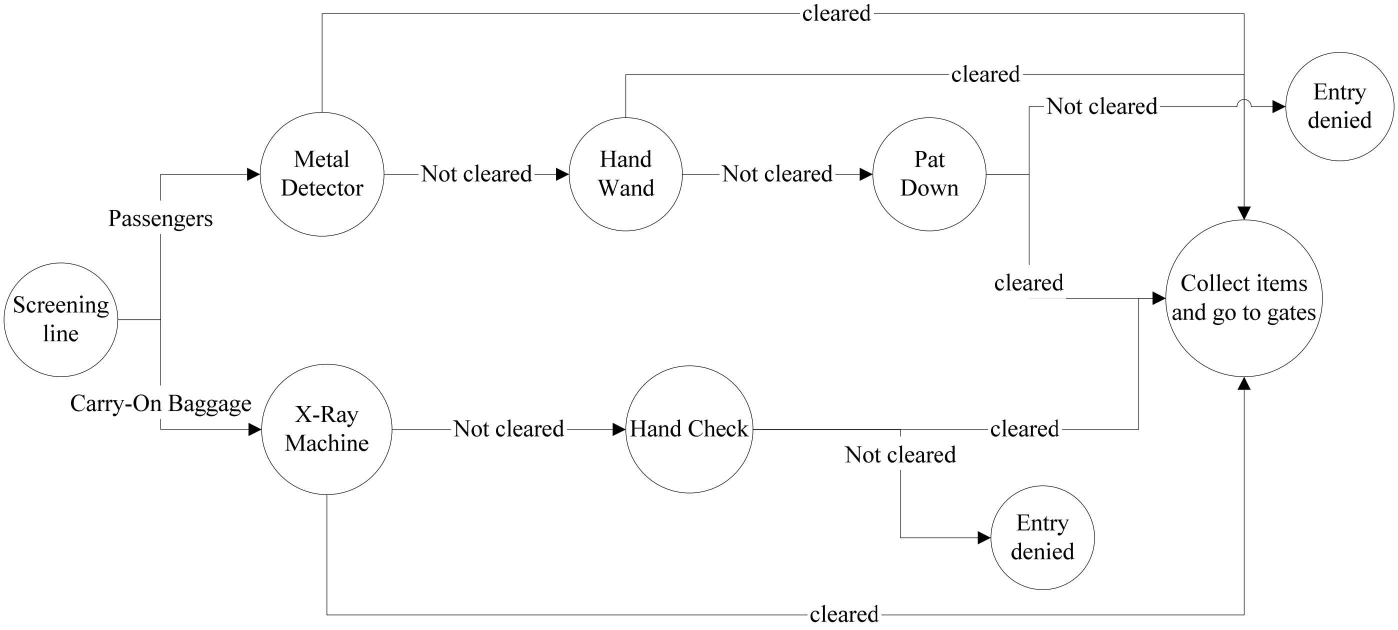

Figure 1: Screening Process for One Screening Lane

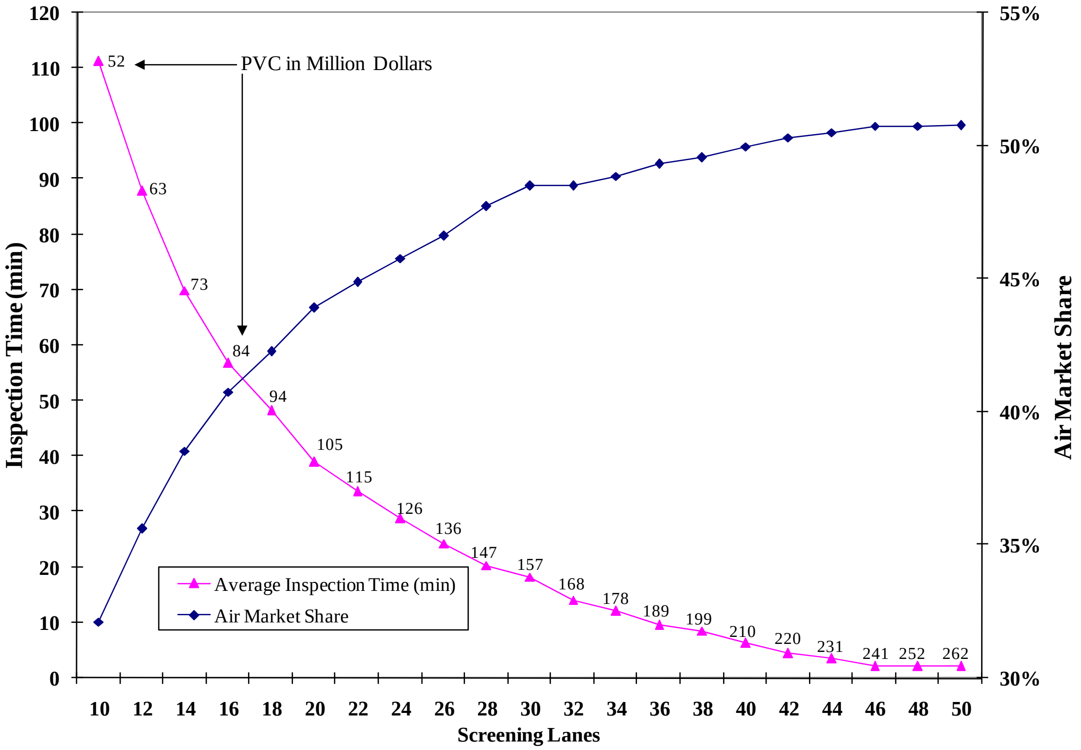

Figure 2: Air Market Share vs. Inspection Time vs. PVC