The Impact of Flight Delays on Passenger Demand and Consumer Welfare

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Abstract

U.S. airline passengers increasingly have access to flight delay information from online sources. As a result, air passenger travel decisions can be expected to be influenced by delay information. In addition, delays affect airline operations, resulting in increased block times on routes and, in general, higher carrier costs and airfares. This paper examines the impact of flight delays on both passenger demands and airfares. Delays are calculated against scheduled block times as well as more idealized feasible flight times. Based on econometric estimations, welfare impacts of flight delays are calculated. We find that flight delays on a route reduce passenger demand and raise airfares, producing significant decreases in both consumer and producer welfare. Since producer welfare effects were estimated to be three to four times as large as consumer welfare effects, we conclude that from an economic efficiency rationale, airlines should be required to pay for the bulk of flight delay remediation efforts.

Keywords: Flight delays; Airfares; Consumer welfare

1. Introduction

Over the last two decades, customer service, and in particular, on-time performance in the airline industry, has drawn the attention of the media, researchers, and

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even Congress. Recent incidents of delays on the tarmac have raised concerns over how to reduce airline delays.[1] For example, in December 2006, passengers on an American Airlines flight were held on board an aircraft on the tarmac for nine hours at the Dallas-Fort Worth Airport while awaiting permission to take-off. Similarly, in February 2007, at the John F. Kennedy International Airport in New York, Jet Blue Airways passengers were held on an airplane on the tarmac for ten hours. As a result, the U.S. Department of Transportation (DOT, 2009) adopted a new rule limiting tarmac delays to three hours, and imposing fines on airlines if they keep enplaned aircraft on the tarmac for longer periods.[2]

Although this new DOT rule may be welcome by the traveling public, the far more costly delays of shorter duration that occur on an everyday basis will likely remain.[3] For example, in 2009, despite the relatively slow economy and decreased traffic experienced by U.S. airlines, 20.5 percent of flights arrived more than fifteen minutes beyond their scheduled time. At any reasonable valuation of time, these delays resulted in costs to the traveling public in the many millions of dollars. In addition, delays are intermittent, so that the variations in travel time require travelers to account for *possible* delays. As a result, passengers are often forced to arrive at their destination the night before a morning meeting in order to increase their odds of not being late. Moreover, delays increase airline costs. System delays lower the utilization rate for aircraft, thus increasing capital costs. In addition, delays cause airlines to adjust their schedules, expanding block times, thus contributing to higher crew costs.

As airline delay data have become more readily accessible by consumers, we hypothesize that consumers factor in the potential for delay before choosing to fly on a particular airline or a particular flight. Thus fight delays are predicted to have an impact

[1] The U.S. Department of Transportation's (DOT) defines on-time flights as flights that arrive within fifteen minutes of their scheduled arrival time. Unless otherwise indicated, this definition is used in this paper .

[2] In addition, at the time this paper was being written, the U.S. Congress was considering a “Passenger’s Bill of Rights” that would restrict the ability of airlines to keep passengers in airplanes on the tarmac for longer than three hours.

[3] There is language in the rule that prohibits airlines from scheduling chronically delayed flights, requires airlines to designate an employee to monitor delays and respond to consumers when complaints are filed, and requires airlines to display delay information on a flight basis on their websites. See U.S. DOT (2009).

on passenger demand. In addition, because flight delays increase airline costs, they are also predicted to have an upward impact on airfares. In this study we estimate the impact of airlines delays on passenger demand and airfares, and then, based on these results, compute the impact of delays on consumer and producer welfare. Specifically, this study addresses the following research questions:

- What is the impact of delays on passenger demand?
- What is the impact of delays on airlines prices?
- What impact do delays have on societal welfare?

In conducting our analysis, we calculate “feasible flying times” for each route, and then compare actual flying times to feasible flying times to calculate route delays. By calculating delays against feasible flying times, instead of against scheduled block times, we explicitly account for the lengthening of block times by airlines to accommodate delays. Our results indicate that the consumer loss from delays, both loss in surplus and dead weight loss, are in the order of $11.23 to $23.51 per passenger. Losses to airlines are estimated to be three to four times higher.

This study proceeds as follows: Section 2 reviews the relevant literature on schedule delays and provides background for this paper. Section 3 describes the data and methodology. Section 4 discusses the findings from the study as well as the limitations, while Section 5 draws conclusions, and discusses the potential for future research in this area.

2. **Background**

There is an extensive body of literature on the determinants of airfares and passenger traffic on airline routes. These determinants can generally be specified into supply, demand, and market structure factors (Oum et al; 1996). On the demand side, factors such as the populations and income levels at endpoint cities have an impact on the passenger traffic between the endpoint cities. On the supply side, factors such as fuel and crew costs, will shift marginal cost curves and impact airfares on a route. Market structural characteristics that impact airfares include the degree of route and airport concentration. For example, Borenstein (1989) found that a dominant airline on a route charges significantly higher prices than its competitors with lower market shares. Other studies have shown that as the number of competitors on a route increases, average airfares decrease (Borenstein, 1992, Hurdle et al., 1989, Morrison and Winston 1990).

The level of passenger delay in an airline market can affect both demand and supply curves for that market. On the demand side, delays add to the cost of travel and therefore, act to reduce passenger traffic. Air system delays also affect air carrier costs, thus the shifting supply curves and leading to increased prices. System delays force carriers to increase anticipated flight (block) times, and thus decrease aircraft utilization and increase flight crew costs.

Very little work has been conducted on the impact of flight delays on supply and demand outcomes. Morrison and Winston (1989), using a multilogit model, found that a one percentage point increase in on-time performance is valued at $1.21 per round trip by a customer. In other words, airlines that achieved better on-time performance can charge slightly higher fares. Forbes (2008) studied the impact of flight delays on airfares for routes between New York's La Guardia Airport and eighteen other airports during 2000 and 2001. He found that delays at La Guardia contribute to lower fares on routes to and from that airport, but to higher fares on routes to and from other New York City airports.

Dresner and Xu (1995) studied the relationship between customer service, including on-time performance, customer satisfaction (measured by the number of complaints lodged to the Department of Transportation against an airline), and firm performance (measured by airline profits). The authors found that flight delays have a negative impact on airline profitability through the mediating variable, customer satisfaction. In a similar manner, Suzuki (1998) found that reductions in on-time performance lead to decreased airline profits and lower carrier market share (Suzuki, 2000). Suzuki (2000) argued that a passenger's willingness to fly on the same airline decreases after the passenger experienced flight delays with that airline.

In this paper, we use aggregate route data for carriers to compute the impact of delays on passenger demand and airline prices. Then, based on our estimated coefficients, we calculate the impact of delays on consumer and producer welfare.

3. Methodology and Data

Over the past several years, delay information on a flight and airline basis has become increasingly available. Our hypothesis is that this information will influence passenger demand; that is, the greater the delays for a carrier on a route, the more reluctant passengers will be to fly on that carrier on that route. In addition, system delays serve to increase airline costs, thus affecting supply curves on routes. The increased cost will shift supply curves to the left, increasing equilibrium prices. Figure 1 illustrates the concept behind our analysis. (Appendix 1 contains a more detailed explanation.)

Insert Figure 1 about here

As shown in the figure, the presence of delays causes both the demand and supply curves to shift to the left, reflecting reduced demand and increased operating costs. As a result, there are the following welfare losses:

- Reduction in consumer surplus (Area 1)
- Reduction in producer surplus (Area 2)
- Consumer deadweight loss (Area 3)
- Producer deadweight loss (Area 4)

In order to examine these potential welfare effects from passenger delays, a simultaneous model is constructed and estimated using three-stage least squares (3SLS). The 3SLS estimation is used to account for the endogeneity between passenger demand and airfares on a route. The model is specified for a given carrier on a given route for a given quarterly period as follows:

$$FARE = \beta_0 + \beta_1 \text{ LAGDELAY} + \beta_2 \text{ PASSENGERS} + \beta_3 \text{ DISTANCE} + \beta_4 \text{ HHI} + \beta_5 \text{ LCC} + \beta_6 \text{ ADJ\_ROUTE\_LCC} + \beta_7 \text{ SLOT\_CONTROL} + \beta_8 \text{ VACATION\_ROUTE} + \Sigma\, \beta_t \text{ TIME}_t \quad (1)$$

$$PASSENGERS = \alpha_0 + \alpha_1 \text{ LAGDELAY} + \alpha_2 \text{ FARE} + \alpha_3 \text{ INCOME} + \alpha_4 \text{ POPULATION} + \alpha_5 \text{ VACATION\_ROUTE} + \Sigma\, \alpha_t \text{ TIME}_t \quad (2)$$

where:

- *FARE* is the average quarterly price charged by carrier *k* on the route between airports *i* and *j*.
- PASSENGERS is the number of passengers carried by airline *k* between airports *i* and *j* in a given quarter.
- *DISTANCE* is the distance measure in miles between airports *i* and *j*.
- *HHI* is the Herfindahl- Hirschman index for the route.
- *LCC* is a dummy variable set to 1 if the airline is a low-cost carrier and 0 otherwise (see Table 1).
- *ADJ_ROUTE_LCC* is a count of the number of low-cost carriers operating on adjacent routes (e.g., BWI-MDW is an adjacent route for IAD-MDW, DCA-MDW, BWI-ORD, DCA-ORD and IAD-ORD).
- *SLOT_CONTROL* is dummy variable set to one if 1 if one or both of the endpoints is a slot-controlled airport.
- *VACATION_ROUTE* is a dummy variable set to one if one or both endpoint airports are tourist destinations.[4]
- *LAGDELAY* is the average number of minutes carrier *k* is late on the route between airports *i* and *j* for quarter t-1. Alternative specifications calculate number of minutes late to a more ideal flight time represented by the 10th percentile or 20th percentile minutes of flight time. (See Appendix 2 for a detailed

[4] These include all airports in Florida and Nevada.

explanation of ideal flight times.) This variable is lagged since prior delay information is most likely to influence current behavior.

- *INCOME* is the population-weighted average income in the metropolitan areas around airports *i* and *j*.
- *POPULATION* is the product of the metropolitan area populations around airports *i* and *j*.
- *TIME* represents dummy variables for each quarter. The second quarter of 2003 is the baseline quarter.

Insert Table 1 about here

Based on the estimated coefficients from the model, the consumer and producer welfare changes are then calculated as indicated in Appendix 1.

Our panel dataset covers sixteen 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 quarterly DB1A pricing information.[5] We collected data only on short-haul routes (less than 500 miles) that were among the top 100 airport-to-airport origin-and-destination (OD) routes in 2006. We chose to estimate our dataset using short-haul routes because we wanted to isolate the flight delays on an OD route as a factor impacting passenger demand. With longer haul routes, it is difficult to match flight delays on given segments to OD flight demand, since passengers on a given OD route will fly to their destination through several different hub airports (or travel nonstop). As a further check, only those short-haul routes where at least 65 percent of the onboard passengers were OD passengers were retained. The final sample includes 1,565 observations from 57 routes and 14 carriers.

[5] Only carriers with a minimum 5 percent market share on a route were included in the dataset in order to exclude carriers that were not viable competitors. In addition, monopoly routes were excluded so that all observations are for carriers operating in competitive markets.

Descriptive statistics for the variables are in Table 2. From the table, it can be seen that the average one-way fare is about $93. Mean carrier and route specific passenger demand was 6,228. The average delay for a carrier on a route is 12.41 minutes.[6] The average route distance is about 326 miles. About one-quarter of the routes are classified as vacation routes and 8 percent of the routes have a slot-controlled airport at one or both endpoints. The average HHI on a route is 5,369, which is a slightly higher level of concentration than would be calculated if two carriers operating on a route each had a 50 percent market share. Thirty-one percent of the observations are for low-cost carriers and, on average, there are 1.83 low-cost carriers operating on adjacent routes.[7]

Insert Table 2 about here

Table 3 contains a correlation matrix for the variables in our dataset. No correlation coefficients are above 0.5 indicating that multicollinearity may not be a significant factor in the estimations. However, to more formally evaluate potential multicollinearity, Variance Inflation Factor (VIF) scores are computed for all independent variables. All VIF scores are less than 5.0, below the suggested threshold of 10, indicating that multicollanerity may not be a serious problem (Kennedy 1998).

Insert Table 3 about here

Figure 2 shows on-time performance for each of the 16 quarters in the sample. A downward trend in on-time performance is observed in the figure; the best on-time performance reached in the second quarter of 2003 (88%) and the worst in the third quarter of 2006 (75%). We observe that on average 2003 had the best on-time performance and 2006 the worst.

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[6] When a carrier arrived early, the delay was set to zero. Therefore, there were no “negative delays” included in the dataset.

[7] If a low-cost carrier operates on two adjacent routes, then it would be included twice. For example, Southwest Airlines operates BWI-MDW and IAD-MDW. Both these routes are counted as adjacent routes for a carrier operating DCA-ORD. Thus, although there are only five low-cost carriers in our dataset, the maximum number of adjacent carrier operations is nine.

Insert Figure 2 about here

Table 4 shows average on-time performance shows significant variation by carrier. During the period of analysis, America West had the best on-time performance, with 83.45 percent of flights arriving within the fifteen minute Department of Transportation on-time window. America West also had the lowest average minutes of delay at 9.29. The worst on-time performance, with only 69.89 percent of flights arriving within the fifteen minute window was recorded by Atlantic Coast Airlines, although this carrier had only two observations in our dataset.

Insert Table 4 about here

4. Results and Discussion

4.1 Estimations of Fares and Demand

The three-stage least square (3SLS) algorithm of the STATA software package was used to estimate the model. The results of our baseline estimation, with delays calculated based on deviations from scheduled block times, are presented in Column 1 of Table 5. In the fare equation, the coefficient for lagged delay, the key variable in our estimation, is positive and significant indicating, as expected, that delays have an upward impact on fares, likely due to increased airline operating costs on congested or often-delayed routes. In the passenger equation, the coefficient for lagged delay is negative and significant, indicating that delays in the prior quarter on a route have a negative impact on passenger demand in the current quarter. The coefficients of the control variables have either the expected signs or are insignificant. In the fare equation, the coefficient for passengers is positive and significant (demand shifts to the right increase fares). The same is true for the distance variable (longer routes, higher fares). In addition, the results from the fare equation show that the degree of competition does not impact airfares, since

HHI is not significant. However, the type of competition does impact fares as evidenced by the negative and significant coefficients for LCC and adjacent route LCC, reflecting the downward impact on prices from low cost carrier competition.

Insert Table 5 about here

In the passengers equation, higher fares have a negative impact on passenger demand, while population, income and vacation routes are all positively associated with demand. The coefficient for *FARE* in the passengers equation provides an estimate for elasticity (given the log-log model) of -1.36, which is in the range of elasticities estimated in previous work (Gillen et al; 2003).

The second and third columns of Table 5 present the results for delays against the 20^{th} and 10^{th} percentile feasible times, respectively. As described in Appendix 1, these estimations illustrate the impact of delays against more ideal flight times – the twentieth percentile best flight time on a route and the tenth percentile best flight time on a route. Airlines increase their scheduled block times in order to reduce reported delays on congested routes. Thus, the block times, themselves, incorporate scheduled delays.

Therefore, in order to provide a more accurate assessment of the cost of delays, scheduled delays should be assessed against flight times purged of their delay component. Thus, ideal or feasible flight times are calculated based on the 20^{th} percentile fastest flight time on a route and the 10^{th} percentile fastest flight time. The results from these estimations are consistent with the base case estimation. In both cases, the coefficient for lagged delays in the fare equation is positive and significant, and in the passengers equation, negative and significant, indicating that delays lead to increased prices (likely through higher operating costs) and to a reduction in passenger demand.

4.2 Impact of Delays on Societal Welfare

Based on the estimated coefficients from our models, it is possible to calculate the welfare effects from passenger delays. As illustrated in Figure 1 and Appendix 1, these delays can be divided into changes in consumer surplus, producer (airline), deadweight loss to consumers and deadweight loss to producers.

Table 6 provides a calculation of the welfare impact of flight delays based on the three specifications of our model. In each case, the potential welfare gains from moving to zero passenger delays are estimated. As shown in the table, the total consumer gain from eliminating delays based on scheduled block times is calculated at $11.23 per passenger, based on actual passenger counts.[8] The estimates, per passenger, based on the 20th percentile and 10th percentile feasible times are $21.10 and $23.51 per passenger, respectively. Table 6 also indicates that the expected gains to airlines (i.e., producer gains) from cost reductions are higher than the gains to consumers. For example, the airline gain from reducing delays based on scheduled block times is $44.24 per passenger, with a total welfare gain (consumer + producer) of $55.47 per passenger.

Insert Table 6 about here

Although these projected gains from eliminating delays are significant, it should be noted that a limitation of our study is that our calculations are based on a partial equilibrium analysis. We examine welfare gains to passengers using (or potentially using) the air transport system. To the extent that these passengers may be diverted from another mode of transport (e.g., automobiles), there may be changes in welfare in that market sector as well, not addressed in this study. Second, it should be noted that unconstrained capacity may increase competition in the airline industry, reducing the pricing power currently enjoyed by some carriers. Therefore, eliminating delays by increasing capacity could lead to “destructive competition” whereby airlines are not able

[8] Note that a shift in demand due to the elimination of delays would increase passenger counts. Our calculations are based on costs per current passengers, not costs per projected passengers.

to exercise pricing power necessary to recover their full costs of operations. Thus, increases in producer surplus from reductions in delays may be illusory. Third, it is important to note that our calculations do not account for some of the important welfare implications from delays on connecting flights. Flight delays often cause passengers to miss connections, thus requiring them to take later flights. These costs can be quite significant if passengers need to wait several hours or until the next day for a rescheduled flight. Fourth, we do not account for the cause of delays in our analysis. Since not all delays are caused by congestion (i.e., there will always be delays due to weather conditions), it is not possible to completely eliminate delays. Therefore, the cost curves will always reflect a delay component. Finally, we do not account for the infrastructure expenditures necessary to reduce the delays. Certainly, there is a cost-benefit trade-off to reducing delays and this paper only examined the benefit side.

5. Conclusions and Future Research

In this paper we demonstrate how flight delays affect passenger travel decisions and airline ticket costs. We find that flight delays by an airline on a route affect both passenger demand and the average fare on that route; passenger demand is reduced and average fares are increased. Based on these results, we estimate the welfare costs to society using three measures of flight delays – the first based on delays against scheduled block time and the second and third based on delays against the 20^{th} and 10^{th} feasible flight times, respectively. We find that flight delays pose significant costs to both consumers and airlines, with producer costs being three to four times the size (per passenger) of consumer costs.

Even though the welfare calculations are based on a number of limiting assumptions and are subject to estimation error, the impact of reducing delays on welfare are very likely to be substantial. When these welfare gains are assessed against the costs of expanding infrastructure, the results are likely to show that there are positive net benefits associated with improving infrastructure. Since these benefits are shared by passengers and airlines, the costs of paying for these infrastructure improvements should likewise be shared. Our calculations show that airlines are the main beneficiaries, so they should be assessed the majority of the costs.

A number of limitations of this study were discussed in the previous section. Future research could expand the scope of this study, for example by accounting for welfare effects from eliminating delays on connecting, as well as direct, flights. In addition, future research could examine welfare effects from delays with a greater degree of granularity, noting that delays due to weather are not as easily reduced by building infrastructure, as are delays due to congestion.

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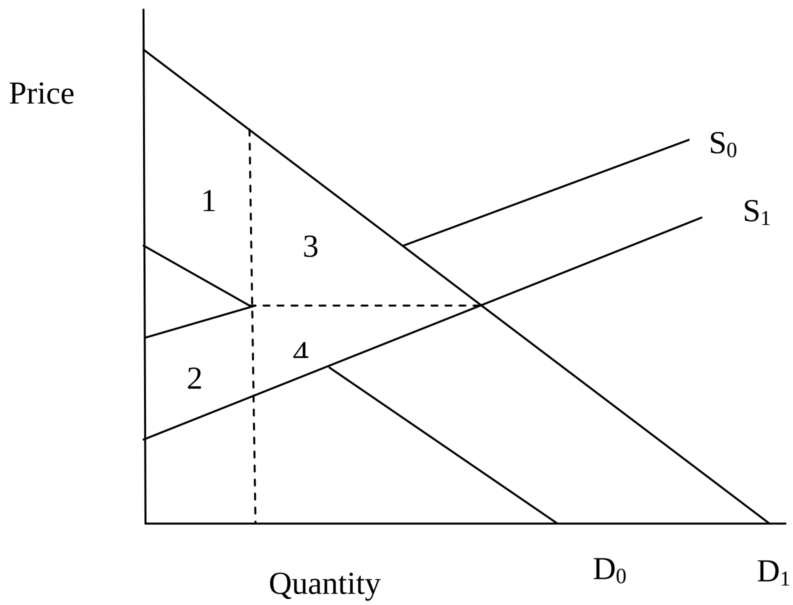
Figure 1: Representation of Welfare Losses Due to Delays



S_0 = Supply Curve with Delays
S_1 = Supply Curve with No Delays
D_0 = Demand Curve with Delays
D_1 = Demand Curve with No Delays

1 = Loss in Consumer Surplus
2 = Loss in Producer Surplus
3 = Deadweight Loss to Consumers
4 = Deadweight Loss to Producers

Figure 2: Simple Average On-Time Performance by Quarter

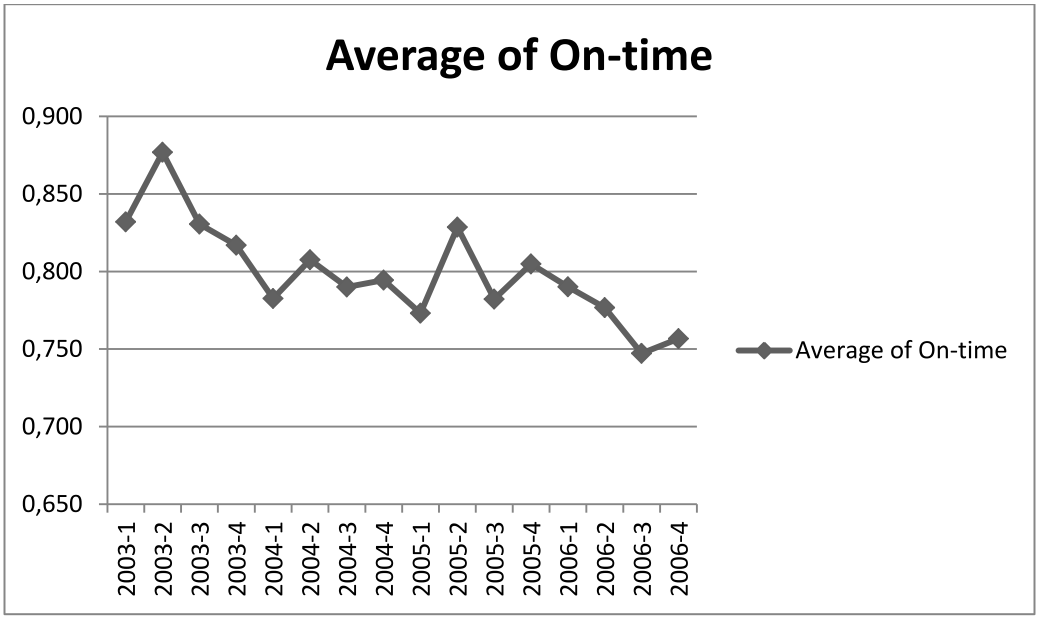


Table 1 – Classification of Low and High Cost Carriers*

Carrier	High_cost/ Low_cost
American Airlines (AA)	H
Alaska Airlines (AS)	H
Jet Blue Airlines (B6)	L
Continental Airlines (CO)	H
Atlantic Coast Airlines (DH)	H
Delta Airlines (DL)	H
Frontier Airlines (F9)	L
AirTran Airways (FL)	L
America West Airlines (HP)	H
Northwest Airlines (NW)	H
American Trans Air (TZ)	L
United Airlines (UA)	H
US Airways (US)	H
Southwest Airlines (WN)	L

*Based on Hofer et al (2008) methodology.

Table 2: Descriptive statistics (N = 1,565)

Variable	Mean	Std. Dev.	Min	Max
FARE ($)	92.91	32.83	33.15	254.61
PASSENGERS	6227.25	4814.60	550	29590
LAGDELAY (MINUTES)	12.41	6.368	0	59.6
DISTANCE (MILES)	325.56	74.96	185	481
VACATION_ROUTE	0.25	0.43	0	1
SLOT_CONTROL	0.08	0.27	0	1
HHI	5368.87	1283.07	2611.86	8951.92
LCC	0.31	0.46	0	1
ADJ_ROUTE_LCC	1.83	2.46	0	9

Table 3: Correlations

	1	2	3	4	5	6	7	8	9	10	11
1 FARE	1										
2 PASSENGERS	-0.20	1									
3 LAGDELAY	0.21	-0.19	1								
4 DISTANCE	0.12	-0.04	-0.04	1							
5 VACATION_ROUTE	-0.13	0.09	-0.04	-0.03	1						
6 SLOT_CONTROL	0.30	0.16	-0.05	-0.23	-0.17	1					
7 HHI	-0.18	0.06	-0.06	0.06	0.19	-0.15	1				
8 LCC	-0.46	0.38	-0.05	0.11	0.14	-0.18	0.22	1			
9 ADJ_ROUTE_LCC	-0.12	0.16	-0.16	0.09	-0.15	-0.06	0.10	0.03	1		
10 INCOME	0.25	0.10	0.02	0.10	-0.18	0.28	-0.17	-0.07	0.36	1	
11 POPULATION	0.24	0.02	0.13	-0.39	-0.36	0.34	-0.10	-0.24	0.30	0.07	1

Table 4: On-time Performance by Carrier

Carrier	Avg. On-time (%)	Avg. DELAY (minutes)	Std. Dev. DELAY	Observations
American Airlines (AA)	77.19	14.92	6.83	300
Alaska Airlines (AS)	79.90	13.71	9.28	71
Jet Blue Airlines (B6)	75.68	19.58	6.64	6
Continental Airlines (CO)	74.29	18.96	7.72	60
Atlantic Coast Airlines (DH)	69.89	22.85	7.00	2
Delta Airlines (DL)	81.07	11.24	7.07	146
Frontier Airlines (F9)	78.11	11.10	2.71	6
AirTran Airways (FL)	75.44	16.22	5.08	117
America West Airlines (HP)	83.45	9.29	4.52	171
Northwest Airlines (NW)	77.38	13.21	5.22	75
American Trans Air (TZ)	83.39	10.36	3.29	11
United Airlines (UA)	81.83	12.69	5.52	168
US Airways (US)	79.96	11.63	5.55	83
Southwest Airlines (WN)	81.92	10.30	4.71	349

**Table 5: Estimation of Fares and Passengers –
Using Three Measures of Delay**

	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	-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		

*** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.
All variables logged except LAG DELAY due to zero values.

Table 6: Estimation of Welfare Gains Per Passenger*
from Eliminating Delays based on the Three Model Specifications

	Scheduled Block Time Delay Data ($)	**20th Percentile Feasible Time ($)**	**10th Percentile Feasible Time ($)**
Increase in Consumer Surplus	10.00	16.71	18.14
Reduction in Consumer DWL	1.23	4.39	5.37
Total Consumer Gain	**11.23**	**21.10**	**23.51**
Increase in Producer Surplus	38.76	45.34	46.23
Reduction in Producer DWL	5.48	19.72	25.86
Total Producer Gain	**44.24**	**65.06**	**72.09**
Total Welfare Gain	**55.47**	**86.16**	**95.60**

*Based on actual, not estimated, passenger totals
DWL = Dead Weight Loss

Appendix 1: Welfare Calculations

The methodology for the calculation of the welfare effects is very basic. Each origin and destination market is assumed to run under monopolistic competition; i.e. a limited number of airlines compete, each offering slightly differentiated products. This allows the airlines to exercise some degree of market power; hence airfares are expected to exceed marginal operating costs. Since the econometric system does not explicitly include cost functions, there is a need to estimate marginal costs (required to calculate the deadweight loss) from the equations. Given the market structure defined above, and assuming that the estimated passenger equation is a reasonable approximation to the market demand function, the marginal cost function will equal the marginal revenue function (derived from demand) at the equilibrium quantity. Since these are local approximations, further simplifications will apply.

According to the formulation of the system, reduction of delays is treated as both a cost-reducing and product-improving innovation. Punctual flights are more attractive in the eyes of consumers as well as cheaper to produce; thus shifting demand upward and fares downward. In view of these opposing effects, the direction of the price change (to the new equilibrium) remains unclear and will be determined empirically. The process is graphically described in Figure A1. The estimated demand function for each market, carrier and quarter (D_0) is compared with the predicted demand in the absence of delays (D_1). The negative sign on the lagged delay coefficient shift implies that in the absence of delays, demand will shift to the right as the other demographic variables remain constant. Therefore, there is a welfare gain to the society in the sense that consumers are willing to pay more for those flights experiencing reduced delays. This effect is measured by the change in the a-coefficient (see the equations below), which represents the scaling factor of the resulting CES demand function.

The same applies to the fare equation, where the positive sign of the estimated delay coefficient implies that the absence of delays will shift the fare equation down since delays increase airline costs, and thus fares, in terms of crew, fuel, and loss of frequencies. Finally, according to economic theory, the expressions of marginal revenue can be obtained from the inverse demand functions by straightforward derivation. These functions, evaluated at the equilibrium quantities, provide local approximations to the marginal cost functions, whose functional forms remain unknown. The proposed system results in two equilibria, either considering zero delays (q_1,p_1) or using the actual on-time figures (q_0,p_0). . In addition, the non-equilibrium pairs (q_0,p_2) and (q_0,p_3) are also obtained.

$Demand_{1\ (no\ delay)} = ap^{-\alpha}$ $\quad$ $Fare_{1\ (no\ delay)} = bq^{\gamma}$

$Demand_{0\ (actual\ delay)} = a'p^{-\alpha}$ $\quad$ $Fare_{0\ (actual\ delay)} = b'q^{\gamma}$

$Marginal\ Revenue_1 = ((\alpha-1)/\alpha)\ a^{1/\alpha}\ q^{-1/\alpha}$

$Marginal\ Revenue_0 = ((\alpha-1)/\alpha)\ a'^{1/\alpha}\ q^{-1/\alpha}$

$a,b = exp\ (x'\beta|_{delay=0})$

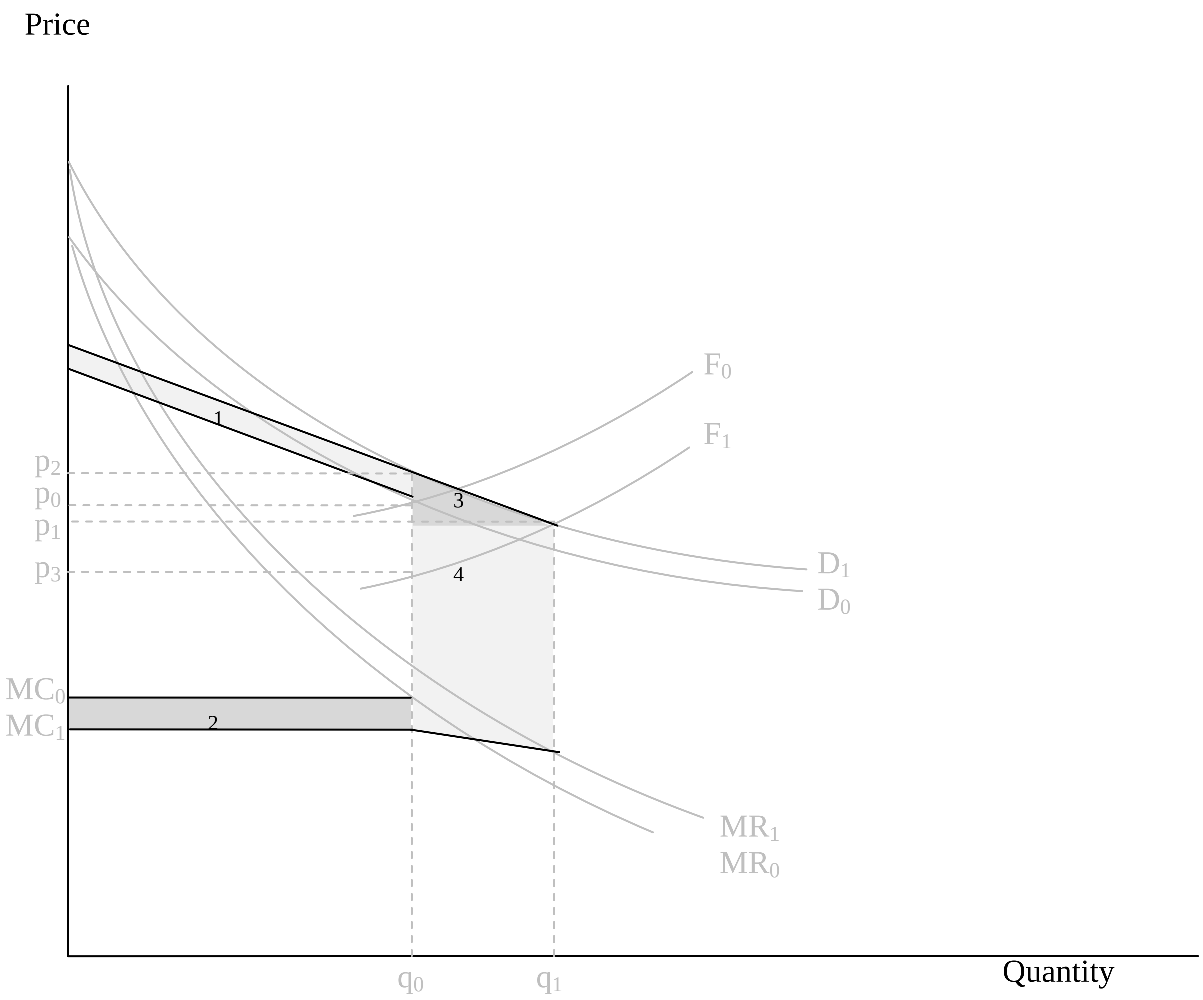
$a',b' = exp\ (x'\beta|_{delay=1})$

The total gain in welfare to each market (ΔW) from reducing delays is measured by the four areas described in Figure A1. The area 1 represents the gain in consumer surplus. For reasons of simplicity, the gain per passenger is assumed to be constant and equal of that of the marginal passenger at q_1, calculated as the difference between the demand functions at this point (p_2-p_1). This explains the linear representation in Figure A1.

The area 2 represents the gain in producer surplus due to the decrease in operating costs gained from reducing delays. However, the marginal cost function in the absence of delays (MC_1) cannot be evaluated at q_0 and its functional form is also unknown. Hence, the difference between the MC functions is also assumed to be constant and equal to that of the marginal passenger at q_0, and approximated as the difference between the fare equations at this point ($MC_{1(q1)}$-$MC_{0(q1)}$) which, as noted, indicate how fares are adjusted to compensate for reduced delay costs.

The area 3 represents the deadweight loss in consumer surplus due to delays. Note that under the linear simplifications, the calculation of this triangular area is straightforward as a function of the predicted quantities and prices. The same applies to the area 4, which represents the deadweight loss in producer surplus due to delays. This area is a function of the two marginal cost point estimations and the previously calculated difference between the fare equations at q_0. Note that, in Figure A1, the MC function is assumed to increase between q_0 and q_1, thus defining a trapezoidal shape. This representation does not imply that this feature actually holds in all markets, though it has no practical impact at the time of calculating the final area.

Figure A1 – Theoretical Model



Appendix 2: Feasible Flight Times

There are a variety of approaches that have been used to statistically analyze airport delay data (Federal Aviation Administration, 1987; Morrison and Winston, 1989; Hansen et al., 1998). Normally, most of the studies follow conventional rules to classify flight delays, with delay against schedule (DAS) being the most common indicator employed in the literature. This indicator calculates flight delays as the difference between scheduled and actual arrival time.

However, the DAS indicator may be subject to manipulation by air carriers that can increase their block times and thus improve their on-time performance. In order to eliminate this distortion, Mayer and Sinai (2003) propose calculating delays as actual travel time minus minimum feasible travel time. Minimum feasible travel time is considered as a useful benchmark for travel time when airports are uncongested and weather is favorable. Travel time is computed as the actual gate-to-gate time and, therefore, the Mayer-Sinai delay (MSD) indicator excludes strategic behavior (i.e., manipulation) by airlines of their block times. However, delays calculated against the very best flight times may be too idealized. For that reason, Martin et. al (2006) propose correcting the MSD calculations by adding an element of departure delay.

This paper uses corrected-MSD indicators to measure delays; that is, delays against the 10^{th} percentile and 20^{th} percentile minimum feasible times. These adjustments allow us to minimize the impact of outliers and/or errors in the observations in the database. In addition, these benchmarks are both carrier- and quarter-specific, in order to account for differences in aircraft/equipment and weather conditions.