Barriers to Entry in the Airline Industry: A Regression Discontinuity Approach*

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Abstract

In the airline industry, passengers pay higher fares at airports where a single carrier controls a high fraction of traffic. The economics of the industry suggests there is an inherent tradeoff between product quality and carrier size and concentration, making the welfare implications of these premia ambiguous. In this paper, we investigate the success of Congressional mandates aimed at increasing competition at highly concentrated major US airports. The mandates required airports above certain concentration thresholds to take concrete steps to ease and encourage new entry and expansion by smaller airlines, primarily by increasing access to airport facilities. We exploit a sharp discontinuity in the law's implementation to identify the effects of the law. In so doing we are able to shed light on the nature high fares at these concentrated airports. We find a statistically and economically significant decrease in fares resulting from an airport's coverage by the legislation. More specifically, we find that in markets where one (two) of the market's endpoints was (were) covered, fares dropped by 10% (20%). Moreover, most of this decrease has come from decreases in dominant carriers' fares at hub airports. We also find that approximately half of this decline in fares is driven by the entry of low-cost carriers into new markets. We find little evidence that the fare declines have been accompanied by decreases in quality measures, with the exception of congestion related delays, suggesting the legislation has been welfare improving for consumers.

Keywords: Regression Discontinuity, Treatment Effect, Airline Industry, Barriers to Entry, Hub Premium. Airport Facilities.

JEL Codes: C14, L50, L13, L93.

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1 Introduction

One of the most enduring features of the post-deregulation U.S. airline industry has been the hub premium-The premium over average fares that large carriers command in markets from airports where they provide a large share of service. Though this phenomenon has been widely documented (see e.g. Borenstein 1989 and Borenstein 1994), its causes and consequences are still in question. To the extent that higher fares are a result of the exercise of market power, they are detrimental to consumer welfare and efficiency. On the other hand, there is substantial evidence that consumers value the large route network and high frequencies airport dominating carriers often provide (e.g. Berry 1990). To the extent that high prices derive from these quality factors, they benefit consumers. Because airport facilities, obviously a necessary input for the provision of air service, are scarce, increased concentration and market power go hand in hand with the airline scope and scale that consumers value and drive down costs. The relative contribution, and the optimality of the balance, of these factors is an empirical question.

In 2000, the U.S. congress enacted the Wendel H. Ford Aviation Investment and Reform Act for the 21st Century (AIR-21). A primary directive of the bill was to require airports, above a given level of concentration, to take concrete steps to ensure that new entrants had ample access to airport facilities.[1]Airport compliance requires filing a *Competition Plan* with the Federal Aviation Administration (FAA), detailing the steps taken. The FAA then reviews the plan and releases federal funding contingent on a satisfactory plan.

In this paper we empirically evaluate the impact of AIR-21 on prices, quality, and market structure in order to investigate the importance of access to airport facilities as barriers to entry in the airline industry. The nature of the implementation of AIR-21 is useful for solving identification problems that are common in industrial organization studies of competition and market structure and are present in our context. The problem is that elements of market structure, e.g. concentration, low cost presence, etc., are determined simultaneously with the level of competition and usually depend on common, market specific, unobserved factors, e.g. demand elasticities or network economies associated with airport geography. We use the design of AIR-21 to formulate a differences in differences and regression discontinuity solution to these problems.

We first argue the AIR-21 mandates were enforced and effectively reduced barriers to entry at covered airports. This generates rarely available variation, with a plausibly known direction,

[1]The law applied to airports in which the top 2 airlines accounted for over 50% of total enplanements at the airport.

over time in barriers to entry within markets. This allows us to control for time invariant, market specific factors using standard panel techniques. Second, having contemporaneous treatment and control groups allows us to use differences in differences to address aggregate and market specific variation in these factors over time.

There are still likely to be selection problems associated with using the full sample for identification. Berry and Jia (2009), observing lower fares and diminished profit margins between the end of the 1990's and the middle 2000's, estimate discrete choice demand systems separately for 1997 and 2005 and conclude that increased passenger price sensitivity combined with increased penetration of low cost carriers were responsible for the change. Since airport concentration itself is likely highly correlated with product quality, the time varying relative valuations of quality found by Berry and Jia (2009) likely interact with our determinant of treatment. This causes differing average trends for treated and untreated markets, invalidating the simple diff-in-diff approach. We solve this and any similar such problem by arguing that, while there is likely a selection problem associated with highly concentrated airports, there is no such problem *locally* around the 50% two carrier concentration level specified by AIR-21. This allows us to develop a regression discontinuity estimator for the local average treatment effects associated with AIR-21. Essentially, we assume the distribution of unobservables for randomly selected market just below the cutoff is identical to a randomly selected market just above the cutoff.

The design of AIR-21 also helps us dismiss concerns about manipulation of the forcing variables. Airport coverage is determined by traffic data from two years prior to coverage, making coverage dependent on the past actions of the carriers which are not subject to manipulation. Given the complexity of airline pricing decisions it also seems unlikely that carriers would adjust fare setting behavior to manipulate enplanements at the airport level. Nevertheless, we design an informal test of manipulation. The test is based on the observation that, for a given two firm airport concentration level, airports with higher one firm concentration levels would be more likely to see manipulation since a single carrier has more control over the coverage variable. This test shows no evidence of manipulation.

Our relatively clean identification strategy represents an contribution to the extant literature on airline market structure and the importance of barriers to entry more generally. A typical structural study of entry and market structure in concentrated industries (e.g. Bresnahan and Reiss (1991), Berry (1992) Mazzeo (2002), Seim (2004), Ciliberto and Tamer(2009)) looks at firm *choices* and uses a revealed preference approach to infer entry barriers. This approach necessarily requires the economist to rely on many restrictions of the empirical model derived from economic theory. Our approach, on the other hand, uses a known source of exogenous variation in entry barriers to investigate their effects on market *outcomes* and requires little in the way of theoretical structure. The minimal structural requirements is useful for an industry as complex as the airline industry and our focus on outcomes makes our results directly relevant for policy.

To preview results, we find AIR-21 had substantial, and evidently positive, impact on competition and fares in the airline industry. We find that markets for which one of the endpoint airports were subject to AIR-21 have seen price declines of 10% on average. Markets for which both endpoints were subject to the mandates have seen price declines of around 20% on average. These price declines were associated with no economically and statistically significant changes in measures of quality, with one exception. We find that the on-time performance of carriers at covered airports decreased. This is not particularly surprising, as we identify increased "low cost" penetration as a driving force behind the declines in fares, suggesting that increased competition at covered airports has resulted in additional congestion related delays. In addition, we find that the magnitude of the decline in fares is larger for carriers with a large presence at an airport than for other carriers. This suggests that AIR-21 was successful at reducing the hub premia identified by Borenstein (1989).

The remainder of the paper is organized as follows. In Section 2, we provide some background on the airline industry and discuss AIR 21 in detail. The data are described in Section 3 and we document some basic patterns in the data over the policy period. In Section 4, we discuss our identification strategy and the results of our analysis. Section 5 concludes and discusses possible extensions of our research.

2 The Aviation Investment and Reform Act for the 21st Century

The Government Accounting Office (GAO) and Transportation Research Board (TRB) released a series of reports, see GAO (1989, 1990, 2001) and TRB (1999), bringing attention to the limited amount of competition at many major US airports. These reports identified two types of barriers to entry in the airline industry, operating and marketing, that have the potential to limit competition and result in higher fares.

Marketing barriers include loyalty programs intended to tie consumers to an airline; frequent flyer programs, corporate incentive agreements, and travel agent commission overrides. A lack of data has limited the study of these type of barriers, Lederman (2007, 2008) and Goolsbee and Syverson (2008) as notable exceptions. Lederman (2007, 2008) finds evidence that improvements in loyalty programs enhance demand and can explain a modest portion of the "hub premium". Goolsbee and Syverson (2008) show that national carriers respond to the "threat of entry" by Southwest Airlines, a low-cost carrier, by lowering fares with the intention of strengthing consumer loyalties prior to entry of Southwest.

Operating barriers include limited access to boarding gates, ticket counters, baggage handling and storage facilities, and take-off and landing slots. Ciliberto and Williams (2010) were the first to directly link these operating barriers to the "hub premium". Using unique data on carrier-specific access to boarding gates, Ciliberto and Williams (2010) show that long-term exclusive-use leasing agreements for boarding gates are a major driver of the "hub-premium". In this paper, we employ a unique identification strategy to examine the success of AIR-21 in reducing these operating barriers and encouraging competition at major US airports. In the sections to follow, we discuss the details of AIR-21's design and implementation

2.1 Legislation and Airport Coverage

In response to governmental, public and academic concern, see GAO (1989, 1990, 2001), TRB (1999), and Borenstein (1989), with the existence of institutional barriers to entry in the airline industry, President Clinton signed into law AIR-21 on April 5, 2000. Section 155 of AIR-21 begins:

> *"The Congress makes the following findings:*
>
> *(1) Major airports must be available on a reasonable basis to all air carriers wishing to serve those airports.*
>
> *(2) 15 large hub airports today are each dominated by one air carrier, with each such carrier controlling more than 50 percent of the traffic at the hub.*
>
> *(3) The General Accounting Office has found that such levels of concentration lead to higher air fares.*
>
> *(4) The United States Government must take every step necessary to reduce those levels of concentration.*
>
> *(5) Consistent with air safety, spending at these airports must be directed at providing opportunities for carriers wishing to serve such facilities on a commercially viable basis."*

Together (1), (4), and (5) demonstrate Congress' clear intentions to reduce concentration by encouraging additional entry at concentrated airports. In order to encourage airports' cooperation in opening up airports to *"all air carriers wishing to serve those airports"*, Congress made federal sources of funding contingent on compliance:

"Beginning in fiscal year 2001, no passenger facility fee may be approved for a covered airport under section 40117 and no grant may be made under this subchapter for a covered airport unless the airport has submitted to the secretary a written competition plan in accordance with this subsection."

Passenger Facility Fees (commonly called PFCs) and Airport Improvement Program (AIP) grants are the primary sources of federal funding for the industry and make up a significant portion of capital (including maintenance) budgets for major airports.[2] PFCs were first authorized by Congress in 1990 and are tied to projects to preserve and enhance safety, reduce noise pollution, and provide opportunities for enhanced competition between carriers. The PFC ceiling, the maximum fee allowed by law, was increased from \$1 to \$4.50 between 1990 to 2001.[3] AIP grants are part of a federal program to help cover costs for approved capital projects aimed at increasing safety and capacity as well as reducing environmental concerns.

A 2009 Airport Council International - North America (ACI-NA) study found that over 40% of airports' capital funding is drawn from PFCs (21.7%) and AIP grants (22.2%).[4] PFCs alone have funded \$50 billion dollars worth of airport capital investments since 1990, including the addition and maintenance of passenger boarding gates and runways necessary to accommodate additional entry. An additional 30% of airports' revenues come from bonds which are often backed with future PFCs revenues. This substantial and stable revenue base allows airports to significantly lower the cost of borrowing and enjoy investment grade ratings. While the quasi-public status of many airports make it difficult to know their exact objectives, the strong dependence of airports' revenues on the federal government's control over the right to charge PFCs and AIP grant funding would seem to imply strong incentives for compliance. All airports covered by AIR-21 are forced to file a Competition Plan with the FAA and the FAA, in turn, must certify the Plan as acceptable in order for funding to be released. [5]

Congress also made it clear that competition "plans" were to be implemented:

"The Secretary shall review any plan submitted...to ensure that it meets the require-

[2] PFCs are charged by airlines at the time a ticket is purchased and are then transferred directly to the appropriate airports.

[3] This ceiling has not been increased since AIR-21 and is not indexed for inflation.

[4] A copy of the presentation describing this report is available from the authors upon request.

[5] The 47 airports required by AIR-21 to file a competition plan include: airport: ABQ, ANC, ATL, AUS, BNA, BUR, BWI, CLE, CLT, CVG, DAL, DCA, DEN, DFW, DTW, EWR, HOU, IAD, IAH, JAX, LAS, MDW, MEM, MIA, MKE, MSP, OAK, OGG, ONT, ORD, PBI, PHL, PHX, PIT, PVD, RNO, SAT, SDF, SFO, SJC, SJU, SLC, SMF, and STL. The majority (43) of the airports were immediately "covered" by the retroactive nature of the legislation. The only airport to be covered later was LAS in 2005.

ments of this section, and shall review its implementation from time-to-time to ensure that each covered airport successfully implements its plan.....The Secretary shall ensure that gates and other facilities are made available at costs that are fair and reasonable to air carriers at covered airports...where a "majority-in-interest clause" of a contract or other agreement or arrangement inhibits the ability of the local airport authority to provide or build new gates or other facilities."

In conversations with those at the FAA assigned to approve and ensure implementation of the competition plans, we learned that approval was not a certainty for any plan. In many cases, the plans were significantly revised after discussions between the FAA, DOT, and airport authorities to ensure the plans meet the goals of the legislation. After filing of the initial competition plan, airports were required to complete two updates (approximately 18 months apart) that demonstrate significant progress towards implementation of the competition plan. There are no mandatory steps after the second update for covered airports, unless the airport denies a carrier access to airport facilities or significantly amends an existing leasing agreement or enacts a new master-leasing agreement.

Section 155 continues:

"A competition plan under this subsection shall include information on the availability of airport gates and related facilities, leasing and sub-leasing arrangements, gate-use requirements, patterns of air service, gate-assignment policy, financial constraints, airport controls over air- and ground-side capacity, whether the airport intends to build or acquire gates that would be used as common facilities, and airfare levels (as compiled by the Department of Transportation) compared to other large airports."

The typical competition plan ranges in length from 75 to 100 pages and contain a vast amount of information about the airports operations. Ciliberto and Williams (2009) use this information to demonstrate that Congress' focus on equal access to sunk airport facilities is not completely misguided. Using cross-sectional variation in gate allocations and leasing terms, Ciliberto and Williams (2009) are able to explain an economically significant fraction of the hub premium, with this fraction being larger at congested airports. In this paper, we focus on measuring any reduction in the hub premium resulting from coverage of an airport by AIR-21.

To identify the impact of AIR-21 on the hub premium, and fares more generally, we exploit the sharp discontinuity in the relationship between coverage and concentration:

> *".....'covered airport' means a commercial service airport....that has more than .25 percent of the total number of passenger boardings each year at all such airports.....at which one or two air carriers control more than 50 percent of the passenger boardings."*

These concentration thresholds create treatment and control groups, airports "very near" either side of the discontinuity, which can be used to measure the impact of the legislation on competition.[6] An airport is covered by the legislation if it qualifies in both the size and concentration dimensions. In Section 4, we discuss how we exploit this feature of the legislation using a regression discontinuity approach to measure a (local) treatment effect, or impact from coverage at the concentration cutoff. Tables 1 and 2 show the show the two-firm enplanement concentration and the fraction of total domestic enplanement at covered and non-covered airports, respectively. While concentration and size are positively correlated, it is far from a perfect relationship. For example, Newark (EWR) is covered while New York (JFK) is not. Similarly, San Fransisco (SFO) is covered while Los Angeles (LAX) is not.

2.2 Implementation of Competition Plans

The majority of the competition plans and subsequent updates are available on the respective airport's website. The details of each competition plan are too vast to review here. However, a 2006 FAA report highlights specific actions taken by airports in a variety of areas to increase competition.[7]

In terms of improving availability of gates and related facilities, airport responses included: asserting control over under-utilized gates, designating Competition Access committees, adopting more entry-friendly leasing terms, removing specific access protections for signatory carriers, streamlining a forced accommodation process. Specific actions included, Hartsfield-Jackson Atlanta International Airport (ATL) invoking recapture authority to convert a leased gate to common-use, Cincinnati-Northern Kentucky International Airport (CVG) negotiating conversion of exclusively leased gates to common and preferentially leased gates, and San Francisco International Airport (SFO) invoking a forced accommodation clause to ensure that temporary needs of new entrant airlines were met. In terms of subleasing agreements, covered airports also began to assert more

[6] As with any analysis examining treatment effects, the treatment must be exogenously applied. In the context of our study, endogeneity of treatment might arise if airports are able to lower concentration of enplanements and/or total enplanements to avoid being covered by the legislation. In Section 4.2.2, we show that there is little or no support for the claim that enplanements were strategically manipulated by carriers with the intention of avoiding coverage.

[7] This report is available through the FAA website at:
http://www.faa.gov/airports/aip/guidance_letters/media/pgl_04_08b_competition_highlights_2006.pdf

control and oversight over sublease fees, terms, and conditions, impose sublease caps on administrative fees, review and/or pre-approve subleases, and notify carriers of gates available for subleases.

Improving access to passenger boarding gates were clearly the focus of a large proportion of each competition plan. However, covered airports put forth effort in a variety of other ways to increase competition. For example, both Charlotte Douglas International Airport (CLT) and San Antonio International Airport (SAT) implemented a marketing plan to attract additional low fare carrier service. In order to make more efficient use of existing common-use facilities, ATL now enforces maximum turnaround times. Oakland International Airport (OAK) installed common use ticketing equipment (CUTE) at ticket counters and gates so that all airlines operating there will use identical gate check-in and gate CUTE equipment, providing maximum flexibility in assignment of gates. CLT reduced landing fees for non-signatory and new entrant carriers to the same level as signatory airlines. Nearly all covered airports implemented measures to record gate utilization, impose minimum-use standards, and notify airlines of gate availability in order to make more efficient use of existing gates. Many airports also amended majority-in-interest (MII) agreements to exempt capital projects necessary for competition from MII votes.

3 Data

3.1 Sources

The majority of our data for this study is taken from the Data Bank 1B (DB1B) of the U.S. Department of Transportation's Origin and Destination Survey for the years 1993 through 2008. The DB1B data is a 10 percent random sample of all domestic itineraries. The unit of observation is the passenger level. The data contains information on the ticketing and operating carrier, details of any connections made by the passenger, and the fare paid for the itinerary used by the passenger. Following Evans and Kessides (1994), we consider round-trip tickets to be two equally priced one-way tickets and drop any inter-line tickets. Due to key punch errors or redemption of frequent flier miles, there are some unusually large and small ticket prices in the DB1B data. For this reason, we drop any fares greater than $2500 and less than $25 and any itineraries.[8] In addition, we drop itineraries with more than 6 coupons (5 connections) for roundtrip itineraries and 3 coupons (two connections) for one-way itineraries. Following Borenstein (1989), we define a market as travel between a unique airport-pair.

[8] We also drop all itineraries the for which the DOT questions the credibility of the reported fare, as indicated by the tktdollarcred variable.

We also collected the enplanement data used by the FAA to determine coverage by AIR-21. There are significant differences between this data and the enplanement data that is publicly available through the DOT's T100 database. These differences arise because the T100 data does not include on-demand (e.g. charter flights) and in-transit (e.g. plane stops to refuel does not deplane) passengers which are a significant source of enplanements at many airports. The differences are significant enough that the determination of coverage for a handful of airports would change depending on the source of enplanement data.

Our final source of data is a survey conducted jointly with the ACI-NA. The survey, completed by 47% of all medium and large hubs, focused on gathering information on carrier-airport specific leasing agreements for boarding gates. For each airport, we observe the total number of gates, number of gates leased by each carrier on an exclusive and preferential basis, and the number of gates reserved for common-use by the airport authority.

3.2 Descriptive Statistics

We summarize the FAA and survey data for medium and large hubs, airports enplaning more than 0.25% of all enplanements at primary airports in the U.S., in Tables 1 and 2. Column 1 in Tables 1 and 2 list the covered and non-covered airports, respectively. The second column of Table 1 lists the year in which each airport was first covered by the legislation. Due to the lag in data collection, coverage in any particular year is determined by enplanement data from two years earlier. For example, the set of airports first covered by the legislation in 2000 was determined using enplanement data from 1998. This is important for our purposes, since it would be very unlikely that an airline could perfectly foresee the details of the legislation two years in advance and manipulate enplanements to avoid coverage of a particular airport. Of covered airports, LAS was the only airport not covered retroactively by the legislation. In Section 4.2.2, we test whether the lack of a significant number of airports first covered in later years is due to potential manipulation of enplanements by carriers.

The next 3 columns of both Table 1 and 2 reports; the fraction of all US enplanements performed at the airport, the mean share of the top-2 carriers from 1998 to 2006, and the maximum share of the top-2 carriers from 1998 to 2006 (determines whether airport is covered from 2000 to 2008). The maximum of the top-2 carriers' shares during this period serves as the predictor of coverage by the legislation. Thus, for each airport in Table 1 (2) this variable is greater (less) than .5. It is also important to note that coverage is not a proxy for the size of the airport. Examining the means at the bottom of Tables 1 and 2 for the fraction of all US enplanements, there is little difference in size between covered and non-covered airports. This is important as it alleviates some concerns over the homogeneity of the treatment and control groups in our analysis.

The final columns of Tables 1 and 2 report the fraction of gates reserved by the airport authority for common-use, fraction leased on a preferential or exclusive basis by legacy carriers, and fraction leased on a preferential or exclusive basis by low-cost carriers[9]. Examining the respective means in 2001 and 2008 of these variables at the bottom of Tables 1 and 2, there is little evidence that gates moved differentially at covered and non-covered airports. However, the large amount of missing data makes drawing any strong conclusions difficult. The lack of a significant movement in the allocation of gates for most airports from 2001 to 2008 suggests that the FAA and DOT largely followed the recommendations put forth by GAO (2001). GAO (2001) cautioned that AIR-21 should not be used as a means to force the divestiture of assets (e.g. boarding gates) from dominant carriers at an airport for two reasons. First, the reallocation of assets among competing carriers may have little to no benefit if the gates were not allocated to a low-cost competitor, see Brueckner (2010) and Ciliberto and Tamer (2009) for strong support for this statement. Second, service in smaller markets would likely be the first affected by divestiture of a dominant carriers assets. This is intuitive, we expect a firm to eliminate or cut service in the least profitable markets and significant economies of density in the industry, see Brueckner (1994), ensures a strong correlation between profitability and size. The lack of a significant difference in the reallocation of gates among carriers at covered and non-covered airports foreshadows our finding that coverage by AIR-21 has little effect on the network of destinations offered out of an airport. It also suggests that if we are to find a significant effect from coverage by AIR-21 on other dimensions of service, it is due to more efficient use of existing assets (the focus of most competition plans) rather than a redistribution of assets among carriers.

Table 3 summarizes the variables we construct from the DB1B data and other sources, before and after AIR-21, separately for the set of covered and non-covered airports. To motivate our approach in Section 4 and emphasize the importance of controlling for trends in the data prior to coverage by AIR-21, we summarize the first difference for each variable. More precisely, for each variable, the difference before AIR-21 is calculated as the level in the first quarter of 2000 minus the level in the first quarter of 1993 while the difference after AIR-21 is calculated as the level in

[9] Low-cost carriers include B6, FL, F9, G4, J7, KP, KN, N7, NJ, NK, P9, QQ, SY, SX, TZ, U5, VX, W7, W9, WN, WV, XP, and ZA.

the first quarter of 2008 minus the level in the first quarter of 2001.

The majority of our variables are calculated at the market-carrier level, where we classify a carrier's service into two types, nonstop or connecting. For each type of service in a market, $Avg.Fare$ is calculated as the average fare across passengers choosing a type of service. 20^{th} Pct. Fare, 50^{th} Pct. Fare, 80^{th} Pct. Fare are constructed similarly for different quantiles of the fare distribution for each carrier, market and type of service. Table 3 shows there has been a significant downward trend in fares in both covered and non-covered markets. However, prior to AIR-21 fares were falling less rapidly at covered airports, while after AIR-21, fares fell more rapidly at covered airports. These differential trends are strongest in the upper quantiles of the fare distribution. In Section 4, we attempt to identify a causal relationship between coverage by AIR-21 and these differential trends in fares, while controlling for a variety of time-varying covariates. $Nonstop$ is an indicator for whether or not a carrier's service is nonstop. $DistanceTraveled$ is the average number of miles traveled by passengers purchasing a type of service from a carrier in a particular market. For nonstop service, $DistanceTraveled$ is equal to the direct distance between the market endpoints. For connecting service, $DistanceTraveled$ is strictly greater than the direct distance. $FractionRoutes$ is the proportion of all the destinations offered out of an originating airport that a carrier offers some type of service on. This variable is intended to measure the extent of a carrier's network out of the originating airport.

From the DB1B data, we also construct a number of market-specific variables. Our measure of the hub premium in a given market is calculated as the difference between the fares charged for a particular type of service by the carriers with the largest share of enplanements at the origin and destination airports and the average of fares charged by all other carriers. For example, in the ATL (Atlanta Hartsfield) to CLE (Cleveland Hopkins), Delta and Continental are regarded as the dominant carriers (those with the largest share of enplanements), and $Avg.\ Hub\ Premium$ is calculated as the difference between the average fare charged by Delta and Continental and the average fare charged by all other carriers. The hub premium measures for the different quantiles of the fare distribution are constructed similarly, replacing the average fare with the appropriate quantile. These variables are summarized in Table 3 and suggest that coverage is associated with a large decline in the hub premium. In addition, we construct two measures of competition in a market, $Lcc\ Penetration$ and $Number\ Firms$. $Lcc\ Penetration$, summarized in Table 3, is an indicator for whether or not a low-cost carrier is present in the market. As has been well documented, low-cost carrier penetration has been steadily increasing over the previous decade and typically results in intense price competition. In Section 4, and as the descriptives suggest, we show that in markets where one or both endpoint airports are covered by AIR-21, the low-cost penetration rate is significantly higher as a result of coverage. $Number\ Firms$ is the total number of firms serving the market and is a commonly used measure of competition in the Industrial Organization literature, see Berry (1992) and Ciliberto and Tamer (2009).

We supplement the DB1B data with information on the frequency of departures from the DOT's T100 database and the frequency and severity of delays from the DOT's Airline On-Time Performance database. From these data, we construct two variables. $Departures$ is calculated as the number of departures per quarter by a carrier on a particular flight segment and $\%OnTime$ is calculated as the proportion of flights that arrive 15 or more minutes late. In addition to those variables we construct from the DOT sources, we also collected data on both population and per-capita income for each MSA from the Bureau of Economic Analysis to serve as controls throughout our analysis.

4 Empirical Analysis

Our final sample includes data from all airports classified as a medium or large hub by the FAA (enplaning at least 0.25% of total domestic enplanements), including highly concentrated hubs, such as Minneapolis and Dallas. A legitimate concern here is that these highly concentrated airports are significantly different from the control group (non-covered airports) in both observable and unobservable ways. For example, since airport presence is known to be an important factor in airline quality, cost, and price competition it is troubling that we have no airports in the control group that are comparable in terms of presence measures. Using these observations with limited covariate overlap means that estimates are forced to rely heavily on our linear specification for identification. Similarly, unobserved airport features, such a geographic location, may affect the network economies of an airport leading it to be both highly concentrated and also have different competitive mechanics than less concentrated airports. The results from Berry and Jia also give an important example of the interaction of unobservable changes in consumer preferences with observable airport presence differences.

To get around these problems we exploit AIR-21's sharp discontinuity at the 50% two carrier enplanement level. Broadly, we assume that the distribution of market level, our level of observation, unobservables changes smoothly across the policy discontinuity. That is, the unobservable features of a randomly chosen market just below the cutoff has the same distribution as the unobservable features of a randomly chosen market just above the cutoff.

With this identification strategy in mind we estimate the local average effects of the law using two approaches. First, we proceed in the spirit of Black (1999) and estimate a series of difference in difference regressions using only those observations in progressively smaller windows around the concentration cutoffs determining coverage. Figure 1 demonstrates this approach. We begin by utilizing the complete sample and then examine the subset of markets within 0.1 of the coverage cutoffs. Using this flexible approach, we identify market outcomes that are impacted by coverage in a statistically and economically significant manner. This approach also allows us to use covariates to control for observable differences in airports and markets. This is potentially useful because, while we have a large number of markets, these markets are drawn from a relatively small number of airports, which may create a small sample problem even if our identifying assumption is correct. For example, New York (JFK) is always included as a control airport and serves markets that are larger, richer and more distant on average than those in the treatment group and due to the large number of markets originating or terminating at the airport it represents a nontrivial fraction of the sample.

In the second step, we employ a true regression-discontinuity approach and allow the window width to collapse to zero. We find that our main conclusions from the first step are robust. In addition, the regression-discontinuity approach allows us to examine variation in the effect of coverage along the cutoffs. This is important as we are able to identify particularly influential steps taken by airports, including those in the control group (ie. JFK), with regards to gate availability for low-cost carriers.

4.1 Window Regressions

Table 3 is suggestive of a significant decrease in equilibrium fares, at all levels of the distribution, as a result of coverage by AIR-21. In this section, we examine the robustness of this descriptive evidence.

4.1.1 Fares

Following Black (1999), we begin under the assumption that coverage is exogenous and homogenous in its effect on fares by estimating the following regression:

$$\begin{aligned}\Delta_t \log(avg_{ijmt}) &= \Delta_t x_{ijmt}\beta + \Delta_t z_{mt}\gamma + \psi Nonstop_{ijmt} + \kappa_1 1[1 \text{ cover}_m] + \kappa_2 1[2 \text{ cover}_m] + \\ &\quad \tau_1 1[1 \text{ cover}_m] * 1[\text{AIR-21}_t] + \tau_2 1[2 \text{ cover}_m] * 1[\text{AIR-21}_t] + \Delta_t \epsilon_{ijmt},\end{aligned} \tag{1}$$

using the complete sample. The dependent variable is the second difference of the logarithm of average fares paid by passengers who purchased product j (nonstop or connecting service) from carrier i in market m, where the second difference is constructed identically to the descriptives in Table 3. The vectors Δx_{ijmt} and Δz_{mt} include the second differences of $FractionRoutes$, $DistanceTraveled$, and the population and per-capita income at the market endpoint airports.[10] In addition, we include an indicator for nonstop service to capture the possibility that fares for nonstop service changed differentially relative to connecting service.

To capture the impact of coverage by AIR-21 on the time-path of fares, we include indicators for whether one or both of a market's endpoints were covered, $1[1 \text{ cover}_m]$ and $1[2 \text{ cover}_m]$, respectively. Under the assumption that coverage is exogenous and homogenous in its effect on fares, κ_1 and κ_2 measure the causal effect on the dependent variable in a market with one and two endpoints covered, respectively. In order to relax these assumptions and ensure a causal interpretation of κ_1 and κ_2, we estimate the same regression on the subsamples of markets in progressively smaller windows around the coverage cutoffs. For such an approach to give consistent estimates, a significant portion of the data must be located within these windows. Figure 2 gives the number of observations for each combination of the predictors of treatment. The histogram shows that the majority of the data is in fact immediately around the coverage cutoffs. This is of particular importance as we shrink the window further in the regression-discontinuity analysis.

The estimates of Equation 1 are presented in Columns 1, 3, and 5 of Table 4. Robust standard errors are calculated by clustering at the market level to account for the interdependence of observations within a market. Our estimates of κ_1 and κ_2 are negative and statistically and economically significant. From Column 5, where we can reasonably interpret our coefficients in a causal fashion, the results indicate that coverage of a single endpoint by AIR-21 results in a approximately a 10% reduction in average fares, while coverage of both endpoints results in approximately a 20% change in average fares. This result is robust across different window widths, suggesting that unobservable differences across airports that may drive selection into the treatment and control groups are not significant. The remaining results in Columns 5 are straightforward to interpret, we find that fares for nonstop service declined more rapidly than those for connecting service, carriers with a larger market presence are able to charge higher fares, and less direct connections are more costly to provide. These results are robust across subsamples.

[10] See Berry (1990), BCS (2006), and Berry and Jia (2010) for a discussion of the impact of the size of a carrier's network on demand for that carrier's services.

To determine what role increased competition played in the decline in fares in those markets with one or both endpoints covered by AIR-21, we augment and re-estimate Equation 1. More specifically, we add a very similar set of time-varying regressors to those employed by Borenstein and Rose (1994) to control for any changes in the competitive environment in a market. The set of controls includes: airport-level enplanement herfindahl indices for both endpoints, a market-level enplanement herfindahl indices, market shares for each carrier, an indicator for whether the carrier offers both nonstop and connecting service, the number of competitors in the market, and an indicator for whether or not a low-cost carriers serves the market. One can then interpret changes in the estimates of κ_1 and κ_2, when the controls are included, as evidence that variation in the competitive explains some portion of estimated effect from coverage. The results from these regressions, are presented in Columns 2, 4, and 6 of Table 4. The results suggest that these controls are able to explain between 40% and 50%, depending on the window width, of the effect from coverage we estimated in Columns 1, 3 and 5. For conciseness, we present only the estimates for the coefficients on $LccPenetration$ and $NumberFirms$.[11] We find no significant change in fares as a result of the change in the number of firms. However, we find that the presence of a low-cost carrier does dramatically reduces fares.

Table 5 presents our results when we re-estimate Equation 1, replacing the dependent variable with various quantiles of the fare distribution. For conciseness and due to the similarity of the estimates, we present the estimates for the subset of coefficients of particular interest. Again, Columns 2, 4, and 6 (1, 3, and 5) present the our estimates with(out) the Borenstein and Rose (1994) controls. Consistent with the descriptive evidence in Table 3, we find that the estimated decline in fares resulting from coverage by AIR-21 is increasing in the fare quantile. Column 5 shows that the 20% fare declined approximately 2% (4%) in markets when one (both) endpoint(s) was (were) covered, compared to 7% (13%) and 13% (24%) for the median and 80% fares, respectively. We also find additional supporting evidence for our conclusions reached from the results in Table 4, in particular, that low-cost penetration drove a significant portion of the decline in average fares in covered markets. Low-cost carriers typically target price-sensetive consumers when setting fares. As a result, we would expect to observe that the Borenstein and Rose (1994) controls, specifically the low-cost penetration indicator, would explain a larger proportion of the estimated effect from coverage for lower fare quantiles. Column 6 of Table 5 shows that inclusion of these controls completely explains away the coverage effect for the 20% fares, while explaining less than half of

[11] The remainder of the estimates are available from the authors upon request.

the coerage effect for the 80% fare.

The last measure of the mandates' impact on fares we look at is the effect on the hub premium. We measure the hub premium as the difference in the logarithm of the fare charged in a market by the carrier with the largest presence at that airport with that of its competitors. These premia range from roughly 15-40% in 2000 and, on average, are sharply increasing in the concentration of an airport. Table 6 reports the results of the regressions. The results are consistent across different window widths. If we focus on Column 3 of Table 6, the narrowest window, we find that these premia have fallen significantly faster in markets with one or both endpoints covered. This decline is larger for the upper tail of the fare distribution. More precisely, the premium on the 20% fare declined (9%) 15% in markets with one (both) endpoint(s) covered, while the hub premium on the 80% fare declined (12%) 28% in markets with one (both) endpoint(s) covered. The declines in the hub premium across the entire fare distribution suggests that AIR-21 was successful in reducing operating practices that gave an advantage to dominant carriers.

4.1.2 Quality

In addition to fares, many other characteristics of service may change as the result of coverage by AIR-21. GAO (2001) suggests that granting authority to regulators to force dominant carriers at certain airports to divest critical assets (e.g. boarding gates) introduces uncertainty and can lead to disinvestment in an airport. In particular, GAO (2001) suggests that smaller markets would be the first to be affected, possibly losing service altogether. If fare reductions are accompanied by diminished service quality, then the welfare consequences of coverage is ambiguous. We focus our attention on four critical dimensions of service quality, the availability of nonstop service (percentage of passengers flying nonstop with a carrier in a market), frequency of service (number of departures in a quarter by a carrier on nonstop flight segments), the on-time performance of carriers (percentage of flights arriving 15 or more minutes late by a carrier on nonstop flight segments), and the number of markets served by a carrier out of an airport (number of destinations served on a connecting or nonstop basis by a carrier out of an airport).[12]

To estimate the impact of coverage on the availability of nonstop service, we estimate the

[12] For a detailed discussion of those dimensions of service quality that have been shown to be the most important to consumers, see Berry (1990), Berry, Carnall and Spiller (2006), and Berry and Jia (2010).

following regression::

$$\begin{aligned}\Delta_t Pct\_Nonstop_{imt} &= \Delta_t z_{mt}\gamma + \kappa_1 1[1 \text{ cover}_m] + \kappa_2 1[2 \text{ cover}_m] + \\ &\quad \tau_1 1[1 \text{ cover}_m]*1[\text{AIR-21}_t] + \tau_2 1[2 \text{ cover}_m]*1[\text{AIR-21}_t] + \Delta_t \epsilon_{imt}\end{aligned}$$

where $\Delta Pct\_Nonstop_{imt}$ denotes the second difference, constructed identically to the dependent variable in Equation 1, in the fraction of passengers flying nonstop in market m. To examine the impact of the coverage on the frequency of service and severity of delays on any nonstop flight segment s, we estimating the following regressions:

$$\begin{aligned}\Delta_t \log(Departures_{ist}) &= \Delta_t z_{st}\gamma + \kappa_1 1[1 \text{ cover}_m] + \kappa_2 1[2 \text{ cover}_m] + \\ &\quad \tau_1 1[1 \text{ cover}_m]*1[\text{AIR-21}_t] + \tau_2 1[2 \text{ cover}_m]*1[\text{AIR-21}_t] + \Delta_t \epsilon_{ist}\end{aligned}$$

and

$$\begin{aligned}\Delta_t \log(\%OnTime_{ist}) &= \Delta_t z_{st}\gamma + \kappa_1 1[1 \text{ cover}_m] + \kappa_2 1[2 \text{ cover}_m] + \\ &\quad \tau_1 1[1 \text{ cover}_m]*1[\text{AIR-21}_t] + \tau_2 1[2 \text{ cover}_m]*1[\text{AIR-21}_t] + \Delta_t \epsilon_{ist}\end{aligned}$$

, respectively, where *Departures* is the number of departures made by carrier i and %OnTime is the fraction of flights by carrier i that arrive 15 or more minutes late. Finally, in order to capture any potential divestiture by carriers in an airport resulting from coverage by AIR-21, we estimate the following regression:

$$\Delta_t \log(Num\_Routes)_{iat} = \Delta_t z_{at}\gamma + \kappa_1 1[\text{cover}_a] + \tau 1[1 \text{ cover}_a]*1[\text{AIR-21}_t] + \Delta_t \epsilon_{iat}$$

where the unit of observation is at the carrier-airport (a) level.

The results of these regressions are presented in Table 8. Robust standard errors are calculated by clustering at either the market, nonstop segment, or airport level to account for the interdependence of observations within the respective group. With the exception of delays, we find no significant declines in the quality of service. With regards to delays, we find a statistically significant increase in the proportion of flights arriving 15 or more minutes late. This is not particularly surprising given the results of Mayer and Sinai (2003) which show that carriers controlling the majority of the operations at an airport have an incentive to internalize congestion related delays. This result does make make conclusions regarding improvements in consumer welfare as a result of the legislation less clear. However, it seems very unlikely that an increase in congestion related delays, which tend to be mild in length relative to weather related delays, would completely offset a 20% reduction in the average fare. It also suggests that the lobbying efforts of the ACI-NA and other trade organizations to raise PFC ceilings (or at least adjust the current ceiling for inflation) in order to expand airport facilities at the most congested airports is not misguided.

4.1.3 Competition

The results in Tables 4 and 5 suggest that increased competition, particular by low-cost carriers, explains a significant portion of the decline in fares in covered markets. However, it is not clear whether this increase in competition is driven by coverage. To test whether the steps taken by covered airports had a significant impact on the number and identify of firms, we estimate two regressions:

$$\begin{aligned}\Delta_t \log(Num\_Firms_{mt}) &= \Delta_t z_{mt}\gamma + \kappa_1 1[1 \text{ cover}_m] + \kappa_2 1[2 \text{ cover}_m] + \\ &\quad \tau_1 1[1 \text{ cover}_m]*1[\text{AIR-21}_t] + \tau_2 1[2 \text{ cover}_m]*1[\text{AIR-21}_t] + \Delta\epsilon_{mt}\end{aligned}$$

and

$$\begin{aligned}\Delta_t \log(LccPenetration_{mt}) &= \Delta_t z_{mt}\gamma + \kappa_1 1[1 \text{ cover}_m] + \kappa_2 1[2 \text{ cover}_m] + \\ &\quad \tau_1 1[1 \text{ cover}_m]*1[\text{AIR-21}_t] + \tau_2 1[2 \text{ cover}_m]*1[\text{AIR-21}_t] + \Delta\epsilon_{mt}\end{aligned}$$

where the dependent variables in these regressions are the number of firms serving the market and an indicator for whether a low-cost carrier is present, respectively. Ciliberto and Tamer (2009) and Brueckner (2010) provide useful discussions of the intense level of competition that results from the presence of a low-cost carrier.

The estimates of the coefficients on the coverage indicators are presented in Table 8. Robust standard errors are calculated by clustering at the market level to account for the interdependence of observations within a market. We find that for markets with one (both) endpoint covered there is a 0.10 (0.43) increase in the probability of a low-cost carrier serving the market. This corroborates our finding that variation in the low-cost indicator played a major role in explaining between 40% and 50% of the reduction in fares as a result of coverage. With regards to the number of firms, we find no statistically significant effect from coverage.

4.2 Regression Discontinuity Design

As discussed above there are many strengths associated with the approach of Black (1999). The results, however, rely on a number assumptions, including homogeneity and exogeneity of coverage, to estimate the effects of coverage by AIR-21. These assumptions can be troublesome because more concentrated airports (those with two carriers enplaning more than 50% of the passengers) are treated while less concentrated airports are not. Therefore, any covariation between fares and concentration after the first quarter of 2001 (the time of the treatment) would be empirically indistinguishable from a treatment effect due to AIR-21. While these assumptions are difficult to formally test, it is possible to measure a local-average treatment effect (LATE) around the treatment cutoff in the absence of these assumptions using a regression-discontinuity approach. Examining treatment and control groups "very near" either side of the treatment cutoff allows us to disentangle those movements in fares that are a result of coverage from those that are simply due to correlation between fares and concentration. We discuss our approach below.[13]

Estimation of the LATEs here is complicated by the two dimensional predictor vector. Instead of a point, our LATE estimates are now functions of the market endpoints' concentrations. Figure 1 makes this clear. Our task is essentially to estimate a nonparametric surface in each quadrant of Figure 1, then look for evidence of statistically significant breaks along the cutoffs determining coverage.

Let $Y_{ijmt}(o, d), o, d \in \{0, 1\}$ denote the outcome variable when the origin treatment status is o and the destination treatment status is d. For each observation, we get to observe one of the four possible values of the variable. When only one endpoint is treated we define the LATEs as:

$$\begin{aligned}
\tau^1_{t,orig}(P^{dest}_m) &= E[Y_{imt}(1,0) - Y_{imt}(0,0)|P^{orig}_m = .5 P^{dest}_m < .5] \\
\tau^1_{t,dest}(P^{orig}_m) &= E[Y_{imt}(0,1) - Y_{imt}(0,0)|P^{orig}_m < .5 P^{dest}_m = .5]
\end{aligned}$$

and when both endpoints are treated:

$$\begin{aligned}
\tau^2_{t,orig}(P^{dest}_m) &= E[Y_{imt}(1,1) - Y_{imt}(0,1)|P^{orig}_m = .5 P^{dest}_m > .5] \\
\tau^2_{t,dest}(P^{orig}_m) &= E[Y_{imt}(1,1) - Y_{imt}(1,0)|P^{orig}_m > .5 P^{dest}_m = .5]
\end{aligned}$$

Our definition of treatment effects is motivated by several considerations. First, are identification considerations. Our data is lumpy in the sense that the predictors of coverage do no vary within an airport, so for a sufficiently small window around a given concentration level all the markets in that window will be drawn from a single airport. For example, consider Dallas-Fort

[13] See Imbens and Lemieux (2007) for an introduction to RDD and Hahn, Todd, and Van Der Klaauw (2001) for a detailed discussion of identification of treatment effects within an RDD framework.

Worth (DFW) which has a predictor value of around 0.8, well away from the coverage cutoff. The estimate of $\tau^2_{t,dest}(0.8)$ compares the path of fares over the period since the passage of AIR-21 in markets originating at DFW and terminating at airports just below the coverage cutoff to those markets originating at DFW and terminating at airports just above the coverage cutoff. This approach allows us to control, to some extent, for fixed unobserved factors associated with given airports that are potentially distant from the coverage cutoffs. Second, in contrast to the window regressions, allowing the treatment effect to vary along the treatment cutoff in addition to the local linear regression implementation, discussed below, we are able to estimate the effect of coverage more flexibly. Figure 2 shows the large number of observations near the treatment cutoff, making such a flexible approach feasible. Moreover, Berry and Jia (2009) suggest there is direct evidence that the treatment effects may differ in airport concentration. Of course, the interpretation of our estimates as a flexible interactive effect is invalid if there is selection inherent in conditioning on the away-from-the-boundary-airport concentration level, which is likely given that a single airport will dominate any small bin. However, even in the presence of such selection, we can still interpret the estimates as an estimate of LATE heterogeneity where the heterogeneity corresponds to interaction with whatever is driving selection.

Our major task in estimation is to adapt the basic regression discontinuity framework to account for a two dimensional predictor vector. This requires flexibly estimating a two dimensional surface that relates Y_{ijmt} to $\{P^{orig}_m, P^{dest}_m\}$. Local linear estimators are particularly attractive for these type of problems, see Imbens and Lemieux (2007). At boundary points of the support for the predictor vector, local linear estimators do not suffer from the inherent bias of kernel estimators and achieve faster rates of convergence. In addition, local linear estimators are easily extended to multiple dimensions. Fan and Gijbels (1996) provides a detailed discussion of the advantages of local-polynomial modeling.[14]

To demonstrate our approach, suppose we are estimating $\tau^1_{t,orig}(P^{dest}_m)$. This requires us to estimate the conditional expectation, $E[Y_{imt}(1,0) - Y_{imt}(0,0)|P^{orig}_m = .5 P^{dest}_m < .5]$, for each $P^{dest}_m < .5$. For a particular value of P^{dest}_m, $\overline{P}^{dest}$, the estimator is defined as

$$\tau^1_{t,orig}(P^{dest}_m) = \widehat{\alpha}^{c+} - \widehat{\alpha}^{c-}$$

[14] The results are nearly identical when we employ a second-order polynomial.

where

$$\min_{\{\alpha^{c-},\beta^{c-}_{orig},\beta^{c-}_{dest}\}} \sum_{\substack{m: \\ \{P^{orig}_m<.5, P^{dest}_m<.5\}}} [Y_{imt}(0,0) - \alpha^{c-}_0 - \beta^{c-}_{orig}(P^{orig}_m - .5) - \beta^{c-}_{dest}(P^{dest}_m - \overline{P}^{dest})]^2 w^-_m \quad (2)$$

and

$$\min_{\{\widehat{\alpha}^{c+},\beta^{c+}_{orig},\beta^{c+}_{dest}\}} \sum_{\{P^{orig}_m \geq .5, P^{dest}_m<.5\}} [Y_{imt}(1,0) - \alpha^{c+}_0 - \beta^{c+}_{orig}(P^{orig}_m - .5) - \beta^{c+}_{dest}(P^{dest}_m - \overline{P}^{dest})]^2 w^+_m \quad (3)$$

The weights, w^+_m, are calculated as

$$w^+_m = \frac{\phi\left(\frac{P^{orig}_m - c^{orig}}{h^{orig}}, \frac{P^{dest}_m - \overline{P}^{dest}}{h^{dest}}\right)}{\sum_{j:\ P^{orig}_j \geq c^{orig}, P^{dest}_j < c^{dest}} \phi\left(\frac{P^{orig}_j - c^{orig}}{h^{orig}}, \frac{P^{dest}_j - \overline{P}^{dest}}{h^{dest}}\right)}$$

where $\phi(\cdot)$ is the bivariate standard normal pdf and h^{orig} and h^{dest} are bandwidths. The weights, w^-_m, are defined similarly. This process is then repeated for a range of values for $\overline{P}^{dest}_m$ to get an estimate of the treatment effect, $\tau^1_{t,orig}(P^{dest}_m)$, along the entire treatment cutoff. The estimators of $\tau^1_{t,dest}(P^{orig}_m)$, $\tau^2_{t,dest}(P^{orig}_m)$, and $\tau^2_{t,dest}(P^{dest}_m)$ are defined similarly.

To simplify the choice of bandwidth in multiple dimensions, we transform the data prior to estimation to have mean zero and identify covariance matrix, see Pagan and Ullah (1999). This allows us to check the sensitivity of our results by varying a single factor of proportionality, k, such that both h^{orig} and h^{dest} are equal to

$$h = kN^{-\frac{1}{4+d}}$$

where N is the number of observations in the quadrant of interest.[15] We find our results to be fairly insensetive to the choice of bandwidth.[16] The results presented in Figures 3, 4, and 5 and Tables 9 and 10 set $k = 3$, which allows for a great deal of flexibility, as we will discuss below, yet adequately smooths the surface.

Calculating asymptotically valid standard errors for our estimates is a nontrivial computational exercise for a number of reasons. First, we are estimating a nonparametric surface in multiple

[15] In Equations 2 and 3,

$$N^+ = \sum_m 1[P^{orig}_m < .5, P^{dest}_m < .5]$$

and

$$N^- = \sum_m 1[P^{orig}_m \geq .5, P^{dest}_m < .5]$$

, respectively.

[16] We also explored cross-validation methods for choosing k, but we find it performs very poorly in our application by suggesting a bandwidth near zero that overfits the data. A few aspects of our application and the method; interdependence of observations, multiple dimensional predictor vector, and the slow convergence rate of the cross-validation method, make this a unsurprising result.

dimensions. Second, we are most interested in the estimates of this nonparametric surface at the coverage cutoffs. Finally, we must account for the dependence in our data resulting from markets having endpoints in common. For these reasons, we appeal to the resampling with dependent data literature to calculate asymptotically valid point-wise standard errors. For a detailed treatment of resampling techniques for dependent data, see Lahiri (2003). The clear dependence structure in our data makes application of these techniques straight-forward. We treat the sample as representative of the population and compute jack-knife standard errors where we leave out blocks of markets with a common endpoint. In particular, for each airport we find all markets with a common endpoint and drop them from the sample. Using the resulting sub-sample, we then reestimate the model. We repeat this process for each market and use the distribution of the estimates across subsamples to infer moments of the asymptotic distribution of our treatment effects.

4.2.1 Results

The results and conclusions of our RDD analysis are consistent and nearly identical to our findings using the window-regression approach. For this reason, we focus our the discussion of our RDD results on the impact of coverage on fares and low-cost competition.

Figure 3 and Table 9 presents the results of our RDD analysis of fares. In examining fares, we follow a very similar approach to the window regressions. The only difference is that we examine the first difference in fares within a carrier, market and type of service (nonstop and connecting) since the passage of AIR-21. Precisely, we take the difference in the logarithm of fares in the first quarter of 2008 and 2001 to construct our dependent variables. This serves as a robustness check on our conclusions from the window regressions, ensuring that any differential trends in fares prior to the passage of AIR-21 are not driving our findings above. We find this not to be the case, which is important as it provides some validation for our approach to identifying the effect of coverage. To summarize the results, we again find that the decline in fares resulting from coverage is statistically and economically significant. We also again find that the decline is increasing in the quantiles of the fare distribution. These are clearly evident in the surfaces plotted in Figure 3 and the statistical significance of the point estimates in Table 9.

As discussed above, one advantage of employing a true RDD approach in our application is the opportunity to look for heterogeneity in the effect of coverage. This heterogeneity is obvious as one looks at the point estimates of the effect from coverage on average fares in the top-left corner of Table 9. Looking down the second column of Table 9, we find a 10% reduction in fares in markets where the destination is covered and the origin has a two-firm concentration of 0.4 and only a 3.7% reduction in fares in markets where the destination is covered and the origin has a two-firm concentration of .5. This result would not be interesting if it were not for the statistical significance of both estimates, since the latter estimate may suffer from the "curse of dimensionality". More precisely, when estimating a surface non-parametrically, the number of observations falling in any locally defined ball falls exponentially in the number of explanatory variables. This problem is exacerbated when attempting to estimate the surface at the boundary of the support for the explanatory variables. Thus, at first glance, this appears to be a discouraging result that is consistent across all quantiles of the fare distribution.

However, in this case, our estimates of the effect of coverage on low-cost carrier penetration provide a clear explanation for the heterogeneity in the effect of coverage on faresewe observe along the coverage cutoffs. Figure 4 and Table 10 report these results. In the top half of Figure 4, we plot the surface which we use to compute the estimates of the coverage effect on low-cost penetration. These surfaces are relatively smooth, with one exception, in which we observe a significant jump in the entry behavior of low-cost carriers. The difference in low-cost entry behavior over this portion of the predictors' support is large enough to generate a negative and statistically significant effect on low-cost entry behavior, the top-left portion of Table 10. This suggests that at least one airport not covered by AIR-21, near the coverage cutoff observed substantial low-cost entry from 2001 to 2008. By examining Table 3, we identified those airports near the cutoff and then re-estimated the surface excluding each airport, one at a time. Through this process, we identified JFK as the driver of this finding. The estimates of the effect of coverage on low-cost penetration, excluding JFK, are presented in the bottom half of Figure 4 and Table 10. After JFK's exclusion, the effect of coverage on low-cost carrier penetration is now strictly positive along each portion of the treatment cutoff. This is not surprising, as JFK provided a low-cost carrier, JetBlue, unprecedented access to airport facilities throughout the period since the passage of AIR-21.

Collectively, the results of our RDD analysis provide additional insights to the findings gleaned from the window regressions. First, the RDD results show that ignoring heterogeneity in the treatment cutoff is important. The JFK example demonstrates this idea perfectly. By assuming a homogenous effect from coverage on low-cost penetration, one actually infers the incorrect sign on the effect of low-cost entry over some range of the support for the predictors and and severely biased estimates along the remainder of the coverage cutoffs. Second, the ability of the RDD analysis to be able to essentially identify individual airport specific treatment effects, provides further support for our conclusion that entry by low-cost carriers was the driving force behind the large declines in fares in markets with one or both endpoints covered.

4.2.2 Regression-Discontinuity Validity

Above, we have discussed why we are comfortable assuming there are no (local) selection effects associated with AIR-21. The validity of our identifying assumption also requires there be no problem with incentive effects. That is, that carriers do not manipulate enplanement levels to avoid treatment. There are a number of reasons why we believe this is a valid assumption. First, coverage is determined at the airport-level, not the airline-level. Therefore, no individual airline can manipulate enplanements and entirely determine coverage, rather it would take a cooperative effort on the part of airlines serving the airport. Second, coverage in each year was determined using FAA enplanement data from two years earlier. An airline(s) attempting to avoid coverage by the legislation would have been required to forsee the exact details of the legislation (including the exact enplanement cutoff) two years in advance of its passage. Finally, manipulating enplanements at any one airport, particularly a large airport, has significant costs to an airline in terms of adjusting traffic in its entire network.

Extending formal tests to check for the strategic manipulation of enplanements, see McCrary (2007), with a two-dimensional predictor vector is not immediately clear. However, we develop an informal test for manipulation of the predictors of treatment and provide evidence that little or no strategic manipulation of enplanements occurred. The test is based on the simple observation that those airports just below the coverage cutoff in which one carrier controls a larger proportion of the traffic will be most vunerable to strategic manipulation of enplanements. For example, consider two airports where the two largest carriers enplane 49% of the passengers. Suppose at the first airport, the top carrier enplanes 35% of all passengers while the top carrier at the second airport enplanes 25% of all passengers. If an airline was attempting to avoid coverage of an airport by AIR-21 by manipulating enplanements, one would expect this to occur at the first airport. At the first airport, the largest carrier would have greater control in ensuring that the airport were not covered.

One way a carrier can lower enplanements is by raising fares. If a carrier was seeking to raise fares and lower their share of enplanements to avoid coverage, one would expect to see less of a drop in fares in markets near the coverage cutoff where one carrier has a larger share of enplanements. Figure 5 shows that there is no evidence to support a claim that enplanements were manipulated.

In the top-half of Figure 5, we plot the joint density of the share of the two largest carriers and the share of the largest carrier. Given the high correlation between these two variables, we are only able to plot the relationship between these variables and changes in fares (difference between average fare in the first quarter of 2008 and 2001), for a small range of values in the bottom-half of Figure 5. If carriers chose to strategically manipulate enplanements, we would expect to see a surface sloping up in the top carrier's share at airports closest to the cutoff. We find no evidence to support this claim, in fact, we find fares were actually lower at airports where one carrier controlled a larger fraction of the enplanements.

5 Conclusions

High fares at concentrated airports have been a fact of life in U.S. air travel since the deregulation of the industry in 1979. The welfare implications of these high fares are ambiguous because consumers value both the size and scope, in the form of frequency and network size, of an airline when flying out of their home airport, however size and scope lead to market power due to scarce airport facilities. In 2000, the U.S. congress took a stand, deciding too much market power at highly concentrated airports was generating too much of the fare difference and enacted AIR-21. Among other things, these mandates required concentrated airports to take steps to increase competition and make airport facilities available to all carriers wanting to serve the airport.

In this paper we have provided evidence that the mandates were successful in encouraging new and intensified competition at its targeted airports. Moreover, we have found evidence that Congress was right in concluding that market power contributed too much to high fares from the perspective of consumers. That is, we find little evidence that competition significantly eroded quality provision, either directly by reducing large incumbent size or indirectly by disincentivizing high frequencies. The only unintended consequence of the legislation appears to be additional congestion related delays, which are unlikely to fully offset the substantial declines in fares.

Our quasi-experimental approach to analyzing the impact of barriers to entry is also somewhat novel in the industrial organization literature, see Angrist and Pischke (2010), and we think our clean identification strategy represents a significant contribution to it. However, our study also highlights some of the difficulties in implementing such a research design, see Einav and Levin (2010) and Nevo and Whinston (2010). While, we are able to explain between 40% to 50% of the decline in fares in covered markets, a result of intensified competition from low-cost carriers, it remains an open question to identify other determinants.

The competition plans and subsequent FAA reports provide at least a subset of the actions taken by airports and seems to provide a good source for identifying other possible explanations. A couple candidates that seem likely to have some explanatory power are the reduction of landing fees for non-signatory carriers to signatory levels as well as limits on subleasing fees that can be charged by one carrier to another for the use of under-utilized boarding gates. Both these steps, discussed in the majority of the airports' competition plans, have the potential to be a significant source of cost pass-throughs from carriers to consumers. In addition, carriers may simply reduce fares to generate outcomes that are consistent with the goals of AIR-21 in order to avoid additional oversight in the future. The list of possible explanations is long and many are difficult to evaluate without making behavioral assumptions and placing additional structure on the econometric model. We leave these questions regarding the source and ultimate welfare implications of the effects we find for future research.

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Figure 1: Coverage Cutoffs

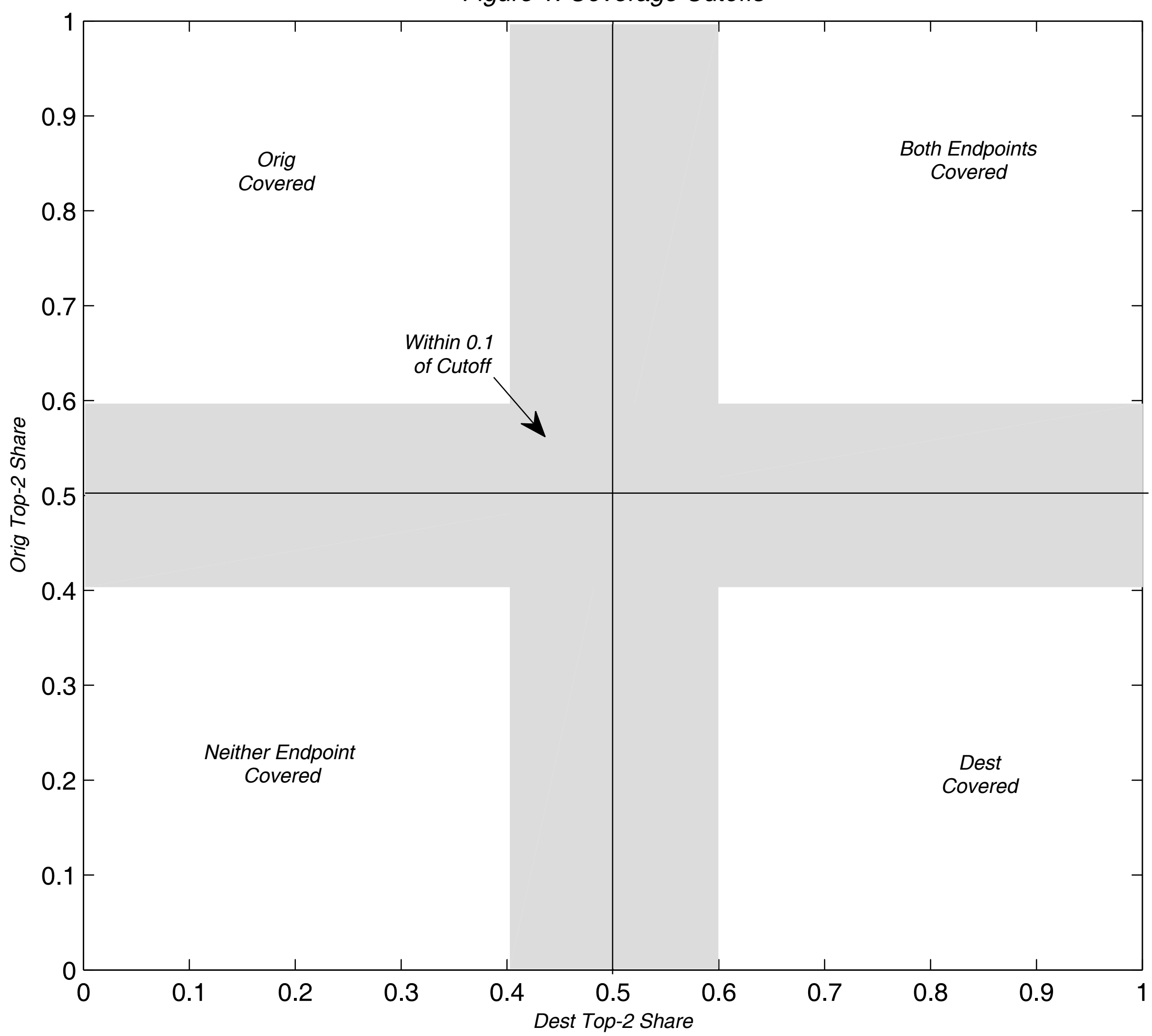


Figure 2: Density over Support of Predictors

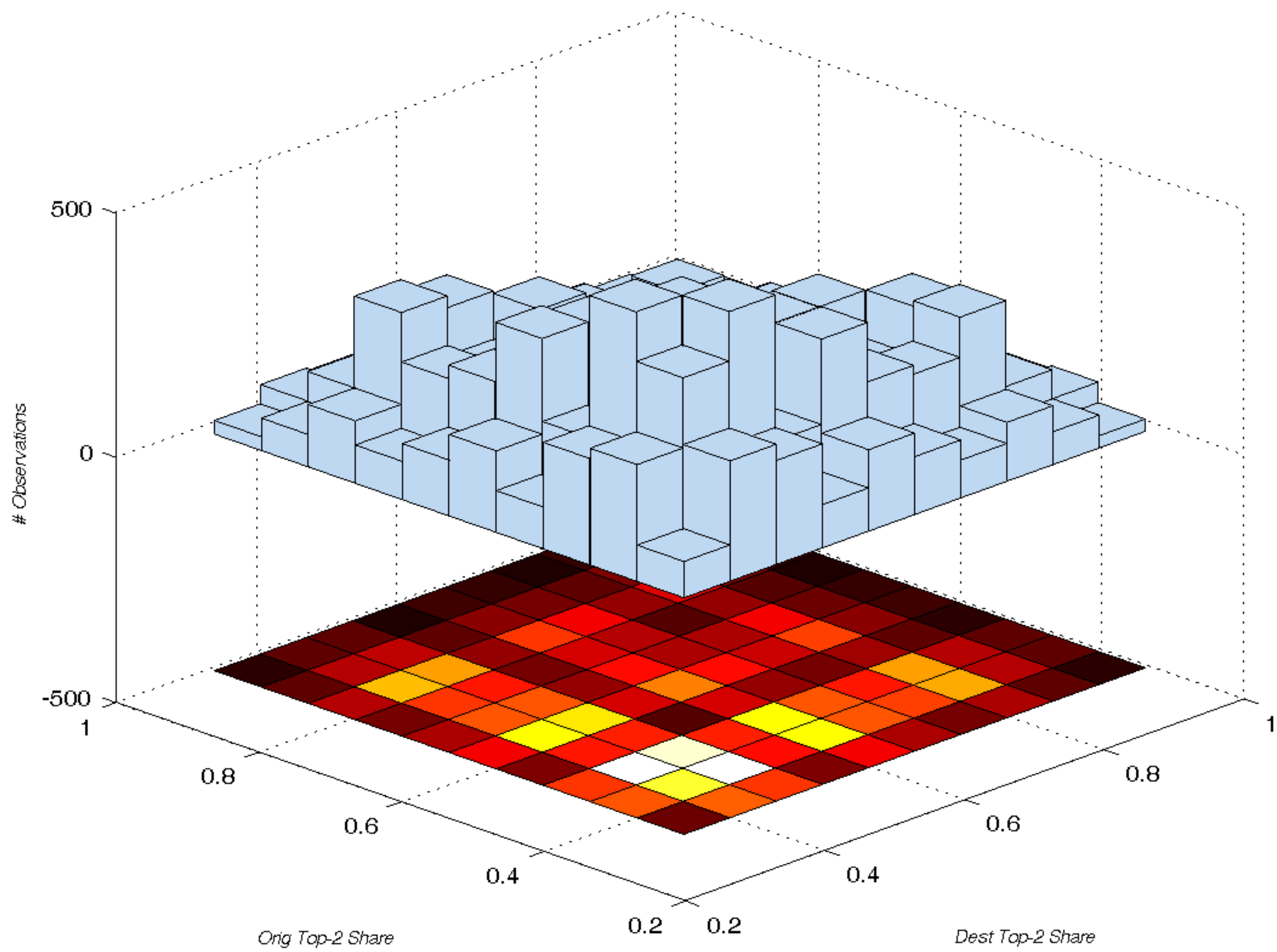


Figure 3: Expectation of Fares

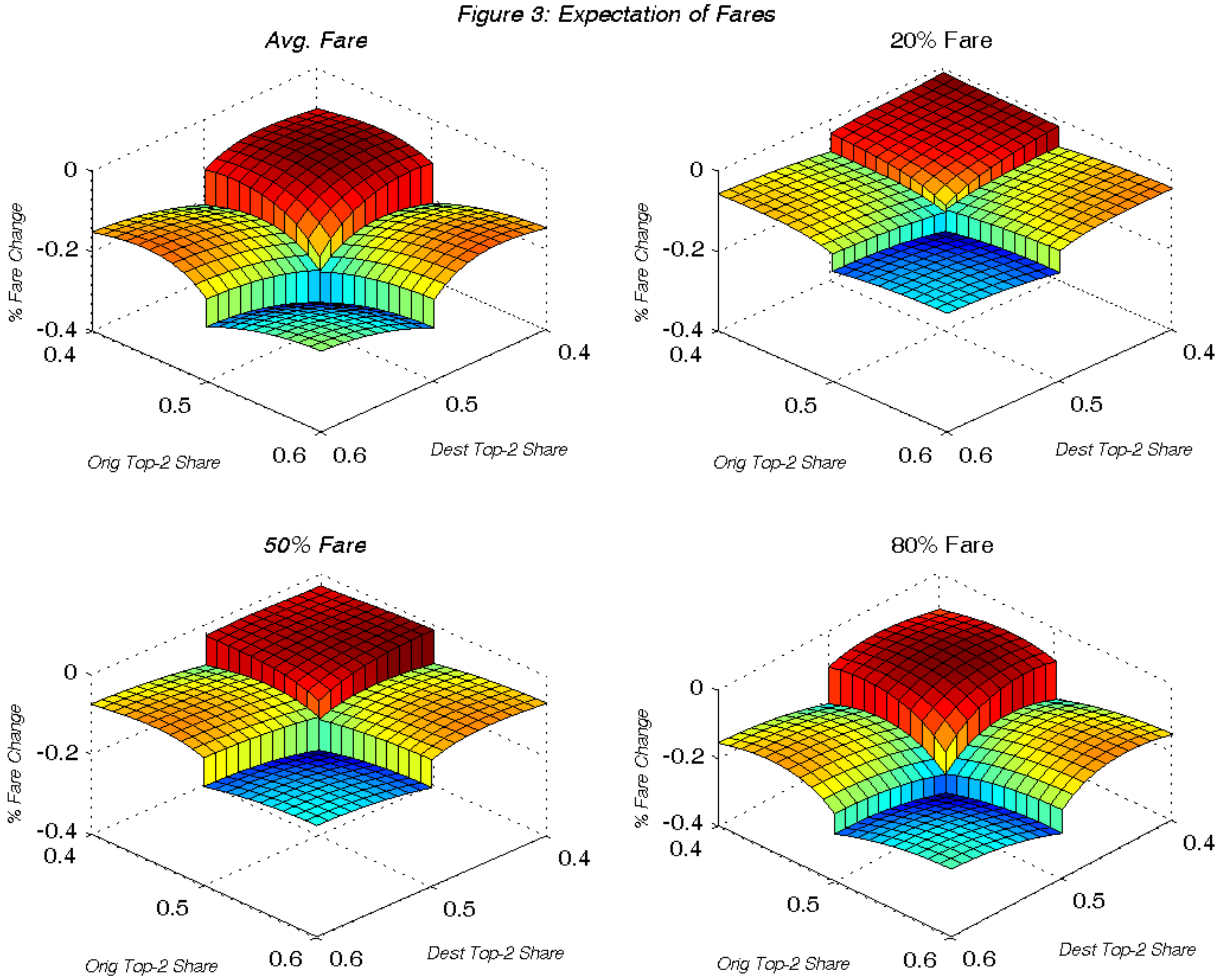


Figure 4: Lcc Presence

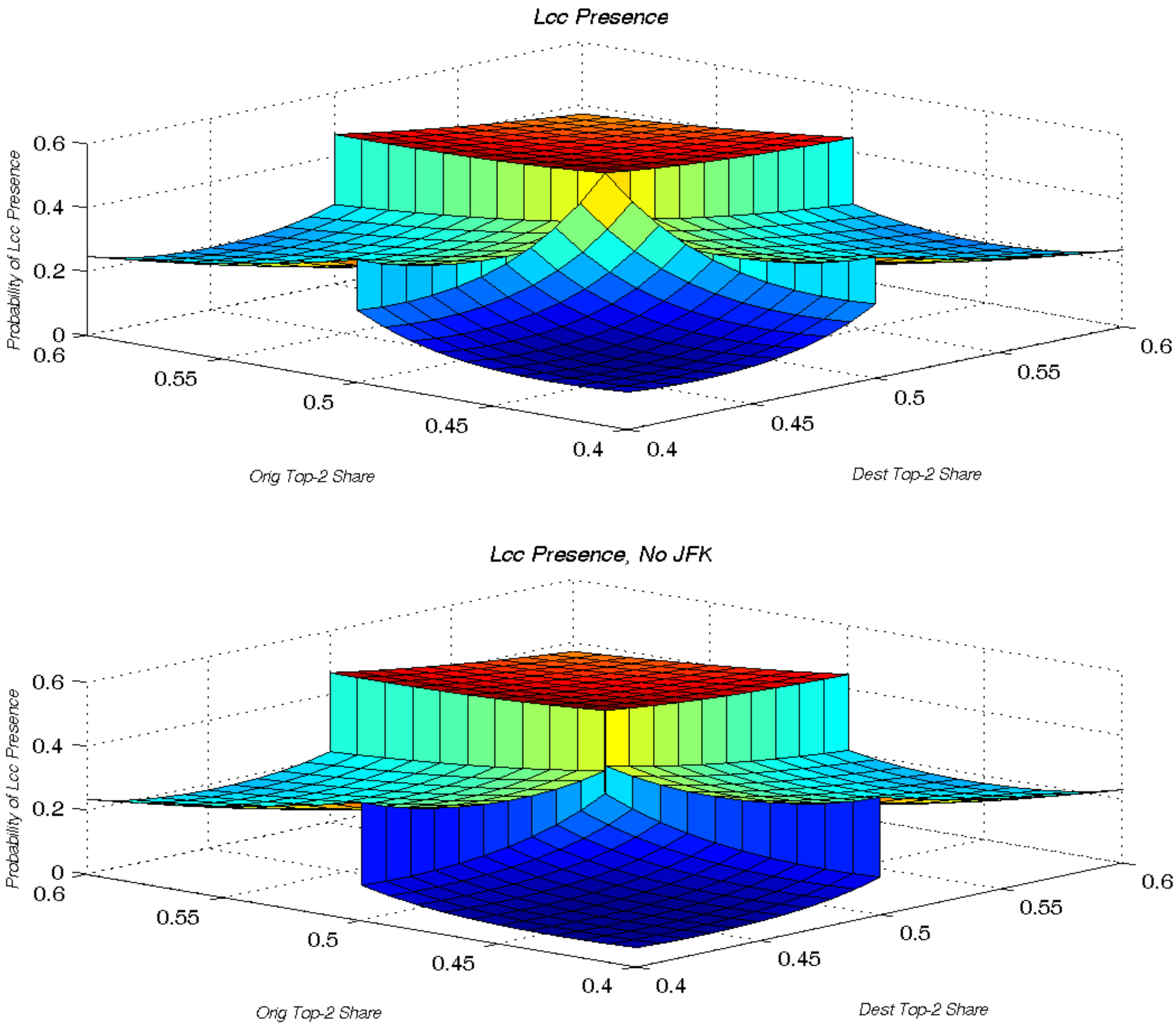
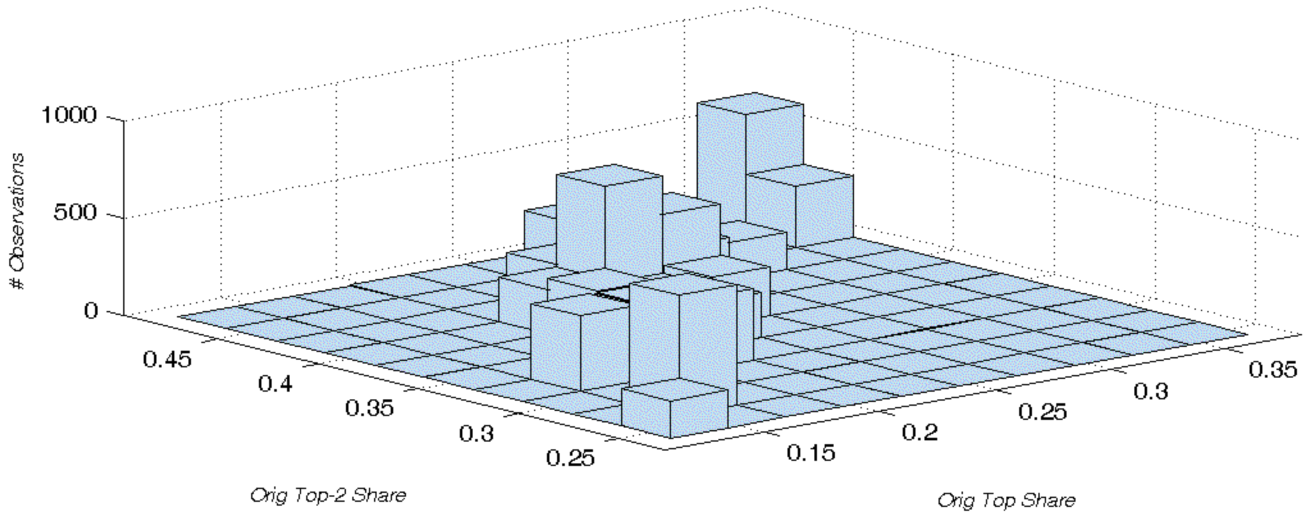


Figure 5: Test for Strategic Manipulation

Density of Observations



Expectation of Fares

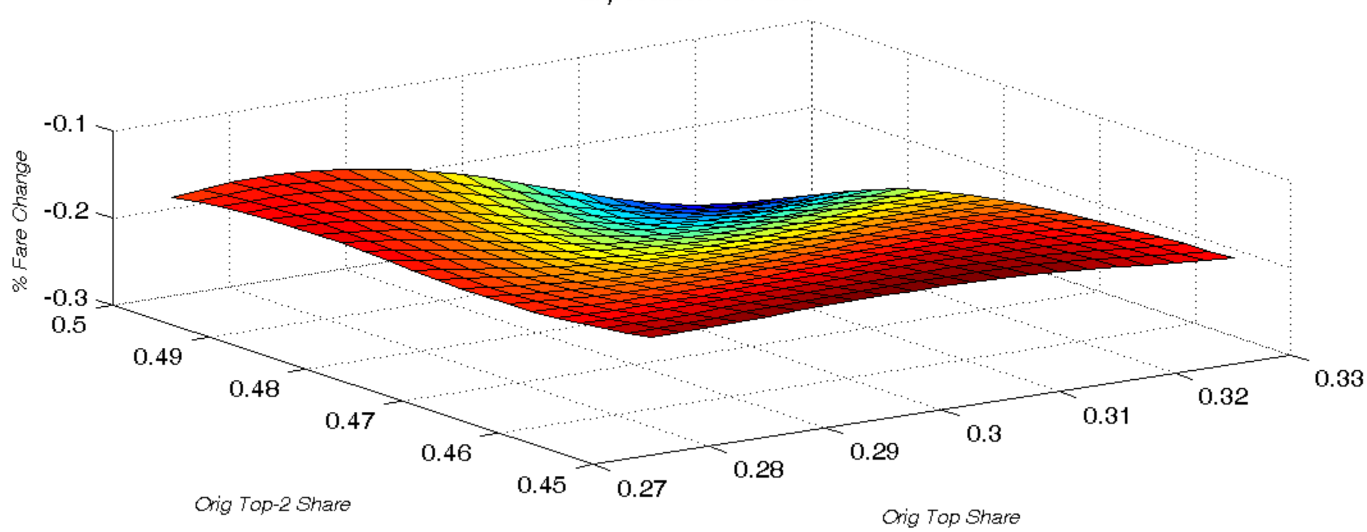


Table 1: Enplanements and Gates for Covered Airports

		Enplanements			Gates					
		US %	Top-2 %		Common %		Legacy %		Lcc %	
Airport	**Yr. Covered**	Mean	Mean	Max	2001	2008	2001	2008	2001	2008
ABQ	2000	0.45%	61.24%	63.97%	26.09%	31.82%	39.13%	63.64%	34.78%	4.55%
ANC	2000	0.36%	55.23%	61.74%	•	•	•	•	•	•
ATL	2000	5.85%	79.17%	82.18%	14.59%	15.08%	72.43%	73.37%	12.97%	11.56%
AUS	2000	0.51%	60.32%	61.80%	28.00%	16.00%	44.00%	52.00%	28.00%	32.00%
BNA	2000	0.64%	59.02%	63.03%	11.48%	9.84%	44.26%	44.26%	44.26%	45.90%
BUR	2000	0.36%	77.98%	83.54%	21.43%	7.14%	28.57%	35.71%	50.00%	57.14%
BWI	2000	1.42%	56.59%	65.95%	•	•	•	•	•	•
CLE	2000	0.84%	58.97%	61.29%	•	•	•	•	•	•
CLT	2000	1.82%	81.43%	86.84%	44.71%	48.35%	55.29%	51.65%	0.00%	0.00%
CVG	2000	1.52%	87.47%	92.87%	•	•	•	•	•	•
DAL	2000	0.48%	97.79%	99.82%	18.75%	0.00%	15.63%	25.00%	65.63%	75.00%
DCA	2001	1.09%	44.06%	50.10%	•	•	•	•	•	•
DEN	2000	2.82%	66.04%	72.44%	•	•	•	•	•	•
DFW	2000	4.06%	77.14%	85.12%	5.47%	17.42%	89.06%	80.00%	5.47%	2.58%
DTW	2000	2.47%	72.71%	76.32%	5.47%	5.08%	84.38%	88.14%	10.16%	6.78%
EWR	2000	2.41%	59.77%	69.90%	•	•	•	•	•	•
HOU	2000	0.61%	89.23%	92.19%	•	•	•	•	•	•
IAD	2001	1.42%	53.70%	59.91%	•	•	•	•	•	•
IAH	2000	2.50%	80.91%	86.12%	•	•	•	•	•	•
JAX	2000	0.37%	46.52%	50.19%	•	•	•	•	•	•
LAS	2005	2.68%	47.81%	52.40%	•	•	•	•	•	•
MDW	2000	1.11%	77.90%	90.37%	•	•	•	•	•	•
MEM	2000	0.80%	72.17%	77.10%	•	•	•	•	•	•
MIA	2001	2.29%	57.22%	68.95%	21.65%	32.04%	74.23%	64.08%	4.12%	3.88%
MKE	2001	0.47%	49.87%	56.49%	17.95%	0.00%	48.72%	21.28%	33.33%	78.72%
MSP	2000	2.44%	75.89%	78.75%	9.52%	8.66%	86.90%	90.55%	3.57%	0.79%
OAK	2000	0.88%	72.26%	78.52%	12.50%	37.93%	16.67%	3.45%	70.83%	58.62%
OGG	2000	0.42%	60.00%	68.59%	•	•	•	•	•	•
ONT	2000	0.48%	59.52%	61.44%	•	•	•	•	•	•
ORD	2000	5.01%	67.79%	74.12%	•	•	•	•	•	•
PBI	2000	0.46%	52.29%	58.64%	50.00%	53.13%	39.29%	34.38%	10.71%	12.50%
PHL	2000	1.92%	60.61%	65.66%	•	•	•	•	•	•
PHX	2000	2.72%	66.85%	68.95%	•	•	•	•	•	•
PIT	2000	1.22%	66.85%	81.65%	•	•	•	•	•	•
PVD	2000	0.39%	56.71%	63.55%	•	•	•	•	•	•
RNO	2000	0.38%	58.91%	62.61%	•	•	•	•	•	•
SAT	2001	0.48%	57.94%	100.00%	16.67%	17.39%	54.17%	52.17%	29.17%	30.43%
SDF	2000	0.27%	45.50%	51.64%	•	•	•	•	•	•
SFO	2000	2.44%	53.42%	56.29%	36.14%	37.04%	60.24%	59.26%	3.61%	3.70%
SJC	2000	0.82%	57.53%	64.18%	•	•	•	•	•	•
SJU	2000	0.74%	62.30%	69.04%	•	•	•	•	•	•
SLC	2000	1.42%	73.60%	80.12%	9.64%	8.43%	80.72%	81.93%	9.64%	9.64%
SMF	2000	0.65%	62.66%	65.90%	21.43%	38.46%	32.14%	19.23%	46.43%	42.31%
STL	2000	1.53%	69.14%	84.04%	4.55%	52.87%	79.55%	34.48%	15.91%	12.64%
Mean	2000.22727	1.45%	64.77%	71.46%	19.79%	22.98%	55.02%	51.29%	25.19%	25.72%

Table 2: Enplanements and Gates for Non-Covered Airports

	Enplanements			**Gates**					
	US %	Top-2 %		Common %		Legacy %		Lcc %	
Airport	Mean	Mean	Max	2001	2008	2001	2008	2001	2008
BDL	0.49%	44.91%	49.15%	•	•	•	•	•	•
BOS	1.87%	34.99%	38.93%	11.90%	10.31%	82.14%	68.04%	5.95%	21.65%
BUF	0.32%	37.59%	49.72%	6.25%	21.74%	78.13%	56.52%	15.63%	21.74%
CMH	0.49%	32.06%	37.66%	19.44%	22.22%	50.00%	58.33%	30.56%	19.44%
FLL	1.27%	35.05%	40.89%	•	•	•	•	•	•
HNL	1.51%	45.34%	48.07%	•	•	•	•	•	•
IND	0.57%	28.50%	32.86%	26.47%	30.00%	52.94%	57.50%	20.59%	12.50%
JFK	2.50%	41.42%	46.15%	•	•	•	•	•	•
LAX	4.22%	34.44%	40.44%	•	•	•	•	•	•
LGA	1.79%	41.34%	44.43%	•	•	•	•	•	•
MCI	0.81%	42.96%	47.56%	•	•	•	•	•	•
MCO	2.16%	36.66%	42.92%	•	•	•	•	•	•
MSY	0.67%	44.68%	47.59%	•	•	•	•	•	•
OKC	0.24%	41.82%	47.67%	0.00%	23.53%	68.75%	52.94%	31.25%	23.53%
OMA	0.28%	39.14%	41.72%	25.00%	35.00%	45.00%	45.00%	30.00%	20.00%
PDX	0.97%	37.15%	38.80%	19.57%	39.13%	32.61%	28.26%	47.83%	32.61%
RDU	0.63%	35.02%	41.34%	2.08%	19.05%	85.42%	66.67%	12.50%	14.29%
RSW	0.43%	39.12%	47.35%	23.53%	39.29%	58.82%	32.14%	17.65%	28.57%
SAN	1.15%	46.34%	47.80%	32.50%	22.50%	42.50%	43.75%	25.00%	33.75%
SEA	2.04%	45.12%	48.33%	21.62%	35.00%	40.54%	25.00%	37.84%	40.00%
SNA	0.62%	36.73%	39.64%	•	•	•	•	•	•
TPA	1.20%	40.40%	42.66%	18.37%	28.81%	63.27%	44.07%	18.37%	27.12%
Mean	1.19%	39.13%	43.71%	17.23%	27.21%	58.34%	48.19%	24.43%	24.60%

Table 3: Means for Covered and Non-Covered Markets

		Pre-AIR21		Post-AIR21			
Market-Carrier-Product	Covered	# Obs.	Mean	# Obs.	Mean	Diff.	Diff. in Diff.
Δ Avg. Fares	yes	11483	-55.650	11950	-55.362	0.288	-35.081
	no	2011	-67.060	2123	-31.691	35.369	
Δ 20^{th} Pct. Fare	yes	11483	-57.158	11950	-11.469	45.689	-9.796
	no	2011	-61.855	2123	-6.369	55.485	
Δ 50^{th} Pct. Fare	yes	11483	-70.439	11950	-26.472	43.967	-23.047
	no	2011	-76.803	2123	-9.790	67.013	
Δ 80^{th} Pct. Fare	yes	11483	-72.178	11950	-92.266	-20.088	-65.638
	no	2011	-97.468	2123	-51.918	45.550	
ΔFlight Distance	yes	11483	0.016	11950	0.007	-0.009	0.008
(Unit = 1000s of Miles)	no	2011	0.021	2123	0.003	-0.017	
Δ Fraction Routes	yes	11483	-0.010	11950	0.049	0.059	-0.001
	no	2011	-0.007	2123	0.052	0.059	
		Pre-AIR21		Post-AIR21			
Market-Carrier	Covered	# Obs.	Mean	# Obs.	Mean	Diff.	Diff. in Diff.
Δ % OnTime	yes	1873	-0.013	1731	0.044	0.057	0.063
	no	133	-0.003	150	-0.009	-0.006	
Δ Departures	yes	3171	66.560	3171	-57.739	-124.299	-85.177
	no	400	22.115	401	-17.007	-39.122	
		Pre-AIR21		Post-AIR21			
Market	Covered	# Obs.	Mean	# Obs.	Mean	Diff.	Diff. in Diff.
Δ Avg. Hub Premium	yes	1999	13.295	1990	-24.720	-38.014	-23.939
	no	253	4.374	262	-9.701	-14.075	
Δ 20th Pct. Hub Premium	yes	1999	1.747	1990	-12.139	-13.886	-13.530
	no	253	-3.125	262	-3.481	-0.356	
Δ 50th Pct. Hub Premium	yes	1999	9.151	1990	-15.428	-24.578	-30.775
	no	253	-4.300	262	1.897	6.197	
Δ 80th Pct. Hub Premium	yes	1999	28.667	1990	-42.235	-70.903	-54.690
	no	253	10.424	262	-5.788	-16.212	
Δ Lcc Penetration	yes	3171	0.319	3171	0.225	-0.095	0.231
	no	400	0.533	401	0.207	-0.326	
Δ Number Firms	yes	3171	0.942	3171	-0.321	-1.264	0.500
	no	400	1.250	401	-0.514	-1.764	
Δ % Nonstop	yes	3171	0.022	3171	0.034	0.013	-0.050
	no	400	-0.013	401	0.050	0.063	

Table 4: Avg. Fare Regressions

	All Markets		0.2 of Cutoff		0.1 of Cutoff	
	N=9,022		N=8,479		N=5,866	
Log(Avg. Fare)	(1)	(2)	(3)	(4)	(5)	(6)
1[1 cover]	-0.108***	-0.069***	-0.108***	-0.070***	-0.102***	-0.078***
	(0.023)	(0.022)	(0.023)	(0.022)	(0.023)	(0.023)
1[2 cover]	-0.195***	-0.102***	-0.191***	-0.100***	-0.202***	-0.124***
	(0.025)	(0.024)	(0.025)	(0.025)	(0.030)	(0.030)
Nonstop	-0.124***	-0.112***	-0.122***	-0.110***	-0.102***	-0.090***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.017)	(0.017)
Fraction Routes	0.448***	0.530***	0.477***	0.545***	0.488***	0.542***
	(0.036)	(0.035)	(0.038)	(0.036)	(0.045)	(0.043)
Flight Distance	0.239***	0.240***	0.238***	0.235***	0.204***	0.190***
	(0.045)	(0.046)	(0.046)	(0.047)	(0.051)	(0.052)
LccPresence	•	-0.174***	•	-0.173***	•	-0.143***
		(0.011)		(0.011)		(0.013)
NumberFirms	•	-0.001	•	0.001	•	0.001
		(0.004)		(0.005)		(0.005)
R^2	0.096	0.175	0.097	0.173	0.099	0.156
Borenstein-Rose (1994) Controls	no	yes	no	yes	no	yes

Notes

1) Additional controls include Population Origin, Population Dest, Per-Cap Income Origin, Per-Cap Income Dest.

Table 5: Fare Distribution Regressions

	All Markets		0.2 of Cutoff		0.1 of Cutoff	
	N=9,022		N=8,479		N=5,866	
Log(20% Fare)	(1)	(2)	(3)	(4)	(5)	(6)
1[1 cover]	-0.022	-0.004	-0.021	-0.004	-0.017	-0.006
	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)
1[2 cover]	-0.073***	-0.029	-0.082***	-0.038*	-0.041	-0.001
	(0.020)	(0.020)	(0.020)	(0.020)	(0.026)	(0.025)
LccPresence	•	-0.087***	•	-0.086***	•	-0.074***
		(0.009)		(0.010)		(0.012)
NumberFirms	•	-0.018***	•	-0.017***	•	-0.013***
		(0.004)		(0.004)		(0.005)
R^2	0.053	0.100	0.056	0.102	0.046	0.087
Log(50% Fare)						
1[1 cover]	-0.080***	-0.049**	-0.080***	-0.051**	-0.074***	-0.060**
	(0.025)	(0.024)	(0.025)	(0.024)	(0.025)	(0.024)
1[2 cover]	-0.161***	-0.085***	-0.158***	-0.085***	-0.132***	-0.069**
	(0.027)	(0.027)	(0.028)	(0.027)	(0.034)	(0.033)
LccPresence	•	-0.158***	•	-0.154***	•	-0.121***
		(0.012)		(0.013)		(0.016)
NumberFirms	•	-0.019***	•	-0.019***	•	-0.017***
		(0.005)		(0.005)		(0.006)
R^2	0.065	0.123	0.065	0.123	0.058	0.105
Log(80% Fare)						
1[1 cover]	-0.136***	-0.085***	-0.135***	-0.086***	-0.128***	-0.100***
	(0.032)	(0.031)	(0.032)	(0.031)	(0.032)	(0.031)
1[2 cover]	-0.245***	-0.123***	-0.231***	-0.111***	-0.244***	-0.141***
	(0.034)	(0.034)	(0.035)	(0.034)	(0.041)	(0.040)
LccPresence	•	-0.230***	•	-0.230***	•	-0.187***
		(0.015)		(0.016)		(0.019)
NumberFirms	•	-0.002	•	0.000	•	-0.005
		(0.006)		(0.006)		(0.007)
R^2	0.077	0.142	0.077	0.140	0.079	0.132
Borenstein-Rose (1994) Controls	no	yes	no	yes	no	yes

Notes

1) Additional controls include Population Origin, Population Dest, Per-Cap Income Origin, Per-Cap Income Dest.

Table 6: Hub Premium Regressions

	All Markets	0.2 of Cutoff	0.1 of Cutoff
	N=1,491	N=1,350	N=906
Hub Premium Avg. Fare	(1)	(2)	(3)
1[1 cover]	-0.137***	-0.139***	-0.126***
	(0.037)	(0.037)	(0.039)
1[2 cover]	-0.246***	-0.246***	-0.232***
	(0.038)	(0.039)	(0.047)
R^2	0.125	0.123	0.148
Hub Premium 20% Fare			
1[1 cover]	-0.106***	-0.105***	-0.095***
	(0.033)	(0.033)	(0.033)
1[2 cover]	-0.195***	-0.198***	-0.153***
	(0.034)	(0.035)	(0.042)
R^2	0.041	0.039	0.036
Hub Premium 50% Fare			
1[1 cover]	-0.190***	-0.187***	-0.178***
	(0.044)	(0.044)	(0.046)
1[2 cover]	-0.328***	-0.318***	-0.276***
	(0.047)	(0.047)	(0.058)
R^2	0.078	0.070	0.074
Hub Premium 80% Fare			
1[1 cover]	-0.145***	-0.147***	-0.118**
	(0.055)	(0.055)	(0.057)
1[2 cover]	-0.285***	-0.277***	-0.278***
	(0.056)	(0.057)	(0.070)
R^2	0.069	0.062	0.080

Notes

1) Additional controls include Nonstop, FractionRoutes, Flight Distance, Population Origin, Population Dest, Per-Cap Income Origin, Per-Cap Income Dest.

Table 7: Quality Regressions

	All Markets	0.2 of Cutoff	0.1 of Cutoff
% Nonstop	(1)	(2)	(3)
1[1 cover]	-0.014	-0.014	-0.012
	(0.010)	(0.010)	(0.010)
1[2 cover]	-0.015	-0.016	-0.016
	(0.010)	(0.010)	(0.012)
R^2	0.000	0.001	0.001
N	12,216	11,435	7,718
Log(Departures)			
1[1 cover]	0.328	0.321	0.420*
	(0.227)	(0.227)	(0.244)
1[2 cover]	0.341	0.340	0.344
	(0.229)	(0.232)	(0.262)
R^2	0.003	0.003	0.006
N	1,465	1,246	771
% OnTime			
1[1 cover]	0.167***	0.169***	0.166***
	(0.029)	(0.029)	(0.029)
1[2 cover]	0.197***	0.188***	0.188***
	(0.029)	(0.030)	(0.033)
R^2	0.052	0.051	0.057
N	1,267	1,066	675
Log(Number Routes)			
1[1 cover]	-0.034	-0.058	-0.092
	(0.075)	(0.080)	(0.104)
R^2	0.011	0.010	0.012
N	366	272	146

Notes

1) Additional controls include Population Origin, Population Dest, Per-Cap Income Origin, Per-Cap Income Dest.

Table 8: Competition Regressions

	All Markets	0.2 of Cutoff	0.1 of Cutoff
	N=2,979	N=	N=1,826
Lcc Presence	(1)	(2)	(3)
1[1 cover]	0.142***	0.145***	0.096**
	(0.045)	(0.045)	(0.046)
1[2 cover]	0.395***	0.404***	0.428***
	(0.046)	(0.047)	(0.058)
R^2	0.033	0.036	0.038
Log(Number Firms)			
1[1 cover]	0.107	0.113	0.109
	(0.138)	(0.138)	(0.148)
1[2 cover]	0.043	0.102	0.190
	(0.143)	(0.144)	(0.179)
R^2	0.003	0.002	0.003

Notes

1) Additional controls include Population Origin, Population Dest, Per-Cap Income Origin, Per-Cap Income Dest.

Table 9: RDD Coverage Estimates, Fares

Predictor	One Endpoint Covered				Predictor	Both Endpoints Covered			
	$\tau(P^{orig}<0.5, P^{dest}=0.5)$		$\tau(P^{orig}=0.5, P^{dest}<0.5)$			$\tau(P^{orig}>0.5, P^{dest}=0.5)$		$\tau(P^{orig}=0.5, P^{dest}>0.5)$	
	Log(Avg. Fare)					**Log(Avg. Fare)**			
	estimate	std. err.	estimate	std. err.		estimate	std. err.	estimate	std. err.
0.4	-0.1***	(0.011)	-0.088***	(0.01)		-0.081***	(0.012)	-0.077***	(0.012)
0.42	-0.09***	(0.01)	-0.079***	(0.009)		-0.077***	(0.012)	-0.075***	(0.012)
0.44	-0.077***	(0.01)	-0.067***	(0.009)		-0.074***	(0.011)	-0.073***	(0.011)
0.46	-0.064***	(0.01)	-0.056***	(0.01)		-0.071***	(0.011)	-0.071***	(0.011)
0.48	-0.051***	(0.012)	-0.045***	(0.011)		-0.07***	(0.011)	-0.071***	(0.011)
0.5	-0.037***	(0.015)	-0.032***	(0.015)		-0.069***	(0.011)	-0.071***	(0.011)
	Log(20% Fare)					**Log(20% Fare)**			
	estimate	std. err.	estimate	std. err.		estimate	std. err.	estimate	std. err.
0.4	-0.051***	(0.007)	-0.046***	(0.007)		-0.048***	(0.009)	-0.053***	(0.008)
0.42	-0.046***	(0.007)	-0.042***	(0.006)		-0.044***	(0.008)	-0.052***	(0.008)
0.44	-0.041***	(0.007)	-0.038***	(0.007)		-0.042***	(0.007)	-0.051***	(0.007)
0.46	-0.034***	(0.008)	-0.033***	(0.007)		-0.042***	(0.007)	-0.052***	(0.007)
0.48	-0.025***	(0.009)	-0.027***	(0.008)		-0.042***	(0.007)	-0.053***	(0.007)
0.5	-0.01	(0.011)	-0.016	(0.011)		-0.044***	(0.007)	-0.056***	(0.007)
	Log(50% Fare)					**Log(50% Fare)**			
	estimate	std. err.	estimate	std. err.		estimate	std. err.	estimate	std. err.
0.4	-0.084***	(0.009)	-0.073***	(0.008)		-0.083***	(0.011)	-0.077***	(0.011)
0.42	-0.076***	(0.008)	-0.063***	(0.008)		-0.078***	(0.01)	-0.073***	(0.01)
0.44	-0.067***	(0.008)	-0.054***	(0.008)		-0.074***	(0.01)	-0.071***	(0.01)
0.46	-0.059***	(0.009)	-0.047***	(0.009)		-0.072***	(0.01)	-0.069***	(0.01)
0.48	-0.052***	(0.01)	-0.043***	(0.01)		-0.071***	(0.01)	-0.069***	(0.01)
0.5	-0.047***	(0.012)	-0.04***	(0.013)		-0.072***	(0.009)	-0.07***	(0.009)
	Log(80% Fare)					**Log(80% Fare)**			
	estimate	std. err.	estimate	std. err.		estimate	std. err.	estimate	std. err.
0.4	-0.112***	(0.012)	-0.109***	(0.012)		-0.054***	(0.016)	-0.055***	(0.016)
0.42	-0.103***	(0.011)	-0.098***	(0.011)		-0.056***	(0.015)	-0.059***	(0.015)
0.44	-0.092***	(0.011)	-0.088***	(0.011)		-0.057***	(0.014)	-0.062***	(0.014)
0.46	-0.082***	(0.012)	-0.08***	(0.012)		-0.057***	(0.014)	-0.064***	(0.013)
0.48	-0.074***	(0.014)	-0.073***	(0.014)		-0.058***	(0.013)	-0.066***	(0.013)
0.5	-0.065***	(0.019)	-0.066***	(0.019)		-0.06***	(0.013)	-0.069***	(0.013)

Table 10: RDD Coverage Estimates, Lcc Presence

Predictor	One Endpoint Covered $\tau(P^{orig}<0.5,P^{dest}=0.5)$		One Endpoint Covered $\tau(P^{orig}=0.5,P^{dest}<0.5)$		Predictor	Both Endpoints Covered $\tau(P^{orig}>0.5,P^{dest}=0.5)$		Both Endpoints Covered $\tau(P^{orig}=0.5,P^{dest}>0.5)$	
	Lcc Presence					**Lcc Presence**			
	estimate	std. err.	estimate	std. err.		estimate	std. err.	estimate	std. err.
0.4	0.158***	(0.021)	0.147***	(0.02)		0.144***	(0.022)	0.153***	(0.02)
0.42	0.115***	(0.019)	0.105***	(0.018)		0.159***	(0.021)	0.168***	(0.018)
0.44	0.074***	(0.02)	0.067***	(0.02)		0.173***	(0.02)	0.182***	(0.017)
0.46	0.023	(0.022)	0.02	(0.023)		0.185***	(0.019)	0.195***	(0.017)
0.48	-0.049	(0.028)	-0.047	(0.03)		0.197***	(0.019)	0.207***	(0.017)
0.5	-0.153***	(0.039)	-0.143***	(0.042)		0.207***	(0.019)	0.219***	(0.017)
	Lcc Presence - No JFK					**Lcc Presence - No JFK**			
	estimate	std. err.	estimate	std. err.		estimate	std. err.	estimate	std. err.
0.4	0.26***	(0.018)	0.249***	(0.016)		0.173***	(0.024)	0.188***	(0.021)
0.42	0.213***	(0.015)	0.206***	(0.014)		0.19***	(0.022)	0.202***	(0.019)
0.44	0.177***	(0.014)	0.173***	(0.014)		0.204***	(0.02)	0.214***	(0.018)
0.46	0.145***	(0.015)	0.144***	(0.017)		0.217***	(0.02)	0.226***	(0.017)
0.48	0.111***	(0.02)	0.117***	(0.022)		0.228***	(0.019)	0.236***	(0.017)
0.5	0.072***	(0.028)	0.087***	(0.032)		0.237***	(0.019)	0.247***	(0.017)