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A hazard-based analysis of airport security transit times

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A B S T R A C T

Airport security screening, and the amount of time it costs travelers, has been a persistent concern to travelers, airport authorities, and airlines – particularly in recent years where changes in perceived threats have resulted in changes in security procedures that have caused great uncertainty relating to security transit times. To gain a better understanding of the factors influencing travelers' security transit times, determinants of security transit times are studied by using anonymous Bluetooth media access control address matching to determine the actual security travel times of individual passengers at the Cincinnati/Northern Kentucky International Airport. These transit-time data are then analyzed using a random-parameters hazard-based duration model to statistically explore the factors that affect airport security transit times. The estimation results reveal, as expected, that a wide variety of factors affect security transit times including the number of enplaning seats (reflecting flight schedules), weather conditions, day of week, as well as obvious variables such as traveler volume and the number of open security lanes. The detailed statistical findings show that current security procedures are reactive instead of proactive, and that substantial reductions in security transit times could be attained by optimizing security operations using a statistical model such as the one estimated in this paper.

1. Introduction

To improve traveler security and deal with new perceived threats, there have been many changes in airport screening practices and technology in recent years (Leone and Liu, 2011). However, as these practices and technologies have evolved over time, there is the continual need to strike a balance between the level of safety provided to travelers and the inconvenience being caused by airport screening practices, which can be measured in terms of factors such as lost time and intrusions on traveler privacy. While traveler perceptions and satisfaction with airport screening procedures can be difficult to measure and may change over time (Gkritza et al., 2006), the factors that affect travelers' transit times through airport security screening can be readily assessed and such an assessment can serve as a basis for new policies and procedures that seek to reduce security transit times.

Airport security transit times have historically been analyzed with traditional queuing theory approaches, using various assumptions with regard to traveler arrival and processing rates, or by applying statistical analyses of observed transit times (Gilliam, 1979; Zografos and Madas, 2006; Castaneda et al., 2007; Marin et al., 2007; Manataki and Zografos, 2009; Lee and Jacobson, 2011; Seo et al., 2012). These approaches (and really all approaches that assess security travel times) require a sizeable amount of data collection. Queue length, the length of time it takes to transit through the queue, and processing time are all potentially important considerations (Goswami et al., 2007; Correia et al., 2008).

Over the years, different methods have been used to collect this airport security data, including manually handing out time-stamped cards at the entrance of security and time-stamping them at the end of security, and using videos to observe queue length, travelers transit times through the queue, and security processing times. More recently, technology such as anonymous Bluetooth media access control (MAC) address matching (Bullock et al., 2010; Remias et al., 2013), radio-frequency identification (RFID) (McCoy et al., 2005), iris or facial recognition (Elgendi, 2005), and WiFi tracking have been used to collect security transit-time data. In addition to providing data for in-depth statistical analysis, these real-time data-collection approaches can potentially allow security operators to make immediate changes to security

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operations in high-demand time periods by opening more security-processing lanes or by adding more personnel to decrease processing times in open lanes.

Unfortunately, security operators are often restricted by staffinglevels and other constraints that can make real-time adjustments in response to such data difficult. However, statistically analyzing technologically-enabled security transit-time data could help security operators to better understand the important variables that affect these transit times and make more informed long-term staffing and operation decisions. The analysis of such security transit-time data would presumably provide important insights into the effects of flight schedules, different days of the week, seasonal and weather changes, as well as security operational configurations such as the number of open checkpoint lanes, the type of security screening protocols, and other important elements of the security-screening process.

In the current paper, anonymous Bluetooth MAC address matching is used to observe security transit times over a one month period at the Cincinnati/Northern Kentucky International Airport. These data are then analyzed using a random-parameters hazard-based duration model to statistically explore the factors that affect airport security transit times. As will be shown, the model estimation results provide information that is useful in quantifying the effect that a variety of factors have on security transit times.

2. Empirical setting

The Cincinnati/Northern Kentucky International Airport was selected as the source of data for this study. The airport serves a wide area throughout Ohio, Kentucky, and Indiana. Since the airport consolidated from being a hub airport, security operations have been shifting to a new terminal facility and Fig. 1 shows the security layout for this terminal. Referring to this figure, as travelers enter the terminal (callout “a”), they either proceed to the ticket counter or directly to the security screening area. As travelers proceed to the security screening along either side of the central staircase, they proceed past either Bluetooth monitoring Station A or Station B. If any traveler has a Bluetooth enabled device, their unique media access control address (MAC address) is collected. Travelers will wait in a queue and then be processed through one of the ten security lanes (callout “b”). For the Cincinnati/Northern Kentucky International Airport, checkpoint lanes are opened in pairs (lanes are operated in groups of two), so there are effectively 5 lane-pairs. Once through security, travelers will recollect their belongings and head down the elevators or escalators (callout “c”). They will finally pass Bluetooth monitoring Station C where their MAC address will again be noted and then continue on down the walkway to the terminals.

The Bluetooth monitoring stations used class II antennas and sampled up to 8 times a second. Because travelers walking through the zone of detection would register multiple entries, careful filtering was used to eliminate repeat observations. Once the repeat observations were removed, travel times could be determined by matching the time of MAC address observed at either Station A or Station B with the time observed at Station C. The difference in the time would be the security transit time. It should be noted that security personnel and airport employees could be filtered based on repeat matches over various days. But filtering these observations was done with care to not eliminate repeat travelers who used the airport multiple times over the month.

It should be noted that security transit time was the measure recorded. This included the walk time, wait time (or time in queue), processing time, and re-composure time (gathering belongings and such). Under “free flow” conditions without a queue, the security transit time was measured at about 3 min and 15 s.

3. Data collection

From November 11, 2011 to December 8, 2011, over 660,000 Bluetooth MAC address records (6200 unique MAC addresses) were

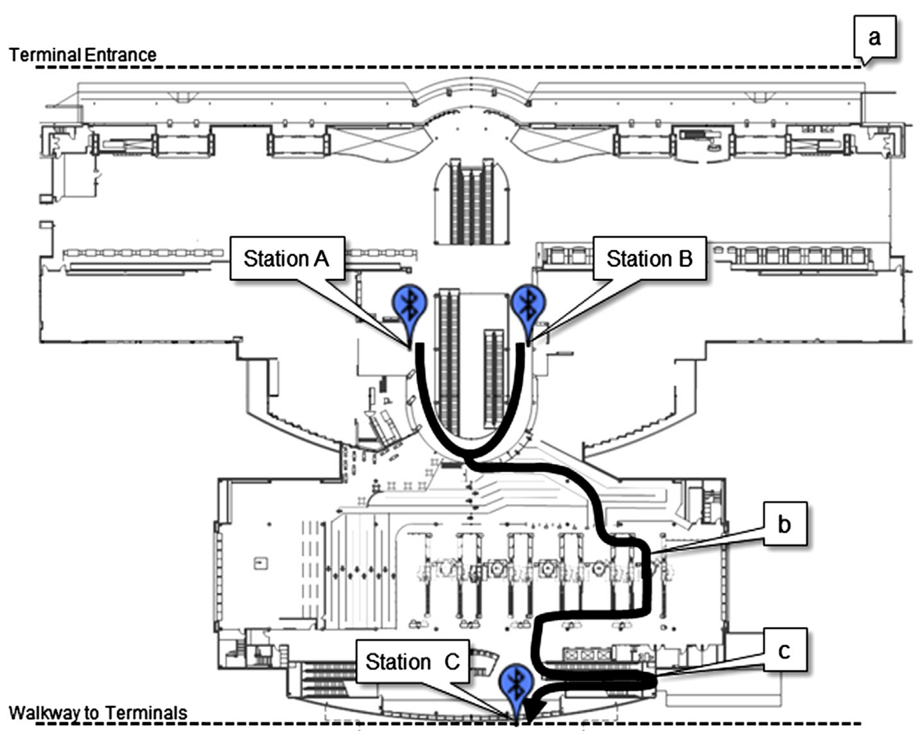

Fig. 1. Airport security arrival process at Terminal 3 of Cincinnati/Northern Kentucky International Airport.

collected. These MAC addressed were successfully matched to generate 4517 security transit-time records (this is roughly 2% of total number of travelers going through security during this time period). To complete the data set, the transit-time records were joined with other data (sometimes aggregated into hourly values and assigned to the individual observation based on travelers' time of arrival at Station A or Station B, see Fig. 1) including airline seating schedules, observed total traveler volumes, security lane configurations throughout each day, weather data and so on. Table 1 gives a summary of the available data. The "lane-pair hours" variable In Table 1 is the effective number of lane-pairs open during the hour. For example, if one lane-pair was open the entire hour and a second was open for only the last 15 min of the hour, the lane-pair hours for this hour would be 1.25.

With regard to other variables, it should be noted that the number of enplaning seats available for each hour is included in the data as a proxy for traveler activity. This is a proxy of actual traveler activity since not all available airline seats may have been sold, and transferring travelers would not have to go through the security process.

Finally, the weather data are included because it is speculated that variations in weather conditions may affect the amount of clothing and other personal articles travelers may have, which may impact security travel times, and that inclement weather may result in changes in traveler arrival times which may spread or condense peak arrival-time periods.

Table 1
Variables available for security transit time hazard duration modeling.

Variable	Mean	Standard deviation
Security transit time (minutes)	16.26	8.87
Average security transit time from the previous hour (minutes)	15.65	3.90
Sunday indicator (1 if Sunday, 0 otherwise)	0.13	0.34
Monday indicator (1 if Monday, 0 otherwise)	0.18	0.39
Tuesday indicator (1 if Tuesday, 0 otherwise)	0.16	0.36
Wednesday indicator (1 if Wednesday, 0 otherwise)	0.14	0.38
Thursday indicator (1 if Thursday, 0 otherwise)	0.13	0.35
Friday indicator (1 if Friday, 0 otherwise)	0.090	0.34
Saturday indicator (1 if Saturday, 0 otherwise)	0.78	0.29
Weekday indicator (1 if Weekday, 0 otherwise)	0.77	0.42
Weekend indicator (1 if Weekend, 0 otherwise)	0.22	0.42
Enplaning seats available for the hour	628.69	599.31
Increase in enplaning seats from previous hour indicator (1 if yes, 0 otherwise)	0.48	0.50
Hour with most enplaning seats available during the day indicator (1 if yes, 0 otherwise)	0.052	0.22
Hour after the hour with most enplaning seats available during the day indicator (1 if yes, 0 otherwise)	0.075	0.26
Hour before the hour with most enplaning seats available during the day indicator (1 if yes, 0 otherwise)	0.084	0.28
Lane pair 1 traveler volume from previous hour	167.60	75.11
Lane pair 2 traveler volume from previous hour	89.64	77.37
Lane pair 3 traveler volume from previous hour	44.78	73.05
Lane pair 4 traveler volume from previous hour	12.57	37.43
Lane pair 5 traveler volume from previous hour	2.09	14.84
Total security checkpoint traveler volume from the previous hour	316.67	188.83
Lane-pair hours during the hour	2.45	1.04
Lane-pair hours during the previous hour	2.31	1.07
Outdoor temperature (°F)	46.71	10.48
Temperature below 32 °F (1 if yes, 0 otherwise)	0.063	0.24
Temperature below 40 °F (1 if yes, 0 otherwise)	0.30	0.46
Temperature above 50 °F (1 if yes, 0 otherwise)	0.34	0.47
Rain indicator during hour (1 if raining, 0 otherwise)	0.27	0.45
Snow indicator during hour (1 if snowing, 0 otherwise)	0.26	0.44

4. Methodological approach

Interest is in the total security transit time, which is the time that has elapsed from arrival at Stations A or B until the traveler completes their journey through security Station C (see Fig. 1). While such transit times are continuous data that can be modeled by traditional ordinary least squares, they can also be considered as duration data and analyzed with hazard-based duration models which can potentially provide additional insights into important duration effects. This is because the hazard-based approach explicitly considers the important possibility that the probability that transit through security will end may change the longer the time spent in security has lasted (Paselk and Mannering, 1994; Martchouk et al., 2011; Washington et al., 2011).

For airport security transit-time durations, hazard-based models consider the conditional probability of a transit-time duration ending at some time t, given that it has not ended until time t and the hazard function can be written as (see Hensher and Mannering, 1994; Washington et al., 2011):

$$h(t) = \frac{f(t)}{1 - F(t)} \quad (1)$$

where $F(t)$ and $f(t)$ are the cumulative distribution function and the density function of security transit times, respectively. The hazard $h(t)$ gives the rate at which security transit times are ending at time t, given that they have lasted up to time t. The hazard function can be increasing as security transit-time duration increases ($dh(t)/dt > 0$) which indicates that the probability that a security transit-time duration will end soon increases the longer the transit time lasts. Alternatively, the hazard function can be decreasing as security transit-time duration increases ($dh(t)/dt < 0$) indicating that the probability that a security transit-time duration will end soon decreases the longer the transit time lasts. There is also the possibility that the probability that a security transit-time duration will end soon is independent of the length of time a transit time has lasted ($dh(t)/dt = 0$).

For developing a statistical model using the hazard approach, the effect of explanatory variables can be incorporated as (see Washington et al., 2011):

$$h_n(t|\mathbf{X}) = h_0(t)\ \mathrm{EXP}\ (\boldsymbol{\beta}\mathbf{X}_n), \quad (2)$$

where $\mathbf{X}_n$ is a vector of explanatory variables associated with air traveler n, $\boldsymbol{\beta}$ is a vector of estimable parameters, and $h_0(t)$ is the baseline hazard that denotes the hazard when all elements of the explanatory-variables vector are zero.

Equation (2) can be estimated using a variety of parametric forms of the underlying hazard function (non-parametric approaches can also used but their duration effects, how the hazard changes over time, can be difficult to interpret). The most widely used parametric forms include the Weibull and log-logistic models. The Weibull model allows monotonically increasing or decreasing hazard functions (implying the probability of a traveler's security transit-time duration ending increases or decreases the longer the transit time lasts). With parameters $\lambda > 0$ and $P > 0$, the Weibull distribution has the density function,

$$f(t) = \lambda P(\lambda t)^{P-1}\ \mathrm{EXP}\left[-(\lambda t)^P\right], \quad (3)$$

with hazard,

$$h(t) = (\lambda P)(\lambda t)^{P-1}, \quad (4)$$

Taking the first derivative of Equation (4) with respect to time, if the Weibull parameter P is greater than one, the hazard increases monotonically with trip duration ($dh(t)/dt > 0$); if P is less than one, it is monotonically decreasing with the trip duration ($dh(t)/dt < 0$); and, if P is equal to one, the hazard is constant over time ($dh(t)/dt = 0$).

The log-logistic model has been previously applied to travel-time durations by Martchouk et al. (2011) and has the advantage of allowing for the sometimes more realistic non-monotonic hazard function. However, because more complex versions of the Weibull model can be considered to account for unobserved heterogeneity across observations (which would include unobserved factors such as traveler experience, number of carryon bags and electronics, etc.), the monotonic hazard function restriction of the Weibull model is effectively relaxed. In our subsequent empirical work, the log-logistic model did not perform as well as the Weibull-model heterogeneity variants that were considered. Thus, the log-logistic formulation is not presented in this paper.

The traditional proportional-hazards approach (see Equation (2)) assumes that the baseline hazard function, $h_0(t)$, is homogenous across observations. As mentioned above, a critical concern in the application of hazard models to security travel times is the possibility of unobserved heterogeneity. One way to address this is to introduce heterogeneity by assuming a distribution of heterogeneity across the population (the gamma distribution has been a popular choice for this, see for example Heckman and Singer, 1984; Gourieroux et al., 1984; Nam and Mannering, 2000; Washington et al., 2011). A second more general way to account for unobserved heterogeneity is to allow some (or all) of the model parameters to vary across observations. To account for heterogeneity in this random-parameters manner (unobserved factors that may vary across observations), Greene (2007) developed a method for incorporating random parameters in hazard-based duration models (see also Washington et al., 2011 for an application of this approach). This approach considers estimable parameters as,

$$\boldsymbol{\beta}_i = \boldsymbol{\beta} + \varphi_i, \tag{5}$$

where φ_i is a randomly distributed term (for example a normally distributed term with zero mean and variance equal to σ^2).

Because maximum likelihood estimation of the random parameters hazard-based duration models is computationally cumbersome (due to the required numerical integration of the duration function over the distribution of the random parameters), a simulation-based maximum likelihood method is used (see Train, 2003). The most popular simulation approach uses Halton draws which have been shown to provide a more efficient distribution of draws for numerical integration than do purely random draws (see Bhat, 2003).

5. Estimation results

Model estimation results for the random parameters Weibull hazards model are presented in Table 2 and corresponding marginal effects are presented in Table 3. With regard to the signs of the estimated parameters, for simplicity of interpretation, we estimate $-\boldsymbol{\beta}$ to get the effect that the variable has on the actual security transit time as opposed to the effect that it has on the hazard function (see Equation (2)). With this, positive parameters in Tables 2 and 3 increase travel-time duration (since it results in a negative parameter in Equation (2), which decreases the hazard and thus increases durations).

Turning first to the interpretation of parameters that were found to be fixed across the population of travelers, the average security transit time for travelers in the preceding hour had a positive parameter, meaning that the security transit time would be higher if the previous hour's security transit time was high. In addition, the total security checkpoint traveler volume from the previous hour also produced a positive parameter estimate. These variables capture the dynamics of the security transit-time process in that residual queues from preceding time periods affect security transit times in the current time period. The variables may also be capturing the procedures of operating personnel and other factors that may overlap from one time period to the next.

Table 2
Weibull model parameter estimates of the security transit time (standard deviations of random parameters in parentheses).

Variable	Estimated parameter	*t*-Statistic
Fixed parameters		
Constant	2.724	75.03
Average security transit time for hour from the previous hour (minutes)	0.0080	4.01
Total security checkpoint traveler volume from the previous hour (in hundreds of travelers)	0.0413	6.01
Monday indicator (1 if yes, 0 otherwise)	−0.0867	−3.83
Wednesday indicator (1 if yes, 0 otherwise)	−0.0661	−3.40
Weekend indicator (1 if yes, 0 otherwise)	0.0919	4.77
Increase in enplaning seats from the previous hour indicator (1 if yes, 0 otherwise)	−0.0602	−3.67
Hour after the hour with most enplaning seats available during the day indicator (1 if yes, 0 otherwise)	−0.0954	−3.48
Hour before the hour with most enplaning seats available during the day indicator (1 if yes, 0 otherwise)	−0.159	−4.25
Temperature below 40 °F (1 if yes, 0 otherwise)	−0.0557	−3.24
Random parameters		
Hour with most enplaning seats available during the day indicator (1 if true, 0 otherwise)	−0.177	−5.08
	(0.351)	(11.06)
Standard deviation of random parameter		
Lane-pair hours during the previous hour	−0.000667	−0.08
Standard deviation of random parameter	(0.0376)	(11.73)
Rain indicator during the hour (1 if raining, 0 otherwise)	−0.0688	−3.80
	(0.0757)	(5.64)
Standard deviation of random parameter		
Weibull P parameter	2.217	98.83
Number of observations	4571	
Log-likelihood at convergence	−3680.478	

Table 3
Marginal effects of the security transit time (effect of a one-unit change in X on the hazard function).

Variable	Marginal effect
Average security transit time for hour from the previous hour (minutes)	0.0146
Total security checkpoint traveler volume from the previous hour (in hundreds of travelers)	0.0750
Monday indicator (1 if yes, 0 otherwise)	−0.1527
Wednesday indicator (1 if yes, 0 otherwise)	−0.1173
Weekend indicator (1 if yes, 0 otherwise)	0.1705
Increase in enplaning seats from the previous hour indicator (1 if yes, 0 otherwise)	−0.1092
Hour after the hour with most enplaning seats available during the day indicator (1 if yes, 0 otherwise)	−0.1662
Hour before the hour with most enplaning seats available during the day indicator (1 if yes, 0 otherwise)	−0.2710
Temperature below 40 °F (1 if yes, 0 otherwise)	−0.0998
Hour with most enplaning seats available during the day indicator (1 if true, 0 otherwise)	−0.3212
Lane-pair hours during previous the hour	0.0124
Rain indicator during the hour (1 if raining, 0 otherwise)	−0.1511

Indicator variables for Monday and Wednesday were both found to be negative, indicating that Mondays and Wednesdays have lower security travel times relative to other days of the week (which are implicitly set to parameter values of zero). This may be the result of factors such as different types of travelers on these days (for example the mix of business travelers and leisure travelers which are known to have different characteristics that would affect security processing times as shown by Dresner, 2006) and airport security operational procedures which may be different on these days (with regard to the number of personnel, personnel experience, and other factors).

Similarly, the weekend indicator parameter estimate shows that weekends were found to result in longer security travel times relative to weekdays. Again, types of travelers and variations in airport security operations or personnel experience may be possible explanations.

Several indicator variables relating to the number of enplaning seats available (from the flight schedules) were found to lower the probability of a longer security transit times including: an indicator variable for whether the number of enplaning seats from the previous hour increased; an indicator variable for whether the study hour was the hour after the hour with the most enplaning seats available for the day; and an indicator variable for whether the study hour was the hour before the hour with the most enplaning seats available for the day. Because the parameter estimates of all three of these indicators are negative, they all result in lower security transit times (the marginal effects in Table 3 show that the indicator variable for whether the study hour was the hour before the hour with the most enplaning seats available for the day had the biggest effect, of these indicators, on security transit times). With regard to the enplaning seat indicator, one might expect that more travelers and thus busier periods would result in increased security transit times, but these enplaning-seat findings are likely capturing the greater efficiency of travelers going through security at busy times, perhaps different types of travelers going through security during busy periods (the mix of business travelers and leisure travelers), and there may be an overall improvement in airport security efficiency during busy periods.

The weather variable, an indicator variable for temperatures below 40 °F, was also found to significantly reduce security transit times. While we are not certain what may be causing this effect, it is speculated and that there may be changes in traveler preparedness and/or security staffing and processing times during such inclement weather events.

With regard to random parameters, the indicator variable for the hour with most enplaning seats available during the day produced a negative mean parameter, but also a relatively high and statistically significant standard deviation. With the estimated mean and standard deviation of this parameter, the parameter has a negative value (reducing security travel time) for 69.3% of the travelers and a positive value (increasing security travel time) for 30.7% of travelers. This finding may reflect variations in airport security practices in terms of staffing time periods with high numbers of enplaning seats. In such time periods there may be uncertainties in demand with regard to the number of travelers arriving closer to departure times and, in the presence of this uncertainty, airport security operations may over or under estimate traveler volumes and this is what may be causing the variability in this parameter estimate over the traveler population.

Lane-pair hours (the effective number of lane-pairs open during the hour) produce a small negative effect (with a small parameter mean) with a relatively large standard deviation. As a result, the parameter estimate for this variable is negative (decreasing security transit time) for 51% of travelers and positive (increasing security travel time) for 49% of travelers. One would expect that higher lane-pair hours would unambiguously decrease security transit times (given the many other variables included in the model that control for traveler demand). While this is true for a bit more than half of the cases, it is not true for the others. This finding likely reflects possible lags in the airport-security operation in terms of opening additional lane-pairs, particularly during high volume periods. For example, an hour with 3 lane-pairs open the entire hour and another open for the last 15 min of the hour (giving a total of 3.25 lane-pair hours) would have an above average number of lanes open (the average is 2.45 as shown in Table 1), but if this occurs in periods of rapidly increasing traveler demand the fact that airport security operators did not open lane-pairs quickly enough could produce negative parameter values for a significant number of travelers. The ambiguity of the lane-pair parameter finding reflects the difficulty that airport security is having responding to traveler demand in terms of staffing, and opening and closing lane-pairs.

Finally, the presence of rain during the arrival hour resulted in a random parameter that decreased security travel times for 81.8% of travelers and increased security travel times for 19.2% of travelers. For the portion of travelers experiencing shorter security transit times during rain events, it is possible, depending on the severity of the rain event, that delays or changes in departure times when going to the airport may spread the “peaking” of traveler demand through security resulting in shorter queues. For the 19.2% that see security transit time increase, it could reflect minor rain events where the presence of extra rain-related paraphernalia when going through security is not offset by changes in airport arrival times.

6. Duration effects

A potentially important operational finding with regard to airport security operational procedures can be extracted by considering the shape of the hazard function and specifically how the probability of exiting the system (having a transit security time duration end) changes with respect to the time that a traveler being in security has lasted. The hazard function for the estimated Weibull model with random parameters is shown in Fig. 2. Fig. 2 shows the hazard function increasing in duration (meaning the longer that the security transit-time duration has lasted the more likely it is to end soon) up to roughly 29 min. Ideally, airport security operations would want to structure a security-staffing policy that would always produce a hazard function with a positive slope ($dh(t)/dt > 0$), meaning that the longer that a travelers security travel time has lasted the more likely it is to end soon. However, after 29 min the slope of the hazard function becomes negative ($dh(t)/dt < 0$) and the longer that a travelers security travel time has lasted the less likely it is to end soon. This is an undesirable condition, and may point to operational or staffing problems that occur roughly when

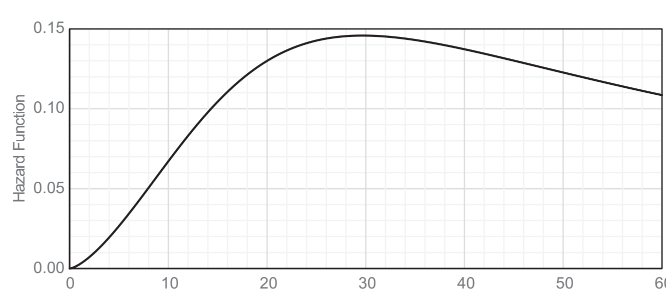

Fig. 2. Hazard function for security transit time.

traveler security time are in the 30-min range. Our statistical finding suggests that very close attention be given to periods where traveler security travel times approach 30 min to determine what might be done operationally to keep the slope of the hazard function positive.

7. Empirical observations

The statistical assessment of Bluetooth security-transit times isolates a number of important factors that determine the duration of time through security checkpoints. The finding that the hazard function begins to slope downward after 29 min suggests that there is room for improvement in terms of when security lane-pairs should be opened. The statistical findings suggest that airport security staffing may be less than optimal. In fact, when looking at the base data there is ample reason to believe that airport staffing (lane-pair openings) seems to be reactive to traveler demand instead of being proactive to meet likely demand. Specifically, the increase in demand during peak periods is often overlooked by security staffing during the initial portion of the demand increase and then much of the remainder of the peak period is spent catching up with demand – with lane-pairs then shut down as demand drops. Fig. 3 shows a sample day (November 14, 2011) of the available data. Fig. 3a shows the observed Bluetooth transit times (244 Bluetooth match travelers) with the hourly average transit times (horizontal bars). Callout "i" denotes a spike in the morning peak security transit time. Fig. 3b shows the actual hourly volume of travelers passing through security (all travelers, whether they have Bluetooth or not). It is also important to consider this with Fig. 3c, which shows the number of enplaning seats available for each hour. Notice callout "ii" which highlights heavy security volumes for the 6:00–8:00 h. This corresponds to callout "vi" denoting a spike in the number of enplaning seats available at 9:00. Finally, callout "x" in Fig. 3d shows that only 2 lane-pairs were operated during the first hour of the morning security peak (in particular the 6:00 h is the busiest hour). This again reflects the reactive nature of the security-staffing schedule not matching the initial increase in demand. The security staffing regime quickly adds the remaining number of lane-pairs during the 7:00 and 8:00 h to help dissipate the queues that have formed due to there initially being too few lanes open. Note that the number of open lane-pairs is efficiently dropped to match security transit demand during the 9:00 h.

A similar reactive security staffing schedule fails to match the rise in security-transit demand in the afternoon peak period. Both

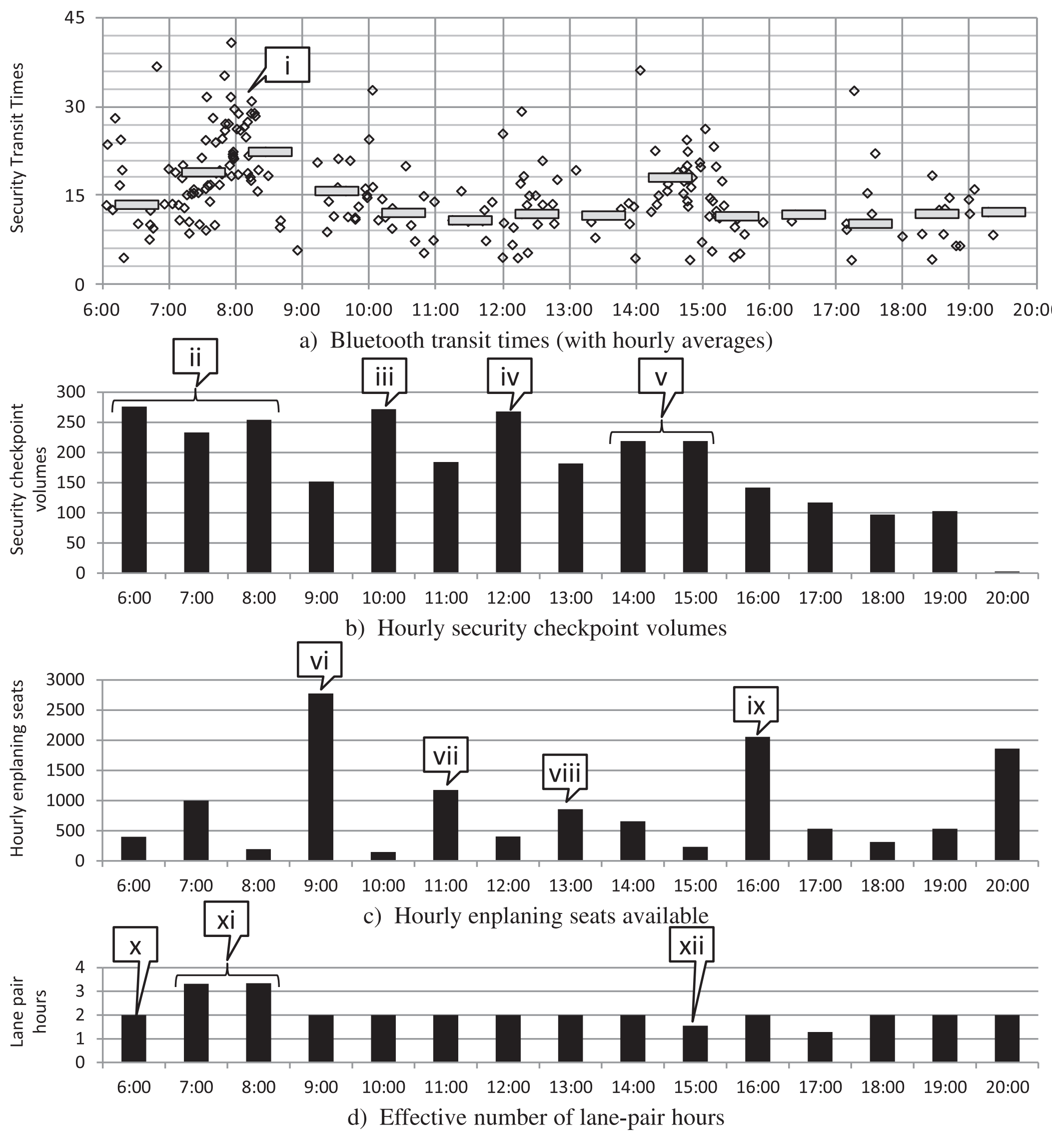

Fig. 3. November 14, 2011 sample airport security screening data.

the 14:00 and 15:00 h have an increase in security-transit volume (callout “v”) which is foretold by the high number of available enplaning seats during the 16:00 h (see Fig. 3c and note that similar increases in security-transit volumes are observed in the current hour when there are more enplaning seats in the following hour, as shown by callouts “iii”/”vii” for the 10:00/11:00 h and by callouts “iv”/”viii” for the 12:00/13:00 h). Unfortunately, the afternoon peak, callout “xii” in Fig. 3d, shows that lane-pairs were dropped during the 15:00 h (when they were needed to satisfy the foretold influx of travelers) and then brought back in the 16:00 h to help dissipate the accumulated queues.

8. Summary and conclusions

To better understand the factors that affect airport security transit times, anonymous Bluetooth media access control address matching was used to observe security transit times over a month long period at the Cincinnati/Northern Kentucky International Airport. The security travel times for over 4500 travelers were observed and a random parameters hazard-based duration model was estimated to statistically determine the effect of variables on transit times and to understand how the likelihood of a transit time ending soon changes the longer the transit time lasted. The estimation results show that wide variety factors affect security transit times including the carryover effects from preceding transit times (reflecting the dynamics in the system), the number of enplaning seats, weather conditions, day of week, traveler volume and the number of security open lanes.

Interestingly, our estimation results found that the hazard function was increasing in duration (a good sign, meaning the longer that the security transit-time duration has lasted the more likely it is to end soon) up to roughly 29 min, but then decreasing after that (a bad sign, meaning the longer that the security transit-time duration has lasted the less likely it is to end soon). This post 29-min finding has important implications in that it suggests that operational procedures are such that, once transit times approach the 29-min mark, security-procedure processing times are fundamentally changing in a bad way (a similar finding was previously reported by Nam and Mannering, 2000, in their analysis of the time it takes emergency personnel to clear vehicle crashes and disablements from Seattle freeways). Special attention needs to be paid to develop operating policies that avoid a negative slope on the hazard function. Also, in a general sense, the estimation results and general analysis of the data suggest that staffing levels appear to be quite reactive (rather than proactive), especially with regard to obviously influential factors such as the number of enplaning seats available for a given hour, and this reactive stance tends to be quite costly in terms of increased security-transit times.

The presence of random parameters in the model suggests that there is considerable unobserved heterogeneity in our data. Clearly, there are many individual-specific characteristics that affect security-processing times (such as age, number of items being carried, type of clothing and shoes, etc.) and these are being captured to some extent with the random parameters approach we have adopted. Still, it is clear that more extensive data that included individual characteristics could provide further insights and this would be a fruitful area for future research. Finally, it should be noted that the Bluetooth data security transit-time data collected is from a self-selected group of travelers (those with Bluetooth-emitting devices). While there is no compelling reason to suspect that these travelers may have different security travel times than the non-Bluetooth emitting travelers, some caution should be exercised when viewing the findings of this paper.

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