The National Center of Excellence

NEXTOR

For Aviation Operations Research

Total Delay Impact Study

A Comprehensive Assessment of the Costs and Impacts of Flight Delay in the United States

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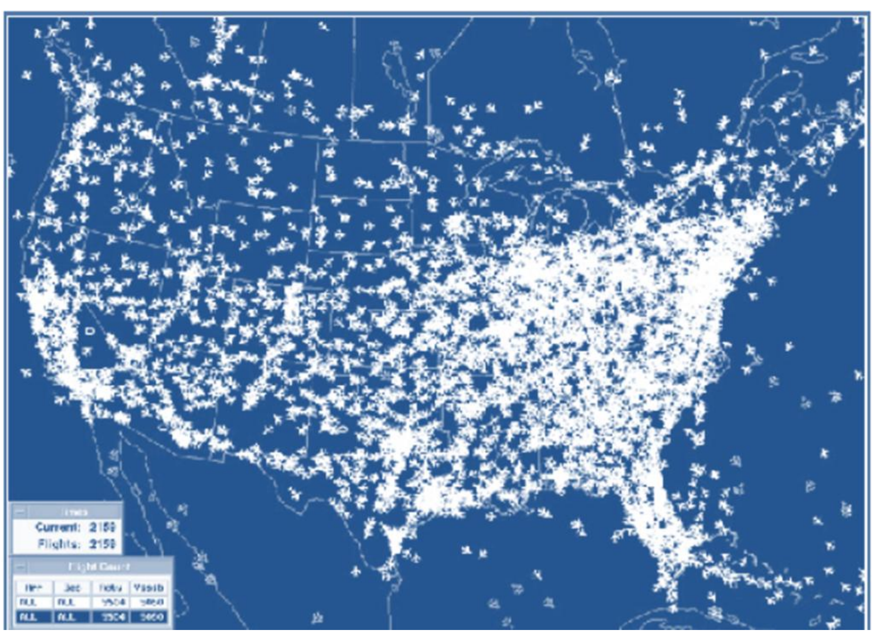

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Executive Summary

Flight delay is a serious and widespread problem in the United States. Increasing flight delays place a significant strain on the US air travel system and cost airlines, passengers, and society at many billions of dollars each year. While a number of previous studies have attempted to estimate the total economic impact of delays, scientific knowledge about the cost of delay is still limited. The Federal Aviation Administration sponsored the five NEXTOR universities and the Brattle Group to conduct a comprehensive study on the total delay impact (TDI) in the United States.

This report analyzes a variety of cost components caused by flight delays, including cost to airlines, cost to passengers, cost of lost demand, as well as the indirect impact of delay on the US economy. This study offers a broader consideration of relevant costs than conventional cost-of-delay estimates, and employs several innovative methodologies for assessing the magnitudes of these costs. Of particular note are the passenger delay cost estimates, which recognize that flight cancellations and missed connections can lead to substantial passenger delays not revealed in traditional flight delay statistics.

The TDI project team estimates that the total cost of all US air transportation delays in 2007 was $32.9 billion. The $8.3 billion airline component consists of increased expenses for crew, fuel, and maintenance, among others. The $16.7 billion passenger component is based on the passenger time lost due to schedule buffer, delayed flights, flight cancellations, and missed connections. The $3.9 billion cost from lost demand is an estimate of the welfare loss incurred by passengers who avoid air travel as the result of delays.

In addition to these direct costs imposed on the airline industry and its customers, flight delays have indirect effects on the US economy. Specifically, inefficiency in the air transportation sector increases the cost of doing business for other sectors, making the associated businesses less productive. The impact here is subtle, however. For example, the airline industry would actually employ fewer people as it becomes more efficient. The overall impact, of course, would be positive. The TDI team estimates that air transportation delays reduced the 2007 US GDP by $4 billion.

Table 0-1: Direct cost of air transportation delay in 2007

Cost Component	**Cost ($ billions)**
Costs to Airlines	8.3
Costs to Passengers	16.7
Costs from Lost Demand	3.9
Total Direct Cost	28.9
Impact on GDP	4.0
Total Cost	32.9

Certainly, some flight delays are unavoidable and are not the result of airspace congestion. For example, delays could be caused by mechanical problems or problems boarding passengers. Even if ample aviation infrastructure is provided, operational uncertainty still exists and flights can be delayed if safety issues arise due to severe weather or other causes. Absent major policy changes, most decisions about how capacity is used are made by users, not the Air Navigation Service Provider (ANSP). Not all delays can or should be eliminated. Nonetheless, this study provides a frame of reference for decision makers to assess the magnitude of the flight delay problem and the need for initiatives to address it. In this regard, it is similar to other studies that attempt to measure the size of a problem, such as air pollution, motor accidents, or crime, while recognizing that the problem cannot be entirely eliminated.

One can certainly expect that new aviation technologies and procedures, including those associated with the Next Generation Air Transportation System (NextGen), coupled with appropriate government policies and infrastructure investments, have the potential to reduce the identified costs by a very large percentage. One should also keep in mind that the air transportation system seeks a new equilibrium any time new capacity is provided. A very large capacity increase could reduce the majority of the delays identified in this report *assuming the demand (in terms of number of operations) placed on the system remained constant.* However, the flight operators would no doubt react to such capacity increases and change their service offerings. The new equilibrium the system would reach is very difficult to predict. The gains from NEXTGEN and other aviation infrastructure investments will be greatest if they are combined with policy innovations, such as pricing NAS resources and services to encourage their more efficient use, setting realistic caps at airports, and so on. This will ensure the most effective use of new capacity in order to reduce flight delay and its associated cost, by reducing problems that arise from the externalization of delay costs in the present system. Assuming the new capacity is efficiently allocated, the cost of the delays that NAS investments would eliminate provides a lower bound on their benefits to society. The results of this study suggest that policies and mechanisms that discourage overscheduling should be considered in concert with capacity enhancements to insure effective use of new capacity in order to reduce flight delay and its associated costs.

1 Introduction

Flight delay is a serious and widespread problem in the United States. In 2007, nearly one in four airline flights arrived at its destination over 15 minutes late (BTS, 2009). About a third of these late arrivals were a direct result of the inability of the aviation system to handle the traffic demands that were placed upon it, while another third resulted from airline internal problems. Most of the remainder was caused by an aircraft arriving late and thus having to depart late on its next flight (BTS, 2009).

Between 2002 and 2007, as the air transport system recovered from the 9/11 attacks, scheduled airline flights increased about 22 percent, but the number of late-arriving flights more than doubled. Since 2007, traffic and delays have declined somewhat because of the recession, but the FAA expects growth to resume, with air carrier flight traffic reaching 2007 levels by 2012, and growing an additional 30 percent by 2025. It is widely recognized that delay increases nonlinearly as demand approaches the capacity in the system (Figure 1-1). If current demand in the system is D_1 with delay at $delay_1$ level, it is likely that, without substantial upgrades to aviation infrastructure, such growth (for example, to D_2) would result in flight delays far in excess of any we have heretofore experienced ($delay_2$).

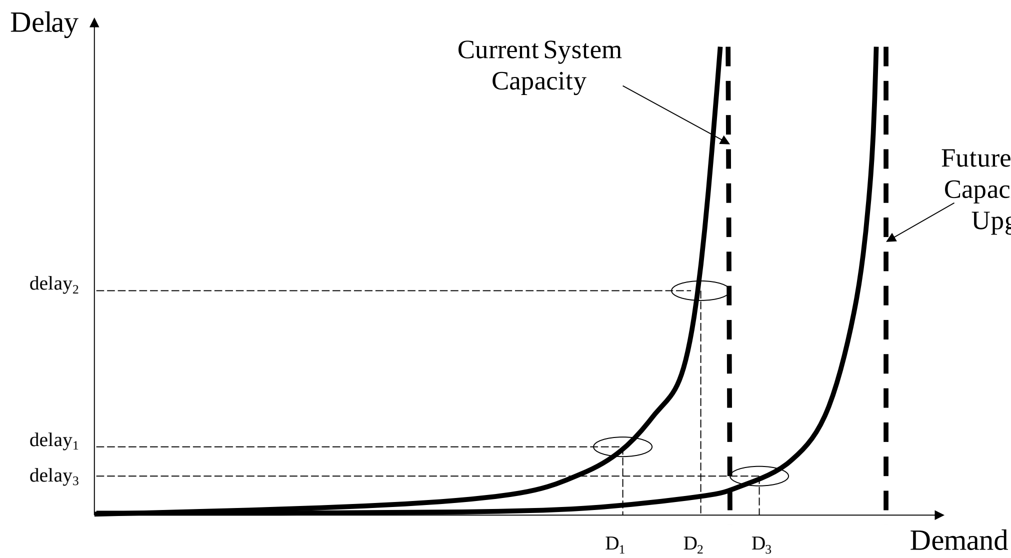


Figure 1-1: Illustration of the relationship between delay, demand and system capacity

Growing delays threaten the competitiveness of the US in the world economy, by limiting the ability of the air transport system to serve the needs of the US economy. The growth in gross domestic product and air travel demand are closely linked; a recent multi-national study found a strong correlation between growth in economic productivity and growth in business travel (Oxford Economics, 2009). Business travel accounts for about half the dollars spent on domestic air transport (BEA, 2009), and with good reason—a recent study estimates that a dollar spent on business travel earns a return of about $12 in increased revenue to the traveler's employer (Oxford Economics, 2009). In addition to improving business performance generally, air transport impacts the economy through the jobs and revenue it directly create in air transport-related industries, the expenditures of air travelers on auxiliary goods and services, and the secondary impacts that result as these dollars recycle throughout the economy. FAA estimates the total economic impact from civil aviation at $1.3 trillion in economic output, nearly $396 billion in earnings, and 12 million jobs in 2007 (FAA ATO, 2009).

Ironically, the airline industry itself has realized very little return from these economic contributions. Most US airlines have operated in the red for most of this decade. US passenger airlines lost over $60 billion between 2000 and 2008, on revenues of just over $1 trillion (ATA, 2009a). Large losses following the 9/11 attacks were followed by a recovery foreshortened by skyrocketing oil prices and a recession, which led to even larger losses. As of December 2009, the total market capitalization of major US carriers was about $26 billion, a drop of 65 percent from early 2007, when the prospects for recovery appeared brightest. Flight delays, by increasing airline costs and reducing demand for air travel, compound these financial challenges.

Building on a strong domestic market, aerospace manufacturing had the highest net exports—some $60 billion – of any U.S. industry in 2008 (FAA ATO, 2009). The four largest airlines in the world are all U.S. carriers, as are five of the world's top ten busiest airports. The FAA Air Traffic Organization is the largest, busiest, and (arguably) most efficient provider of air navigation services in the world. It may be difficult to maintain such competitive strength if future growth is stifled by high delays.

Substantial investments are required in order to modernize and expand our aviation infrastructure so that it can accommodate anticipated growth without large increases in delay. The Next Generation Air Transportation System (NextGen) will deploy improved systems for communications, surveillance, navigation, and air traffic management and also require flight operators to invest in new on-board equipment. Substantial improvements in air transportation capacity also require airport infrastructure enhancement. Estimates of these combined investments reach well into the 10's of billions of dollars (GAO, 2008; ACI, 2009).

The Federal Government together with the air transportation industry must decide on a level of investment to make in future system capacity. Other approaches to reducing delay, such as reducing incentives to over scheduling flights, might also be considered. To help inform decision making on such issues, the FAA has sponsored this study of the total economic impact of flight delay in the United States. Focusing on the year 2007—the worst on record in terms of flight delays—the study attempts a comprehensive accounting of the economic cost of flight delays to airlines, air travelers, and the rest of society. The analysis assesses the cost to society of all air transportation system delays. To be sure it would be impossible to eliminate all of these delays and their costs, and even unwise to seek to do so. In this regard, the TDI study is similar to others that attempt to measure the size—i.e. the social cost--of a problem, such as air pollution (e.g. Muller et al, 2007), motor accidents (e.g. Cambridge Systematics, 2008), or crime (e.g. Anderson, 1999), while recognizing that the problem cannot be entirely eliminated. At the same time, it is quite reasonable to seek to eliminate—through policy innovation, research and development, and capital investment--a substantial portion of these delays and the magnitude of the costs involved suggests that doing so could benefit society significantly. The calculation of the cost of delays is one way to estimate the potential benefits of capacity increases. The air transportation system will react to any capacity increases by altering service patterns. For example, if future capacity is increased, the system might move to D_3 and $delay_3$ in Figure 1-1, instead of D_2 and $delay_2$. Thus, the benefits of such capacity increases could manifest themselves as both delay decreases and better service offerings. Nonetheless, assuming capacity is used efficiently, the cost of the delays that the capacity could eliminate provides a lower bound on the benefits the capacity increases provide to society.

Table 1-1: Comparison of TDI and JEC delay cost estimates ($ billions)

	TDI	JEC
Costs to Airlines	8.3	19.1
Costs to Passengers	16.7	12.1
Indirect Impact on Economy	4.0	9.6
Costs from Lost Demand	3.9	N/A
Total Cost	32.9	40.7

Other studies have examined the total cost of delay. According to a report prepared for the Senate Joint Economic Committee, the total cost, to airlines, passengers, and the rest of the economy, is estimated to be as high as $41 billion in 2007, including $31 billion in direct costs and $10 billion in spillovers (JEC 2008). The Air Transport Association, using a different methodology, estimates costs (for the year 2008) to be $14 billion, not including spillovers (ATA, 2009b).

Part of the motivation for the present study is the disparity of the above estimates. In addition, the JEC and ATA results, as well as several earlier studies on the same subject, overlook factors whose importance has become increasingly recognized within the aviation research community. They do not, for example, recognize the rather complex relationship between flight delay and passenger delay, or consider how degraded service quality affects the demand for air travel. This suggests the need for a more comprehensive and careful look. Table 1-1 provides a comparison of the TDI aggregate numbers, presented in the executive summary, and the JEC aggregate numbers. Note several significant discrepancies. The TDI airline cost estimate and the TDI indirect cost estimate are both substantially smaller than the corresponding JEC numbers. The TDI and JEC estimation approaches differed substantially. In both cases, we employed economic models calibrated on historical data. The JEC work relied on a simple allocation of costs based on total flight time for the airline cost estimate and a generic macroeconomic impact multiplier for the indirect economic impact estimate. On the other hand, the TDI passenger cost estimates are higher. This is principally due to our inclusion of estimates of the passenger costs due to flight cancellations and missed connections. The JEC report did not calculate an estimate of the costs associated with lost demand.

This report summarizes the findings from our cost assessment. Section 2 provides an overview of the flight delay phenomenon, the types of costs that are incurred from delay, and our final estimates of the magnitudes of such costs in 2007. Section 3 provides a more detailed description of the methodologies employed to obtain the cost estimates. It covers relevant components such as delay and buffer cost to airlines (section 3.1), to passengers (section 3.2), cost of voluntary passenger schedule adjustment (section 3.3), capacity induced schedule delay cost (section 3.4), value of demand lost due to delays (section 3.5), and indirect impact of delays on US economy (section 3.6). Section 4 provides additional perspectives on the results by relating them to practical experiences of air travelers and industry trends. It also suggests areas where further investigation may be warranted and discusses related costs and delays not covered. Finally, Section 5 suggests some possible policy implications of the results.

2 Delays and Their Impact

To understand the impact of congestion and delays on the air transportation system, we start with a stylized view of how the system would operate in their absence. An airline might start the process of scheduling a flight by determining an *ideal flight departure time (IDT).* The IDT would take into account not only preferred passenger travel times, but also internal airline constraints, such as those necessary to create efficient crew schedules and fleet plans. As part of this process, the airline would then choose the most appropriate aircraft type from its fleet for the flight. Using the characteristics of that aircraft and assuming it could fly the optimal, unimpeded origin-to-destination trajectory, an *ideal arrival time* could be computed as illustrated in Figure 2-1. This *unimpeded flight time* is a key quantity in our analysis whose estimation will be discussed later in this document.

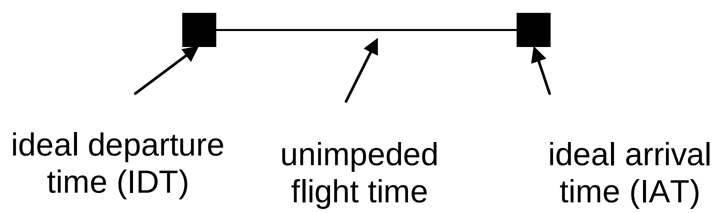


Figure 2-1: Ideal flight

Now let us consider how congestion and delays alter this situation. As illustrated in Figure 2-2, the airlines will typically increase scheduled flight times over unimpeded ones in order to account for delays resulting from flight restrictions imposed to organize traffic, congestion, and a variety of other factors. We call this added time, the *schedule buffer* (SB). Once an unimpeded flight time has been determined the schedule buffer can be computed from historical data.

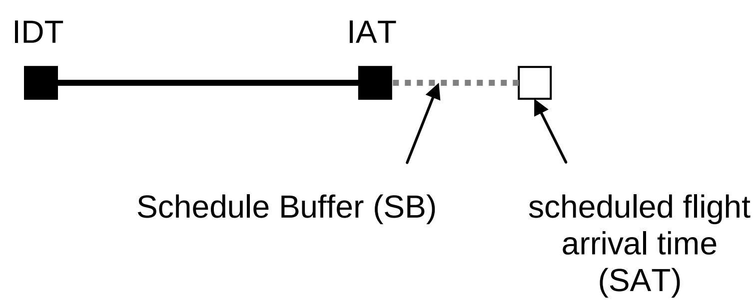


Figure 2-2: Schedule buffer (SB)

Of course, the type of delay most typically discussed occurs when the arrival is later than scheduled. This is illustrated in Figure 2-3. Such flight delay against schedule (FDS), like SB, reflects excess travel time much of which is related to congestion in the air transportation system. However, while SB is known in advance for a particular flight, FDS is not. FDS varies unpredictably from day to day and flight to flight; it can even be negative because the SB may exceed the delays incurred for a particular flight. This gives FDS a very different character when compared to SB.

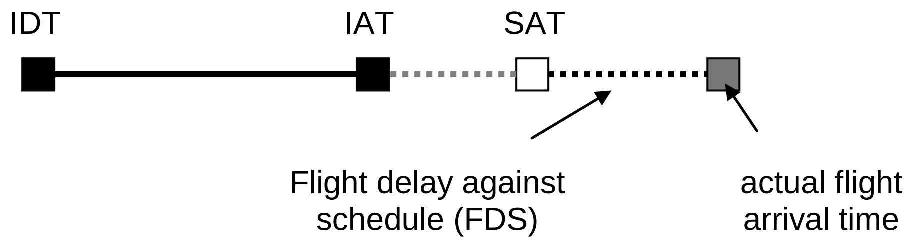


Figure 2-3: Flight delay against schedule (FDS)

Congestion and delays affect both airlines and passengers, albeit in different ways. These phenomena have a definite impact on airline costs, which we assess. Passengers see increases in the time required for travel, experience inconvenience and stress, and may face additional expenses for food and lodging. The costs to airlines and passengers—some in the form of added expense and lost revenue, and others in the form of decreased convenience and additional misery—are the direct costs of flight congestion and delay. We note that infrastructure congestion, e.g. at an airport, can actually benefit an individual airline by limiting access by competitors and allowing that airline to charge higher prices. This effect is not captured in our work.

This discussion has implicitly assumed that the number of passengers remains fixed as system delays change. In fact, if air transportation delays were eliminated or reduced then air travel would become more attractive and the demand for it would increase. This increase in demand will provide benefits that are apportioned in some way between airlines and passengers. In fact, it can be difficult to isolate one benefit from the other so we calculate and discuss this effect in the section on passenger delay costs (see 3.5.1). Of course, such demand increases could in turn spur additional flight traffic and restore some delays in the system. We do not consider this feedback effect here.

These direct congestion costs propagate through the rest of the economy, creating a third cost category. Any phenomenon that makes one industry segment, e.g. air transportation, more expensive leads to higher costs and lower efficiency in other segments, e.g. manufacturing, retail, etc. The added costs and reduced profits of any industry that depends on air travel, and the resulting impact on its customers, constitute the indirect impact of flight congestion and delay. Accordingly, we break down our discussion of costs into three categories: airlines (Section 2.1), passengers (Sections 2.2 and 2.3) and indirect impact on US economy (Section 2.4). We develop an estimate of the cost impact for each category.

2.1 The Airline Perspective and Airline Costs

As discussed we will estimate the impact of delays on airline costs in terms of two measurable quantities: schedule buffer (SB) and flight delay against schedule (FDS). To illustrate the impact of SB on airline costs, we note that the typical pilot contract specifies that pilots are paid based on the maximum of scheduled block time and actual block time. Thus, the SB directly increases pilot (and airline) costs. Further, airlines create their fleet plans based on the scheduled flight arrival and departure times so that increasing SB leads to changes in schedules and eventually to poorer aircraft utilization and larger fleets. The high degree of uncertainty associated with FDS gives it a very different character. Since airline fleet and crew schedules are based largely on the scheduled times, excessive or even moderate amounts of flight delays can be highly disruptive causing extra crew costs, various costs associated with accommodating disrupted passengers and even aircraft repositioning.

We employ translog models, which incorporate both delay against schedule and schedule buffer to estimate airline cost functions. Our estimation results support the view that poorer operational performance (i.e. more FDS and SB) leads to more expensive operations. Such airline cost models establish an empirical basis for translating delay and buffer into monetary terms. Using these models, the potential cost savings that could result from reducing FDS and SB are estimated. Table 2-1 gives a summary of our estimates for 2007. Note that our cost model includes 7 major U.S. airlines whose service dominates in the entire air transportation system. An estimate covering the entire industry is also calculated. We investigated the relevant airline cost under two scenarios. In the first scenario, FDS is entirely eliminated; in the second scenario, we further reduce SB to zero. Section 3.1 provides more detail. We also tried an alternative approach to modeling the relationship between airline cost and operational performance. This second approach yields somewhat higher costs estimates—as much as $13 billion industry wide. This is also discussed in Section 3.1. We report the lower value here because it is based on a more standard approach for characterizing flight delay and buffer.

Table 2-1: Airline cost estimates for 2007 ($ billions)

	Delay Against Schedule	Buffer	Total
7 major airlines	3.3	2.6	5.9
Industry wide*	4.6	3.7	8.3

* Includes airlines with $20 million annual operating revenue only.

Of the $8.3 billion total, $4.6 billion is attributed to the most common notion of delay, FDS. The contribution of SB, $3.7 billion, is of comparable magnitude. These figures, like those in the presented elsewhere in this report, reflect cost savings that would result from an unattainable ideal case in which all schedule buffer and delay against schedule were eliminated. They are intended to establish an upper bound for the airline cost savings that could result from improving the operational performance of the air transportation system. The question of how much of these savings is actually attainable is addressed in Section 5 of this report.

2.2 The Passenger Perspective and Passenger Costs

It is common to view flight delay statistics as representative of passenger delays. In fact, NEXTOR research over the past several years has demonstrated that there can be very dramatic differences between flight delays and passenger delays.

To see the differences and also to understand passenger costs let us take a simple view of how a passenger approaches air travel in an ideal environment. A passenger might start with a *preferred arrival time (PAT)*. Based on the travel times offered by a chosen airline this could be converted into a *preferred departure time (PDT)* as illustrated in Figure 2-4. We note that this time is a bit different from the unimpeded flight time described earlier. First, it could be that the scheduled itinerary time involves multiple flights. Of course, a passenger in most cases would prefer a single nonstop flight. However, multi-flight-leg itineraries are a way in which the airlines provide cost effective service to passengers. Passengers also benefit from this by enjoying more frequent services. Thus, while the extra time associated with such itineraries might be viewed as a type of delay, it is not caused by congestion or deficiencies in air traffic management but rather by mechanisms used by airlines to provide cost effective service. On the other hand, the schedule buffer included within each constituent flight is a result of congestion as discussed above and certainly represents extra passenger travel time and thus a cost to passengers.

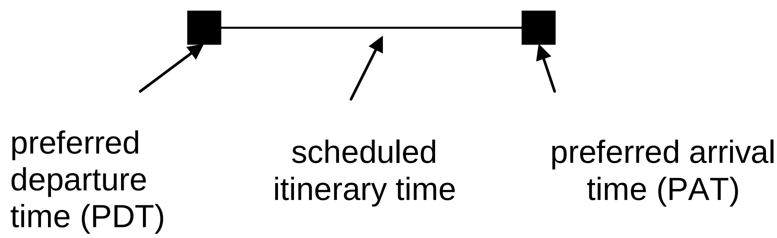


Figure 2-4: Preferred passenger trip

It is frequently assumed that flight delay statistics provide an accurate depiction of passenger delay. However, the quantity analogous to FDS, *passenger delay against schedule* (PDS), can be very different from FDS. If a passenger books a direct flight to his or her destination and is able to take that flight, then the delay of that flight corresponds to the delay of the passenger. However, average flight delay statistics do not capture the delays associated with *disrupted passengers*. A passenger's trip is disrupted if that passenger is not able to take one or more of his or her booked flights. The two most typical cases for trip disruptions are:

- a passenger arrives at the airport and, subsequently, the booked flight is canceled;
- a passenger misses a connection on a multi-leg trip.

Figures 2-5 and 2-6 illustrate these phenomena. Note from Figure 2-6, the rather complex relationship between the delay on the first leg of a two leg trip and the passenger's final delay. If the passenger makes his or her connection then the final delay depends only on the delay on the second flight leg. Thus, small delays on the first flight leg have no impact on the final delay. On the other hand, larger delays on the first leg can have the very dramatic effect of causing a missed connection and subsequent, sometimes extreme, delays. This illustrates the fact that average PDS depends on the distribution of flight delays (as well as other factors), not just average FDS. Thus, while there are readily available statistics that allow direct compilation of total FDS, it is more difficult to compute (or estimate) total PDS. In the past, NEXTOR has obtained proprietary airline data and has calculated passenger delays for individual airlines over limited time periods. For this study, new models in section 3.2 have been developed that allow more accurate estimation of passenger delays for an entire year on a NAS-wide basis. We note that passenger delays depend on flight delays but also on flight cancellation rates and load factors. The relationship to cancellation rates is easy to see based on Figure 2-5. Note from both Figures 2-5 and 2-6 that both a flight cancellation and a missed connection require that passengers be accommodated on flights for which they were not originally ticketed. Doing this requires available space on the flights in question. As load factors become higher such space is harder to find, increasing delays for disrupted passengers.

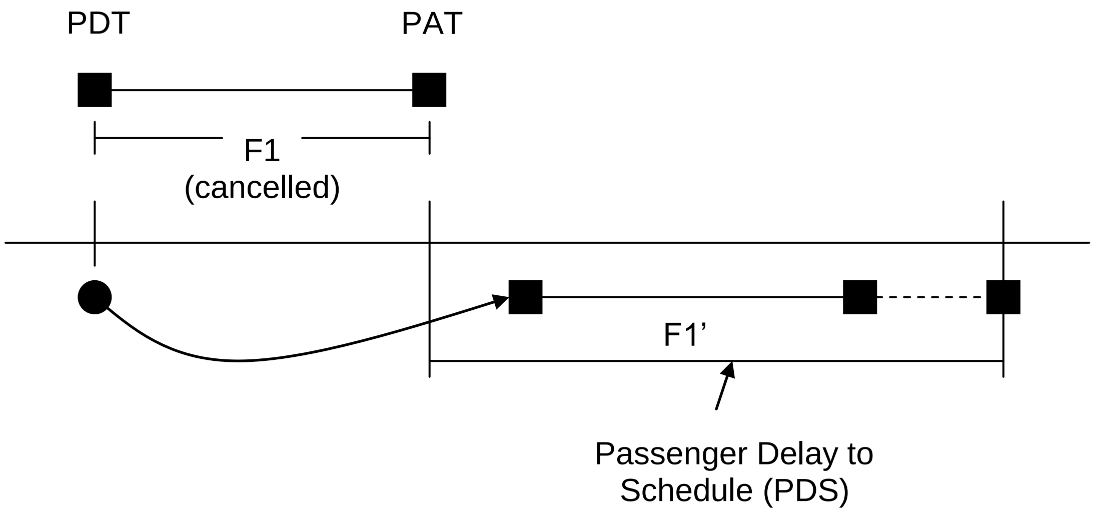


Figure 2-5: Illustration of passenger delay to schedule (PDS) for the case where the passenger is booked on a flight (F1) that is cancelled and is accommodated on another flight (F1')

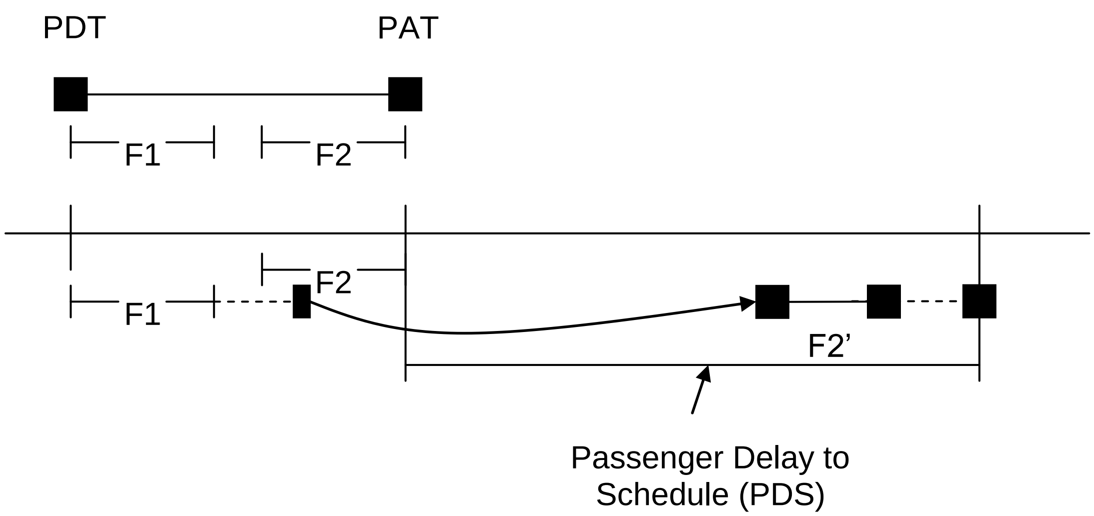
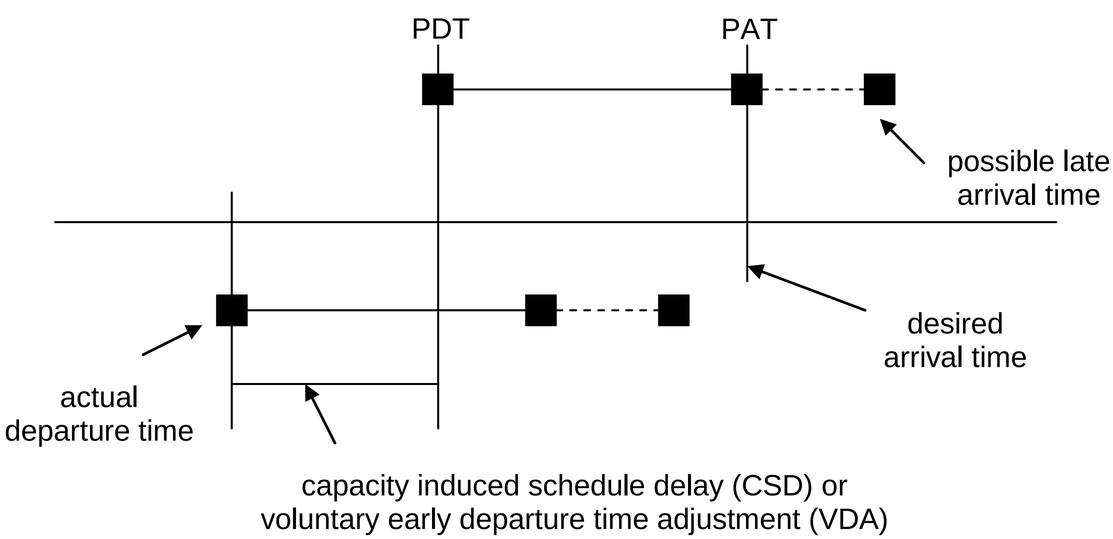


Figure 2-6: Passenger delay to schedule (PDS) for the case where the passenger has two leg itinerary and the first flight (F1) is delayed inducing a missed connection. The passenger is accommodated to his or her final destination on a third flight (F2')

To summarize the above discussion, passenger delay costs can be related to a combination of SB and PDS. While statistics on SB can be readily derived from historical data, PDS statistics must be estimated based on sophisticated models that depend of flight delays, cancellation rates and load factors.

Just as airlines add buffers to flight schedules to increase schedule reliability in light of uncertain flight delays, passengers often plan their departure times taking into account the possibility of arrival delays. If a passenger absolutely needs to be at a destination by 10:00 AM he or she typically would not take a flight scheduled to arrive at 10:00 AM. Rather the passenger would take a flight scheduled to arrive earlier to ensure arrival by 10:00 AM even in the case of significant flight delays. In fact, it is not uncommon for a traveler to fly in the night before, only to ensure timely arrival at a morning meeting. As illustrated in Figure 2-7, we call this phenomenon and the associated adjustment in departure time *voluntary departure time adjustment (VDA)*

While passengers and airlines might adjust departure times for specific reasons, it is also the case that there are many factors that influence scheduled flight times. Flights are rarely available at exactly the time when a given passenger would like to fly. For example, a passenger might wish to arrive at a destination at 9:00 AM via a one hour flight. Thus, ideally the passenger would book an 8:00 AM flight. However, it could be that the only flight offered before 9:00 was a 7:00 AM flight. Thus, the passenger would be "forced" to take the 7:00 AM flight and we would say the passenger suffered one hour of *schedule delay.* Generally, schedule delay is the result of airline scheduling practices, which depend on a wide range of factors the airlines must take into account in order to produce cost effective schedules. Thus, most schedule delay cannot be "blamed" on NAS capacity constraints. However, at highly constrained airports, it could be that the airlines are forced to flatten their schedules and offer flights at inconvenient times when they otherwise would seek to provide better service to their passengers. Using techniques specifically developed for this project, we are able to estimate the schedule delay resulting from scarce capacity, isolating it from the schedule delay resulting from normal airline scheduling practices. Figure 2-7 also illustrates this case; we call this phenomenon and the associated added time *capacity induced schedule delay (CSD).* Clearly the delays just discussed are different from more traditional notions of delay. However, they would not occur in a system with ample capacity that and much less congestion.



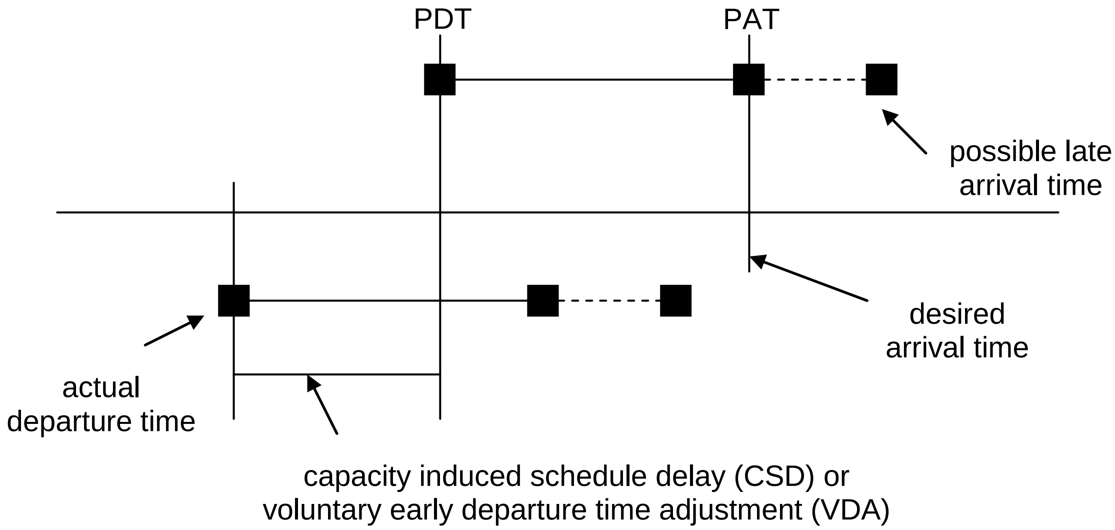


Figure 2-7: Illustration of delays related to difference between actual and desired departure time

Before presenting our statistics on passenger costs and delay, it may be worthwhile to consider all of the cases we have discussed and their potential interaction. One can view the passenger decision-making process sequentially, as starting with a preferred arrival time, then calculating a preferred departure time. Associated with this hypothetical flight is the potential for an unknown passenger delay (PDS). Based on the expected PDS, the passenger might further adjust the departure time by VDA to add certainty to the arrival time. Finally, schedule constraints could impose a further change by CSD. Our explanation has assumed a passenger begins with a preferred arrival time; however, a similar sequence could have been created assuming the passenger began with a preferred departure time. Clearly, these delays and schedule adjustments are inter-related but when one considers a particular passenger trip they are largely independent phenomena. VDA and CSD represent adjustments to the passenger's chosen departure time due to generally independent mechanisms. SB is an expansion of the passenger's scheduled (and actual) flight time. This expansion is known in advance and anticipated by the passenger. PDS is highly stochastic and can be extremely disruptive. In the calculations that follow, we independently estimate each of these and associate a cost with each one. These costs are then added together. One might argue that there is a degree of "double counting" in this approach. For example, if a passenger chooses to leave the night before to insure getting to a morning meeting on time, then the passenger has already adjusted for, and paid the price for, possible PDS. However, such a passenger may plan to have a leisurely dinner and/or get to bed at a convenient time. If that passenger arrives three hours late, then these planned activities would be disrupted and further costs would be incurred. Thus, we argue that, once a passenger has planned a trip, with or without substantial departure time perturbations, the SB and PDS costs of the associated flight are still real and can be added to any costs related to the adjusted departure time.

Table 2-2 provides the overall passenger delay costs. These are obtained by first deriving a cost estimate (or a lower bound on the cost) of each delay component: TC[SB], TC[PDS], TC[CSD], TC[VDA]. The notation TC[] refers to the total cost of the respective component over all domestic passengers during 2007. Calculations of SB, PDS, CSD, and VDA are discussed in detail in sections 3.2 – 3.4. Based on the above discussion the various components are combined via a simple addition, i.e

Total Passenger Cost = TC[SB] + TC[PDS] + TC[CSD] + TC[VDA].

The preceding analysis discussed the estimation of the increased value of air travel assuming that the existing passenger made the same trips before and after delays were eliminated (and implicitly that they paid the same price). In general, passengers are willing to pay a higher price for less delayed flights and airline costs are reduced as delay decreases. Thus, delay reductions would lead to a new equilibrium in the supply/demand relationship between the airlines and their passengers with both the airlines and passengers accruing a portion of the overall welfare gain. Rather than trying to apportion the benefit of the reduced delay between the airlines and passengers, this analysis implicitly allocates the entire benefit to the passengers, i.e. passenger delay is reduced and passengers pay the same price. This accounts for the entire welfare gain while not attempting to accurately determine how the gain is apportioned between airlines and passengers. For similar reasons, the elimination or reduction of delays would also increase the demand for air travel. These new passengers would also incur a benefit. That benefit is the difference in the value of their travel over the value of travel on the alternative transportation mode they use today. To estimate this effect we take a social welfare approach and estimate that increase in social welfare accrued by these new trips using the air transportation system. This work is summarized in the next section.

Table 2-2: Passenger delay cost estimates for 2007 ($ billions)

Delay Category	**Delay Cost**
1. SB (schedule buffer)	6.0
2. PDS (passenger delay against schedule)	
2a. Delay due to delayed flights	4.7
2b. Delay due to flight cancellations	3.2
2c. Delay due to missed connections	1.5
Total estimated PDS (2a+2b+2c)	9.4
3. CSD (capacity induced schedule delay)	0.7
4. VDA (voluntary early departure time adjustment)	0.6
Total cost of passenger delay	16.7

* In calculating the delay cost for category 1 and 2, a standard cost per unit time ($37.6/hr) is assumed (DOT, 2003; inflated to 2007 value). Cost of CSD and VDA are based on the respective estimates.

2.3 Cost of Lost Demand

Flight delay degrades the quality of the airline product. While many air travelers choose to "grin and bear it" others respond by switching to alternative transportation modes, or simply not traveling at all. Such travelers do not bear the costs of air travel delay discussed in Section 2.2, but still incur a loss in welfare. In the air transportation market, both passengers' decision on traveling and airlines' pricing behavior are influenced by flight delays. We explicitly model passenger demand and fare to be functions of flight delays (see Section 3.5.1). By simultaneously estimating the demand and fare functions, the demand and supply interactions on the route level are investigated. The model results indicate that delays have an upward impact on fares, while at the same time decreasing people's willingness to pay for travel by air. Using a discrete choice model, we find some of the trips are shifted to automobile, and the additional road traffic generates congestion costs on other road users and environmental costs on society at large. Table 2-3 summarizes these results. The first component is an estimate of the difference in the value (or welfare) that certain air travelers would have achieved using air transportation in a delay-free (or low delay) environment and the value they did achieve having chosen to shift to another mode because of air transport delays. There is an additional externality due to the switch to automobile. Specifically, car travel is less safe than air travel so that this switch from air to car will cause additional fatalities (see Section 3.5.2). An estimate of this cost is also provided in Table 2-3.

Table 2-3: Cost of lost air transport demand for 2007 ($ billions)

Cost Component	**Cost**
1. Welfare loss due to switch from air to automobile	3.7
2. Externality cost from increased road traffic	0.2
Total cost of Lost Air Transport Demand	3.9

2.4 Indirect Impact on US Economy

The impacts of flight delays are not confined to airlines and their passengers. Other segments of the economy are also affected. Increases in airline costs caused by delay and schedule padding cause passengers to pay higher fares. These higher fares affect not just the demand for leisure travel but also lead to increases in the cost of production for industries that rely on air transportation to conduct business. Demand for the output of such industries in turn decreases. Schedule padding and flight delays also add to the time required for business trips, leaving business travelers with less time to do their work. As a result, delays cause employers to experience a loss in productivity.

Tracing out these various effects requires an integrated model of the national economy. For this purpose, we utilized a single-region Computable General Equilibrium (CGE) model.[1] This model was modified to reflect our findings on the direct costs of delay. We explicitly modeled the increases in airline costs caused by delay, and the loss in productivity for business travelers. The CGE framework then traced the effects of these changes in cost as they rippled through the economy. The model traced the effects of cost increases on the growth of the U.S. economy over the period from 2005 through 2013.

[1] Specifically, we employed the USAGE model (see Section 3.6).

Two sets of simulations were performed to assess the macroeconomic impact of flight delays. A baseline simulation projected the effects of changes in income, consumer tastes, and technology on the demand for air transportation and the amount of flight delay over the period from 2005 and 2013, assuming no policies or actions are taken to reduce flight delays. The second set of simulations assumed the elimination of delays (actually reduction by 90%) for a given level of industry output. In this way we calculate that in 2007 U.S. GDP was approximately $4 billion lower than it would otherwise have been in the absence of delays. Of course, the investments and expenditures required to reduce delays would also generate economic impacts, but these are not considered here. We note that this estimate is lower than others that have previously been published (see, for example, the JEC study -- JEC 2008). Many of these prior studies focus solely on delay-induced changes in cost, and fail to account fully for how these cost changes affect the growth of the economy. In contrast, our analysis took into account the fact that increases in the efficiency of air transportation would actually decrease certain direct economic activities associated with this sector since fewer pilots, flight crews, etc would be required to carry out the same business functions. On the other hand, there would be an increase in the economic activity of other businesses due to the reduction in the cost of a component of their production (air transportation). The net effect is certainly a positive increase in economic activity but perhaps not as great as some earlier studies have estimated.

2.5 Summary

Table 2-4 provides a compilation of all cost components. Certainly by any objective standards these costs are large and indicate that appropriate mitigation actions should be considered. At the same time, one should keep in mind that total elimination of all delays is neither practical nor desirable. Perspective on this issue as well as possible policy implication is discussed in Section 5.

It is instructive to compare these results with the results provided in the JEC report (JEC, 2008). Our estimate of airline cost is smaller (JEC: $19.1 B, TDI: $8.3 B). The difference may be due to the use of completely different approaches. This JEC number, as pointed out by the report itself, "may overstate the relevant costs" (JEC, 2008). In fact, the JEC study also reported their cost estimates using an alternative approach which produced much lower airline cost estimates ($3.6-6.1 B). Our results just lie between their high and low ends of estimates. On the passenger side, our estimated costs are somewhat larger in magnitude (JEC: $12.0 B, TDI: $16.7 B). One reason for the passenger cost discrepancy is the inclusion in the TDI analysis of delays due to flight cancellations, missed connections and other factors. The JEC study did not estimate the cost of lost demand.

Table 2-4: Overall cost of US air transportation delays for 2007 ($ billions)

Cost Component	**Cost**
Cost to Airlines	8.3
Costs to Passengers	16.7
Cost from Lost Demand	3.9
Total Direct Cost	28.9
Impact on GDP	4.0

The two studies did diverge somewhat significantly in their estimate of the impact on the GDP (JEC: $9.6 B, TDI: $4.0 B). As discussed earlier, the TDI modeling approach sought to capture both positive and negative impacts on GDP; this perhaps could explain this difference.

3 Underlying Models and Justification

3.1 Impact of Delay on Airlines

The research team employs a statistical cost estimation methodology to estimate how delays affect airline costs. This method differs from most previous research on this subject, which used cost factors to estimate airline delay costs. The cost factor approach involves decomposition of delay into different types and multiplying the quantity of each type by a cost factor. While simple and useful, this approach is problematic because it is difficult to know how to properly categorize delay, quantify delay by category, and determine the appropriate cost factors. In addition, most studies of this kind only account for delay against schedule, but ignore the fact that airlines routinely build buffer into schedule, in order to enhance their on-time performance record and preserve operational integrity. On the other hand, the cost impact of schedule buffer is more difficult than delay against schedule for airline managers to directly observe or account for.

We take an alternative approach based upon developing airline cost functions. The cost function approach investigates the statistical relationship between airline cost and its various influencing factors. The formulation is built upon production theory in economics. The cost function is derived assuming that each airline minimizes its cost of producing a certain output, given the costs of its input factors for production such as labor and fuel, as well as other factors that influence its production process. One factor among the latter can be delay. The statistical cost estimation approach provides an empirical basis for translating delay into monetary terms, which, unlike the cost factor approach, involves a minimum of assumptions about the delay–cost interaction mechanisms.

3.1.1 Cost Model Set-up

The cost function of a firm is defined as the lowest cost at which it can produce a given amount of output Y_{it} , provided the input prices $\vec{W}_{it}$ it faces: $C = f(Y_{it}, \vec{W}_{it})$. Subscript *i* denotes a particular firm (airline), and *t* identifies the time period. A typical output measure can be airlines' revenue ton-miles. Inputs include labor, fuel, capital, and materials. The functional form represents the cost of acquiring the optimal set of inputs, given the output and input prices (Hansen et al, 2001). In reality, however, capital inputs cannot be adjusted to the optimal level instantaneously (Caves et al., 1984; Gillen et al., 1990). We therefore relax the assumption of optimal capital stock by treating capital input, denoted by *S*, as quasi-fixed and employing a variable cost function to reflect the short-run cost minimization process. The airline variable cost function can then be written as a function of its output Y_{it} , the price of the three variable inputs (fuel, labor, and materials) $\vec{W}_{it}$, and capital input S_{it} , i.e. $VC_{it} = f(Y_{it}, \vec{W}_{it}, S_{it})$.

In the airline cost literature, it has long been recognized that costs depend on the nature and quality of airlines' output as well as the quantity. Because the nature and quality of output also vary over time and across carriers, the specification of the airline cost function above needs to take these into account. A set of additional variables $\vec{Z}_{it}$ describing the nature of the output are introduced. Variables of this kind that often appear in literature include a measure of the size of the airline's network (often measured as the number of points served) and the average flight distance (stage length). We hypothesize that airlines' operational performance also affects cost, and add a new variable (or vector of variables) N_{it} . The cost function then becomes $VC_{it} = f(Y_{it}, \vec{W}_{it}, \vec{Z}_{it}, S_{it}, N_{it})$. As we will see in the ensuing sub-sections, we estimated two versions of this model with different characterizations of operational performance.

3.1.2 Delay-based Model

The first version of the airline cost model employs the concepts of delay against schedule (FDS) and schedule buffer (SB) explained in Section 2.1. As discussed in Section 2.1, delay against schedule and schedule buffer are both manifestations of limitations in the NAS that prevent airlines from adhering to schedules built on unimpeded flight times, although the former is more readily observable than the latter. Both delay against schedule and schedule buffer need to be considered in order to assess the full cost impact of delay in the NAS. Exclusion of the schedule buffer could result in an underestimate of the true cost impact.

To measure delay against schedule, we use average positive arrival delay, a widely accepted metric. The positive delay against schedule for a given flight is the difference between its actual and scheduled gate arrival times, truncated so that delays of early flights are counted as zero. The quantification of schedule buffer is less straightforward, because less attention has been paid to this phenomenon and no consensus has been achieved on its measurement. In this study two schedule buffer metrics are developed and investigated. The two metrics differ from each other in terms of defining the unimpeded flight time. For a given flight segment, airline, and quarter, the unimpeded flight times under the two metrics are the 10^{th} and 20^{th} percentiles of the observed block time over all flights. We distinguish by airlines to account for potential aircraft/equipment difference across carriers. Not choosing the minimum travel time makes the calculation more robust to measurement error, and reduces the influence of unusually favorable conditions, such as strong tailwinds. Then for each flight, the schedule buffer is defined as the difference between its scheduled block time and the unimpeded flight time. The average schedule buffer is obtained by averaging the schedule buffer across all flights for each airline and quarter.

The models presented here use the sum of the average positive arrival delay and the average schedule buffer as the measure of operational performance. We also estimated models in which these variables were included individually, but results suggested that the single combined measure was adequate.

Delay against schedule and schedule buffer are constructed using the Bureau of Transportation Statistics (BTS) Airline On-Time Performance database. The database contains scheduled and actual arrival and departure times, as well as wheels-off and wheels-on times, for every domestic flight operated by major carriers that account for at least one percent of domestic scheduled passenger revenues in the US. The airline-quarter panel consists of nine US major airlines (American, Alaska, Continental, Delta, American West, Northwestern, United, US Airways, and Southwest) spanning from the first quarter of 1995 to the fourth quarter of 2007. These nine airlines provide the majority of passenger transportation service in the U.S. airline industry, and are particularly dominant at airports with high delays. As a consequence, we expect that these airlines will absorb the majority of the increased costs resulting from delay.

For other variables in the cost model, data are extracted from the airline balance sheet, traffic, and expenditure information published in the BTS Form 41 database. We focus on domestic data, since airline on-time performance records are only for domestic flights. In our study, the selected airlines are all passenger service focused, with only a small portion of their traffic undertaking cargo, mail, and other types of business. For this reason we use total revenue-ton-miles (RTM) to represent the aggregate output. Fuel and labor input prices are calculated using fuel expense per gallon and labor expense per employee per quarter. To account for the difference brought by full- and part-time employees, we use a weighted sum of employment based on the hours paid to employees. As a proxy for materials price, we choose the producer price index (PPI), which varies by quarter but not by airline. Index data are collected from the US Bureau of Labor Statistics. Capital input is obtained by multiplying the capital stock with the utilization rate, for which load factor is used as a proxy. Our measure of capital stock consists of the asset values plus investment for each airline-quarter. Four types of assets are included: flight equipment, ground property and equipment, capital leases, and land. Among the variables in vector $\bar{Z}_{it}$, we divide the total distance flown by the total number of departures performed to obtain the average stage length. The number of points served is extracted from the BTS Airline On-Time Performance database. Table 3-1 presents the summary statistics of the variables in the sample. Overall, our data set is larger than the ones used in many previous airline cost studies, and thus provides richer information and greater variation of relevant variables, contributing to better estimates of the cost functions.

Table 3-1: Descriptive statistics of key variables

	Mean	**Std. Dev.**	**Min.**	**Max.**
Revenue-ton-miles (million)	1266.5	662.5	176.6	2541.9
Fuel price ($/gallon)	0.94	0.52	0.36	2.68
Labor price ($/employee)	17800.7	4111.1	8688.8	30729.4
Materials price (PPI)	147.9	22.3	109.3	187.9
Capital stock (million $)	11314.7	8524.8	589.4	29127.7
Load factor (%)	72.0	5.7	55.3	87.4
Stage length (miles)	815.9	187.2	396.5	1167.9
Number of points served	80.4	26.0	34.0	130.0
Variable cost (million $)	1548.3	864.3	183.2	3513.6
Delay against schedule (min)	12.2	3.2	5.5	28.8
Delay against 10^{th} percentile feasible flight time (min)	25.4	4.2	14.8	39.9
Delay against 20^{th} percentile feasible flight time (min)	22.2	3.8	13.1	36.7

We choose a translog model as the specific cost functional form for estimation. A translog cost model is in general an extension of the classic Cobb-Douglas cost model form, by introducing quadratic and interaction terms.[2] Compared to the Cobb-Douglas cost model, a translog model adds more flexibility and does not assume constant elasticities. In our study, we keep the delay variable in level form instead of taking its log value. This allows delay to be reduced to zero in the cost impact analysis. All continuous variables are normalized by removing their sample means. Therefore, the translog model can be regarded as a second-order Taylor expansion of a general function about the mean values of the data. The model also includes a time trend variable

[2] For illustration purpose, suppose cost C is only a function of output Y and one input W, i.e. C=*f* (Y, W). A Cobb-Douglas cost function has the form: logC= $\hat{a}_0$+ $\hat{a}_1$logY+ $\hat{a}_2$logW. $\hat{a}_0$+ $\hat{a}_1$logY+ $\hat{a}_2$logW. In a general translog cost set-up, logC= $\hat{a}_0$+ $\hat{a}_1$logY+ $\hat{a}_2$logW+ $\hat{a}_{11}$ $\hat{a}_0$+ $\hat{a}_1$logY+ $\hat{a}_2$logW+ $\hat{a}_{11}$(logY)^2+ $\hat{a}_{22}$ $\hat{a}_{22}$(logW)^2+0.5 $\hat{a}_{12}$ $\hat{a}_{12}$(logY)(logW).

to capture the evolution of productivity over time,[3] and a set of airline fixed effects to account for systematic differences between carriers in efficiency and other factors that influence cost but not captured by the included variables.

The translog cost function is jointly estimated with cost share functions and additional constraints, in order to conform to the underlying economic theory (e.g. Shephard's Lemma and homogeneity of input prices) and increase estimation efficiency. The seemingly unrelated regression (SUR) technique is used to account for the contemporaneous correlation across equations. For further details regarding the estimation process, please refer to Caves et al. (1984), Gillen et al. (1990), and Oum and Yu (1998). Estimation results appear in Table 3-2. We have two versions of translog cost models, which differ only with regard to the two delay variables constructed. To conserve space, only coefficients for first order variables are reported here. Coefficients for dummies and higher order variables are provided in the technical support document.

Table 3-2: Estimation results of delay-based Translog cost functions

	Model 1		**Model 2**	
	Est.	**Std. Err.**	**Est.**	**Std. Err.**
Output (RTM)	0.4798***	0.0339	0.4743***	0.0342
Fuel price	0.2011***	0.0016	0.2009***	0.0016
Labor price	0.3861***	0.0022	0.3859***	0.0022
Materials price	0.4128***	0.0032	0.4132***	0.0032
Capital service	-0.0542***	0.0009	-0.0541***	0.0009
Stage length	-0.1749**	0.0775	-0.1571**	0.0776
Points served	0.6596***	0.0556	0.6658***	0.0558
Delay against 10th percentile feasible flight time	0.0065***	0.0014		
Delay against 20th percentile feasible flight time			0.0061***	0.0015
R^2		0.9900		0.9899
Adjusted R^2		0.9889		0.9888

Notes: *** p<0.01, ** p<0.05, * p<0.1

The first-order coefficients in Table 3-2 suggest the sensitivity of cost to changes in relevant variables, at the sample mean. The first-order coefficients for input prices indicate that at the sample mean, fuel and labor inputs account for about 20% and 38%, respectively, in the total variable cost. This leaves the materials input to account for 41% of the total variable cost. The

[3] A time trend variable takes the value 1 in the first quarter in the dataset, and 2 in the second quarter, etc.

first-order coefficient for capital input is negative, implying a positive shadow value of capital input. The coefficient for average stage length indicates that a 1 percent increase in average stage length, output held constant, causes a decrease in variable cost of about 0.16~0.17 percent. This should be interpreted as the effect on cost of flying fewer passengers over a longer distance each to obtain the same level of output. The coefficients for points served, about 0.66, suggest a 1 percent increase in network size leads to an increase in total variable cost of 0.66 percent. Of particular interest to this study are the delay variables, the estimates of which support our hypothesis that excessive flight time affects airline cost. The coefficient estimates are significant and rather consistent between these two models. The coefficients suggest that, at the sample mean, one minute increase in delay would cause around 0.6% increase in variable cost. The first order effect is, by construction, non-linear, since each additional minute of delay has the same percentage impact on cost. As discussed below, the quadratic delay term is insignificant, suggesting that the first order relationship is a reasonable approximation of the overall one.

Overall, the two models have very high goodness-of-fit (as indicated by their R^2's which are close to 1). In order to be consistent with the economic theory, the curvature conditions are further checked. The curvature conditions are derived by requiring the concavity of a cost function in its input prices, which is expected as a result of adjusting inputs quantities to their prices in the production process. Our results show that, about 67.6 percent of the data points in the sample satisfy the curvature conditions, which compares favorably to the other airline cost studies in which such a statistic is reported.

Before proceeding to delay cost estimation, we notice that the coefficients for some higher order terms involving the delay variable are not significant in the above two models. Keeping these variables in the model will certainly jeopardize the robustness of our subsequent cost estimates. As a consequence we removed insignificant delay terms (in our models these are delay*delay and delay*stage length) and re-estimated the two models. The estimates for the remaining coefficients are almost unchanged. The percentage of data points satisfying curvature conditions is slightly higher (68.3 percent). Moreover, all the terms involving the delay variable now have coefficients that are statistically significant. Table 3-3 documents the first-order coefficient estimates for these new models.

Table 3-3: Estimation results of delay-based Translog cost functions
with insignificant delay terms removed

	Model 3		Model 4	
	Est.	**Std. Err.**	**Est.**	**Std. Err.**
Output (RTM)	0.4840***	0.0339	0.4793***	0.0342
Fuel price	0.2012***	0.0016	0.2010***	0.0016
Labor price	0.3861***	0.0022	0.3859***	0.0022
Materials price	0.4127***	0.0032	0.4131***	0.0032
Capital service	-0.0542***	0.0009	-0.0541***	0.0009
Stage length	-0.1753**	0.0771	-0.1603**	0.0771
Points served	0.6628***	0.0558	0.6672***	0.0559
Delay against 10th percentile feasible flight time	0.0061***	0.0013		
Delay against 20th percentile feasible flight time			0.0058***	0.0013
R^2		0.9899		0.9898
Adjusted R^2		0.9888		0.9887

Notes: *** p<0.01, ** p<0.05, * p<0.1

3.1.3 Time-based Model

In this section, we consider a model with an alternative set of operational performance variables, $\bar{N}_{it}$, that characterize the relationship between the times when a given flight is scheduled to be, and actually is, active. Three new time measures are introduced: total absorbed time, scheduled time, and actual flight time. The total absorbed time (TAT) of a flight is defined as the time interval between the earlier of scheduled and actual departure times, and the later of the scheduled and actual arrival times. Scheduled time (S) is a subset of TAT, defined as the time between the scheduled departure and scheduled arrival. Actual flight time (A) denotes the time from the actual departure to the actual arrival; it is thus also a subset of TAT.

Using these three measures, the TAT for any flight can be categorized into the following subsets: scheduled-active time (S∩A), scheduled-non-active time (S∩~A), active-non-scheduled time (~S∩A) time, and non-scheduled-non-active time (~S∩~A). S∩A denotes the time falling into both the scheduled flight time and actual flight time intervals. S∩~A is the time within the scheduled flight time but outside the actual flight time. It can be caused by either late departures or early arrivals. ~S∩A represents the converse, which results from early departures and late arrivals. In the (rare) events of extremely early or late departures, time between the actual arrival and scheduled departure, or between the scheduled arrival and actual departure, is ~S∩~A. Theoretically there are six possible situations, as illustrated in Figure 3-1. For each situation, the solid and dashed arrow lines represent the scheduled and actual flight time respectively. For example, if the scheduled departure time of a flight is 7:00am and it actually left the gate at

7:30am, then $|S \cap \sim A|$ = 30 min. At the arrival end, the scheduled arrival time is 9:00am but the flight pulled up to the gate at 9:20am. In this case $|\sim S \cap A|$ is just the arrival delay, equal to 20min. The time between the actual departure and the scheduled arrival is $S \cap A$, amounting to 90min. This corresponds to the top-left situation, i.e. late-departure-late-arrival. The other five situations can be described as: early-departure-early-arrival (top right), late-departure-early-arrival (middle left), early-departure-late-arrival (middle right), extremely-late-departure (bottom left), and extremely-early-departure (bottom right). Note that, however, it is quite rare for the last two situations to take place.

Based on the above time categorization, we employ three new operational performance variables: the duration of TAT, denoted T_{tot}, the fraction of this time in $S \cap \sim A$ (i.e. $|S \cap \sim A|/T_{tot}$), which we denote $P_{S\sim A}$, and the fraction that is in $\sim S \cap A$ (i.e. $|\sim S \cap A|/T_{tot}$), denoted $P_{\sim SA}$. These variables replace the delay variable that was used in the delay-based model. T_{tot} measures the total amount of time the aircraft and crews of an airline are dedicated, in either plan or execution, to performing flights. The other two variables quantify the deviations between realized and scheduled flight activity. T_{tot} is integral to airline production and we therefore keep this variable in logarithmic form. The other two variables are included in level form since they can, in principle, be eliminated under ideal operating conditions.

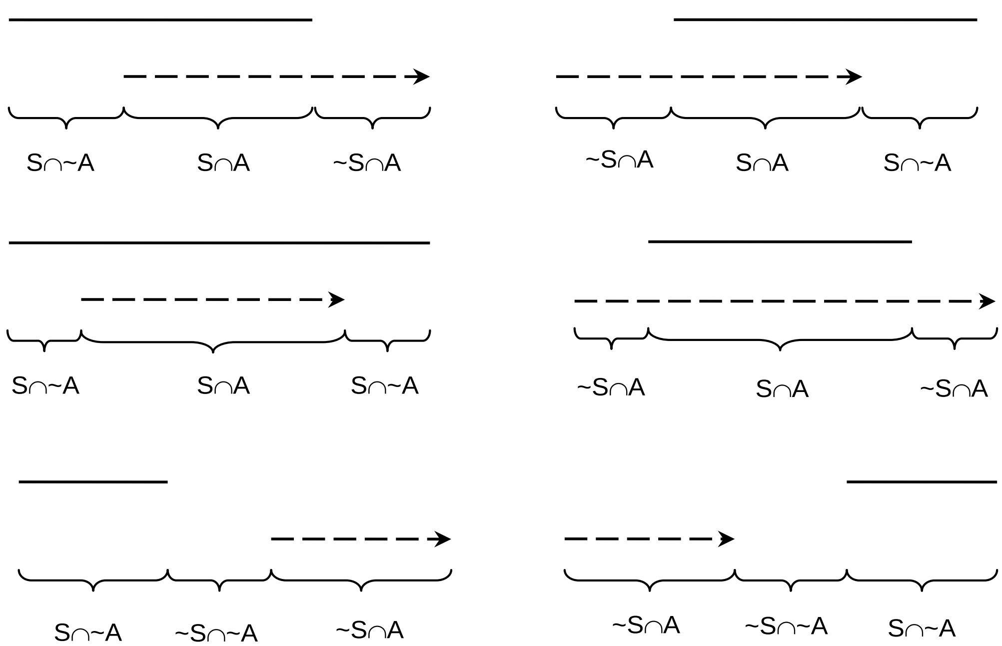


Figure 3-1: Identification of time components in the six possible situations

Table 3-4 provides the coefficient estimates for the first-order terms (Model 5). Comparing with Models 1-4, the factor price coefficients remain largely unchanged. The RTM coefficient is substantially lower, due to the inclusion of the total relevant time variable. Stage length is no longer significant and has a seemingly counter-intuitive sign, its effect captured by the total absorbed time variable, since longer average stage length allows the same output to be produced with less flight time.

Turning to the operational performance variables, the coefficient for T_{tot} has the expected positive coefficient and is highly significant. The $P_{\sim SA}$ variable has a significantly positive coefficient, suggesting everything else held equal, flight activity outside the schedule window results in additional cost. The $P_{S\sim A}$ variable does not seem to have a significant impact on cost. This suggests that flight inactivity during the schedule window—either because of departing late or arriving early—does not significantly reduce costs.

Similar to the previous cost models, the time-based model also has very high goodness-of-fit. Checking the curvature condition reveals that an even higher 77.6 percent of the data points satisfy the concavity requirement using this model. To make the subsequent cost estimate more robust, we check with the higher-order time variable terms in Model 5. We find that the majority of such terms not involving input prices are statistically insignificant.[4] Considering that these variables are not subject to homogeneity restrictions, we re-estimate a simplified version of Model 5. In the simplified model (Model 6), higher-order time variables not involving input prices are dropped out. Estimation results are reported in the 3rd and 4th columns of Table 3-4. The sign and significance of the first-order coefficients are largely unchanged, as does the percentage of data points satisfying the curvature conditions. The coefficient for $P_{S\sim A}$ remains insignificant and is now much smaller. The $P_{\sim SA}$ coefficient is also somewhat smaller (but still significant), apparently as a result of absorbing the effect of higher-order terms in the original model.

Table 3-4: Estimation results of time-based Translog cost functions

	Model 5		**Model 6**	
	Est.	**Std. Err.**	**Est.**	**Std. Err.**
Output (RTM)	0.2102***	0.0561	0.2424***	0.0531
Fuel price	0.1997***	0.0016	0.1995***	0.0016
Labor price	0.3860***	0.0021	0.3858***	0.0021
Materials price	0.4143***	0.0031	0.4147***	0.0031
Capital service	-0.0537***	0.0009	-0.0536***	0.0009
Stage length	0.0918	0.0880	0.0979	0.0783
Points served	0.5111***	0.0718	0.4901***	0.0590
T_{tot}	0.4368***	0.0725	0.4424***	0.0687
$P_{S\sim A}$	-0.4211	0.5167	-0.0492	0.4383
$P_{\sim SA}$	1.0875***	0.3740	0.7111**	0.3201
R^2		0.9901		0.9896
Adjusted R^2		0.9885		0.9884

Notes: *** p<0.01, ** p<0.05, * p<0.1

[4] Only one among the 15 such variables has a coefficient estimate that is significant at 5% level.

3.1.4 Cost Impact of Delay and Buffer on Airlines

In this sub-section, the previously estimated cost models are used to gauge the potential cost impact of delay and buffer on airlines, assuming these estimated models still apply to the improved operational scenarios described below. We choose the more robust Models 3, 4, and 6. Using Models 3 and 4, two scenarios are considered. In the first scenario delay against schedule is entirely eliminated, without changing the buffer, and in the second one we further reduce schedule buffer to the zero level. The new operating costs for each airline-quarter are predicted under the two scenarios, and compared to predicted costs at 2007 values for delay and schedule buffer. The difference between these new operating costs and baseline predicted values gives the cost of delay against schedule and the total cost of delay respectively. The difference between the cost of delay against schedule and the total cost of delay corresponds to the schedule buffer cost. Estimates for these costs for 2007 appear in the first three rows of Table 3-5.

We also use Model 6 to investigate the airline cost under two scenarios. In the first, T_{tot} is set to be the sum of SchAct and SchNonAct time over all flights, and the values $P_{\sim SA}$ and $P_{S\sim A}$ are reduced to zero. Under this scenario, aircraft's departure and arrival times exactly coincide with the current schedule, which contains some schedule buffer. In the second scenario, we also reduce T_{tot} to the unimpeded flight time, the calculation of which is described in section 3.1.2. Therefore, under this scenario all flights fly not only strictly following the schedule, but also take an optimal, unimpeded amount of time. As before, airline costs are predicted under these two scenarios, and compared to cost predictions using 2007 operational performance levels. We consider the difference between the original cost and the cost in the first scenario as the cost of delay against schedule, and the difference between the original cost and the cost of the second scenario as the total cost of delay. Their difference is the cost of schedule buffer. Estimates are reported in Table 3-5. We obtain somewhat larger estimates of delay-against-schedule and total cost from using the time-based model than from using the delay-based model. This may be because the counterfactual considered for the time-based model entails perfect adherence to both arrival and departure time schedules, whereas the delay-based model only considers arrivals. In any case, the similar magnitude of the cost estimates obtained from the two models provides some cross-validation of the basic approach. Also buffer cost estimates from the two models are very similar—$2-2.5 billion for the seven major airlines.

As a first-order industry-wide estimate, we extrapolate the above cost to the entire system based on the portion of available seat miles (ASM) provided by the major airlines in all carriers reporting data to BTS. Results are also reported in Table 3-5. Although this leaves out some regional and commuter airlines (those whose annual operating revenue is below $20 million), such airlines account for a very small fraction of the total ASM, so excluding them will have little effect on the system-wide result.

In our cost summary, we have elected to emphasize estimates derived from the delay-based model. This model features a simpler and more conventional representation of operational performance, has a slightly higher R^2, and has lower standard errors for the relevant coefficients. The higher estimate derived from the time-based model is also quite plausible however, making the choice largely as matter of judgment.

Table 3-5: Airline cost estimates ($ billions), for 2007

	Cost category		Delay against 10 percentile feasible flight time	Delay against 20 percentile feasible flight time
7 major airlines*	Delay-based model	Delay against schedule	3.3	3.1
		Buffer	2.6	1.9
		Total	5.9	5.0
	Time-based model	Delay against schedule	6.7	6.7
		Buffer	2.4	1.8
		Total	9.1	8.5
Industry wide**	Delay-based model	Delay against schedule	4.6	4.4
		Buffer	3.7	2.7
		Total	8.3	7.1
	Time-based model	Delay against schedule	9.4	9.4
		Buffer	3.4	2.7
		Total	12.8	12.1

* US Airways and American West are excluded due to merger.
** Includes airlines with annual operating revenue greater than $20 million.

As a final remark, we reiterate that a delay-free NAS is a limiting—and unreachable—case. As long as there are winds and storms, aircraft parts fail, and people make mistakes, there will be delays. As long as there are delays, airlines will seek to mitigate their impacts through schedule buffer. As a consequence, the cost estimates presented here—and elsewhere in this report—should be regarded as an upper bound on the cost savings that could be obtained from improving the capacity and operational efficiency of the NAS at 2007 activity levels.

3.2 Passenger Delay Cost

The primary mission of the national air transportation system is the rapid, affordable, and safe transportation of passengers and cargo between geographically distant and/or remote destinations. Flight delay impairs this mission by increasing passenger trip times and reducing schedule reliability. In this section, we estimate the resulting costs to passengers in 2007. Most of the effort went to estimating passenger arrival delay against the ticketed schedule, which we term *Passenger Trip Delay*. We also consider the additional passenger travel time resulting from schedule padding. The final step was to monetize these passenger time costs. Section 3.2.1 describes ways in which passenger trip delays can occur. Section 3.2.2 provides an overview of the algorithm used to compute the passenger trip delay metrics and identifies the associated data sources. Section 3.2.3 briefly describes the workings of the algorithm and identifies some of the methodological contributions made by this study. Section 3.2.4 provides the results generated by using publicly available data sources and our algorithm to compute passenger trip delay performance for 2007. Section 3.2.5 presents estimates of additional passenger travel time from schedule padding, while Section 3.2.6 estimates the monetary value of the passenger delays computed in the previous sections.

3.2.1 Passenger Trip Delay Causes

Passenger Trip Delay is defined as the positive difference between the actual time of arrival of the passenger and the scheduled time of arrival on the ticket purchased by the passenger. It is analogous to flight delay against schedule; we consider the effect of schedule buffer on passenger delay cost later on.

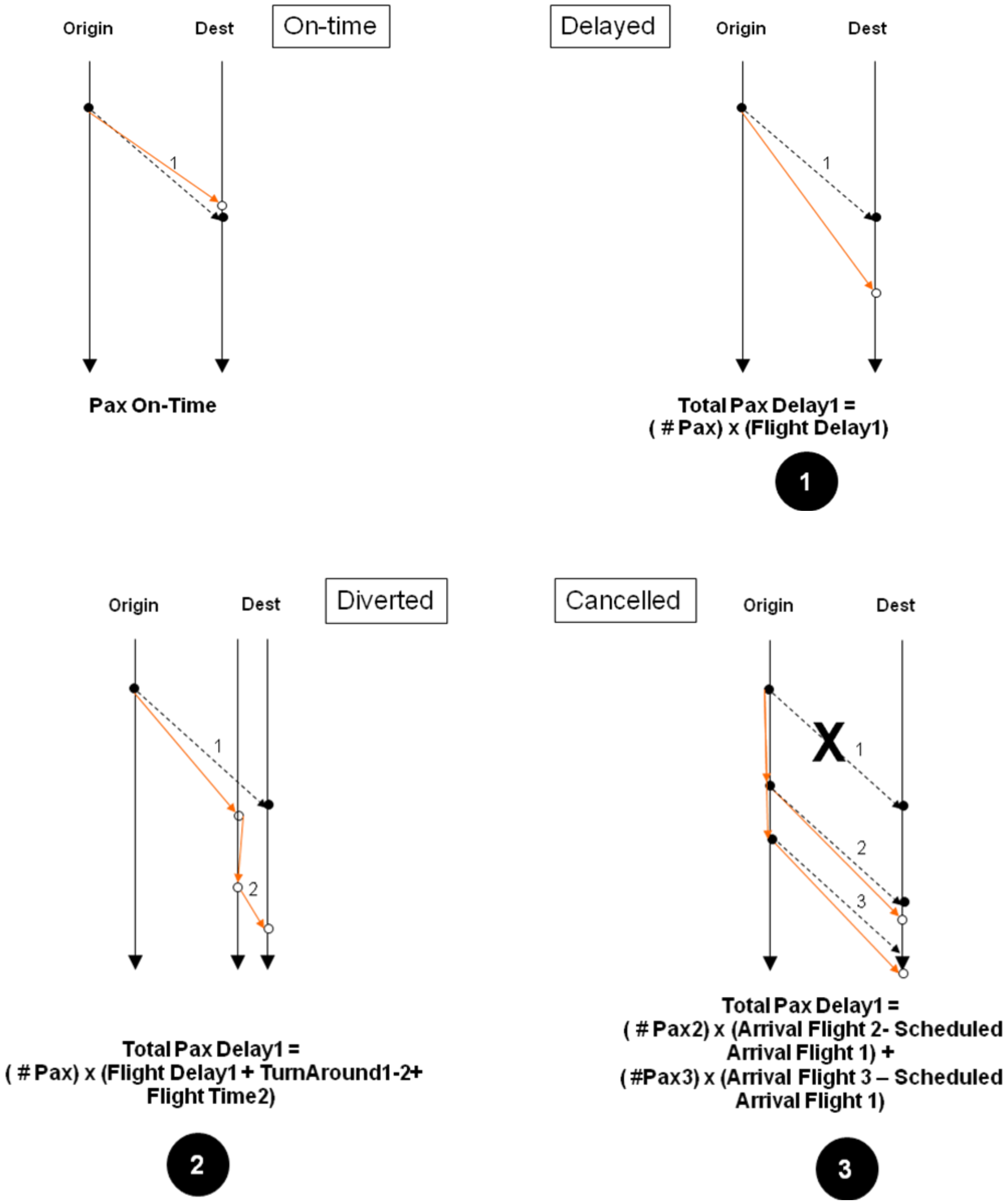
Passenger Trip Delay = max (Actual Time of Arrival – Scheduled Time of Arrival, 0)

Passenger Trip Delay can occur as a result of one of the following scenarios:

1. Passenger arrives late on the last ticketed flight of an itinerary.
2. Passenger arrives late because a ticketed flight was diverted to another airport.
3. Passenger arrives late after being re-booked on a later itinerary when a ticketed flight is cancelled.
4. Passenger arrives late when the passenger misses a connection and is re-booked on a later itinerary.

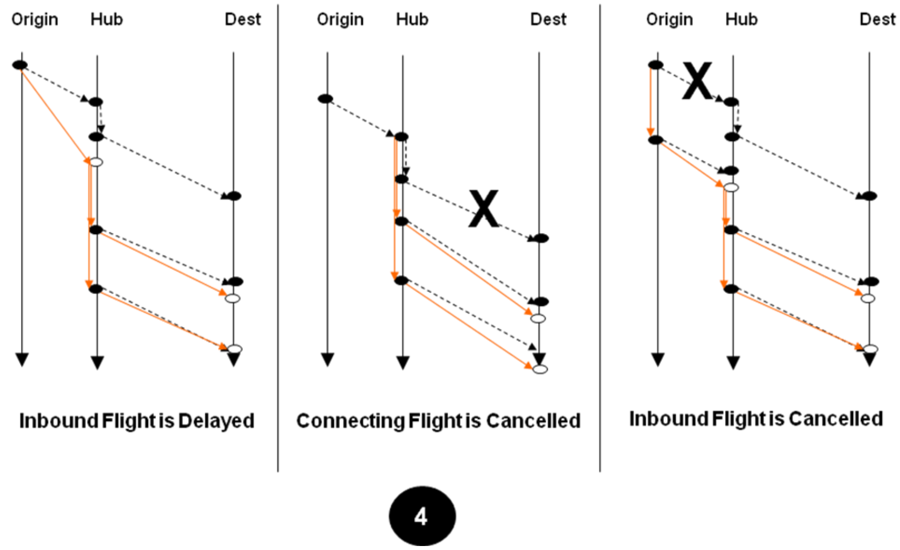
Scenarios 1, 2, and 3 are illustrated in the Time-Space diagrams in the Figure 3-2. Scenario 4 is illustrated in Figure 3-3, in which the term "hub" refers to airports where a connection is made.

The trip delays experienced by passengers on late flights and on diverted flights (Scenarios 1 & 2) are proportional to the magnitude of the delay of these flights. The trip delays experienced by passengers that have to be rebooked due to a cancelled flight or missed connection (Scenarios 3 & 4) are a function of the frequency and load factors (i.e. the percentage of seats filled) on other flights to the desired destination. As the frequency of the flights diminishes and/or the load factor of candidate rebooked flights increases, the trip delay experienced by these passengers typically increases non-linearly – and at a very high rates when load factors are high and/or the frequency of flights is low.



Total Pax Delay1 refers to the total passenger delay experienced by the passengers on Flight 1.

Figure 3-2: Time-space diagram for Scenarios 1-3



The scenario for passengers who miss connections: inbound flight is delayed, connecting flight is cancelled, or inbound flight is cancelled.

Figure 3-3: Time-space diagram for Scenario 4

3.2.2 Overview of Algorithm and Data Sources

Figure 3-4 provides an overview of the computation of Passenger Trip Delay for each of the scenarios described in Section 3.2.1. The algorithm is based on the work of Bratu and Barnhart (2005), Wang and Sherry (2007), Sherry and Calderon-Mesa (2008), and Zhu (2009) at MIT and GMU. This body of work has been extensively refined and enhanced in research performed specifically for this study.

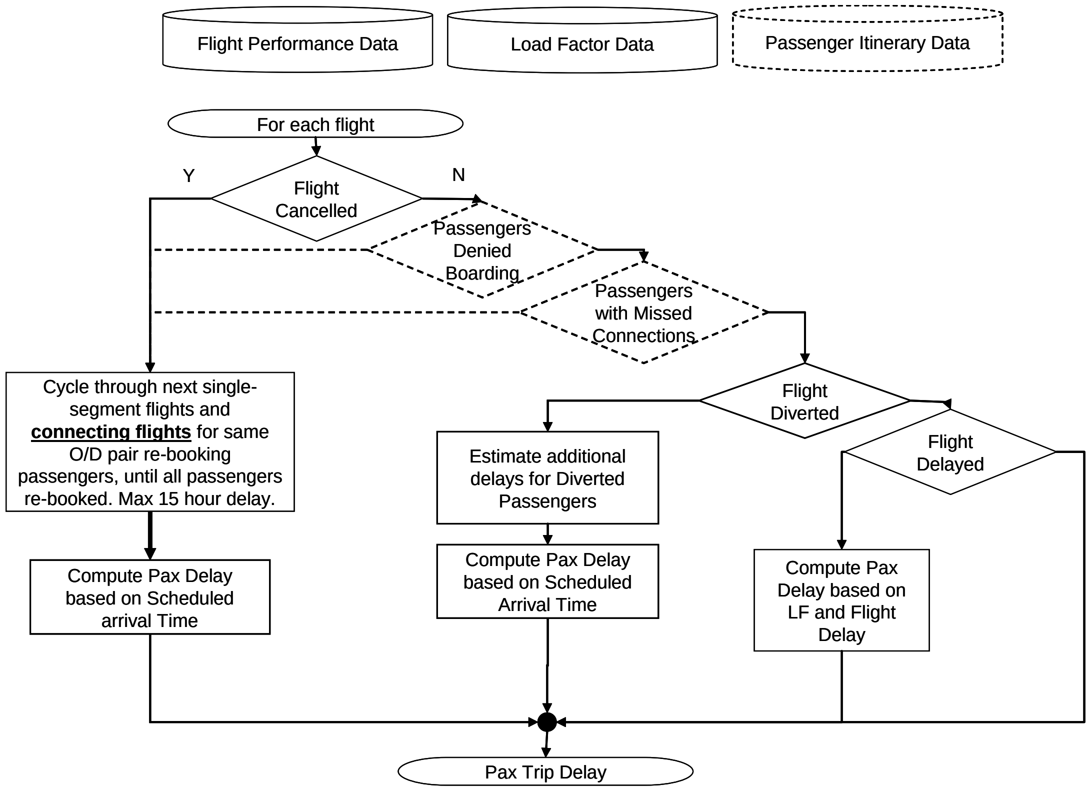
The algorithm is summarized in Figure 3-4 below, which also indicates at its top part the three sets of data that are required. These are:

1) Airline Flight Performance Data

Airline flight performance information is required to determine flight delays for each individual flight, as well as diversions and cancellations of individual flights. This information is derived from the BTS Airline On-Time Performance database, which is reported by US certified air carriers that account for at least one percent of domestic scheduled passenger revenues.

2) Aircraft Seat Capacity and Load Factor Data

Aircraft seat capacity and load factors for each flight are required by the algorithm for rebooking passengers on cancelled flights and/or missed connections. This data is derived from the BTS T-100 data-base.



Data-sources and Algorithm used to compute Passenger Trip Delays.

Figure 3-4: Overview of the algorithm

3) Passenger Itinerary and Flight Load Factors

Passenger Itineraries are estimated using aggregated, average monthly load factors from the BTS T-100 data-base. The algorithm for estimating passenger itineraries and load factors is described in section 3.2.3 below.

The specific databases used to provide the 2007 estimates reported in Section 3.2.4 are:

• T-100 Domestic Segments Data (U.S. Carriers) – domestic segment data aggregated by month

• DB1B Coupons Data – a 10% sample of domestic itinerary data aggregated by quarter

• Flight On-Time Performance Data (ASQP) – daily on-time arrival data for domestic flights operated by major U.S. carriers

• Innovata Flight Offerings Data – expected flight offerings for 2007 as of January 1st, 2007

• Proprietary Passenger Bookings Data – proprietary legacy carrier bookings data for Q4 2007 (used for the purpose of validating the proposed approach)

• Other Data – FAA Aircraft Registry, which includes seating capacities by carrier and aircraft type

3.2.3 Description of Algorithm

This section provides a brief description of the algorithm utilized to calculate passenger delays. A more detailed description can be found in a technical support document for the passenger delay calculation algorithm. The algorithm proceeds in three steps:

1. Generation of potential passenger itineraries.
2. Estimation of passenger demand allocation to each potential itinerary.
3. Determination and rebooking of disrupted passenger itineraries.

In the first step, we generate all potential itineraries that passengers may take based on the flight schedule data in ASQP and the sampled passenger itinerary data in the DB1B Coupon database. For the purposes of our analysis, we only include non-stop and one stop itineraries, as itineraries with more than one stop account for only 2.5% of the one-way trips in DB1B. A non-stop itinerary is generated for every flight in ASQP, whereas a one-stop itinerary is generated only for valid flight pairs. Using the 2007 ASQP and DB1B data sets, this procedure leads to the generation of some 270 million itineraries, of which about 7.5 million are non-stop.

In the second step, we utilize a statistical approach to estimate the passenger demand associated with each of the potential itineraries. To do so, we use one quarter of proprietary booking data from a large legacy carrier to estimate the passenger utility associated with itinerary features such as local time of departure, day of week, and connection time. Next, we use these estimated utilities to calculate the probability that each itinerary would be selected. Finally, we use the estimated probabilities to sample an itinerary that matches each passenger's route. We determine the number of monthly passengers traveling on each route by combining the passenger demand data available in T-100 and DB1B databases. The results of these three steps can then be fed into the Passenger Trip Delay Algorithm of GMU (or alternatively the Passenger Delay Calculator of MIT) to estimate total passenger delays.

Computing these estimates of passenger bookings is necessary in order to estimate the passenger delays due to missed connections and to refine the estimates of delays due to cancellations and diversions. Historical information on passenger bookings is considered proprietary and highly sensitive by the airlines. Absent such proprietary data, a good estimate of bookings based on approaches that utilize published data is the best that can be realistically achieved. The approach described above estimates two intermediate sets of data that are then utilized to estimate passenger delays: (a) load factors and aircraft size for all scheduled flights on a day-of-week and time-of-day basis, and (b) itineraries for all passengers including connections at transfer airports.

In the last step, the algorithm processes each individual flight, starting with the first flight in the period under investigation and terminating with the last flight of the period. If the flight was cancelled or diverted, all the corresponding passengers are rebooked to their final destinations. For the purpose of our analysis, we treat diversions as cancellations, because the ASQP database does not provide the destination of the diversion. Diversions represent approximately 0.2% of total flights, so we do not expect their treatment in this approximate manner to significantly impact the results. Passengers that miss connections are treated in the same manner as passengers on cancelled flights and are rebooked from the connecting airport to their final destination. The generation of estimates of delays due to missed connections had not been possible until this study due to the unavailability (in the public domain) of passenger itinerary data. In today's air transportation system, missed connections are a very important cause of passenger delays.

The results described in this report include both re-booking on direct (i.e. single segment) flights, as well as connecting (i.e. two segment) flights. Because all flight options are not available in the ASQP database (e.g., non-reporting carriers) and to ensure that our overall estimates are conservative, we limit the amount of rebooking-incurred delay. For passengers disrupted during the day (e.g., between 5:00am and 5:00pm) we limit the rebooking delay to a maximum of 8 hours, whereas for passengers disrupted during the evening (e.g., between 5:00pm and 5:00am), we limit the rebooking delay to 16 hours. Thus, if passengers cannot be rebooked to their final destination, we assume their trip delay equals the maximum allowed in their case (i.e. either 8 hours or 16 hours). Prior to assigning to a passenger the maximum rebooking delay, we also attempt to rebook the passenger on carriers other than the ticketed carrier or its subcontracted carriers.

Finally, delay for passengers whose itineraries are not disrupted is computed based on the publicly available data reporting flight delays for all scheduled commercial flights in the US.

3.2.4 Results for 2007

This section provides estimates of Passenger Trip Delay for January – December 2007. The analysis is based on data provided by BTS for the airlines with more than 1% of enplanements per annum and the MIT algorithm for estimated passenger itineraries and flight load factor.

In 2007, 7.45 million flights provided transportation for 487.2 million passengers on 4437 direct routes between 267 airports. The average number of flights between O/D pairs in 2007 was 4.57. The total estimated delay accrued by passengers due to delayed flights, cancelled flights, and missed connections was 28,539 years. The monthly differences, as reported in Tables 3-7 and 3-8, are due to seasonal weather and traffic factors. Despite these influences, results are fairly consistent throughout the year. The average delay experienced, computed for all the passengers in 2007, was 31 minutes per passenger.

Table 3-6: Passenger delay estimates for calendar year 2007

	2007
Number of Flights Operated	7,455,458
Number of Passengers Boarded	487,197,014
Percentage of Flights Delayed 15+ Minutes	24.2%
Percentage of Flights Cancelled	2.2%
Average Delay for Operated Flights	15.0
Average Delay for all Passengers	30.8
Number of Disrupted Passengers	16,419,439
Percentage of Passengers Disrupted	3.4%
- Disrupted due to Cancellations	69.7%
- Disrupted due to Missed Connections	30.3%
Average Delay for Non-disrupted Passengers	15.9
Average Delay of Disrupted Passengers	456.9
- Due to cancellations	68.5%
- Due to missed connections	31.5%

Table 3-7: Monthly passenger delay estimates for the 1st and 2nd calendar quarters of 2007

	January	**February**	**March**	**April**	**May**	**June**
Number of Flights Operated	621,559	565,604	639,209	614,648	631,609	629,280
Number of Passengers Boarded	36,351,929	34,397,205	42,640,307	41,407,749	42,679,424	43,924,679
Percentage of Flights Delayed 15+ Minutes	24.2%	28.0%	23.9%	22.3%	20.8%	28.8%
Percentage of Flights Cancelled	2.5%	4.5%	2.6%	1.8%	1.1%	2.7%
Average Delay for Operated Flights	14.1	17.2	14.9	13.5	12.3	19.6
Average Delay for all Passengers	28.4	43.0	34.6	27.3	22.6	43.0
Number of Disrupted Passengers	1,318,378	1,948,863	1,675,589	1,201,043	946,770	1,931,463
Percentage of Passengers Disrupted	3.6%	5.7%	3.9%	2.9%	2.2%	4.4%
- Disrupted due to Cancellations	72.5%	79.1%	74.9%	69.1%	62.5%	70.8%
- Disrupted due to Missed Connections	27.5%	20.9%	25.1%	30.9%	37.5%	29.2%
Average Delay for Non-disrupted Passengers	14.3	18.0	15.8	14.6	13.1	21.6
Average Delay of Disrupted Passengers	402.9	459.3	493.8	453.5	439.6	508.5
- Due to cancellations	70.7%	79.6%	75.9%	68.1%	59.5%	70.2%
- Due to missed connections	29.3%	20.4%	24.1%	31.9%	40.5%	29.8%

Table 3-8: Monthly passenger delay estimates for the 3rd and 4th calendar quarters of 2007

	July	**August**	**September**	**October**	**November**	**December**
Number of Flights Operated	648,560	653,279	600,187	629,992	605,149	616,382
Number of Passengers Boarded	45,613,812	44,915,170	37,400,161	40,784,536	39,087,925	37,994,117
Percentage of Flights Delayed 15+ Minutes	27.8%	26.2%	17.1%	20.5%	18.8%	31.9%
Percentage of Flights Cancelled	2.1%	1.9%	1.1%	1.2%	1.0%	3.5%
Average Delay for Operated Flights	18.1	16.8	10.1	12.0	10.9	19.8
Average Delay for all Passengers	37.0	33.6	18.5	21.1	18.6	41.0
Number of Disrupted Passengers	1,664,301	1,501,007	777,976	868,813	750,117	1,835,119
Percentage of Passengers Disrupted	3.6%	3.3%	2.1%	2.1%	1.9%	4.8%
- Disrupted due to Cancellations	67.2%	66.0%	63.4%	60.5%	60.8%	71.7%
- Disrupted due to Missed Connections	32.8%	34.0%	36.6%	39.5%	39.2%	28.3%
Average Delay for Non-disrupted Passengers	19.8	18.2	10.6	12.8	11.4	20.2
Average Delay of Disrupted Passengers	491.8	478.1	391.7	402	387.2	449.4
- Due to cancellations	65.5%	64.5%	57.1%	55.1%	55.8%	71.3%
- Due to missed connections	34.5%	35.5%	42.9%	44.9%	44.2%	28.7%

3.2.5 Passenger Buffer

We employ an aggregate approach to quantify passenger buffer. As discussed in section 3.1, airlines routinely build buffer into flight schedules. Once a flight is flown, each passenger on that flight will have to bear this extra amount of time. In order to be consistent with the airline cost model, we employ the same "Avg. buffer10" measure. The same airline-quarter data as in section 3.1 are used. For each airline-quarter observation, the average buffer time per flight is multiplied by the average number of seats per flight and the load factor, and then by the total number of flights flown. Values are summed up across all airlines and quarters. For 2007 the total passenger buffer amounts to 9,526 million minutes, or an equivalent 159 million hours.

3.2.6 Monetary Value of Passenger Delays

There exist numerous studies about how travelers value their time during the trip. One way to obtain the value of travel time is by using wage rates. Economic theories postulate that individuals will adjust the amount of time they devote to work and leisure such that an additional small increment of either may be valued at the wage rate. More sophisticated models recognize that constraints on the ability of workers to alter work schedules or the conditions under which time is devoted to either work or leisure can cause the value people place on an incremental gain or loss of time to deviate, perhaps significantly, from the wage rate (GRA, 2004, Small, 1992). Alternative approaches have been adopted to infer passenger value of travel time. One intensively utilized method is based upon random utility theory and mode/itinerary choice models, where most popular are the multinomial logit model and its variants. A few studies explicitly investigate how passengers value air travel delays, prominent among which are Adler et al. (2005) and Forbes (2008).

The Department of Transportation provides recommended values of travel time in their departmental guidance (DOT, 2003). The values are based on a survey conducted by the Air Transportation Association in 1998 and updated it with changes in median annual income from 1998 to 2000. Certain percentage rates are factored in to generate the value of time for different travel purposes. The TDI team follows this guidance and uses weighted average across business and leisure travelers, inflated to 2007 U.S. dollars. The number used here is the same as the one adopted in JEC (2008), valued at $37.6/hour.

The above value of travel time is then applied to passenger buffer and delay against schedule. The TDI team finds that the total passenger delay cost amounts to $15.4 billion, with breakdown detailed in Table 3-9.

Table 3-9: Passenger cost estimates (in $ millions), for 2007

Delay Category	**Delay Cost (million dollars)**
1. SB (schedule buffer)	5,969
2. PDS (passenger delay against schedule)	
2a. Delay due to delayed flights	4,699
2b. Delay due to flight cancellations	3,221
2c. Delay due to missed connections	1,480
Total estimated PDS (2a+2b+2c+2d)	9,400
Total	15,369

3.3 Estimate of Costs of Voluntary Passenger Schedule Adjustments Due to Anticipated Schedule Delays

3.3.1 Data Sources

In order to measure the extent to which delay and unpredictability cause travelers to leave the night before their scheduled meetings we need information on the timing of their departures. The aim of this piece of the project is to understand how delay and other variables such as cancellations and arrival time influence passengers' decision of what time to fly. In order to undertake this analysis we require flight-level data describing arrival and departure times.

We focus on simple round trips. We sample itineraries that are contained entirely within the confines of a single work week, which we define as the period from midnight Monday morning through midnight Friday evening.

We categorized the outbound departure window as follows:

- Early (Midnight to 8am)
- AM Peak (8am to 10am)
- Midday (10am to 4pm)
- PM Peak (4pm to 7pm)
- Evening (7pm to Midnight)

Information on the timing of departures cannot be obtained from publicly available data sources. The on-time arrival database maintained by the FAA provides a wealth of information about aircraft arrivals, but no information about the itineraries of the passengers traveling on those aircraft. The OD1A and OD1B databases provide a wealth of information about passenger itineraries, but virtually no information about the timing of passenger travel (other than the quarter in which the trip took place). In order to carry out an empirical study of the effects of delays on departure timing, therefore, we needed to identify a new source of data.

That source of data turned out to be the Sabre system. Sabre is the oldest and the largest of the original airline computerized reservation systems.[5]

Sabre covers a large but not necessarily representative fraction of the total universe of air travel. Missing from Sabre are tickets purchased from other GDS systems, from dedicated airline websites, or from certain new electronic distribution channels such as Priceline. As a result, Sabre tends to under-represent low cost carriers and low cost fares. It tends to over-represent travel booked through travel agencies, and corporate travel. The distinctive footprint of Sabre complicates the task of generalizing results based upon Sabre data. At the same time, however, that distinctive footprint makes Sabre a well-equipped and suitable laboratory for investigating hypotheses about business travel behavior.

Sabre contains data on passenger itineraries as booked. Changes made prior to departure are captured as long as they are made through Sabre, which generally requires that they be made by the travel agency that originally booked the flight. Changes made at the airport or directly through the airline may not be reflected in the Sabre data. Sabre records contain complete information on dates and times of departures and arrivals of all flights within a passenger's itinerary. The system also captures the carrier, the fare, and

[5] These systems are now referred to as Global Distribution Systems, or GDS.

the airport endpoints of each flight segments. Sabre retains the full detail on each booking for a period of three years. Confidentiality provisions in Sabre's agreements with participating airlines restrict the information it is allowed to release to third parties. For the most part, it is prohibited from releasing individual itinerary data. It can however, provide aggregated summaries that contain a considerable amount of detail.

3.3.2 Structural Model Specification

We model choice of departure window as a standard discrete choice problem. We assume that a passenger, having selected an airport pair, seeks to maximize utility across departure windows. We model utility as being a function of the time at which the passenger can expect to arrive at his or her destination and of the delay the passenger can expect to experience.

Let *j* be an index of departure windows. At a high level, we can characterize the utility associated with choosing departure window *j* as follows:

$$U_j = D_j + A_j + L_j + \varepsilon \qquad \text{(Equation 3-1)}$$

where:

D_j is the disutility associated with schedule delay.
A_j is the disutility associated with the arrival time dictated by choosing departure window j.
L_j is the disutility associated with arriving late.
ε is a random variable.

3.3.2.1 Schedule Delay

The more departures there are, the greater the chances are of finding a departure at a convenient time. The schedule density, defined as the number of flights per unit of time, varies over the course of the day. All else equal, a passenger will desire a higher schedule density. However, the value of an additional flight declines as the number of flights increases and the schedule becomes saturated. Thus, a reasonable specification for schedule delay is given by:

$$D_j = \lambda / N_j \qquad \text{(Equation 3-2)}$$

Where N_j is the number of scheduled departures per minute[6] for that route and quarter and λ is an estimated coefficient. For each cell, we record the number of flights found in the On Time Performance dataset.

3.3.2.2 Arrival Time Disutility

Travelers will generally prefer to arrive at some point during the business day. We will assume that there is some disutility associated with arriving during each hour interval of the destination day. Call these π_i. Let the set of dummy variables d_{ji} equal 1 if a departure during window *j* implies an arrival in hour *i*, and 0 otherwise. We can calculate d_{ji} from T_j, the scheduled flight time, and the time required to exit the airport.

[6] It is important to scale N_j by the length of the departure category in order to make the D_j's comparable across departure categories. This could be accomplished by dividing the number of flights by the number of hours in the departure category; we divide by the number of minutes simply to produce regression coefficients of a magnitude similar to those on our other variables. Because this is a mere scaling, it has no impact on other regression coefficients or on the measured significance of any of our results.

We can then express the arrival time disutility as:

$$A_j = \sum_i \pi_i d_{ji} \qquad \text{(Equation 3-3)}$$

where the π_i are estimated coefficients.

For each cell, we calculate arrival probabilities for each of seven time windows, measured in local time for the destination airport: the two-hour increments from 6am-8am, 8am – 10am, 10am – 12pm, 12pm – 2pm, 2pm – 4pm, and 4pm – 6pm, and the six hour increment from 6pm – 12am. These probabilities are calculated from the scheduled arrival times from the On Time Performance dataset for each cell. That is, if, for a given quarter, route and departure window there are 100 flights in the On Time Performance dataset, and 25 of them arrive between 10am and 12pm, then we simply assign a 25% probability of arrival within that time window for that cell; if 27 of them arrive between 12pm and 2pm we assign a 27% probability of arrival within that time window; etc.

3.3.2.3 Late arrival disutility

To account for late arrival disutility we will need to divide the time period around the scheduled arrival time into a series of time intervals. Let *k* be an index of these intervals. In our analysis, we use:

k = 1 implies early or on-time,

k = 2 implies arrival more than half an hour late

We measure the probability with which a traveler experiences delay by calculating the fraction of flights in each year, quarter, route, and departure category that fall into each delay interval. Define the set of variables g_{jk} to equal the probability of arriving within delay interval *k* for passengers in departure category *j*.

The late arrival disutility, then, is then given by:

$$L_j = \sum_k \gamma_k g_{jk} \qquad \text{(Equation 3-4)}$$

where the γ_k's are estimated coefficients.

We represent lateness as the probabilities of being late by various amounts, based on the empirical distribution of delay observed in the On Time Performance Dataset. Thus, we calculate the percentage of flights that arrived early and the percentage that arrived more than half an hour late. We employ the four-quarter lag of observed delay, specific to the relevant year, quarter, and O-D pair.

We estimate this model as a standard conditional logit model, in which the probability of selecting a given departure window is a function of its characteristics and those of the other departure windows available to a passenger traveling in a given year, quarter, and origin-destination pair.

3.3.3 Results

We present our econometric results in Table 3-10.

We observe an appropriately negative sign on the inverse of flights per hour. The pattern of coefficients observed on our arrival time windows suggests that passengers prefer to arrive early in the morning or late in the workday. The coefficients on early and late arrival are measured relative to the implicit coefficient of zero on the excluded category of lateness, from on time arrival to half an hour late. The implication is that passengers experience a small amount of disutility for early arrival (which can cause them to have to wait for rides or to meet business contacts), and a substantially larger level of disutility for arrival more than half an hour late.

Table 3-10: Conditional logit regression results

Left-Hand Variable is Choice of Departure Window

Observations (Trips) = 4,258,827

Variable	
Inverse of Flights per Hour	-0.376***
	(0.002)
Arrival 6am-8am	2.044***
	(0.021)
Arrival 8am-10am	2.020***
	(0.020)
Arrival 10am-12pm	1.556***
	(0.020)
Arrival 12pm-2pm	1.455***
	(0.021)
Arrival 2pm-4pm	1.836***
	(0.020)
Arrival 4pm-6pm	2.311***
	(0.020)
Arrival 6pm-12am	0.839***
	(0.020)
Cell-Specific Lateness: Early, Lag 4 qtrs	-0.0641***
	(0.009)
Cell-Specific Lateness: Greater than 30 Minutes Late, Lag 4 qtrs	-0.204***
	(0.014)

Notes:

Arrival and Lateness variables are probabilities expressed in decimal terms, i.e. 5% = 0.05.

Arrival prior to 6am and lateness between 0 and 30 minutes are excluded.

*** p<0.01, ** p<0.05, * p<0.1

3.3.4 Calculation of VDTA Costs

To calculate the number of passengers who make Voluntary Schedule Time Adjustments made in response to delay we set all delay probabilities to zero and use the results shown in Table 3-11 to recalculate departure window shares.

Table 3-11: Predicted schedule adjustments between departure windows without delay

Voluntary Time Adjustment

Departure Category	Predicted Trips in Sample	Predicted Trips in Sample - No Delay in Departure Window	Predicted Gross Increase	Difference as Percent of Predicted Trips in Previous Departure Window
Early	848,661	843,745	5806	3.03%
AMPeak	900,058	883,949	10722	1.26%
Midday	1,666,114	1,669,603	26832	2.98%
PMPeak	652,072	666,937	23343	1.40%
Evening	191,922	194,594	8478	1.30%
Total	**4,258,827**	**4,258,827**		

Notes

The increase in the predicted number of trips without delay is equal to the predicted number of trips with delay plus the predicted gross increase less the predicted gross increase of the following period - i.e., it measures the *net* change, so that the total number of trips predicted remains constant

We calculate the extent of schedule shifting one departure window at a time.[7] For each departure window, we calculate the number of trips predicted in our regression sample with observed delay. We then calculate the number predicted for each departure window if the probability of delay greater than half an hour is set to zero for that departure window only. The difference between these two is the predicted gross increase for the departure window.

In order to translate these adjustments into hours (and ultimately, dollars) lost, we must make an assumption concerning the departure window *from which* these passengers are switching. We assume that they are switching from preceding departure window – *e.g.*, from Early to AMPeak, from AMPeak to Midday, and so on. Thus, we assume that the *net* change in each departure window under the assumption of no delay is equal to the gross increase for that departure window less the gross increase for the following departure window.

The first two columns of Table 3-11 present the results of this exercise. The second column is the *net* predicted number of trips in the departure window with no delay. The third column is the predicted gross increase for the departure window. Of course, in each case, with delay set to zero, the *gross* increase for each departure window is positive. The right-most column of Table 3-11 expresses the predicted gross increase in demand for each departure window as a percentage of the preceding window (from which, we continue to assume, the gross increase is pulled).

We next apply these estimates to the universe of passenger air travel represented by the DB1B 10 percent ticket sample. Table 3-12 presents the total number of passengers represented in this dataset in each quarter of 2006-2008, and the number departing in each departure window calculated from the distribution observed in our Sabre dataset.

[7] We carry out the calculation one departure window at a time in order to be able to observe the gross number of shifts. If we were to recalculate all windows simultaneously we would observe the net results of people shifting out of one departure window to the next, and shifting into that same departure window from the previous window.

Table 3-12: Departures by quarter and departure window, 2006-2008

Year	**Quarter**	**[1] DB1B Passengers**	**[2] Early Departures**	**[3] AMPeak Departures**	**[4] Midday Departures**	**[5] PMPeak Departures**	**[6] Evening Departures**
2006	1	47,442,475	12,637,897	11,773,993	15,361,202	5,506,529	2,162,853
2006	2	53,492,824	14,249,611	13,275,533	17,320,220	6,208,778	2,438,682
2006	3	50,879,894	13,553,569	12,627,072	16,474,190	5,905,502	2,319,561
2006	4	51,289,444	13,662,666	12,728,711	16,606,797	5,953,037	2,338,232
2007	1	49,055,672	13,067,626	12,174,347	15,883,533	5,693,769	2,236,397
2007	2	55,655,455	14,825,700	13,812,242	18,020,449	6,459,789	2,537,274
2007	3	53,250,926	14,185,173	13,215,500	17,241,897	6,180,702	2,427,654
2007	4	52,523,820	13,991,484	13,035,052	17,006,470	6,096,308	2,394,506
2008	1	50,282,916	13,394,544	12,478,917	16,280,897	5,836,212	2,292,346
2008	2	54,944,882	14,636,415	13,635,896	17,790,376	6,377,315	2,504,880
2008	3	50,415,908	13,429,971	12,511,922	16,323,958	5,851,648	2,298,409
2008	4	47,863,452	12,750,038	11,878,469	15,497,509	5,555,391	2,182,045
Total		**617,097,668**	**164,384,693**	**153,147,656**	**199,807,498**	**71,624,982**	**28,132,838**

[1] = DB1B 10% Ticket sample multiplied by 10 to obtain total population estimate; see also Table 5

[2] = [1]*26.6%, percent of Sabre Bookings with Early Departures, from Table 8

[3] = [1]*24.8%, percent of Sabre Bookings with AMPeak Departures, from Table 8

[4] = [1]*32.4%, percent of Sabre Bookings with Midday Departures, from Table 8

[5] = [1]*11.6%, percent of Sabre Bookings with PMPeak Departures, from Table 8

[6] = [1]*4.6%, percent of Sabre Bookings with Evening Departures, from Table 8

We were able to identify an empirical study presenting estimates of how traveler value of time varies over the course of the day.[8] See Table 3-13. We rely on these estimates in our calculation, so that the value of time we express is in terms of the hourly wage of a 'representative passenger'.[9]

Table 3-13: Value of time lost to voluntary departure time adjustment

Activity	Value of Time as Multiple of Average Hourly Wage
Leisure	0.93
Work	1.86
Sleep	5.67

We assume that the time saved by a passenger switching departure category is the difference between the mean departure times of the relevant windows, as measured by the flights in the On Time Performance dataset. We treat passengers that switch from an evening departure to an early departure the next morning

[8] Mehndiratta, Shomik Raj, 1996, "Time-of-Day Effects in Inter-City Business Travel," *Institute of Transportation Studies at UC Berkeley Dissertation Series*.

[9] The hourly wage we employ is that measured for private sector production workers in the Bureau of Labor Statistics' Consumer Expenditures Survey, which averages $17.42 over 2006-2008.

somewhat differently, reducing the difference between these two departures by eight hours to allow for time spent sleeping.[10] Table 3-14 shows the average departure time associated with each departure window across our three year sample.

Table 3-14: Mean departure time, 2006-2008

Departure Category	Mean Departure Time
Early	6:47 AM
AMPeak	8:54 AM
Midday	12:57 PM
PMPeak	5:26 PM
Evening	8:23 PM

We assume that a passenger that adjusts from an AMPeak departure to an Early departure loses sleep time, and that a passenger that adjusts from an early departure time to a departure the night before loses leisure time. All others lose work time. Based on these assumptions, we estimate of the cost to passengers of voluntary departure time adjustment. These are presented in Table 3-15.

In columns 1-5 of Table 3-15, we apply our estimates of the percentage of passengers in each departure window that would adjust their schedule in the absence of delay to the passenger counts in Table 3-12. In column six we translate these passenger counts into hours lost to voluntary departure time adjustment. Column 7 further translates these estimates of time lost to delay into the dollar value of that time. Finally, in column 10, we present our estimates of passenger costs assuming that, in addition to the value of the time lost to voluntary departure time adjustment, passengers who travel the night before their preferred departure also incur the cost of a one-night stay in a hotel and a meal on the road.

[10] This implicitly assumes that the passenger is indifferent between sleeping in his or her own bed and one on the road.

Table 3-15: Estimates of cost of voluntary time adjustment

Year	Quarter	[1] Early to AMPeak Switches	[2] AMPeak to Midday Switches	[3] Midday to PMPeak Switches	[4] PMPeak to Evening Switches	[5] Evening to Next-Day Early Switches	[6] Hours Saved	[7] Passenger Time Costs	[8] Average Hotel Cost	[9] Meal Cost	[10] Total Passenger Costs
Estimated Percent Switching		*1.26%*	*2.98%*	*1.40%*	*1.30%*	*3.03%*					
2006	1	159,674	350,997	215,219	71,592	65,434	3,082,220	$ 111,961,779	$ 125	$ 40	$ 122,758,433
2006	2	180,037	395,759	242,666	80,723	73,779	3,492,743	$ 127,624,505	$ 125	$ 40	$ 139,798,059
2006	3	171,243	376,428	230,813	76,780	70,175	3,320,008	$ 122,416,630	$ 125	$ 40	$ 133,995,551
2006	4	172,621	379,458	232,670	77,398	70,740	3,371,151	$ 126,451,345	$ 125	$ 40	$ 138,123,469
2007	1	165,103	362,932	222,537	74,027	67,659	3,197,441	$ 122,352,409	$ 132	$ 40	$ 133,989,800
2007	2	187,315	411,759	252,476	83,986	76,762	3,626,193	$ 141,219,140	$ 132	$ 40	$ 154,422,185
2007	3	179,223	393,970	241,569	80,358	73,445	3,457,039	$ 137,555,107	$ 132	$ 40	$ 150,187,731
2007	4	176,775	388,590	238,270	79,260	72,443	3,435,208	$ 137,956,074	$ 132	$ 40	$ 150,416,208
2008	1	169,233	372,011	228,104	75,879	69,352	3,271,544	$ 131,917,892	$ 129	$ 40	$ 143,638,364
2008	2	184,924	406,502	249,253	82,914	75,782	3,582,831	$ 144,457,866	$ 129	$ 40	$ 157,264,998
2008	3	169,681	372,995	228,708	76,079	69,535	3,294,334	$ 133,877,181	$ 129	$ 40	$ 145,628,652
2008	4	161,090	354,111	217,129	72,228	66,015	3,112,303	$ 127,038,268	$ 129	$ 40	$ 138,194,785
Total		**2,076,919**	**4,565,514**	**2,799,414**	**931,223**	**851,122**	**40,243,016**	**$ 1,564,828,196**			**$ 1,708,418,237**

[1] = Early Departures (Table 11)*1.26%, percent switching from Early to AMPeak with no AMPeak delay

[2] = AMPeak Departures (Table 11)*2.98%, percent switching from AMPeak to Midday with no Midday delay

[3] = Midday Departures (Table 11)*1.4%, percent switching from Midday to PMPeak with no PMPeak delay

[4] = PMPeak Departures (Table 11)*1.3%, percent switching from PMPeak to Evening with no Evening delay

[5] = Evening Departures (Table 11)*3.03%, percent switching from Evening to Next-Day Early with no Early delay

[6] = Total hours saved, assuming the mean departure time within each year, quarter, and departure window.
Hours saved for switching from Evening to Next-Day Early are equal to the difference in mean departure time less eight hours sleep time.

[7] = Total Passenger Time Costs saved, assuming Mehndiratta values for value of time
Switches from AMPeak to Midday, Midday to PMPeak, and PMPeak to Evening departures are assumed to save 'Work' time.
Switches from Evening to Next-Day Early departures are assumed to save 'Leisure' time.
Switches from Early to AMPeak departures are assumed to save 'Sleep' time.

[8] = Average Hotel Cost. Source: National Business Travelers' Association 2009 Business Travel Overview and Cost Forecast

[9] = Assumed Meal Cost

[10] = [7] + ([8] + [9])*([5]), i.e. total costs including hotel and meal costs for incremental overnight stays

3.4 Capacity Induced Schedule Delay (CSD)

In following their business models, airlines tend to generate “peaked” schedules. The two reasons that stand out most clearly are:

i) to support a large number of low delay passenger connections as part of a banking operation;

ii) to satisfy the natural hourly peaks in customer demand over the course of a day (especially for business customers).

As the number of scheduled flights gets closer to the runway capacity constraints, airlines may have to change their schedule, by moving flights to a less congested time of day. That is, capacity constraints may force a “flattening” of schedules. De facto flattening can also arise in other ways. For example even if flight schedule is peaked, actual times may be flattened as a result of delays. Here, however, our focus is on flattening of the actual schedule. Thus, we hypothesize that there is a negative relationship between the degree to which airline schedules are peaked and the capacity utilization of an airport. To test this hypothesis and quantify this relationship we first need to develop metrics for both “peakedness” (or schedule variability) and airport capacity utilization. We quantify the relationship between them using a regression model. We then use this model to address the problem of estimating the cost impact of capacity constraints on schedule delay. Specifically, this regression model allows us to estimate what the peakedness measure would be in the absence of a capacity constraint for the airports analyzed. We then estimate the decrease in schedule delay that passengers would experience when a schedule with the higher level of peakedness replaces the current schedule (with the lower level). By converting this schedule delay savings to a cost savings we are able to place a monetary value on capacity-induced schedule delay.

To perform the analysis outlined, we start by measuring the number of scheduled flight operations (arrivals and departures) in each fifteen-minute period at individual airports. The variance of the number of flights per 15-minute period computed over an entire day can be viewed as a measure of the peaking of the schedule. While variance is a good measure of peakedness, it increases with the number of operations even if the pattern of the schedule remains unchanged. To account for this scale effect, we consider the coefficient of variation (CVAR) as our metric for the peaking of the schedule:

$$\text{CVAR} = \sigma / \mu \qquad \text{(Equation 3-5)}$$

where μ = mean number of operations per 15 minute period,

σ^2 = variance in number of operations per 15 minute period.

Figure 3-5 illustrates the average value of this metric for both New York's LaGuardia Airport (LGA) and Cincinnati/Northern Kentucky International Airport (CVG) for the month of August, 2007. Note that the CVG profile has much more volatility (peaks and valleys) and has a correspondingly higher CVAR: 1.2565 vs 0.2883 at LGA.

A capacity utilization metric should indicate the degree to which an airport is operating close to its runway capacity for a given day. The generic definition of utilization is the ratio of actual usage to capacity. We note that airport capacity can vary from day to day and over the course of a day, largely as a result of changing weather conditions. Two readily available and reasonably accurate measures of airport arrival and departure capacity are the airport acceptance rate (AAR) and the airport departure rate (ADR). These are nominal assessments made by FAA specialists of the number of flights that will be able to land or take off (respectively) in a specific hour given the weather conditions and runway configuration. Data are available for flight arrival ("wheels on") and departure ("wheels off") times and these would seem to be most appropriate data sources to base measures of airport usage within each hour. Within our analysis we consider arrival utilization (# arrivals/AAR), departure utilization (#departures/ADR) and overall utilization ([#arrivals + #departures]/[AAR + ADR]). We should note that the actual number of operations performed (arrivals or departures) can indeed occasionally exceed the AAR or ADR in a given 15 minute time period, since conditions can vary and the fleet mix can be more or less favorable. We compute a daily metric, which is defined to be the total number of operations (arrival, departure, and combined) divided by the total capacity. The analysis is performed on a monthly basis so that we obtain results for a given airport and month. The ratios are computed for each Tuesday, Wednesday, and Thursday in the month based on operations between 6 AM and 10 PM. As will be discussed later, results were obtained for several months in 2007.

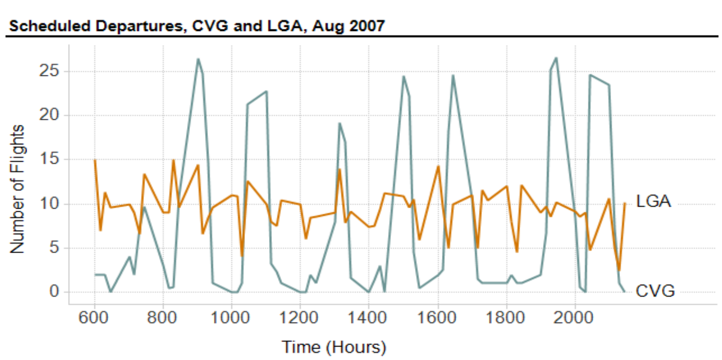


Figure 3-5: CVAR Scheduled Departures for CVG and LGA

To illustrate the data compiled see Figures 3-6 and 3-7. ADR and actual departure count are plotted for both LGA and CVG per quarter hour over the course of a day; this is the profile for the month of August, 2007 created by process described above. Note that, on an aggregate level, the counts for LGA are much closer to the ADR than for CVG, which results in a higher utilization metric (0.9076 for LGA vs. 0.3303 for CVG).

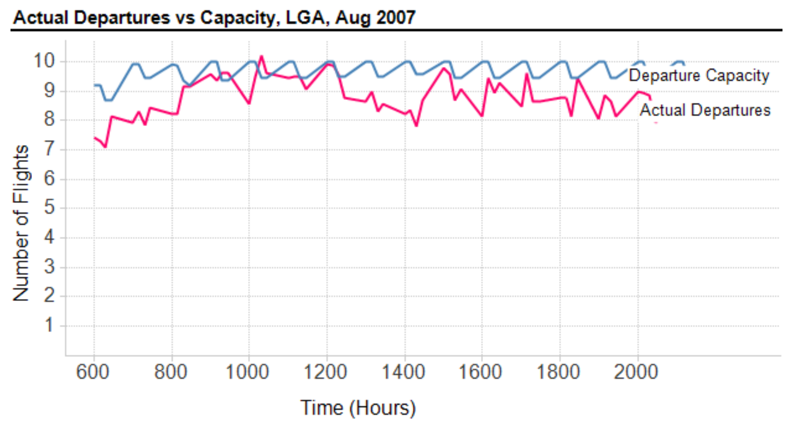


Figure 3-6: Capacity (AAR) utilization for LGA

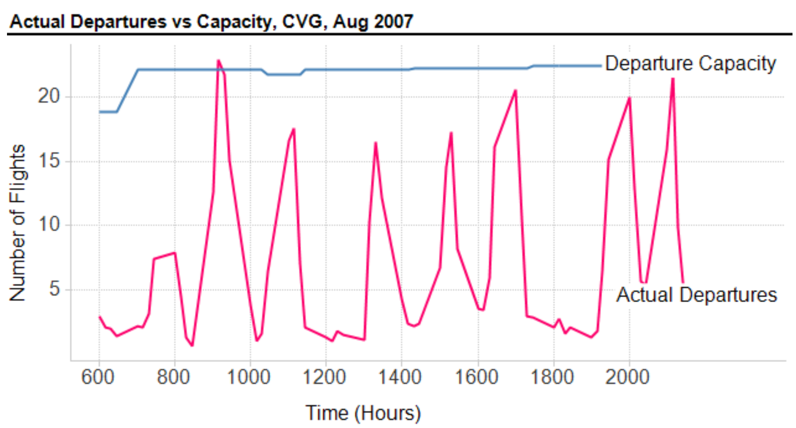


Figure 3-7: Capacity (AAR) utilization for CVG

We developed a regression model to evaluate the relationship between our capacity utilization metric and the peaking metric. Generalized linear regression was used to handle auto-correlation in the residuals with differing moving average lag periods (denoted as "q") between 0 and 9. We picked the model that had the best fitness (using Bayesian Information Criterion measure of model fitness). Results are shown in Table 3-16 for the departure capacity model. We found that an airport-specific model showed the best results with many, but not all, airports demonstrating a significant relationship. Note that our hypothesis is confirmed by a negative relationship, i.e. CVAR decreases as utilization increases. In the table, β_1 refers to estimated regression coefficient for the departure capacity utilization metric. We have models for arrivals, departures, and combined arrivals and departures. While all generally confirmed our hypothesis, there are several airports in each case where the relationship is not confirmed.

Table 3-16: Regression results for departure model

Airport	q	β_1	p-value	Constrained?	Airport	q	β_1	p-value	Constrained?
ATL	7	0.1650	0.1796	No	LGA	2	**-0.1835**	0.0029	Yes
BOS	1	**-0.3559**	0.0000	Yes	MCO	1	**-0.4304**	0.0022	Yes
CVG	3	0.1945	0.0214	No	MIA	3	0.0313	0.7489	No
DAL	1	-0.0914	0.2336	No	MSP	1	0.0912	0.1270	No
DCA	5	0.0594	0.1827	No	OAK	6	0.0032	0.9537	No
DEN	3	**-0.2057**	0.0446	Yes	ORD	4	**-0.5459**	0.0000	Yes
DFW	1	0.3141	0.1296	No	PDX	6	0.0439	0.5370	No
DTW	2	-0.0770	0.2820	No	PHL	4	**-0.4744**	0.0093	Yes
EWR	1	**-0.2881**	0.0019	Yes	PHX	5	0.0068	0.9368	No
IAD	5	**-0.2425**	0.0164	Yes	SAN	2	**-0.2137**	0.0013	Yes
IAH	1	**-0.2085**	0.0349	Yes	SEA	4	-0.1046	0.1220	No
JFK	4	**-0.2197**	0.0028	Yes	SFO	5	**-0.2793**	0.0093	Yes
LAS	8	**-0.0997**	0.0327	Yes	SLC	5	**-0.1691**	0.0071	Yes
LAX	4	**-0.2754**	0.0000	Yes	STL	2	0.7307	0.0000	No

In addition to confirming our hypothesis, the regression models allow us to estimate the CVAR when the utilization is zero (or close to zero). This corresponds to the lack of an airport capacity constraint. Thus, for an airport where the model results were significant we could measure the present-day utilization metric and CVAR value and then use the model to estimate CVAR under zero-utilization. This provides an estimate of what CVAR would be today in the absence of a capacity constraint.

The next step in the process we outlined at the beginning of this section is to associate a schedule with the CVAR values estimated to occur when the capacity constraint is eliminated. A comparison between this projected schedule and the current schedule will form the basis of our schedule delay reduction estimate. Figure 3-8 illustrates our model for constructing a schedule that achieves the zero-utilization CVAR value from the existing schedule. The algorithm is driven by a parameter γ, which partitions the points in the existing schedule into "peaks" and "valleys". All peaks are increased by a constant factor α and all valleys are decreased by a constant factor β. Given γ, α and β are determined by the two constraints that insure the new schedule hits the target CVAR and has a number of operations equal to the existing total number of operations. Of course, each γ will produce a different schedule and so we may "optimize" the schedule chosen over possible γ values. We chose an approach that minimizes the cost of the flight movements required to convert the existing schedule into the projected one. We will defer discussing the cost of flight movements until after describing our passenger schedule delay model. The goal of the schedule construction is that the new schedule should be "similar" to the existing schedule but have the higher CVAR value. Figure 3-9 gives an example of the application of this procedure.

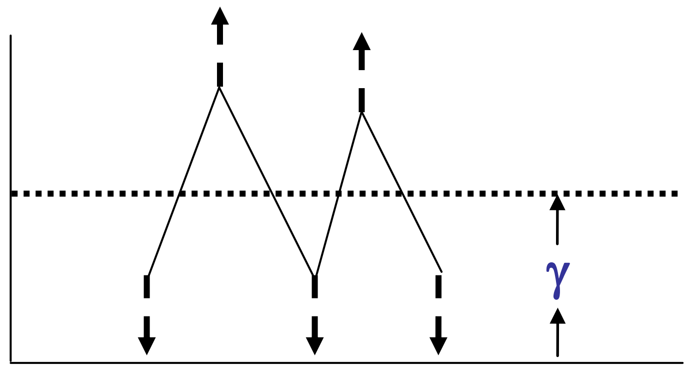


Figure 3-8: Schedule adjustment algorithm driven by parameter γ

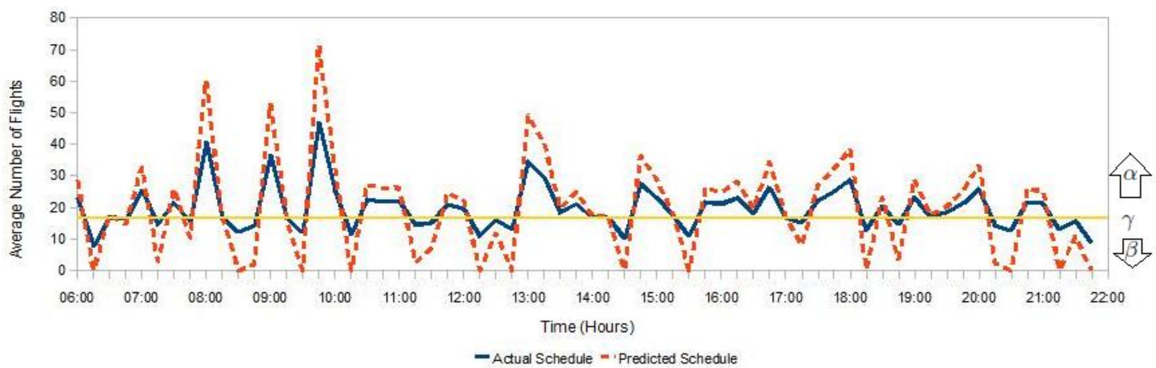


Figure 3-9: Result of schedule adjustment algorithm applied to ORD departures data for August, 2007. Actual (constrained) schedule had CVAR=0.3940; projected schedule had CVAR=0.8056, which was the value estimated by the regression model.

The final step in the process outlined earlier is to calculate the cost savings incurred by moving from the existing schedule to the "unconstrained" schedule. We use an approach that estimates the passenger benefits associated the reduction in schedule delay. (We do not expect airlines costs to be greatly affected by the change in schedule; if anything increases in scheduling peaking would increase airline costs.) Prior research has investigated issues related to schedule delay in air transportation and, in particular, the cost-per-unit time of schedule delay has been estimated for both leisure and business travelers (e.g. Adler et al., 2005).

In order to develop an estimate of the schedule delay impact of moving from one schedule to another as in Figure 3-9, let us consider the context of an entire schedule. We start by discretizing time and setting a minimum move size. Here we use 15 minutes (since this is the threshold at which a late flight is called delayed, it is reasonable to use it as a minimum length for a flight movement considered noticeable to a passenger). Now define x_i as the number of flights that are moved by i (15 minute) intervals in order to convert the original schedule to the unconstrained schedule. Also define $\delta_i = 15\ i$. The analysis provided in our technical support document for capacity induced schedule delay shows that we can write the schedule delay savings incurred by converting the original schedule to the unconstrained schedule as:

$$\sum_i K\, \delta_i^2/T\ x_i \qquad \text{(Equation 3-6)}$$

where K is an estimate of the number of passengers per flight and T the headway between flights so that K/T is an estimate of passenger demand density. The intuition behind this expression is that the number of passengers affected by a move of length δ_i is δ_i K/T and the schedule delay increase is δ_i. It is interesting to note that this expression is quadratic in δ_i, the length of a flight movement. This implies that, in the process of searching to find a minimum cost set of flight movements needed to convert the original schedule to the unconstrained schedule, we should employ an objective function that is quadratic in the length of a flight movement. We were able to do this in structuring our γ-search procedure.

We analyzed data from several airports for August of 2007. Results are given in Table 3-17. We used the values from Adler et al. (2005) to determine the cost of schedule delay. Taking a weighted average of these two numbers, we obtain $15.77 per hour of schedule delay. This was used to convert delay to dollars. We computed average values of K and T for the studied airports. The airport-wide values were obtained based on a weighted average of city pair market values. Weighting was based on the number of passengers served in that market. The passengers served in a market and the average number of passengers per flight were obtained by multiplying the respective aircraft size by the average load factor for that month and airport. These numbers give us some indication of the overall magnitude of the cost impact of this component of the changes in the timing of airline schedules. For example, the average monthly value for the airports studied is about $4M and the annual value about $60M. Thus, the annual NAS-wide value considering a comprehensive set of airports exceeds seven hundred seventeen millions of dollars.

Table 3-17: Summary of schedule delay results

Airport	Actual CVAR Aug 07	Predicted CVAR Aug 07	Min Optimal Daily Schedule Delay Cost ($)	Schedule Delay Cost for Aug 07 ($)
BOS	0.43	0.68	99,353	2,980,590
DEN	0.62	0.68	22,470	674,100
EWR	0.41	0.66	84,431	2,532,930
IAD	1.1	1.17	23,371	701,130
IAH	0.56	0.72	25,973	779,190
JFK	0.53	0.71	107,619	3,228,570
LAS	0.36	0.48	120,948	3,628,440
LAX	0.31	0.53	133,076	3,992,280
LGA	0.3	0.5	205,450	6,163,500
MCO	0.47	0.64	197,590	5,927,700
ORD	0.39	0.81	273,928	8,217,840
PHL	0.59	0.87	32,255	967,650
SAN	0.48	0.67	381,627	11,448,810
SFO	0.41	0.59	141,462	4,243,860
SLC	0.86	0.91	143,971	4,319,130
NAS-wide Total Cost for Aug 07				59,805,720
NAS-wide Extrapolated Cost for 2007				717,668,640

3.5 Value of Demand Lost Due to Delays

The previous analyses consider the economic impacts of flight delay of flight delay on airlines and passengers. An additional set of impacts arise as the result of lost demand. Flight delay, by degrading the quality and increasing the cost of air travel, causes some people to avoid air travel. These individuals would be better off if they could fly in a system free of delay than they are not flying in the existing system. Moreover, many of the trips that are "delayed off" the system are shifted to automobile, and it is well known what auto trips generate external social costs not borne by the traveler.

3.5.1 Value of Demand to Travelers

Our hypothesis is that flight delays, information about which has become increasingly available in the last several years, influence passenger demand. As flight delays increase on a route, fewer passengers will be willing to fly on the route (i.e., the lower the demand). Flight delays may also affect airline costs, driving operating costs higher and influencing prices. Figure 3-10 illustrates the concept behind our analysis. The base demand, with current passenger delays, is D_0 with a marginal revenue curve at MR_0, a marginal cost curve at MC_0 and a price, p_0. If delays are eliminated, then there will be a demand shift to the right (to D_1) since delay, like the airfare, contributes to the total cost of travel. (This is true whether delay is measured against the scheduled arrival time or against some ideal unimpeded time. We will discuss the delay measures used in this analysis below.) As well, marginal revenue will shift up to MR_1 and marginal cost down to MC_1. The new price would be p_1 and the output will increase from q_0 to q_1.

Figure 3-10 indicates the gains to society as a result of a reduction in delays. Areas 1 and 3 show the positive change in consumer (passenger) welfare resulting from the shift in the demand curve from D_0 to D_1. Area 1 represents the gains to current users of the air transportation system while Area 3 represents the deadweight (DWL) loss to consumers from schedule delays. In a parallel fashion, Areas 2 and 4 represent the gain in producer (airline) surplus and the reduction in producer (airline) deadweight loss, respectively, that would result from a decrease in operating costs due to a reduction in delays. Here, the focus is on how schedule delays impact passengers, rather than airlines (i.e., Areas 1 and 3 in Figure 3-10).

In order to examine potential consumer welfare gains from the elimination of passenger delays, an econometric model is estimated using simultaneous (three-stage least squares) methodology. The model contains both fare and passenger demand equations, to model the simultaneous relationship between supply and demand at the route level. The level of travel demand on a route is modeled as a function of demographic variables (income and population at the route endpoints), air fare, and the average flight delay on the route. In addition, whether the route is a vacation route is considered as another demand influencing factor. As passengers perceive delay on a route based on their past experience, the one-quarter lagged delay rather than the contemporaneous delay is used. One may argue that, as shown in section 3.2, there could be differences between the average flight delay and average delay experienced by each passenger on the route. Nonetheless high correlations exist between the two variables. This discrepancy is therefore not a big concern since it will be taken into account by the co-variations in an econometric model. On the fare side, we model fare as a function of the market demand (the number of passengers on the route), route distance, the density of competition,[11] as well as the level of delays. We further hypothesize that the presence of low-cost carriers on the route, or an adjacent route(s),[12] whether a slot-controlled airport at one or both endpoints, and whether the route is a vacation route would impact the fare charged by an airline on the route. Therefore, these variables are also included in the fare equation.

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[11] We use the Herfindahl-Hirschman Index (HHI) to measure the competition on a route. In each OD pair market (route), HHI is defined as the sum of market shares of all carriers operating.

[12] Low-cost carriers are classified based on the method used by Hofer, et al (2008).

The panel dataset used to estimate our model covers 16 quarters from 2003 to 2006. The key information was collected from two data sources: Department of Transportation (DOT) DB1A and Air Travel Consumer Report (ATCR). The ACTR data were collected on a flight basis but aggregated to represent average delays for a carrier over a quarter in order to match the DB1A pricing information.

Three measures of delay are calculated. The first measure is the average number of minutes of delay on a route against scheduled block times. However, this measure may underestimate delay since airlines pad their schedules in order to minimize the ATCR reported delays. Therefore, we calculate two more idealized measures of delay. These assess delay against measures of minimum feasible flight times; specifically, delays against the 10th percentile minimum (i.e., fastest) flight time and 20th percentile minimum flight time on a route for each airline-quarter.

Table 3-18 provides the results of our demand and airfare estimations. From the estimations, it can be noted that delays on a route increase fares and reduce passenger demand. Since the consumer surplus portion of the welfare gain to consumers has already been accounted for in the passenger delay cost analysis discussed in Section 3.2, for this section, we calculate the reduction in consumer DWL. Based on the notation in Figure 3-10, the gain in deadweight loss attributed to the elimination of delays is calculated as $((p_2-p_1)*(q_1–q_0))/2$ for each of the three scenarios. The price differences (p_2-p_1), generated traffic (q_1-q_0), and DWL gain are all shown in Table 3-19. The value of the reduction in DWL varies from $840 million to $3.66 billion, depending on the model specification, and based on 681 million origin and destination passengers in 2007. The DWL component—the gain to passengers who would be attracted to the system as a result of eliminating delays—is not counted elsewhere, and is therefore added to the delay cost estimates presented in Section 3.2.

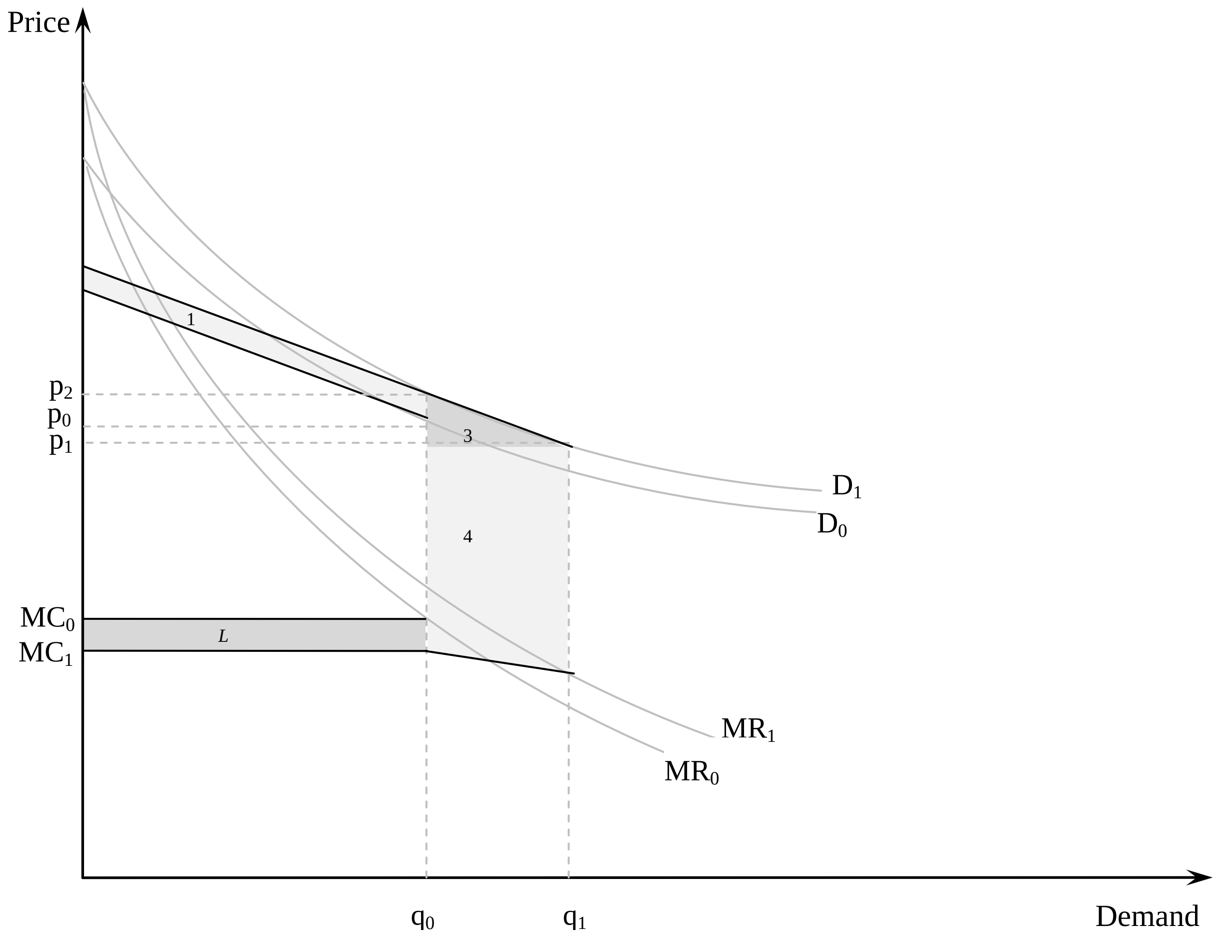

Figure 3-10: Welfare changes from elimination of delays

Table 3-18: Estimation of fares and passengers – using three measures of delay[13]

	Delays Against Scheduled Block Time	Delays Against 20th Percentile Feasible Flight Time	Delays Against 10th Percentile Feasible Flight Time
FARE			
CONSTANT	-20.30**	-14.88***	-13.77***
LAG DELAY	0.05***	0.04***	0.04***
PASSENGERS	2.07**	1.54***	1.44***
HHI	0.03	0.04	0.04
DISTANCE	1.26***	1.01***	0.96***
LCC[14]	-1.12*	-0.90***	-0.85***
ADJ_ROUTE_LCC	-0.13***	-0.10***	-0.09***
SLOT_CONTROL	0.18	0.20	0.19
VACATION_ROUTE	-0.32*	-0.21**	-0.19**
			Time Dummies Included
Passengers			
CONSTANT	-6.28***	-6.95***	-7.14***
LAG DELAY	-0.01***	-0.01***	-0.01***
FARE	-1.36***	-1.33***	-1.33***
POPULATION	0.01***	0.01***	0.01***
INCOME	1.73***	1.78***	1.80***
VACATION_ROUTE	0.24***	0.24***	0.24***
			Time Dummies Included

Note: *** p<0.01, ** p<0.05, * p<0.1

[13] All variables are logged except LAGDELAY (due to zero values). The delay variable was lagged one quarter since it was thought that prior information on delays would affect future demand. Other variables included in the estimations measured the density of the route (PASSENGERS), the market concentration (HHI), route distance (DISTANCE), the presence of a low-cost carrier on a route (LCC), the presence of a low-cost carrier on an adjacent route (ADJ ROUTE LCC), a slot-controlled airport at one or both route endpoints (SLOT CONTROL), whether the route was a vacation route (VACATION ROUTE), and the population (POPULATION) and income levels (INCOME) at the route endpoints.

[14] LCC is the presence of low-cost carrier dummy, equal to one if at least one low-cost carrier operates on the market, and zero otherwise.

Table 3-19: Estimation of welfare gains per passenger from eliminating delays from the three model specifications

	Scheduled Block Time	20th Percentile Feasible Time	10th Percentile Feasible Time
Price Difference ($)	19.91	31.54	34.19
Generated Traffic (millions of passengers)	84.4	189.6	214.1
DWL Gain ($ Billions)	**0.84**	**2.99**	**3.66**

DWL = Dead Weight Loss

3.5.2 Traffic Diversion Impacts

3.5.2.1 TSAM Model

To further quantify other impacts of passenger loss to other modes of transportation, such as accident fatalities and automobile external costs, we employ the Transportation Systems Analysis Model (TSAM). TSAM has been described in the literature (Trani et al., 2004; Baik et al, 2008) and only the basics of the model are presented here for completeness. The TSAM model is nationwide transportation analysis model developed at Virginia Tech to predict nationwide intercity and commuter travel demand. The Transportation Systems Analysis Model (TSAM) is an effort to understand the complex inter-relationships between ground and air transportation demand in the country. TSAM has potential use in strategic transportation planning applications such as studying the air transportation demand impacts of fielding a New Generation Air Transportation System (NextGen); studying future mobility trends in the nation with many secondary airports offering more point-to-point services; or understanding the impacts of new aerospace technologies – such as very light jets – operating into the National Air Transportation System (NAS).

TSAM is designed to forecast the number of annual round trips by automobile and commercial airline between all the counties in the United States. The demand estimation process differentiates between business and non-business trip purposes and five household income group levels. The core of TSAM is based on the classic four-step model employed in transportation systems planning. The trip generation module calculates the number of produced and attracted round trips at the county level. The trip distribution module distributes the produced trips from each county to all other counties. The mode choice module assigns a mode to each roundtrip. Finally, the network assignment module loads the commercial airline demand onto the National Airspace System (NAS).

A limitation of TSAM for this analysis is that it considers demand changes arising from mode shifts, while keeping aggregated travel volumes constant. We have thus relied on the econometric model presented in Section 3.5.1 to assess the value of lost air travel demand that results from delays. However, TSAM has the unique capability to predict how changes in air service effect traffic on other modes, in particular automobile traffic. Auto traffic is recognized to have high social costs, and we therefore employ TSAM to quantify the additional auto traffic that results from flights delays, and its associated external social costs.

For this analysis we employ version 5.8 of TSAM calibrated in September 21, 2009. The trip generation forecast comes from a combination of data from the American Travel Survey (ATS) and Woods and

Poole socio-economic projections (version 2009). The model employs a disaggregate Box-Cox Logit model (Mandel et al., 1997) to estimate the utility of travel between any origin and destination in the U.S. The model differentiates travel choices across five income levels (< $25,000 and up to > $125,000 household incomes per year) and two trip purposes (business and non-business). Mode choices in TSAM depend on travel cost (*TC*) and travel time (*TT*). The specification of the Box-Cox model requires estimation of the utility of travel by air U_{Air} and automobile U_{Auto} (or other modes if available). These utilities are then converted to probabilities of travel calibrated using actual traveler data from ATS. The coefficients of the model calibration in TSAM 5.8 are shown in Table 3-20.

$$U_{Auto} = \alpha_{TT} \frac{TT_{Auto}^{\lambda_{TTAuto}} - 1}{\lambda_{TTAuto}} + \alpha_{TC} \frac{TC_{Auto}^{\lambda_{TCAuto}} - 1}{\lambda_{TCAuto}}$$

$$U_{Air} = \alpha_{TT} \frac{TT_{Auto}^{\lambda_{TTAir}} - 1}{\lambda_{TTAir}} + \alpha_{TC} \frac{TC_{Auto}^{\lambda_{TCAir}} - 1}{\lambda_{TCAir}}$$

For this analysis, airport demand projections made with the model are relative to the baseline year (i.e., 2007). These projections represent the growth expected in commercial airline traffic at all commercial airports with commercial services in the continental U.S. (Hawaii, Alaska and other U.S. territories are excluded from this analysis). We assume OD pairs whose flight frequency was less than 3 flights per week are not reliable and neglected them in our calculation. In the year 2007, there were 378 airports with reliable commercial service in the U.S. (based on weekly schedule of more than 3 flights per week).

Table 3-20: TSAM model calibrated coefficients

Coefficient	**Value**	
Travel Time	<$25K	*-0.6400*
	$25K - $50K	-0.6980
	$50K - $75K	-0.9264
	$75K - $125K	-1.0819
	>$125K	-2.0143
Travel Cost	<$25K	-1.2501
	$25K - $50K	-1.8478
	$50K - $75K	-0.9520
	$75K - $125K	-0.7610
	>$125K	-0.0074
Lambda Travel Time Auto	<$25K	-0.0669
	$25K - $50K	-0.1561
	$50K - $75K	-0.0098
	$75K - $125K	0.0467
	>$125K	0.1694
Lambda Travel Cost Auto	<$25K	0.1748
	$25K - $50K	0.0834
	$50K - $75K	0.1660
	$75K - $125K	0.2057
	>$125K	0.4676
Lambda Travel Time Commercial Air	<$25K	0.6301
	$25K - $50K	0.5030
	$50K - $75K	0.3081
	$75K - $125K	0.3352
	>$125K	0.2485
Lambda Travel Cost Commercial Air	<$25K	-0.0156
	$25K - $50K	-0.0621
	$50K - $75K	0.0594
	$75K - $125K	0.0936
	>$125K	0.9964

3.5.2.2 Mode Diversion Impacts from Flight Delay

A comparison between block and actual flight times is a good indicator of the efficiency (or inefficiency) of the air transportation system. The analysis presented in this section provides an estimate of the number of passengers lost due to airline schedule padding practices. We calculate flight padding as the difference between the published schedule times from the Official Airline Guide and the observed and corrected travel times between airports including unimpeded taxi-out and taxi-in times. Observed flight times (corrected for wind allowances) are derived from the FAA Enhanced Traffic Management System and the Aviation Systems Performance Metrics (ASPM). Variations of block times are encountered in practice because airlines have to account for exogenous factors in route planning such as variable aircraft performance, cost indices, and wind conditions. Figure 3-11 illustrates an example of flight times recorded in ETMS for flights of US Airways between LGA and BOS using Airbus A319/320 aircraft. A single airline and a single aircraft type are used in this example to isolate the effects of dissimilar aircraft operating a single origin-destination airport-pair. The graph shows the cumulative density function of flight times as reported in ETMS. The mean flight time using the Airbus aircraft is calculated to be 0.51 hours. For this route we can estimate that a maximum difference of 4 minutes exists for flights between LGA-BOS and BOS-LGA. That is, a four-minute allowance for winds is expected in the route. Similarly, unimpeded taxi-out and taxi-in travel times at LGA are 12.5 and 5.6 minutes, respectively. For Boston, unimpeded taxi-out and taxi-in travel times are 13.5 and 5.8 minutes, respectively. Considering these factors, the average block time (assuming the slowest flight condition) between LGA-BOS is then 0.86 hours or 51 minutes. According to the Official Airline Guide, airlines schedule between 61 and 72 minutes of block time for these flights (depending upon the departure time). This translates into build-in delay allowances of 10 to 21 minutes or equivalent to a 20 - 41% increase in travel time over unimpeded travel time. The increase in flight times results in an increase to the door-to-door time, which affects mode choice decisions made by passengers.

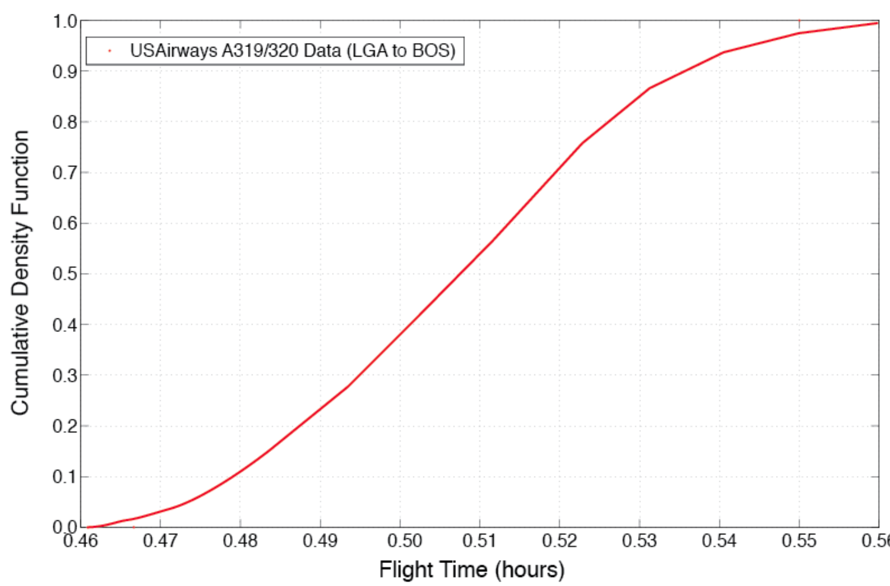

Figure 3-11: Cumulative density function of flight times between LGA and BOS by Airbus A319/320 aircraft

Using a combination of ASPM, ETMS and T100 data we estimate the minimum feasible block times between Origin and Destination airports for the top 45 airports in the country. These minimum block times are compared with published block times in the Official Airline Guide (OAG) to derive scheduled padding times for individual origin-destination airport pairs. Figure 3-12 shows the schedule buffer for 1294 origin-destination pairs as a function of great circle distance between airport pairs. It is important to note that the derivation of feasible block times employs actual routes flown in the NAS and not great circle distances. Block times for smaller airports were computed using the 50th percentile value of all available records for each airport which increased the number of origin-destination pairs to 3433.

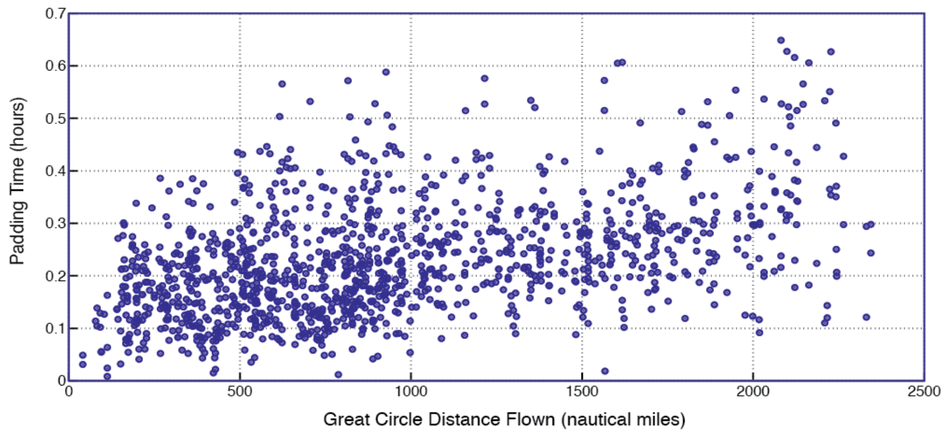

Figure 3-12: Estimated padding times for 1294 origin-destination pairs in the national airspace system

Table 3-21 provides estimates in the changes in various travel metrics that are predicted to result from eliminating schedule buffer in the system. This table illustrates that as a result of removing schedule buffer, we could expect an increase in 3.3 million annual round person trips nationwide using commercial air transportation. Since the analysis considers just two modes of transportation nationwide, all travel is shifted from automobile. This translates into roughly 8.6 million enplanements in the system. According to these calculations, the total door-to-door travel-time savings to commercial air passengers would be on the order of 12.2 million hours nationwide. This number accounts for reductions in the average travel time per air trip and the additional 3.3 million round person trips added to the system as a result of reduced door-to-door travel times. With a more efficient air transportation system, the average trip distance by air is reduced by 9 statute miles on average. This is the result of the added attractiveness of commercial air travel for shorter distances.

While many of these changes are significant, they cannot all be counted toward the total cost of flight delay, since this would result in double counting. Two results that are not accounted for elsewhere are accident fatalities and external costs to other motorists. Table 3-22 summarizes these impacts. Eliminating schedule padding would result in a reduction of 15 automobile fatalities and $199.5 million in automobile externalities. The latter is based on an estimated externality cost per auto vehicle mile of 10.45 cents (Parry et al., 2007).

Table 3-21: Changes in 2007 nationwide intercity passenger demand
(minimum feasible block times vs baseline system)

Metric	Automobile	Commercial Air
Change in County-to-County Annual Round Trips (millions)	-3.3	+3.3
Change in Total Door-to-Door Travel Time (millions of hours)	-115.5	-12.2
Average Trip Length (statute miles)	-1	-9
Average Travel Cost ($)	-1	-1
Total Travel Cost (Billion $)	-0.7	+1.0

Table 3-22: Changes in 2007 nationwide safety impacts
(minimum feasible block times – baseline system)

Metric	Net Change (Minimum Feasible Block Time System – Baseline)
Total Intercity Road Fatalities	-15
Auto Fatalities	-25
Commercial Airline Access Fatalities	+5
Commercial Airline Egress Fatalities	+5
Total Intercity Vehicle Miles Traveled (billions)	-1.0
Automobile Vehicles Miles Traveled (billions)	-1.8
Commercial Airline Access Vehicle Miles Traveled (billions)	0.4
Commercial Airline Egress Vehicle Miles Traveled (billions)	0.5
Automobile Externality Cost ($ millions)	-199.5

3.6 Estimating the Indirect Impact on the US Economy

Delay affects the overall economy in a variety of different ways. Because of dual role that air transportation plays as a mover of people and a mover of goods, the impacts of flight delays are not confined to airlines and their passengers, but will affect other segments of the economy. Increases in passenger fares, needed to recover costs to airlines from delayed flights, will not just affect the demand for leisure travel but also lead to increases in the cost of production for industries that rely on air transportation to conduct business. When schedule padding and flight delays add time to a business trip, employers experience a loss in productivity.

We trace and quantify these effects using a computable general equilibrium (CGE) model. Specifically, for this purpose we use a version of the USAGE model that has been modified to include a more detailed representation of the air transportation sector and an explicit description of the various interconnections between the level and composition of economic activity, and the level of delay in the system.

3.6.1 USAGE Model Description

The USAGE model is based on the MONASH model (Dixon and Rimmer, 2002) of Australia that has been developed for the U.S. International Trade Commission (USITC). The model database contains information on 539 commodities produced by 535 industries. This large degree of commodity and industry disaggregation will reduce the possibility that important economic linkages will be obscured in the model simulations. This will be important in understanding which industries will be most affected by the cost of flight delays. Unlike other CGE models, the USAGE model links the demand for air transportation to the demand for domestic and foreign leisure travel, the demand for air transportation by industries, and to the shipment of commodities to purchasers (e.g., domestic margins). However, the model's database does not distinguish between passenger and freight services directly. As described below, the air transportation sector in the USAGE data is disaggregated into two industries that provide either domestic or international flights.

The USAGE model is a recursive-dynamic model that is capable of identifying the adjustment time paths for the endogenous variables in the model (e.g., prices, quantities, etc.). The dynamic feature of the model will allow forecasted changes in economy activity, such as Gross Domestic Product (GDP), that will affect the demand for air transportation and therefore the level of flight delays to be incorporated in the analysis. Staff at the USITC have developed a baseline forecast (e.g., changes GDP, employment, consumer preferences, rates of technical change, etc.) that covers the base period of 2005 through 2013 (see U.S. International Trade Commission, 2009). This baseline includes projections on GDP, employment, and other macro variables from sources such as the Congressional Budget Office (CBO). But it also includes projections on changes in consumer preferences and rates of technical change based on historical simulations that allow the USAGE model to be consistent with available statistical information. Finally the USITC baseline also incorporates forecasted changes in industry output from various sources. One drawback with the current USITC baseline is that it treats the period from 2005 to 2013 as a "single" time period.

3.6.2 Disaggregation of Air Transportation in USAGE Database

Because delay will mainly affect passenger rather than freight services, domestic air transportation in the USAGE database is disaggregated into two industries and two commodities: domestic air passenger services and all other domestic air transportation services. In the base year (2005), the value of output of air transportation services equaled $122.8 billion. Of this total, $83.9 billion is accounted for by intermediate use by firms and leisure travel, $38.7 billion by air freight, and $0.2 billion for inventory changes. The air transportation industry provided the majority of these transportation services – $115.0 billion – with the remainder provided by the freight forwarding, wholesale and retail trade, and state and local government enterprises. We assume that only the air transportation industry provides passenger services that are susceptible to delay.

The output of the air transportation industry is allocated to either air passenger services or other air transportation based on who purchases the services. All purchases for intermediate use, except for intermediate purchases by the Postal Service, and for leisure travel are assumed to be air passenger services. The use of air transportation by the Postal Service and air transportation is assumed to be freight services and are allocated to other air transportation. Based on these assumptions, approximately 69.5 percent of value of air transportation output, $80.2 billion, is allocated to air passenger services. The intermediate inputs used by air transportation are allocated to air passenger and other air transportation proportionally, based on their above output shares. The exception is that all own-use of air transportation is allocated to air passenger services.

3.6.3 Incorporating Delay into the USAGE Model

A logistic function is used to determine the level of delay associated with a given level of air passenger output. The advantages of using a logistic function is that it is a smooth and twice differentiable function and can represent both linear and non-linear responses over a range of air passenger output level. We estimate the relationship between the level of flight delay and the output of air passenger services econometrically using monthly data on the percentage of flights delayed and the number of flight operations from the Bureau of Transportation Statistics (2009). The estimated elasticity of flight delay with respect to flight operations, evaluated at the sample means, is 1.5. The parameters of the logistic flight delay function are chosen such that a 1% increase in air passenger output results in a 1.5% increase in flight delay, with the initial level of flight delay equaling the annual average of 20% in the 2005 base year (Bureau of Transportation Statistics, 2009). Because the delay elasticity is subject to estimation error, alternative elasticity values of 1.0 and 2.0, which correspond to a 95% confidence interval for the estimated coefficients, are utilized in a sensitivity analysis.

A logistic function is also used to represent the relationship between the level of flight delay and airline costs. The trans-log cost function estimated in section 3.1 is not used directly in this analysis for two reasons. First, the concavity of the trans-log cost function cannot be guaranteed for all factor prices and second, it is short-run function that assumes a fixed level of capital. Because USAGE model will be solved for an 8 year time period, the level of capital used in the air transportation sector will not likely remained fixed. In addition, even though the parameter estimates for the short-run cost function in 4.1 suggests differential effects of delay on input usage, because the level of capital is held fixed, those differentials cannot be translated into a long-run cost function. The parameters of the function used in the model are chosen such that a 1% increase in flight delay will increase airline costs by 0.18%. Again, because the estimated coefficients in the trans-log cost function are subject to random error, alternative elasticity values of 0.06% and 0.3%, which correspond to a 95% confidence interval for the estimated coefficients, are utilized in a sensitivity analysis.

Finally, a logistic function is also used to represent the relationship between flight delay and labor productivity for industries that use air passenger services (e.g., business travel). Because the impact of delay on labor productivity will depend on how intensively a sector used air passenger services, the logistic function is weighted by each industry's cost share of air passenger services relative to the average cost share across all industries in the base year. Thus, the more intensively an industry uses air passenger services, and thus business travel, the greater the effect of a change in delay will be on that industry. A change in labor productivity from a change in flight delay is treated as a biased labor technical change and is included in the labor demand functions and the zero profit conditions for all industries that use air passenger services as an intermediate input.

The relationship between a change in flight delay and a change in labor productivity is based on the estimated hours of delay compared to the total number of hours worked in the U.S. economy. The total hours of passenger delay due to airline schedule buffers, flight delays, capacity-induced delay, and voluntary schedule adjustments is estimated to equal 458.1 million in 2007. The total number of hours worked in the U.S. economy is computed as the number of nonfarm employees, including those in the public sector, multiplied by the average weekly hours of private sector production workers (obtained from the Bureau of Labor Statistics). This assumes that the average weekly hours worked for all nonfarm employees is the same as for production workers. Using these assumptions, there were approximately 242.0 billion hours worked by all nonfarm employees in 2007.

Because business travelers comprise only a fraction of total air passengers and not all hours lost to delay are unproductive, several assumptions are necessary to determine the number of hours of productive work lost due to flight delay. First, the fraction of air travel dollars spent for business purposes is assumed to equal to the fraction of hours lost to delay that can be attributed to business travel. In 2007, the Bureau of Economic Analysis reported that business travel accounted for 48% of all dollars spent on domestic flights by U.S. residents. However, while business travelers like face the same probability of having their flight delayed as do leisure travelers, they generally pay higher fares. This would imply that the delay experienced by business travelers may be less than proportional to business travel cost share. In determining the productive hours lost to delay, three alternative values of fraction of total delay attributed to business travel, 0.24, 0.36, and 0.48, are considered.

With an array of "coping strategies" available to business travelers, not all hours lost to delay are unproductive. Because the effect of these coping strategies is not fully known, three alternative assumptions are used: all hours lost to delay are unproductive, one-half of the hours lost to delay are unproductive, and one-quarter of the hours lost to delay are unproductive. Finally, an adjustment must be made concerning the productivity of a business traveler to the average productivity of other employees. If the employees who make business trip are more likely to hold management or sales positions, then their labor productivity may be higher than the average worker (or at least are compensated at a higher wage than the average worker). Therefore, two alternative productivity values are use: the business traveler has the same average productivity as all employees and the business traveler has twice the labor productivity as the average employee.

Based on these assumptions, the total hours of delay attributable to business travel and are unproductive, as a percentage of the total hours of U.S. employment ranges from 0.011% to 0.182%, with an average of 0.06% in 2007. Since the level of flight delay in 2007 was 20% higher than in 2005 (Bureau of Transportation Statistics), if the change in labor productivity is proportional to a change in flight delay, the average increase in unproductive hours of business travel due to delay would equal 0.012%. Thus, the parameters in the logistic function for labor productivity are chosen such that a 20% increase in flight delays will result in a 0.012% loss in average labor productivity. A range of 0.005% to 0.02% is utilized in the sensitivity analysis.

3.6.4 USAGE Model Simulation

The simulations used to assess the macroeconomic costs of flight delays are comprised of two parts. The first is the baseline forecast simulation, where information on economic growth and other relevant macroeconomic variables in the USITC baseline is introduced into the modified USAGE model. This simulation will determine how forecasted changes in income, consumer tastes, and technical change will affect the demand for air transportation and the amount of flight delays if no policies or actions are taken to reduce the amount of flight delays.

The second is the policy simulation, where it is assumed that some action or policy is implemented that reduces the level of delays for a given level of industry output. In this simulation, an exogenous variable is shocked in order to achieve a "target level" of reduction in the 2005 level of flight delay. By comparing the model results for the forecast and policy simulations, one is able to estimate the impacts of a reduction in flight delays on the U.S. economy.

3.6.5 Simulation Results

The first column of Table 3-23 presents the key results for the baseline forecast simulation that uses the base (mean) values of the delay parameters. Real GDP, in 2005 dollars, is forecast to grow by 25.97%, or an average of 2.93% per year, between 2005 and 2013. Because the labor supply and employment hours are forecasted to grow by approximately 7% between 2005 and 2013, the real wages are forecast to grow by 21.2%, or 2.43% per year. Aggregate real investment is forecast to grow 28.3% between 2005 and 2013, or 3.16% per year (not shown in Table 3-23). Because of the faster growth in investment and therefore capital stocks, the increase in the real capital rental rate, 8.8% between 2005 and 2013, is much smaller than the increase in the real wage rate.

The resulting increase in economic activity and household income (through increased factor payments) results in a 21.3% increase in the output of (domestic) air passenger services and a 40.8% increase in the output of international air passenger services supplied by domestic air carriers.[15] The increase in the output of air passenger service is larger than the 14.6% increase in domestic revenue passenger miles forecasted by the FAA (2009) for the 2005 to 2013 period. Some of this difference may be explained by the lower projection of growth in U.S. real GDP (22.3% over the 2005-2013 period) used by the FAA in their forecasts. However, our projected increase in the output of international air passenger services is similar to the FAA forecast of a 37.6% increase in international revenue passenger miles provide by domestic carriers. Apparently the demand function for air transportation contained in our model differs somewhat from those implied by the FAA's forecast.

The increase in output of air passenger services results in a 32.1% (21.3*1.5 elasticity of delay) increase in passenger delay, from 20% of all flights delayed in 2005 to 26.4% of all flights delayed in 2013. This increase in delay also results in a 5.7% increase in airline cost (32.1*0.18 airline cost elasticity). Overall, due to increase in demand for air passenger services, increases in input prices (e.g., wage rate), and increased costs from delay, airline costs and fares increase by 30.3% between 2005 and 2013.[16] The increase in the level of flight delay also leads to a 0.02% loss in average labor productivity. Because the increase in flight delay in the forecast simulation is approximately 1.6 times larger than 20% change which was used to calibrate the logistic function, the average productivity loss is approximately 1.6 times larger than the average change in labor productivity of 0.012%.

A reduction in flight delay has two economic effects. First, a reduction in delay will lead to a reduction in airline costs. Because of the model's assumption of perfect competition, this reduction will also lead to a reduction in air fares. The reduction in air fares will lead to an increase in the demand for leisure travel by domestic residents to domestic destinations, represented as the Holiday industry in the USAGE model, and to an increase in leisure travel by foreign residents to domestic destinations, represented by the Export Tourism industry in the USAGE model. A decrease in domestic air fares will reduce the price of a domestic vacation for both domestic and foreign residents. An increase in leisure travel will also increase the demand for the output of tourism related industries, such as hotels, restaurants, entertainment, and other forms of transportation, such as car rentals. The decrease in air fares will also reduce the cost of business travel, leading to a reduction in firm costs and prices.

The second main economic effect is an increase in labor productivity from a reduction in the number of unproductive hours lost to delay. This increase in productivity will itself have three economic effects. First, it will reduce the demand for labor at constant prices because firms can produce the same level of output with less labor. Second, because labor is more productive, it becomes relatively less expensive to employ than capital (e.g., there is a reduction in the "effective price" of labor). This will encourage firms to substitute labor for capital. Third, the reduction in the effective price of labor will lead to lower firm costs and price. This reduction in price will lead to an increase in demand for the firm's product, thereby

[15] Data on international flights provided by domestic air carriers are contained in the Air industry in the USAGE data. Because this sector also provides domestic margin services, only the change in Air services provided as an intermediate input is used to compute the change in international air passenger services.

[16] Since all industries are assumed to be perfectly competitive in the USAGE model, zero economic profits are assumed to hold in an equilibrium implying that the percentage change in price is equal to the percentage change in cost.

encouraging firm expansion and increasing the demand for labor. As shown in Table 3-23, the last two effects dominate the first, resulting in an increase in the demand for labor and an increase in real wages in the policy simulation compared to the forecast simulation.

One issue left is to what extent can (or should) flight delays be reduced. As stated earlier, even if ample aviation infrastructure is provided, some flight delays will persist in that flights can be delayed due to reasons other than congestion. Our hope is to reduce delay be a very large percentage with more advanced aviation technologies (such as NextGen), adequate infrastructure investment, and appropriate government policies. Because the amount of reduction in flight delay that is achievable is uncertain, we evaluate eight different delay reduction scenarios. To focus the discussion, scenario that reduces the 2005 level of flight delay by approximately 20% will be presented first, followed by a comparison across the different delay reduction scenarios. In this first scenario, the level of delay decreases by 21.0% from the 2005 level to 15.8% of all flights, which corresponds to a 40.2% reduction in flight delay compared with the forecast simulation.[17] The reduction in delay leads to a 3.9% reduction in the base level of airline costs, or a 9.2% reduction compared to the forecast simulation. The decrease in cost from a reduction in delay accounts for approximately 90% of the reduction in air fares in the policy simulation compared to the forecast simulation. An additional 10 percentage point increase in reduction in delay the leads to a 1.8 percentage point larger reduction in airline costs and a 2.0 percentage point larger reduction in air fares compared with the forecast simulation. For example, the reduction in airline costs from a 31% reduction in flight delay is 5.7%, or a 1.8 percentage point increase from the 3.9% reduction in airline costs from a 21% reduction in delay.

The reduction in air fares for domestic flights leads to 1.3% increase in domestic leisure travel by domestic residents for a 21% reduction in delay compared with the forecast simulation. Each 10 percentage point reduction in delay leads to a 0.25 percentage point increase in domestic leisure travel by domestic residents. The reduction in domestic air fares also leads to 0.7% increase in domestic leisure travel by foreign residents. Each additional 10 percentage point reduction of flight delays leads to a 0.15 percentage point increase in domestic leisure travel by foreign residents.

The reduction in domestic air fares and resulting increase in domestic leisure travel cause the output of domestic air passenger services to increase by 2.1% for a 21% reduction in flight delay compared with the forecast simulation. The output of air passenger services increases by an additional 0.5 percentage points for each additional 10 percent point reduction in domestic flight delay. If all delay were eliminated, the output of air passenger services would increase by 6.1% compared with the forecast simulation.

A reduction in domestic flight delay will also affect the output of international air passenger services provided by U.S. air carriers. The increase in domestic leisure travel by foreign residents increases the demand for international flights to the United States. However, because the reduction in flight delay is assumed to only affect domestic flights, domestic air fares decrease relative to air fare for international flight for U.S. residents. This makes international leisure travel relatively more expensive than domestic leisure travel, causing domestic residents to reduce their travel to international destinations. Overall, the output of international air passenger services provided by U.S. air carriers increases by 0.6%. Each additional 10 percentage point reduction in delay increases the output of international air passenger services provided by U.S. carriers by an additional 0.1 percent points. If all domestic delay were eliminated, the output of international air passenger services provided by U.S. carriers would increase by 1.4% compared to the forecast simulation.

The overall macroeconomic effects of a reduction in domestic flight delay are measured by the dollar increase in real GDP and net welfare gain. For a 21% reduction in delay, the decrease in domestic airline costs and increase in labor productivity yields a 0.08% larger increase in the growth of real GDP between

[17] The percentage change in delay between the policy and forecast simulation is computed as [(1+(% change in delay in policy simulation/100))/(1+(% change in delay in forecast simulation/100))-1]*100.

2005 and 2013 compared with the forecast simulation. Based on a $12,073.4 billion value of U.S. GDP in 2005, this implies an $11.59 billion additional increase in real GDP between 2005 to 2013 period, or an annual increase of $1.449 billion. Each additional 10 percent point reduction in delay increases the total gain in real GDP by approximately $3.053 billion, or about $0.375 billion per year. If domestic flight delay were totally eliminated, there would be a $35.8 billion increase in real GDP over the entire period, or approximately $4.475 billion per year.

A limitation of the USAGE model is that it does not allow for substitution between transportation modes when relative prices change. For example, in the model a decrease in domestic air fares will lead to a reduction in the price (cost) of domestic leisure travel. The model assumes that the resulting increase in the demand for domestic leisure travel will increase the demand for all transportation modes proportionally.

A related limitation of the USAGE model is that it does not allow the mix of inputs purchased by an industry to vary with changes in relative prices. Each industry in the model relies upon a fixed "recipe" of inputs from other industries that does not change as prices change. Thus, as reductions in delay lower the price of air transportation, the model does not allow industries that rely on air transportation to produce output in a more air transportation manner. To the extent that such substitution possibilities exist, the USAGE model may underestimate the net economic effect of eliminating delay.

A May 2008 report by the Joint Economic Committee, United States Congress estimated that the total costs of air traffic delay equaled $40.7 billion in 2007. The majority of this estimate reflected increased airline operating costs and other costs to the economy. This estimate is much larger than our estimated GDP impact because it treats the entire increase in cost as an economic loss. However, increases in spending on inputs such as fuel or labor mainly represent a transfer from the buyers of air passenger services and not an economic loss. Reductions in airline costs and airline fares lower the amounts paid by users of air transportation services, but also reduce the number of employees, aircraft and other inputs the airline industry need to produce a given level of output. Reductions in airline costs thus have offsetting positive and negative economic effects. As discussed above, the real economic loss to the economy from air traffic delay arises from the increased use of labor and capital by airlines and industries that supply inputs to the airlines, leaving less labor and capital available to produce other goods and services in the economy. There is also a loss in labor productivity by business travelers. Both effects represent a deadweight net loss to the economy, which in general are smaller than gross transfers between agents that result from the elimination of delay.

3.6.6 Sensitivity analysis

Because of the uncertainty about the values of the parameters in the logistic flight delay functions, a sensitivity analysis is performed for the elasticity of delay with respect to air passenger output, the airline cost elasticity, and the average percentage change in labor productivity using symmetric order three Gaussian quadratures. This procedure assumes that each uncertain parameter has an independent uniform distribution with known (or estimated) endpoints. A sample of parameters is drawn from these distributions and the model is resolved using each set of parameter values.

The dollar increase in real GDP achieved from the alternative reductions in flight delay reported in Table 3-23 is shown as the solid line in Figure 3-13. Resolving the model using the alternative sets of parameters identified by the Gaussian quadratures, one can compute the standard deviation for the increase in real GDP. Across the alternative reductions in flight delay, the standard deviation for the dollar increase in real GDP is approximately equal to 0.325 times the mean value reported in Table 3-23. Its value ranges from $3.767 billion for a 20 % reduction in flight delay to $10.645 billion for a 90% reduction in flight delay. The dashed red line in Figure 3-13 represents a one standard deviation increase or decrease from the mean increase in real GDP.

Table 3-23: USAGE model results using base values of the delay parameters

Variable	Forecast	Policy Simulation – Target Reduction in Flight Delay 20%	30%	40%	50%	60%	70%	80%	90%
									Percentage Change
Real GDP	25.97	26.07	26.09	26.12	26.14	26.17	26.19	26.22	26.24
Real wages	21.21	21.37	21.40	21.43	21.46	21.49	21.52	21.55	21.58
Flights delayed	32.1	-21.0	-31.0	-41.1	-51.4	-61.7	-72.3	-82.9	-92.2
Domestic passenger output[a]	21.3	23.9	24.4	25.0	25.6	26.2	26.9	27.5	28.1
International passenger output[a]	40.8	41.6	41.8	41.9	42.1	42.3	42.5	42.6	42.8
Average labor productivity	-0.02	0.013	0.019	0.025	0.031	0.038	0.044	0.050	
Domestic air fares: from delay[b]	5.7	-3.9	-5.7	-7.6	-9.6	-11.6	-13.6	-15.6	-17.4
Domestic air fares: total[b]	30.4	17.2	14.6	12.0	9.4	6.8	4.1	1.3	-1.0
Domestic leisure travel									
Domestic residents	21.4	23.0	23.3	23.6	23.9	24.2	24.6	24.9	25.2
Foreign residents	77.7	79.0	79.2	79.5	79.7	80.0	80.3	80.6	80.9
Foreign leisure travel	2.7	1.8	1.6	1.4	1.2	1.0	0.7	0.5	0.4
									$ millions (2005)
Increase in real GDP		11,590.4	14,234.5	17,578.8	20,705.8	23,639.7	26,766.7	29,760.9	32,755.1
Net Welfare Gain		15,446.0	18,829.8	22,919.4	26,724.7	30,432.7	34,037.0	37,989.2	41,615.2
Equivalent variation		13,081.8	15,339.7	18,292.2	20,937.9	23,486.3	25,897.2	28,656.0	31,235.0
Opportunity Cost for Leisure Travel		2,364.2	3,490.1	4,627.2	5,786.8	6,946.4	8,139.8	9,333.2	10,380.2

[a] Refers to output by U.S. carriers for domestic and international flights

[b] Because all industries are assumed to be perfectly competitive in the USAGE model, the percentage change in the output price must equal the percentage change in the cost of production in all industries. Thus the percentage change in domestic air fares is equal to the change in airline cost for domestic flights.

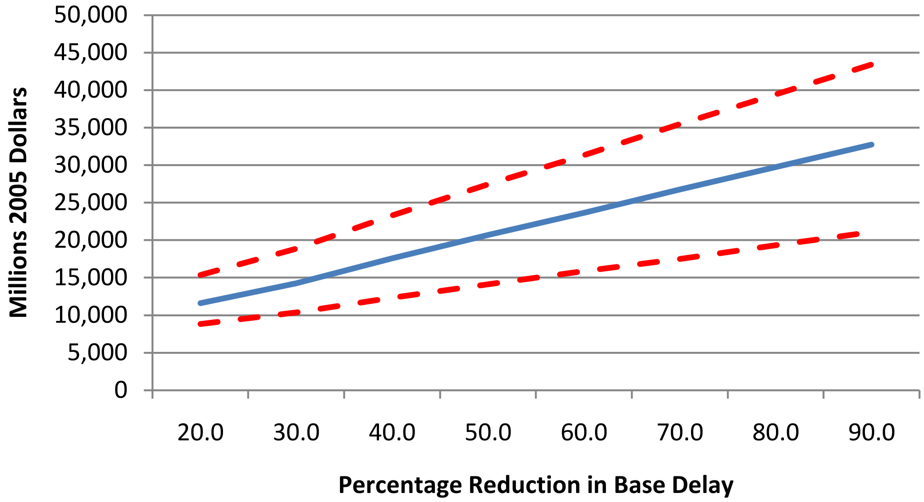

Figure 3-13: Change in real GDP from reduction in flight delay: mean value and one standard deviation

4 Individual Perspectives on Passenger Delay

Over the course of this project we have examined the issue of how delay affects the air transportation system from a variety of different perspectives. We have studied the effects that delay has on airline costs. We have examined the mechanisms through which delayed aircraft arrivals and departures translate into longer passenger trips and delayed passenger arrivals. We have computed the amount of passenger time consumed by delay, and we have studied the effects that delay and unpredictability have had on passenger behavior.

This research has been based upon careful analysis of large datasets describing the actual behavior of large groups of passengers and large segments of the air transportation system. We have thus taken a quantitative and macro-level approach, searching for statistically reliable evidence of large-scale patterns of behavior. This approach has many significant advantages, including objectivity, statistical reliability, and the ability to extrapolate study findings to the level of the system as a whole. At the same time, however, this macro approach abstracts from the rich detail of individual behavior, and in the process loses some of the human perspective on passenger delays.

In order to obtain a deeper appreciation of how passengers – in particular, business travelers – have been affected by passenger delay (and possibly other factors such as security changes, "hassle factor", coping with airport services, etc.), we also conducted qualitative research into the effects of delay. Our goal in carrying out this research was first to see whether a comparison of the macro and micro perspectives on delay would produce confirmation or contradiction. In other words, do the reports of individual travelers describe the same patterns of behavior we see at the system level? We also sought to deepen our understanding of how passengers are affected by delay, and how their responses to the problem of delay might alter in the future.

This qualitative research was based upon detailed interviews with a large number of individuals heavily involved in the world of business air travel. We also conducted an extensive review of discussions in the trade and popular press of issues relating to delays and business travel. This literature-based approach has permitted us to engage in a bit of "time travel," and sample opinions and perspectives expressed a year or two in the past when congestion was more severe, delays were more common, and strategies for coping with delay were a much more common topic of discussion. We summarize the insights we have gained from these investigations below.

4.1 Qualitative Reports Confirm Study Findings

In our qualitative research we found a high degree of consistency between the experiences reported by individual travelers, the efforts they describe to minimize the impacts of air travel delays, and our macro level findings on how air travel delays are affecting the air transportation system. Travelers report altering their behavior – sometimes in significant ways – in efforts to avoid the most delay-prone parts of the system. Like the airlines, they also report a growing tendency to pad travel schedules in efforts to cope with the uncertainty of when they will arrive at their destinations.

4.1.1 Avoiding the Most Delay Prone Parts of the System

When they must travel, employees attempt to minimize the uncertainty and avoid delays as much as possible by selecting alternative flights, modes of transport and airlines.

One of our significant macro-level findings has to do with the disproportionate role played by missed connections as a source of passenger delay. Reports from experienced business travelers reflect a high degree of awareness of this phenomenon. Road warriors recommend flying non-stop whenever possible:

> Try to schedule your air flight without a layover to prevent the possibility of having no problems with the first flight but a travel delay with the second flight (Cherrineb, 2009).

Business travelers also recognize that

> Avoiding the major hubs by using smaller airports will help you to avoid flight delays. These secondary airports are mostly less congested and therefore they are less prone to flight delays. Avoid the major hubs like Chicago O'Hare, New York and Atlanta and book your flights from the secondary airports near them whenever possible (Newell, 2009).

Following this advice, others suggest:

> Avoid airline hubs whenever possible. "Secondary" airports are usually less congested and less prone to delays (AOL Travel, 2010).

Other reports from business travelers are indicative of a high degree of awareness of which parts of the system are especially prone to delay, and a willingness to act upon this information. A 2007 Orbitz for Business Survey found that

> One-third (33 percent) of [the 838 customers] surveyed … opted to travel through a smaller regional airport to avoid possible flight delays (Orbitz, 2007a).

The timing of flights is also crucial. Road warriors suggest:

> Booking your flight departure during the early morning hours [which] may decrease your chances of a flight delay since there is less air traffic from nearby airports and the flights can come and go smoothly (Cherrineb, 2009).

Business travelers also report an increasing willingness to use alternative modes of transport to get them to their destinations. To avoid air travel delays, business travelers are driving and taking trains, buses and private jets in lieu of commercial airlines.

> … [W]hen the trip takes four hours or less by car, companies urge employees to drive (Ippolito, 2010).

and employees are listening:

> … [M]ore business travelers are, themselves, opting to drive, citing less stress and more productivity (Brooke, 2010).

In fact,

> 11% [of business travelers] are choosing to drive to their destination more frequently rather than fly (Orbitz, 2008).

Other travelers with the means to do so have resorted to flying in private jets:

> As one client summed it up, “Flying privately used to be a luxury, but today it’s a necessity.” (Butler, 2008)
>
> Many clients come to us for the first time after they’ve reached the breaking point with the airlines. I can’t tell you how many calls we get from new clients who say, “I just had a horrible experience with the airlines. I’m not doing that again. What are my options?” (Butler, 2008)

4.1.2 Personal Schedule Padding

Passengers, like airlines, are also increasingly building extra time into their schedules.

> Regardless of which airport they are using, almost 70 percent of travelers are leaving for the airport earlier than they used to, with nearly 40 percent saying they have added an extra 30 minutes to their travel time (Orbitz, 2007a).

Furthermore, ensuring a seat on the plane and saving time at the airport, sixty percent of survey participants report that they check in before heading to the airport (Orbitz, 2007a).

Our quantitative analysis found that in delay-prone markets travelers were significantly more likely to depart early, even if that meant leaving the night before. Reports from business travelers reflect similar behavior. If a meeting is early the next day or particularly important, business travelers may need to invest even more of their time by traveling the day before:

> "When I can, I try to arrive the night before," says Russell Hayward, a USA TODAY Road Warrior. "But that eats up a whole work day, wasted travel time due to airline uncertainty." (Woodyard, 2001)

However, this strategy raises out of pocket costs:

> Many travelers fly to meetings a day early and pay for an extra night in a hotel just to make sure their business appointments stay on schedule. (Woodyard, 2001)

However, given the importance of the travel that is taking place, the practice of departing early has become increasingly common:

> Thirty-two percent of [838 Orbitz for Business Survey respondents said] … they now book the earliest flight of the day or travel the night before a meeting or appointment, to minimize risk of delays and ensure arrival at their destination ahead of time (Orbitz, 2007a).

Overall, the results of our quantitative and qualitative research appear to be highly consistent. Experienced business travelers seem to be generally aware of the phenomena revealed by our qualitative analysis.

4.2 Delays and Unpredictability are Changing the Experience of Air Travel

The flying experience is not what it used to be. Decades ago, air passengers, dressed up for the occasion, viewed the experience of flying as a privilege and a luxury. Things have changed. At the present time “the misery of modern air travel [which has taking its toll, as passengers spend more time in less pleasant conditions than ever before] … has de-glamorized the business junket." (Conlin, 2008) Flying is now seen as a necessary evil that has to be endured. Many passengers may accept this lower standard of service as a worthwhile sacrifice to obtain cheap fares, but as has been shown delays at once degrade the service and increase airline costs.

Factors contributing to the increasingly negative experience of travelers include flight delays, increased security measures, and the degradation of airline service standards. Flight delays have extended trip duration, often considerably, and added a dimension of unpredictability to air travel. Security measures in place since 9/11 have had the same effect as increased delays - extended travel time coupled with increased uncertainty. Relentless financial pressures on airlines have resulted in degraded customer service, including the reduction or elimination of in-flight food service, reduced flights, smaller aircraft, tighter seating standards and more crowded planes. If a passenger misses his scheduled flight, because, for instance, he was stuck in a security line or was one of the last to arrive for an over-booked flight, the next available seat could be on a flight several hours or several days later.

The confluence of flight delays, ever increasing security measures, and a succession of economic downturns has created an environment in which business travelers, who used to arrive just in time to catch their flights, now spend considerable amounts of time waiting in security lines, at gates, and on the tarmac both before and after their flights. Confounding the problem even further is the unpredictability of air travel.

> Even more than being late, travelers are pestered by uncertainty. If they knew they were going be late, early or on time consistently, it would take a lot of the bother out of air travel (Woodyard, 2001).

What all of this means is that when air passengers are delayed, they wind up spending extra time – perhaps substantial amounts of extra time – in environments that are far more crowded and far less pleasant than was once the case.

These coping strategies travelers employ in an effort to deal with these realities fall into a number of different categories.

4.2.1 Substitution of Electronic Communications for Travel

Despite widespread recognition and acknowledgement of the advantages of face-to-face interaction, the growing time, uncertainty and overall unpleasantness of air travel seem to be stimulating a growing interest in and acceptance of alternatives to travel:

> The super surge in oil prices and resulting spike in airfares is just one reason companies are ordering their road warriors home. … HR types also have a new appreciation for how the frequent-flier lifestyle can wreck executives' health and family lives. And they have come to realize that jetting off for a one-hour meeting, while instinctual for corporate strivers, is rarely productive…
>
> So, if managers aren't flying to meetings, what are they doing? Using newfangled technology that is finally delivering the kind of Star Trek-y, space- and time-shifting experiences that tech executives have blabbered on about forever. Videoconferencing, Web-enabled meetings, online collaboration tools—all are giving workers the ability to dart around the globe from their desk chairs.

> Take HP's Halo and Cisco's TelePresence technologies, which cost up to $300,000 a pop. Chief information officers of big companies say the systems usually pay for themselves within nine months (Conlin, 2008).

A variety of other frequent travelers voice similar sentiments:

> 42 percent [of business travelers said they] are exploring alternatives to travel, including video/web conferencing (Wilkening, 2008).

> In a subsequent Orbitz for Business survey of 612 respondents 50% … said they had tried videoconferencing when asked about alternatives to travel (Orbitz, 2008).

> … [T]here are those of us who, tired of traveling several times a month on business only to encounter utter incompetence and indifference at the airlines - have given up travel and rearranged the meetings as telecons and videoconferences. Anything to keep the team working rather than stuck in an airport or on the tarmac somewhere (USAToday, 2007).

4.2.2 Information Strategies

As the comments reported above indicate, the growing problem of delay doesn't just make trips longer. It also makes them less predictable. In response travelers are seeking out more comprehensive and up-to-date information on flight status in order to learn of emerging problems in time to respond effectively. One frequent traveler recommends:

> Call your airline carrier three or four days before a major snow storm for any information about cancellations/delays. Also, check with your airline carrier 3-4 hours before departure to check on your flight status since you may miss telephone/e-mail notifications (Cherrineb, 2009).

Several internet companies are taking advantage of the demand for better and timelier information. One particularly geared towards business travelers seeking information to avoid delay prone airports and flights is Flight Stats, which "delivers real-time and historical flight information that lowers travel-related costs and improves the travel experience." (Flight Stats, 2009) Another, Delaycast, offers predictions for flight delays (Delaycast, 2009).

These developments suggest that even if it fails to eliminate air travel delays the NextGen program might still provide substantial benefits by facilitating the widespread dissemination of more timely and accurate information about the status of the air transportation system. Better information could make delay easier to live with, and in that way reduce the costs that delay imposes on air travelers.

4.2.3 Productivity Strategies

As the time required to complete business trips increases, business travelers have focused increasing attention on how that time is spent, striving to assure that it is used as productively as possible, or at minimum, as enjoyably as the situation permits.

> … the worst uncertainty or delay need not be idle, says personal-productivity expert Don Wetmore. …

> Wetmore, a lecturer who makes 70 airline trips a year, says he always arrives at the airport ready with enough work to see him through any delay. In fact, he says he's learned that being marooned in an airport terminal or on a plane can be the most productive hours of the day.
>
> Stuck at Nashville International Airport one day last month waiting for a plane to take him home to Connecticut, Wetmore says, he used the uninterrupted 6 hours to write two chapters of his new book, *Organizing Your Life*, to be released later this year.
>
> "When I get these blocks of time thrown at me, it's a gift if you are prepared for it," he says (Woodyard, 2001).

Another road warrior suggests that travelers:

> [t]ake a favorite book, a crossword puzzle, or work-related materials to keep yourself occupied if your flight is delayed for a few hours. Also, take a few snacks such as fruit, granola bars, or low-calorie, low-fat chips for eating (Cherrineb, 2009).

As noted by this road warrior, business travelers do not always partake in business activities during a delay:

> When stuck in the airport waiting for a flight, … business travelers … pass the time … [engaging in various activities.] 59% … [read] a book or the newspaper… 21% catch up on work, e-mail, [and/or] phone calls… 8% enjoy people watching… 5% go to the bar for a drink… [and] 2% sleep, shop or enjoy a meal... (Orbitz, 2007b)

Not all travelers have these options. A confluence of factors – flight delays and the economy – has led to employees having more work to do with less time to do it.

> Doing work during travel time is often a necessity with more time waiting in airports meaning less time to take care of work at the office (RoadWarriorTips, 2007).

Increasing travel times are stimulating more concerted efforts to use travel time productively. And while electronic communication has become a substitute for air travel, the ubiquity of email, phone and internet access has also turned communications into a complement to air travel, enabling business travelers to work productively in situations where this would not previously have been possible. In this way it has helped to reduce the burden of air travel. Before the advent of laptop computers, mobile phones and the internet, passengers had to travel with hard copies of everything they needed in transit. Now, with the cooperation of the airport, it is possible for passengers to take a virtual office with them:

> In the view of David Stempler, president of the Air Travelers Association
>
> …a data port is the least an airport can do to make up for what he considers unduly long wait times.

> "We have seen more of a desire for Internet access as people are spending more than they might have liked at airports," he says. "We have had so many delays ... with people sitting in the airports for so long, that having access to e-mail and sports and news has become very desirable and very needed." (Katz-Stone, 2001)

One road warrior finds these amenities invaluable:

> David Wolf of Annapolis spends 70 percent of his work time on the road. He logged 120,000 miles last year as a principal applications architect with software firm Sybase, mostly flying out of Dulles International Airport.
>
> In Wolf's world, connectivity is everything. Accessing the Internet "is probably the single biggest thing I do when I am at the airport," he says. "You get there an hour or an hour and a half before your flight, and that ends up being some of your best quiet work time." (Katz-Stone, 2001)

Another road warrior concurs:

> … [W]ith wireless internet, handheld devices, and a bit of strategy I find that airport transit times can be among my most productive (Gary, 2008).

A further manifestation of efforts to utilize travel time more productively is growing demand for access to airport lounges. According to one commentator:

> For me, there's a certain Zen to the Admiral's Club (yes, I fly a lot and I fly American). I leave early, usually arriving at least 2 hours before my flight.
>
> Traveling four days a week, but working from a home office, I'm often alone in my home office. Thus, the buzz of commerce, people, and energy around me has motivated me to close some of the best business deals of my life.
>
> I can say surely that I rarely spend more than ten minutes at the gate before boarding, but the time I spend in my little oasis is often the most valuable time of my week (Zinger, 2007).

Some passengers find that airport lounges provide stress-relieving benefits during a delay:

> …another huge perk reveals itself when you need to be rebooked on another flight because yours was cancelled or delayed. Would you rather stand in line with scores of the bumped and grumped, or go to the club, where the lines will be shorter? (Club receptionists are also able to rebook flights and assign seats.) And for some, just having enough power outlets to charge computers and phones is reason enough to join (Habica, 2007).

However, the popularity of the lounges has reduced their positive impact:

> Once a place of sanctuary amid the chaos of a busy airport, the airline lounge was originally intended to render the flying experience more pleasurable to premium passengers. But these days many lounges are often far too busy and crowded for genuine comfort (Lizards, 2006).

4.3 Implications for Future Policy and Research

The results of this qualitative research have significant implications for future research into the phenomenon of delay, and for the design of policies aimed at solving this significant problem.

First, these reports from the field highlight the fact that delay is as much a problem of unreliability as it is of longer trip times. When the air transportation system is plagued by delay, travelers become less able to predict when they will arrive, and so they become less able to plan their trips efficiently. The widespread practice of schedule padding demonstrates the significance of the problem of unreliability. Travelers are adding significant amounts of time to their travel schedules in order to increase their probability of reaching their destinations in time to conduct their business.

Second, these findings suggest that we may begin to see noticeable changes in the way in which passengers trade travel time off against cost or other trip attributes. Several findings support such a conclusion. Reports from travelers indicate that the quality of the travel experience (especially for business travelers) has declined significantly. For this reason alone one might expect to see changes in what passengers are willing to pay or do to avoid an additional hour of travel time. In addition, as the practice of schedule padding becomes more prevalent, the amount of "hidden" time buried in travel itineraries is likely to increase. Traditional analyses of travel behavior that consider only the characteristics of the flight actually taken are unlikely to account properly for time wasted at the destination because the traveler selected an earlier departure in order to increase his chances of arriving in time for a crucial appointment. Conversely, efforts by frequent travelers to find new ways of spending travel time productively or enjoyably might decrease the "disutility" of travel. To the extent that these efforts are successful, the amount of time needed to complete a trip might become less of a concern than it has been in the past.

Our sense from these investigations is that the nature and extent of opportunities for spending travel time productively is evolving rapidly. This change and the other changes discussed above suggest that policymakers should exercise caution in extrapolating the results of value of time research conducted in the past under substantially different air travel conditions.

A final implication of this research is that polices aimed at lowering the costs of delay ought to consider a range of options. Reducing the amount of delay is vitally important and badly needed. At the same time, however, it may be possible to take steps that would make delay easier to live with. Information about projected departure and arrival times that is more accurate, more timely and more readily available would help travelers to cope more effectively with schedule unreliability. Improvements in communications, improved workspaces, and steps to facilitate the productive use of travel time would lower the costs associated with scheduling padding and extended wait at airports. If some amount of delay and schedule unreliability is likely to remain forever with us, we ought to be devoting some thought and effort to assisting travelers in their efforts to cope with the effects of delay.

5 Public Policy Implications

The results of this study indicate that air transportation delays impose a large cost on society. The obvious implication of this conclusion is that efforts to reduce these costs could certainly be worthwhile.

The most obvious way to do this is to add capacity. The NAS is a queuing system; albeit, a very complex queuing system. As such it exhibits the classic queuing behavior that, as demand approaches capacity, delays increase at a greater than linear rate. The large delays experienced in 2007 are a manifestation of this phenomenon. This perspective implies that increases in capacity -- even modest increases -- can substantially reduce delays. The capacity of the system can be expanded in a number of ways. The NextGen initiatives seek to increase NAS capacity. However, another large, related investment category consists of infrastructure investment-- most notably, runway construction and other airport-capacity-improving activities.

Of course, one needs to consider carefully how much investment in capacity improvements can be justified based on the delay cost estimates provided in the report. In one important respect our report understates the case for investments in capacity. Flight demand is expected to grow in the coming years so a certain amount of capacity enhancement is required just to keep pace with growth. For example, air carrier operations are expected to grow by 30% between 2007 and 2025. Comparable capacity enhancement should be required just to keep pace with this growth. Of course, this report strongly suggests that capacity enhancement that not only keeps up with increases in demand but also leads to some reduction in delay is certainly justified.

A key question whose answer has major implications for how much we ought to invest in capacity improvements is what percentage of the delay (and delay costs) we might reasonably expect to eliminate. The history of transportation systems has shown that, as capacity increases, demand "materializes" and fills up (and generally saturates) available capacity. Increasing the capacity of the system reduces delay, and makes travel easier and faster. The total cost of travel goes down as a result, and, in response, demand increases until congestion and delay begin to recur. Congestion and delay thus become part of the mechanism that equilibrates supply and demand. It is logical to expect that delay reductions produced by capacity enhancements will be diminished as result of this mechanism, although they clearly enable more users to share in the benefits of the system.

As has been repeatedly stated in this report, the complete elimination of delay is certainly neither a realistic nor an advisable goal. Certain causes of delay, e.g. aircraft mechanical problems, passenger-related aircraft loading delays, etc., will not be affected by NextGen technologies or by infrastructure improvements and are likely to remain with us into the foreseeable future. And while NextGen has a goal of eliminating or drastically reducing the difference between good weather and poor weather airport arrival and departure rates, safety considerations will always lead to the need to adjust operations and effectively reduce capacity in the advent of certain weather events. Some delays occur because of the inability of the system to accommodate demands during peak periods. It rarely makes sense to size the system to fully accommodate peak period traffic flows, and so there will almost always be some amount of queuing and delay during those periods. Finally, it is important to note that there can be tradeoffs between throughput and delay. The uncertainty of flight times very often leads to the need to create buffers of arriving flights (airborne queues) in order to insure that arrival capacity to an airport is maximized. All of these reasons indicate that it is virtually impossible and also undesirable to attempt to eliminate all air transportation delay. It is also perhaps safe to say that even eliminating a high percentage, e.g 80 or 90%, may be unrealistic. On the other hand, eliminating a larger percentage, e.g. 50 or 60%, may be a quite reasonable goal. Estimating precisely the percentage of delay reduction that could reasonably be achieved by capacity enhancements represents a challenging research question, which was not addressed as part of the TDI research.

Some delays arise because of externalities that result in inefficient patterns of usage. An operator considering the addition of a new flight to a crowded system will take into account the delay it is likely to experience, but is unlikely to take into account the delays its flights will impose on other users. On the other hand, an operator considering drawing down flights to improve the efficiency of its own operations at an airport is highly cognizant of the potential response of other airlines to the market opportunities that this would open up for them. This so called “backfill problem” has bedeviled efforts to encourage airlines to drawn down schedules voluntarily. The result is levels and patterns of system usage that are inefficient in the sense that the benefits enjoyed by some users are less than the total costs they impose on the system. Appropriately pricing the ANSP services can significantly mitigate this phenomenon and help insure that the benefits of capacity enhancements are well used. For example, the ANSP cost of providing services to a flight is largely independent of the weight and gauge of that flight. Yet, ANSP fees and/or taxes implicitly or explicitly decrease with weight and/or number of passengers. Since existing charges favor smaller aircraft, charges that better reflect costs would tend to encourage the use of larger aircraft and better utilization of available capacity (from a passenger throughput perspective). Likewise, mechanisms that restrict airport demand, such as slot controls and congestion pricing, represent approach to insuring airport capacity is not saturated to the extent that excessive delays result.

In fact, slot controls exist at virtually all major European airports but are relatively rare in the US (currently formal slot controls exist at the three NY airports: EWR, JFK and LGA and at Reagan National (DCA); certain limitations also exist at Chicago O’Hare (ORD)). Recent research at MIT has shown that slot levels at the US slot-controlled airports are generally set to higher values when compared to similar European airports (some of these could be explained by weather differences). Natural questions to ask then are whether slot controls should be used more widely in the US and whether the associated caps on the number of operations at existing slot-controlled airports should be reduced.

One can view the decision on setting the appropriate level of operations as trading off two cost components. The first is the passenger delay against schedule (PDS). This is the classical queuing delay, which increases as the number of scheduled operations approaches system capacity. The second includes several costs that increase as the level of operations decreases. One component we have estimated is capacity-induced schedule delay. That is, setting caps on operations is equivalent to instituting an artificial capacity constraint. As this report has shown such constraints force the movement of flights to less desirable time slots, leading to increased schedule delay. An extension of this impact for more severe restrictions is an overall decrease in the number of scheduled flights and a decrease of the frequency of service offered in a market. A somewhat different but potentially quite significant effect is a reduction in the level of competition in certain city-pair markets. For example, as the number of slots available to a carrier at a particular airport decreases, that carrier might decide to eliminate service in certain markets. Such a move would reduce the number of carriers offering service in those markets and thus afford greater market power to the remaining ones. In the case where a single carrier remained, that carrier would be able to charge a premium for its services, which would impose an obvious extra cost on passengers. While we have not carried out a complete analysis of these cost components and the rate at which they change, it should be noted that our estimate of total capacity induced schedule delay ($718 million) is dwarfed by our estimate of passenger delay against schedule directly due to delayed flights ($4,699 million). This would seem to provide some evidence that reducing the level of operations, e.g. through tighter slot controls, should have a positive benefit, despite potential fare changes. Certainly, a more careful analysis of this topic is warranted. Nonetheless, the results of this study certainly suggest that policies and mechanisms that limit the level of operations at airports should be considered in concert with capacity enhancements to insure effective use of new capacity in order to reduce flight delay and its associated costs.

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