The "Southwest Effect" Revisited: An Empirical Analysis of the Effects of Southwest Airlines and JetBlue Airways on Incumbent Airlines from 1993 to 2009

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Abstract

The expansion of Southwest Airlines and JetBlue Airways has sparked new empirical interest in the effects of low-cost carriers (LCC) on existing airfares. Namely, empirical studies have attempted to capture the threat, or potential competition, of an entrant. This paper examines incumbent airline prices as a result of potential and actual competition from both Southwest Airlines and JetBlue Airways from 1993 to 2009 by analyzing mean airfares as well as price dispersion on incumbent routes. I incorporate a panel OLS with fixed effects model as well as GLS model with random effects. Consistent with recent literature, this paper finds that legacy incumbents cut fares significantly when threatened by Southwest Airlines. However, low-cost incumbents do not exhibit the same magnitude of pre-emptive price cutting. When threatened by JetBlue, neither legacy nor low-cost carriers cut fares significantly, suggesting that incumbents react differently when threatened by Southwest versus JetBlue. The evidence of increased price dispersion is mixed with price dispersion decreasing on legacy carrier routes as a result of Southwest threat and entry but increasing on legacy carrier routes as a result of JetBlue threat and entry.

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I. Introduction

The Airline Deregulation Act of 1978 dramatically altered the competitive landscape of the US airline industry, ushering in an era of head-to-head competition between low-cost carriers (LCCs) and legacy carriers. In particular, the continued expansion of Southwest Airlines, the most profitable player in the LCC space today, has become a principal driving force behind the growth of LCCs and the ubiquity of low fares across routes in general. The impact of LCCs has attracted an increasing amount of empirical attention within the industrial organization literature in the past. Unlike legacy carriers which utilize a hub-and-spoke network and operate with a variety of different aircrafts, LCCs operate within a point-to-point network, allowing them to implement considerable flexibility in routes flown and operate with lower costs. For example, the number of passengers flying LCCs more than doubled from 1997 to 2007 and LCCs entered a total of 598 routes from 1997 to 2007 (Tan 2010). From 1993 to 2004, Southwest alone nearly tripled its revenues from \$2.3 to \$6.5 billion (Goolsbee and Syverson 2008). Figure 1 depicts the growth in airports serviced by Southwest and JetBlue from 1993 to 2009.

The main objective of this paper is to extend upon previous empirical work on the impact of LCC *entry threat* by focusing on the particular expansionary nature of Southwest Airlines and JetBlue Airways, the two most dominant LCCs in the industry today. Within the airline industry literature, entry threat captures the scenario in which a particular LCC has begun operations in two endpoints of a route, *but has not started flying the route itself*.[2] Because an incumbent airline senses the increased probability that an entrant may potentially enter the route, existing fares would likely decrease well in advance of actual entry as the incumbent looks to deter entry or to generate brand loyalty among existing customers and "cushion" the impact of imminent competition. With Southwest and JetBlue's staggering expansion in the past decade which has witnessed the consolidation of several legacy carriers (i.e. United Airlines-Continental merger in May 2010) and the bankruptcy of others (Japan Airlines in January 2010), the airline industry is an excellent place to examine the strategic nature of entry deterrence.

2 Tan (2010) provides a succinct distinction between *potential* (or entry threat) and *actual* competition. Suppose Southwest operates out of both Boston Logan International Airport (BOS) and Philadelphia International Airport (PHL) and that it services the BOS-PHL route. Actual competition is said to occur if the incumbent on the route, say US Airways, services the route at the same time as Southwest. In this case, there is no entry threat because actual entry onto the route is guaranteed. Suppose Southwest also operates out of New York La Guardia (LGA) but not the BOS-LGA route. In this case US Airways *potentially competes* with Southwest on the BOS-LGA route at the time that Southwest operates out of both airports but not the actual route itself. Here, the BOS-LGA route is threatened by Southwest and US Airways, the incumbent on the route, may likely cut fares before any actual Southwest competition.

The remainder of this paper is organized as follows: Section 2 discusses existing literature on this topic. Section 3 discusses the data collection methodology. Section 4 suggests an empirical strategy to examine the effect of entry threats and the motive for preemptive price cutting. Section 5 presents the empirical findings and discussions. Lastly, Section 6 concludes the paper.

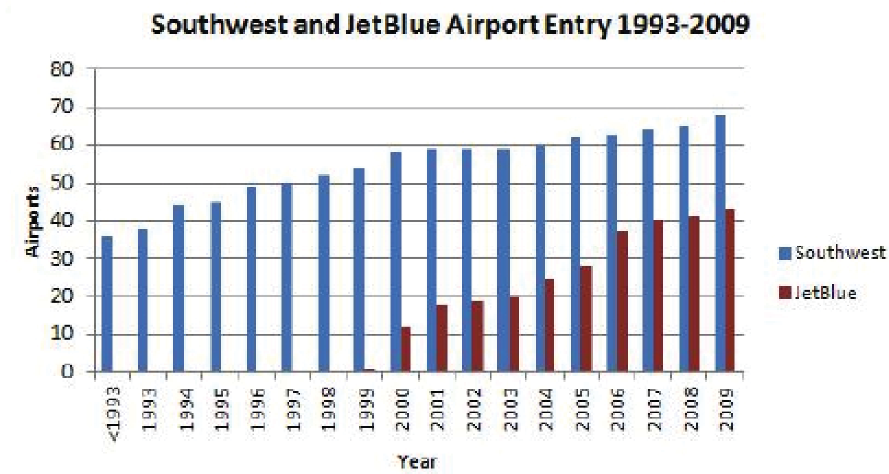

Figure 1: Southwest and JetBlue aggressively expanded operations out of metropolitan airports from 1993 to 2009.

II. Literature Review

The airline transportation literature is dense with studies imparting the salutary impacts of LCC entry on airfares and air travel. Morrison (2001) found that the estimated savings (or decrease in competitor airfares), due to actual, adjacent and potential competition from Southwest, totaled $12.9 billion by 1998, of which $3.4 billion of these savings were directly attributable to Southwest's lower fares. Tan (2010) examined both legacy and LCC responses to several potential entrants and found that legacy incumbents cut fares more aggressively than LCC incumbents. Bennett and Craun (1993) studied Southwest's expansion into California in the early 1990s by examining discrete price drops on the Oakland-Burbank route and found that Southwest's operations resulted in a 55% decrease in prices as well as a sixfold increase in passenger traffic. On a similar note, Dresner, Lin and Windle (1996), examined the spillover effects of Southwest by examining fares on routes from nearby airports and suggested that the presence of a low-cost carrier on a particular route induced competitive price pressures in the form of spillovers onto other routes, resulting in higher passenger traffic and increased consumer welfare.[3]

It is only until recently that economists have started to examine what happens to prices *before* low-cost entry. Goolsbee and Syverson (2008) examined how incumbents respond to the threat of Southwest entry as opposed to actual entry by analyzing average airfares from 1993-2004 with the following question in mind: Are entry threats credible? They restricted their sample to Southwest airports only and focused on scenarios where Southwest started operating in both endpoints of a route but before it actually started flying the route. Controlling for airport-specific cost shocks, they found that incumbents cut fares significantly when threatened by imminent Southwest entry and that over half of Southwest's total impact on incumbent fares occurred from mere threat alone, with fares initially dropping 17% in the quarter[4] of threat (ie Southwest operates both endpoints) and ultimately dropping 29% three years after route entry.

Goolsbee and Syverson's (2008) findings that airlines do in fact cut prices prior to entry run counter to the classic view of limit pricing, promulgated by the Chicago School, which implies that airlines are static players and should not cut prices before they have to. Other traditional arguments center around the notion that preemptive price-cutting is irrational because it entails decreased short-term profits and costly competitive actions with no material impact on future profits (Goolsbee and Syverson 2008). So then, why might an incumbent preemptively cut fares before actual competition has occurred?

Theoretical articles by Klemperer and Roberts (1982) and Fudenberg and Tirole (1986) suggest that incumbents may resort to preemptive price cutting as a signaling mechanism to appear as if they too are low-cost and subsequently deter entry in hopes of reaping monopoly-like profits on passenger-heavy routes.[5] Another theoretical construct in the entry deterrence literature is "predatory pricing," a scenario in which an incumbent engages in a war of attrition against the entrant by slashing fares well below costs and thereby sacrificing short-term profits in hopes of inducing exit. Once the entrant exits, the incumbent charges supracompetitive prices in a monopolistic setting. Because the incumbent firm is often better established and financially stronger, it may be able to sustain predatory practices in order to achieve greater profits when

3 The authors studied how airlines operating from Washington Reagan National (DCA) might change fares as Southwest enters Washington-Baltimore (BWI). DCA and BWI serve air travelers in the greater Washington DC area and are located within 50 miles of each other.

4 The term "quarter" is understood to be fiscal quarter. Quarter 1 is the 3-month period beginning with January 1 and ending with March 31.

5 Alternatively, incumbents may welcome entry if the entrant is a good candidate for an alliance, merger or buyout.

exit is all but certain. Both arguments assume that entry threats are credible. Figure 2 delineates incumbent prices surrounding LCC entry and exit events in the event of predatory pricing and entry deterrence. Here, P_0, P_1, and P_2 represent the pre-entry, post-entry and post-exit equilibrium prices of the incumbent.

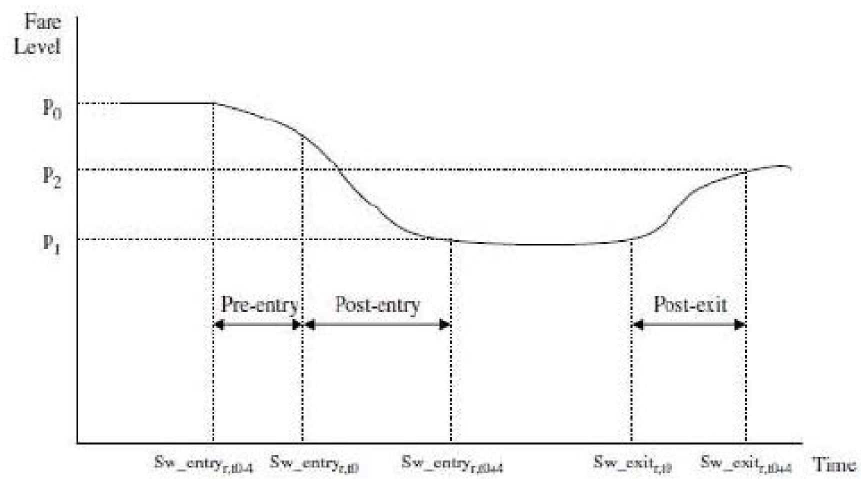

Figure 2: Illustrative impact of Southwest entry and exit events on incumbent airfares. Source: Daraban and Fournier (2008)

The predatory pricing argument has received mixed reception within empirical experiments. McGee (1958) was among the the first skeptics of predatory pricing. By examining the Standard Oil Company back in 1911, McGee (1958) found that predatory pricing did not drive out competing refiners and that Standard Oil achieved its monopoly through other means such as mergers and acquisitions. On the other hand, Milgrom and Roberts (1982) argued that predatory pricing can result from perfectly rational behavior in anti-competitive settings. Indeed, the airline industry is a perfect example. Several landmark antitrust suits brought forth by low-cost carriers against legacy incumbents have reignited interest in whether firms engage in predatory pricing in order to drive out competitors. In the 1999 case *United States of America vs. AMR Corporation*, the US government alleges that American Airlines priced its fares and products well below costs, attempting to exclude competition via "reputation for predation." Other recent cases have involved Air Canada, Quantas and Deutsche Lufthansa, each involving an injunction against the more established incumbent for manipulating fares to exclude competition.

Other authors have examined the price distribution resulting from LCC entry. Borenstein and Rose (1994) and Gerardi and Shapiro (2009) both provide compelling but contrasting evidence on the effects of competition on directional movements in price dispersion. Borenstein and Rose (1994) used cross-sectional data to analyze price dispersion on routes and concluded that the absolute difference in fares between two passengers on a route is roughly 36 percent of the airline's average ticket price. In addition, this dispersion was more pronounced on routes with more competition or lower flight density. In contrast, Gerardi and Shapiro (2009), utilizing a panel data, found that price dispersion decreases with competition.

Apart from the airline industry, entry deterrence has been closely researched in several other industries. Ellison and Ellison (2007) tested for strategic entry deterrence in the drug and pharmaceutical industry by examining the behavior of pharmaceutical incumbents just prior to losing patent protection. They found that in markets of intermediate size, incumbents reduced advertising immediately prior to patent expiration as evidence of strategic entry deterrence. Along the same vein, Dafny (2005) investigated whether hospitals and other medical establishments also engage in strategic entry deterrence by examining the growth in Medicare claims for electrophysiological studies (EP), a corrective heart procedure, after a 1990 Medicare policy that effectively lowered entry barriers for hospitals seeking to perform EPs. Dafny (2005) found that the growth in the volume of EPs was highest in markets with intermediate attractiveness, or markets where potential entrants are mostly on the fence about entering. In other words, incumbent hospitals in markets facing the most uncertainty around potential competition performed more EPs than hospitals in markets where entry was either extremely likely or unlikely.

2.1 Contribution to the Literature

This paper incorporates recent findings on low-cost carrier competition into a comprehensive analysis and expands the empirical findings in the literature in several key ways. Namely, this paper: (1) uses panel data on airfares to examine the extent of incumbent price-cutting from Southwest and JetBlue potential and actual competition during a window of nearly 20 years on both the legacy and low-cost carrier cohorts, (2) examines pricing behavior on routes that Southwest eventually exits to determine patterns of predatory pricing, (3) documents fare-cutting across routes with varying market concentrations of legacy and LCC carriers and across other route characteristics, (4) and analyzes price dispersion on Southwest and JetBlue threatened routes using the Gini coefficient as a measure of price inequality.

III. Methodology

The data used in this paper originates from the Bureau of Transportation Statistics' Airline Origin and Destination Survey (DB1B) database from the first quarter of 1993 through the fourth quarter of 2009. The DB1B database contains quarterly data on airfares and provides a random 10% sample of all domestic tickets from reporting carriers.

I pulled the following data from the DB1B database: the origin and the destination airports identified by the airport's three letter airport code (i.e. Boston Logan is "BOS"), the fare reported by the carrier on a specific route, the operating carrier, the reporting carrier, the ticketing carrier, the type of trip (i.e. one-way, roundtrip, etc), the coupon type (i.e. first-class), distance printed on the itinerary, the market distance flown, and the number of passengers who paid that particular fare. The obtained raw DB1B data are at the itinerary level meaning that each observation provides the carrier fare for a particular passenger itinerary in a particular quarter. Additional steps were taken to aggregate and clean the raw data.

First, all observations were aggregated to the route-carrier-quarter level to resemble a panel dataset with each observation reflecting the average carrier fare, weighted by the number of passengers who paid that fare, on a route in a given quarter. Hence, the average market fare can be expressed below as:

$$\bar{P_{ijt}} = \frac{\Sigma_j p_{ijt} * n_{ijt}}{N_{ijt}}$$

where p_{ijt} is the reported fare on route *j* serviced by carrier *i* in quarter *t*, n_{ijt} is the number of people who paid that particular market fare, and N_{ijt} is the total number of passengers flying carrier *i* on route *j* in quarter *t*.

Second, because the raw DB1B lists three separate carrier variables for each observation (reporting carrier, operating carrier and ticketing carrier), a simplifying assumption was made to identify each observation with only the ticketing carrier.[6] Because an air-traveler chooses a particular airline based on the price of the airline that issues the ticket and not based on the airline that actually operates or reports the fare, the ticketing carrier was used to simplify the analysis, similar to Tan (2010). Market share values were calculated by dividing the total number of tickets issued by that carrier in a given route and quarter by the total number of tickets issued by all the carriers on that route.

6 The reporting carrier refers to the carrier that reported the fare to the Bureau of Transportation Statistics. The operating carrier refers to the carrier that actually flies the route. The ticketing carrier refers to the carrier that issues the passenger the ticket for the flight. While they are the same in most instances, the three variables may differ under certain codeshare agreements whereby a regional airline operates the route under a legacy carrier name.

Third, the following was used to clean the raw DB1B data and narrow the original data set. Any observation with fares below $20 or fares above $9998 was dropped from the dataset. Furthermore, the Standard Industry Fare Level (SIFL) dataset was obtained to rule out fares five times the SIFL for that particular route. Tickets with more than 2 coupons for a one-way trip or more than four coupons for a round-trip were dropped. Observations with an unidentified ticketing carrier or connecting flights were dropped. All observations involving a change of planes or to a non-US destination were dropped. Only one-way and roundtrip were included in the sample---open-jaw trips were excluded.[7] Moreover, consistent with previous literature, I focused only on routes flown by the following carriers: American, AirTran, Alaska, Continental, Delta, Frontier, JetBlue, Northwest, Southwest, Spirit, United, and US Airways. This effectively yields a sample of six legacy carriers and six low-cost carriers.

Fourth, because fares are affected by a variety of route or airport characteristics (i.e. distance, size of air traffic hub), various types of routes were identified in the empirical exercise to examine the effect of LCC entry across these route characteristics. Flights that stop in either Florida or Las Vegas were identified as leisure routes, as those routes tend to have relatively higher concentration of tourists who travel for leisure. Routes with a LCC market share of over 90% were marked as LCC routes and routes with a legacy market share of over 90% were marked as legacy routes. Routes connecting large endpoint hubs were also marked as these routes tend to be congested and more passenger-heavy.[8] Four airports -- New York LaGuardia (LGA), New York JFK (JFK), Chicago O'Hare (ORD) and DC Reagan National (DCA) -- had quotas on landing slots at some point during my sample period. Routes connecting any of these airports were marked as "slot-controlled" routes.

Lastly, the Southwest and JetBlue routes were marked. All routes in which Southwest or JetBlue had presence in both endpoints of a route from 1993 to 2009 were included in the regressions. I confirmed that the routes in my cleaned dataset were in fact Southwest (or JetBlue) threatened routes through press releases (via Lexis-Nexis) and through Southwest's and JetBlue's corporate websites. The variables t_0, t_e, and t_d will be used throughout the paper to denote the quarters of threat (entry into second endpoint), actual route entry and exit, respectively.[9] This effectively ensures that all routes included in the

7 Open-jaw trips are those from airport A to airport B but a return trip from airport B to airport C involving a change of planes.

8 The BTS classified an airport as a "large" airport if its market share was at least 1% of total enplaned passengers in 2009.

9 Similar to Daraban and Fournier (2008), I mark the exit quarter t_d as the first quarter that SW's market share drops below 3% preceded by at least four consecutive quarters with market share above 3% or greater. JetBlue did not exit any routes in my dataset.

regressions are aggregated and "aligned" with respect to Southwest or JetBlue threat and entry events to resemble an event study. I then create Southwest and JetBlue binary variables that turn on if the current quarter of an observation happens to be the quarter during which Southwest or JetBlue threatened, entered or exited that route.[10]

Table 1: Summary statistics for Southwest airports sample

Variables	Description	Obs	Mean	Std. Dev.	Min/Max.
fare_dir	average fares on direct flights	611,466	189.31	98.87	21/2195
ln_fare_dir	Log mean fares on direct flights	611,466	5.13	0.48	3.04/7.69
pax	No. of pass. with identical itinerary	611,466	290.14	841.18	1/19,235
distance	Distance on itinerary	611,466	1051.54	699.63	4/5134
PSpaxshare	Market share of carrier	611,466	0.32	0.35	0/1
Herfindahl	Herfindahl index on route	611,466	0.56	0.24	0.12/1
GINI	Gini coefficient of route	611,466	0.109	0.06	0/0.60
cost_d_mile	Cost per mile of first airport	507,301	0.31	0.21	0.01/3.55
cost_d_mile2	Cost per mile of second airport	410,370	0.32	0.21	0.01/3.43
big_airlines	Legacy airlines	611,466	0.73	0.44	0/1
lcc_airlines	Low-cost carriers	611,466	0.14	0.35	0/1

Summary statistics for Southwest data sample that regressions were performed on. Only the top 100 airports (ranked by passengers served domestically in year 2000) were considered in this sample. The cost_d_mile *variables denote cost controls of endpoint airports. The max value of 3.55 for* cost_d_mile *is a result of the minimum distance reported (4 miles).*

In order to capture the lagged effects of all quarters surrounding Southwest's and Jetblue's entry into both the endpoint and the route, dummy variables were also generated up to 4 quarters before the threat period to three quarters after the exit period. For instance, the time dummy variables $Southwest\_Threat_{t0-2}$ and $Southwest\_Threat_{t0-1}$ represent two quarters and one quarter prior to Southwest's endpoint entry and $Southwest\_Entry_{t0+1}$ and $Southwest\_Entry_{t0+2}$ designate one quarter and two quarters after Southwest's entry into the route, respectively.

Table 2: Summary statistics for JetBlue airports sample

Variables	Description	Obs	Mean	Std. Dev.	Min/Max.
fare_dir	Mean fares on direct flights	466,204	188.13	99.01	21/2704
ln_fare_dir	Log mean fares on direct flights	466,204	5.12	0.47	3.04/7.90
pax	No. of pass. with identical itinerary	466,204	331.77	921.75	1/19,235
distance	Distance on itinerary	466,204	1118.76	732.35	4/5134
PSpaxshare	Market share of carrier	466,204	0.29	0.34	0/1
Herfindahl	Herfindahl index on route	466,204	0.55	0.24	0.13/1
GINI	Gini coefficient of route	466,204	0.108	0.06	0/0.57
cost_d_mile	Cost per mile of first airport	397,038	0.27	0.19	0.01/3.55
cost_d_mile2	Cost per mile of second airport	319,470	0.32	0.21	0.01/3.43
big_airlines	Legacy airlines	466,204	0.63	0.48	0/1
lcc_airlines	Low-cost carriers	466,204	0.15	0.35	0/1

Summary statistics for JetBlue data sample that regressions were performed on. Only the top 100 airports (ranked by passengers served domestically in year 2000) were considered in this sample. The cost_d_mile *variables denote cost controls of endpoint airports. The max value of 3.55 for* cost_d_mile *is a result of the minimum distance reported (4 miles).*

10 As an illustrative example, Southwest entered PHL in quarter 2 of 2004 and BOS in quarter 2 of 2009. For all routes connecting PHL and BOS, the *Southwest_Threat* dummy equals one if that observation occurred in quarter 2 of 2004 and 0 otherwise. The *Southwest_Threat* dummy equals one if a PHL-BOS observation occured in quarter 2 of 2009 and is 0 otherwise.

As a technical note, because each Southwest or JetBlue dummy variable essentially turns on for one quarter and remains off otherwise, they are mutually exclusive. In order to isolate the impact of Southwest quarter over quarter, I would take the difference of the reported coefficients. For instance, if the reported coefficient of the dummy in quarter t_0 (initial threat quarter) were $ß_0$ and the reported coefficient in quarter t_e (actual entry quarter) were $ß_1$, the actual impact of Southwest entry alone vs threat is $ß_1$- $ß_0$. Here $ß_1$ would be the cumulative impact of entry *and* threat. From 1993 to 2009. Southwest threatened and entered a total of 1,141 routes and JetBlue entered a total of 588 routes. In all, the dataset contains 31,388 unique carrier-route-quarter Southwest observations with a mean log-fares of 5.13 and a standard deviation of 0.48. For the JetBlue regressions, there are 22,793 unique carrier-route-quarter observations with a mean log-fares of 5.12 and a standard deviation of 0.47. These results are summarized in Tables 1, 2 & 3.

Table 3: Summary statistics for on Southwest and JetBlue routes

Variables	Southwest	JetBlue
Routes threatened and entered	1,141	588
Routes entered immediately upon entry of second endpoint	334	76
Routes exited	44	0

Table 3 contains number of threatened, immediately entered and exited routes by Southwest and JetBlue.

IV. Methodology

As mentioned in the previous sections, the empirical models in this paper attempt to capture incumbent pricing responses as a result of LCC threat and entry under the framework of an event study. Similar to Goolsbee and Syverson (2008), I run a probit regression to first determine the probability that Southwest flies a route in a given quarter, conditional on the number of endpoints that Southwest has already operated out of in the previous quarter.

From Table 4, the probability that Southwest enters a route given that Southwest operated out of only one endpoint is a 0.26%. However, dual presence in endpoints raises this probability to 17.8%---an increase by a factor of 68. Furthermore, as suggested by Goolsbee and Syverson (2008), not only does Southwest presence in both endpoints raise the probability of entry into the route, the mere announcement, speculation of threat of entry into the endpoint should heighten incumbents' perception of Southwest's imminent entry.

Table 4: Probability of Southwest and JetBlue Entry Into a Threatened Route

Variables	
Southwest establishes presence in one endpoint of a route in previous quarter	0.0026***
(single presence)	(0.000)
Southwest establishes presence in both endpoint of a route in previous quarter	0.178***
(dual presence)	(0.013)
Number of observations in Southwest probit regression	314,849
JetBlue establishes presence in one endpoint of a route in previous quarter	0.0026***
(single presence)	(0.000)
JetBlue establishes presence in both endpoint of a route in previous quarter	0.069***
(dual presence)	(0.011)
Number of observations in JetBlue probit regression	206,308

*Probit regression results of Southwest and JetBlue entry into a route in a particular quarter, conditional on the number of route's endpoint airports with Southwest/JetBlue presence in the previous quarter. Standard errors are shown in parentheses and are clustered at the route-carrier level. *Denotes significance at 10% level. **Denotes significance at 5% level. ***Denotes significance at 1% level.*

Similarly, a probit regression was also performed to determine the probability of JetBlue's entry into a route conditioned on the number of endpoint airports with JetBlue presence in the preceding quarter. Single presence of JetBlue, like Southwest's single presence scenario, does not indicate anything meaningful. However, JetBlue's dual presence on the endpoints of a route gives only a 6.9% probability that JetBlue enters the route in the next quarter--roughly a third of Southwest's 17.8%. This suggests that incumbents may react less drastically to JetBlue's threat given that JetBlue's dual presence is less indicative of actual entry.

4.1 Mean-fare Regression Model

Prior studies such as Morrison (2001) utilized cross-section models in order to measure the effect of low-cost competition on incumbent airfares. However, because cross-section models do not necessarily account for unobserved characteristics inherent to a particular airline or route, I employ both fixed- and random-effects panel regressions to account for these unobserved effects. The logarithm of mean airfares were calculated to be the dependent variables in the specification and the coefficients on the Southwest or JetBlue dummies are the main covariates of interest. The baseline regression, borrowing from Goolsbee and Syverson's (2008) empirical methodologies, is given below:

$$ln(P_{ijt}) = \gamma_{ij} + \mu_{ij} + \theta_{ijt} Herfindahl_{ijt} + \sum_{\tau=-4}^{+3} \beta_\tau (Southwest\_Threat)_{j,t_0+\tau}$$
$$+ \sum_{\tau=0}^{+3} \beta_\tau (Southwest\_Entry)_{j,t_e+\tau} + \sum_{\tau=0}^{+3} \beta_\tau (Southwest\_Exit)_{j,t_e+\tau} + \alpha X_{ijt} + \epsilon_{ijt}, \quad (5.1)$$

where $ln(P_{ijt})$ is logged mean airfares for incumbent i flying route j in quarter t, γ_{ij} and μ_{it} measure carrier-route and carrier-quarter fixed effects respectively, θ_{ijt} measures the effect of route concentration (using the Herfindahl index), X_t accounts for controls such as seasonality and route characteristics (i.e. leisure route, LCC route, etc), and ε_{ijt} is random noise. I included four dummies for four quarters prior to t_0, one dummy for the first quarter after t_0, one dummy for two quarters after t_0 and a single dummy for three or more quarters after t_0. I also included three dummies after the exit quarter t_d. The coefficients on the time dummies *Southwest_Threat* measure the effect of Southwest's presence in both endpoints of a route on incumbent airfares while the coefficients on the *Southwest_Entry* time dummies measure the effect on incumbent airfares surrounding the period when Southwest actually flies the route relative to the excluded period (i.e. 5 quarters before the threat and 4 quarters after exit). Furthermore, the *Southwest_Exit* time dummies capture discernible shifts in prices after Southwest exits a route.

The fixed-effects (FE) regressions are weighted by the number of identical itineraries per reported fare level, and standard errors are clustered at the carrier-route level. The Herfindahl index, a measure of market concentration on a route, is included to control for competitive effects.

I report both FE and RE for the regression specification in (5.1) and perform a Hausman test to determine the suitability of each model.[11] While the FE is the more appropriate model to use (Hausman statistic ≈ 0) and the one that is predominantly used in the airline literature today, I include RE regression results for both Southwest and JetBlue main regressions as the results are similar to those derived from FE.

4.2 Gini Coefficient Regression

The second model specification attempts to measure the discrete changes in the price dispersion rather than the average price and is modeled on Gerardi and Shapiro's methodology (2009). In order to measure price dispersion, I first calculated the Gini coefficient on a route as a measure of the dispersion in fares paid using the following from Borenstein and Rose (1994):

$$GINI = 1 - 2 \times \sum_{m=1}^{N} (fare_m \times \frac{PAX_m}{totalrevenues}) \times [\frac{PAX_m}{totalPAX} + (1 - \sum_{k=1}^{m} \frac{PAX_k}{totalPAX})] \tag{5.2}$$

where N is the number of different fare levels reported by carrier i on a

11 Recall that the Hausman test checks the validity of the null hypothesis that the constant term is uncorrelated with the error term ε_{ijt}. If the Hausman statistic is large (i.e. $p<0.05$), then we can reject the null hypothesis and conclude that FE is a more efficient estimator than RE.

route, $fare_m$ is the reported fare for the m^{th} ticket, and PAX_m is the reported number of passengers traveling at that fare. A Gini coefficient of zero corresponds to perfect uniformity in prices: everyone pays the same price. On the flipside, a Gini coefficient of one means that everyone pays different prices. Then, in order to obtain an unbound statistic (recall that the Gini coefficient is strictly between zero and one), the log-odds Gini ratio, G_{ijt}^{lodd}, was calculated by $\ln \frac{GINI}{1-GINI}$.

Similar to the mean-fare regression specification, I include Southwest dummies surrounding the quarter of SW threat, SW entry and SW exit:

$$G_{ijt}^{lodd} = \gamma_{ij} + \mu_{jt} + \theta_{ijt} Herfindahl_{ijt} + \sum_{\tau=-4} \beta_\tau (Southwest\_Threat)_{j,t_0+\tau} + \sum_{\tau=0}^{+3} \beta_\tau (Southwest\_Entry)_{j,t_e+\tau} + \sum_{\tau=0}^{+3} \beta_\tau (Southwest\_Exit)_{j,t_e+\tau} + X_{ijt}\alpha + \epsilon_{ijt}, \quad (5.3)$$

where G_{ijt}^{lodd} is the log-odds Gini coefficient of carrier *i* on route *j* in quarter *t*.

We may expect G_{ijt}^{lodd} to decrease due to Southwest threat and entry. A plausible explanation here is that an increase in competition, or merely the threat of competition in the future, may induce a decrease in an incumbent's market power (Gerardi and Shapiro 2009). Thus, as the power to price discriminate effectively diminishes, we would expect to observe less variation in the price distribution.

On the flipside, price dispersion can increase as routes become more congested with LCCs, as empirically verified by Borenstein and Rose (1994). In this scenario, incumbents may charge higher prices for a price inelastic segment of the customer base, since those customers are likely to continue flying that carrier despite higher fares and lower fares for price elastic consumers. This effectively widens the tails of the price distribution and thus increases price dispersion.

V. Discussion of Results

5.1 Threat of Entry from Southwest

The regression results from specification 5.1 is shown in Column (1) of Table 5 in the Appendix and Figure 3 in the Appendix. Southwest's presence in both endpoints, but before flying the route, equates to a drop in prices of 10.6% ($1 - e^{-0.112}$) in quarter t_0, the threat quarter and is significant at the 5% level. The reported coefficients of the *Southwest_Threat* dummies in quarters t_0 - 4, t_0 - 3, t_0 - 2, and t_0 - 1 show that fares decrease slightly, but imprecision in my estimation strategy precludes these results from being statistically significant. On routes where Southwest threatens, but does not enter for at least three quarters after entry into second airport (i.e. t_0 + 3\$ to t_0 + 12\$), fares drop 15.5%, reflective of the entry deterrence behavior of incumbents. By the time Southwest enters these routes in quarter t_e, fares have dropped slightly over 14% ($1 - e^{-0.157}$) relative to the excluded period. Ultimately, fares drop 18% one to two quarters after Southwest flies the route and 23% at least three quarters after Southwest route entry. Both results are significant at the 1% level.

Column (2) of Table 5 reports the dummy coefficients of the LCC incumbents. Contrary to the aggressive price cutting seen from legacy incumbents, low-cost incumbent fares do not drastically decrease fares in quarter $t_{0.}$ On routes where Southwest threatened for at least three quarters before entry, fares decreased by only 7.4% and the coefficients are largely insignificant. In fact, we don't observe a sizable drop in prices until at least the first quarter *after* Southwest actually flies the route (t_e +1) where fares drop 9.9% and ultimately drop 12.2% 3 quarters after route entry. The disparity between the results in Columns (1) and (2) can be partially explained by a low-cost entrant's strategy, which is to match, or undercut, the prices of a low-cost carrier incumbent. Because legacy fares tend to be much higher than LCC fares on a given route, legacy carriers are more prone to decrease their prices in response to the entrant's lower fares. This downward price pressure is only transient in low-cost carrier incumbents case as low-cost carriers are less engaged in direct price competition with one another.

To determine whether the trend in prices is suggestive of actual predatory pricing or simply a direct product of Southwest competitive effects, we examine what happens to fares after Southwest exits a route. During the sample period from 1993 to 2009, Southwest exited three airports: Detroit Metro (DET) in 1993, San Francisco (SFO) in 2001 and Houston George Bush International (IAH) in 2005.[12] Columns (1) and (2) of Table 5 reports the coefficients on the Southwest exit dummy variables. Overall, the results show an increase in fares in the legacy incumbents cohort particularly between the quarter of exit t_d and one quarter after t_d. In fact, fares were 23% lower from t_e + 3 to t_e + 12 but only 11% lower during t_d, suggesting a 12% spike in fares during those two periods. While subsequent post-exit dummy coefficients are statistically insignificant, due to the small sample of routes that Southwest exited, we observe that prices were in general higher during Southwest's post-exit quarters than before exit.

The post-exit dummy coefficients for the low-cost incumbent in Column (2) did not increase to the same extent as the legacy fares. One possible explanation for the discrepancy in pricing behavior between legacy incumbents and

12 Southwest would later reenter SFO in 2007.

low-cost incumbents is that legacy carriers, due to their size and considerable market share, can afford to raise prices knowing that customers on those routes have few low-cost alternatives after Southwest exits. For instance, selecting for routes with endpoints at either SFO or IAH, the two airports Southwest exited from 2001 onward, legacy carriers had a mean total market share of 73.1% on these routes with the largest single LCC average market share at 5.1%. If legacy carriers were indeed hit by the Southwest Effect of low fares, it would seem rational for them to increase fares once Southwest leaves to recoup for losses as a result of Southwest competition.

5.2 Sensitivity Analysis

Table 6 reports the coefficients of the dummy variables across several specification criteria in order to see whether incumbent pricing behavior alters significantly across different route characteristics. Note that the sensitivity analysis restricted incumbents to legacy carriers only since the LCC cohort was much smaller and harder to break down by category. Furthermore, this portion of the analysis only looked at Southwest as a potential entrant since there was more data to base the analysis on. Column (1) of Table 6 reports the regression results for the baseline specification. Columns (2), (3) and (4) report the coefficients for leisure routes, LCC routes and legacy routes.[13] While incumbents on all three route types ultimately reduced fares, price cuts on the LCC routes and the legacy routes were most prominent. In Column (2), one can see that legacy carriers flying to a tourist destination were highly sensitive to potential competition from Southwest. Because neither Las Vegas nor the major airports in Florida (except Miami) are large legacy carrier hubs, flyers who travel to these destinations are most likely flying to their final destinations rather than using these airports as a connecting hub. Moreover, flyers traveling to these destinations are likely tourists with lower demand elasticity, meaning that they are most likely choosing the lowest fare they can find. Hence, legacy carriers are more likely to respond by cutting fares in order to stay competitive with Southwest and other LCCs, even under mere threat alone.

Columns (3), (4), and (5) report the coefficients on LCC routes, legacy routes and routes involving large endpoint hubs. Compared to the pooled results in Column (1), the results in Columns (3) and (5) suggest that fares decreased more drastically on routes with heavy legacy carrier concentration and those involving dominated hubs. The results in Column (4) are consistent with

13 Recall that leisure routes were routes connecting airports in Florida or Las Vegas, LCC routes were identified as routes where the mean market share of LCCs was at least 90%, and legacy routes were those with mean market share of legacy carriers at least 90%

Morrison (1997) who concluded for instance that, despite Delta Air Lines's dominance in Salt Lake City (SLC), fares in SLC were 16% lower as a result of Southwest presence in 1996 and 39% lower when compared to non-Southwest airports. Because legacy concentrated routes and dense traffic hubs have higher fares to begin with -22% higher than other airports according to Morrison (1997) - it appears logical that fares would decrease more from potential entry vis-a-vis routes with that are less heavily traveled.

Column (6) of the sensitivity reports the coefficients for those airports with slot controls (LGA, JFK, ORD and DCA). Upon inspection, one can see that Southwest has only marginal impact during the quarters surrounding the threat period and the results are largely inconclusive except three quarters after entry with fares dropping 13.3%. In theory, slot-controlled airports should in fact have lower fares than airports that are not slot-controlled since the slot system is meant to decrease congestion and encourage LCC entry and regulating the number of takeoffs certain airlines are permitted to have. There are two main reasons why fares on these routes are immune to the Southwest Effect. First, the slot-system is inefficient. Morrison (1997), in a testimony before the US House of Representatives in 1997, concluded that the fare premia on routes involving ORD, LGA and DCA in 1996 were 11 to 15% higher than flights involving other airports. Second, all of these four airports are hubs of major legacy carriers: American Airlines' hubs include ORD and JFK, US Airways is DCA's largest carrier, and Delta Air Lines has major operations out of LGA. Hence, many passengers flying to other destinations must fly through one of these hub airports, suggesting that these passengers have higher demand inelasticity, which translates into higher market power for incumbent airlines. It would appear logical that incumbents on these routes can afford to keep prices high until Southwest actually enters.

5.3 Evidence of Entry Deterrence

Table 7 displays the effect on airfares for routes that Southwest entered immediately upon entry, routes that Southwest still threatens but has not entered for over 12 quarters after the threat quarter and routes connecting airports within 50 miles of a Southwest airport in Columns (2), (3) and (4) respectively. The behavior of incumbents on pre-announced routes is significantly different - none of the coefficients on the quarters before actual entry is significant nor substantially negative, suggesting that incumbents do not preemptively slash fares when Southwest entry is certain. Only in the actual entry quarter do fares drop. In Column (3), we see that incumbents do not significantly slash fares until at least two quarters after entry and that fares decreased by 16.2%

between three quarters and 12 quarters after the threat period, suggesting that even on routes on which Southwest does not fly, the mere possibility of Southwest flying in the future drives fares lower. Lastly, Column (4) examines routes in nearby airports and suggest that there is no discernible pattern in airfares on routes connecting hubs within close proximity to a Southwest airport. The results in Column (4) run counter to the findings of Dresner, Lin and Windle (1996) who concluded spillover effects onto other routes existed, although the authors focused only on actual entry.

5.4 Threat of Entry by JetBlue

The mean fare regressions for JetBlue are reported in Table 8. In contrast to the Southwest results, it appears that *neither* legacy nor low-cost carriers respond to JetBlue threat. The reported coefficients in the threat periods are neither sizable nor significant, suggesting that JetBlue has minimal effects on incumbent fares. The greatest drop in fares occurs around one to two quarters after JetBlue entry, with fares dropping 7.6% and 8.8% in quarters $t_e + 1$ and $t_e + 2$ respectively for legacy incumbents and dropping 11% during the same periods for LCC incumbents. Upon further inspection, it does not appear that fares drop further afterwards with the reported coefficients on $t_e + 3$ to $t_e +12$ appearing small and insignificant for both incumbent cohorts. This suggests that incumbents react less aggressively to JetBlue's threat and entry than to Southwest's. These results are graphically depicted in Figure 4 in the Appendix.

Several reasons can be hypothesized as to why fares are lower on the Southwest routes. First, because of its larger network as well as a longer-standing reputation as an low-cost airline, Southwest may elicit a stronger response from incumbents. Tables 3 and 4 show that Southwest not only threatened and entered into twice as many routes as did JetBlue during our sample period but entry is almost three times as likely to occur if Southwest establishes dual presence in the endpoints than if JetBlue establishes dual presence (17.8% vs. 6.9%). In 2003, Southwest served roughly seven times more passengers (65.7 million vs 9 million) and roughly ten times (2,800 daily flights vs 252 flights) more daily flights than JetBlue did.[14]

Yet, a second hypothesis is that Southwest engages in more direct price competition with an incumbent by more frequently undercutting existing fares rather than by simply matching the fares. Table 10 reports the frequency and percentage that either Southwest or JetBlue enters a route with an average price higher than, equal to, or below an incumbent's average price weighted

14 Chris Woodyard,``Pitting Southwest vs. JetBlue," \emph{USA TODAY}.

by the number of identical itineraries.[15] From the data, it is rare for either Southwest or JetBlue to set a price higher than an incumbent's average fare, which helps explain why incumbent prices would fall after entry. Moreover, upon closer inspection, one can see that Southwest tends to undercut its legacy incumbents more so than JetBlue. For instance, on routes with American Airlines as the incumbent, Southwest undercut AA 57.3% upon entry, while JetBlue undercut AA 31.5% upon entry. If Southwest sets initial fares lower than the incumbent's existing fares more often than does JetBlue, then incumbents will be more likely to react in the form of larger cuts.

Third, differences between Southwest's and JetBlue's operating models may shed additional insight into Southwest's slight advantage in the low-fare battle. Southwest's competitive advantage germinates from its dense operations out of smaller and less-conveniently located airports, helping the airline save money on landing fees. With lower operating costs, Southwest has the financial flexibility to lower costs without compromising profitability. On the other hand, JetBlue has attempted to develop a business model that resembles both the legacy carrier and LCC models.[16] In particular, JetBlue has aimed to "modernize" the customer traveling experience by affording free DirectTV, XM Satellite Radio, leather seats, in-flight entertainment and other amenities - an aspect of consumer travel that Southwest had not paid as much attention to. Because legacy incumbents may realize that they are not simply competing with JetBlue on a pure price basis, drops in existing fares may not be as sensitive to JetBlue competition as to Southwest competition.

5.5 Price Dispersion

The regression results of specification (5.3) is reported in Table 9 in the Appendix and shown in Figure 5 of the Appendix. Column (1) shows that the log-odds Gini ratio decreased in general on routes threatened by Southwest relative to the excluded period. The greatest drop in the Gini coefficient occurs in quarter t_0 with the Gini dropping 9.3%. This suggests that fares on Southwest threatened routes became more uniform, especially during the quarters surrounding the threat and entry events. The regression results in Column (1) are consistent with Gerardi and Shapiro's (2009) findings that price dispersion decreases as competition increases on a route. The intuition here is that Southwest competition diminishes incumbents' market power and thus their ability

15 Following Tan (2010), I constructed a $20 window such that price matching occurs if the entrant's average fares falls within the $20 window. In order for the entrant to have set a price higher (lower) than the incumbent's price, the entrant's average fare must be at least $20 greater (lower) than the incumbent's average fare. Each observation is weighted by the number of identical itineraries.

16 Stephen Ellis, "The Decline of Southwest and the Rise of JetBlue," *The Motley Fool*.

to price discriminate. As a result, prices become less dispersed on routes that are more competitive. Column (2) reports the coefficients for the low-cost incumbents. Similar to the mean-fare regressions, the price dispersion results are inconclusive with the coefficients negative during quarters before Southwest entry, and positive after entry. Perhaps because of the smaller distribution in fares set by low-cost carriers to begin with, there is little subsequent effect and movement in price dispersion that can be picked up with the methodologies presented.

Columns (3) and (4) contain the analogous results for routes threatened by JetBlue. Interestingly, the results in Column (3) suggests that price dispersion *rose* on JetBlue-threatened routes. The general increase in the Gini coefficient quarter-to-quarter is consistent with Borenstein and Rose's (1994) findings that price dispersion increases as routes become more competitive. Since those who frequently fly accumulate credit through frequent flyer and other reward programs and would subsequently lose out on those rewards by switching to another airline, brand-loyal consumers are willing to pay a higher fare rather than incur a switching cost. Hence, incumbents may keep higher-end fares the same knowing brand loyal consumers will likely not switch airlines while decreasing discount fares to lock in the price-sensitive consumers. Under the aforementioned scenario where higher-end fares are approximately the same level while the discount fares are cut, the price distribution has become flatter which would likely result in the increase in price dispersion we see in Column (3).

VI. Conclusion

The impact and threat of low-cost carriers on incumbent fares have been well documented in the field of applied economics and industrial organization. The purpose of this study is to add additional insight into why incumbent airlines reduce fares as a result of LCC entry and whether this behavior changes across various incumbent and route types. In addition, this paper also briefly examined discrete changes in the Gini coefficient of both Southwest and JetBlue routes as a result of the threat and entry events and offered suggestive evidence in line with previous research.

Using airline data on US domestic flights from 1993 to 2009, I find evidence that legacy incumbents engaged in preemptive and aggressive price-cutting to Southwest threat and entry but in much milder fashion to JetBlue threat and entry. Furthermore, low-cost incumbents did not react significantly to either Southwest or JetBlue threat, although fares ultimately declined upon actual entry. Using sensitivity analysis across route types to extend upon the main regression, I concluded that fares on leisure routes, legacy-dominated routes and routes connecting endpoints with high traffic volume all witnessed severe drops in fares from Southwest threat and entry. Routes involving airports that were slot-controlled surprisingly were not all that much affected from Southwest threat. Furthermore, by examining fares on routes that Southwest eventually exited, this paper provided some suggestive evidence of predatory pricing as fares in the post-exit periods gradually rose. Lastly, I also examined changes in price dispersion and concluded that legacy carrier prices became more uniform as a result of Southwest threat and entry and less uniform as a result of JetBlue entry.

The application of empirical models to the airline industry and the findings presented in this paper have powerful policy implications. If the impact of Southwest is as beneficial to the average traveler as the research suggests, policies should be designed to promote low-cost carrier presence in markets with high congestion and fares. There is significant value in understanding the dynamic nature of strategic entry deterrence as it applies across industries - future empirical work on this topic should garner considerable attention from both academia and industry.

References

Bennett, Randall and James Craun, "The Airline Deregulation Revolution Continues: The Southwest Effect," *Washington, DC: Office of Aviation Analysis, US Department of Transportation*, 1993.

Berry, Steven and Panle Jia, "Tracing the Woes, an Empirical Analysis of the Airline Industry," *American Economic Journal: Microeconomics*, v. 2(3), pp. 1-43, 2008.

Borenstein, Severin, "The Evolution of U.S. Airline Competition," *The Journal of Economic Perspectives* 45-73, 1992.

Borenstein, Severin, "Hubs and High Fares: Dominance and Market Power in the U.S. Airline Industry," *The RAND Journal of Economics*, p. 344-365, 1989.

Borenstein, Severin and Nancy Rose, "Competition and Price Dispersion in the U.S. Airline Industry," *The Journal of Political Economy*, p. 653-683, 1994.

Cairns, Robert D. and John W. Galbraith, "Artificial Compatibility, Barriers to Entry, and Frequent-Flyer Programs," *The Canadian Journal of Economics*, Vol. 23, No. 4, 1990.

Dafny, Leemore, "Games Hospitals Play: Entry Deterrence in Hospital Procedure Markets," *Journal of Economics and Management Strategy* Vol. 14, p. 513-542, 2005.

Daraban, Bogdan and Gary Fournier, "Incumbent Responses to Low-cost Airline Entry and Exit: A Spatial Autoregressive Panel Data Analysis," *Research in Transportation Economics* Vol. 24, p. 15-24, 2008.

Dixit, Avinash, "A Model of Duopoly Suggesting a Theory of Entry Barriers," *The Bell Journal of Economics*, Vol. 10, No. 1, p. 20-32, 1979.

Dixit, Avinash, ``The Role of Investment in Entry-Deterrence," *The Economic Journal*, Vol. 90, No. 357, p. 95-106, 1980.

Dixit, Avinash, ``The Role of Investment in Entry-Deterrence," *The Economic Journal*, Vol. 90, No. 357, p. 95-106, 1980.

Dresner Martin, Chris Lin and Robert Windle, "The Impact of Low-Cost Carriers on Airport and Route Competition," *Journal of Transport Economics and Policy*, Vol. 30(3), p. 309-328, 1996.

Ellis, Stephen, "The Decline of Southwest and the Rise of JetBlue," *The Motley Fool* 2006.

Ellison, Glenn and Sara Ellison, "Strategic Entry Deterrence and the Behavior of Pharmaceutical Incumbents Prior to Patent Expiration," MIT Working Paper, 2007.

Fudenberg, Drew and Jean Tirole, "A Signal Jamming Theory of Predation,"

Rand Journal of Economics, Vol. 17, p. 366-376, 1986.

Gerardi, Kristopher and Adam Shapiro, "Does Competition Reduce Price Dispersion? New Evidence from the Airline Industry," *The Journal of Political Economy*, p. 653-683, 1994.

Goolsbee, Austan and Chad Syverson, "How Do Incumbents Respond to the Threat of Entry? Evidence from the Major Airlines," *The Quarterly Journal of Economics*, p. 1-37, 2008.

Klemperer, Paul, "Markets with Consumer Switching Costs," *The Quarterly Journal of Economics*, p. 375-394, 1987.

Klemperer, Paul, "Competition when Consumers have Switching Costs: An Overview with Applications to Industrial Organization, Macroeconomics, and International Trade," *The Review of Economic Studies*, Vol. 62, No. 4 p. 515-539, 1995.

Klemperer, Paul, "Collusion via Switching Costs: How ``Frequent-Flyer" Programs, Trading Stamps, and Technology Choices Aid Collusion," Working Paper 786, Graduate School of Business, Stanford University, May 1986.

McGee, John, "Predatory Price Cutting: The Standard Oil (N.J.) Case," *Journal of Law and Economics* Vol. 1, p. 137-169, 1958.

Milgrom, Paul and John Roberts, "Limit Pricing and Entry Under Incomplete Information: An Equilibrium Analysis," *Econometrica* Vol. 50, p. 443-460, 1982.

Morrison, Steven A., "Actual, Adjacent, and Potential Competition: Estimating the Full Effect of Southwest Airlines," *Journal of Transport Economics and Policy*, p. 239-256, 2001.

Rosenthal, Robert, "A Model in which an Increase in the Number of Sellers Leads to a Higher Price," *Econometrica*, p. 1575-1579, 1980.

Tan, Kerry, "Incumbent Response to Entry by Low-Cost Carriers in the US Airline Industry," *Ohio State University Working Paper*, p. 1-33, 2010.

Vowles, Timothy, "The Effect of Low Fare Air Carriers on Airfares in the US," *Journal of Transport Geography*, p. 121-128, 2000.

Vowles, Timothy, "The Southwest Effect In Multi-Airport Regions," *Journal of Air Transport Management*, p. 251-258, 2001.

Winston, Clifford and Steven A. Morrison, "The Fare Skies: Air Transportation and Middle America," *The Brookings Institution*, Fall 1997.

Woodyard, Christopher, "Pitting Southwest vs. JetBlue," *USA TODAY*, July 5, 2004.

Appendix

1. Tables

Table 5: Incumbent Response on Southwest Threatened Routes

Dependent variable: $\ln(P_{ijt})$

	Fixed Effects Model		Random Effects Model	
Incumbent type:	Legacy	Low-cost	Legacy	Low-cost
Variables	(1)	(2)	(3)	(4)
$(t_0 - 4)$	-0.010	0.008	-0.066***	0.067
	(0.036)	(0.110)	(0.018)	(0.106)
$(t_0 - 3)$	-0.020	0.050	-0.050***	-0.012
	(0.033)	(0.079)	(0.018)	(0.097)
$(t_0 - 2)$	-0.033	-0.037	-0.080***	0.006
	(0.039)	(0.072)	(0.017)	(0.120)
$(t_0 - 1)$	-0.034	-0.053	-0.072***	-0.045
	(0.043)	(0.085)	(0.018)	(0.111)
Entrant Threat:				
(t_0)	-0.112**	-0.043	-0.144***	-0.079
	(0.044)	(0.064)	(0.017)	(0.114)
$(t_0 + 1)$	-0.081**	-0.053	-0.148***	-0.012
	(0.043)	(0.071)	(0.018)	(0.127)
$(t_0 + 2)$	-0.091*	-0.062	-0.166***	-0.002
	(0.051)	(0.070)	(0.0188)	(0.126)
$(t_0 + 3 \text{ to } t_0 + 12)$	-0.169***	-0.077	-0.186***	-0.015
	(0.050)	(0.076)	(0.016)	(0.130)
Entrant Actual Entry:				
(t_e)	-0.157**	-0.057	-0.207***	-0.107
	(0.051)	(0.066)	(0.019)	(0.126)
$(t_e + 1)$	-0.202***	-0.104*	-0.234***	-0.112
	(0.049)	(0.059)	(0.019)	(0.126)
$(t_e + 2)$	-0.191***	-0.111*	-0.243***	-0.073
	(0.049)	(0.016)	(0.020)	(0.130)
$(t_e + 3 \text{ to } t_e + 12)$	-0.263***	-0.130**	-0.287***	-0.071
	(0.053)	(0.066)	(0.016)	(0.126)
Entrant Exit				
(t_d)	-0.120**	-0.088**	-0.079	-0.098
	(0.062)	(0.043)	(0.076)	(0.151)
$(t_d + 1)$	-0.081*	-0.112**	-0.022	-0.055
	(0.052)	(0.043)	(0.067)	(0.155)
$(t_d + 2)$	-0.033	-0.117**	0.017	0.044
	(0.064)	(0.045)	(0.052)	(0.160)
$(t_d + 3)$	0.066	-0.136*	0.099	0.102
	(0.066)	(0.078)	(0.062)	(0.161)
Number of observations	31,388	2,533	31,388	2,521
R^2	0.64	0.86	0.72	0.88

*All regressions include route-carrier and carrier-quarter fixed effects and are weighted by passengers. Standard errors are shown in parentheses and are clustered at the route-carrier level. *Denotes significance at 10% level. **Denotes significance at 5% level. ***Denotes significance at 1% level. Although the regressions were performed within the 25-quarter window, I report only 4 quarters prior to* t_0.

Table 6: FE Sensitivity Analysis Across Southwest Route Types

Dependent variable: $\ln(P_{ijt})$

Variables	Pooling all routes (1)	Leisure routes (2)	LCC routes (3)	Legacy routes (4)	Large endpoint hubs (5)	Slot-controlled (6)
SW_Threat (t_0-4)	-0.010	-0.049	0.030	-0.048	-0.131**	-0.023
	(0.036)	(0.062)	(0.043)	(0.043)	(0.053)	(0.055)
SW_Threat (t_0-3)	-0.020	-0.088	-0.046	-0.011	-0.086	-0.033
	(0.033)	(0.068)	(0.044)	(0.044)	(0.063)	(0.056)
SW_Threat (t_0-2)	-0.033	-0.134**	-0.066	-0.078*	-0.131**	0.021
	(0.039)	(0.065)	(0.051)	(0.047)	(0.058)	(0.061)
SW_Threat (t_0-1)	-0.034	-0.081	-0.015	-0.037	-0.131**	0.010
	(0.043)	(0.065)	(0.051)	(0.047)	(0.061)	(0.058)
Southwest Presence:						
SW_Threat (t_0)	-0.112**	-0.121***	-0.099*	-0.104**	-0.199***	-0.051
	(0.044)	(0.070)	(0.056)	(0.048)	(0.064)	(0.052)
SW_Threat (t_0+1)	-0.081**	-0.182**	-0.118**	-0.151***	-0.175***	-0.077
	(0.043)	(0.090)	(0.054)	(0.052)	(0.060)	(0.053)
SW_Threat (t_0+2)	-0.091*	-0.201***	-0.117**	-0.175***	-0.222***	-0.021
	(0.051)	(0.087)	(0.057)	(0.058)	(0.055)	(0.055)
SW_Threat $(t_0+3$ to $t_0+12)$	-0.169***	-0.223***	-0.112*	-0.231***	-0.271***	-0.093*
	(0.050)	(0.077)	(0.063)	(0.059)	(0.070)	(0.056)
Southwest Actual Entry:						
SW_Entry (t_e)	-0.157**	-0.131*	-0.113	-0.247***	-0.191***	-0.101*
	(0.051)	(0.075)	(0.057)	(0.064)	(0.070)	(0.055)
SW_Entry (t_e+1)	-0.202***	-0.234***	-0.121**	-0.264***	-0.208***	-0.074
	(0.049)	(0.073)	(0.058)	(0.065)	(0.061)	(0.053)
SW_Entry (t_e+2)						
SW_Entry $(t_e+3$ to $t_e+12)$	-0.263***	-0.272***	-0.179**	-0.325***	-0.251***	-0.144**
	(0.053)	(0.078)	(0.064)	(0.072)	(0.083)	(0.057)
Southwest Exit						
t_d	-0.120**	–	-0.102	-0.093	-0.210**	–
	(0.062)			(0.082)	(0.083)	
t_d+1	-0.041	–	-0.055	-0.001	-0.038	–
	(0.082)		(0.078)	(0.068)	(0.082)	
t_d+2	-0.033	–	0.022	-0.037	–	
	(0.064)		(0.066)	(0.050)	(0.064)	
t_d+3	0.066	–	0.043	0.022	0.057	–
	(0.066)		(0.072)	(0.057)	(0.098)	
Number of observations	31,388	1,009	5,018	16,362	7,480	1,528
R^2	0.64	0.69	0.66	0.70	0.75	0.46

*All regressions include route-carrier and carrier-quarter fixed effects and are weighted by passengers. Standard errors are shown in parentheses and are clustered at the route-carrier level. *Denotes significance at 10% level. **Denotes significance at 5% level. ***Denotes significance at 1% level. Although the regressions were performed within the 25-quarter window, I report only 4 quarters prior to t_0.*

Table 7: FE Sensitivity Analysis Across Southwest Routes

Dependent variable: $\ln(P_{ijt})$

Variables	Threat and Eventual Entry (1)	Preannounced Entry (2)	Threat but no entry (3)	Adjacent Competition (4)
SW_Threat $(t_0 - 4)$	-0.010	-0.023	0.007	-0.015
	(0.036)	(0.042)	(0.058)	(0.049)
SW_Threat $(t_0 - 3)$	-0.020	-0.053	0.033	0.089**
	(0.033)	(0.045)	(0.061)	(0.044)
SW_Threat $(t_0 - 2)$	-0.033	0.001	-0.072	0.023
	(0.039)	(0.053)	(0.062)	(0.045)
SW_Threat $(t_0 - 1)$	-0.034	0.038	-0.044	0.015
	(0.043)	(0.052)	(0.067)	(0.050)
Southwest Presence:				
SW_Threat (t_0)	-0.112**		-0.070	-0.017
	(0.044)		(0.056)	(0.053)
SW_Threat $(t_0 + 1)$	-0.081**		-0.068	-0.063
	(0.043)		(0.054)	(0.065)
SW_Threat $(t_0 + 2)$	-0.091*		-0.133*	0.001
	(0.051)		(0.076)	(0.062)
SW_Threat $(t_0 + 3$ to $t_0 + 12)$	-0.169***		-0.177**	0.013
	(0.050)		(0.081)	(0.072)
Southwest Actual Entry:				
SW_Entry (t_e)	-0.157**	-0.051		-0.042
	(0.051)	(0.069)		(0.064)
SW_Entry $(t_e + 1$ to $t_e + 2)$	-0.202***	-0.176***		-0.005
	(0.049)	(0.057)		(0.074)
SW_Entry $(t_e + 3$ to $t_e + 12)$	-0.263***	-0.265***		-0.007
	(0.053)	(0.060)		(0.082)
Southwest Exit				
t_d	-0.120**	-0.189*		-0.093
	(0.062)	(0.105)		(0.082)
$t_d + 1$	-0.041	-0.094		-0.001
	(0.082)	(0.163)		(0.068)
$t_d + 2$	-0.033	0.016		-0.037
	(0.064)	(0.101)		(0.050)
$t_d + 3$	0.066	0.167		0.022
	(0.066)	(0.160)		(0.057)
Number of observations	31,388	12,126	4,919	12,098
R^2	0.64	0.68	0.62	0.60

*All regressions include route-carrier and carrier-quarter fixed effects and are weighted by passengers. Standard errors are shown in parentheses and are clustered at the route-carrier level. *Denotes significance at 10% level. **Denotes significance at 5% level. ***Denotes significance at 1% level. Although the regressions were performed within the 25-quarter window, I report only 4 quarters prior to t_0.*

Table 8: Incumbent Response on JetBlue Threatened Routes

Dependent variable: $\ln(P_{ijt})$

	Fixed Effects Model		Random Effects Model	
Incumbent type:	Legacy	Low-cost	Legacy	Low-cost
Variables	(1)	(2)	(3)	(4)
$(t_0 - 4)$	0.005	-0.034	-0.005	-0.059**
	(0.023)	(0.027)	(0.017)	(0.019)
$(t_0 - 3)$	-0.012	-0.026	-0.016	-0.049**
	(0.024)	(0.028)	(0.017)	(0.020)
$(t_0 - 2)$	-0.023	-0.062*	-0.027	-0.079***
	(0.025)	(0.029)	(0.018)	(0.021)
$(t_0 - 1)$	-0.018	-0.028	-0.033*	-0.054**
	(0.026)	(0.030)	(0.018)	(0.021)
JetBlue Presence:				
(t_0)	-0.033	-0.029	-0.043**	-0.045**
	(0.026)	(0.031)	(0.019)	(0.022)
$(t_0 + 1)$	-0.026	-0.044	-0.034*	-0.070***
	(0.029)	(0.032)	(0.019)	(0.020)
$(t_0 + 2)$	-0.043	-0.011	-0.067***	-0.031
	(0.031)	(0.035)	(0.019)	(0.023)
$(t_0 + 3$ to $t_0 + 12)$	-0.019	-0.015	-0.032*	-0.047*
	(0.033)	(0.038)	(0.018)	(0.025)
JetBlue Actual Entry:				
(t_e)	-0.050	-0.088*	-0.074**	-0.153***
	(0.041)	(0.051)	(0.029)	(0.034)
$(t_e + 1)$	-0.080**	-0.117**	-0.098***	-0.149***
	(0.039)	(0.051)	(0.030)	(0.037)
$(t_e + 2)$	-0.092**	-0.116**	-0.124***	-0.139***
	(0.039)	(0.051)	(0.032)	(0.036)
$(t_e + 3$ to $t_e + 12)$	-0.032	-0.070	-0.070	-0.101***
	(0.039)	(0.048)	(0.023)	(0.030)
Number of observations	22,793	7,990	22,793	7,990
R^2	0.77	0.90	0.71	0.84

*All regressions include route-carrier and carrier-quarter fixed effects and are weighted by passengers. Standard errors are shown in parentheses and are clustered at the route-carrier level. *Denotes significance at 10% level. **Denotes significance at 5% level. ***Denotes significance at 1% level. Although the regressions were performed within the 25-quarter window, I report only 4 quarters prior to t_0.*

Table 9: Price Dispersion Changes on Southwest and JetBlue routes

Dependent variable: $Gini^{todd}_{ijt}$

	Southwest Airlines		JetBlue Airways	
Incumbent type:	Legacy	Low-cost	Legacy	Low-cost
Variables	(1)	(2)	(3)	(4)
$(t_0 - 4)$	-0.010	-0.085	0.089**	-0.054
	(0.022)	(0.102)	(0.041)	(0.036)
$(t_0 - 3)$	-0.031	-0.058	0.093**	-0.078*
	(0.023)	(0.101)	(0.041)	(0.040)
$(t_0 - 2)$	-0.050**	-0.090	0.060	-0.079**
	(0.023)	(0.100)	(0.046)	(0.039)
$(t_0 - 1)$	-0.089***	-0.078	0.060	-0.052
	(0.023)	(0.098)	(0.046)	(0.048)
Entrant Threat:				
(t_0)	-0.099***	-0.073	0.078	-0.048
	(0.024)	(0.102)	(0.049)	(0.044)
$(t_0 + 1)$	-0.022	-0.076	0.069	-0.070
	(0.026)	(0.106)	(0.053)	(0.053)
$(t_0 + 2)$	-0.064**	-0.034	0.096*	-0.063
	(0.028)	(0.122)	(0.056)	(0.055)
$(t_0 + 3$ to $t_0 + 12)$	-0.090***	-0.008	0.107*	-0.086
	(0.028)	(0.106)	(0.062)	(0.058)
Entrant Actual Entry:				
(t_e)	-0.076***	0.084	0.112*	0.018
	(0.027)	(0.100)	(0.064)	(0.145)
$(t_e + 1)$	-0.051*	0.061*	0.129*	-0.183*
	(0.027)	(0.103)	(0.067)	(0.100)
$(t_e + 2)$	-0.086***	0.100*	0.141**	-0.239*
	(0.029)	(0.104)	(0.066)	(0.129)
$(t_e + 3$ to $t_e + 12)$	-0.075***	0.018**	0.132**	-0.148*
	(0.028)	(0.099)	(0.068)	(0.087)
Entrant Exit				
(t_d)	0.028	0.179**	–	–
	(0.043)	(0.361)		
$(t_d + 1)$	-0.097*	-0.262**	–	–
	(0.047)	(0.361)		
$(t_d + 2)$	0.044	0.242**	–	–
	(0.043)	(0.261)		
$(t_d + 3)$	0.067	0.132*	–	–
	(0.045)	(0.257)		
Number of observations	31,388	1,834	22,068	7,150
R^2	0.56	0.52	0.87	0.92

*All regressions include route-carrier and carrier-quarter fixed effects and are weighted by passengers. Standard errors are shown in parentheses and are clustered at the route-carrier level. *Denotes significance at 10% level. **Denotes significance at 5% level. ***Denotes significance at 1% level. Although the regressions were performed within the 25-quarter window, I report only 4 quarters prior to t_0.*

Table 10: Frequency of Price Matching by Entrant (window = incumbent price ±20)

			Entrant's price > Incumbent's price			
			Incumbent			
	American	Continental	Delta	Northwest	United	US Airways
Southwest	385 (8.5%)	236 (5.3%)	446 (10.0%)	248 (5.5%)	402 (8.8%)	355 (8.2%)
JetBlue	51 (6.1%)	63 (7.2%)	75 (8.9%)	79 (9.5%)	63 (8.2%)	87 (10.5%)
			Entrant's price = Incumbent's price			
			Incumbent			
	American	Continental	Delta	Northwest	United	US Airways
Southwest	1,545 (34.2%)	1,512 (33.7%)	1,477 (33.2%)	1,501 (33.5%)	1,577 (34.6%)	1,300 (29.9%)
JetBlue	522 (62.4%)	550 (63.0%)	498 (59.4%)	554 (66.5%)	510 (66.1%)	486 (58.8%)
			Entrant's price < Incumbent's price			
			Incumbent			
	American	Continental	Delta	Northwest	United	US Airways
Southwest	2,591 (57.3%)	2,740 (61.1%)	2,530 (56.8%)	2,728 (60.9%)	2,574 (56.5%)	2,689 (61.9%)
JetBlue	264 (31.5%)	260 (29.8%)	265 (31.6%)	200 (24.0%)	199 (25.7%)	253 (30.6%)
			Entrant's price > Incumbent's price			
			Incumbent			
	AirTran	Alaska	Frontier	JetBlue	Southwest	Spirit
Southwest	155 (18.6%)	92 (18.9%)	56 (12.6%)	78 (12.1%)	–	84 (14.9%)
JetBlue	133 (22.6%)	107 (15.6%)	38 (7.8%)	–	42 (12.4%)	22 (13.8%)
			Entrant's price = Incumbent's price			
			Incumbent			
	AirTran	Alaska	Frontier	JetBlue	Southwest	Spirit
Southwest	444 (53.2%)	293 (60.0%)	278 (62.4%)	302 (46.8%)	–	213 (37.9%)
JetBlue	156 (26.4%)	223 (32.5%)	193 (39.5%)	–	47 (13.9%)	14 (8.8%)
			Entrant's price < Incumbent's price			
			Incumbent			
	AirTran	Alaska	Frontier	JetBlue	Southwest	Spirit
Southwest	235 (28.2%)	103 (21.1%)	111 (24.9%)	265 (41.1%)	–	265 (47.2%)
JetBlue	300 (51.0%)	359 (51.9%)	257 (52.7%)	–	250 (73.7%)	123 (77.4%)

2. Charts

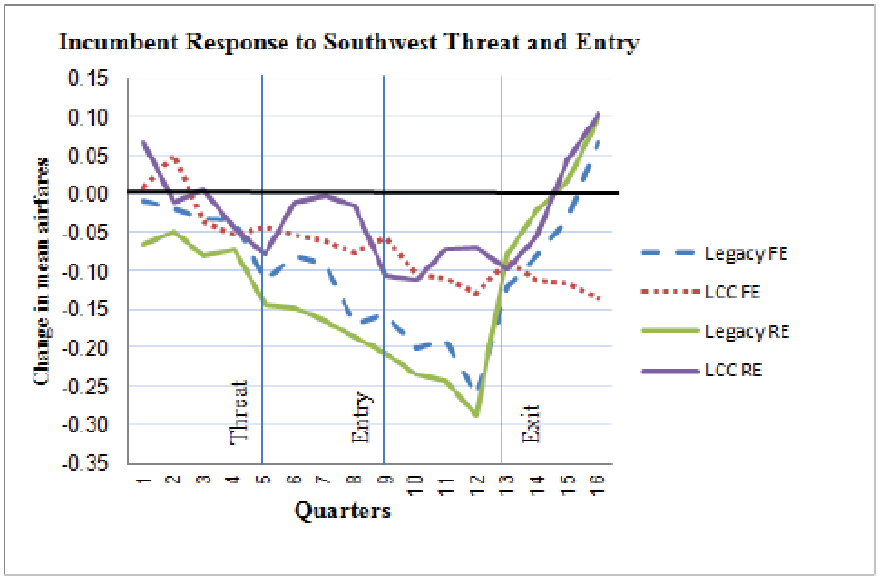

Figure 3: Incumbent price response from Southwest threat and entry.

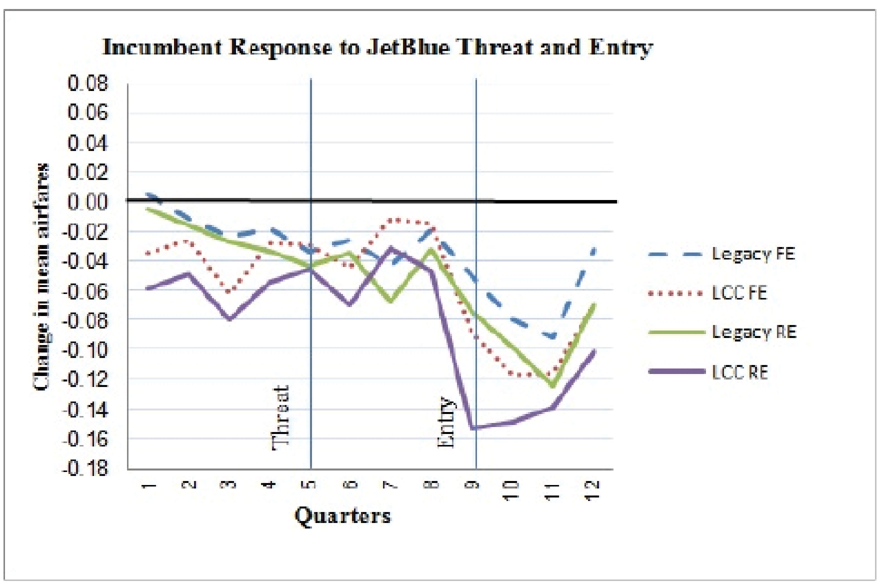

Figure 4: Incumbent price response from JetBlue threat and entry

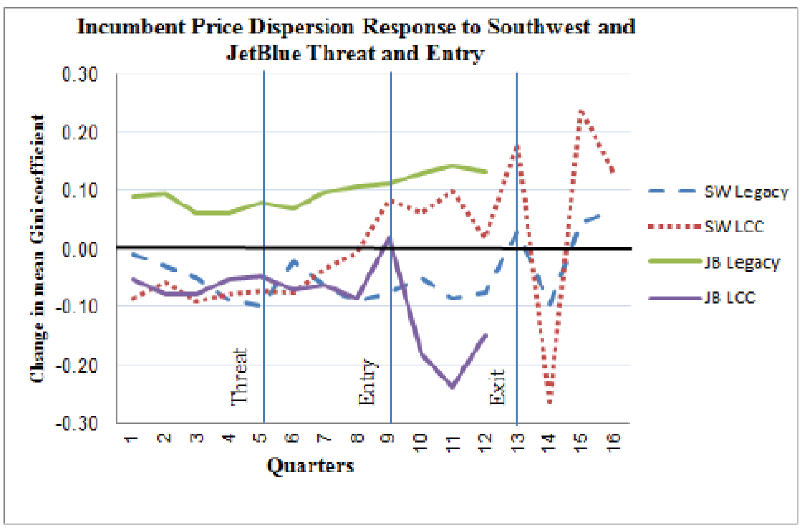

Figure 5: Incumbent price dispersion response from Southwest and JetBlue threat and entry.