Journal of Air Transport Management 23 (2012) 17–24

Contents lists available at SciVerse ScienceDirect

Journal of Air Transport Management

journal homepage: www.elsevier.com/locate/jairtraman

An assessment of the impacts of inspection times on the airline industry's market share after September 11th

José Holguín-Veras [a,*], Ning Xu [b], Chandra Bhat [c]

[a] Center for Infrastructure, Transportation, and the Environment, Department of Civil and Environmental Engineering, Rensselaer Polytechnic Institute, 110 Eighth Street, 4049 Jonsson Engineering Center, Troy, NY 12180-3590, USA
[b] Pricing Systems Development, Delta Air Lines, Dept 665, 1030 Delta Blvd, Atlanta, USA
[c] Department of Civil, Architectural & Environmental Engineering, The University of Texas at Austin, 1 University Station C1761, Austin, TX 78712, USA

Keywords:
Airport security screening
Behavioral impacts
Discrete choice modeling
Extreme events
Mixed logit

ABSTRACT

This paper studies the behavioral changes produced by the events of September 11th, 2001 on intercity air travel behavior, the impacts that increases in security inspection times had on the airline industry's market share, and the economic optimality of inspection time goals. We develop an modeling framework is developed that includes a discrete choice models estimated with stated preference data collected after September 11th to assess passenger behavior changes, a discrete event simulation of security screening operations to quantify the performance of alternative screening configurations, and an economic formulation to compute welfare. The modeling system is then applied to an idealized airport, based on composite data from two real life airports, to gain insight into the impacts of security screening configurations and to identify the optimal inspection time.

1. Introduction

Following the events of September 11th, 2001, passengers' concerns about the safety of air travel and the long inspection times that resulted from the hastily implemented security screening procedures, led to a sharp drop in air travel demand. It is estimated that in the first week after the events, the US airline industry lost $1–$2 billion in revenues (Goodrich, 2002). Some of these impacts lingered. Surveys conducted two years later revealed that, though most travelers felt as safe as they did before September 11th, significant numbers were avoiding air travel, either out of fear or because of the increased security and the uncertainty of airport inspection times (MIT Global Airline Industry Program, 2004).

These impacts reflect the fact that security screening added a new component to the generalized cost of travel by air, which immediately had a negative effect on air transport demand. This was promptly recognized by the Transportation Security Administration (TSA) when, two months after the attack, it announced as a goal that 95% of passengers would wait no more than ten minutes to go through security screening (Wald, 2001). However, this proved 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 ten minutes 14% of the time" (Frank, 2005). TSA says reported that it has reduced the passenger waiting times in 2004 and that it was on its way to meet the goal of an average wait of ten minutes at each airport each day (Frank, 2005). According to Gkritza et al. (2006), wait time at security checkpoint significantly increased the probability of a passenger being unsatisfied with screening procedures. Blunk et al. (2006) suggested that, the impacts of the attack were not transient: as long as passengers need to arrive at the airport earlier than before the pre-September 11th period, revenue passenger miles will be expected to be lower than that would have been without the event.

The possibility that inspection times could have such an impact on air transport demand brings to the forefront the important policy question of how much should the public sector invest in security screening. At one end, investing a minimal amount on security screening would lead to long inspection times, a potential drop in air demand, and long delays to travelers. At the other end, investing too much would minimize inspection times and delays to travelers and maximize air market share, though at the expense of an investment that could indeed be very large. In between these end conditions, there is an optimal investment policy that leads to an optimal inspection time. Identifying such optimal is important because it provides guidance on the inspection time goals that should be pursued. Moreover, there are fairness and equity considerations to take into account. The issue here is that, although

* Corresponding author.
E-mail address: jhv@rpi.edu (J. Holguín-Veras).

0969-6997/$ – see front matter © 2012 Elsevier Ltd. All rights reserved.
doi:10.1016/j.jairtraman.2012.02.004

it would be appropriate for the public sector to invest if the benefits to society are larger than the investment made, investing tax payers resources in excess of the optimal would provide a subsidy to the airline industry and travelers, without concomitant economic benefits that justify the expense.

Thus, the estimation of optimal inspection times requires finding the proper balance between the private interest and the cost of implementing security screening procedures. Achieving this goal requires assessing the impacts of alternative security screening scenarios on the key agents involved: airline industry, airports, homeland security agencies, and the traveling public. The objectives of these groups are not necessarily the same. From the standpoint of the airlines, the shorter the inspection times the better as this would enable them to enhance their competitive advantage over potential modal competitors, e.g., rail. Airports face a more nuanced situation because—though short inspection times increase their competitive edge over other airports and competing modes—they are likely to incur on long term infrastructure costs that may or may not be recovered from fees. In contrast, the traveling public is likely to side with the airlines in favor of the shortest possible inspection times, as this would minimize their delay costs. Finally, homeland security agencies—with a primary mission of maximizing security given their budget constraint—are themselves neutral in terms of inspection times, though they may face public pressure to minimize inspection times. However, since it is their responsibility to design and implement security screening procedures, they are the ones that must strive to implement optimal policies. In essence, there are two counteracting effects: the desire of airlines and customers to have the shortest possible inspection times, and the need to keep security inspection costs under control. The key policy question is what is the optimal value of inspection time, i.e., the one that maximizes economic welfare.

The paper focuses on three interrelated things. First it identifies behavioral changes produced by September 11th on passengers' mode choice. Second it quantifies the impacts of the security investment made after the event on the market share of the airline industry. Finally it determines the optimal inspection time.

2. Overall methodology

At the core of our methodology (Fig. 1) is the estimation and use of a discrete choice model based on data collected after September 11th. This model provides insight into behavioral changes, and a mechanism to assess market shares as a function of inspection times. The second component of the methodology is a discrete event simulation that estimates the inspection times associated with alternative security screening setups. The inspection times from the simulation were used as an input to the discrete choice model to estimate how passengers would react in response to that particular security screening configuration, and to compute the market share of air transport. Finally, the economic model uses the output of both the discrete choice model and the discrete event simulation to compute economic welfare.

Taken together, the models assess the performance of alternative security screening procedures, gain insight into the impact that the resulting inspection times have on airline industry's market share, and quantify the corresponding economic welfare.

3. Estimation of behavioral models

The data used for estimation of the model were collected by a survey sponsored by the National Science Foundation to assess the changes produced by September 11th on intercity passenger travel behavior. Preliminary analyses of the data can be found in Holguín-Veras et al. (2003). The data consist of a convenience sample of 214 individuals providing stated preference (SP) responses on hypothetical intercity travel choice situations. All respondents were New York City residents. The survey was conducted from March to May of 2002, about six months after September 11th. The response rate was about 50%.

The choice situation used in the SP scenarios involved a hypothetical business trip for which a number of alternative modes were available. A business trip was used because it eliminates the choice of not to travel that is available for non-compulsory trips, and presents a fairly clear choice situation that minimizes misunderstandings on the part of the respondents. Moreover, using a business trip enables to interpret the behavioral changes identified as lower bounds of impacts, because non-business trips are likely to be more impacted than business trips. Another important decision when designing the choice situation was the trip distance considered in the scenario. The issue is that for long distances air transportation may be the only practical alternative, which may lead respondents to feel captive of air modes. In contrast, the opposite happens for short trips as respondents may feel captive to the ground alternatives. For these reasons, the authors focused on the mid range of trip distances, for which there are modal alternatives that effectively compete with air travel. In this context, the behavioral changes would reveal themselves as components of the systematic component of the utility functions.

The survey focused on three intercity corridors in the Northeast of the US: (a) New York City–Washington DC, (b) New York City–Boston, and (c) Boston–Washington DC The respondents

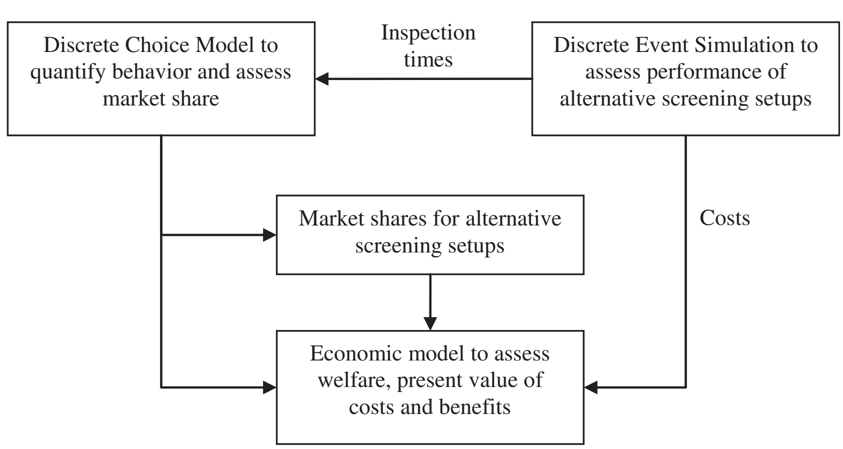

Fig. 1. Schematic of overall methodology.

were asked to choose the preferred mode for nine travel hypothetical scenarios in one of these corridors, which were presented in random 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 train alternatives differed in travel time and cost to reflect the fact that Acela takes less time, though 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 min), (c) cost of travel time, and (d) the departure and arrival times (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.

3.1. 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 asked whether or not the respondents had made that trip. If the answer was yes, the respondents were asked to provide the trip purposes of the trips, the reasons why they chose the mode they used, and who paid for the last trip. For a complete analysis, see Holguín-Veras et al. (2003).

The survey also collected information about the psychological impacts of September 11th on the respondents. This was based on two sets of variables derived from the questionnaire: the stated impact produced by September 11th (*Change*) and respondents' stress level (*Stress*). The variable *Change* was estimated using a seven point ordinal scale using the question: "How much did September 11th 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 also asked how September 11th affected their choice of travel. The data show 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) (Cohen and Williamson, 1988) that assessed the degree to which respondents appraise their life as stressful. Respondents indicated how frequently they felt unable to control 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 stress score (PSS4), that could theoretically range from 4 to 20, was calculated by summing item responses. The lowest and highest 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.

3.2. Modeling methodology

The research used discrete choice models based on random utility maximization, which is a behavioral/economic theory that postulates that decision makers choose alternatives as a function of the utility derived from them. This theory assumes that utility has two components: (a) a systematic component, which depends upon the socio-economic characteristics of the decision maker and the alternatives' attributes, and (b) a random component that accounts for the fact that the analyst does not have full information about all relevant variables and the underlying decision process. Different assumptions about the distribution of the random terms lead to different models. If the random terms are independent and identically distributed Gumbel across alternatives, one obtains the multinomial logit (MNL) (Ben-Akiva and Lerman, 2000).

However, in spite of its usefulness, the MNL model is not well suited for modeling the problem. First, it 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. The issue is that this is not likely to be the case because there are two train alternatives, i.e., Metroliner and Acela, that may share unobserved (train-related) characteristics. Third, the MNL model assumes that repeated choices made by the same respondent are independent (Algers et al., 1998). Since each respondent provided attitudinal data for nine 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.

In contrast, 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. Two hundred draws per individual of the Halton sequence are used in a maximum simulated likelihood (MSL) estimation approach (see Bhat, 2003). 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.

3.3. Modeling results

The behavioral models of mode choice were estimated using car as the base alternative. Two travel cost variables were considered: *Company Costs* and *User Costs* (in $ teerms) 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 variables. *Inspection Time* refers to the time spent at the airport checking-in and going through security inspections. *Main Travel Time* is the time spent in door-to-door travel excluding inspection time, i.e., travel time minus inspection. *Extra Time 1 before Meeting* represents the extra time before the meeting up to the cutoff value of 30 min, while *Extra Time 2 before Meeting* represents the extra time in excess of 30 min. *Extra Time 1 and 2* are a piecewise linear approximation to nonlinear effects.

A set of binary variables were created to indicate 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. Another variable, *Change 2-3*, was created to represent the case in which the score is between 3 to 7 (moderate to significant). Similarly, three binary variables were created for *Stress*, though none of them was found to be statistically significant.

Several error components structures (to generate correlation and heteroscedasticity across alternatives at the individual level) and varying sensitivities across individuals to the time and cost variables were considered. The final model 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, inspection time, extra time before meeting (1 and 2), interaction term between main travel time and the binary variable indicating how individuals changed their decision of travel after September 11th (*Change 2-3* corresponds to *Change* scores from 3 to 7), and a variables indicating if the respondent is married.

Table 1 shows that 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 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 the company pays, users behave as having a much higher valuation of travel time than when they pay themselves. 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/h if company pays and $122.3/h 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 Jara-Díaz et al. (2005), who 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. The coefficient of *ET1* (extra time before meeting up to 30 min) is positive, while that of *ET2* (extra time before meeting in excess of 30 min) 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 2–3* (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 September 11th 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 September 11th 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 times, 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 September 11th than the other alternatives. This is consistent with the fact that, after September 11th, people avoided traveling by air either out of fear or because of the increasing security and the uncertainty of passenger processing times at the airport. The implication is that the massive security investment post September 11th—by significantly reducing inspection times—had a large impact in restoring the airline industry's market share.

The subject of parameter stability deserves mention. The issue is that, since the data were collected before the trauma of September 11th fully dissipated, one could expect that they captured some of the psychological impacts the event had on the respondents. Most likely, some of these impacts were captured by the coefficient of the variable TT2CH23 (an interaction term between travel time and a binary variable equal to one if the respondents indicated that they were affected the events of September 11th). In this context, since some of these effects may dissipate over time as the initial trauma fades away, one would expect that the coefficient of TT2CH23 would decrease as time passes. Regrettably, there are no data that could be used to estimate such changes. Thus, the only possible course of action is to assume that the behavioral effects captured by the ML model are stable over time. For that reason, the estimates of market shares of the air industry should be interpreted as lower bounds of what may be observed in real life.

4. Simulation of security screening procedures

This section describes the simulation system developed to assess the impacts of alternative security screening procedures on inspection times. In undertaking the analyses, it would have been

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
Standard deviations for alternative specific constants	–	2.4165 ***	–	–
Main travel time	−0.0367 ***	−0.0367 ***	−0.0367 ***	−0.0367 ***
Standard deviations for main travel time	0.0422 ***	0.0422 ***	0.0422 ***	0.0422 ***
IT (inspection time)	–	–	−0.0347 ***	–
CC (company cost/income in thousands)	−0.2826 ***	−0.2826 ***	−0.2826 ***	−0.2826 ***
UC (user cost/income in thousands)	−0.7932 ***	−0.7932 ***	−0.7932 ***	−0.7932 ***
ET1 (extra time before meeting $<=$ 30 min)	0.0533***	0.0533***	0.0533***	0.0533***
ET2 (extra time after meeting $>$ 30 min)	−0.0075	−0.0075	−0.0075	−0.0075
TT2CH23 (Main travel time $\times$ Change 2 or 3)	–	–	−0.0106 ***	−0.0039 ***
MARRIED (=1 if married)	1.8609***	1.5599***	–	2.1982***
Mean Log likelihood function	−1.374			
Number of Cases	1755			
Adjusted rho-squared bar with respect to constants	0.112			

ideal to have data for a real life airport immediately after September 11th, when passengers experienced huge delays at the security checkpoints. Unfortunately, no publicly available data were found. For that reason, authors decided to simulate an idealized airport with passenger traffic and checkpoint configurations similar to the ones prevailing in the days after September 11th. The hypothetical airport is a hybrid of 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 (Customs and Border Patrol, 2012; Atlanta International Airport, 2005), while the service time distributions come from TPA. Given the data constraint, this seems a reasonable assumption. The data on the security screening process at TPA comes from Yalcin et al. (2005) and Mitchell et al. (2006).

Fig. 2 shows the schematic of the screening process used in the discrete event simulation. The process starts when passengers arrive at the checkpoint and join the line where a security guard checks IDs and passports. As passengers approach the screening lanes, passengers remove metal items, take off their coats and shoes, and load them on trays for the scan machines. Then the carry-on baggage screening process and passenger screening start. 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 and ends 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 remaining 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.

Since the objective of this analysis is to assess how security infrastructure impacts inspection time, the simulations considered different numbers of security lanes. For each configuration, the present value of costs (PVC) was 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 (Frank, 2006). Wages of the security personnel were assumed to be $15 per hour with 100% overhead and 36% fringe benefits. It was assumed that there are five security guards at each security lane and that all lanes are open for 12 hours a day. These assumptions are comparable to conditions at large airports on weekdays (Bradley and Goyal, 2003).

Table 2 shows the results from simulation runs and the corresponding values of the PVCs of inspection. As shown, if there are only 10 inspection lanes, the average inspection time is close to two hours, which is what was observed at major airports after September 11th. As expected, the larger the number of screening lanes available, the shorter the inspection times, and the larger the PVCs. The results show that if the number of screening lanes increased from 10 to 36, the inspection time would decrease to about 10 min. However, the PVC increases from $52.48 to $188.92 million. Further reductions in inspection times require significant increases in the number of screening lanes, e.g., to reduce inspection times from 9.8 to 4.5 min, an additional six lanes are needed at an extra cost of about $32 million.

The next step of the analysis was to estimate the market shares corresponding to security screening configurations using a sample enumeration technique (Ben-Akiva and Lerman, 2000). As part of this process, the market shares were estimated by applying the discrete choice model to the estimation data with the test value of inspection time, and then computing an estimator of the market share, i.e., the average values of the individual choice probabilities for the various alternatives.

Table 3 shows the market shares estimated using the ML model and the average inspection times from the simulation models. The results clearly show that the lower the inspection times, the larger the market share of air. However, the estimates show that the initial increases in the number of security lanes have a larger impact that the increases that follow. For instance, increasing the number of lanes from 10 to 20, increases air market share by 11.8%. In contrast, increasing number of lanes from 20 to 30, and from 30 to 40, only increases air market share by 4.6% and 1.4% respectively. Moreover, the table indicates that the gains in the market share of air come primarily at the expense of the rail alternatives and to a lesser extent from car users. For reference purposes, the market shares for the case with zero inspection times are also shown.

5. Economic impacts

The estimates produced in the previous section suggest that the security investment made after September 11th provided a significant boost to the airline industry's market share. However, some important questions remain: Was this investment justified from an

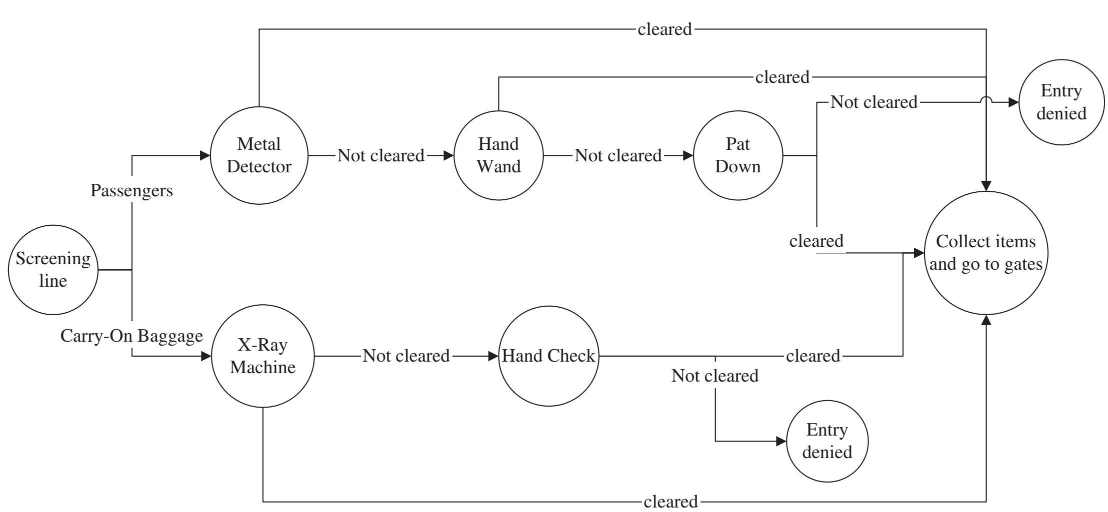

Fig. 2. Screening process for one screening lane.

Table 2
Estimation of costs based on simulation results.

Screening lanes	Inspection time (min)	Construction cost ($ million)	Labor cost ($ million/yr)	Present value of cost ($ million)
10	111.26	20	7.75	52.48
12	87.90	24	9.30	62.97
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

economic point of view? What is the optimal amount of investment in security screening procedures? These are important policy questions because of their potential impacts on inspection time guidelines. This section describes the formulation used to answer these questions through the computation of the economic welfare associated with alternative security screening procedures.

To start with, it is important to mention that, from the standpoint of economic analysis, what really matters are the benefits and cost to the overall economy, and not necessarily which agent incurs the costs or enjoy the benefits. From this perspective, there are two aspects that truly matter: the benefits and costs to passengers and the cost associated with security screenings. Other aspects, such as airline revenues are not relevant because these revenues are the result of the payments made by the passengers, which are internal transactions in the economy, that cancel out. Similarly, it does not matter much if the airports or the government pay for the security screening costs, as long as the costs are correctly captured. For these reasons, the formulation used considers the passengers' consumer surplus (C_S) associated with the mode choice, and the government expenses (G) associated with security screening. C_S represents the economic value of the increase in utility generated by an improvement in the service provided by the transportation modes. In the case of the air alternative, since the inspection time is part of the utility function, the effect of delays produced by security screening is directly taken into account. In this context, welfare (W) is equal to:

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

In computing the consumer surplus, we use the expression derived by Williams (1977) for discrete choice models. As demonstrated by Williams (1977), the expected utility 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 as noted by Jara-Díaz (2007) is equal to the negative of the marginal utility of cost from the discrete choice models:

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

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:

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

Table 3
Estimation of market shares based on simulation results.

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

Table 4
Economic indicators.

Number of lanes	Inspection time (min)	PVC of inspections	PVB of mode choice	NPV
10	111.26	52.48	27.06	-25.42
12	87.90	62.97	77.68	14.70
14	69.96	73.47	119.58	46.11
16	56.86	83.97	152.86	68.89
18	48.22	94.46	176.75	82.28
20	39.05	104.96	203.35	98.39
22	33.71	115.45	220.34	104.89
24	28.86	125.95	236.47	110.52
26	24.25	136.44	252.36	115.91
28	20.37 = 20	146.94	266.41	119.47
30	18.27	157.44	275.04	117.60
32	14.11 = 15	167.93	290.58	122.65
34	12.18	178.43	298.95	120.52
36	9.80 = 10	188.92	308.97	120.05
38	8.50	199.42	315.32	115.91
40	6.30	209.91	324.92	115.00
42	4.48 = 5	220.41	333.26	112.85
44	3.50	230.91	338.69	107.78
46	2.23	241.40	345.23	103.83
48	2.15	251.90	347.39	95.50
50	2.14	262.39	349.49	87.10

Note: As noted in the table, it is assumed that the inspection times of 20.37, 14.11, 9.8, and 4.48 are adequate estimates of the inspection times of 20, 15, 10, and 5 min.

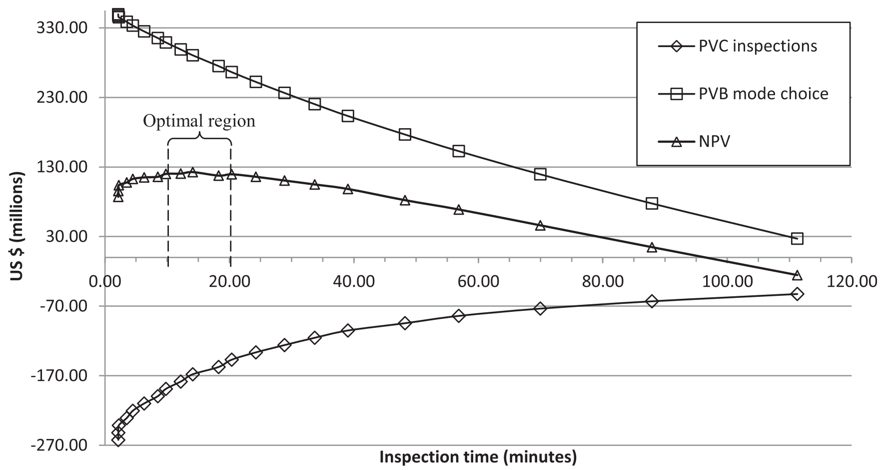

Fig. 3. Present values of benefits and costs as s function of inspection times.

Eq. (5) is the used to estimate welfare for both the base case condition and the alternative screening configurations. Once welfares are computed, the benefits attributable to the improvement are computed as differences between the corresponding welfare values (Jara-Díaz, 2007). The estimates of consumer surplus and the various cost components were projected for a planning horizon of ten years to compute present value of benefits (PVB) and present value of costs (PVC). The results are shown in Table 4 and Fig. 3.

However, it is advisable to caution against assuming that the estimates in the table are highly accurate. In spite of the authors' best efforts to ensure that the estimates are as accurate as possible, the reality is that the optimal inspection time depends on a host of local factors (e.g., value of time of users, actual design and configuration of the security screening area) that cannot be captured in a generic analysis like this one. Moreover, there are numerous sources of uncertainty (e.g., demand, service times, attributes of the competing modes) that cannot be controlled for in full.

For that reason, the authors suggest interpreting these results are order of magnitude estimates of what may be expected in a typical large airport. The results are discussed in reference to the corresponding inspection times. However, it should be noted that, from the standpoint of public policy, it is reasonable to set inspection time goals as multiples of five minutes. For that reason, taking into account the inherent variability and uncertainty of the estimates produced, the authors assumed that the results for the set of interest of inspection times (i.e., 20.37, 14.11, 9.80, and 4.48 min) apply to the closest multiple of five minutes (i.e., 20, 15, 10, and 5 min). This simplifies the exposition and provides a more practical set of estimates. These values have been shaded in Table 4.

As shown, reductions in inspection times increase economic welfare (in the figure this is a movement from right to left). However, the reductions in inspection times lead to diminishing increases in the PVB of mode choice. In contrast, the PVC of inspection increases with decreasing values of inspection times reflecting the additional resources which required to expedite the flow of passengers through screening lanes. The NPV consistently increases with the reductions in inspection times, reaching a maximum at about 15 min, and a plateau with NPV values relatively close to the optimal in the range of ten to twenty minutes (shown in the figure as the "optimal region").

These results imply that, relaxing the TSA goal from ten to 15 min would increase NPV by 1%, saving $18 million/year in inspection costs (per airport). As shown in Fig. 3, the NPV is maximized at about 15 minutes ($122.65 million). Moreover, the finding that an inspection time of twenty minutes is about the same as the goal of ten minutes suggested by TSA should be seriously pondered. This is because the NPV for ten minutes ($120.05 million) is only 0.05% higher than the one for twenty minutes ($119.47 million), though it costs 29% more. Taking into account that security agencies have budget constraints that are defined by a political process that does not consider optimal investment patterns, it seems that a relaxation of the ten minutes goal may be in order. Although the uncertainty of the estimates prevents the exact determination of what the true optimal value of inspection time, it seems clear to the authors that the ten minute goal is sub-optimal for the type of airports considered in this research.

6. Conclusions

We use a discrete choice model, a discrete event simulation, and an economic formulation to: assess the behavioral changes produced by September 11th, examine the role played by the investment in security screening in restoring the airline industry's market shares, and estimate the (economic) optimal security screening investment. 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 was more adversely affected by September 11th than other modes. This is consistent with the fact that after September 11th 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 security screening configurations. Construction, labor costs and present value of costs (PVCs) for different setups were estimated, as well as the market shares of the transportation modes considered. The computations indicate that the reduction of inspection times significantly increased the market share of the airline industry, and that reducing inspection times from two hours to ten minutes may 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, reaching a maximum value at about fifteen minutes. Thus, relaxing the TSA goal to fifteen minutes would increase economic welfare by 1% while saving $18 million/year-airport in inspection costs.

Moreover, the NPV values for inspection times in the range of ten to twenty minutes are very close. The NPV for ten minutes ($120.05 million) is only 0.05% higher than the one for 20 minutes ($119.47 million), though it costs 29% more. The main implication of these results is that, taking into account the budget constraints typical of the public sector, a relaxation of the ten minutes goal to either fifteen or twenty minutes seems advisable.

Acknowledgements

This research was supported by grant CMS-0301391 "Impacts of Extreme Events: A Systematic Analysis of Individual Travel Choice Decisions" from the National Science Foundation. This support is both acknowledged and appreciated. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. The authors thank Grisselle Centeno at the University of South Florida for providing data for the discrete event simulations.

References

Algers, S., Bergstrom, P., Dahlberg, M., Dillen, J., 1998. Mixed Logit Estimation of the Value of Travel Time. Working Paper, Uppsala University, Department of Economics.

Ben-Akiva, M., Lerman, S., 2000. Discrete Choice Analysis: Theory and Application to Travel Demand. The MIT Press, Cambridge, MA.

Bhat, C.R., 2003. Simulation estimation of mixed discrete choice models using randomized and scrambled Halton sequences. Transportation Research, B 37, 837–855.

Blunk, S.S., Clark, D.E., McGibany, J.M., 2006. Evaluation the long-run impacts of the September 11th Terrorist Attacks on US Domestic Airline Travel. Applied Economics 38, 363–370.

Bradley, M.P.T., Goyal, J., 2003. Staff and Lane modeling methodology for TSA Checkpoint passenger screening. transportation research E-Circular, Number E-C060, Washington DC.

Cohen, S., Williamson, G.M., 1988. Perceived stress in a probability sample of the United States. In: Spacapan, S., Oskamp, S. (Eds.), The Social Psychology of Health. Sage, Newbury Park.

Customs and Border Patrol, 2012. Airport wait times. Available at: http://apps.cbp.gov/awt/index.asp (accessed 22.02.12).

Department of Aviation, Hartsfield-Jackson Atlanta International Airport, 2005. Year-to-date Airport Traffic Report (online). Available at: http://www.atlanta-airport.com/sublevels/airport_info/pdfs/Traffic/200512.pdf (accessed 06.02.07).

Frank, T., 2005. Checkpoint or choke point? USA today. Available at: http://www.usatoday.com/travel/flights/2005-07-14-airport-checkpoint_x.htm (accessed 15.04.08).

Frank, T., 2006. Frustratingly, small Airports Get Screeners as big terminals suffer. USA Today, (online). Available at: http://www.usatoday.com/travel/flights/2006-06-18-airport-waits_x.htm (accessed 01.08.06).

Gkritza, K., Niemeier, D., Mannering, F., 2006. Airport security screening and changing passenger satisfaction: an exploratory assessment. Journal of Air Transport Management 12, 213–219.

Goodrich, J.N., 2002. September 11, 2001 attack on American: a record of the immediate impact and reaction in the USA travel and tourism industry. Tourism Management 23, 573–580.

Hartsfield-Jackson Atlanta International Airport. Monthly Airport Traffic Report. Available at: http://www.atlanta-airport.com/sublevels/airport_info/pdfs/Traffic/200512.pdf (accessed 01.08.06).

Holguín-Veras, J., Paaswell, R.E., Yali, A., 2003. Impacts of extreme events on intercity passenger travel behavior: the September 11th Experience. In: Impacts of and Human Response to the September 11, 2001 Disasters: What Research Tells Us. Natural Hazards Research and Applications Information Center, University of Colorado, Boulder, CO. Special Publication #39.

Jara-Díaz, S., 2007. Transport Economic Theory. Elsevier, Amsterdam.

Jara-Díaz, S., Muñizaga, M., Guerra, R., 2005. The amazing sensitivity of the value of time savings to income dependent utility functions. European Transport Conference 2005.

MIT Global Airline Industry Program, 2004. The Airline Industry and current challenges. Available at: http://spacestation.mit.edu/airlines/the-airline-industry/the-airline-industry.htm (accessed 08.07.05).

Mitchell, S., Anthony, K., Austin, A., Scott, T., Iorio, P., Miller, L., 2006. Tampa International Airport 2005 Master Plan Update. Submitted to the Aviation Authority. Available at: http://www.tampaairport.com/about/development/master_plan/index.asp (accessed 01.08.06).

Wald, M., 2001. A nation challenged: airline security; official says He'll miss screening goal, New York Times. Available at: http://query.nytimes.com/gst/fullpage.html?res=9A03E3DC163DF93BA15752C1A9679C8B63 (accessed 17.04.08).

Williams, H., 1977. On the formation of travel demand models and economic measures of user benefit. Environment and Planning 9, 285–344.

Yalcin, A., Centeno, G., Zayas-Castro, J., Bhattacharya, Arka, Bhattacharya, Abhik, Al-Tamimi, R., and Yankov, D., 2005. Simulation, analysis and re-design of security checkpoints at major commercial airports. Final Report Submitted to the US Department of Transportation, Federal Transit Administration, Washington DC.