DOCUMENTED
BRIEFING

How Much Is Enough? Sizing the Deployment of Baggage Screening Equipment by Considering the Economic Cost of Passenger Delays

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PREFACE

Shortly after the terrorist attacks against the World Trade Center on September 11, 2001, Congress passed a new law that mandated the screening of all baggage carried on all commercial aircraft by the end of Calendar Year (CY) 2002. The Transportation Security Agency (TSA), a newly formed organization that is part of the Department of Homeland Security, was given the responsibility for ensuring that all bags would be screened. To its credit, TSA made sure sufficient equipment was acquired and installed at all U.S. commercial airports to satisfy the spirit, if not exactly the letter of the law.

The imperative of meeting the congressionally mandated short deadline completely overshadowed any planning to address airport security needs over the long term. Left undone was any attempt to determine how to best balance the two principal criteria commonly put forward for sizing the machine deployments at individual airports. These two criteria—keeping the cost to the government of acquiring, installing, and operating the baggage-scanning equipment as low as possible, and not seriously disrupting the passenger flow through the airport—are critical for answering the question in the title of this briefing, "How much [baggage-scanning equipment] is enough?"

Determining how much is enough is important for several reasons, not the least of which is keeping the overall cost to the flying public to a minimum while still providing the mandated level of security. Failure to have deployments that minimize the overall cost to the public will unnecessarily hurt the aviation industry, and will impose a drag on the nation's economic growth.

This documented briefing is part of a larger study by the RAND Corporation of the implications of airport security measures on airports, airlines and, more broadly, the nation's economic growth. RAND funded this study as a component of an even broader effort to expand its understanding of the implications of terrorist threats against the United States and its allies.

The breadth and depth of this study was inherently limited by time, cost, and access. We had neither the opportunity nor the time to visit many U.S. commercial airports or to interact with the TSA to ensure that the assumptions in this study are fully consistent with what TSA and the airports are doing.

Despite these shortcomings, the results should be of interest to organizations and individuals committed to retaining and fostering a vigorous transportation industry and unrestricted access to long-range travel by the public. The commerce associated with air travel is a vital element of this nation's economy. Ensuring both its safety and its continued growth is a challenge that requires both a high degree of security and a minimum of impedance to convenient flight.

Briefing Outline

1. **Background, Introduction, and Findings**
2. **Calculating Maximum and Average Baggage-Scanning Delays at a Major Airport (Dallas–Fort Worth)**
3. **Implications for Passenger Delays**
4. **Sensitivity of Results to Assumptions**
5. **Extending Analysis to Include a Second Major Airport (Chicago O'Hare)**
6. **Balancing Costs and Consequences**
7. **Profiling as a Means to Reduce Costs and/or Lessen Consequences**
8. **Observations and Recommendations**

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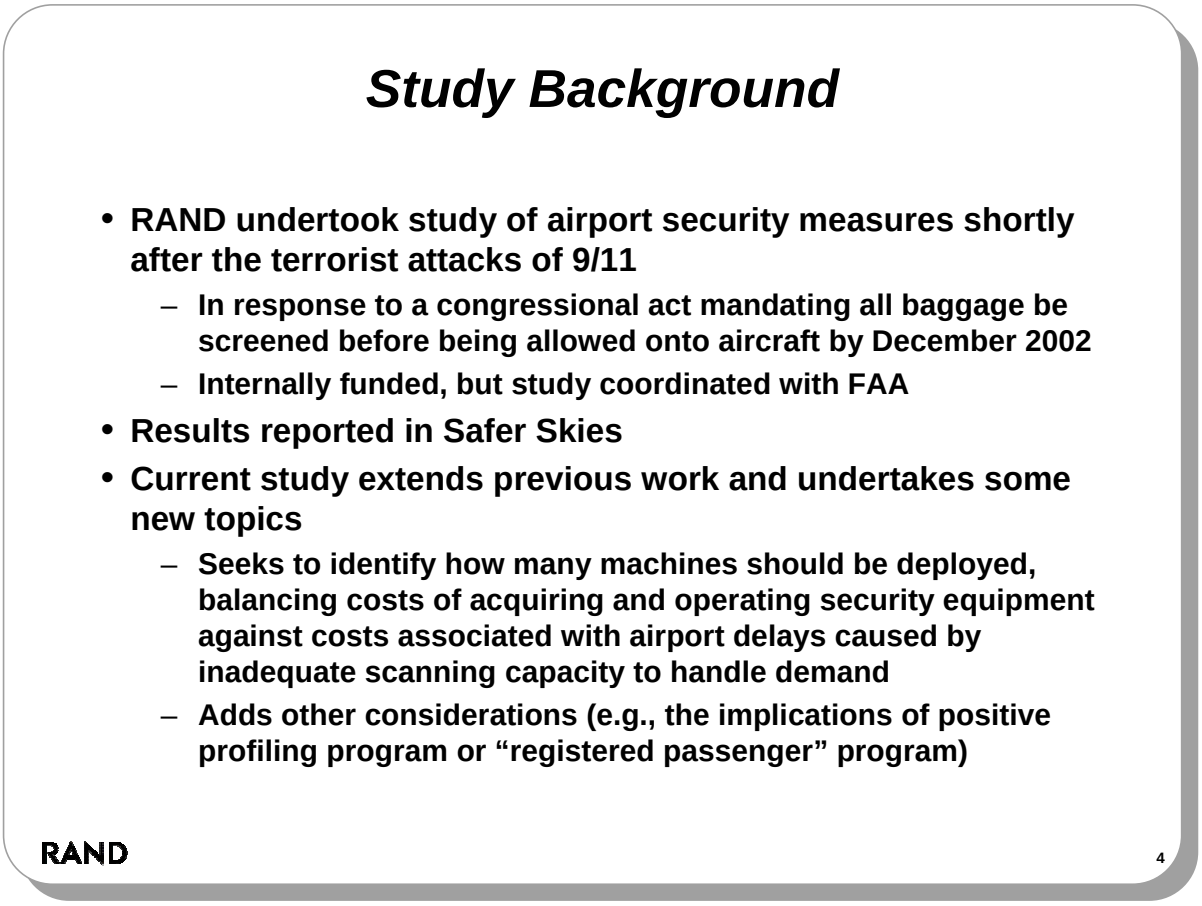
We begin by giving some background on the problem we are addressing, including a summary of our prior work in this area and what we recommended to the government in March 2002. We then describe our findings from this work, connecting it to the prior work and pointing toward a new set of recommendations.

We lead the reader through the steps of the analysis, starting with how we calculated the various baggage-scanning delays, how those delays were translated into passengers choosing to arrive at the airports earlier than otherwise necessary, and how that behavior is ultimately reflected in additional cost to the nation's economy.

This briefing is relatively long because a number of important sensitivities need to be addressed.



Immediately after the terrorist attacks of 9/11, RAND management made a strategic decision to employ a major portion of its internal research money toward studies of how the United States might best meet the new threat. Among the studies undertaken was one dealing with how the government might best respond to the congressionally imposed demands on improved airport security. Congress had just passed a security bill that, among other things, mandated that all passenger baggage be electronically scanned for explosives prior to its being placed onboard the aircraft. The Administration was given until December 2002 to fully comply. That part of the FAA already involved in acquiring security equipment (subsequently moved to TSA after its formation) was given the mandate to carryout the mandate.

Based on its own work, the FAA believed that the task imposed by Congressional mandate was nearly impossible. Among the shortfalls were (1) the lack of adequate certified equipment and the unlikelihood that a sufficient production of new EDS* machines could be achieved in time, (2) the lack of space at the airports for installing the new equipment, even assuming that it would be available, and (3) the shortage of trained machine operators. The FAA asked RAND for an independent assessment of these shortfalls. Our initial results were provided in January 2002. The formal study report was released in March 2002 (see reference 1). The figure on page 6 summarizes the findings of the study.

Missing from this initial study was a clear evaluation of the proper size of the total EDS* machine buy. We knew that the evaluation would trade the costs of additional machine acquisition, installation, and operations against the cost of inadequate baggage-scanning throughput and what that would mean in terms of passenger inconvenience. Moreover, we also know that a successful "registered traveler" positive profiling program could significantly reduce baggage-scanning requirements, perhaps to a degree that would alleviate the need for additional machines. However, we did not know whether the planned deployment was anywhere near the proper size. How these and other considerations would affect the "best" answer needed serious study.

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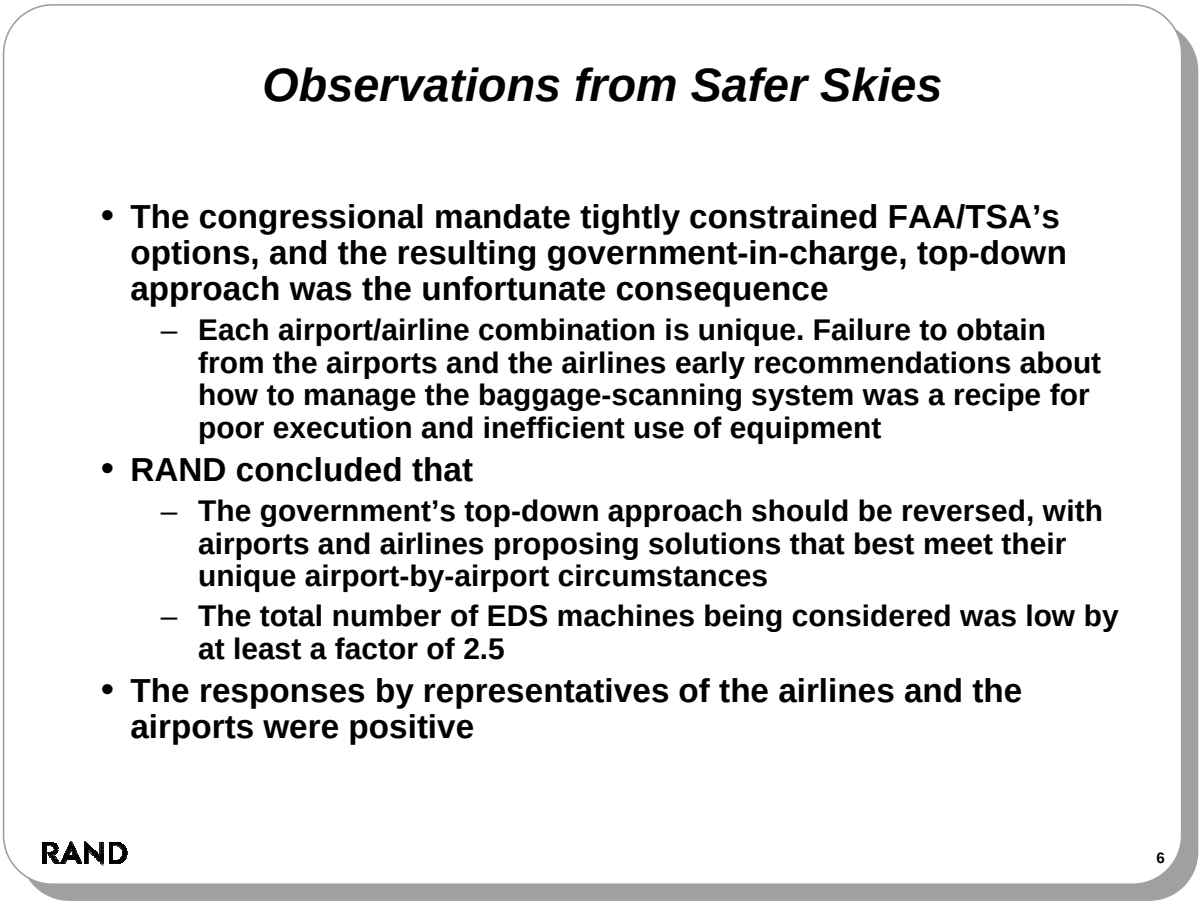
* Electronic Detection System. The label EDS is commonly use for machines that use magnetic resonance techniques to provide images of objects within a bag being scanned.



The observations from Safer Skies,* detailed in this figure, were provided informally in January 2002. Nevertheless, they were either too late or too difficult to handle for TSA to act positively on them.

Remarkably, and to TSA's credit, by December 2002 all but a few airports were judged to be in compliance (the remainder obtained waivers). This rapid compliance was facilitated by a change in the requirements for baggage-scanning capabilities. One example is the partial substitution of trace detection equipment for EDS equipment. Instead of imaging the contents of the bag, trace detection equipment "sniffs" for minute quantities of bomb-related molecules. This substitution is recognized by all as a temporary answer, and over time the more capable EDS machines will be deployed and used in the manner originally envisioned by the law.**

RAND's sizing analysis focused on passenger demand levels predicted for CY2010. The study focused on future demand levels for three reasons: essentially no opportunity

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*See reference 1.

**Trace detection equipment will continue to be used in airports in roles that complement other security equipment, including EDS and x-ray machines.

Exited to effect near-term machine deployments; the near-term focus did not allow any serious examination how to do the mission efficiently, including airport configuration changes and the like; and a longer-term target was needed, assuming that there would be time to evaluation the outcome of the near-term deployments and plan on how to improve the process over the long haul.

Our conclusions were intended to help TSA's short-term efforts. Nevertheless, they are appropriate for the longer term as well.

What's New in This Study Since Safer Skies

- **Expanded number of airports examined**
  - **Added Chicago O'Hare (ORD) to Dallas–Fort Worth (DFW)**
- **Modified passenger demand levels**
  - **Obtained lower 2010 demand numbers from MITRE**
- **Developed new performance criteria**
  - **Average rather than maximum baggage delays**
  - **Passenger pre-departure arrival times vs. risk of having bag miss plane**
- **Added a new metric (sizing the number of EDS machines deployed to minimize the impact on the nation's economy)**
- **Examined "Registered Traveler" schemes for lowering baggage-scanning demand**
- **Refocused concern from "Doing the Job Right" to "Doing the Right Job"**

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This briefing is at least in part a follow-on to what was done in the "Safer Skies" white paper. The following are some of the changes

- We added another large major hub airport to our analysis, to ensure that the selection of a single airport was not unduly biasing our results. It was not.
- We obtained some new demand numbers for these airports, resulting in somewhat fewer flights in 2010. Consequently, the total sizing numbers shown in "Safer Skies" have been reduced somewhat for a given level of performance.
- We developed two new criteria, in our attempt to better capture how the passengers would react to the baggage-scanning delays that they would encounter.
- We added a new metric for sizing the total buy. Roughly, the metric is intended to answer the question, "How much is enough?" in terms appropriate for government decisionmakers.
- We have added some numbers on what a "Registered Traveler" program would mean for sizing the machine buy size or lowering the overall cost to the nation for better security at major airports. A companion report on this work has also being produced (see reference 2).

Major Finding

- **Two competing costs are imposed on the flying public (and indirectly on the nation's economy) from the baggage-scanning requirements**
  - **The cost of performing the scanning, which includes the cost of acquiring, installing, and operating the scanning equipment**
  - **The cost imposed on the passengers associated with spending more time at the airport than would be normal otherwise**
- **The overall sum of these costs is minimized when sufficient machines are bought to keep passenger delays to at most a few minutes**
  - **The derived size of the buy is substantially higher than the numbers now in place (or soon to be in place) at major airports**
- **This result is very robust, insensitive to wide changes in assumptions**

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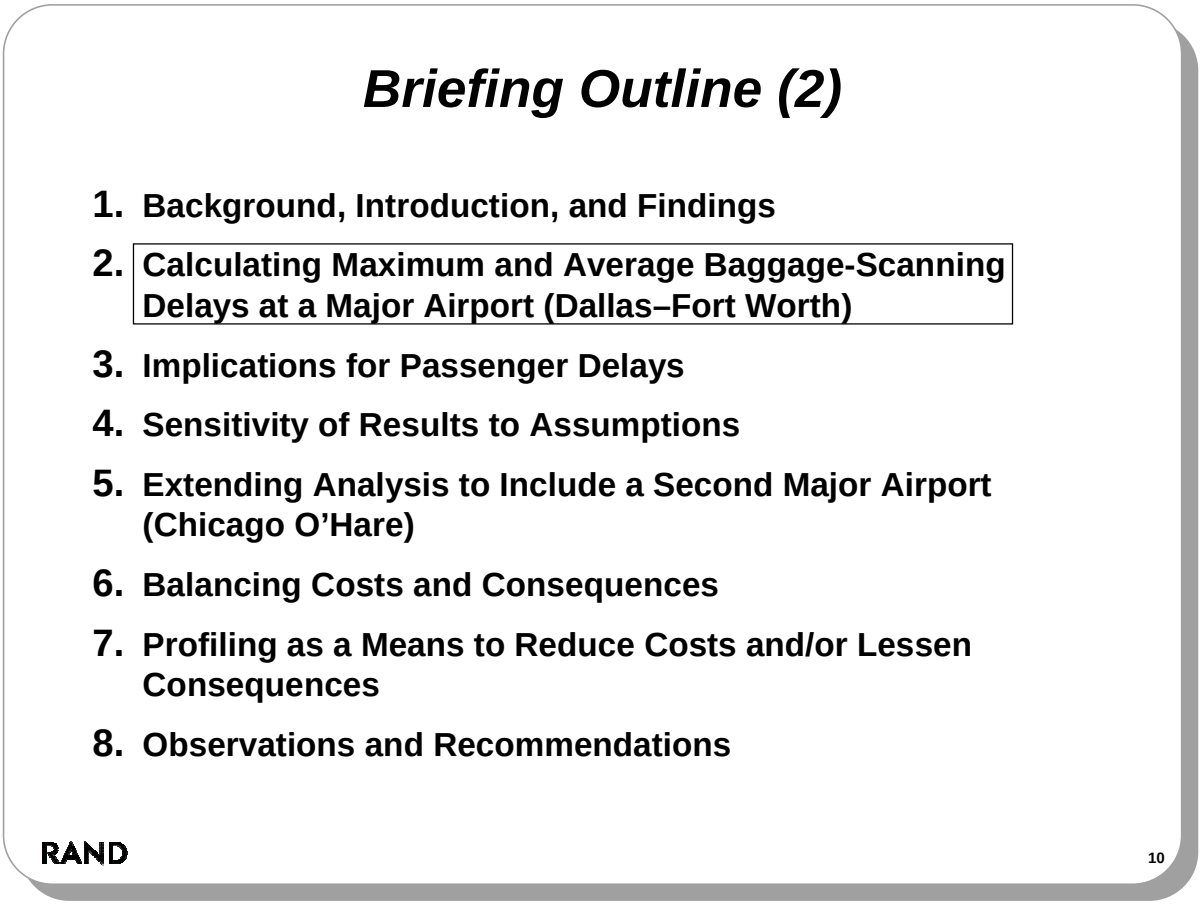
The acquisition, installation, and operation of baggage-scanning equipment has already cost several billion dollars and that cost is likely to grow over time. The operational costs alone will be substantial, given the need for approximately 50,000 TSA employees. Although it is not clear to the authors exactly what portion of these costs will be charged back against the airlines and their passengers, we assume that eventually most of it will show up in increased ticket prices.

Adding more machines and manpower to operate them will simply increase this cost.

On the other hand, adding more machines at an airport will lessen the likely delays that would occur in scanning the baggage, reducing the amount of time that passengers must spend at the airport waiting for their bags to be inspected. Forcing the passenger to spend extra time at the airport imposes another form of cost on him. Adding more machines lowers this cost.

An optimum balance between these two competing costs exists when the overall cost to the passenger is minimized. Our calculations show that the minimum is at machine deployment levels where maximum baggage-scanning delays are less than five minutes. Knowing the answer, it is easy to understand why. There are hundreds of million or more baggage-toting passengers travel per year, each suffering to some degree from the delay. Even a small delay would add substantial costs under these circumstances. For example, if a passenger valued his time at $40 per hour, a five-minute delay would cost him $3.33.

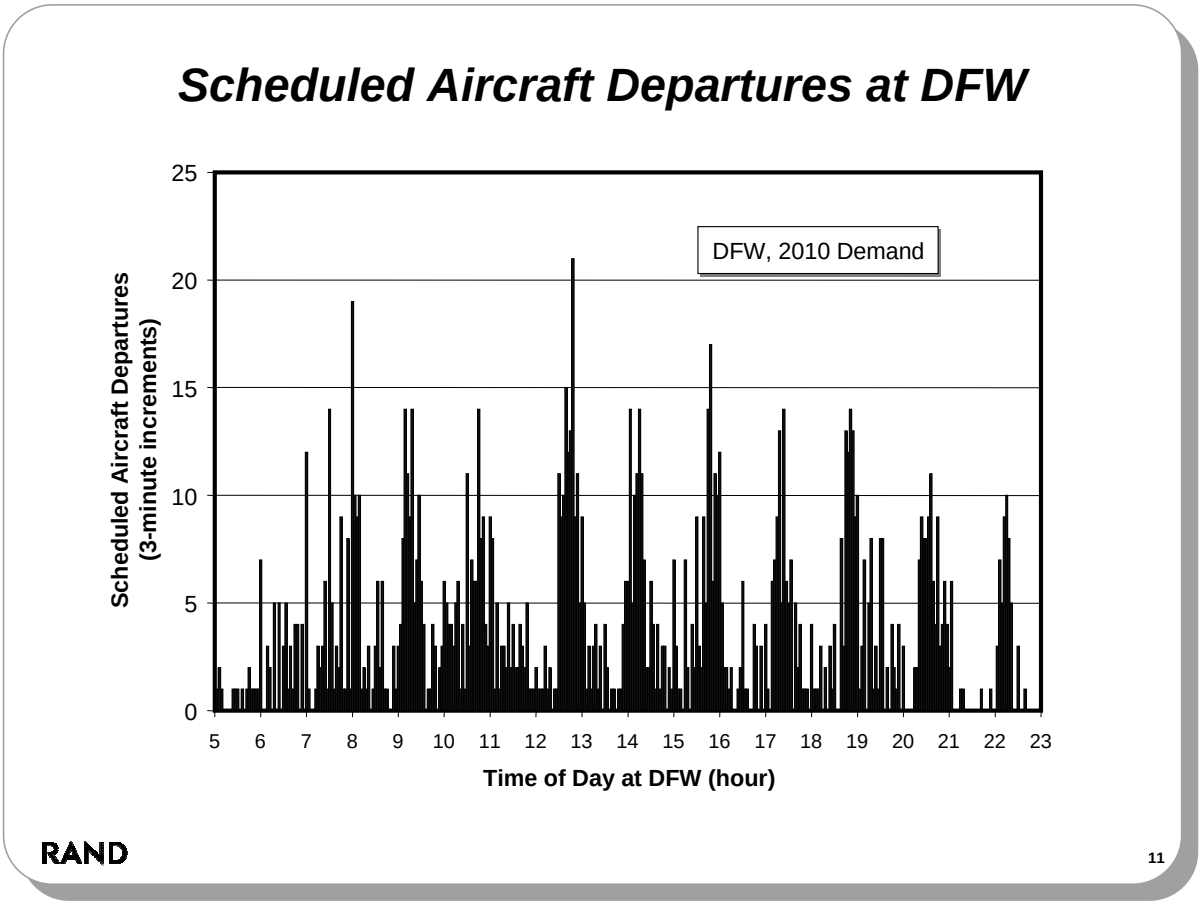


This figure repeats the structure of the remainder of the briefing.

We begin with a description of our inputs into the analysis, followed by a short description of how we did the calculations and then will focus the majority of our discussion on the results we obtained for a single large airport (Dallas–Fort Worth International). We will take several viewpoints on the results, focusing on both the airline's potential perspective and that of the passengers. We then show some of the sensitivities inherent in the analyses, with attention to machine performance (both reliability and its false positive alarm rate).

Next, we show a similar set of results for a second major airport, Chicago's O'Hare International. This comparison is intended to test whether we can reliably generalize the results.

Using data from both airports, we show results that allow us to balance the competing objectives of higher airport throughput (i.e., buy and deploy more machines) against the implied long-term costs associated with their acquisition and operation. Not having adequate data from the airports, our analysis could not take full account of all the potential costs to the airports (and potentially to the fliers if the costs are passed along to them) related to the need for facility reconstruction and/or expansion. See Appendix A for a fuller discussion of how these economic calculations were performed

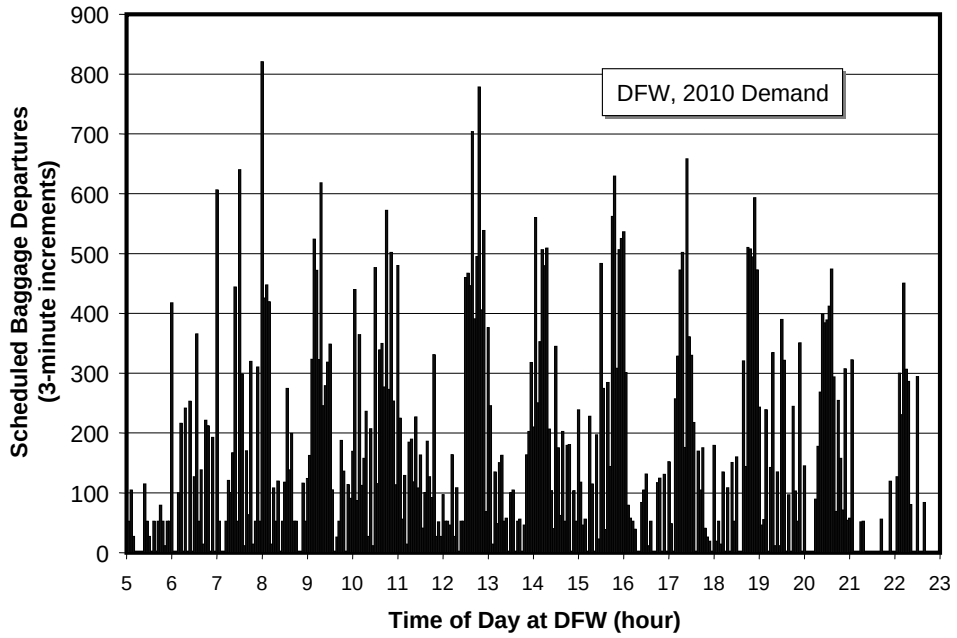


This figure shows the activity rate (in terms of aluminum aircraft bodies departing from DFW airport) over the course of an average midweek day. The number and timing of the flights are taken from projections for 2010 and are based on an original Official Airlines Guide (OAG) schedule which was computer-augmented to reflect the anticipated additional flights that would arrive in 2010 (the data was provided to RAND by MITRE).

The peaks and valleys in the data are characteristic of major airports where significant hubbing occurs. Hubbing is the practice common to most of the major airlines. It is characterized by a "bank" of aircraft arriving at almost the same time of day and departing 30–60 minutes later, also at almost the same time. The "banks" bring people from different cities to a common transfer point (the hub airport) and provide them with a choice of aircraft that they can connect with that are going to other cities. A bank of 10 aircraft allows the airline to generate approximately 100 city-pairs of service (nine destination cities from each of the originating cities, plus the hub city for each). In general, hubbing greatly expands the number of profitable routes that an airline can serve, providing a valuable transportation service for small or midsize cities that cannot offer sufficient traffic to economically justify direct flights to other cities.

The spikes are a cause for concern in terms of airport throughput. They also ensure that the passenger flow into and out of the airport will have similar peaks, causing congestion within the airport itself. It is this latter congestion that is the concern of this briefing.

Expected Baggage Demand per Time of Day



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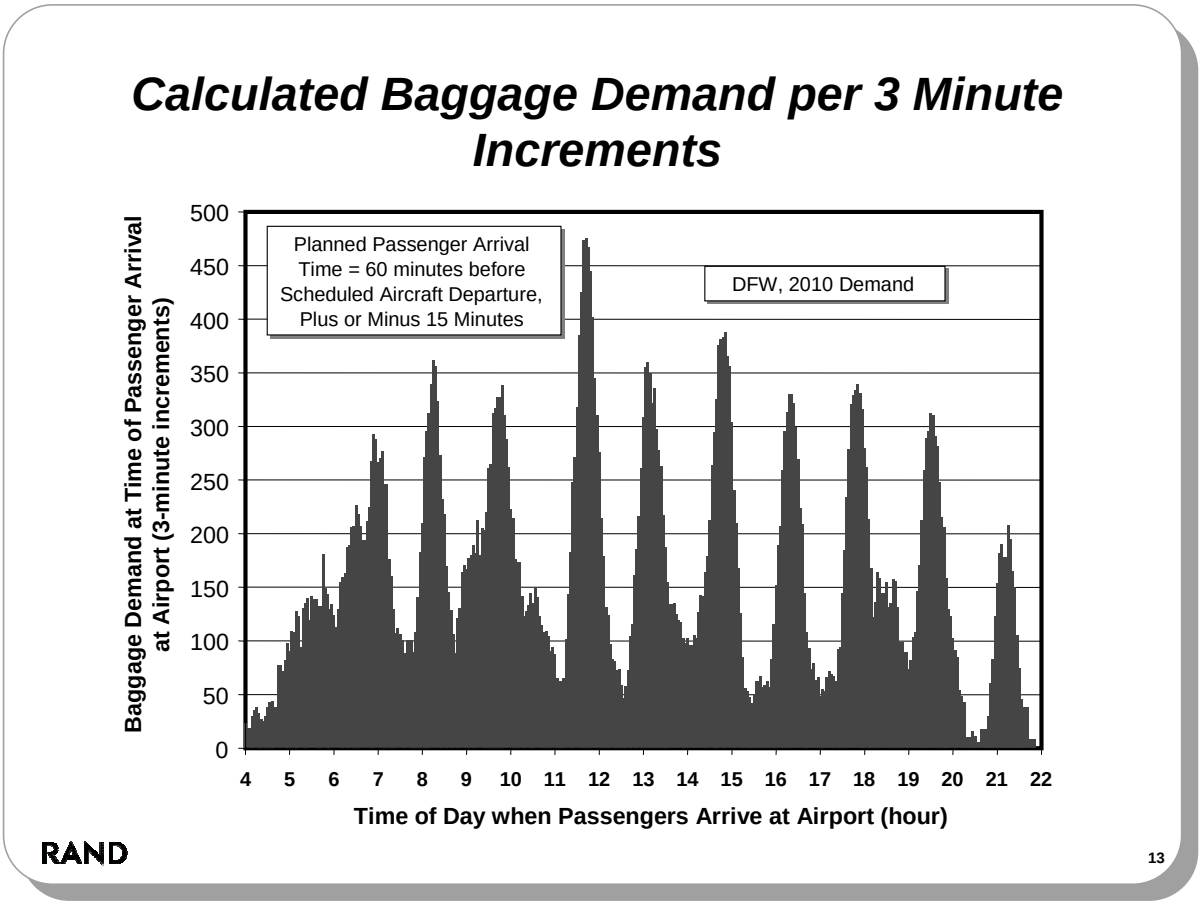
Because we are interested in the requirement to scan all bags, we focus solely on passengers who are entering the airport as the first leg of their trip. We will assume throughout this briefing that transiting bags—bags that arrive on aircraft from another city and are transferred from the arriving plane to another departing plane—have already been inspected at the original departing airport and do not need to be scanned again. This is an important assumption because the transfer of baggage as part of hubbing needs to be done quickly to ensure that the aircraft are not held on the ground for an extended period. Time on the ground is time wasted, in terms of airline revenues, so the times between the ingress and egress of the banks are kept as short as possible.

This figure shows the average number of "*newly checked*" bags loaded on the aircraft at time of departure, assuming that the number of bags per plane scales according to the seating capacity of that plane. It also assumes a specific load factor (70 percent throughout this briefing) and 1.1 check-in bags per arriving passenger (hand-carried bags that the passenger takes onto the aircraft are not included here because they do not go through the inspection equipment studied here).

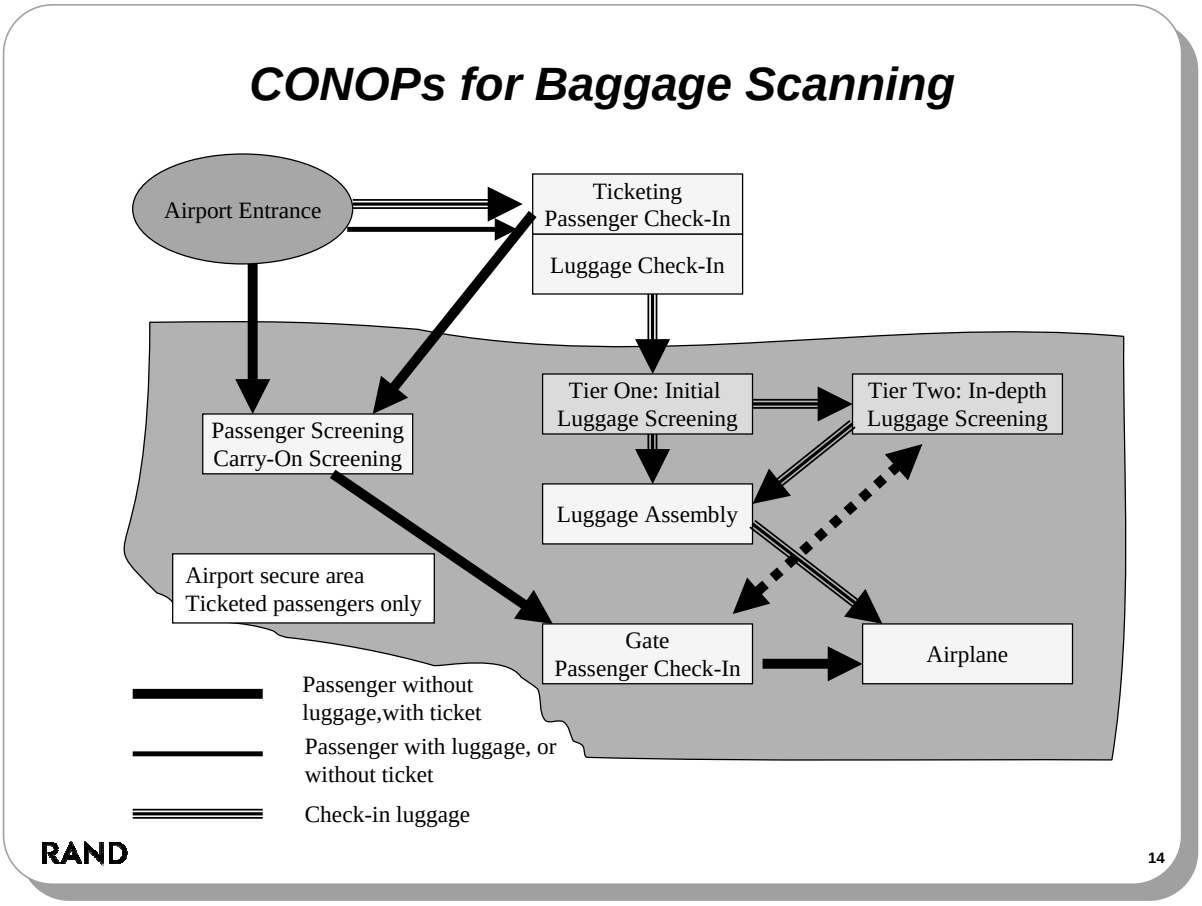
To match the prior figure, we have plotted the baggage demand summed over three-minute intervals.



The previous figure showed the demand associated with each flight departure time. Most passengers arrive at airports well before that time, leaving substantial time for getting to the ticket counter and checking their baggage. To mimic this behavior, we have assumed that the passengers arrive at the airport at least X minutes before the scheduled flight departure time (in this figure X = 60), with a flat distribution around that arrival time to account for failure to achieve the planned arrival time. In most of our calculations we have set the width of that distribution at 30 minutes (i.e., plus or minus 15 minutes). In real life the distribution would be more complicated, with a likely bias toward early arrival, but we lacked the data to reflect the more accurate distribution. Having tested several types of distributions, we do not believe that our simplified assumption makes a noticeable difference in our results.

This figure shows the baggage arrival times associated with the assumed passenger behavior. It is not as spiked as the departure times, leading to a somewhat easier baggage flow rate for the airline to manage.

Reference 1 showed some sensitivity calculations related to how assumptions about this passenger arrival spread affected the results. Here, we note that the assumptions are passenger arrival spread do not materially affect the answer so long as that arrival spread around the planned time of arrival is on the order of 30 minutes or longer.



This figure shows the schematic used for testing the baggage flow through the airport. We assumed that a fraction of the passengers would arrive with baggage that they would want to check in and have it carried in the hull of the airport. Based on limited discussions with airport personnel, we set this fraction at 70 percent.

Check in could occur at the curb or at the counter. For our purposes, we did not differentiate. We assumed that all checked bags would be placed on a conveyor belt and transported to a baggage queue line that fed the bags into the first tier of the baggage inspection.

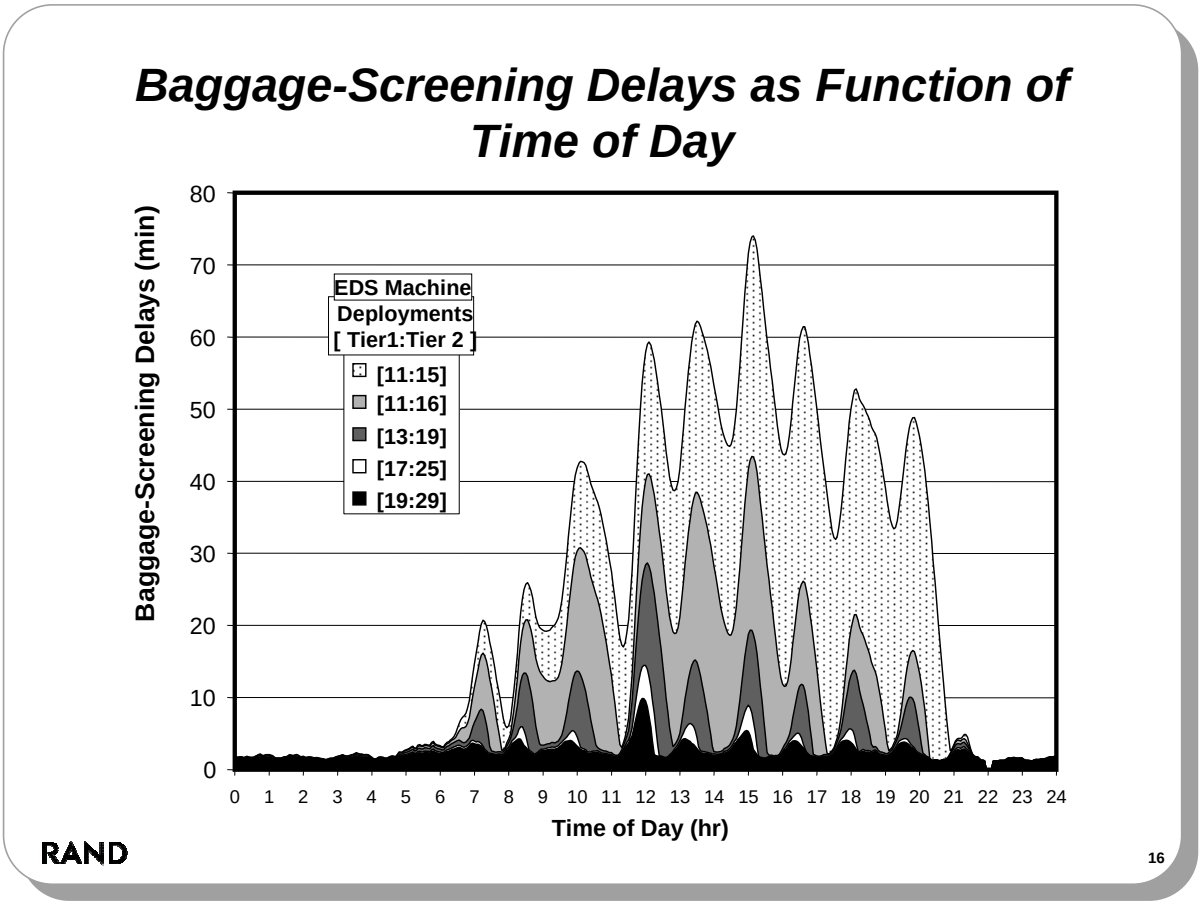
Tier one is assumed to be a high speed EDS machine. In these calculations, we have assumed that the machine inspects baggage at an average rate of 350 bags per hour. Detection is accomplished using machine algorithms and backed up with human examination of the images provided by the machine scans. Based on some operational data taken by the FAA, we set the machine's false alarm rate at 25 percent. Three bags out of four would go directly to the baggage assembly area; the remainder are sent to a second inspection tier where a more intensive examination of the bag's contents takes place.

Tier two also uses an EDS machine, but the human is the prime determinant of whether something in the bag merits removing the bags from the inspection area and taking it to another location where it would be opened and hand searched. We assume that the

probability of this happening is very small and (for the purposes of this analysis) something that we can ignore. The scan rate in tier two was set at 60 bags per hour.

If the bag is not verified to be safe, then the passenger would be called from the gate area and asked to accompany the bag while it is being opened.

Both tier one and tier two scan rates are based on operational experience in field tests of existing EDS machines.



This figure shows the magnitude of the queue delays in three-minute increments over the entire day. The delays are plotted as a function of the number of machines in tiers one and two.

First, note that the delays fluctuate over the course of a day, reflecting the spikes that characterize the airlines' departure schedule. If the total number of machines is in the 40s or higher, then the maximum delays experienced during the day are relatively small and probably would not be cause for concern. If the number of machines is substantially smaller, then the maximum queue delays can become uncomfortably large.

In the following pages, we will focus on several measures for judging performance. These include

- The peak delay over the day for the specific machine deployment
- The expected peak delay, where we take into account the probabilities that a specific machine deployment exists on a random day (we will vary machine reliability between 1.0 and 0.8)
- The average expected delay that a passenger would encounter, reflecting the fact that not all passengers choose to fly at the busiest hours
- A measure of the confidence a passenger or airline can have that a bag makes the plane.

Ultimately, we are interested in how airlines and passengers change their behavior to avoid unpleasant situations (in the airline's case, it is facing an angry passenger who finds that his bag did not make it onto his flight; in the passenger's case, it is incurring long waits at the airport, waits necessitated by the fear that his bag would not make it onto the plane if he arrived later).

EDS Deployment Options Considered
All Commercial Flights at DFW, CY 2000 and 2010

The assumed reliability of the EDS machines is 90%, except for "max point delays," where it is set at 100%.

DFW 2000	Number of Machines		
Total Bags = 40,714	Tier 1	Tier 2	Total
No queue > 60 min	8	11	19
No queue > 30 min	10	14	24
No queue > 15 min	13	19	32
No queue > 10 min	15	22	37
No queue > 7 min	16	24	40
No queue > 5 min	18	27	45

Max Delay (min)		Criteria (% less than)			Days over criteria		
Point	Exp Value	10 min	30 min	60 min	10 min	30 min	60 min
46.76	155.92	0.0%	0.0%	13.5%	365.0	365.0	315.7
28.63	45.58	0.0%	8.0%	88.9%	365.0	335.9	40.5
13.66	20.45	0.0%	95.8%	99.9%	365.0	15.4	0.4
8.89	13.82	2.0%	99.8%	100.0%	357.6	0.9	0.0
6.75	10.98	29.1%	100.0%	100.0%	259.0	0.2	0.0
4.73	7.52	85.9%	100.0%	100.0%	51.5	0.0	0.0

DFW 2010	Number of Machines		
Total Bags = 63,068	Tier 1	Tier 2	Total
No queue > 60 min	11	16	27
No queue > 30 min	13	19	32
No queue > 15 min	17	25	42
No queue > 10 min	19	29	48
No queue > 7 min	22	33	55
No queue > 5 min	24	37	61

Max Delay (min)		Criteria (% less than)			Days over criteria		
Point	Exp Value	10 min	30 min	60 min	10 min	30 min	60 min
43.43	151.38	0.0%	0.0%	5.8%	365	365	344
28.66	54.12	0.0%	3.4%	76.7%	365	352	85
14.49	21.47	0.0%	96.9%	99.9%	365	11	0
9.89	15.15	0.6%	99.8%	100.0%	363	1	0
6.47	10.06	63.7%	100.0%	100.0%	132	0	0
4.68	7.32	96.4%	100.0%	100.0%	13	0	0

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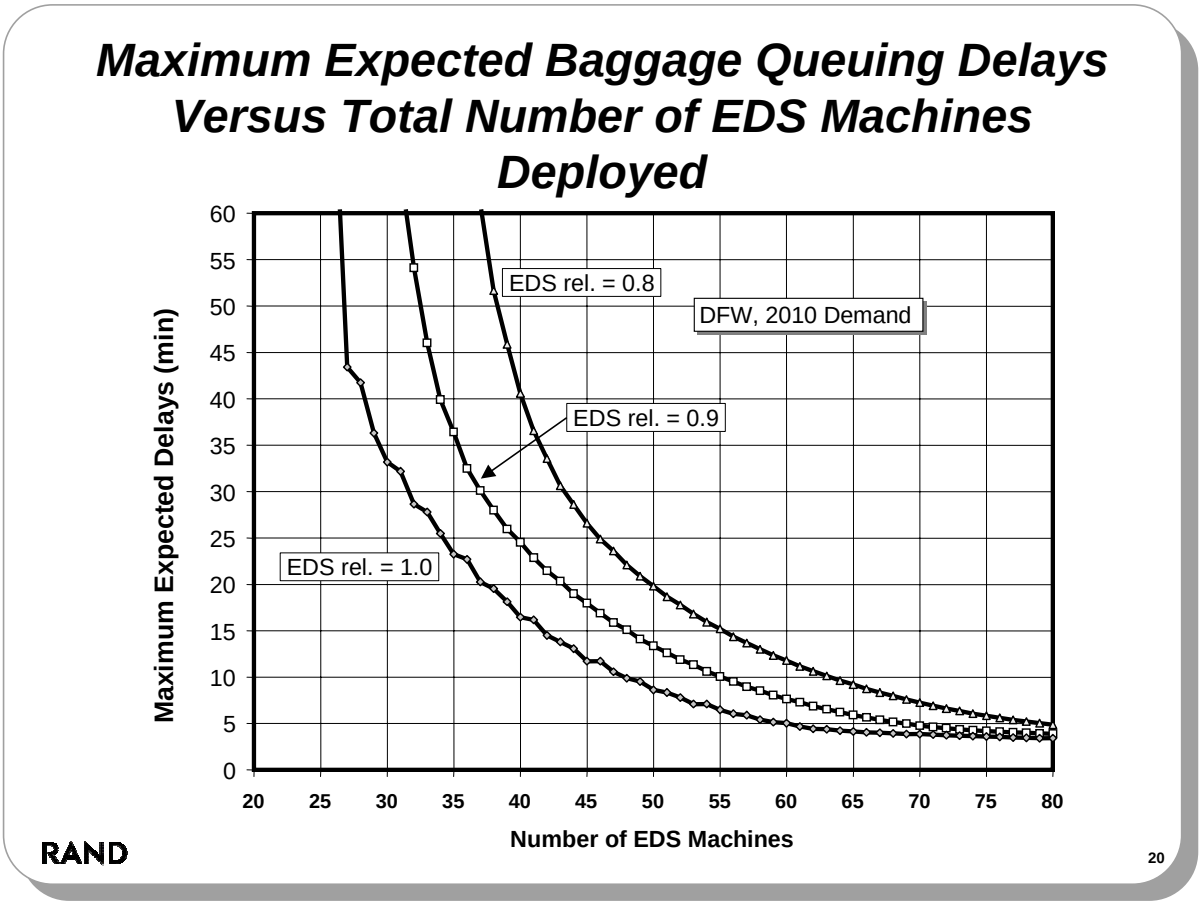
This is our first results figure. For purposes of comparison, we have included results at DFW for passenger baggage demands in CYs 2000 and 2010. The demand in 2000 is based on actual experience. The demand in 2010 is based on a projection that predates the events on 9/11 and thus probably overstates the future demand level. Nevertheless, the recent rise in airline travel suggests that this projected demand is likely to be reached no later than CY 2012.

The rows reflect different machine deployments, each selected to meet the specific criteria of being the lowest number of total machines consistent with a maximum queuing delay not greater than a specified amount. The left-hand column shows the criteria used in specifying the deployments. For example, in 2010, at least 27 machines (optimally balanced between the two tiers) are needed if the maximum delay is to be less than 60 minutes. For maximum delays less than 10 minutes, 48 machines are needed.

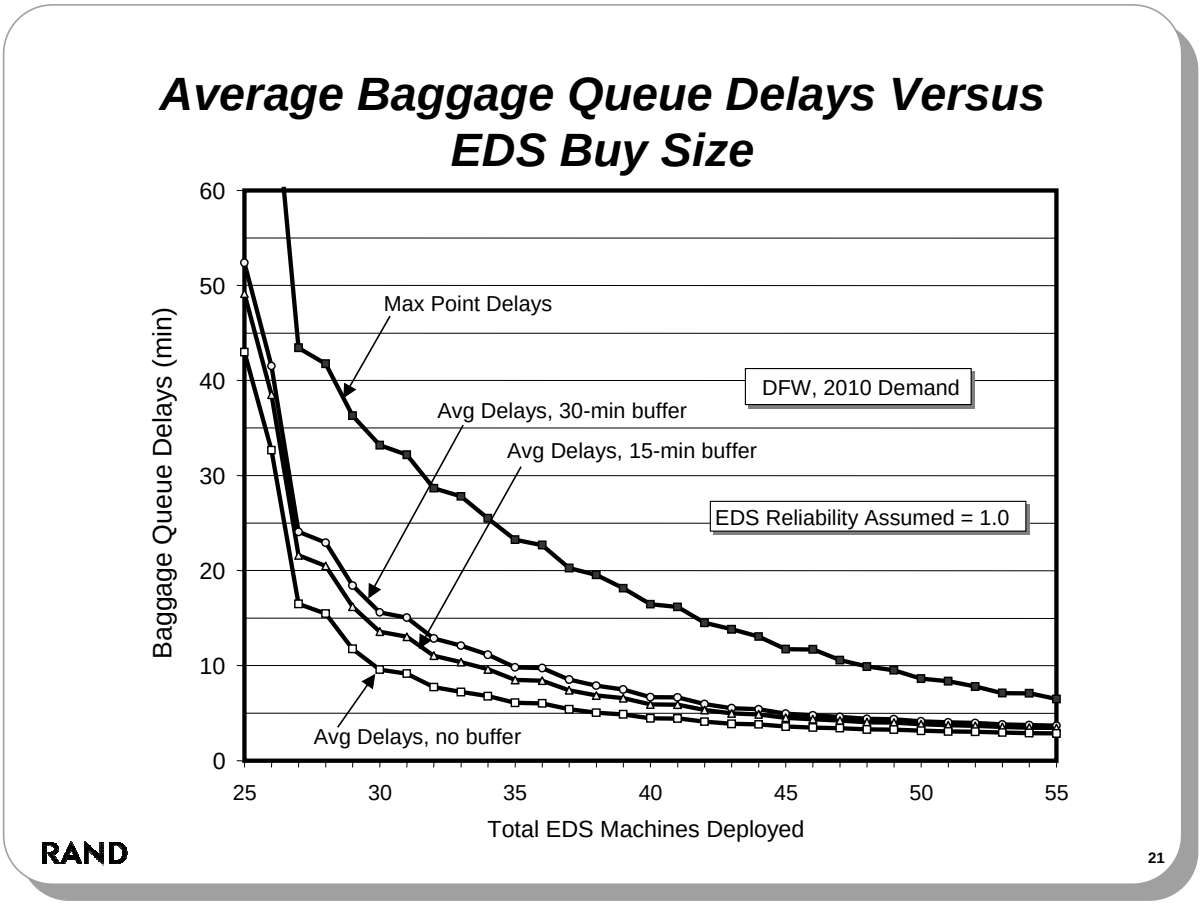
Each row shows potential measures of performance. The maximum point delay ("point" delay is defined as the specific delay that would occur if the reliability of all the machines were 100 percent) for the 27 machine case is 43.43 minutes. The expected delay is 151 minutes, where we have assumed that the machine's reliability is only 90 percent. The middle columns on the right hand side of the figure show the probability that on any given day a passenger would incur a delay no greater than the criteria listed at the top (10 minutes, 30 minutes, or 60 minutes). The three far-right columns translate the percentages in the three middle columns into days of the year that the criteria would fail.

Obviously, adding more machines improves the outcomes. However, more machines means higher costs to the airport and airlines in acquiring and deploying the equipment, costs that will eventually be reflected in higher ticket prices.



This figure shows the expected delays as a function of the total machine deployment. The numbers shown assume that it is not practical to alter machine deployments between tier one and tier two. Thus, the actual number of machines operating in each tier is calculated independently. The buy size along the bottom axis assumes that the machines are divided between the two tiers in a manner that is optimum at that deployment size. We have already explained this for the point delay calculations (i.e., machine reliability = 1.0). In the expected delay outcomes, the optimum deployment need not be the same as the point delay solution. The briefing will offer some examples of this below.

What the reader should understand is that reliability is an important factor in sizing the EDS deployment. The additional number of machines needed to hold expected delays constant is larger than would be determined if we simply divided the point delay outcome by the reliability. This results from the highly nonlinear growth in delays as the number of operating machines shrinks.



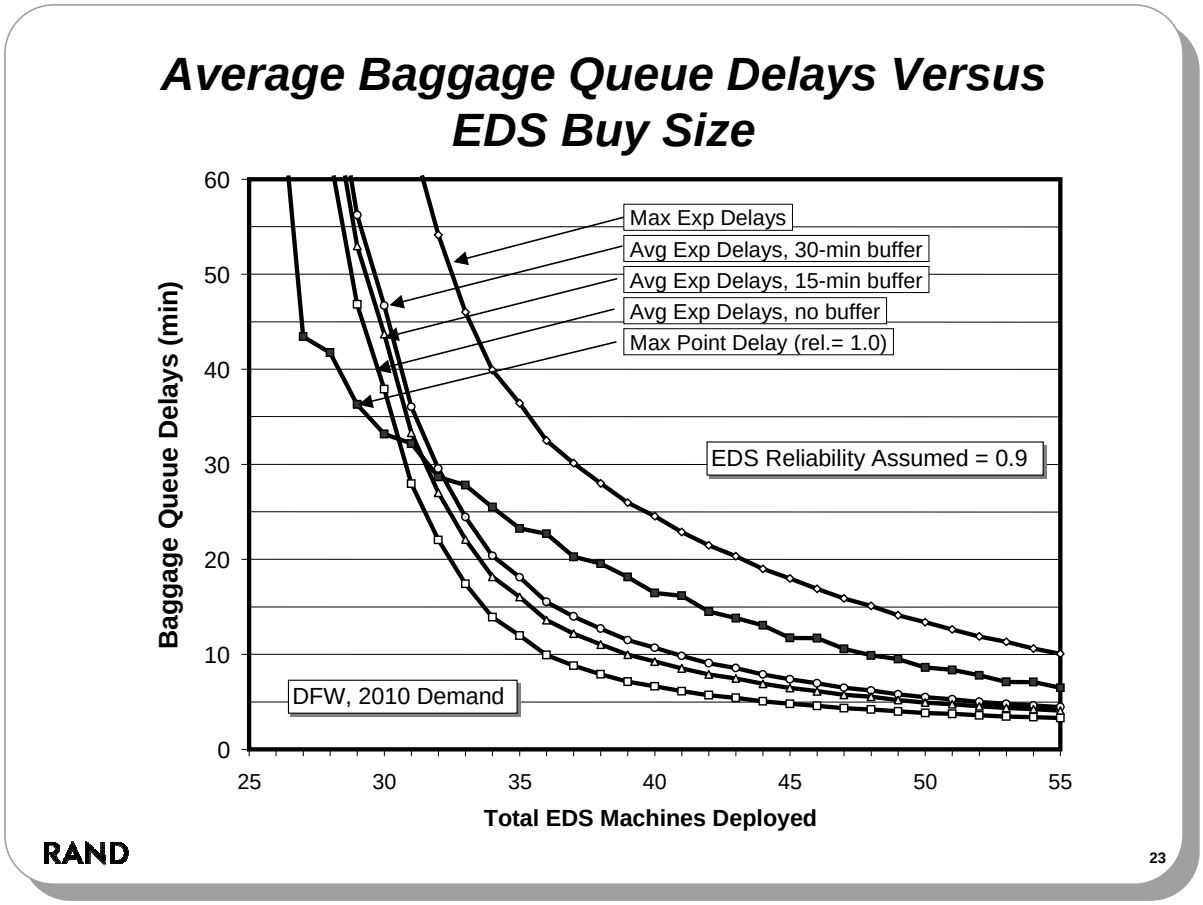
Thus far we have only discussed the maximum delays over the course of a day. Arguably, a better measure for overall passenger discomfort would be the average delay that the passenger would suffer at the specific time of day that he or she was planning to fly. This average, weighted by the number of passengers at that time, would give a better measure of the overall amount of time lost by the passengers.

This figure shows three variants for average delays. The lowest line is marked "no buffer." It is calculated by taking the delays for each time increment, multiplied by the number of bags arriving during that increment, and summed over all increments, dividing the result by the total number of bags. As shown in the figure, the average delays calculated in this manner are far smaller than the maximum point delays also shown. It strongly suggests that using the maximum delays would overstate the impacts on the passengers.

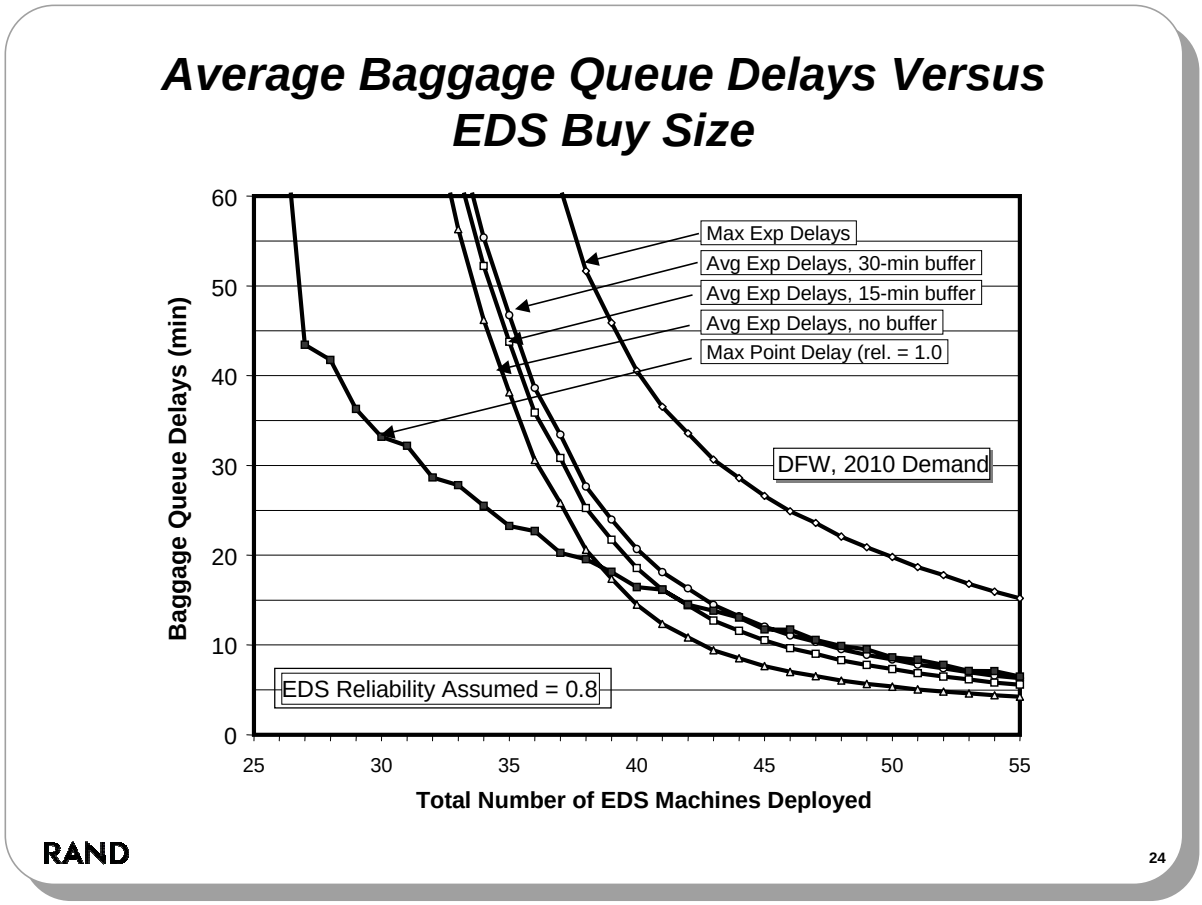
However, the average is optimistic, because it does not consider the uncertainties from the passenger's perspective. While the delay in this time increment might be small, the delays a few increments away might be large. The passengers might wish to hedge against running into large delays by arriving earlier. To anticipate this concern, we have also calculated averages, where the largest delays in the neighborhood of each increment are used in the calculation. "Neighborhood" is determined by the number of time increments (plus and minus) that we include. Thus, the 15-minute buffer looks 5 increments earlier

and 5 increments later, selects the largest of the delays in those increments, and uses it in the average calculation

We show two examples, one for a 15-minute buffer and one for a 30-minute buffer. Note that the curves are pretty close to each other, suggesting that the average delays are not particularly sensitive to modest hedging by the passengers.



The previous figure assumed a reliability of 1.0. This figure assumes a reliability of 90 percent and averages over the expected delays. The shape of the curves are not significantly different from those in the previous figure, but the deployment sizes for a given average delay are increased by an amount that reflects the impact of reliability. We have shown the point delay curve from the prior figure for comparison. Note that the average delays actually can exceed those on the point delay curve for small deployment numbers.



This figure shows the average delay curves for an assumed machine reliability is 80 percent.

We will use the average delay numbers (usually tied to a 90 percent machine reliability assumption) in those calculations that transform delays into economic impacts.

Briefing Outline (3)

1. **Background, Introduction, and Findings**
2. **Calculating Maximum and Average Baggage-Scanning Delays at a Major Airport (Dallas–Fort Worth)**
3. **Implications for Passenger Delays**
4. **Sensitivity of Results to Assumptions**
5. **Extending Analysis to Include a Second Major Airport (Chicago O'Hare)**
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8. **Observations and Recommendations**

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The previous section talked about bags and delays that they would suffer as a function of the total number of EDS machines deployed. But bag delays are not the metric of interest. We need to translate these baggage-scanning delays into passenger and airline behavior. That is the subject of this part of the briefing.

Relating Passenger and Airline Behavior to Baggage-Scanning Capabilities

- **Airlines want to get all checked bags onto proper aircraft**
  - **Even a small number of checked bags that miss their planes poses a public relations problem**
  - **Airlines will hedge against baggage-scanning delays by urging passengers to arrive early at the airport**
- **Passengers will adjust arrival time at airport as function of their risk tolerance in having their checked bag miss the plane**
  - **Some passengers will have low risk tolerance and will arrive well before scheduled aircraft departure time**
  - **Other passengers will be less willing to spend extra time at the airport and will arrive closer to departure time**
  - **Still others will avoid checking their bags altogether (use carry-on only) or simply chose not to fly**

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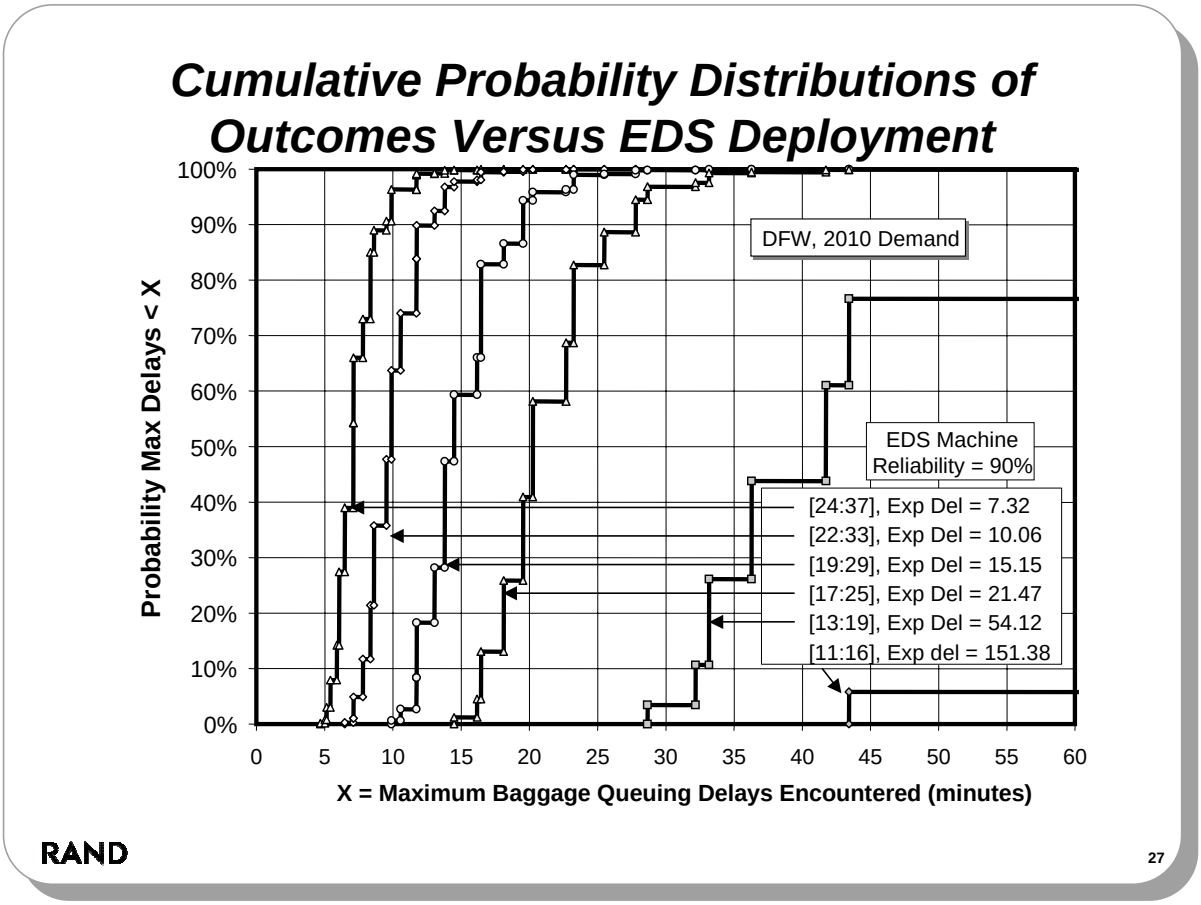
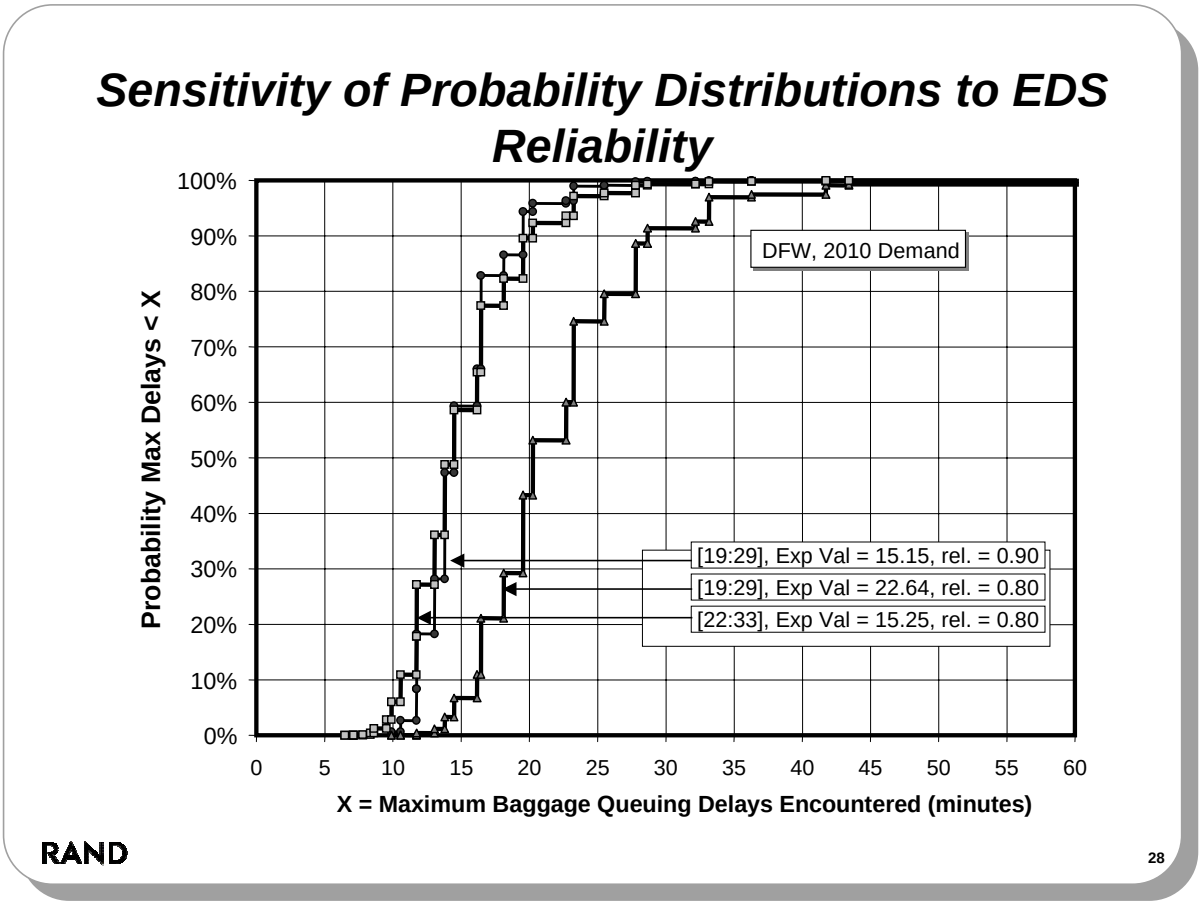
We have looked at two aspects of baggage-scanning delays and their impacts on airline and passenger behavior. For airlines, we will look at the number of bags that are likely to fail to make the intended plane in time as a function of the size of the baggage-scanning system and as a function of how early the airlines will suggest that passengers arrive prior to departure time.

For the passengers, we also looked at arrival time as a function of the baggage-scanning capabilities at the airport. In contrast to the airlines, the passengers can to some degree determine their own fate by adjusting their arrival time. As we will discuss later, the total transportation time of the passenger is an important economic variable and will have an impact on future demand.



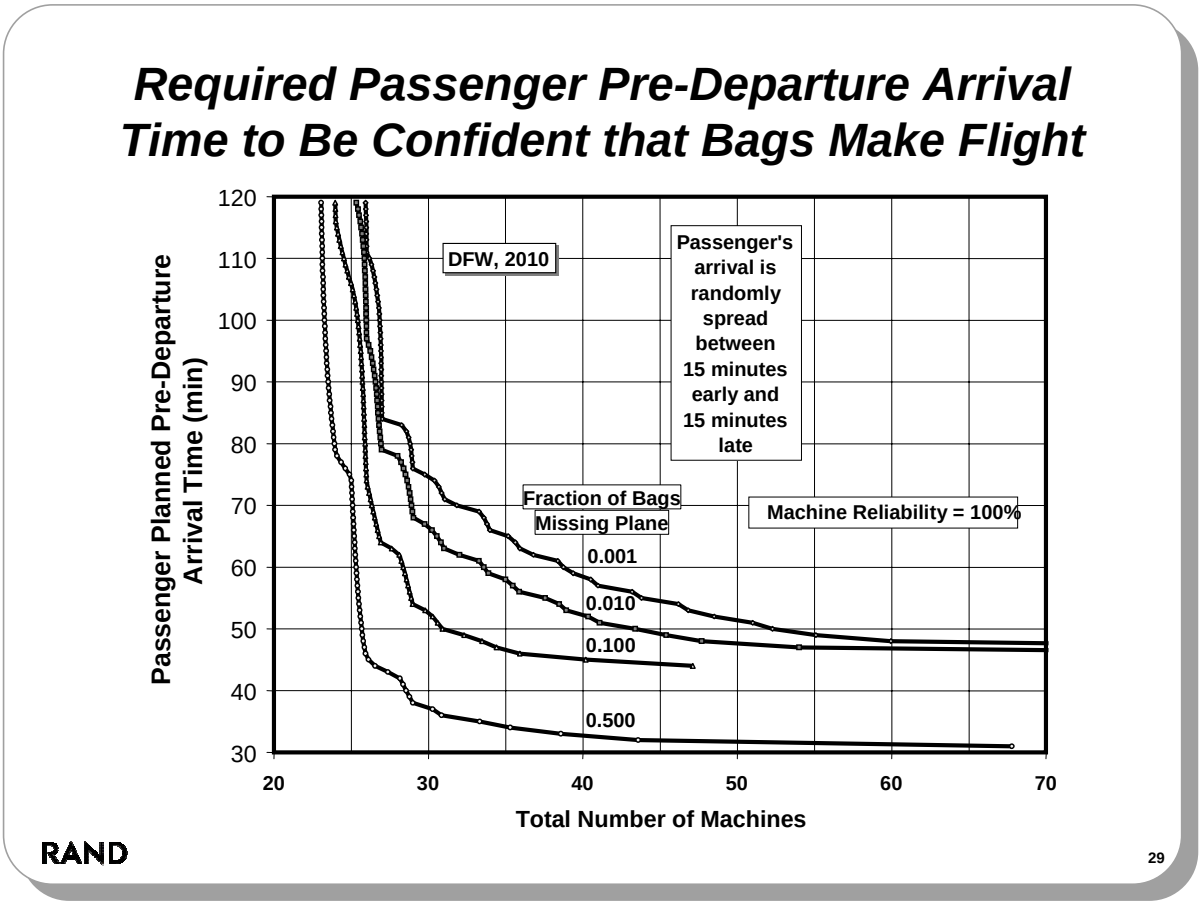
This figure plots for specific machine deployments the cumulative probability distribution as a function of maximum delay encountered. The machine deployments shown here are the same as those shown in the results figure.

From either the airline's or passengers' perspective, small probabilities of large delays are important. The airlines are eager to make certain that all the bags make the plane. Even a small fraction of bags missing the plane means a large number of complaints, unhappy passengers and a potential loss of revenue. Passengers may be less risk-averse than the airlines, but most will set their arrival time sufficiently early to reduce the likelihood to nil. Expected values don't quite capture these concerns. And point values—the measure of merit initially used by the FAA (and TSA) to size deployments at individual airports—are significantly deficient.



This figure gives an example of the sensitivity of the cumulative probability distributions to the assumed machine reliability.

Starting with a deployment of 19 machines in tier 1 and 29 in tier 2 (a "balanced" deployment), we can compare the distributions for reliabilities of 0.9 versus 0.8. The latter is moved to the right by a significant amount. After some search, we have found that for a reliability of 0.8 the distribution of 22 machines in tier 1 and 33 in tier two almost matches the original 0.9 reliability distribution. To the extent they fail to match, the differences are greatest at the highest delays. If we wanted to keep the highest delay levels from growing, we would need more machines.



This figure looks at the likelihood of the baggage reaching the plane in time from the passenger's perspective.

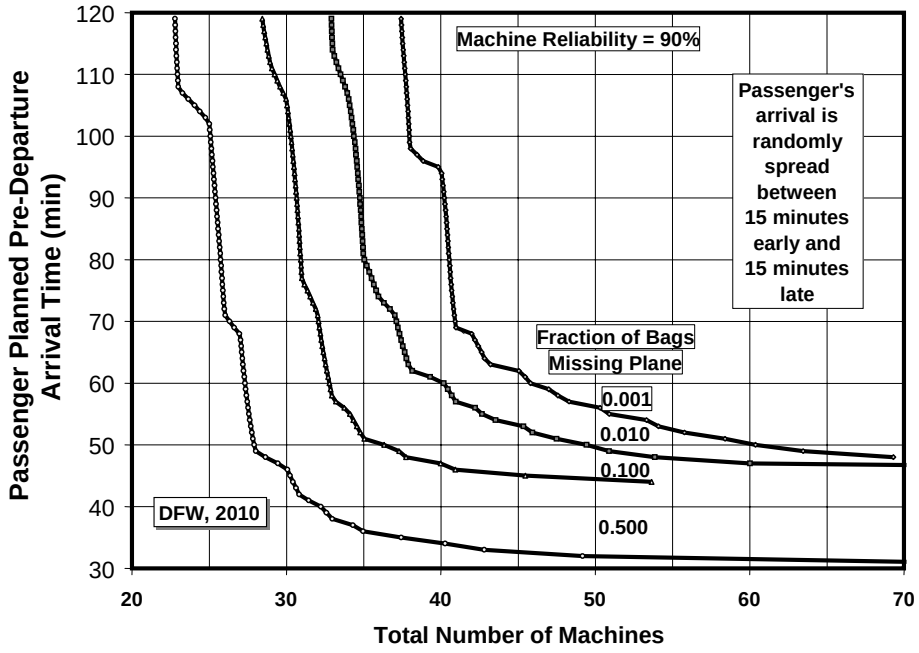
First, note that we assume that the passenger's actual arrival at the airport is stochastic, randomly spread plus or minus 15 minutes around the planned pre-departure arrival time. This assumption is identical to what we assumed when we built the demand function.

Also assumed in the figure is a 30 minute baggage handling requirement. This handling time is independent of delays associated with baggage screening, and consists of the times required for baggage check-in, movement to the baggage assembly area, sorting by flight number, and transport to the plane. These times vary by airport, by airline, and by mode of check-in (at counter or at curb). If the passenger arrives less than 30 minutes before the airplane's departure, our assumption is that his bags would fail to make the plane. Any baggage-scanning delays are added on top of that minimum time. Thirty minutes is probably near the high end of handling times across the airports, but the exact number has no direct affect on our outcomes.

For purposes of calculation, we assumed that all machines are in operation (i.e., machine reliability is 100 percent) and that the passengers know how many machines are deployed. Under these circumstances, the minimum planned arrival time for most passengers would be 45 minutes, hedging against the unfavorable event of a 15 minute delay in arrival.

Selecting the 99 percent successful curve, and assuming a robust deployment of [19:29] machines, the average passenger would be safe if he or she planned to arrive 50 minutes before departure. If, instead, the deployment size were only [13:19], the passenger would be well advised to come at least 65 minutes before departure.

Required Passenger Arrival Time to Be Confident That Bags Make Flight



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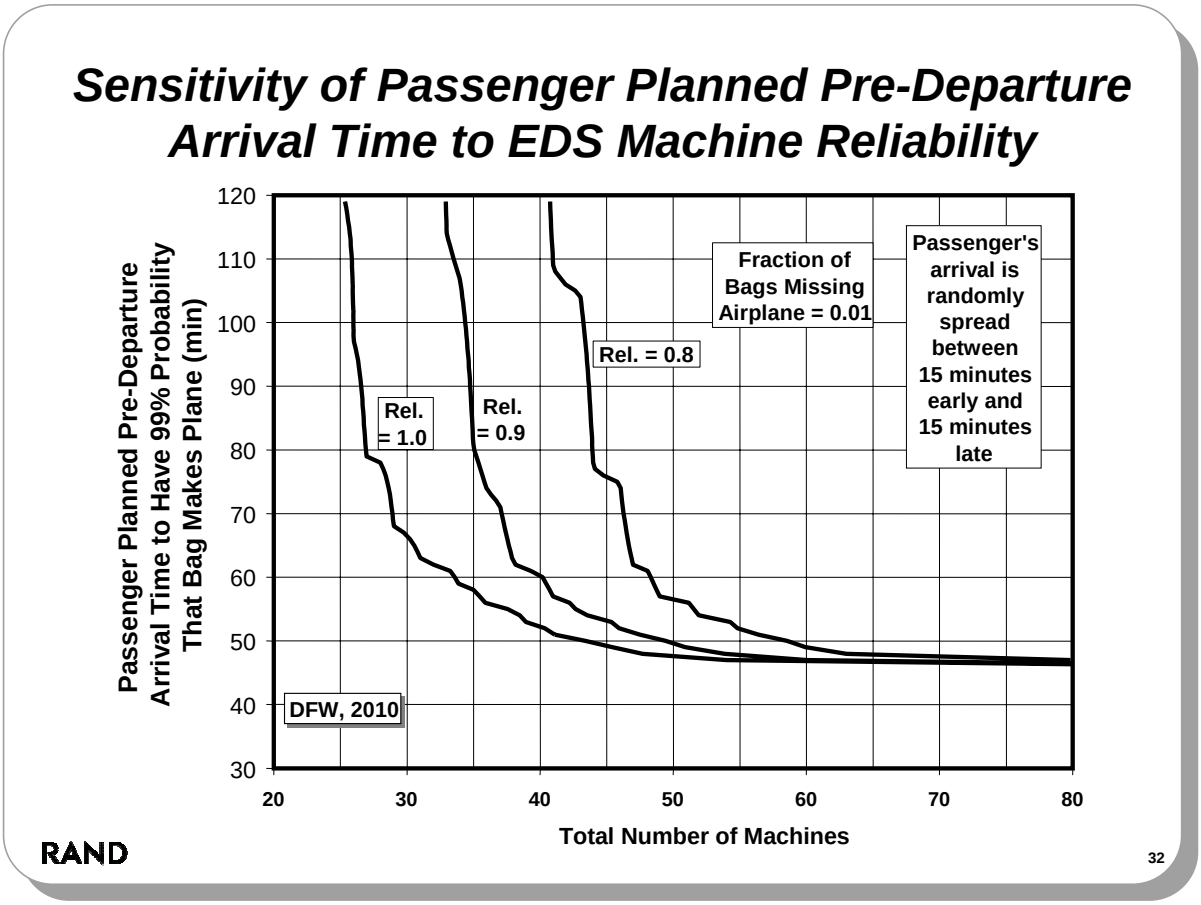
If we assume a lower, more likely machine reliability of 90 percent, the sensitivities increase noticeably. At a robust deployment of [19:29] machines, the desired pre-departure arrival time increases by only a small amount. However, for the smaller deployment of [13:19] machines, the pre-departure time for a 99 percent likelihood that the bag makes the plane increases to more than two hours.



Selecting the "99 percent likelihood of making the plane" curves, this figure shows the required pre-departure arrival times as a function of machine reliability. The curves demonstrate that the sensitivity is greater than a simple increase in the expected number of machines operating. The "edge" effects associated with relatively random occurrences when more machines than normal are out of operation drives these curves. In effect, there is no substitute for buying a robust number of machines or having the ability to ensure that overall operational reliabilities are at or above the 90 percent level.

Briefing Outline (4)

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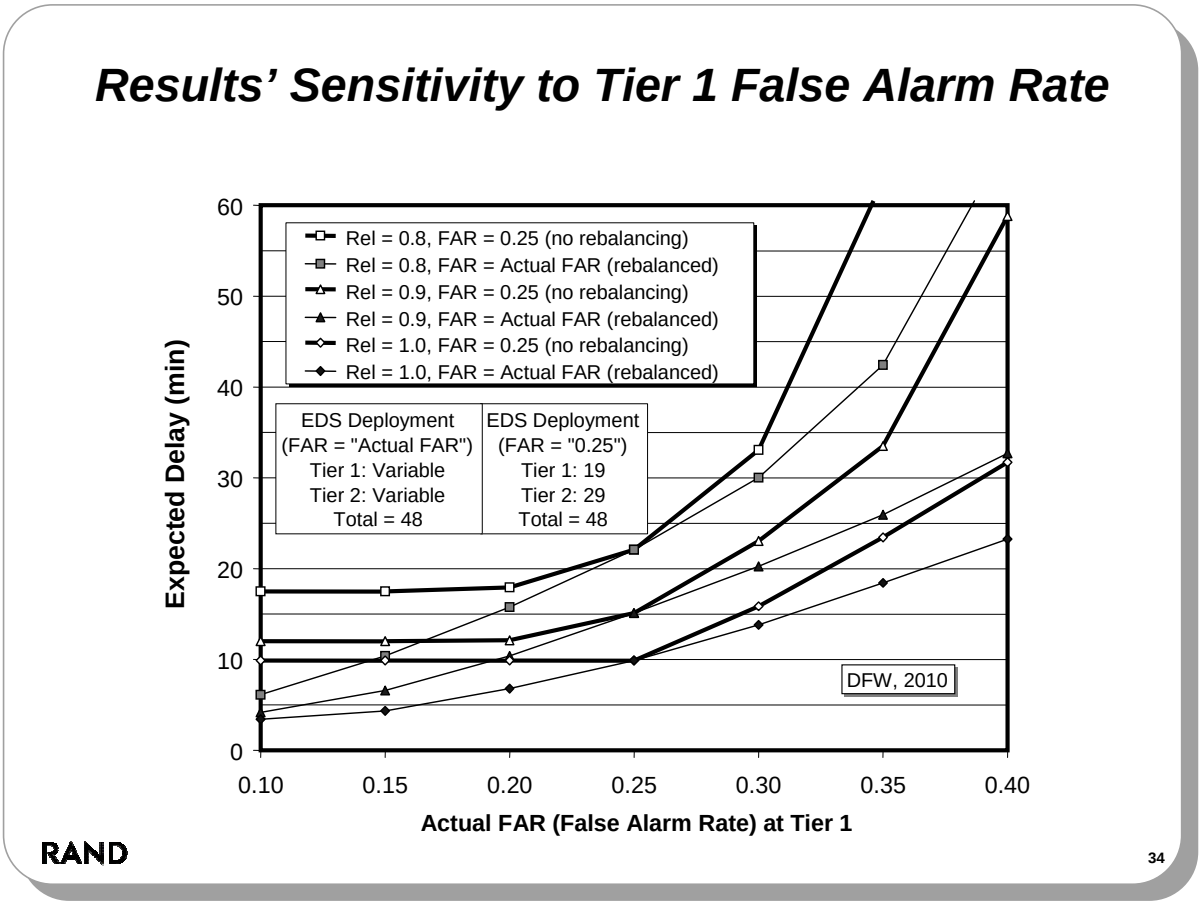
A number of sensitivities merit attention. We will show only two. One deals with the failure to properly guess the false alarm rate in tier 1. The second deals with the impacts of not knowing the reliability before having to specify the number of machines in each tier.



The bold curves in this figure show the expected maximum delays that occur when the initial machine deployment of 49 machines is held fixed. If the false alarm rate is higher than expected, the tier 2 machines would become the bottleneck. Not being able to "rebalance" the number of machines in the two tiers leads to significant deterioration in performance as the false-alarm rate grows. Similarly, if the false-alarm rate were better than expected, little gain in performance would occur because tier 1 machines would be the bottleneck.

The narrower curves in the figure assume that rebalancing is possible. The benefits are substantial for all FARs that differ by any significant amount from the 0.25 value used as our norm in this study.

Rebalancing can be done in several ways, including postponing full deployment until such time as the true false-alarm rate has been tested and validated.

Deployment Sensitivity to Machine Reliability

Deployment			Machine Reliability									
T1	T2	Tot	1.00	0.98	0.96	0.94	0.92	0.90	0.88	0.86	0.84	0.82	0.80
24	37	61	4.68	5.14	5.61	6.13	6.70	7.32	7.99	8.73	9.53	10.41	11.37
Best			4.68	5.14	5.61	6.13	6.70	7.29	7.92	8.62	9.39	10.24	11.16
22	33	55	6.47	7.12	7.77	8.48	9.24	10.06	10.93	11.88	12.91	14.03	15.25
Best			6.47	7.12	7.77	8.48	9.24	10.06	10.93	11.88	12.91	14.03	15.20
19	29	48	9.89	10.93	11.92	12.94	14.01	15.15	16.38	17.70	19.15	20.77	22.64
Best			9.89	10.93	11.92	12.94	14.01	15.10	16.26	17.52	18.88	20.39	22.08
17	25	42	14.49	15.88	17.20	18.55	19.96	21.47	23.14	25.05	27.35	30.23	33.95
Best			14.49	15.88	17.20	18.55	19.96	21.47	23.14	25.05	27.35	30.12	33.57
13	19	32	28.66	31.17	34.29	38.79	45.27	54.12	65.60	79.86	96.97	116.97	139.89
Best			28.66	31.17	34.29	38.79	45.27	54.12	65.60	79.86	96.97	116.97	139.89
11	16	27	43.43	63.06	82.88	103.92	126.67	151.38	178.19	207.20	238.49	272.16	308.31
Best			43.43	63.06	82.88	103.92	126.67	151.38	178.19	207.20	238.49	272.16	308.31

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This figure shows the expected maximum delays for reliabilities varying from 1.0 to 0.8. Six deployment sizes are shown. For each deployment, we show two cases. One assumes that the deployment to tiers one and two is fixed at its optimum "balanced" value, assuming a reliability of 1.0. The other assumes that the deployments are optimally balanced at each probability value. The rows are color coded to make comparisons easy. The optimum values at each deployment and reliability level are light gray; those that are not optimum are dark gray. It is immediately obvious that very little sensitivity is related to deployment configuration for different levels of reliability.

Briefing Outline (5)

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The following five figures show results of delays at Chicago's O'Hare International Airport (ORD). We detail these results because it is important to know that DFW is not unique or unusual in the problems associated with the deployment of baggage-inspection equipment. Like DFW, ORD is a major hub airport and has similar peaks and valleys in its traffic flows. The results are slightly different because the predicted traffic levels are somewhat different.

The projected 2010 demand at ORD is only about 88 percent of that at DFW. Moreover, its schedule is slightly less peaked. These two factors lead to reduced requirements for machines, as the next four figures show.

This section also shows results of delays that combine DFW and ORD.

In addition, we include a figure that looks at ORD and its partitioning (from a baggage-scanning perspective) into three centralized units. Prior to this figure, all calculations assumed that baggage scanning was centralized at the airports. In reality, this will rarely be the case except at the smallest airports in the system. This calculation will assess the degree of inefficiency associated with not having the ability to concentrate all the bags in a common baggage-scanning area.

We end this part of the briefing by extrapolating the results for DFW and ORD to nationwide deployments at all U.S. commercial airports.

EDS Deployment Options Considered
All Commercial Flights at ORD, CY 2000 and 2010

The assumed reliability of the EDS machines is 90%, except for "max point delays," where it is set at 100%

ORD 2000	Number of Machines		
Total Bags = 55,476	Tier 1	Tier 2	Total
No queue > 60 min	10	14	24
No queue > 30 min	11	15	26
No queue > 15 min	13	19	32
No queue > 10 min	15	22	37
No queue > 7 min	16	24	40
No queue > 5 min	18	27	45

Max Delay (min)		Criteria (% less than)			Days over Criteria		
Point	Exp Value	10 min	30 min	60 min	10 min	30 min	60 min
52.92	182.56	0.0%	0.0%	8.0%	365.0	365.0	335.9
27.27	112.06	0.0%	6.5%	38.3%	365.0	341.4	225.2
13.93	25.85	0.0%	83.6%	95.8%	365.0	60.0	15.5
8.79	14.15	2.0%	98.6%	99.8%	357.6	5.0	0.9
6.88	11.02	29.0%	99.7%	100.0%	259.0	1.2	0.0
4.96	7.57	85.9%	100.0%	100.0%	51.3	0.0	0.0

ORD 2010	Number of Machines		
Total Bags = 72,362	Tier 1	Tier 2	Total
No queue > 60 min	12	18	30
No queue > 30 min	13	19	32
No queue > 15 min	15	23	38
No queue > 10 min	17	26	43
No queue > 7 min	19	29	48
No queue > 5 min	21	33	54

Max Delay (min)		Criteria (% less than)			Days over Criteria		
Point	Exp Value	10 min	30 min	60 min	10 min	30 min	60 min
41.79	177.34	0.0%	0.0%	4.2%	365.0	365.0	349.5
23.46	112.73	0.0%	3.4%	26.1%	365.0	352.5	269.7
14.93	31.50	0.0%	75.7%	92.3%	365.0	88.6	28.1
9.93	16.58	1.1%	97.5%	99.5%	361.1	9.1	1.9
6.62	11.19	47.4%	99.8%	100.0%	191.8	0.7	0.0
4.67	7.60	93.5%	100.0%	100.0%	23.9	0.0	0.0

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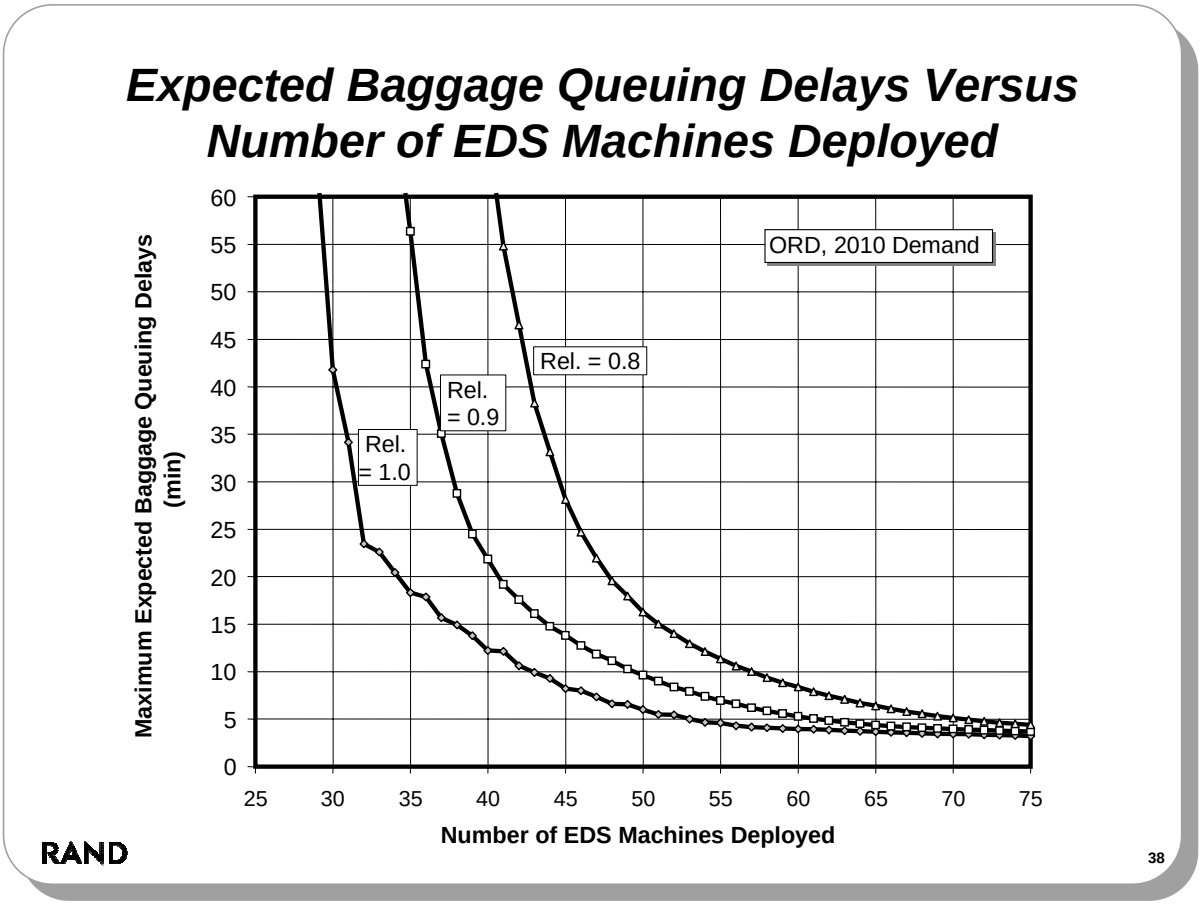
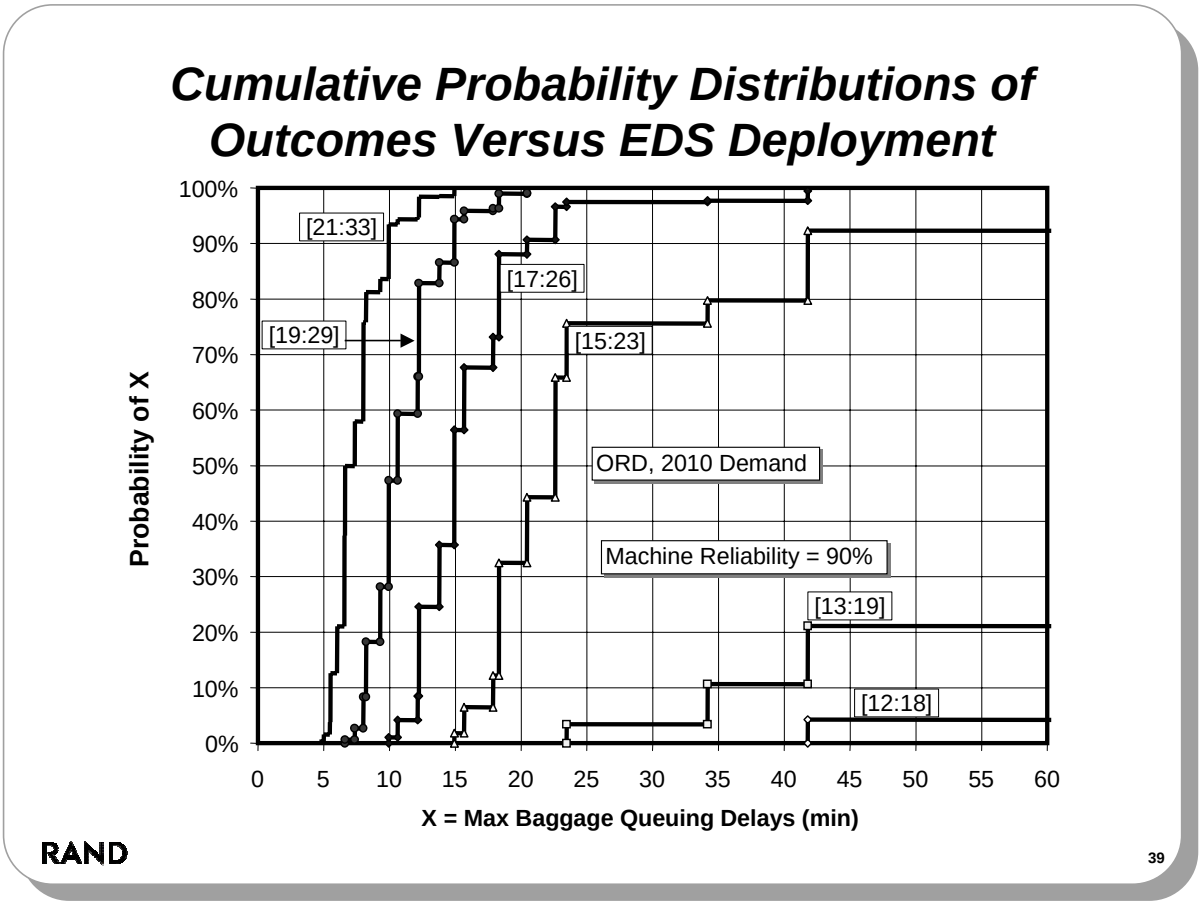
This figure is a repeat of an earlier figure, modified to make the data consistent with our analysis of ORD. As in that earlier figure, we have included results for CY 2000 as well as CY 2010. And as earlier, the demand in 2010 is based on a projection that predates the events on 9/11 and thus probably overstates the future demand level. Nevertheless, the recent rise in airline travel suggests that this projected demand is likely to be reached no later than CY 2012. Instead, we will offer a few comments on comparisons between the two airports.

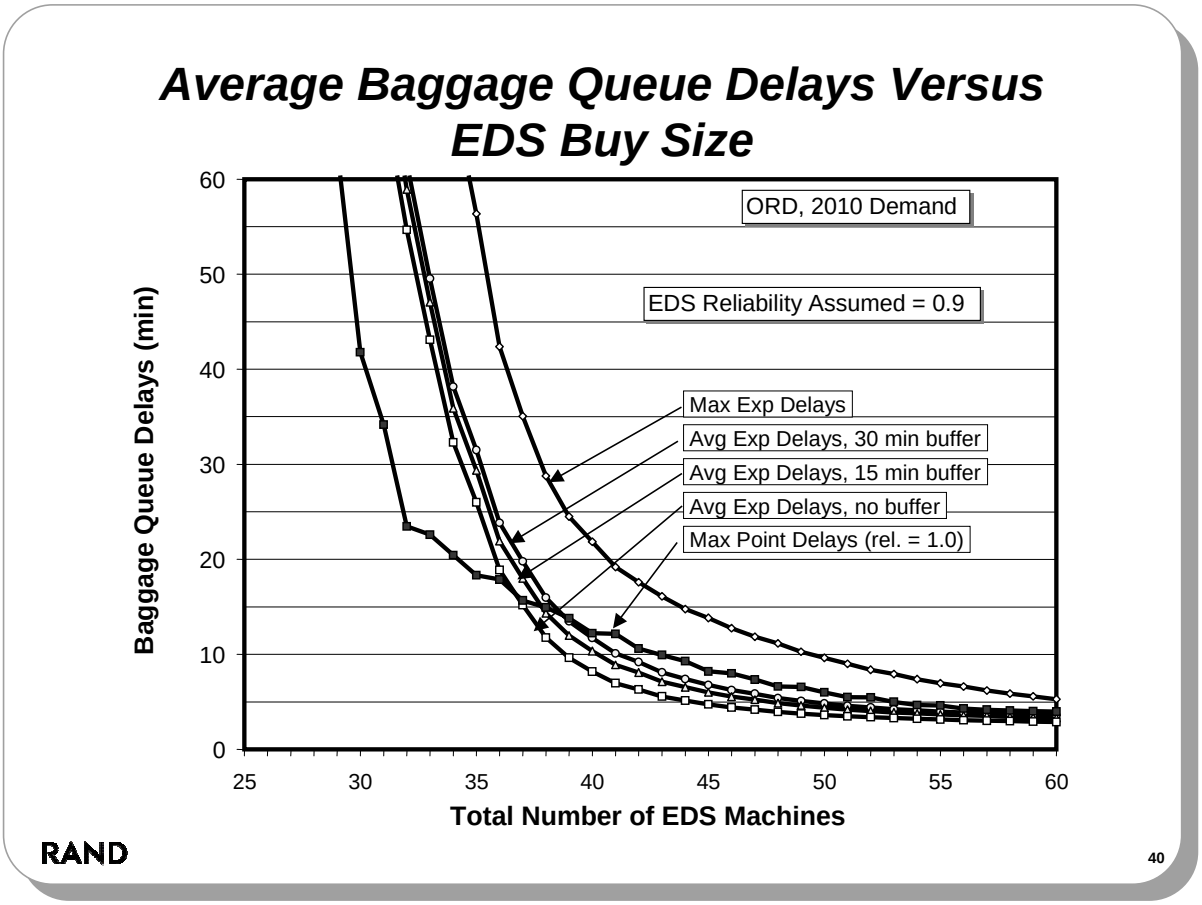
In general, there is not a lot of difference between the two results. Because of the schedule differences, it is more difficult to achieve minimal delays at ORD, but easier (i.e., takes fewer machines) to reduce the maximum delays.



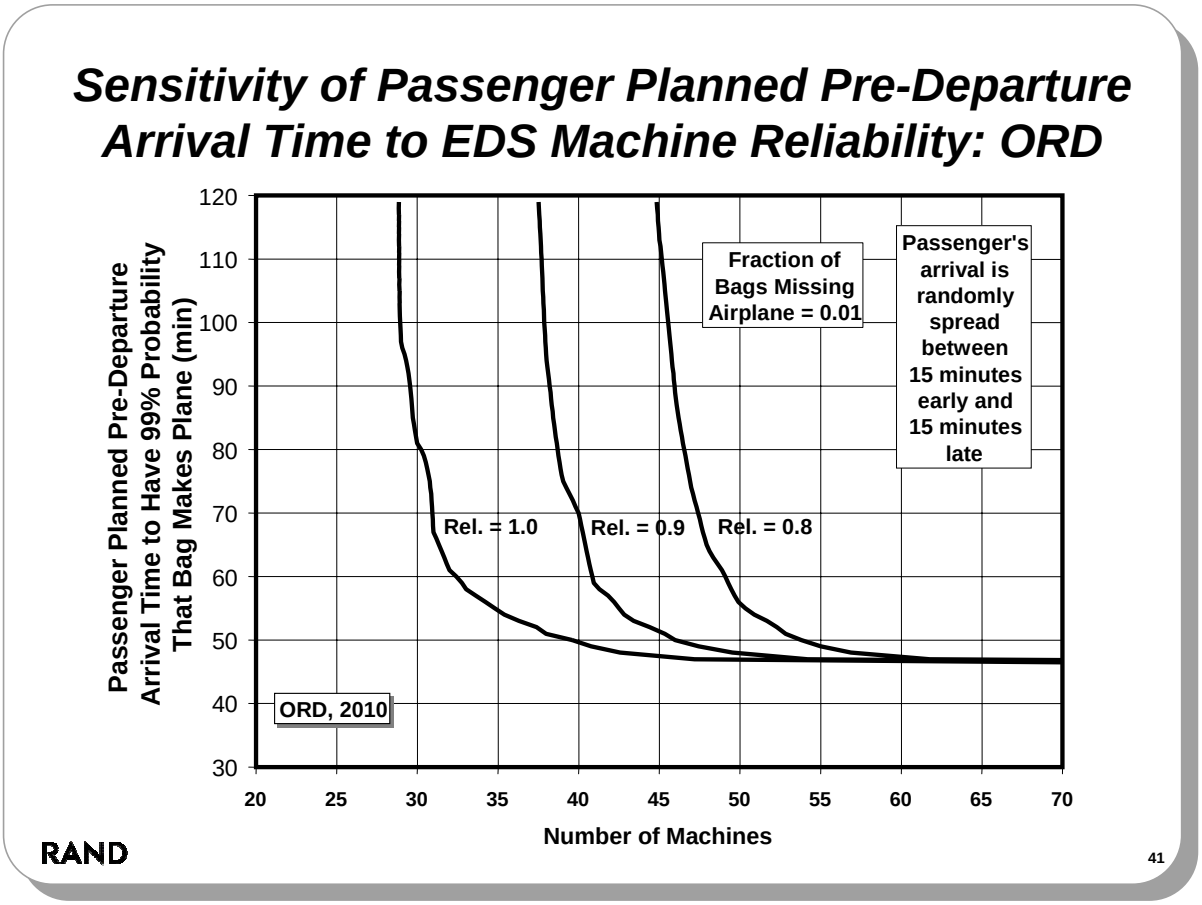
The figure is very similar to the DFW figure of the same description. There is nothing new worth adding.



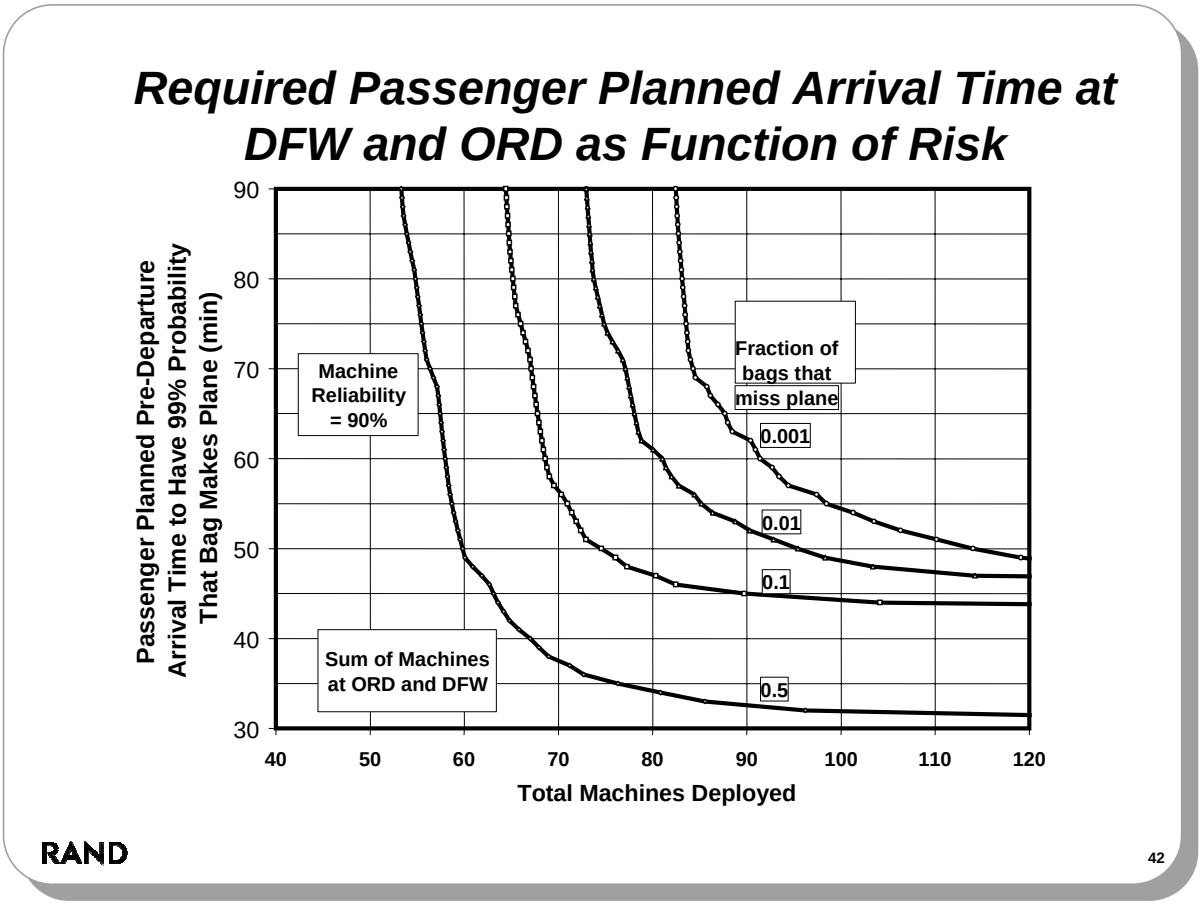
Again, this figure is very similar to the comparable DFW figure.



This figure also closely resembles the corresponding figure for DFW.

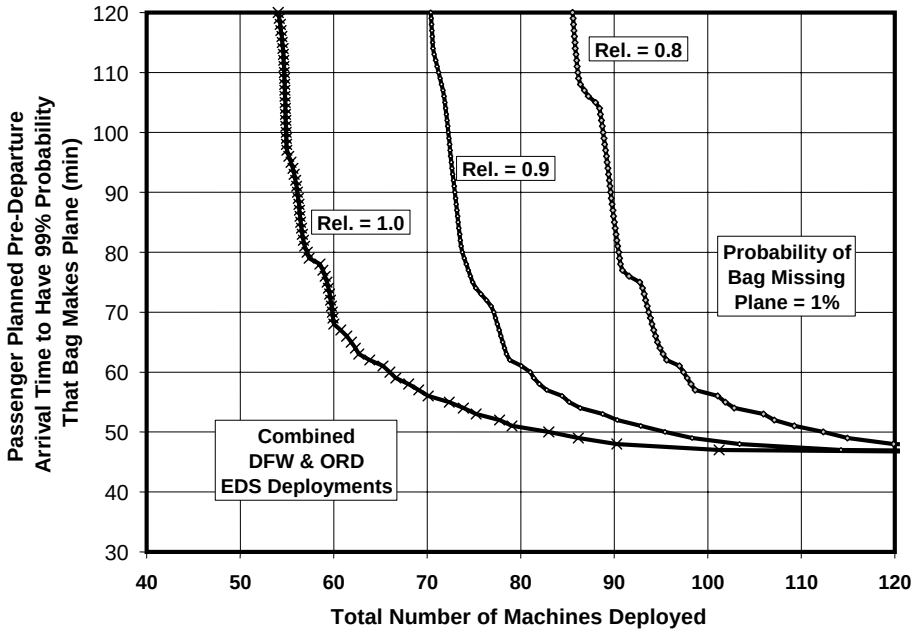


This figure also corresponds closely with the data for DFW.



This figure builds on the passenger planned pre-departure arrival time curves for DFW and ORD. It is calculated by holding constant the arrival time at each airport and reading the machine requirements from the ordinate. Reliability is held fixed at 0.9, and the sensitivity to passenger risk tolerance is displayed by the four individual curves.

Sensitivity of Machines Deployed at DFW and ORD as Function of Machine Reliability



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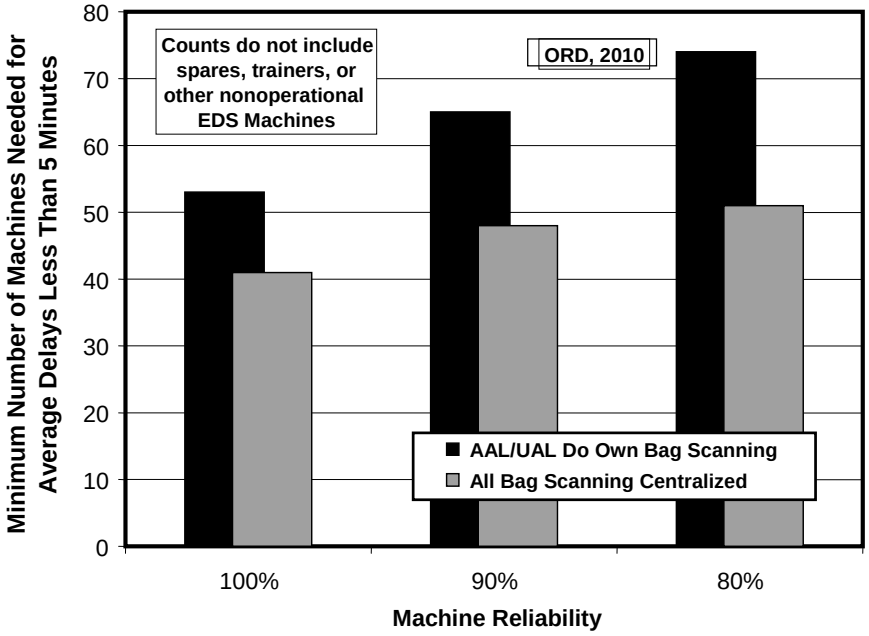
This figure also builds on the prior work. It shows for combined DFW and ORD deployments how passenger planned pre-departure arrival times vary as a function of machine reliability, holding constant the criterion that the probability of the bag missing the plane is not greater than 1 percent.

These two airports collectively handle about 6 percent of the total arrivals and departures in the National Airspace System. We will address below how we transformed requirements for machines at these two airports into overall machine deployments for all the nation's airports. First, we address the inefficiencies at larger airports associated with the inability to concentrate baggage-scanning equipment in one area.

Scaling Up the Required EDS Machine Buy: Reflecting Airline Preferences



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This figure shows how airline preferences can scale up the number of machines that need to be purchased. We have used ORD data to show the dependence.

It is the airlines' preference to keep to themselves those bags that were checked onto their aircraft. The calculations shown were derived using the following assumptions:

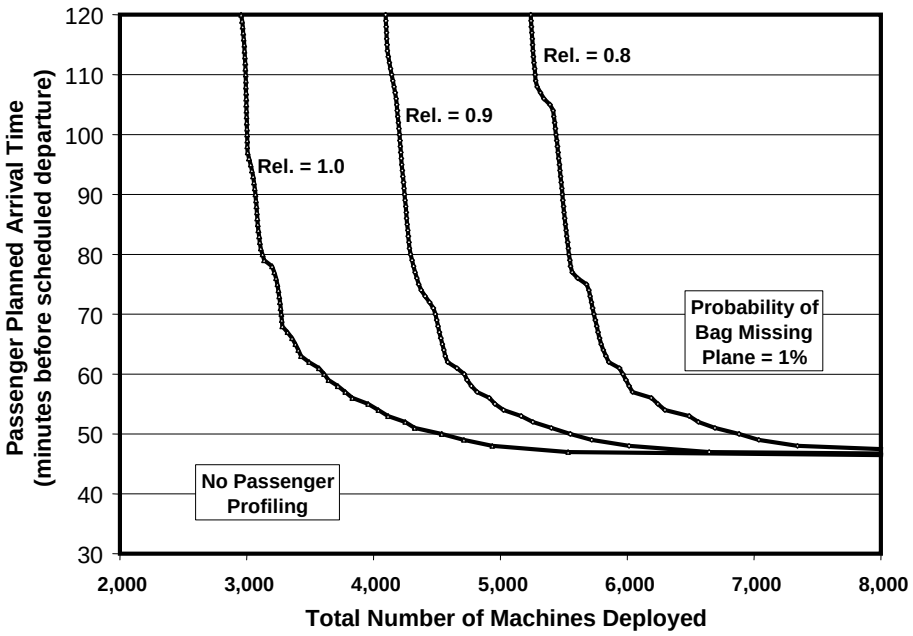
- The demand at ORD was subdivided into three mini-demands; one for all United Airlines flights, one for all American Air Lines flights, and one for all other flights
- The machines needed by each of the three mini-demands was calculated, and the buy size required for each were assessed individually
- The machine requirements for each were added, yielding a total demand for the airport.

The total machine buy size for the partitioned demand is the higher bar in the figure. We have shown the result as a function of machine reliability. The actual fractional increase is a function of reliability, growing as reliability decreases. The scale factors used in our following analysis assumed the following values:

- 25 percent growth for reliability of 1.0
- 33 percent growth for reliability of 0.9
- 40 percent growth for reliability of 0.8.

We should note that this calculation understates the likely need. Additional factors (especially the existence of individual terminals) will force additional fractionation of the machines at the airport, leading to further inefficient usage. A serious examination of machine needs must take these factors into account if the result is to be satisfactory.

Passenger Arrival Time Versus Machines Deployed (Scaled for Nationwide Deployment)



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Finally, we end this section of the briefing with a figure that shows how passenger pre-departure planned arrival times would vary as a function of EDS machine reliability and the *total* EDS deployments across all the airports. The underlying criterion for passenger behavior is that the baggage would go through scanning and successfully be placed on the airplane before departure 99 percent of the time. Obviously, passenger behavior would vary at individual airports, and this calculation is an approximation for what would happen in the real world.

This figure is derived from Chart 72 by increasing the number of machines required to achieve any given passenger planned arrival time by two factors. First is the percentage increase due to airline preferences, as just discussed: 40 percent at a reliability of 0.8, 33 percent at a reliability of 0.9, and 25 percent at a reliability of 1.0. Second is the ratio of machines in the country as a whole to those at DFW and ORD, using a factor of 43.75. This is the ratio of total EDS machines needed in the country to those needed at DFW and ORD calculated by the FAA shortly after 9/11. (Their calculation used assumptions different from ours with regard to performance and the behavioral response of passengers to risk. However, because their approach was essentially identical to ours, we are comfortable with using the same degree of scaling.)

It may be worth noting that the total number of EDS machines would need to be above about 5,000 to keep passenger pre-departure arrival times from becoming substantially

earlier than would have been the case if no baggage scanning were required. (Note: as already mentioned, this ignores the other delays that the passenger would face in the airport, especially those associated with passenger-screening stations; a more comprehensive study of total airport throughput would certainly include these other delay factors.)

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The next set of figures describes one of the fundamental outcomes of this study—i.e., the overall economic cost to the nation of the baggage-scanning requirements at U.S. airports and how this varies with the amount of EDS equipment acquired. This section takes as given that every bag will be scanned and addresses the issue of minimizing the overall cost of doing this scanning, taking into account both the resource cost of acquiring and operating scanning equipment, and the extra time that air travelers must spend at airports given the delays associated with any level of EDS equipment acquired. As the previous sections have shown, the level of passenger delays that will occur depends on how much equipment is purchased. This clearly indicates two separate costs associated with baggage scanning. The first is the cost of buying, installing, operating, and maintaining the equipment over its expected life span. This cost grows directly with the amount of equipment purchased. The second is the cost associated with the passenger's unnecessary wasted time in the airport. This cost is lessened as more equipment is purchased.

In this section, we discuss how we estimate the level of equipment purchases that minimizes overall economic cost—i.e., the sum of the baggage-scanning equipment and delay costs.

We do this estimation in two ways. First is a very straightforward way in which we simply cost the scanning equipment levels and delay times shown in Chart 76. Second, we use a more detailed model of the U.S. economy, which includes such phenomena as the impact

of price and delay time on the amount of personal and business flying, the impact of price and delay time on business productivity, and the temporal effects of changes in economic activity in any given year arising from price and delay time of air travel on future GDP levels, through changes in investment flows. This model is fully documented in Appendix A. Both the simple methodology and the more complex modeling approach give similar results on the optimum amount of scanning equipment to purchase. The result in a nutshell is that sufficient scanning equipment should be procured so that very little delay time occurs for air travelers.

Costing Assumptions

- **Factors included in total machine cost**
  - **Acquisition costs, based on estimated costs for EDS machines**
  - **Personnel costs for operating and maintaining the equipment**
  - **Facility modification costs for machine installation**
- **First-order estimates only, scaled for annual life-cycle costs assuming a 10-year machine life**
- **Value of time from Department of Transportation guidelines**

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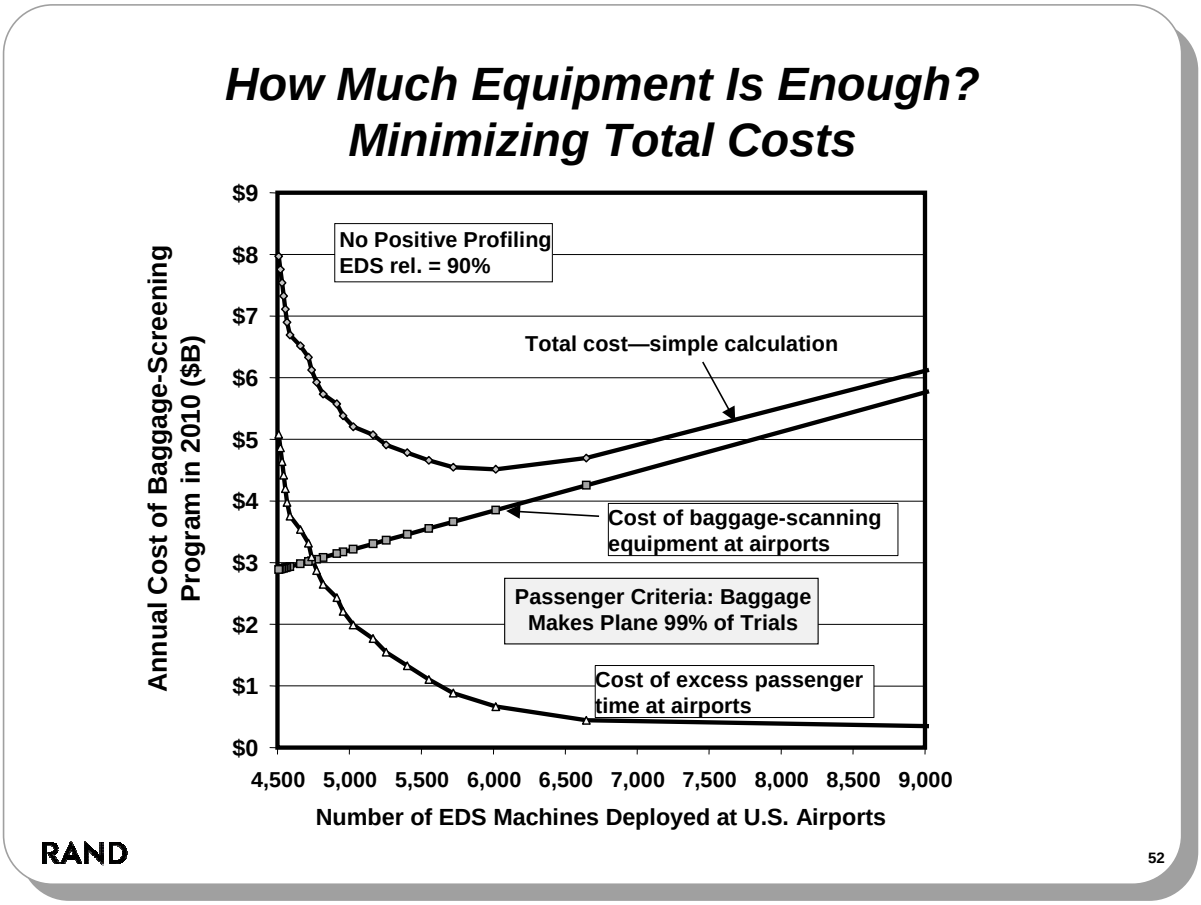
We calculated the annualized cost of any overall EDS machine buy using the following assumptions (all in dollars of 2002 purchasing power). Procurement cost is $1 million per machine, and machines must be replaced every 10 years. There is an installation cost of $4 million per machine, which is not again incurred when the machines are replaced. Machines operate two-thirds of the time, and are attended by one technician when operating. The fully burdened cost of an operator is $80,000 per year, and five operators are required to provide full-time coverage of one machine. We derived the "five" figure in the following way. From 52 weeks per year, we deduct two weeks for holidays, two weeks for vacation, and two weeks for sick leave. The remaining 46 weeks per year, at 40 hours of machine operation per week, would lead to a staffing ratio of 4.75. We judgmentally increase this to five to account for such miscellaneous activities as continuing and refresher training. An additional $50,000 per year maintenance cost per machine is assumed. The present value cost of buying, installing, and operating a machine for 30 years (at a 3 percent real discount rate, which we use) is $9.5 million, which translates into an annual charge of $630,000 per machine. Since our calculations are done in dollars of 2003 purchasing power, this grows to $640,000 per year to account for inflation.

As illustration, from Chart 76 we see that 5,550 machines would be needed in 2010 nationwide to achieve a five-minute average delay per passenger checking baggage (at 90 percent machine reliability). The total annualized cost of operation of these would thus be

$3.55 billion dollars per year. Our machine-sizing calculations are based on a level of air travel in 2010 of 967 billion revenue passenger miles (RPM), so the total cost is 0.37 cents per RPM. This can be contrasted to the average cost (including taxes) of an RPM in 2002 of about 15 cents, so it represents about 2.5percent of that.

We value delay time at $31.67 per hour, based on the Department of Transportation recommended value (found at api.hq.faa.gov/economic/742SECT1.PDF) of $28.60 per hour in dollars of 2000 purchasing power, adjusted upward by the change in nominal GDP per employed person between 2000 and 2003. Our machine sizing calculations are based on 600 million trips in 2010 (900 million emplanements from the U.S. Department of Transportation (2002) forecast, and our assumption that the ratio of trips to emplanements is two-thirds—that one-third of emplanements are people changing planes on the same trip). We assume that 70 percent of passengers check bags. Thus, the time cost of a five minute delay in 2010 is $1.1 billion. ($5 \times 600$ million $\times$ [$31.67/60] $\times 0.7$)



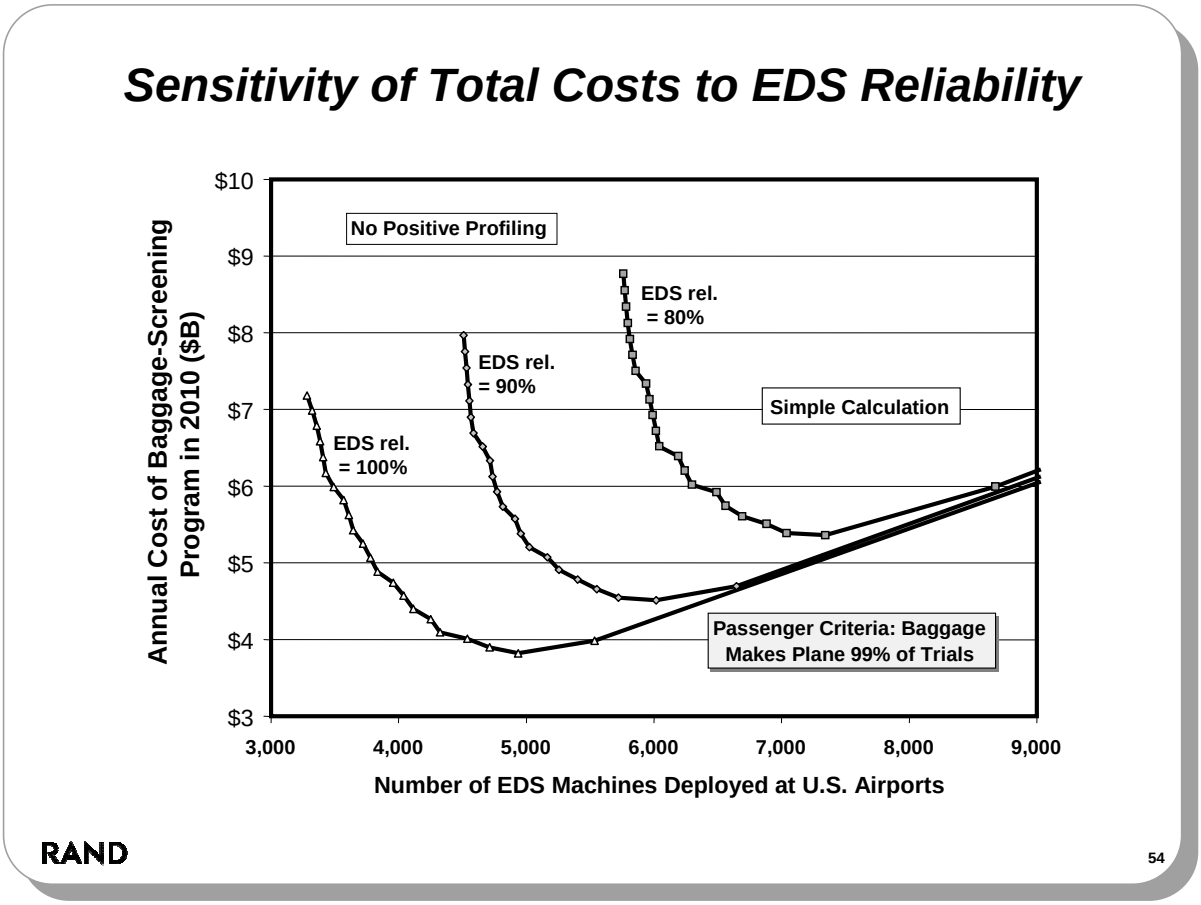
This figure shows as a function of the total number of machines acquired (1) the annualized costs of the acquiring, installing, operating, and maintaining the EDS equipment; (2) the annual passenger delay costs; and (3) the arithmetic sum of these two costs. The reliability of the equipment is assumed to be 90 percent, and the passenger demand is assumed to be the forecast in the year 2010 (967 billion RPM and 600 million trips).

The equipment costs are a simple linear function of the size of the total buy. As seen earlier, the amount of wasted time imposed on the passenger to avoid having his or her bag fail to reach the aircraft on time is a function of the number of these machines, decreasing rapidly from the point where the equipment can barely keep up with the average demand during the day to a point where even the peaks of the day can be handled. Note that for a total buy of 5,550 machines, machine cost is $3.55 billion and delay cost is $1.1 billion, as discussed on the previous figure.

Adding these two curves together gives our estimate of the total *cost* that the traveling public will pay over the course of one year (cost in italics, because the wasted time is not monetary in character). Note that near the left-hand axis delays dominate the cost, and toward the right-hand of the axis machine costs dominate. The total cost has a minimum at around 6,000 machines. Buy sizes less than this amount incur greater overall economic costs because the passengers will be forced to arrive at the airport earlier than is economically efficient. Buy sizes greater than this amount add cost not justified by the

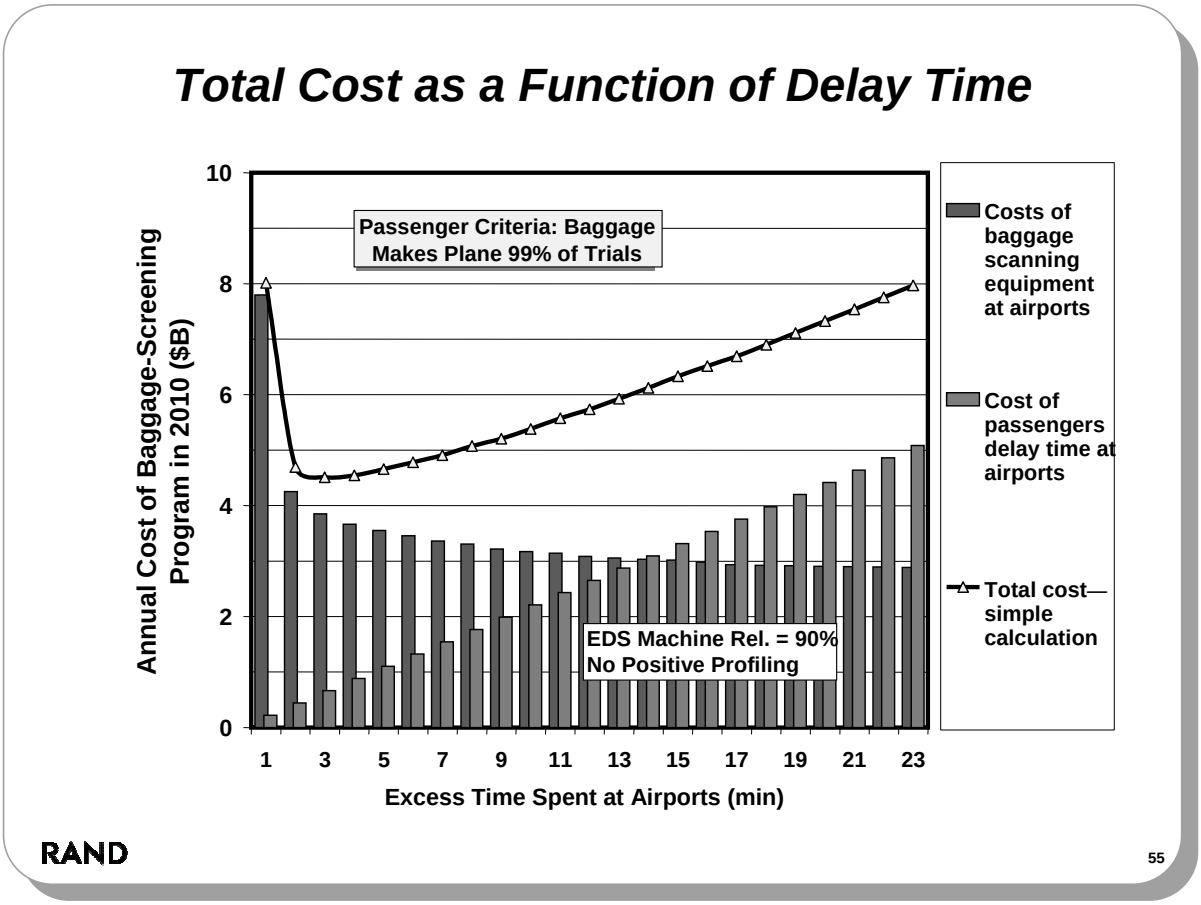
decrease in passenger time it leads to. Given the slopes of the curves, it is clearly better to overbuy EDS machines than to underbuy them.

Note that the annual minimum cost to the flying public is around $4.5 billion.



This figure extends the total cost results on the prior figure, including results for equipment reliabilities of 1.0 and 0.8.

It is worth repeating the observation that the long-term operating reliability of the machines is uncertain at this time. Given the consequences in terms of cost to the flying public if that reliability turns out worse than anticipated, it is clearly better to hedge toward acquiring a larger number than might be calculated as the optimum.



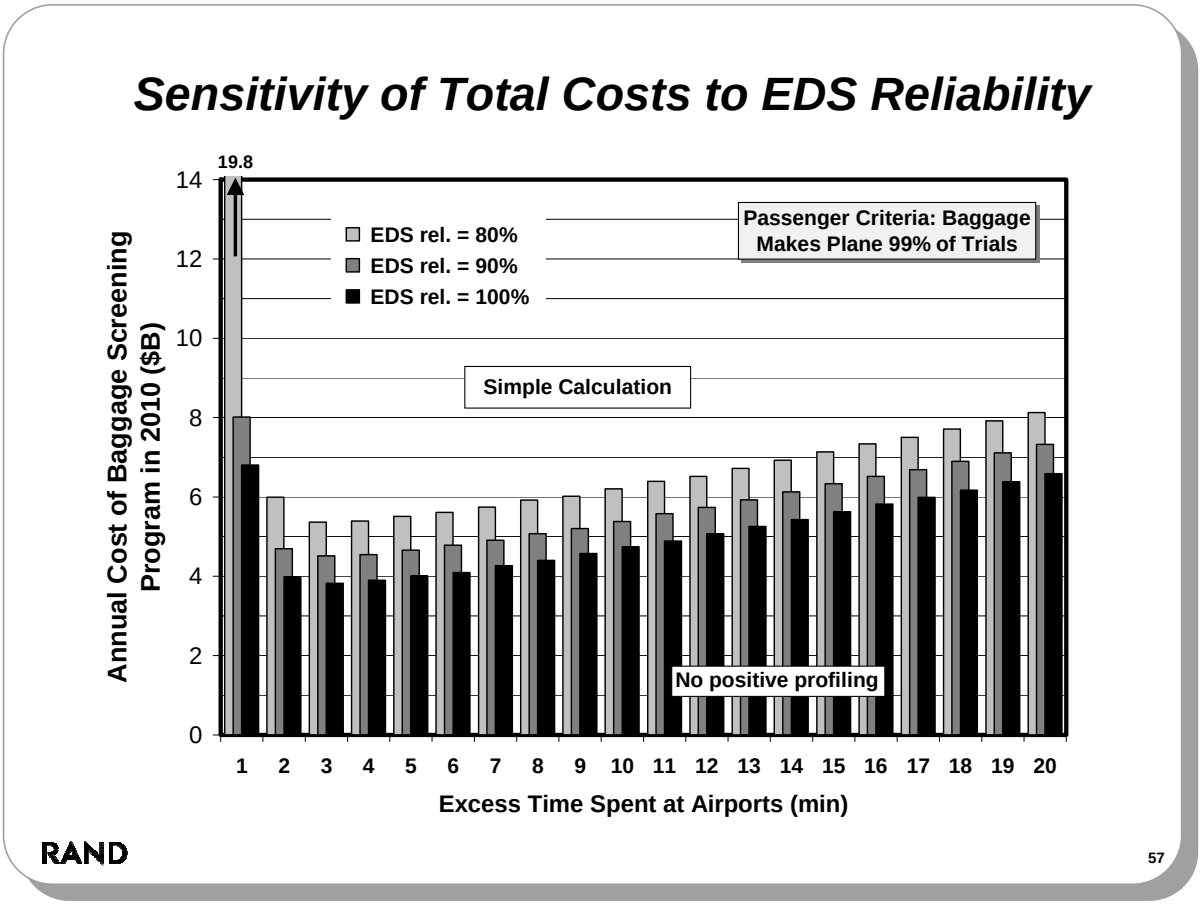
An important point can be made by viewing costs as a function of delay time rather than number of machines. This figure does that. The cost-of-delay curve is now a linear function of the delay time, given the cost of delay ($31.67 per hour) and our other assumptions noted above—that 70 percent of passengers check baggage and that 600 million trips will occur in 2010. The cost of machines drops as average delays are allowed to grow. The sum of these two curves again yields the total cost to passengers. Note that for a delay time of five minutes, machine cost is $3.55 billion and delay cost is $1.1 billion, as discussed previously figure.

Note that the minimum cost occurs at average delays in the vicinity of three minutes. This remarkable result is surprising at first glance, but a simple explanation illustrates why it is valid. Machines, their manning, and maintenance are expensive items. Their numbers are very small when compared to the number of passengers that flow through U.S. airports every year. That number, estimated in this work to be 600 million in 2010, is sufficiently large that the costs associated with delays of a few minutes can add up to a very hefty sum.

The minimum cost point is of course the same as before, at $4.5 billion.

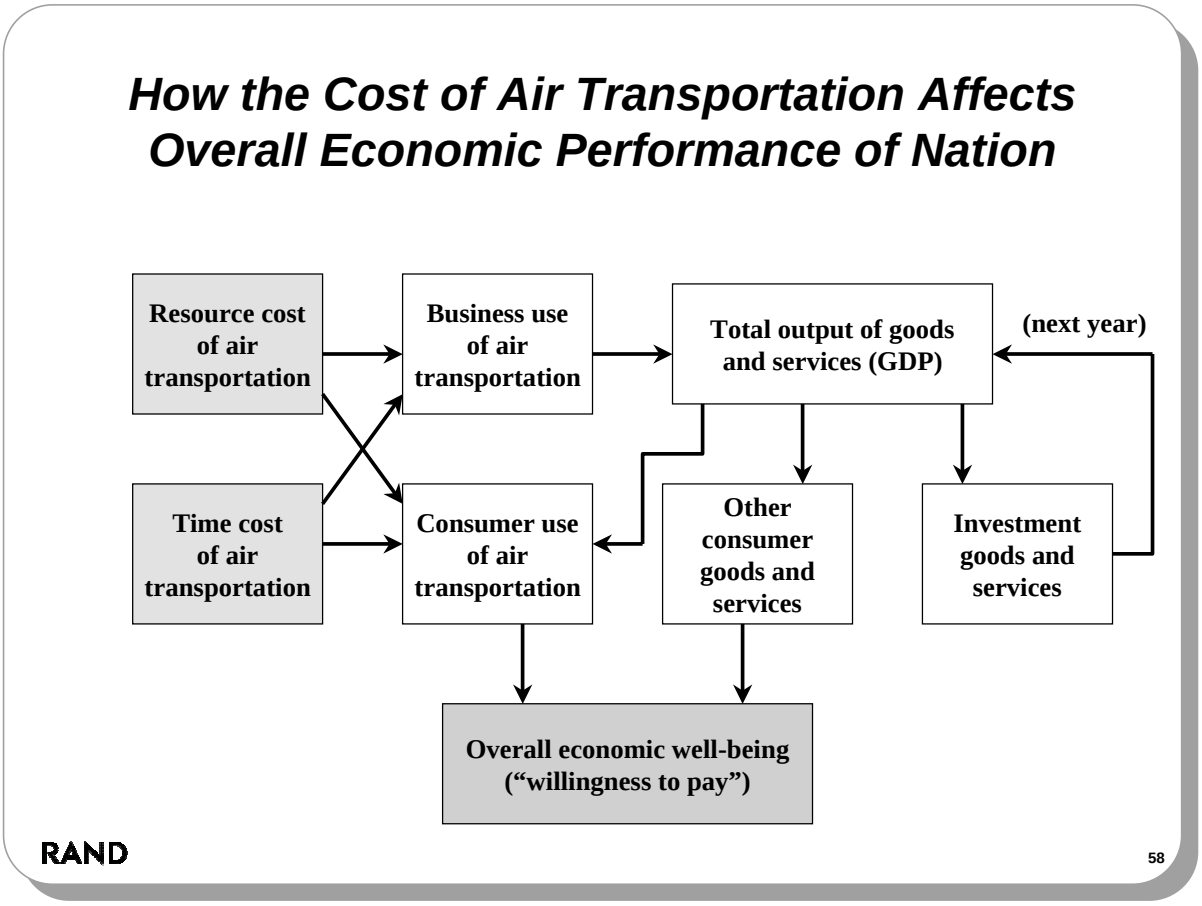
An additional point merits note. The delays discussed here are related to hedging against baggage-scanning delays and pertain to only a portion of the total number of passengers (70 percent used in this analysis). As anyone who has flown in the past two years knows,

the most obvious delays—namely the delays at the passenger-screening stations—have nothing to do with checked baggage. The greater of these two delays will dominate and drive the passenger costs. In other words, the costs estimated here are the least that the passenger is likely to incur. The authors are not aware of a similar study pertaining to delays associated with the passenger-screening stations but believe that matching an average delay of three minutes at these screening station may also require additional investment on the part of the government and the airports.



This figure expands the prior calculations to include other reliability assumptions. Noteworthy is that the minimum costs all occur for average delays in the vicinity of three minutes. As a policy observation, this gives the government a good criterion for judging how much is enough. The total costs vary, as would be expected, because of the markedly different machine buy sizes for different reliabilities at these levels of delay.

As discussed above, we also did a more detailed calculation of the overall economic cost of any machine deployment policy, using a model of the entire U.S. economy and the role of air transportation in it. We did this because the simple calculations ignore many important phenomena that may affect the result on the best machine deployment policy. Among these are the impact of price and delay time on the amount of personal and business flying, the impact of price and delay time on business productivity, and the temporal effects of changes in economic activity in any given year because of price and delay time of air travel on future GDP levels, through changes in investment flows. We did this second more complex approach to calculating economic cost to capture the effects of such phenomena.

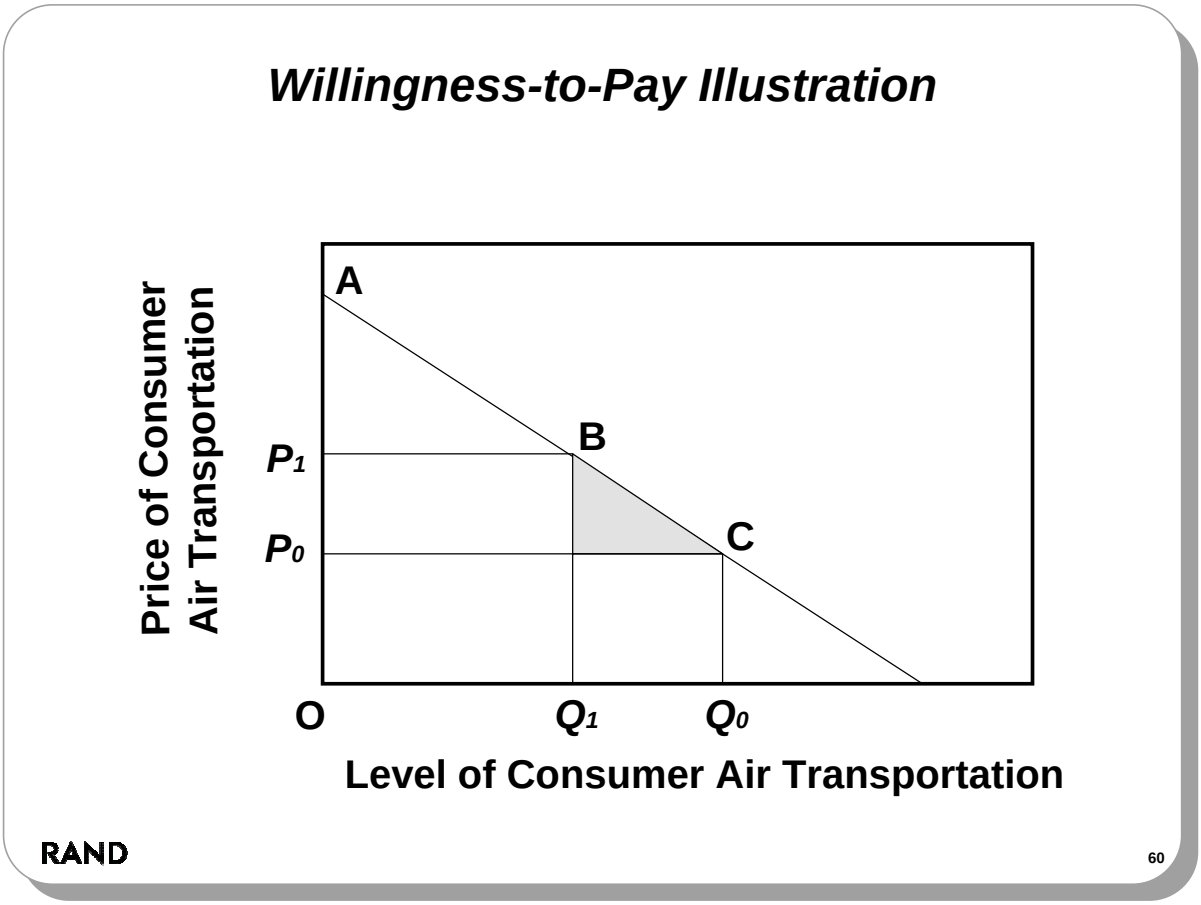


This flow chart illustrates the second methodology by which we calculate the overall economic cost of any level of baggage-scanning equipment and its associated delay. The methodology is a model of the entire U.S. economy and the role of air transportation in determining overall GDP and consumer well-being. (A complete mathematical statement of the methodology is given in Appendix A.) For this calculation we include consideration of how the level of air travel depends on both its dollar or resource cost, and the time it takes. For each level of delay, we calculate the average cost per RPM, and in the economic model we add this to the cost of air travel, in effect assuming that the cost will be passed on to air passengers in proportion to their RPMs flown. We also assume that the level of machines required to achieve the given level of delay is proportional to the volume of air travel, as measured by RPM.

Thus, as the flow chart shows, we begin each calculation with the delay level ("time cost of air transportation") and the increase in the cost of air travel ("resource cost of air transportation"). Changes in these variables have two primary effects. First, air travel is an input to the production process in the economy as a whole. Increases in either its resource cost or time cost will lower the overall level of output, or GDP, and will result in a decrease in air travel for business. GDP determines consumer income. Decreases in GDP, and increases in either the resource or time cost of air transportation, will lower consumer economic well-being, as well as decrease consumer use of air transportation. It is the

decrease in the economic well-being of consumers that we use as the measure of economic cost in these calculations. It is precisely defined as the amount consumers would be willing to pay to avoid the changes in resource and time cost, called consumer "willingness to pay."

A further effect captured in the model is that investment in any year depends on GDP, and a decrease in GDP will lead to a decrease in investment, which will in turn lead to a decrease in GDP in future years from what it would have been. This thus affects consumer well-being in future years as well, and our calculations capture this effect on consumer well-being over time.



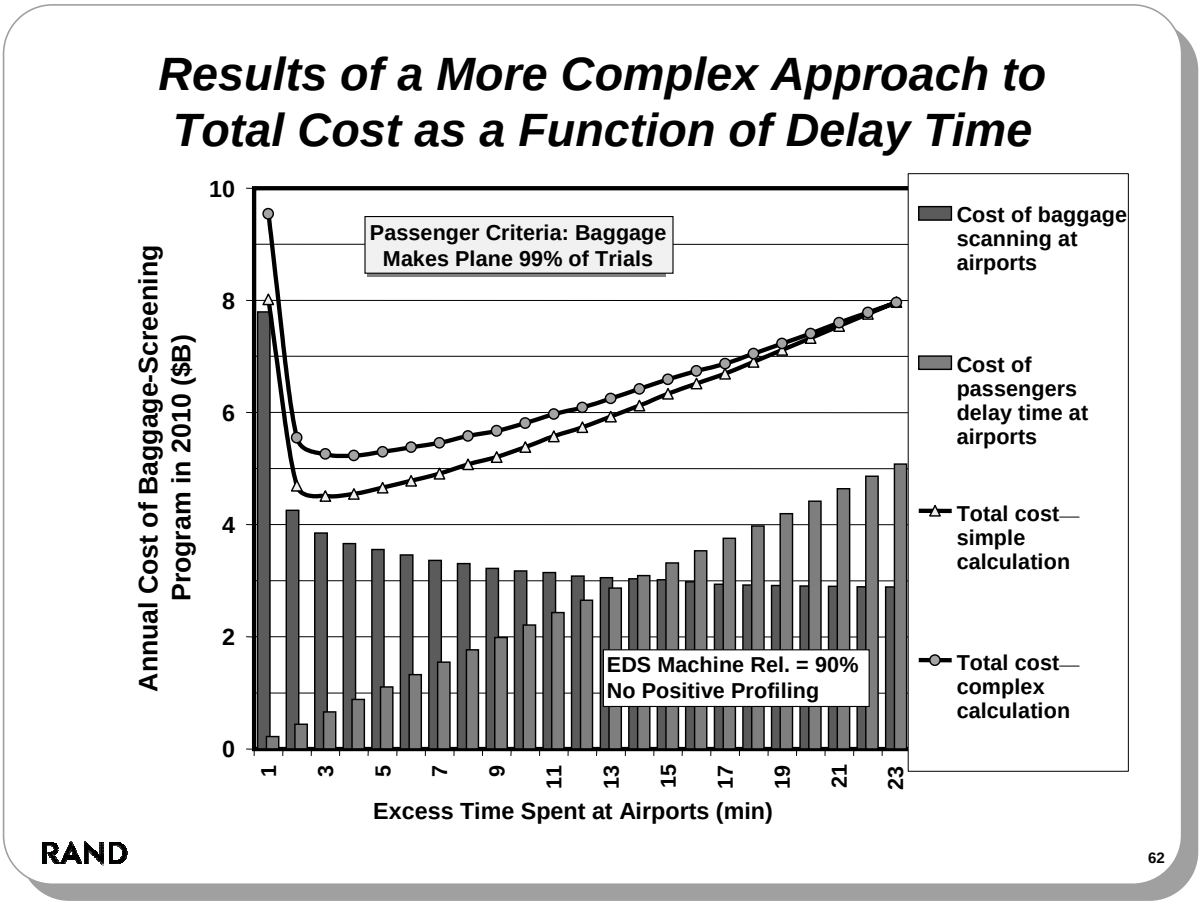
We illustrate here the "willingness-to-pay" measure of consumer well-being, for the case of an increase in the dollar cost of air transportation. A standard demand curve is shown on this figure, with the level of consumer air transportation purchased on the horizontal axis, and the price of air transportation on the vertical. This shows the standard downward-sloping demand relation, in which the quantity purchased decreases with price.

The interpretation of the demand curve is that the height of the curve at any level of air travel represents the amount consumers are willing to pay for that increment of air travel. Thus, at a zero level of purchases the height of the demand curve is A, implying that no unit of air travel has value more than A because otherwise some would be purchased at that price. The highest consumers are willing to pay for any unit of travel is in fact A, and at that price units of air travel begin to be purchased. The value of unit Q_0 of travel is P_0, since the Q_0th unit is purchased only when the price falls to that level. By an extension of this logic, the height of any point on the demand curve is the value of that associated unit of consumption to the consumer, and thus the consumer's willingness to pay for that unit. The total value, or willingness to pay, to consumers of any quantity of output is the area under the demand curve up to that quantity because this is the summation of the value of all the units of output. Thus, the total value to consumers of consuming quantity Q_0 would be the area ACQ_0O. If the market price to consumers is P_0, they will purchase an

amount Q_0 , for which they would be willing to pay, as just discussed, ACQ_0O. However, they only pay an amount P_0CQ_0O, so the difference between what they would be willing to pay for this output and what they do pay is the area AC P_0, which is also referred to as "consumer surplus." It is the amount consumers would be willing to pay to participate in this market.

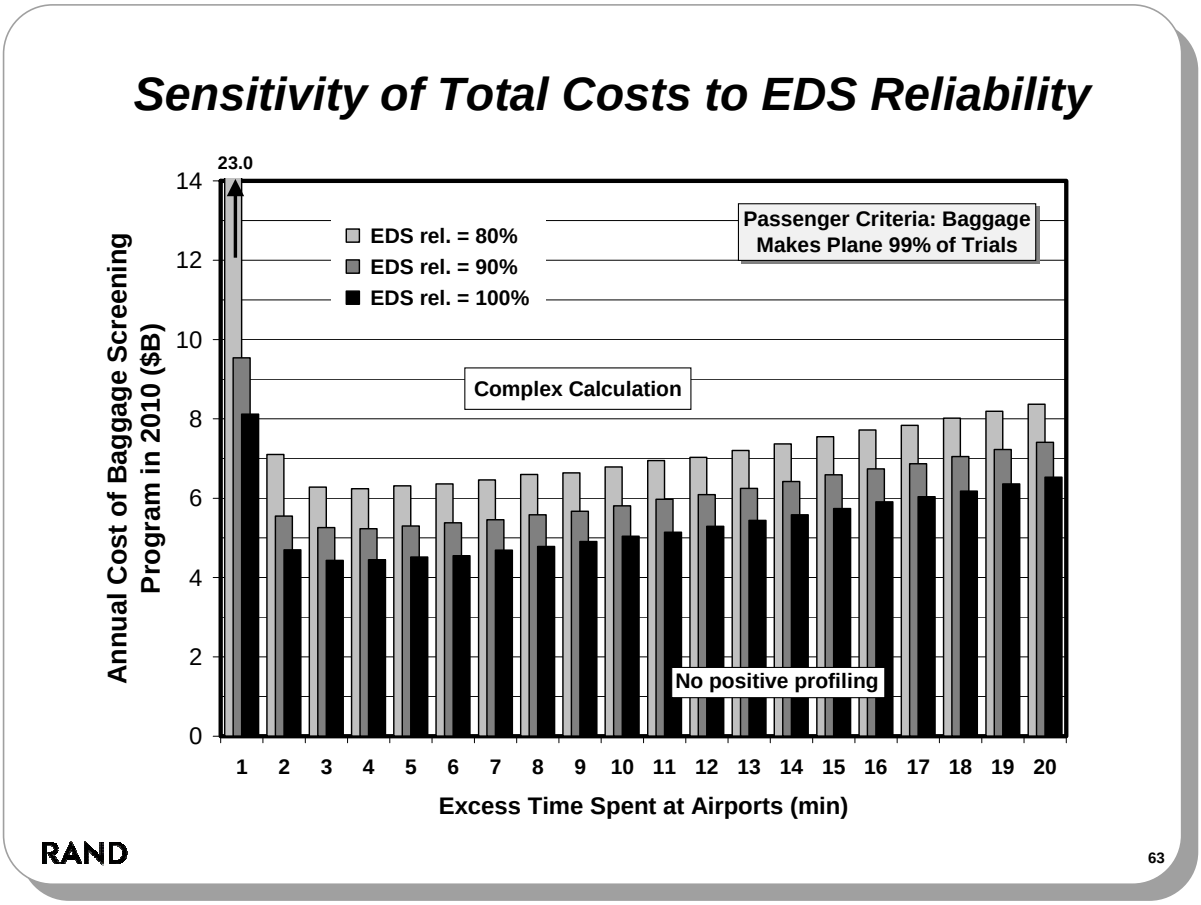
The impact of a price increase on consumer well being is measured by the change in consumer surplus that results. For example, if the price were to rise from P_0 to P_1, consumer surplus would fall from ACP_0 to ABP_1. The difference, P_1BCP_0 , is the measure we use for the economic impact of a price increase on consumers. It is the amount consumers would be willing to pay to avoid the price increase.

In our overall analysis, we also include the impact of price increases on GDP production levels and the impact of changes in the time required for air transportation. The overall impact of these changes is measured by the willingness of consumers to pay to avoid them, and this is the measure of economic impact. The mathematical details of how we do the overall calculation are in Appendix A.



This figure overlays the results of the more complex approach on the results of the simple approach as shown on Chart 86. The results are very close. Thus we conclude that including the considerations of the impact of price and delay time on the level of air travel, and on the level of business productivity and the resulting rate of economic growth do not change the basic finding of the simple approach—i.e., that sufficient machines should be procured to reduce delay times to very low levels.

Because the more complex approach, as shown in Appendix A, includes the interaction of changes in resource costs and time costs, the separate contribution of the two cannot be disentangled in this approach. Similarly, because the results of the more complex approach are mediated through the various elasticity parameters, no direct comparison is possible with the more simple approach. For example, because in the more complex approach air travel falls with price and delay increases, this might mitigate to some degree the size of the economic cost. On the other hand, because in the more complex approach any change in costs leads to a lower GDP that, through its effect on investment, lowers future years' GDP, this might magnify the effect. This figure shows that on balance the magnifying effects are calculated to be higher. We offer one explanation of why this magnification is falling as delay levels increase. This may stem from economic growth effects—all of machine usage costs feed into investment and lower future GDP, while some of the time cost is borne every year but does not compound.



This figure shows the results of the more complex model at different machine reliabilities. Again, these results are very similar to the simple calculation results.

Sensitivity of Results to Uncertainties in Passenger Delays and Equipment Costs

Name x Number => cost category (delay or machine) x cost multiplier
(Number) => minutes of delay where minimum occurs

	Machines x 0.5	Machines x 1.0	Machines x 1.5	Machines x 2.0
Pass Delay x 0.5	$2.35 (2)	$4.10 (4)	$5.82 (7)	$7.43 (9)
Pass Delay x 1.0	$2.57 (2)	$4.51 (3)	$6.38 (4)	$8.21 (4)
Pass Delay x 1.5	$2.79 (2)	$4.84 (3)	$6.77 (3)	$8.65 (4)
Pass Delay x 2.0	$3.01 (2)	$5.14 (2)	$7.10 (3)	$9.03 (3)

No profiling, EDS rel. = 0.9

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This figure addresses a sensitivity that we have until now ignored, namely our estimates of the costs associated with acquiring and operating the EDS machines and the costs incurred by the passengers when they must arrive earlier than necessary to get their baggage on the plane. To show the sensitivities, we have varied these two costs independently, reducing and increasing them by a maximum factor of two.

The numbers shown in the table are the minimum cost (in unit of $B) and (in parentheses) the minutes of passenger delay where the minimum occurs.

The results related to the relationship between passenger delay costs and optimum sizing show that increasing the cost estimates does not markedly change the optimum delay that minimizes the costs. If delay costs are substantially reduced, then the optimum delay increases substantially. But our expectation is that the costs in both categories are more likely to be larger than smaller.

It might also be noted that if the costs are larger, the importance of seeking ways to keep them to a minimum is increased.

Briefing Outline (7)

1. **Background, Introduction, and Findings**
2. **Calculating Maximum and Average Baggage-Scanning Delays at a Major Airport (Dallas–Fort Worth)**
3. **Implications for Passenger Delays**
4. **Sensitivity of Results to Assumptions**
5. **Extending Analysis to Include a Second Major Airport (Chicago O'Hare)**
6. **Balancing Costs and Consequences**
7. **Profiling as a Means to Reduce Costs and/or Lessen Consequences**
8. **Observations and Recommendations**

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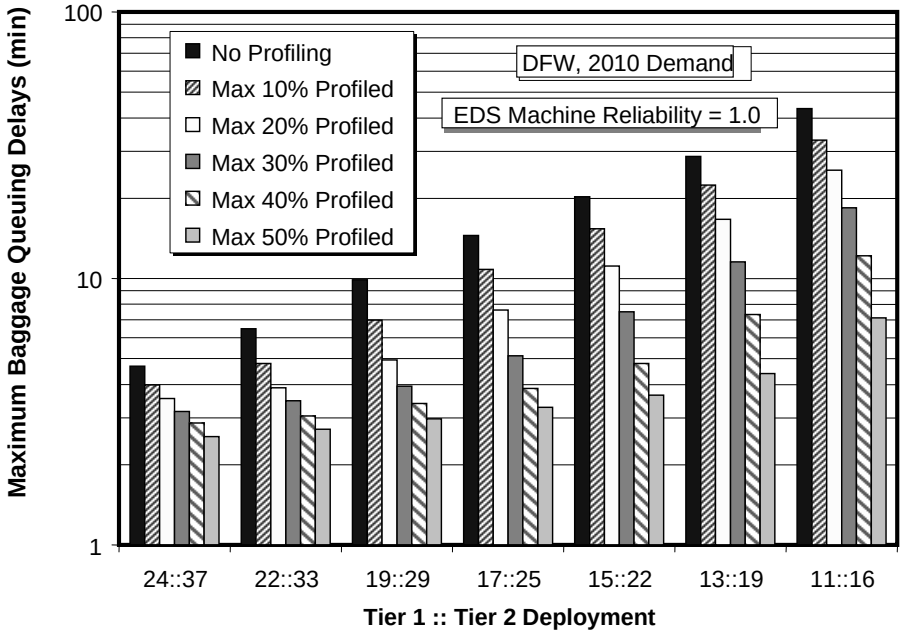
The final topic in this briefing relates to the possibility that positive passenger profiling will allow airports and airlines to obtain the desired scanning performance at a much lower overall economic cost. A more extensive discussion of profiling can be found in reference 2. We will mostly summarize what is in that reference.

First, positive profiling is defined here as the identification of passengers that are almost certainly not terrorists and treating them differently. Among the options are (1) reducing the number of bags that need to be scanned, (2) exposing bags from profiled passengers to less intrusive scanning, and (3) setting up a two-tier system that allows profiled passengers easier entry into the secure portion of the airport.

We will not dwell on the arguments—pro and con—concerning positive profiling. Intelligent people can differ on the balance of risks and rewards associated with profiling. But there is no question that the only assured way to know whether a bomb is inside a bag is to inspect the bag. This briefing will simply show some of the positives that might accrue if positive profiling were implemented.

Profiling Can Significantly Reduce Point Delays



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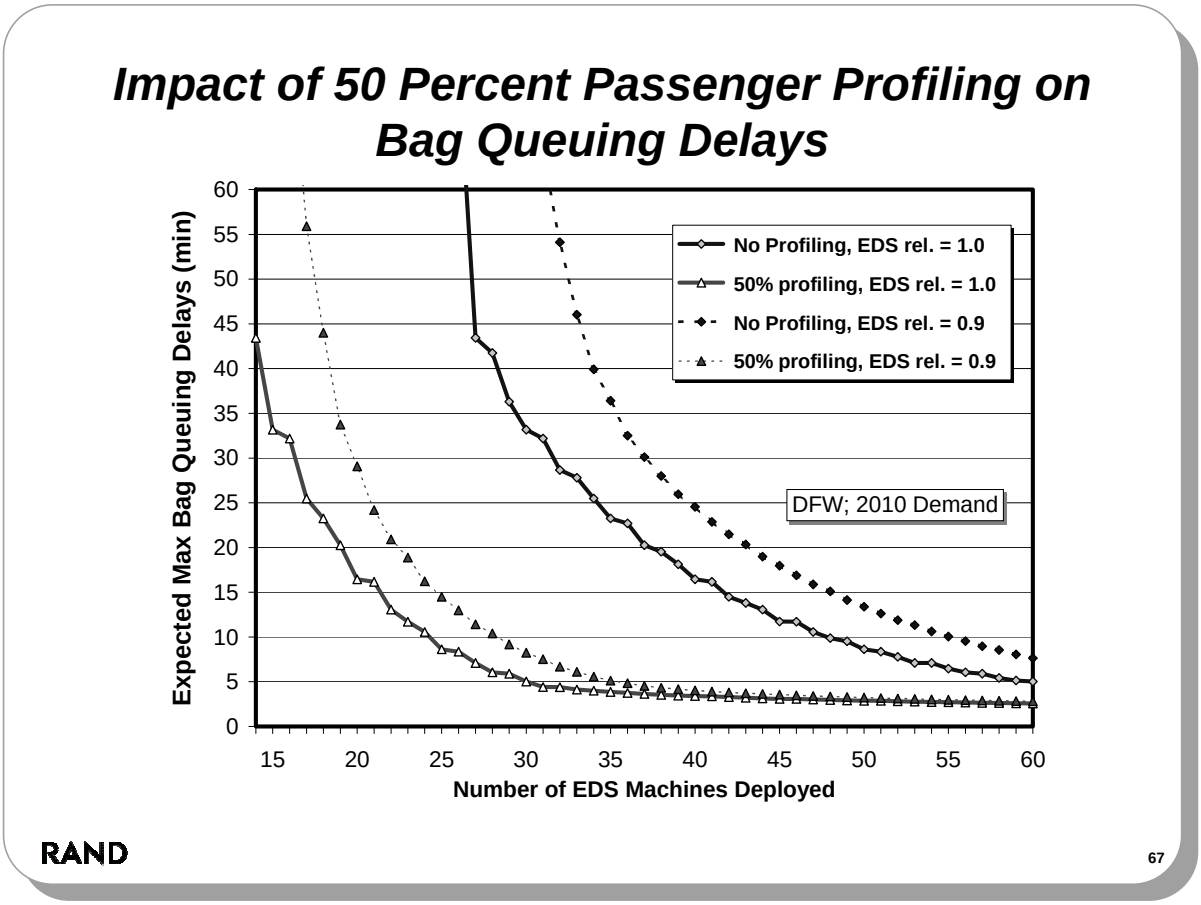
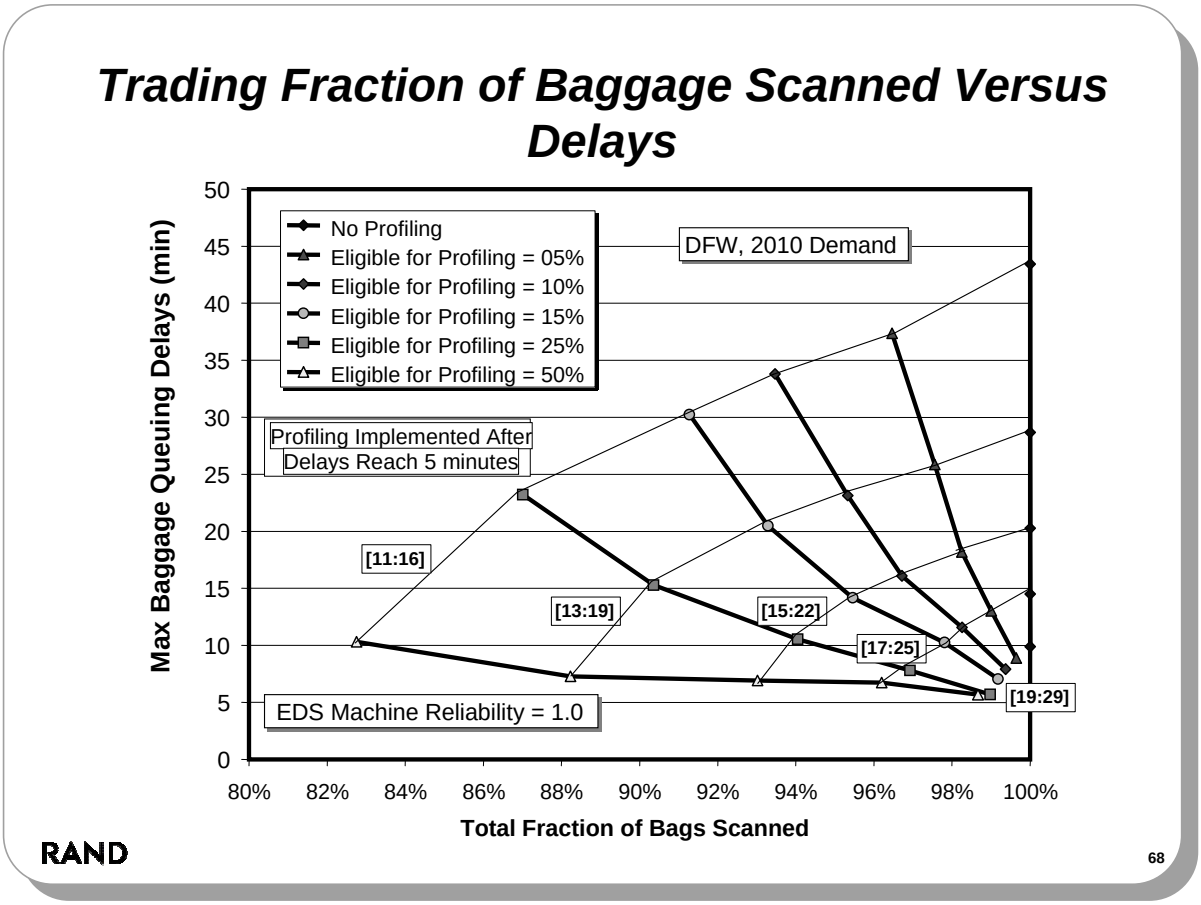
We start with a plot of how point delays (all machines are 100 percent reliable) are reduced if profiling reduces the number of bags that need to be scanned. It is clear that for a given deployment, delays can be sharply reduced if a reasonable fraction of the bags can be eliminated from scanning.

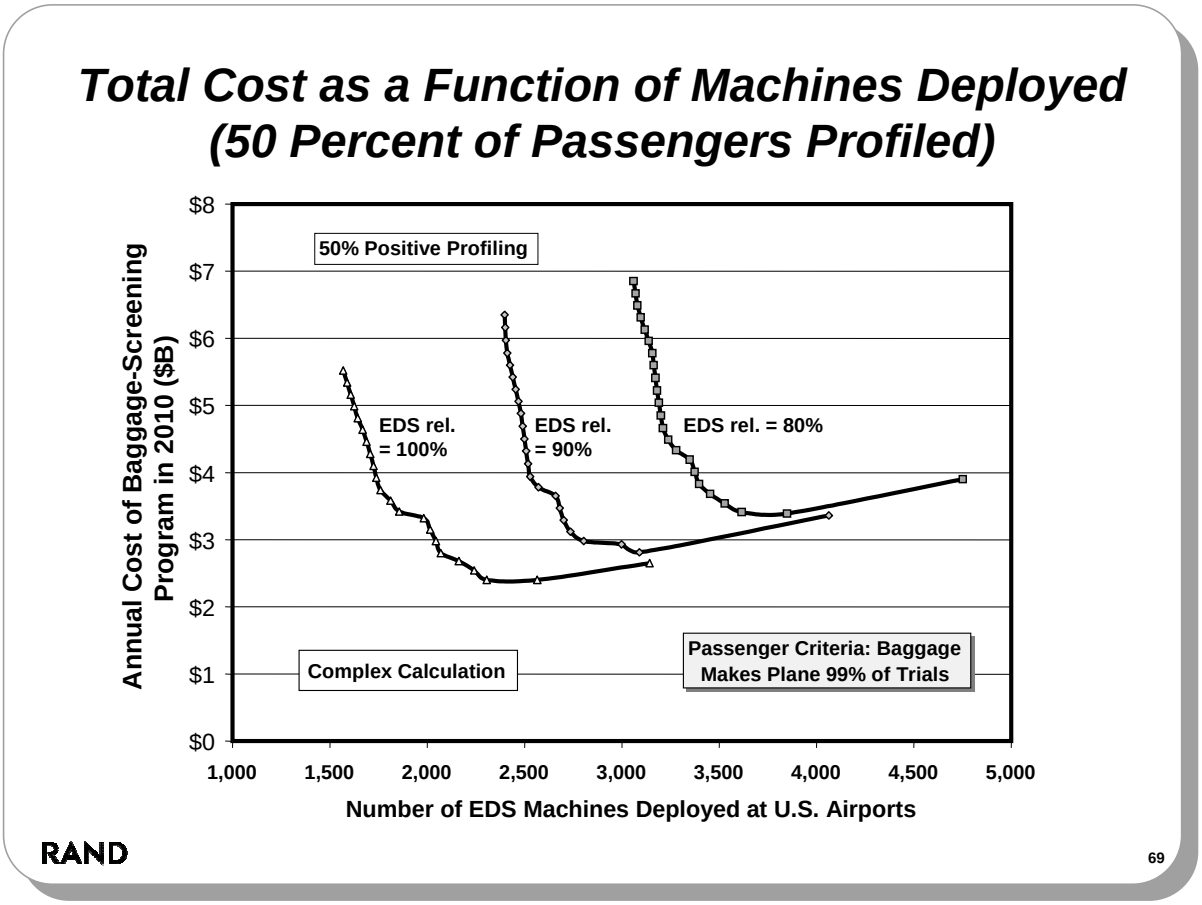


This figure shows the savings as a function of reliability. For simplicity, we only show curves for 50 percent profiling, and for reliabilities of 1.0 and 0.9. As might be expected, the number of machines required to achieve a specified level of delays with 50 percent profiling is approximately half of that without profiling. It is probably self-evident that a reduction of half the bags leads to a requirement of half as many machines, holding delays constant. It is useful, however, to show it graphically, after a computer program generates the numbers.



This figure introduces a new concept—responsive profiling. For argument's sake, assume that all bags were scanned until delays started to build. In our calculations we set a threshold level for delays. If delays exceeded the threshold, profiling was used; if delays were less than the threshold, all bags were scanned. This is the simplest of rules, and obviously improvements are possible.

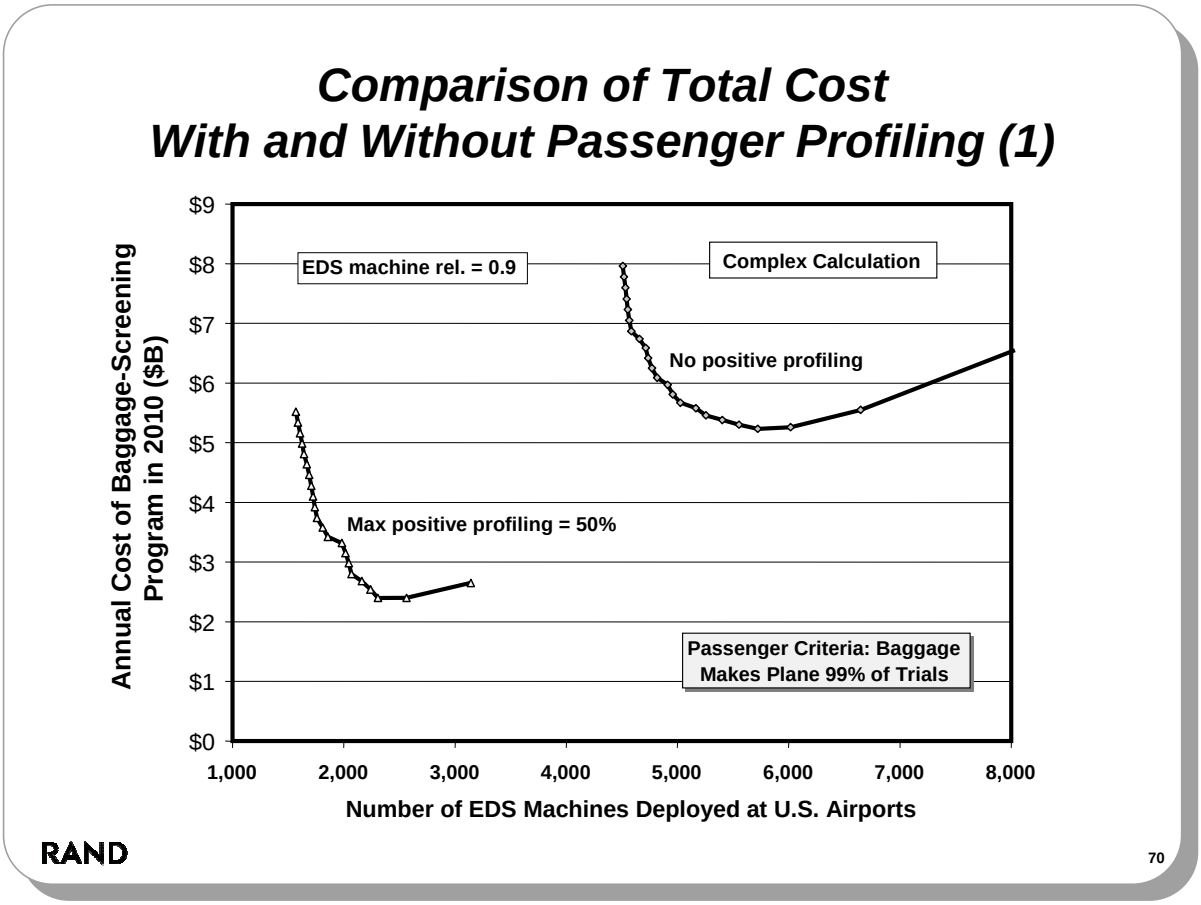
Even this simple rule offers some impressive results. Even with 50 percent profiling, it is possible to reduce delays by about 80 percent while still inspecting more than 85 percent of the bags. The carpet plot shows that numerous combinations are possible.



The figure shows the total costs of baggage scanning as a function of the number of baggage-scanning machines deployed, assuming that 50 percent of the passengers are eligible for positive profiling. As noted in an earlier figure, this does not mean that 50 percent of all the bags are exempt from being scanned. Instead, it does mean that *during peak hours* up to 50 percent of the bags may not be scanned.

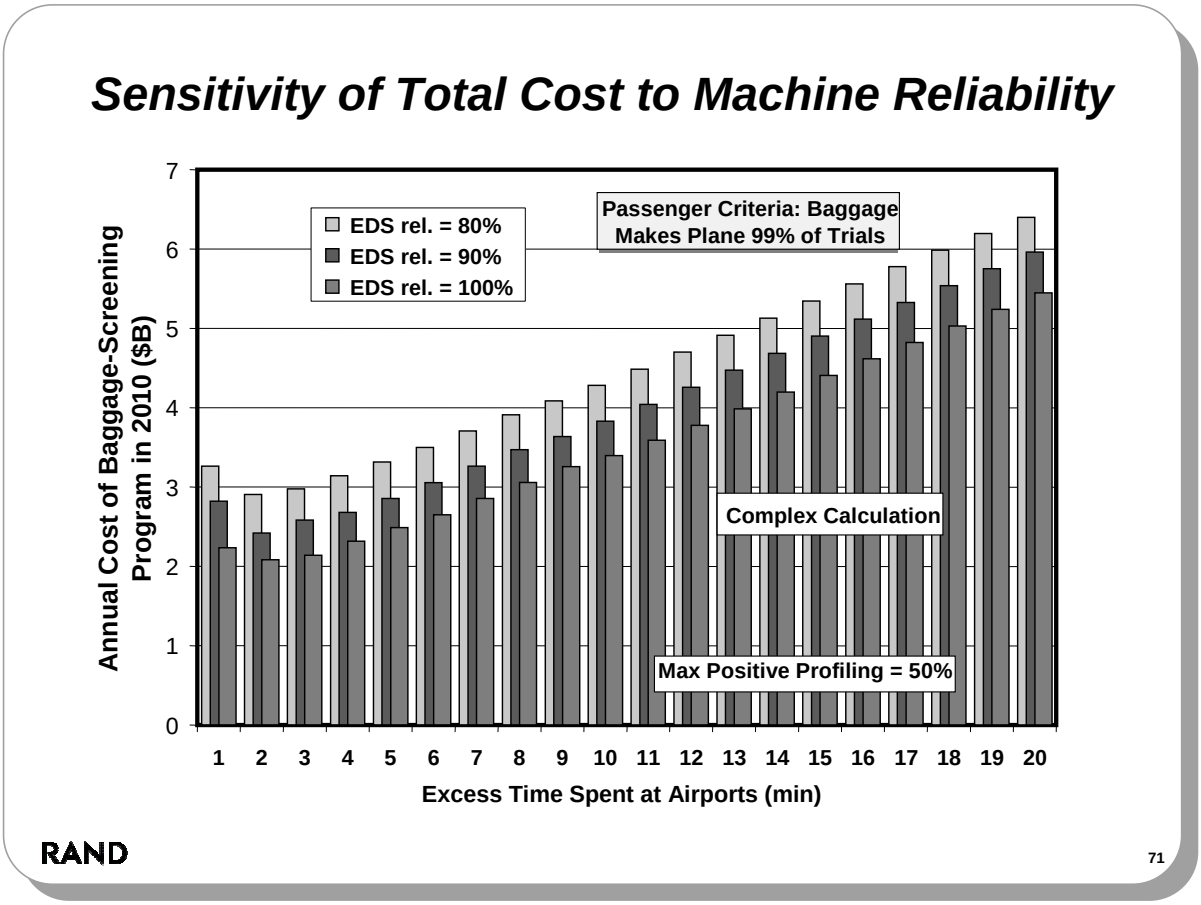
The shape of the curves match those shown on a similar figure where no profiling was allowed. The total number of machines is significantly smaller, as expected, but the character of the curves are essentially unchanged.

These results, and the rest in this section, were derived from the complex form of the calculations described in the previous section. The simpler approach gives very similar results.



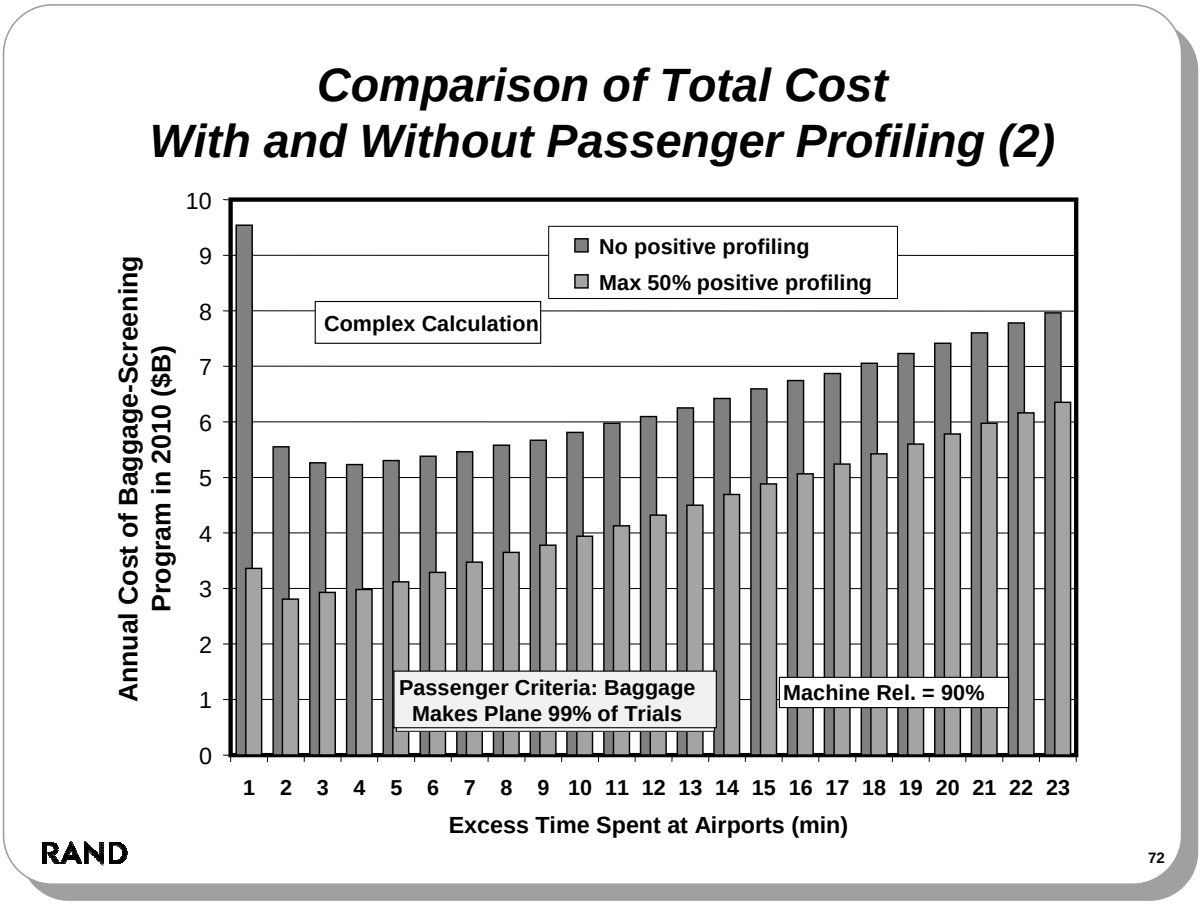
This figure compares the with and without profiling outcomes.

1. First, total cost of the baggage-scanning program is reduced by approximately 40 percent. In itself, this is a reasonable motivation for taking positive profiling seriously
2. The minimum cost occurs at a machine buy level approximately half of that for the no-profiling case.
3. This reduction has several positive aspects not necessarily captured adequately in this analysis:
    - The smaller deployment sizes imply significantly fewer problems with deployments within current airport facilities, easing full deployment and lowering the overall costs associated with new airport facilities
    - The smaller numbers also make more feasible the replacement of the current EDS equipment with newer, higher-performance equipment in the future.
    - The smaller numbers suggest that full EDS deployments could be achieved at earlier, allowing rapid phase-out of some of the current trace detection machines.



This figure shows the 50 percent profiling results as a function of the average passenger delay (e.g., time wasted in airport) and machine reliability.

These results are fundamentally the same as those for the no-profiling case. It is worth noting that the minimum passenger costs occur where average delays are only about 2 minutes. The minimum costs are in the $2 billion to $3 billion range, depending on reliability. As was true in the no-profiling case, the magnitude of these "optimum" delays is remarkably small, albeit easy to explain.



This figure compares the 50 percent profiling results with the no-profiling results, assuming a machine reliability of 90 percent.

The comparisons show that positive profiling can lower the minimum traveler costs by about 40 percent. They also show that the optimum delay is somewhat smaller in the profiling case.

Briefing Outline (8)

1. **Background, Introduction, and Findings**
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5. **Extending Analysis to Include a Second Major Airport (Chicago O'Hare)**
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7. **Profiling as a Means to Reduce Costs and/or Lessen Consequences**
8. **Observations and Recommendations**

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We conclude with a few short observations.

Observations

- **Congress mandated that all bags be scanned by the end of CY 2002**
  - **TSA, the airlines, and the airports worked very hard to satisfy that mandate**
  - **Some airports fell short and Congress gave them another year to comply**
- **A prior RAND white paper ruminated on the wisdom of this mandate in light of the many constraints facing all concerned in its implementation**
- **This briefing adds some details to that prior work, suggests ways to determine "how much is enough." and estimates the overall economic consequences if we don't meet the mandate in a sensible way**
- **The analysis suggests that a "good" design would seek deployments that yield expected delays of no greater than five minutes. In general, this implies that the government must acquire substantially more machines than they originally planned**

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The congressional mandate on airport security has in principal been met. It remains to be seen whether the results will satisfy the dual objectives of (1) increasing airport security while (2) not significantly inconveniencing the flying public. A prior RAND white paper (reference 1) concluded that it was likely that the second objective would not be met, a conclusion also supported by this work

This briefing adds some new information to the earlier work. It concludes that baggage queuing delays and the corresponding increased time that travelers would have to spend in the airport dominate the "costs" to the nation of the added security measures. Rather than being just an annoyance, delays need to be driven to relatively small amounts if the overall impact on the country is to be kept to a minimum. Moreover, having enough machines to handle peak baggage demands would improve overall baggage-scanning performance, allowing human operators more time to inspect suspicious bags.

Two clear options for minimizing queuing delays exist.

- Deploy and operate a sufficient number of baggage-scanning machines (we strongly suspect that the current deployment size is significantly less than optimal)
- Reduce the baggage demand but implementing a "registered traveler" program.

We believe that a combination of these two would best serve the interests of the nation but recognize that cogent arguments can be made against positive profiling (the prime ingredient in a registered traveler program) that cannot be dismissed without further serious study.

We emphasize that the results of this work reflect analyses of only two airports. Moreover, this work did not have access to ongoing TSA plans. It is possible that TSA already understands the importance of baggage queuing delays and is implementing steps to ensure that passengers are not inconvenienced. We certainly hope so. But if not, this analysis should aid them in understanding the real need and in proceeding promptly toward meeting the nation's interest by resizing the buy.

Recommendations

- **The government should undertake a serious study to validate the conclusions of this work**
  - **We urge the government to adopt the economic measures developed here in sizing the full deployment of baggage-scanning machines**
- **If our work is validated, the Government should suitably alter their deployment plans for baggage-scanning equipment deployments**
  - **Less than optimum deployments will hurt the U.S. economy unnecessarily**
- **The government should come to terms with the pros and cons of passenger profiling**
  - **The potential is substantial, but some risks need to be addressed**
  - **The technology needs to be fully defined and tested before a practical and foolproof system can be designed and deployed**

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Even though this study was done with limited funds, short timelines, and inadequate access to relevant government and private data, we believe that our results will stand the test of time. We urge the government to validate what we have done and to act on our results, modifying the baggage-scanning equipment plans to reflect deployment sizes that minimize the overall cost of the deployments to the nation. At no time do we suggest that less than complete scanning of all threatening bags should be our objective, and if that means scanning all the bags because we cannot be confident that we can pick potential terrorists out of the full pool of passengers, then so be it. But if we can have confidence to exclude some of those passengers on grounds that are so convincing that nobody could object, then positive passenger profiling should be given a hard look.

As a final comment, we urge the government to not only consider doing the job right, but urge them to appreciate and undertake the right job. The country deserves nothing less.

References

1. Gary Kauver, Bernard Rostker, and Russ Shaver, "Safer Skies: Baggage Screening and Beyond," Santa Monica, Calif.: RAND Corporation, WP-131, 2002.
2. Russ Shaver and Michael Kennedy, "The Benefits of Positive Passenger Profiling on Baggage-Screening Requirements," Santa Monica, Calif.: RAND Corporation, DB-411-RC, forthcoming.
3. Russ Shaver and Michael Kennedy, "How Much Is Enough? Sizing the Deployment of Baggage Screening Equipment to Minimize the Cost of Flying: Executive Summary," Santa Monica, Calif.: RAND Corporation, DB-412-RC, forthcoming.

APPENDIX A

A METHODOLOGY FOR ASSESSING THE ECONOMIC IMPLICATIONS OF INCREASES IN THE RESOURCE AND TIME COST OF AIR TRANSPORTATION

INTRODUCTION

As discussed in the main body of this report, we calculated the overall cost of any baggage-screening machine procurement policy (i.e., number of machines procured) in two ways. One was the simple and straightforward way of adding our estimate of the cost of buying, installing, and operating the machines to our estimate of the value of the time lost caused by early airport arrivals. The estimate of the time lost itself was done by us and is described in the main body of the report. The time was valued at the rate ($31.67 per hour in dollars of 2003 purchasing power) prescribed by the Federal Aviation Administration at its Web site, api.hq.faa.gov/economics/742SECT1.PDF. This simple methodology is fully presented in the main body of the briefing.

We realize, of course, that this simple method, though it has the virtue of transparency, does not take into account many phenomena that bear on this issue. Among those are the reactions of air travelers to changes in the dollar and time cost of travel and the impacts of changes in air travel costs on overall GDP and thus investment, future capital stock, and future GDP. These all have implications not captured in the first, simple calculation. To address them, we developed the second approach described in this appendix. This approach has the disadvantage that it is not particularly transparent. For example, in the simple approach, one can separately calculate the cost associated with machine procurement and that associated with time delays and show how their sum achieves a minimum at a given procurement policy. This conceptual separation of the effects cannot be done in the more complex methodology described here because, among other complications, the level of the dollar cost of air travel affects the impact of time cost changes and vice versa. For example, the higher the dollar cost, the lower the level of air travel and thus the lower the impact of any change in the time cost. Of course, it is precisely because such interactions exist that we chose to develop and apply this more complex methodology for estimating the effects of alternate policies. As discussed in the main body of this briefing, it turns out in this case that the complex and the simple methodologies give very similar answers in terms of optimal policy. But we could not know that without applying the more complex methodology. The rest of this appendix describes the model that was developed and gives some additional results from it.

MODEL OVERVIEW

In our modeling framework, the economy consists of air transportation and all other goods and services. Air transportation is broken down into personal travel, business travel, and air freight. We use the following symbols for each sector:

Personal air travel	T
Business air travel	B
Air freight	F
All other goods and services	Q

Table A.1 characterizes the U.S. economy in 2000 in terms of these sectors. Data is from *Economic Report of the President* and *Survey of Current Business*, various issues, and the Air Transport Association Web page (www.airlines.org).

Because these data sources do not distinguish between business and personal air travel in the detail needed for the model, we made the following assumptions that resulted in Table A.1. Based on discussions with industry personnel, we have assumed that expenditure on business air travel is twice the expenditure on personal air travel, while the number of revenue-passenger miles is the same in the two sectors. Total U.S. revenue-passenger miles in 2000 were 690 million, and total emplanements were 695 million (U.S. Department of Transportation (2002)). Based on discussions with industry personnel, we assumed that trips were two-thirds of emplanements and that trips were also evenly distributed between personal and business travel. Thus, we assume 230 million business trips and 230 million personal trips in 2000. We further assume that the level of resources used to produce these passenger miles is proportional to the price charged for them, reflecting the cost of producing the extra convenience and flexibility that business travelers receive. We also assume that the use of labor, capital, and other goods and services is proportionately the same in provision of business travel, personal travel, and air freight and that all air freight is for business uses.

We note here that the model includes neither the joint production characteristics of personal and business air travel nor the peak-load characteristics of air travel—i.e., how demand varies by time of day and season. This was a strategic decision on our part to ensure the existence of general equilibrium. We require a general-equilibrium solution to generate internally consistent projections of overall investment and thus GDP growth, and the impact of air travel security policies on the overall level and rate of GDP was one of the concerns that motivated us to pursue the more complex modeling approach. We acknowledge that this was a judgment call and that a partial equilibrium approach that focused more on the

joint production and peak load characteristics of the industry and less on a complete model of the implications for overall GDP, investment, and growth would have also been a valuable approach. We would recommend further work along these lines for further informing policy decisions. For an overall view of computable general equilibrium models, see the comprehensive handbook by Amman, Kendrick, and Rust (1996). The model described here is in the tradition of previous work done by one of the authors modeling patterns of economic growth. See Kennedy and Rostow (1979) and Rostow with Kennedy (1990).

We begin with an overview of the model. Each of the four goods is produced by a constant-returns-to-scale production function, with labor, capital services, and intermediate goods as inputs. The three air transportation sector outputs are produced by constant proportions of intermediate input of all other goods and services, labor, and capital. (For convenience from now on, "all other goods and services" will be called OGS as shorthand.) OGS is produced in variable proportions by business travel, air freight, labor, and capital. An index of the time required for business travel is also an argument of this production function, as a technical shift parameter called τ. (In any given model simulation, τ is an exogenous variable.) For a fixed level of the inputs, a higher τ implies lower total output, reflecting the lost productivity of workers during the time they are traveling.

τ is an index of the average time required for one trip, and in the model only this average time is included. τ is a function of the delay time associated with any level of baggage-screening equipment procurement, as discussed in the main body of the briefing. As stated there, we assume that an average trip takes 270 minutes, so that a 10-minute delay results in a 3.7 percent increase in τ.

Table A.1

U.S. Economy in 2000
(billion $; employment in millions)

From sector	Into Sector					
	Q	B	F	T	Final Demand	Total
Q	0.0	40.4	8.6	20.2	9,834.7	9,903.9
B	75.6	0.0	0.0	0.0	0.0	75.6
F	16.2	0.0	0.0	0.0	0.0	16.2
T	0.0	0.0	0.0	0.0	37.8	37.8
Wages	6,371.8	26.4	5.7	13.2		6,417.1
Return to Capital	3,440.5	8.7	1.9	4.3		3,455.4
Total (Gross Output)	9,903.9	75.6	16.2	37.8	9,872.5	
Employment	134.52	0.4	0.09	0.2		135.21
Wage Rate	47.4	66.6	66.6	66.6		47.5

Note: Totals may not add due to rounding.

The parameters of the production functions in the model are chosen so that they fit the U.S. economy in 2000 as described in Table A.1 and also so that they have certain elasticities. This model calibration will be further discussed when the formal model structure is presented below.

Total income and GDP in this model is simply the total earnings of labor and capital. An exogenous fixed percentage of this (called *s*) is allocated to investment. *s* is fixed at a value of 0.18 in accordance with recent U.S. experience. The remainder of GDP will be called "consumption" for the purposes of the model, although of course it includes government spending and net exports. (International trade is not explicitly represented in the model.)

Consumption spending is allocated across personal air travel and OGS to maximize an index of utility. The time required for personal travel is also an argument of this utility index, and it is also represented by the technical shift parameter called τ. Thus, we are assuming that the index of business and personal travel are the same. For any given level of consumption of air travel and OGS, consumers would prefer to spend less time traveling. Consumers cannot do anything to change τ; it is simply a given technical parameter to them, and they maximize the utility index as a function of personal air travel and OGS for each given level of τ. How τ explicitly enters the utility index will be shown below when the model structure is presented.

The model is closed by finding a set of factor (capital and labor) and product (*T, B, F, Q*) prices and quantities in any year with the following properties. Final and intermediate production and factor usage fall on the production functions, and product and factor prices are such that there are no excess profits in any sector (i.e., all profits are equal to the return to the capital stock). Consumption of personal air travel and OGS are chosen to maximize the consumer utility index, subject to a constraint that spending be no more than $(1 - s)GDP$, where *GDP* is the total of factor rewards (i.e., the wage rate multiplied by the quantity of labor plus the return to capital multiplied by the amount of capital). Investment spending is equal to s (*GDP*). The net quantity produced of consumption and investment goods equals the consumption and investment demands. In other words, we find the year-to-year general equilibrium of the economy.

The capital stock in any year equals the depreciated value of the capital stock in the previous year, plus the amount of gross investment in the previous year. Thus, we assume a one-year gestation period for gross investment. The depreciation rate is assumed to be 5 percent. By fixing *s* exogenously, we do not allow intertemporal optimization of consumption and investment but instead solve a series of one-year general-equilibrium models, with the fixed parameter *s* linking economic outcomes from one year to the next through the propagation of the capital stock.

MODEL STRUCTURE

Overall Framework

Readers of this section of the report are required to have a familiarity with input-output economics models and terminology. We begin by defining the following variables:

$X_{i,j}$ Use of product *i* in production of product *j*. (*i,j* = *Q,B,F,T*) (Values of the $X_{i,j}$ are in the first four rows and columns of Table A.1.)

X_i Gross output of product *i*. (*i* = *Q,B,F,T*) (Values of the X_i are in the seventh row as well as the sixth column of Table A.1.)

Y_i Final demand for product *i*. (*i* = *Q,B,F,T*) (Values of the Y_i are in the fifth column of Table A.1. They sum to GDP.) (For each sector *i*, we have the relation $Y_i = C_i + I_i$, where C_i is consumption of output of sector *i*, and I_i is investment of output of the sector. and Only C_Q and C_T are positive of the C_i. Only I_Q is positive of the I_i. Government spending and net exports are not explicitly modeled but implicitly included in the other aggregates. In the model, investment is only done out of output of sector *Q*.)

The economy satisfies the resource constraint equation (1).

$$X_i = \Sigma_j X_{i,j} + Y_i \qquad \forall i \qquad (1)$$

Next we define the variables.

p_i Price of product *i*.

L_i Labor used in production of product *i*.

K_i Capital used in production of product *i*.

w_i Wage rate of labor used in production of product *i*.

r_i Gross return on capital used in production of product *i*.

GDP Value of gross domestic product.

We then have the value relations (2) and (3).

$$p_i X_i = \Sigma_j p_j X_{j,i} + w_i L_i + r_i K_i \qquad \forall i \qquad (2)$$

$$GDP = \Sigma_i \; p_i Y_i = \Sigma_i \; (w_i L_i + r_i K_i) \qquad (3)$$

The model is solved by finding a set of X_i, Y_i, $X_{i,j}$, p_i, L_i, K_i, w_i, and r_i that satisfy relations (1) and (2), as well as the production and demand relations that will be described next.

Production Relations

This section describes the "supply" side of the model.

We begin with a description of the how production of X_Q, output of all goods and services besides air transportation, is modeled. In the most general representation, output of "all other goods and services," or Q, is represented as a function of the inputs of labor, capital, business travel, and air freight devoted to it, as well as of the average duration of air trips. A general representation of the production function would be

$$X_Q = f_Q(K_Q, L_Q, X_{B,Q}, X_{F,Q}, \tau) \qquad (4)$$

Here, τ is an index of air transportation trip duration. (Note that we use only one index to represent trip duration, and thus delays, for both business travel and air freight. This could be usefully generalized in future work.) For this analysis, we actually work with the *unit cost function* that is dual to the production function (4), which has a general representation

$$p_Q = g_Q(X_Q, r_Q, w_Q, p_B, p_F, \tau) \qquad (5)$$

That is, the price of one unit of output of sector Q (equal to its total cost, including return on capital) is a function of the level of output, all input prices, and the index of air transportation duration. We use a nested translog cost function, with the parameters chosen to result in a given set of elasticities. (For a more complete description of the translog function, and the rationale for the parameter restrictions later shown in equations (9) through (12), see Varian (1992).) (Later in this appendix we summarize the range of elasticity estimates in the relevant literature; the elasticities chosen here are meant to be representative of that literature.) We use the following specific elasticities in the simulations reported here (with a note on the rationale for each parameter choice):

(1) elasticity of output of X_Q with respect to τ of –0.0042. This was not derived from any reported estimates but was based on the recommended $40.10 per hour value for business travel (2000 $) given by the U.S. Department of Transportation (api.hq.faa.gov/economics/742SECT1.PDF). It is also based on our assumptions discussed above that 230 million business trips occurred in 2000 with an average length of 270 minutes, that 70 percent of passengers check baggage, and that gross

output in 2000 was $9,903.9 billion. If the delay associated with screening is one minute, this means 0.7 additional minutes of trip time, which is a 2.6/10 of one percent increase. The 0.7 additional minutes per trip have a value of $0.47 per trip, or $110 million per year, which is about 1/100 of one percent of gross output. Since the value of gross output in 2000 was $9,903.9 billion, we solve the simple elasticity equation $(9{,}903.79/9{,}903.9)=(270.7/270)^{\eta}$ for η to derive the value of the elasticity.

(2) elasticity of demand for business travel with respect to its price of -0.7. Table A.2 at the end of this appendix, which summarizes empirical elasticity estimates, shows a wide range of estimates for this parameter, from –0.18 to –3.51. –0.7 represents our judgment of the central tendency of the estimates and was also informally vetted with industry experts.

(3) elasticity of demand for business travel with respect to τ of –0.3. Table A.2 also shows a wide range of estimates for this parameter, from –0.16 to –1.8. –0.3 here again represents our judgment of the central tendency of the estimates and was also informally vetted with industry experts.

(4) elasticity of demand for air freight services with respect to its price of –0.7. We judgmentally chose this to be the same as the parameter for business travel. We again informally vetted this with industry experts.

(5) elasticity of demand for air freight services with respect to τ of –0.3. We judgmentally chose this to be the same as the parameter for business travel. We again informally vetted this with industry experts.

(6) elasticity of demand for capital, labor, business travel, and air freight services with respect to XQ of 1.0. This is an implication of our assumption of constant returns to scale in production, which we made to ensure the existence of general equilibrium. We note that this is not strictly necessary for existence and that an assumption of diminishing returns to scale would also have guaranteed existence. However, constant returns is much more generally used in overall economic growth analysis (see, for example, Barro and Sala-i-Martin (2003) for a survey of contemporary growth analysis).

(7) elasticity of demand for (KQ/LQ) with respect to (rQ/wQ) of –1.0 (commonly referred to as the "Cobb-Douglas" assumption). This is also the most widely used form of the capital-labor substitution relationship used in contemporary economic growth analysis. (See again Barro and Sala-i-Martin (2003).)

The specific cost function (5) we use is in nested form, in which p_Q is represented as a function of two new variables, q and c, as well as of τ. q is a cost index of capital and labor and is a function of w_Q and r_Q. c is a cost index for air transport and is a function of p_B and p_F. The specific trans log functions are

$$\ln p_Q = a_q \ln q + a_c \ln c + a_\tau \ln \tau + (1/2)\left[b_{q,q}(\ln q)^2 + b_{c,c}(\ln c)^2 + b_{\tau,\tau}(\ln \tau)^2\right] + b_{q,c}(\ln q)(\ln c) + b_{q,\tau}(\ln q)(\ln \tau) + b_{c,\tau}(\ln c)(\ln \tau) \quad (6)$$

$$\ln q = a_{w_Q} \ln w_Q + a_{r_Q} \ln r_Q \quad (7)$$

$$c = p_B = p_F \quad (8)$$

We note here that all price variables in this model are indexes, with their values in 2000 equal to unity. Equation (8) illustrates our assumption that $p_B = p_F$. Given the definition of prices as indexes, this is equivalent to assuming that the prices of business travel and air freight will move in proportion to each other. The absence of terms of the power two in equation (7) embodies the Cobb-Douglas assumption of substitutability between capital and labor, in which the elasticity of substitution is –1.

The absence of quantity terms in equations (6), (7), and (8) embodies our assumption of constant returns to scale in the production of other goods and services (i.e., we assume that if input prices are unchanged and output increases, then all inputs would increase in the same proportion that output increases). This also implies assumption (6) given above that the elasticity of demand for all inputs with respect to output is unity.

The parameters of equations (6) and (7) are not free but are constrained by the relation that if all input prices increase by a given factor, then output price increases by the same factor. (This is an immediate consequence of the assumption of cost-minimizing behavior.) The implied constraints on the parameters of equations (6) and (7) are

$$a_q + a_c = 1 \quad (9)$$

$$b_{q,q} = b_{c,c} = -b_{q,c} \quad (10)$$

$$b_{q,\tau} = -b_{c,\tau} \quad (11)$$

$$a_{wQ} + a_{rQ} = 1 \qquad (12)$$

Subject to these constraints, we choose parameter values for equations (6) and (7) which lead to the elasticity values specified above, as well as being consistent with the actual values of inputs, outputs, and prices in 2000.

Roy's identity shows that the demand for inputs as a function of output level and input price is simply the partial derivative of the cost function with respect to input price. (See any graduate-level economics textbook—for example, Mas-Colell, Whinston, and Green (1995)—for a discussion of Roy's identity.) Thus the demand for the capital-labor composite and the air transportation composite goods can be represented as:

$$s_q = a_q + b_{q,q}(\ln q) + b_{q,c}(\ln c) + b_{q,\tau}(\ln \tau) \qquad (13)$$

$$s_c = a_c + b_{q,c}(\ln q) + b_{c,c}(\ln c) + b_{c,\tau}(\ln \tau) \qquad (14)$$

Here, s_q and s_c are the shares of the two composite goods, from which the demand levels are immediately recoverable. The production function (4) is also immediately recoverable from equations (13) and (14). Varying input cost ratios generates input-output ratios, which generate the unit isoquant of the production function. The unit isoquant itself generates, through the assumption of constant returns to scale, the entire production function.

We now turn to the production of air transportation services. For these sectors, we assume no substitutability among inputs, but fixed proportions at 2000 levels instead. We also assume that the proportions are the same for the three kinds of air transportation, as shown in Table A.1. This assumption implies that the prices of the three kinds of air transportation move in proportion, as illustrated in equation (8).

We chose this representation, with no substitution possibilities among labor, capital, and intermediate inputs, for the following reason. Many of our simulations imply substantial changes in the short-run ratio of labor to capital costs in the production of air transportation. In particular, sharp decreases in the short-run return to capital as costs rise. Our view of the technology for producing air transportation services is that there is very little short-run substitutability. In particular, as the short-run demand for air transportation falls, airlines cannot produce a lower level of output by fully utilizing the sunk capital stock and only reducing labor inputs—i.e., flying all the existing aircraft at the pre-2001 rate and using a sharply lower number of workers per airplane. Instead, our judgment is that in the short run, the decreases in capital utilization and labor are approximately proportional, which we represent as exactly proportional in this choice of production function functional form.

In summary, a production function with substantial capital-labor substitution would not properly represent short-run production possibilities as we understand them.

There may indeed be capital-labor substitution in the long run as aircraft designs can change. Thus, a production function with substantial capital-labor substitutability in the long run, but not in the short run, would be a reasonable modeling choice. However, in our simulations the long-run ratio of labor costs, adjusted for labor-saving technical progress, to capital costs does not change in the economy as a whole. Labor-saving technical progress occurs at the same rate in both air transportation and the rest of the economy in the model. Thus, in the long run in this model, airlines eventually face the same costs of labor and capital as the rest of the economy does. Introducing a production function with a long-run/short-run capital-labor substitutability distinction would not affect the results and was not therefore worth the additional modeling complexity in our judgment.

Consumption Relations

This section describes the "demand" side of the model.

The model includes a representation of consumer preferences for the amount and quality of personal air transportation. Quality is represented by average trip duration, represented by the variable τ, as defined above. It is meant to include all time costs of a trip, from the beginning of the transit to the airport to the arrival at the ultimate destination. We note that based on these preferences, the "willingness-to-pay" of the consumer to avoid air travel time delays can be calculated. Based on preferences for the amount and quality of air travel, a market demand curve can be derived.

Preferences of individuals in the economy for the amount and quality of air travel is represented in the model by a utility function. It indexes the economic well-being of individuals as a function of three variables. These are

(1) the amount of personal air travel consumed (C_T);

(2) time used for these trips (τ); and

(3) consumption of all other goods and services (C_Q).

Utility is increasing in variables (1) and (3) and decreasing in (2). As with the interpretation of τ in the production function, τ here is an exogenous variable in the utility index. Consumers take it as given and adjust their purchases in reaction to it. Consumers are thus assumed to allocate their total expenditure to maximize the index of utility, given the price and time length of air trips. Total expenditure is given by the expression $(1–s)GDP$. Here, s is the saving rate, and $(1–s)GDP$ is the value of consumption. As discussed above, s is taken as exogenous in this study.

As with our parameterization of the production function, we parameterize the utility function so that it results in certain numerical characteristics of market demand. Again, the

elasticities chosen here are meant to be representative of the values from the literature summarized in Table A.2 later in this appendix. We use the following specific elasticities in the simulations reported here (with a note on the rationale for each parameter choice):

(1) price elasticity of demand of –1.0. Table A.2, which summarizes empirical elasticity estimates, shows a wide range of estimates for this parameter, from –0.4 to –4.4. –1.0 represents our judgment of the central tendency of the estimates and was informally vetted with industry experts.

(2) income elasticity of demand of 1.3. Table A.2, which summarizes empirical elasticity estimates, also shows a wide range of estimates for this parameter, from 0.5 to 2.1. 1.3 represents our judgment of the central tendency of the estimates and was also informally vetted with industry experts.

(3) elasticity of travel demand with respect to trip time of –0.2. Table A.2, which summarizes empirical elasticity estimates, also shows a wide range of estimates for this parameter, from –0.1 to –1.8, although most estimates fall between –0.1 and –0.4. –0.2 represents our judgment of the central tendency of the estimates and was also informally vetted with industry experts.

We must choose a utility functional form with enough flexibility to simultaneously lead to all the above numerical implications. The commonly used Cobb-Douglas form is not a possible choice since it implies unitary income elasticities for all purchased items; we require a nonhomothetic form to generate the nonunitary income elasticity. We choose the addilog functional form, introduced by Houthakker (1960). Recent applications of this function form are Ogaki (1992) and Clarida (1996), who were also analyzing economic quantities—in these cases food consumption and imports, respectively—that may have nonunitary income elasticities. We chose it because of the intuitive appeal of representing the amount of time spent *not* in air travel as a good, just as air travel services and other goods and services are. The functional form is:

$$U = \frac{\alpha C_T^{(1-\sigma)}}{(1-\sigma)} + \frac{\beta(1-\tau C_T)^{(1-\gamma)}}{(1-\gamma)} + \frac{C_Q^{(1-\rho)}}{(1-\rho)} \qquad (15)$$

α, β, σ, γ, and ρ are parameters. The scaling of τ is chosen so that $(1 - \tau C_T)$ represents the proportion of available time spent not in air travel. Because τ is simply an index in the production relations, the same scaling can be used for them without loss of generality. As discussed above, we assume that consumers took 230 million trips in 2000 and that each trip took 270 minutes. Thus the total time used in trips was assumed to be 1,035 hours. We assumed a total time availability for consumption of 2,200 hours per year per person, and our measure of "persons" in 2000 is simply the U.S. population of 280 million. Thus personal air travel in 2000 was assumed to require .00167 of total time available for

consumption, and this is the value of $(1 - \tau C_T)$ assumed for 2000 in calibrating the model. The assumptions about total time available are admittedly arbitrary. However, at the low levels of time usage in these simulations, the elasticities are the primary drivers of the results, not the initial conditions.

Consumers are assumed to maximize utility function (15) subject to the budget constraint

$$(1 - s)GDP = p_T C_T + p_Q C_Q \quad (16)$$

This, together with equation (3), implies that $s(GDP)$ is the value of investment, which is $p_Q (I_Q)$.

Given that consumers maximize the utility indicator (15) subject to the income constraint (16), the demand for trips will be a function of the price of trips, trip time, and total expenditure. This demand function can be derived from the Lagrangian expression.

$$\Lambda = \frac{\alpha C_T^{(1-\sigma)}}{(1-\sigma)} + \frac{\beta (1 - \tau C_T)^{(1-\gamma)}}{(1-\gamma)} + \frac{C_Q^{(1-\rho)}}{(1-\rho)} + \lambda((1 - s)GDP - p_T C_T - p_Q C_Q) \quad (17)$$

The first-order conditions for a maximum are

$$\frac{\partial \Lambda}{\partial C_T} = \alpha C_T^{-\sigma} - \tau\beta(1 - \tau C_T)^{-\gamma} - \lambda p_T = 0 \quad (18)$$

$$\frac{\partial \Lambda}{\partial C_Q} = C_Q^{-\rho} - \lambda p_Q = 0 \quad (19)$$

$$\frac{\partial \Lambda}{\partial \lambda} = (1 - s)GDP - p_T C_T - p_Q C_Q \quad (20)$$

Combining these expressions gives the (implicit) demand function

$$\frac{\alpha C_T^{-\sigma} - \tau\beta(1 - \tau C_T)^{-\gamma}}{(p_T / p_Q)} = \left[\frac{(1 - s)(GDP - p_T C_T)}{p_Q} \right]^{-\rho} \qquad (21)$$

in which C_T is (implicitly) a function of p_T, p_Q, τ, and expenditure $((1-s)GDP)$.

Model Equilibrium

This section describes the conditions of market equilibrium in the model. The model finds a set of prices of all outputs and inputs for which supply and demand are equated in all markets.

The model is solved on an annual basis. Labor is assumed to be transferable across sectors over this time period, so the overall unemployment rate in the economy is assumed to be unaffected by the kinds of changes simulated in the model. This assumption could usefully be generalized in future work; its reasonableness in this case will be discussed with the results shown below. This assumption implies that *relative* wages among various labor categories will vary proportionately. As Table A.1 shows, wages in the air transportation sector are substantially above those in the rest of the economy, about 40 percent higher. (The wage rate shown in Table A.1 is the *gross wage*, including fringe benefits and payroll taxes.) This wage rate differential is assumed to reflect higher productivity on the part of workers currently in the air transport industry, and they are assumed to retain that productivity advantage if they move to other sectors. This assumption could also reasonably be varied in future work. It is especially suspect in the case of pilots.

Capital is assumed *not* to be transferable across sectors after it has been installed. As long as capital stocks are growing in all sectors, the rate of return will be equalized in them. However, if no gross investment in any given sector occurs, its rate of return will fall below that in the rest of the economy. Gross investment is assumed to be 18 percent of total GDP, consistent with the 1990s experience. The underlying rate of growth in the economy is assumed to be the same as that projected in the *Economic Report of the President, 2002*. This is an underlying growth rate of 3 percent per year, based on employment growth of 1 percent and labor productivity growth of 2 percent. This is consistent with a long-run rate of growth of real per capita GDP of 2 percent as well.

Actually solving the model is quite simple given its simple structure. We begin with an initial guess of labor and capital prices. These immediately imply the level of GDP because GDP equals factor income, and imply product prices through the cost functions, because there are no quantity variables in the cost functions, stemming from the constant-returns-to-scale assumptions. The level of GDP and the product prices imply final demand through the consumption and investment relations, which imply total output through the input-output

structure, which implies factor demand through the input demand functions. If factor demand equals factor supply, this is a general equilibrium. If not, labor and capital prices are adjusted as a function of the ratio of demand to supply of the relevant factor, and in practice the general equilibrium set of prices and quantities is found very quickly.

MODEL RESULTS

The main text of this briefing shows the results of changing air transportation resource and time costs in the model to represent the baggage-screening policy options being assessed. Here, we present the results of some gross changes in overall parameters to illustrate more vividly how the model responds to changes in parameter assumptions.

We first illustrate the results of a very large increase in the cost of providing air transportation. Figure A.1 shows the impact of a 100 percent increase in the amount of nonlabor and capital resources needed to produce a unit of air transportation. In model terms, this is a 100 percent increase in the ratio of $X_{Q,k}$ to X_k in the fixed-proportions production function for X_k, $k = B$, T, and F. As Table A.1 indicates, the ratio of the value of these nonlabor and capital resources to the value of the total output of air transportation services is about 50 percent. Therefore, this amounts in general terms to a 50 percent increase in the cost of air transportation.

Model results are shown in terms of "willingness-to-pay" to avoid this result. They are literally the value of nonair transportation goods and services that consumers in the economy would be willing to give up, based on preference function (15), in return for not suffering the consequences of the cost increase postulated. These results are in dollars of 2003 purchasing power. The results begin in the year 2003. The base case assumption is that nominal GDP will be $11.2 trillion, which is from the projection from the *Economic Report of the President, 2002*. It is assumed that air travel will have recovered so that its ratio to real GDP is the same as it was in 2000—i.e., that it will have grown 6 percent from its 2000 level by 2003. Because actual air transportation in summer 2002 was about 8 percent below the 2000 level, this assumes a robust recovery of air transportation.

Figure A.1 shows that the annual overall cost to the economy of this increase in air transportation costs is about $60 billion in 2003, growing by about a factor of three by the last year of the analysis, 2033. This factor of three represents an almost 4 percent annual growth. This is more than the 3 percent underlying growth in the economy as a whole because of the consumer income elasticity of demand of more than one. Personal air transportation becomes more important as the economy grows, so the penalty of cost increases in it grows relative to the overall economy.

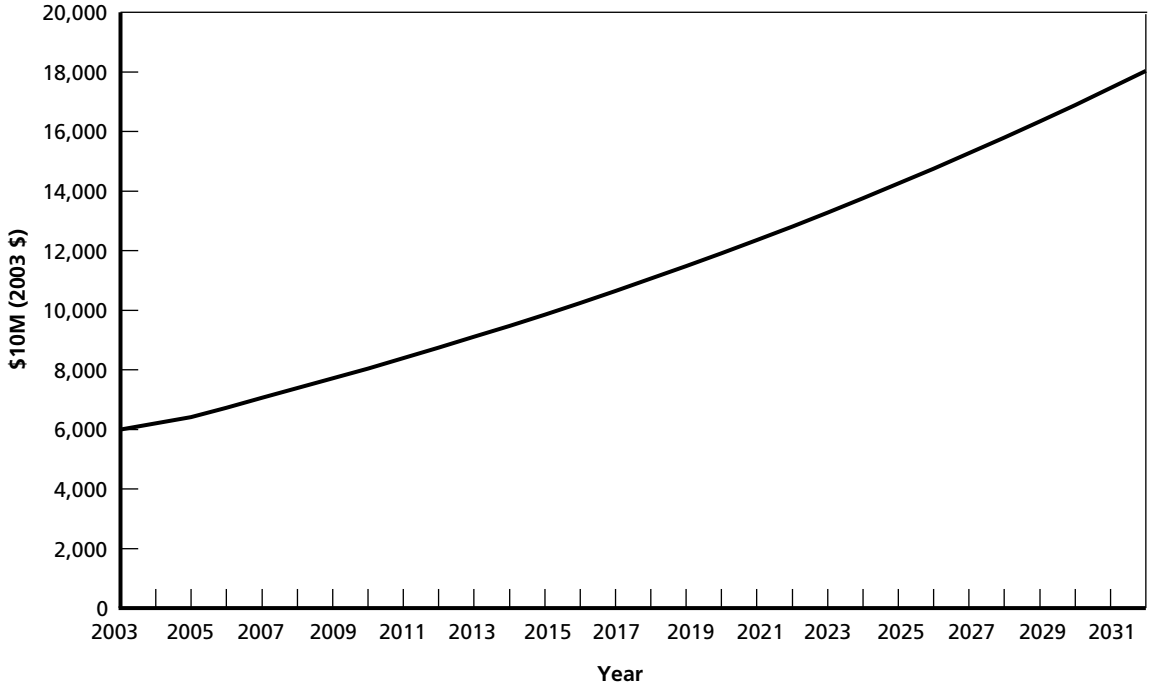

Figure A.1—Value of Avoiding 50 Percent Air Transport Cost

We note that the $60 billion penalty in 2003 is not markedly different from 50 percent of overall airline revenues, meaning that the estimated penalty to the economy is roughly the same as a more simple measure of the penalty—namely the percentage cost increase applied to total revenue.

The sectoral implications are striking. Figure A.2 shows estimated employment in the air transportation industry in both the base case (no cost increase) and in the case of the 50 percent cost increase. It shows a dramatic decrease of about 200,000 in air transportation employment between the two cases, and employment does not reach its base case 2003 level (about 700,000) in the higher cost case until around 2030. The underlying employment trend is 1 percent annual growth because airline workers in the model are assumed to have the same productivity increase as those in the rest of the economy. This assumption could usefully be investigated further in future work.

As discussed above, the overall unemployment rate in the economy is *not* assumed in this simulation to change in the face of this decrease in air transport employment. (Although the model could be easily modified to show the effects of differing assumptions about this issue.) While 200,000 is a large number of jobs, it should be viewed in the context of the 300,000 to 400,000 *weekly* initial unemployment insurance claims in the U.S. economy. This

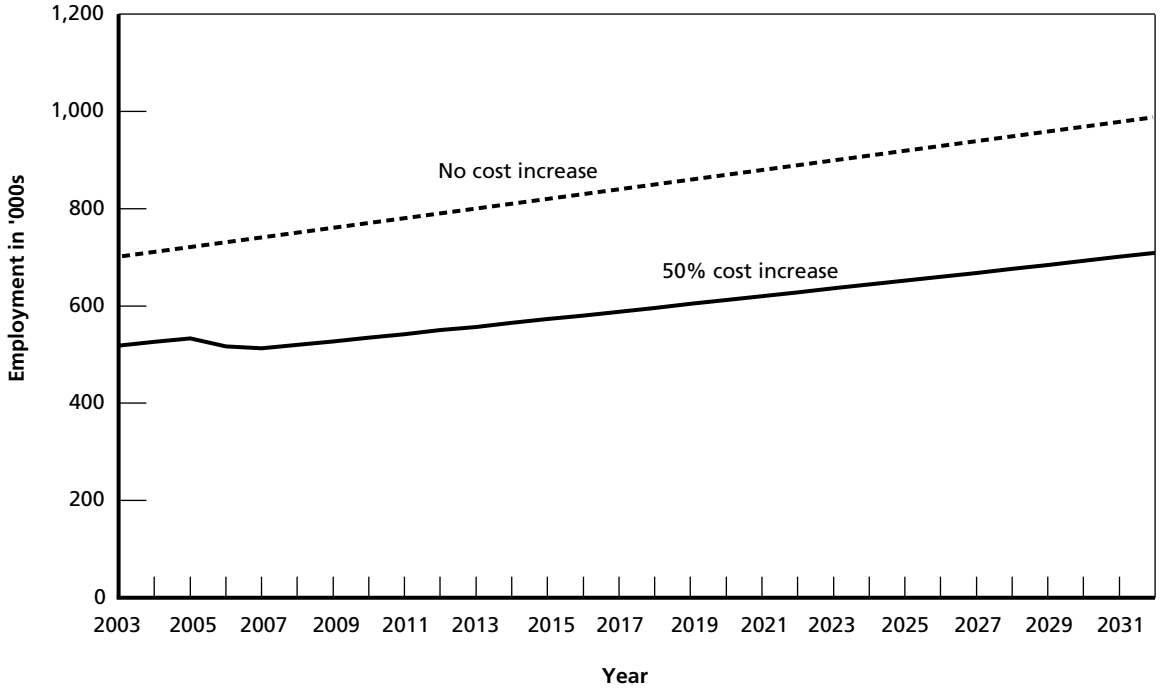

Figure A.2—The Effect of Air Transport Employment of a 50 Percent Cost Increase

300,000 to 400,000 is in fact much less than those who are newly seeking work in any week because it excludes new job entrants, reentrants, and those who do not apply for unemployment insurance because they either voluntarily left their previous job or are otherwise ineligible for it. In addition, airline jobs are spread evenly across the country, so no regional concentration of unemployment would be expected. The 200,000 job losses in air transport are thus less than 1 percent of new job seekers on an annual basis, and this is the reason we do not model it as leading to an increase in the unemployment rate. Exploring this assumption further would be a worthwhile extension of the analysis.

The second dip in employment in 2006–2007 stems from air transport prices that rise somewhat in those years as airlines return to profitability. Airline profits in the model fall to zero in 2003–2005 as a result of the cost increase, as price elasticities drive down traffic in the face of the resulting price increases. The underlying growth in the economy allows a return to profitability in 2006–2007, with a modest attendant price increase.

This is illustrated further in Figure A.3, which shows gross investment done by the air transportation industry in both the base and the increased cost cases. It shows zero gross investment until 2007, at which time profitability rises to a level at which new investment would be made. Gross investment by the air transport industry consists of many general-

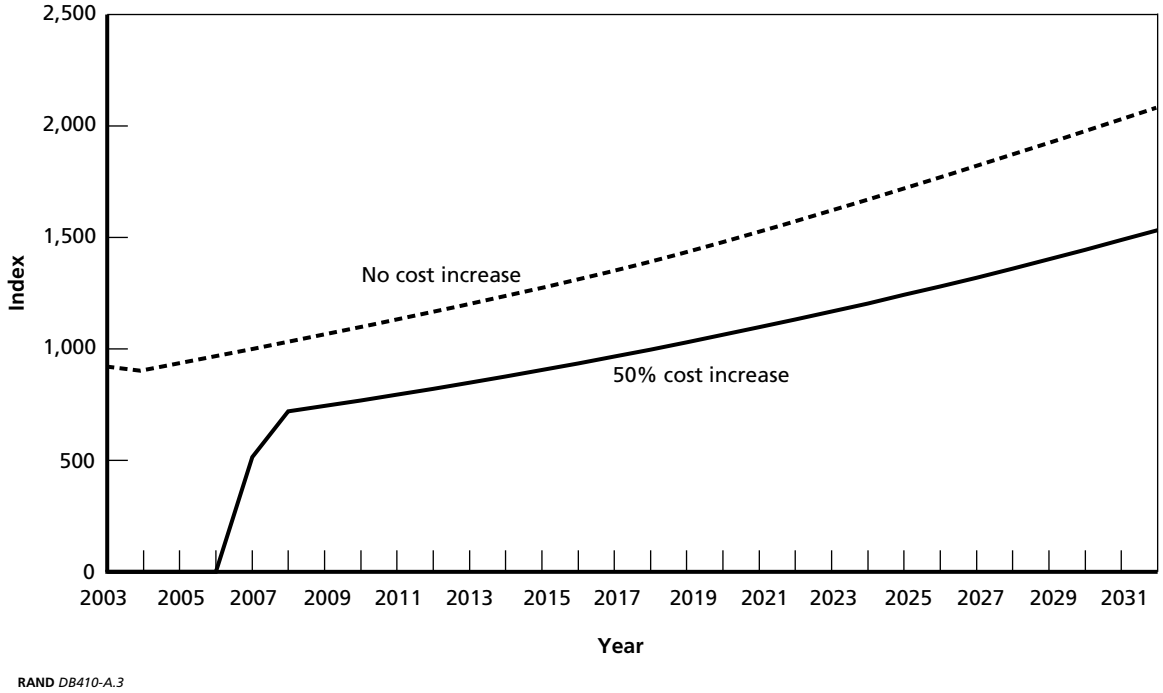

Figure A.3—The Effect on Air Transport Gross Investment of a 50 Percent Cost Increase

purpose investment goods, such as computers and structures, but it is of course dominated by aircraft purchases. The model literally predicts no new aircraft purchases for four years as a result of this cost increase and the resulting decrease in traffic. This is a standard result of microeconomic modeling—namely, that no investment flows into an industry unless its rate of return is at least at the economywide level. A more sophisticated approach could be taken, which recognizes more completely how airlines might smooth their purchases over time, and it might not show such a drastic result. A more detailed approach would be useful for further work in this area. Nevertheless, the basic thrust of the model, that new investment would be seriously decreased by such a cost increase, is correct. Here, the unemployment effects might be more pronounced than the direct effects of airline employees being laid off because the aircraft industry is much more geographically concentrated, particularly in the Seattle area. Again, more research in this area would be useful in future work.

We next addressed the issue of how any cost increase associated with air transport would be financed. All the results to date have assumed that the increased costs would be directly borne by the airlines and only recoverable by them by increasing their prices. In the model, they do indeed increase their prices because no other source of financing for these costs exists. We did an alternate analysis with the model, in which the costs were borne by the U.S. government and not passed on to users of air transportation. In the model, these costs were financed by a lump-sum tax on all income. As Figure A.4 shows, this leads to a higher

overall cost to the economy. This is for two reasons. First, because users of air transportation do not pay the cost, the use of air transportation is not reduced, so a higher overall cost is incurred. Second, an inefficiency is introduced into the economy when the cost increase is centrally financed. In this case, both business and personal users of air transportation face a price below its true cost. When deciding whether to buy air transportation or other goods and services, they therefore use more air transportation than is socially optimal, making decisions on the basis of too low a price. The difference is relatively low in the first few years because this policy avoids the underutilization of the airline capital stock for the first two years, until the airlines return to profitability.

The policy of central financing does avoid the specific sectoral employment and investment consequences, since the industry is sheltered from the cost increase. Figures A.5 and A.6 show air transport employment and gross investment, respectively, under the base case; the 50 percent cost increase case borne by airlines and users of air transport; and the 50 percent cost increase financed by the government (called "Equivalent General Tax" on these charts). Base case and government-financed cost increase cases are almost identical because relative prices of air transport and other goods and services are not directly affected. There is a

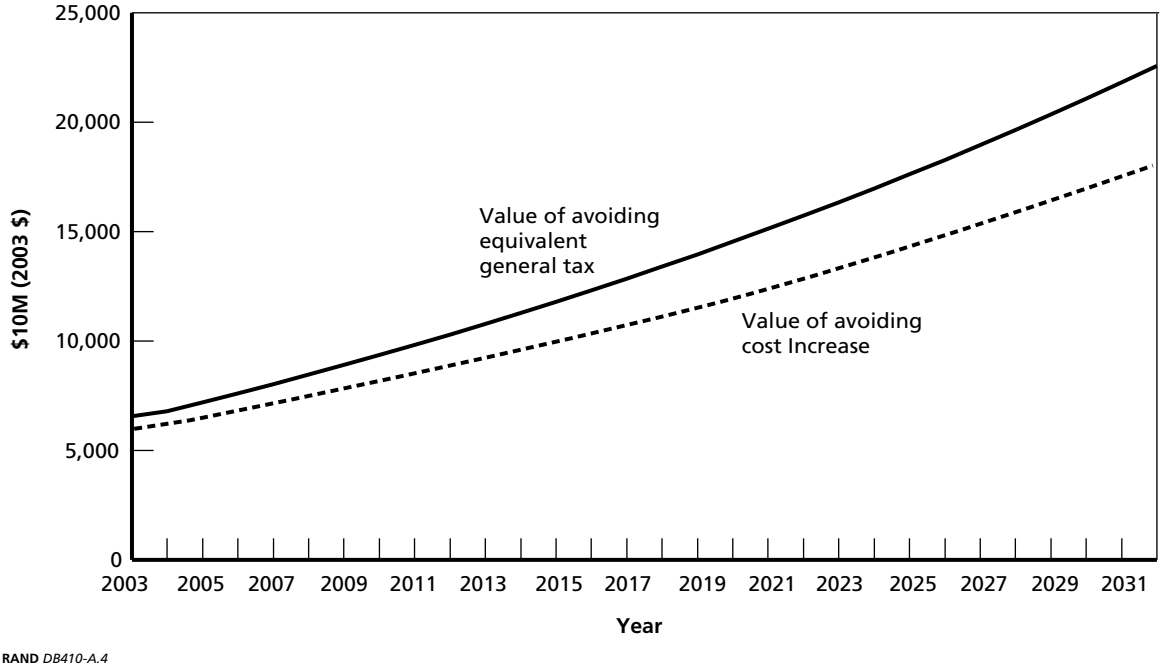

Figure A.4—Values of Alternate Policies

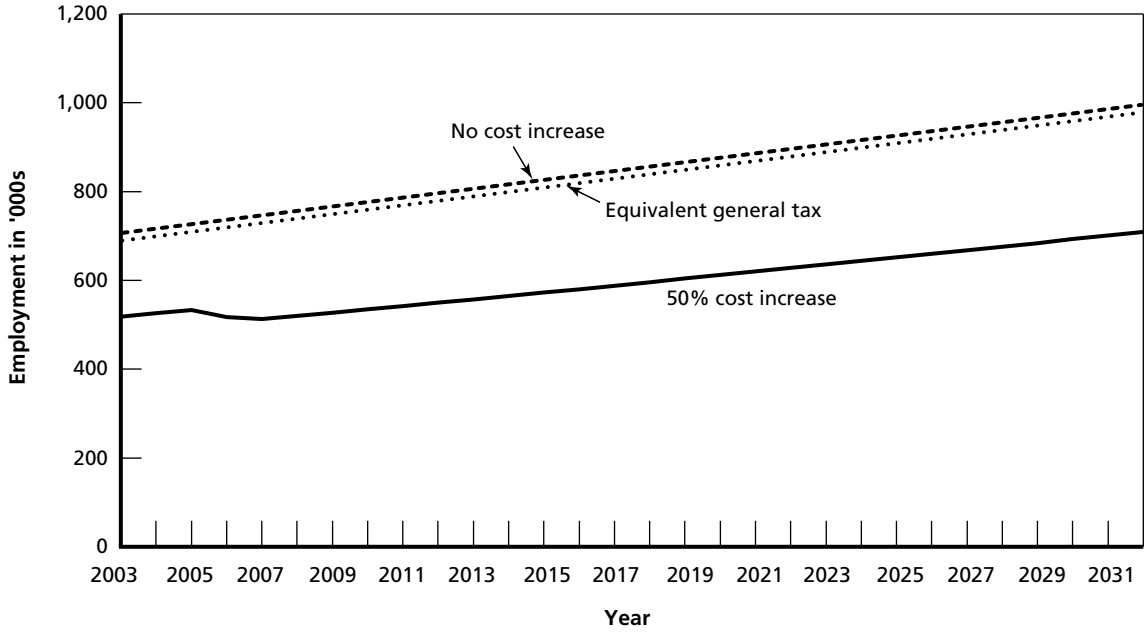

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Figure A.5—Air Transport Employment Under Alternate Policies

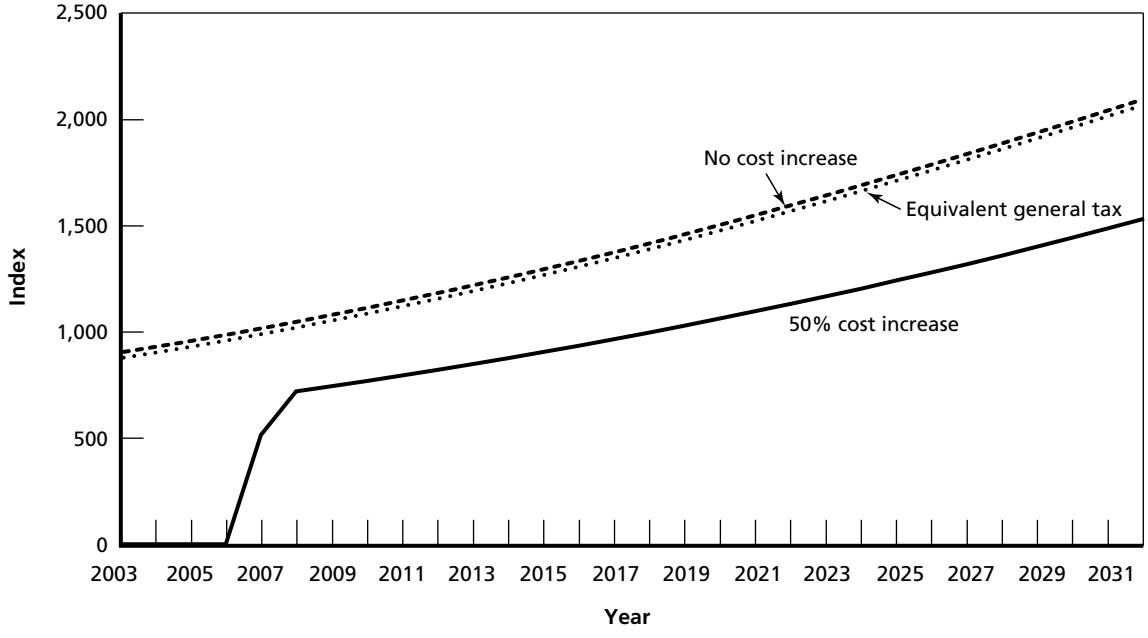

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Figure A.6—Air Transport Gross Investment Under Alternate Policies

minimal decrease in air transport, and thus employment and gross investment, simply because overall disposable income is down because of the tax increase. But this difference is small indeed, amounting to about one-half of 1 percent of employment, and a similar figure for investment after the first year. In the first year, the impact on investment is somewhat greater, stemming from a one-time shift of capital to the sectors producing the extra inputs for air transportation.

Just as centrally financing an actual cost increase in air transportation leads to efficiency losses, so would financing through air transport fees a cost not related to the volume of air travel. If the government were to undertake some policy measures whose cost is truly fixed, in the sense that it does not vary with the amount of air transport used, then it is most efficient to finance this centrally. There is an efficiency loss associated with making users of air transport bear it. This is because efficiency is maximized when users face a price equal to the *marginal* cost of the product they are purchasing. If the cost of the policy initiative is unrelated to the level of air travel (such as a new intelligence effort directed at those who would threaten air travel), then financing it through prices charged to air transport users leads to efficiency losses.

Figure A.7 illustrates this. It shows the cost to the economy of undertaking a given policy initiative, whose level is independent of air travel, under conditions of both central financing and financing through air transport prices. The former cost is below the latter for the reasons explained above. The cost divergence here is greatest in the early years because the underutilization of airline capital stock in the early years after an air transport price increase here exacerbates the overall efficiency loss. (The specific policy modeled here is assumed to have a cost equal to the additional costs associated with Figure A.1 for ease of comparison. Again, we assume that the central financing is through a lump-sum tax on all income. There is no specific rationale behind this cost because it is by assumption no longer related to the level of air transport.)

In addition, financing a policy whose cost does not vary with air transport volume with air transport taxes has the additional disadvantages of leading to the major sectoral disruptions shown in Figures A.2 and A.3. We have not specifically included their costs here for the reasons given above, but further work would be warranted to improve our understanding of their magnitudes, as also indicated above.

To show the sensitivity of our results to changes in numerical parameters, we show Figures A.8 and A.9, which add to Figures A.2 and A.3 the results of a case of a 30 percent increase in the ratio of $X_{Q,k}$ to X_k in the fixed-proportions production function for X_k, $k = B, T$, and F. We label this the "15 percent cost increase" case. (For precision, we note that the ratio of $X_{Q,k}$ to X_k in Table A.1 is actually 53.4 percent, so we are using the term "cost increase" loosely in labeling these cases. The actual cost increase also varies as a result of airline profitability and the wage rate. The cases are strictly defined by the changes in the fixed-proportions production functions as defined above.)

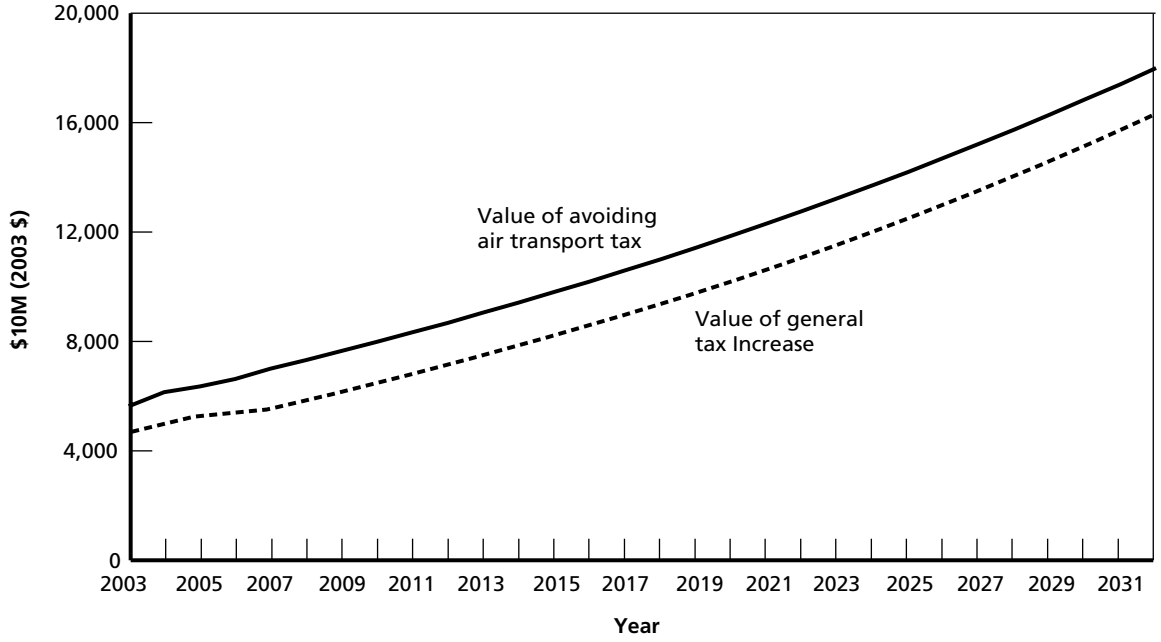

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Figure A.7—Value of Alternate Policies

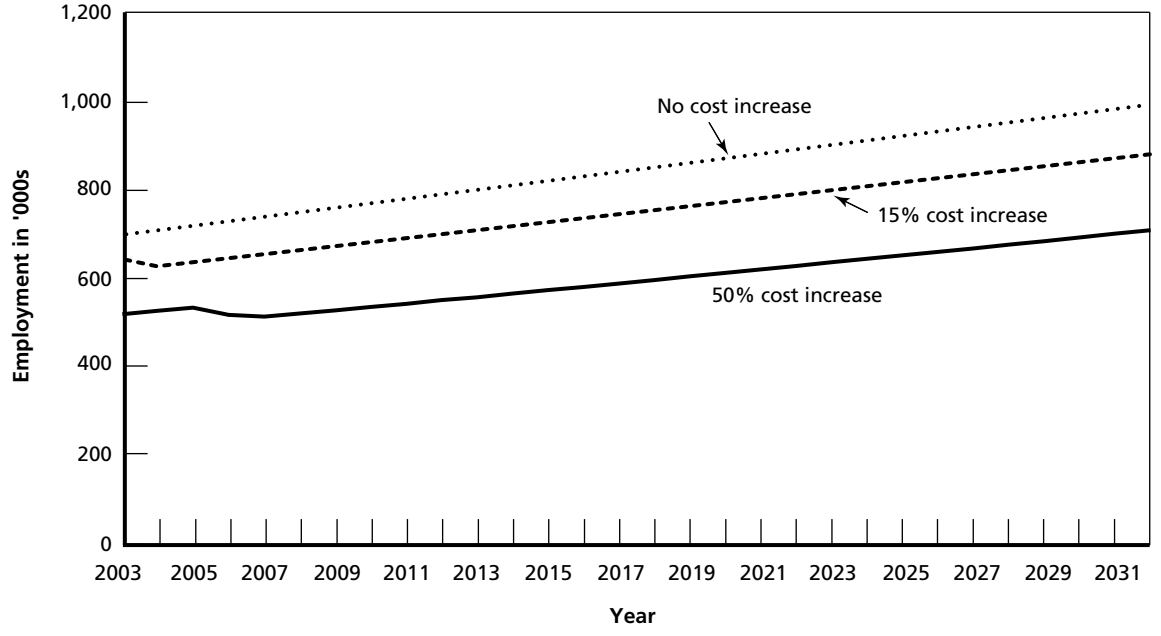

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Figure A.8—Air Transport Employment Under Alternate Cost Increase

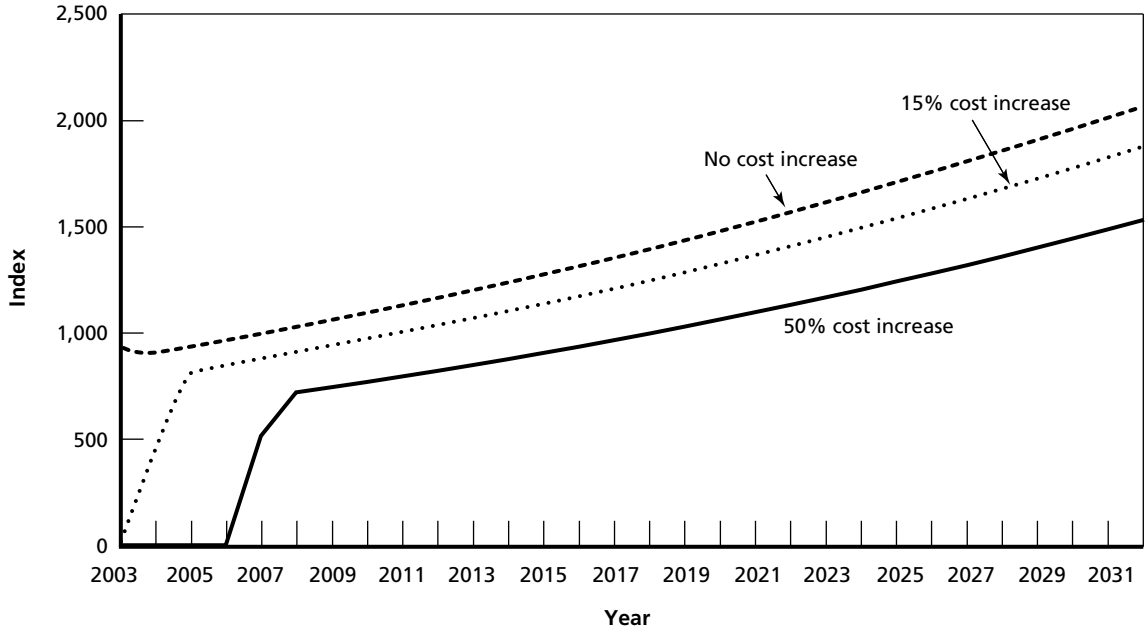

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Figure A.9—Air Transport Gross Investment Under Alternate Cost Increases

The change in employment is more or less proportional to the change in cost increase. The behavior of gross investment is qualitatively different, as it only takes until 2004 for a return to profitability and a positive level of gross investment.

The model can also be used to assess the impact of a change in trip duration, represented by the index variable τ. (This index also represents the duration of the air freight process in the model. In future work, a separate representation of passenger and air freight trip duration would be useful.) An increase of 50 percent in trip duration has overall effects not qualitatively dissimilar from the "30 percent cost increase" case in terms of impacts on employment and gross investment. Willingness to pay to avoid such a change in trip duration begins at about half the level associated with the "50 percent cost increase" case but grows at about 5 percent per year rather than 4 percent. This is a direct result of the limited ability to substitute away from the longer-duration trips, as embodied in the relatively low elasticity estimates. Of course, the numerical impacts of these effects depend very dramatically on *all* the assumed elasticities of output and business and personal air transportation use with respect to trip duration. As can be seen in the annex, these are economic magnitudes for which relatively few estimates exist in the literature, so there is substantial uncertainty about their true values. There is corresponding uncertainty about the value of avoiding increases in trip duration. Here again, more work would be very helpful in informing policy decisions.

PROMISING AREAS FOR FURTHER RESEARCH

In the kind of economic model used here, decisions about employment and gross investment are based on current levels of output, and many of the frictions and adaptive processes of the real world are abstracted from it. Econometric work to measure how employment and investment flows have actually varied in the air transportation industry would be useful here.

Additional sectoral detail would lead to more kinds of policy insights. Specific representation of the aircraft manufacturing industry; other transportation sectors; travel-related sectors, such as hotels and restaurants; and the security industry are all interesting candidates.

ANNEX

A SURVEY OF DEMAND ELASTICITIES FOR COMMERCIAL AIR TRAVEL

One of the key features of most economic models of commercial air travel is the treatment of the relationships between various travel characteristics, such as price, frequency of departure, or the time involved in travel, and the demand for air travel. In economics parlance, a percentage change in a travel characteristic that is associated with a percentage change in travel demand is called the elasticity of demand with respect to that characteristic. Numerically, these percentage changes are expressed as a ratio, with the travel characteristic percentage on the bottom. For example, if a 1 percent increase in price leads to a 2 percent decrease in demand, then the elasticity of demand with respect to price is equal to (–2)/1, or –2. A positive elasticity means that when the characteristic increases, demand increases as well. A negative elasticity means that the travel characteristic and demand move in opposite direction, when one increases the other decreases. Therefore, given our example above, a 10 percent increase in price would be expected to lead to a –2 times 10 percent, or –20 percent, increase in travel demand—i.e., a 20 percent *decrease* in travel demand. These estimates of demand elasticities inform many of our calculations, and this section of the briefing surveys the elasticities found in the economics literature.

Table A.2 lists a number of different elasticity estimates from the literature for a variety of travel characteristics. This draws in part on work done by the Federal Aviation Administration for a 1995 report to Congress (U.S. Department of Transportation (1995)). Elasticity estimates often vary, frequently depending on the sample from which the estimate was made. Different periods in time, geographical locations, and traveler demographics can all affect an elasticity value. The challenge is to understand how these estimates may (or may not) be valid when applied to a new time, place, or group of people. The other important consideration is what other factors were controlled for when the estimate was made. A study that analyzes several factors that influence demand at the same time is likely to find that each factor has a smaller influence on demand than a study that includes only a single factor in its analysis.

Price elasticities are the most commonly estimated and most important of the travel demand elasticities. These elasticities depend greatly on the passenger sample from which the estimate was made. The smallest and largest price elasticity estimates listed in the table vary by more than an order of magnitude. The estimates range from the Morrison and Winston (1985) value of –0.180 for business travel pre-deregulation, based on a U.S. intercity

passenger transportation demand model with frequency and travel time variables included in the analysis, to the Royal Commission on National Passenger Transportation (1992) value of –4.5 for nonbusiness, low-income travelers. Looking across the estimates, we can generalize that business travel is less responsive to price than leisure travel and low-income travelers are more responsive to price than high-income travelers. The Royal Commission on National Passenger Transportation (1992) study of Canadian transportation stands as the outlier in the group. Studies that incorporate multiple air travel characteristics in a mode choice model usually have lower price elasticities than market demand studies that may use only a single measure. Oum, Waters, and Yong (1992) did a survey of the literature and found that the majority of estimates fell between –0.8 and –2.0. Work published since then has generally been in that range or lower, spanning –0.48 to –1.58. Morrison and Winston (1996) take –0.7 as a rule-of-thumb value and argue that it is consistent with the elasticities implied by their model.

Income elasticities measure the change in travel when incomes change, and unlike the price elasticities, these are grouped somewhat more narrowly. Three out of the four studies in Table A.2 have estimates that are 1.0 or above, and these values appear to have held up to scrutiny since 1981.

The remaining elasticities all involve time of one sort or another. Pels, Nijkamp, and Rietveld (2001) provide an estimate of access time elasticity in a study of groundside transport time to get to airports in the San Francisco Bay Area. This elasticity would most closely capture changes in wait times stemming from enhanced security measures. Other time measures related directly to the air travel portion include measures of travel time, wait time between departures, and flight frequency. For travel time and frequency elasticities, Mandel, Gaudry, and Rothengatter (1997) appears to be the outlier. These measures matter more for analysis of flight delays and changes in scheduling as a result of congestion or changes in demand.

Table A.2

Elasticity Estimates for a Variety of Travel Characteristics

Study	With Respect to What?	Value	Range	Comments
Morrison and Winston (1996)	Price	–0.7		Cited as rule of thumb, and consistent with implied elasticity in model
Apogee Research Inc. (1994)	Price	–1.10	–0.86 to –1.21	Nonbusiness
Apogee Research Inc. (1994)	Price	–0.59	–0.58 to –0.61	Business
Royal Commission on National Passenger Transportation (1992)	Price	–3.51		Business, low-income
Royal Commission on National Passenger Transportation (1992)	Price	–1.57		Business, high-income
Royal Commission on National Passenger Transportation (1992)	Price	–4.50		Nonbusiness, low-income
Royal Commission on National Passenger Transportation (1992)	Price	–4.38		Nonbusiness, high-income
Oum, Gillen, and Noble (1986)	Price		–0.6 to –0.8	First class
Oum, Gillen, and Noble (1986)	Price		–1.2 to –1.4	Standard economy
Oum, Gillen, and Noble (1986)	Price		–1.5 to –2.0	Discount economy
Oum, Zhang, and Zhang (1993)	Price	–1.58	–1.24 to –2.34	Used 20 city pairs; no correlation between trip distance and price elasticity
Oum, Waters, and Yong (1992)	Price	–1.52		Leisure travel; based on survey of two studies
Oum, Waters, and Yong (1992)	Price	–1.15		Business travel; based on survey of two studies
Oum, Waters, and Yong (1992)	Price		–0.76 to –4.51	General; based on survey of 11 studies; majority fall within –0.8 to –2.0 range
Borenstein and Zimmerman (1988)	Price		–0.50 to –0.63	Passenger mile demand based on 1978–1985 sample
Morrison and Winston (1985)	Price	–0.378		Pleasure travel; based on pre-deregulation intercity travel demand model
Morrison and Winston (1985)	Price	–0.180		Business travel; based on pre-deregulation intercity travel demand model
Mandel, Gaudry, and Rothengatter (1997)	Price		–0.62 to –0.69	Model for Germany 1979–1980; Box-Cox Logit Model of intercity travel

Table A.2—continued

Study	With Respect to What?	Value	Range	Comments
Wingrove et al. (1998)	Price		–0.95 to –1.39	U.S. 1985–1994; for scheduled major, national, regional, and shuttle operations with competition
Dresner, Lin, and Windle (1996)	Price		–0.48 to –0.53	Passenger demand model for U.S., early 1990s
Russon and Riley (1993)	Income	1.833		Model for travel up to 650 miles, southeast U.S., 1985 data
Wingrove et al. (1998)	Income	2.069		U.S. 1985–1994; passenger mile
Borenstein and Zimmerman (1988)	Income		0.46 to 1.38	Passenger mile demand based on 1978–1985 sample
Nesbit (1981)	Income		1.5 to 2.0	No specific empirical work cited, but expressed as range favored by forecasters
Pels, Nijkamp, and Rietveld (2001)	Access Time		–0.12 to –0.37	Business passengers in San Francisco Bay Area; based on airport/airline choice model; no prices in choice
Pels, Nijkamp, and Rietveld (2001)	Access Time		–0.12 to –0.32	Leisure passengers in San Francisco Bay Area; based on airport/airline choice model; no prices in choice
Morrison and Winston (1985)	Travel Time	–0.434		Pleasure travel; based on pre-deregulation intercity travel demand model
Morrison and Winston (1985)	Travel Time	–0.158		Business travel; based on pre-deregulation intercity travel demand model
Mandel, Gaudry, and Rothengatter (1997)	Travel Time		–1.69 to –1.79	Model for Germany 1979–1980; Box-Cox Logit Model of intercity travel
Morrison and Winston (1985)	Time between Departures	–0.047		Pleasure travel; based on pre-deregulation intercity travel demand model
Morrison and Winston (1985)	Time between Departures	–0.206		Business travel; based on pre-deregulation intercity travel demand model
Pels, Nijkamp, and Rietveld (2001)	Frequency		0.64 to 0.72	Business passengers in San Francisco Bay Area; based on airport/airline choice model; no prices in choice
Pels, Nijkamp, and Rietveld (2001)	Frequency		0.55 to 0.71	Leisure passengers in San Francisco Bay Area; based on airport/airline choice model; no prices in choice
Mandel, Gaudry, and Rothengatter (1997)	Frequency		0.10 to 0.16	Model for Germany 1979–1980; Box-Cox Logit Model of intercity travel
Russon and Riley (1993)	Frequency	0.813		Model for travel up to 650 miles, southeast U.S., 1985 data

APPENDIX B:
PASSENGER DELAYS TRANSITING THE AIRPORT AND THEIR IMPACT ON SIZING THE EDS BUY

Other Passenger Delays and What They Imply for Sizing the EDS Deployment

- Other passenger delays transiting the airport include
  - Ticket counter check-in lines
  - Passenger screening stations
- Ticket counter check-in delays may or may not affect our results
  - These delays essentially meter the flow of bags to be checked, thus smoothing the baggage flow into the scanning area
    - Baggage check-in delays are thus modified, but total passenger delays may actually be greater
  - If delays are partially caused by passengers without bags to be checked, then total delays will be greater, but optimal buy size may be smaller
- Delays caused by passenger screening stations are unrelated to baggage delays; the greater of the two will determine total passenger delays
- The following figures address passenger screening delays and how they modify the optimum baggage-scanning equipment buy size

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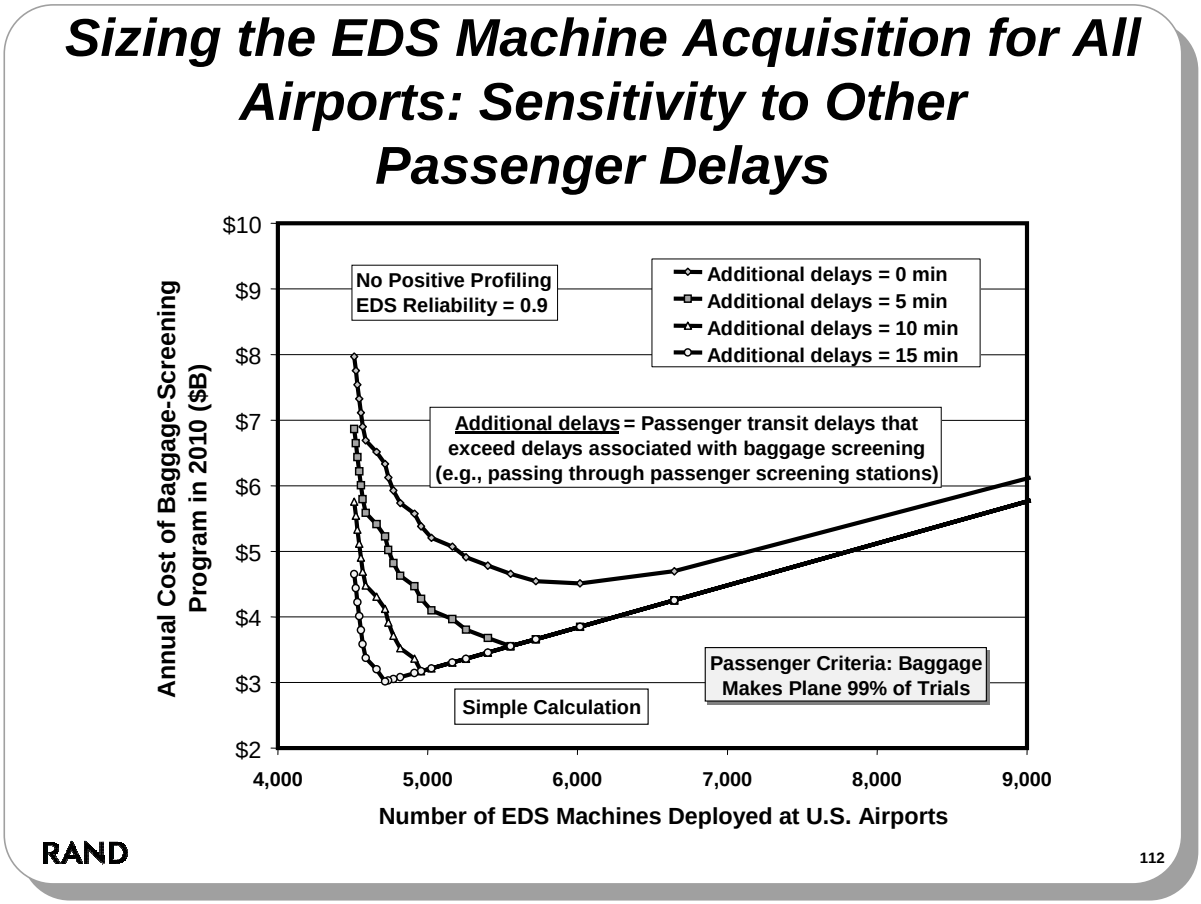
The briefing made an implicit assumption that baggage-scanning delays dominate over other passenger delays. This might not be true, in which case, the optimum buy size would be modified. The purpose of this appendix is to examine how much modification is likely—that is, is this a big deal or is it just a curiosity.

This figures points out two delays common to all passengers bringing baggage to be checked at the airport. The first is the waiting line associated with getting the baggage checked. This line could be at the curb or at the ticket counter. For the purposes of this appendix it does not matter. In both cases, the waiting line for getting the bags checked occurs before the bags are put into the baggage-scanning queue, and thus the delays are added to those in that queue. Counterbalancing this additional delay is the observation that the waiting line essentially moderates the arrival of the bags into the scanning queue, essentially lowering the peaks (and raising the valleys) of the input flow. The natural consequence would be a lowering of the maximum queues, but with only a small impact on the average delays. It is clearly best for the passenger to never encounter delays prior to checking the bags, so we judge that any impact on baggage-scanning size requirements are likely to be minimal.

The second delay is the waiting to pass through the passenger screening stations. This delay occurs after the baggage check in, and thus does not affect the baggage queues.

However, if the extent of the screening station delays is large, then the passengers total transit time from the baggage check-in to the gate may exceed the 30 minutes that we assumed as minimal for the checked baggage to confidently get onto the plane. Assuming that the passenger's planned arrival time took this screening delay into account, any time greater than the nominal 45 minutes (30 minutes nominal plus 15 minutes to hedge against delays in arrival because of traffic or whatever) should be attributable to screening delays and not baggage delays. The results would be a greater tolerance for baggage delays and thus a somewhat lower requirement for EDS machine deployments.

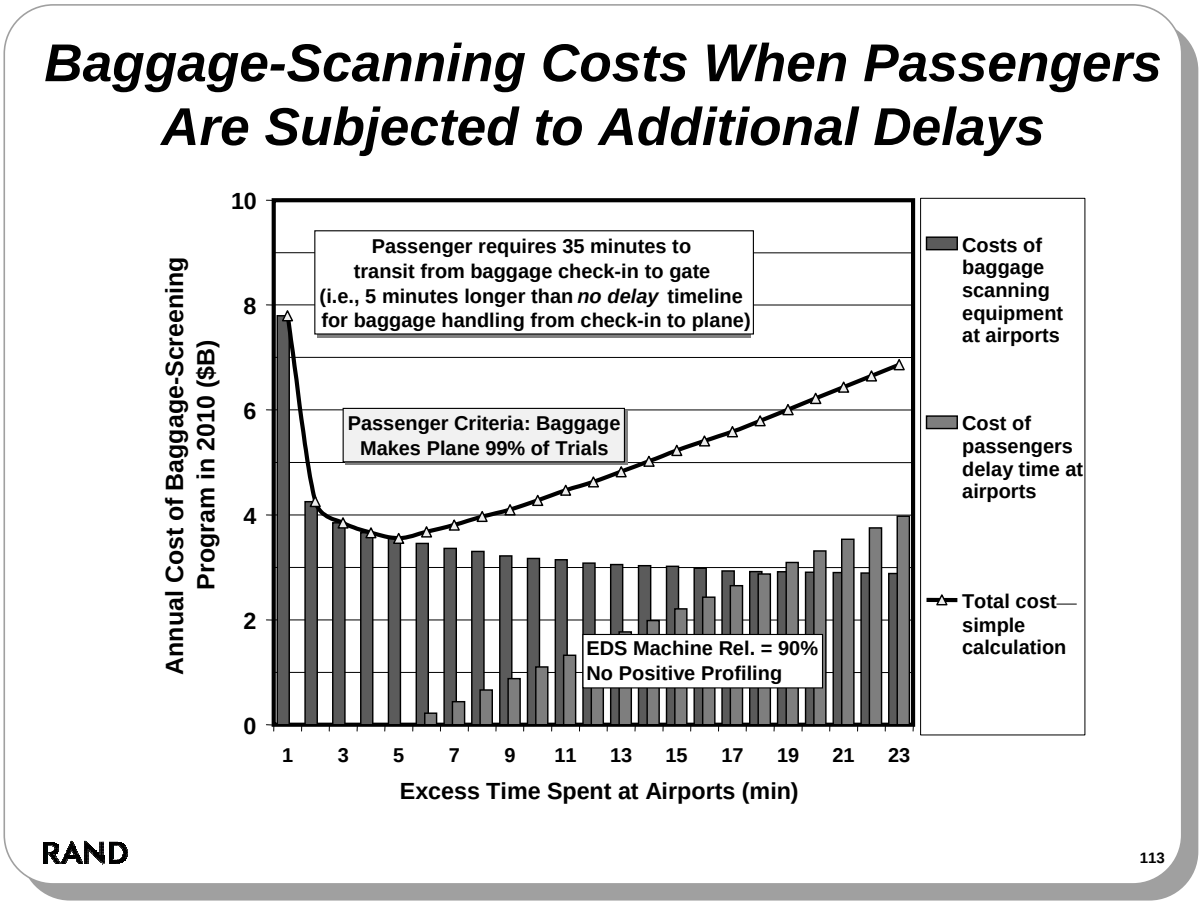
We have not collected the needed statistics, etc., that would allow us to do a rigorous analysis of passenger screening delays. Thus, we have parameterized the travelers transit time from the baggage check-in counter to the airplane gate over a range from 30 minutes to 45 minutes. Less than 30 minutes has no impact on the baggage-scanning calculations. Greater than 45 minutes puts this analysis into a range where we would need to do further analysis of the baggage-scanning queues.



One of the basic results in the main briefing is the total cost to the passenger (a sum of the cost of acquiring and operating the EDS equipment at the airports and the cost to the passenger for arriving at the airport earlier than would be needed if no baggage queuing delays existed) as a function of the total number of machines deployed at U.S. airports. The top curve in the figure represents that cost, where we have assumed a machine reliability of 0.9. The minimum cost is around $4.6 billion and occurs in the neighborhood of 5,900 machines.

The three other curves in the figure are this same cost, except we have only included the passenger delay costs if the delays exceeded those needed to transit the airport. For example, the five-minute-additional-delay curve assumes that there is no cost to the passenger if the 99 percent confidence curve for baggage arrival at the plane is 35 minutes or less. For the 10-minute-additional-delay curve, that 35 minutes would move to 40 minutes.

Increasing the amount of time available for baggage scanning without incurring additional delay to the passenger allows for a reduction in total buy size. Thus, for a five minute additional delay, the optimum EDS deployment size drops to about 5,500 machines, and the overall cost to the passenger because of baggage scanning to around $4.5 billion.

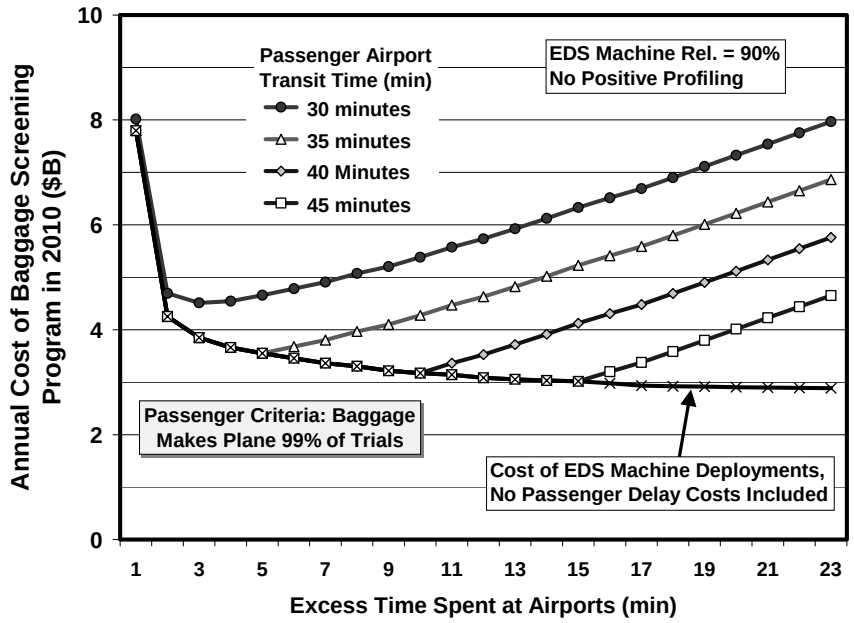


This figure is a copy of one in the main text, except it has been modified to take into account a five-minute-additional-delay for the passenger reaching the gate. In this figure the total costs are plotted against the delay that the passenger experiences with baggage screening. Because of the assumed additional passenger delay in transit to the gate, the first five minutes of baggage-scanning delay does not increase the delay cost to the passenger (the cost of delay in the first five minutes are attributable to whatever caused this delay—e.g., the passenger screening stations). Past five minutes, however, an further delay would be attributable to baggage scanning.

Thus, for the first five minutes of delay, the total cost to the passenger associated with baggage scanning is just the cost of the equipment. The baggage-scanning costs kick in after that, as shown on the figure. This alters the overall cost curve, yielding a minimum cost associated with baggage scanning of around $3.5 billion, as noted on the previous slide.

The criterion of minimum cost to the flying public associated with baggage scanning leads to sizing the deployment so that the passenger did not add time to his planned arrival to account for baggage-scanning delays (subject to the 99 percent confidence of the bag reaching the plane in time).

Additional Passenger Transit Delays Can Dominate Passenger Arrival Time Choice



RAND

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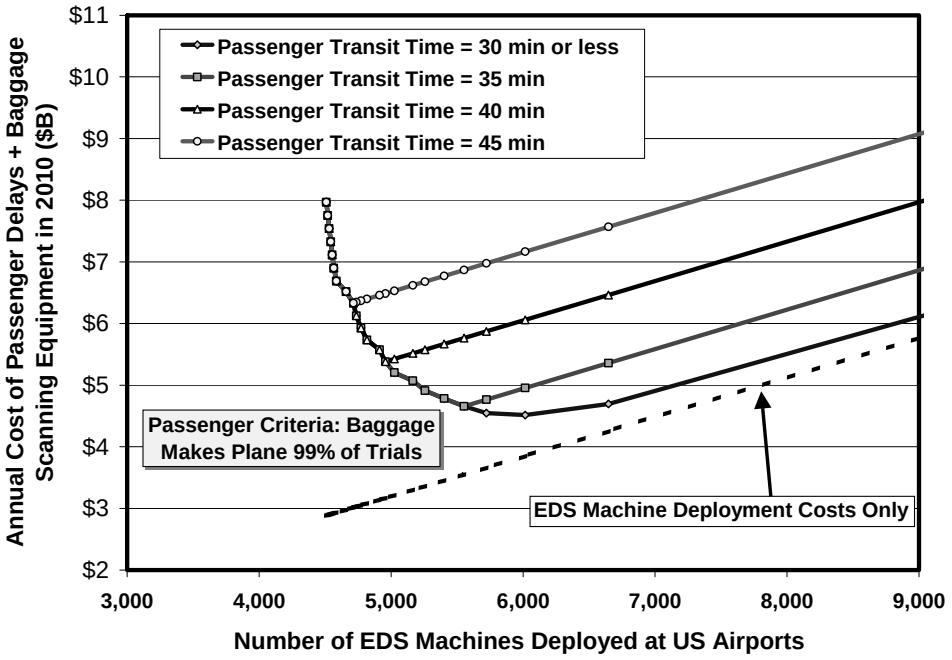
The result on the prior figure also pertains to passenger transit times larger than 35 minutes. Minimizing the cost to the flying public associated with baggage scanning leads to sizing the EDS deployment so that the passenger does not add time to his planned arrival to account for baggage-scanning delays. In this context, passenger transit times from the airport check-in counter to the gate dictate the planned arrival time of the passenger. As this figure shows, the requirement on baggage scanning is thereby relaxed, allowing for reduced buy sizes and longer baggage-scanning queues without adding time to the passenger's delays in the airport.

Of course, this may not be the overall optimum for the passenger if we took into account the costs of passenger delays associated with increasing passenger transit time. The next figure will address this element of the problem.

Including All Passenger Delay Costs in the Analysis (Cost Versus Number of EDS Machines Deployed)



RAND

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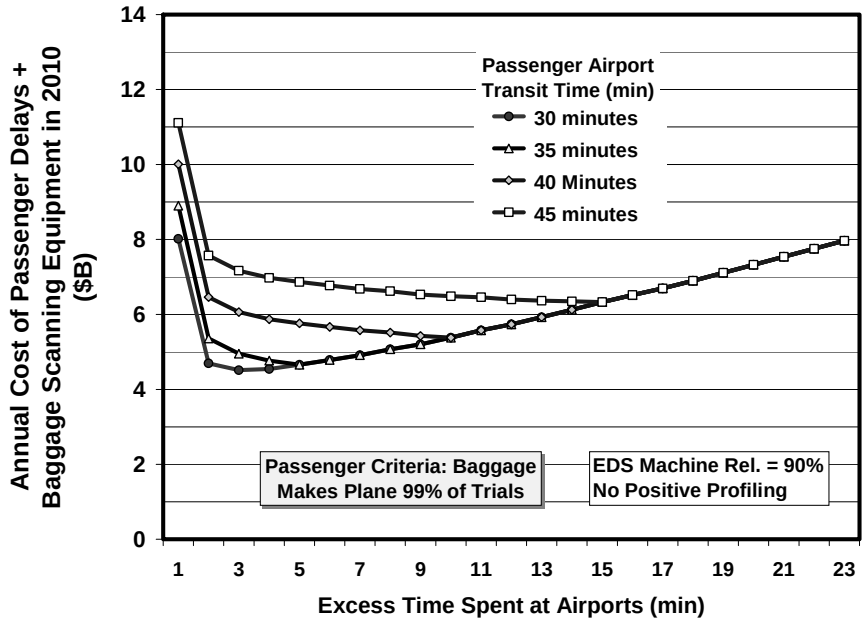
Including all passenger delay costs shows clearly that these additional delays do in fact add further costs to the results where passenger transit times were not included in the analysis. And the optimum number of EDS machines is exactly where the passenger delay costs associated with airport transit times are equal to the delay costs associated with baggage scanning. Or, more directly, the two delay costs, which are independent of each other, are equal.

Including All Passenger Delay Costs in the Analysis (Cost Versus Excess Time in Airport Caused by Baggage Scanning)



RAND

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This figure replots the results of the previous figure, using excess passenger time spent in the airport caused by baggage scanning as the variable along the ordinate. This figure clearly shows that reducing the baggage-scanning delays below the point where the passenger transit time curves intersect would increase overall costs to the passenger and, more generally, to the overall public.

These figures raise the following questions:

- What are the passenger transit times expected to be in 2010?
- How much do these screening stations cost in terms of acquisition of the equipment, installation at the airports, operating both the machines and manning the individual inspections required, and maintaining the machines.
- What is the optimum number of these screening stations at individual airports, and what would be the airport facility reconstruction costs needed to enable them to be deployed. Is there sufficient room at the airports to accommodate such reconstruction or are new facilities required
- Combining all costs, what then are the optimum number of passenger screening stations and baggage-scanning machines at individual airports.

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