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**Do Internet Converge Prices to the 'Law of One Price'?**
**Evidence from Transaction Data for Airline Tickets**

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# Do Internet Converge Prices to the "Law of One Price"? Evidence from Transaction Data for Airline Tickets

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## Abstract:

Internet presumably reduces search cost driving price to the competitive level. Evidence from empirical research quantifying dispersion in the electronic based markets has yield mixed results. More recent research has documented near zero dispersion in the electronic markets using transaction prices. This paper is one of only a handful of papers to examine the impact of internet on price dispersion using contemporaneous online and offline transaction data for airline ticket prices. The paper finds strong empirical evidence of lower dispersion in the electronic markets compared to the traditional markets, but fails to find evidence of near zero dispersion in the electronic markets, even with transaction prices. The results suggest that electronic markets exhibits significantly lower but positive dispersion, in contrary to the near zero dispersion as found in more recent empirical literature.

Keywords: Price Dispersion, Search cost, Online, Offline, Transaction Prices.
JEL Classification: L9.

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# I. Introduction

The proposed research undertakes a comprehensive analysis of comparing price dispersion in the internet based electronic markets and traditional market for airline tickets. This novel data set includes data on individual ticket transactions including the ticket characteristics associated with each transaction, carrier, flight level load factor, the date of issue, departure date and whether the ticket was purchased online or offline. The data also includes particular ticket characteristics including refundability, advance purchase requirements, travel and stay restrictions including Saturday stay-over, and other hedonic factors affecting the pricing of airline seats.

This paper will use this data set to compare the magnitude of price dispersion between the electronic and traditional markets. This paper is one of only a handful of papers to examine the impact of internet on price dispersion using contemporaneous online and offline transaction data. More importantly, this paper will provide some of the first direct comparisons of online versus offline price dispersion for one of the major industries in US, where the identity of the online and offline transactions involve the same ultimate supplier. The results of this study will contribute substantially to our understanding of the internet, its impact on market efficiency, and the role of product characteristics and load factor in determining the dispersion in prices of the airline seats.

Price dispersion is an important index of market efficiency. Internet presumably reduces search costs, creating more efficient, competitive and frictionless markets. Improved information presumably should foster convergence to the 'law of one price'.

Despite these strong theoretical predictions, the empirical literature has been limited, investigating prices in only a few settings. Bailey (1998) compares the prices of books, music CDs and software titles sold through Internet and conventional outlets to find an equal magnitude of price dispersion across these channels. Brynjolfsson and Smith (2000) compare the prices of CDs and books in both traditional and electronic markets and find online prices and price dispersion to be lower than in offline market. Scholten and Smith (2002) however, find higher price dispersion in the Internet market for a variety of consumer goods.

In a more recent work, Ghose and Yao (2006) finds empirical evidence of near-zero dispersion in the internet markets as compared to a positive dispersion in the more traditional markets. Using contemporaneous online and offline transaction data on paints, brushes and other merchandise, the authors report near absence of dispersion in the internet markets, supporting the ‘law of one price’.

The proposed study parallels Ghose and Yao (2006), though the dimension of product heterogeneity is more complex. Further, this study revisits some of the well established literature in airlines industry to investigate the role of the ticket characteristics in explaining the price dispersion for airline tickets.

The airlines market differs from those of CDs, books, insurance and others analyzed. In the airline market, each city pair generally represents a distinct market. Put differently, the Dallas-Chicago route comprises a group of travelers who wish to travel by air between the two cities, roughly constituting a market. Some of these purchases occur online, while others offline. Customers can and do purchase tickets online or offline, allowing one to directly compare pricing and dispersion for these distinct channels. There is also considerable variation in passenger characteristics across city-pairs. For example, Dallas to Chicago consists primarily of business travelers while Dallas to Las Vegas consists primarily of tourist (leisure) travelers.

This study fills some of these voids in the existing literature comparing market efficiencies between the traditional and internet markets. Much of the existing empirical literature relies on posted data on the internet as their source of 'internet prices' to estimate price dispersion. Use of such posted data may lead to an overestimation of the effect of price dispersion because in principle a sale may not have occurred at that posted price. Additionally, some studies fail to adequately control for product characteristics and consequently overestimate the degree of price dispersion in a market. Further, these studies often compare the 'national' internet prices to the local store prices while comparing market efficiencies in the two markets. In this sense, much of these studies suffer from the drawback of a well defined market. The unique data used in this study minimizes these limitations.

We use a unique contemporaneous online and offline transaction data where the identity of the ultimate seller is same. Also, our data allows for a well defined market, where the market is an airport city pair. Finally, this data controls for numerous ticket characteristics namely refundability, advance purchase requirement, travel and stay restriction, load factor at time of purchase, departure and return day of the week as well time of the day. Use of such an exhaustive set of control allows us to measure the degree of dispersion net of product characteristics and market specific effects, which the existing literature fails to offer.

Our analysis also contributes to the existing literature of price dispersion in airlines and the sources of price dispersion. Borenstein and Rose (1994) attribute price dispersion to monopolistically competitive markets but do not control for ticket characteristics. Stavins (2001) uses a sub-set of ticket characteristics to explain price discrimination but fails to control for flight level load factors which is an important driver of the dispersion. This study uses better data to correct these deficiencies and also controls for internet purchases, contributing significantly to our general understanding of the dynamics of airline pricing.

This analysis is made possible by a unique data set from one of the computer reservation system. Apart from the standard variables used in the empirical airline literature namely we also use a complete set of ticket characteristics. This includes prices paid, refundability of tickets, advance purchase requirement, days prior to departure the ticket is bought and contemporaneous load factor, booking class, cabin class, minimum or maximum stay requirements, travel restrictions, issue-departure-return day, and flight numbers. We use the information to construct other variables. The complete set of variables used is discussed in the estimation technique section.

The set of variables provides us with a unique set of control that is required to analyze the issues at hand. This analysis distinguishes itself from the existing literature both in the area of airline pricing and effect of electronic markets on the market for airline tickets. This study, to the best of our knowledge is only a handful of studies that use a contemporaneous online and offline transaction data to compare the market efficiencies between electronic market and traditional market. This underscores the scope and significance of this study.

## II. Literature Review

Internet has revolutionized the way people buy and sell. The ease of search on the internet has led to a surge of interest among the economists to study its impact on prices and price dispersion in different markets. There has been considerable research in recent years that have attempted to investigate if internet creates a 'frictionless' market and cause the distribution of prices to shrink to the law of one price as the economic theory would predict in markets with perfect information. Recent research has also attempted to compare the distribution of prices in online and offline markets to find empirical evidence of shrinking price dispersion in the online markets. This section provides a comprehensive overview of the more important research findings in recent years.

Empirical literature on analysis of the effects of the internet on prices, both levels and dispersion, is mixed. Bakos (1997) was one of the first to empirically find evidence of lower dispersion in the internet markets as compared to the physical retailers, attributing this difference to the typically lower search costs in the internet markets. Brynjolfsson and Smith (2000) compared the prices and dispersion for online and offline markets individually, for twenty titles of books and compact discs (CDs) over a period of year to find similar magnitudes of dispersion in the two markets. They found that the online prices were lower in the online markets while the dispersion in the two markets was comparable. The dispersion in the online markets was marginally lower once the market share of the online retailers (measured by web traffic) was accounted for. Lee and Gosain (2002) studied the price dispersion in the market for music CDs to find similar results that there was not much difference in the level of price dispersion between the two markets while the internet prices were generally lower than the physical retailer, confirming the results of Brynjolffson and Smith (2000).

Contrary results to those mentioned above were found in some markets. Erevelles, Rolland and Srinivasan (2001) finds persistent higher dispersion in the internet markets for vitamins when compared to other channels of physical retailing namely drug stores, discount retailers, super markets and warehouse retailers. Also, they found that the average prices in the electronic retailers were significantly higher than the more traditional retailers.

Clemons, Hann and Hitt (2001) studied the issue of dispersion in the airline ticket prices across different online travel agents (OTA) using data from 1997. After controlling for different ticket attributes like Saturday night stay-over, time of arrival and departure, number of connections or stop over they find prices vary by almost 18 percent across the different online websites, even after controlling for ticket heterogeneities. One argument for this apparently large dispersion can be attributed to the lack of control for other product heterogeneities namely ticket characteristics like refundability, advance purchase restriction, travel restrictions, meal offering among others, that have been found to explain the variations in the prices to a great degree. Chen (2006) using data from online travel agents in 2002, however, finds evidence of little fare disparity among the OTAs and contributes to the maturity of the OTAs over time.

The mixed bag evidences of the comparisons of price dispersion and average prices between the conventional and internet markets, has contributed much to the ongoing research in this field. All of these earlier works suffer from one common drawback. Most of these studies have been performed on electronic markets at a time when the internet markets have not reached its maturity such that much of the higher dispersion in the internet markets can be attributed to the lack of maturity in the electronic marketplaces. The implications of information dissemination and hence the internet on levels and dispersion of prices can be better understood with a data that spans a period where the presence of internet in a marketplace grew over time, from being non-existent to a significant presence.

More recent studies of price dispersion show that the level of price dispersion in the internet market is decreasing over time. Pan et. all (2003) provided the most recent evidence on online price dispersion. Comparing prices for different products line books, CDs, DVDs, computers and other varieties of consumer electronic goods, covering a time period between November 2000 and February 2003; they report a 10 percent decline in average prices from 38.5 percent to about 28 percent. These findings are consistent to what Baye, Morgan and Scholten (2004) finds by studying online monthly prices for thirty six popular consumer electronic products listed on one of the established websites, Shopper.com. Using a 18 month sample period for the products, they report a significant decrease of percentage price difference from 70 percent to about 30 percent, more than a 100 percent decline.

A variety of other factors can also be argued to contribute to the persistent dispersion in the internet markets. Brand loyalty (Lal and Sarvary (1999), bundling of products (Varian (1980)), difference in service (Pan et. all (2002)) quality are some of them. Analysis of these factors affecting the price dispersion lie beyond the scope of this dissertation and hence is left for future research.

The existing body of literature, with a few exceptions, is often criticized on the basis of two arguments. Firstly, some amount of dispersion can be explained by product heterogeneity and not difference in search. A second line of skepticism is that dispersion in posted prices may not be in consonance with uniformity in prices actually paid. Those who post higher prices may not sell anything such that it requires prices to be weighed by the market shares of the sellers resulting in less dispersed prices than if all sellers are given equal weights. A final line of criticism lie in the comparison between the posted 'national' internet prices with prices from disparate local stores. The latter price, though from a traditional physical store, can be region specific and may not be representative of the national level of prices which the internet prices are on average. In this spirit, prices recorded from the local stores (Scholten and Smith (2001)) may not be comparable to the posted prices on the internet.

One of these criticisms is addressed in a more recent work by Ghose and Yao (2006). Most of the existing research has relied much on posted price data to estimate price dispersion. This in principle can lead to overestimation of the effect of price dispersion since a sale may not have occurred at that posted price. Ghose and Yao (2006) using a contemporaneous online and offline transaction data on variety of products (office supplies, packaging materials, hardware tools) re-evaluates the magnitude of price dispersion in the electronic and traditional markets individually. Using this transaction data, the authors find strong empirical evidence of almost no dispersion in the electronic markets as compared to the traditional markets. The near-zero dispersion in electronic markets suggests that the "law of one price" is a valid argument in some markets, specifically when transaction data is used to measure the dispersion. The paper also finds evidence of a persistent lower dispersion in the electronic markets, for all categories of products.

This proposed study parallels Ghose and Yao (2006) by comparing price dispersion in the internet based electronic markets and traditional markets for airline tickets. We use a novel data set for airline tickets that includes data on individual ticket transactions including the ticket characteristics associated with each transaction, carrier, flight level load factor, the date of issue, departure date and whether the ticket was purchased online or offline. The data also includes particular ticket characteristics including refundability, advance purchase requirements, travel and stay restrictions including Saturday stay-over, and other hedonic factors affecting the pricing of airline seats. We use this data set to compare the magnitude of price dispersion between the electronic and traditional markets using transaction data and investigate if the "law of one price" holds valid in the market for airline tickets.

## III. Dynamics of Airline Pricing

Airlines offer a wide variety of different fares for travel on the same flight and the same day. The available evidence indicates that airlines offer tickets for sale in a conceptual series of "bins" or "buckets," where a bucket is defined by a series of ticket characteristics including class of travel, refundability, advance purchase requirements, and travel and stay restrictions such as minimum and maximum stays and/or Saturday stay-over.[2] The received wisdom is that airlines limit the quantity of low price tickets by limiting the number of tickets in low price buckets. For example, certain combinations of characteristics may only be used during certain days of the week (e.g. TWF), and certain tickets may only be available for round trips. Certain fares may not be available on certain flights for a period of time, and then later become available. High priced tickets

[2] See Smith (2001).

are sometimes sold far in advance of departure, and deeply discounted tickets in certain bins may be available on the day of departure.

Airlines can alter the prices passengers ultimately pay for tickets both by changing the price of tickets within a given bucket and by rationing the number of tickets in that bucket.[3] The general analysis of this issue is beyond the scope of this paper.

For the present analysis it is simply important to note that airlines price using these ticket characteristics, which implicitly place tickets in particular bins that feature different prices. The analysis below shows that variation in ticket prices is driven largely by variation in ticket characteristics in that a simple regression of price on ticket characteristics, carrier and route dummies explains roughly 80 percent of the variation in ticket prices.

Airline customers and travel agents search for airline tickets by attempting to find sets of characteristics the customer is willing to accept at the lowest possible price. The most important component of this search, in terms of its impact on the ultimate price, is to find an open "bucket" with acceptable characteristics that has a low price. An empirically smaller effect is found by identifying low priced tickets within a given bucket. The analysis below separately identifies internet price reductions that occur due to finding lower priced buckets and from finding lower prices within a given bucket. It also identifies the externality of increased internet purchases in terms of driving down overall fares.

The search for low price tickets may take place either online where the customer directly investigates the fares offered by one or more online sites, or it may take place offline where the ultimate customer uses a travel agent.

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[3] See Smith (2001).

## IV. **Data**

This study uses a unique data set consisting of contemporaneous online and offline transaction data of airline tickets for the last quarter of 2004.[4] This data were provided by a leading Computer Reservation System (CRS) vendor and include all transactions for a large number of domestic routes handled by the CRS during that quarter. The CRS offers services to airlines, travel agents, and numerous online sites, so that the data include transactions for all three outlets, though we believe the share for airline sites is small. As noted above, the data from the CRS includes airline and flight number, origin and destination, fare, booking class, a fare code, and dates of purchase, departure and return. Overall, these data represent roughly thirty percent of domestic tickets sold. These data do not include refundability, advance purchase requirements, and travel and stay restrictions.

To obtain these variables, we electronically matched the data with a separate data set from a different CRS containing both fares offered and purchased for travel in particular city-pairs, by departure dates on particular airlines. These data included the ticket characteristics not available from the first data set.[5] The data set from the second CRS was incomplete in that certain fares had been deleted from the archive, and so we were only able to match the fares imperfectly.[6] The criterion used was to keep transactions if we were able to match the fares within 2 percent; for multiple matches

[4] The data and construction of variables are discussed at length in Appendix A.
[5] We have been informed that fares offered on the various CRSs are normally the same, but that at times a fare will only be offered on some CRSs. This permits the use of departure dates to match the route, carrier, fares and fare classes in the first data set with the detailed ticket characteristics found in the second data set. The details are provided in the appendix.
[6] The data in the second archive are kept for unknown intervals of time. Individual fares are then deleted in an unknown pattern over time.

within two percent we kept the closest.[7] The resulting data set contains individual ticket transactions that include ticket characteristics and restrictions, together with carrier, flight information, and dates of purchase, departure, and return.[8] This procedure matches roughly 35 percent of the observations from the first data set.

This study uses data for 150 U.S. domestic city-pairs (routes), including a mix of both business and tourist routes, and routes with varying groups of customers. We define a route as a city-pair regardless of direction. Following Borenstein (1989) and Borenstein and Rose (1994), we include itineraries with at most one stop-over in either direction. The prices used are for roundtrip fares, doubling the fares for one-way tickets to obtain comparability. We exclude itineraries with open-jaws and circular trip tickets. This study includes tickets for flights operated by American Airlines, Continental, Delta, Northwest, US Airways, United Airlines, Frontier, Air Tran, Spirit, Alaska, American Mid-west, Sun Country, Hawaiian Airlines and American Trans Air.[9]

Each observation is a measure of price dispersion in the electronic or conventional market computed on basis of some criteria. The data also includes control variables for carrier and route effects, route market shares, HHI, hubs, and other standard variables measuring tourism, income, and population. We also include variables indicating the corresponding market (online or offline) to the measure of dispersion, the presence of discount carriers on routes, and a separate variable for Southwest.

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[7] The Appendix Table A3 reports results using a 5 percent matching criterion. Those results are qualitatively similar to the results reported below.
[8] Since the CRS de-regulation in 2004, the airlines are free to provide different fares to any distribution channel including the major CRSs, their own CRS and web-site and online travel agencies like Expedia. This necessitated the adoption of the matching rule(s) as discussed in the paper. Please refer to the appendix for discussion on the matching procedure.
[9] We can identify routes served by Southwest, but we do not have data regarding Southwest's ticket characteristics because they are not included in one of the data bases.

## V. **Estimation Methodology**

*Measuring Price Dispersion:*

Price dispersion is the upshot of different firms charging different prices for the exactly same product in different regions. This definition can be extended to argue that price dispersion may also arise because firms charge different prices in different channels of distribution, namely online and offline markets.

One critical component to measure price dispersion is to ascertain the good is homogenous and we are not measuring dispersion in prices as a result of product differentiation or dispersion arising out of difference in product characteristics. In this spirit to maintain homogeneity among the products and measure dispersion in the two channels of sales, this analysis proposes multiple methodologies as discussed below.

## Methodology 1: A Residual Variation Analysis

*IA. Residual Variation in Prices corresponding to different days in advance tickets are purchased before departure*

This methodology adopts a similar procedure as used in Brown and Goolsbee (2002) and consequently by Sengupta and Wiggins (2006). This method uses a two step process that measures dispersion in prices net of product characteristics.

Ghose and Yao (2006) compare the market efficiency for homogenous products bought online and offline. The markets for airline tickets, unfortunately is more complicated in terms of defining a ticket as a product in comparison to hardware and office supply products.

To measure dispersion in online and offline markets net of the ticket characteristics, we follow a two step regression procedure. In the first stage, we regress the prices on ticket characteristics along with carrier and route fixed effects for each individual market (online/offline). We obtain the residual from this first step regression which implies the variation in prices net of the ticket characteristics. We then construct measures of dispersion for the calculated residuals, namely coefficient of variation of the residuals, standard deviation of the residuals and the range of residuals for a route-carrier-days in advance (advance) the ticket was bought combination.

In the second stage, we pool the offline and online measures of dispersion and regress it on online control variable (a dummy variable that takes a value of 1 if the residual was obtained from the online regression and 0 otherwise) along with other controls, namely market structure variables like markets share of a carrier on a route, Herfindahl index on a route; hub and slot restricted airports, tourist index measured by the absolute temperature difference across the endpoints on a route; demographic variables including population, and per capita income averaged across the two endpoints on a route. We also include the non-stop distance between the two endpoints on the route. These latter set of variables parallels Borenstein and Rose (1994). This methodology purely captures the dispersion in prices net of the ticket characteristics unlike Borenstein and Rose (1994) where a significant proportion of the dispersion may have been attributed to the ticket characteristics which they cannot control for.[10]

This underlying methodology, we believe, compares dispersion in the offline and online markets and provide empirical evidence to the theoretical hypothesis that online markets exhibits a lower dispersion (close to zero).

[10] See Sengupta and Wiggins (2006) for a detailed discussion on the same.

*IB. Residual Variation in Prices for a specific Departure date*

While the approach proposed in IA measures the variation in prices for a particular departure date, an alternative approach is to calculate these dispersion measures at the route-carrier-departure date level. This approach measures dispersion for tickets bought for the same day of travel, but bought different days in advance before scheduled departure. The rest of the methodology is akin to that described above.

*Econometric Issues*

*(i) Endogeneity Issues*

The methodology described above is subject to a few econometric issues. Firstly, market share is going to be endogenous. To take care of this endogeneity issue, we instrument market share by the enplanement share (GEOSHARE). The motivation behind using this as an instrument is that the share of all passengers carried by a carrier from a particular airport will be correlated with the market share of a carrier on a certain route but will not be correlated with the prices charged by a carrier on a route. Consequently, if market share is endogenous so will be Herfindahl index (HHI) as HHI is defined as the sum of the squared market share of the carriers on a route. We use the fitted values from the first stage regression as use the formula below to calculate (XTHERF) to be used as an instrument for HHI.

(ii) *Censoring of Observations*

The second issue is that of censoring and is more relevant when the dispersion measures are calculated at the route-carrier-departure date level. It is plausible that for a certain departure date we observe only one transaction (either offline or online or both). In such cases the standard deviation will be reported as missing. To take care of this we alternatively estimate a Tobit model. We will discuss the significance of Tobit model estimation in the next section.

## Methodology II: Measuring dispersion at the product level

Earlier studies that have tried to measure dispersion in the market for airline tickets have suffered from a common drawback, namely lack of control over the product attributes. These product attributes or ticket characteristics play an important role in determining the prices paid for an airline seat. The ticket characteristics mainly include refundability, advance purchase requirement, travel and stay restrictions, cabin and booking class. Sengupta and Wiggins (2006) shows that these ticket characteristics along with carrier and route fixed effects only explains almost 80 percent of the variation in prices.[11]

Ghose and Yao (2006) compare dispersion across online and offline markets for the same set of products. In IA and IB, we measured the dispersion net of the ticket characteristics but not at the product level. In the spirit of Ghose and Yao (2006), we propose methodologies to measure dispersion in two dimensions: product level and time.

We use the ticket characteristics to define a particular product or a bin.[12] We define a bin as a set of tickets which shares the same ticket characteristics.[13] For example, consider two tickets. One is a non-refundable ticket which requires a 3 day advance purchase requirement and also requires a minimum stay of 1 day before they could return to their origin. Another ticket is a non-refundable ticket requiring a 14 day advance

[11] Please refer to Section II for a more detailed discussion on the dynamics of airline pricing.
[12] See Section II for a detailed discussion on 'bins'.
[13] See literature related to yield management for a discussion on the bins. Please refer to Smith (2001) with reference to bins in airline pricing. Also, see Puller, Sengupta and Wiggins (2007) (mimeo) for further discussions.

purchase requirement and also is valid for travel on a Tuesday or a Thursday. These two tickets may be priced very close to each other but these are two different products.

The different combinations of the different ticket characteristics constitute the different 'bins' or 'products'. Without loss of generality one can aggregate similar 'products' into broader categories. For econometric simplicity, we assign these 'bins' into four broader categories based on their pricing and ticket characteristics. This categorization into four broad categories simplifies the estimation procedure without any loss of generality.

*II A. Measuring dispersion at departure date*

This analysis parallels that of I A. The only difference is that we now construct measure of dispersion at the product level where the product is defined by a certain set of ticket characteristics, namely refundability, advance purchase requirement, travel and stay restrictions, first and/or business class travel.

We use a two step procedure. In the first step, we look at the online and offline markets individually. We measure the standard deviation (coefficient of variation and percentage price differences) of transaction prices at route-carrier-category-departure date level. For every category, then, we have a measure of standard deviation (coefficient of variation and percentage price differences) of prices for each online and offline markets individually. In the second step, we pool together the online and offline markets and the measure of dispersion that we constructed in the first step.

We regress the standard deviation of prices on the online dummy (which takes a value of 1 if the standard deviations belongs to online the ticket transaction and 0 otherwise) and market structure variables. We also include individual category dummies. We also use some additional variables in addition to the other standard market structure variables and demographic variables used in IA and IB to parallel our analysis to Ghose and Yao (2006).

The estimating equation is written as:

$$CV_{ijtkm} = \beta_0 + \beta_1(Online_j) + \beta_2(Price_{ijtkm}) + \beta_3(X_{ijtkm}) + \varepsilon_{ijtk} \qquad \text{(I)}$$

where i represents the 'bin' or product, j denote the market, t denotes the time and k denotes the carrier while m denotes the route.

Price used in this estimation is the average price for a particular category over the selected time period (average price for all tickets sold in a bin for departure on date t). We include price as a control for the value of the product. Sorensen (2000) argues that the customers may be willing to incur a higher search cost for high value products which would lead to lowered dispersion in prices. Online denotes the market where the transaction took place. It takes a value of 1 if the transaction took place online and 0 otherwise. X denotes a vector of control variables. In addition to the market structure and route specific variables discussed in IA and IB, we also include some additional variables following Ghose and Yao (2006). These additional variables include total quantity of transactions (QTY), purchase time (DAYS), average stay (STAY) of an itinerary, average number of tickets that include a Saturday night stay (SAT), average number of tickets that involve a roundtrip (RTRIP) and direct (DIRECT) travel, along with dummies for product categories (CAT) and departure date (DEP).

Transaction quantity (QTY) is the total number of tickets that were purchase in a bin for departure on a specific date. This variable controls for the popularity (demand) for a certain kind of ticket. This is in keeping up with recent findings that argue that price dispersion varies with the sales of a product.[14] DAYS measure the average difference in the number of days between the departure date and the date of issue of the ticket within a bin. A larger average difference implies lower prices associated with lower dispersion.

We use both OLS and Tobit regressions (with and without instruments) for similar reasons as explained in IB. The use of Tobit regressions can be expected to be of higher significance since it is quite plausible to observe singleton transaction for a particular departure date and product category, since our data includes roughly 30 percent of the overall transactions.

*II B. Measuring dispersion at route-carrier-category-advance level*

This is similar to IA, but dispersion is now calculated at route-carrier-category-days in advance to departure ticket is bought (advance). We use both OLS and Tobit (simple and IV) estimation techniques as explained in the earlier sections, though the incidence of missing standard deviations calculated at the route-carrier-category-advance level will be much undermined as compared to the calculations in the previous sub-section.

## VI. Empirical Findings

A. Descriptive Analysis

Price in the data set is the base price of the tickets. The base price does not include federal taxes, airport taxes, segment taxes, airport security taxes or any other forms of surcharges. We use three common measures of price dispersion: standard deviation (SD), coefficient of variation (CV) and percentage price difference (PD). CV is

[14] See Baye et all. (2004a)

defined as the ratio of the standard deviation of prices (residuals) over the mean prices (residuals). PD is defined as the difference between the highest and lowest transaction prices divided by the mean price of transactions of a certain product (category) for a certain combination of route, carrier, departure date and days prior to departure ticket is purchased, as the case may be.

All measures of dispersion are calculated separately for the online and offline markets. As a result, we have two sets of dispersion measures, one for the electronic and another for the conventional markets respectively.

Using data for the 150 largest city pairs in US, we have records of 491390 transactions. We use these half a million observations to construct different measures of dispersion according to the different methodologies that we use in this analysis, as discussed earlier.

Table I shows price dispersion measured by SD, CV and PD where the data is segmented in different ways. Table Ia and Ib presents the measurements of the different dispersion measures calculated from the residual variations. Based on the residuals predicted from the first stage linear regression we calculate the dispersion at route-carrier-departure date-category and route-carrier-advance-category level.

In Table Ic and Id the dispersion measures are calculated on the roundtrip fare based on route-carrier-departure date-category and route-carrier-advance-category level.

All the four tables presented strongly suggest that dispersion in the online market is significantly lower than in the offline. However, note that the CV and PD in Table Ib are negative. This, though surprising is not and outlier since the mean (expected value) of the residuals can be negative, positive or zero in which case the CV and PD will not contain much sense.[15] Ignoring these two calculations, the remaining measures of dispersion suggest that the online dispersion is consistently and significantly lower than the offline markets. Based on the different data segmentation and the measures of dispersion calculated thereof, we can conclusively claim that dispersion in the online markets is lower than in the offline markets but not considerably close to zero as predicted by Ghose and Yao (2006).

One reason for the absence of near zero dispersion in the online markets contrary to the theoretical predictions can be attributed to the product differentiation in the market for airline markets. The airlines offer a huge selection of tickets with varying restrictions. Despite the exhaustive controls of different tickets there still exists a strong possibility of adverse selection problem that cannot be controlled econometrically. This unobserved heterogeneity, in both online and offline markets, can to some extent explain this positive and absence of near zero dispersion in the online markets.

A plausible reason for the lower dispersion in the online markets can be attributed to the customer segmentation in the two markets. It is quite likely, that price sensitive customers looking for the lowest price enters the online markets. In such circumstances the average fares for online transactions would be lower leading to lower dispersion. In contrast, population of offline customers may be diverse such that dispersion would be much higher. Unfortunately, analyzing this customer heterogeneity in the two markets in beyond the scope of current paper and is left for future research.

[15] Note that CV is defined as the ratio of the standard deviation of residuals divided by the expected value of the residuals (in a certain combination/level) while PD is defined as the ratio of the difference between maximum and minimum values of residual within a certain combination divided by the mean of the residuals.

## B. 1. Comparing Price Dispersion Online and Offline: A Graphical Approach

To visualize price dispersion, we aggregate our data by averaging SD, CV and PD both across all product categories and without averaging across different categories. In Figure 1a and 1b, we plot average dispersion measured by the standard deviation of roundtrip fares across all carriers and routes with and without averaging across all product categories for different departure days in the sample.[16] Similarly, Figures 2 and 3 plots the coefficient of variation and proportional price difference of the roundtrip fares corresponding to the different departure dates.

Figures 1-3 suggest that the average daily dispersion in the roundtrip fares are consistently lower in the online markets, irrespective of the measure of dispersion. Contrary, to Ghose and Yao (2006) who finds near zero price dispersion in the electronic markets, Figures 1-3 strongly suggest a substantial positive dispersion in the electronic markets. This positive dispersion in the online markets has been documented by Pan et al (2004); Clay, Krishnan and Wolff (2001) as well as other existing literature. The positive dispersion in the electronic markets, even after controlling for product characteristics (and also without controlling for the same) can be attributed to either adverse selection problem or customer segmentation in the two markets. In sum, Figures 1-3 while providing evidence of lower dispersion in online markets as compared to traditional markets, falls short to support the central hypothesis that online markets exhibits near zero dispersion, as some earlier works using transaction data has documented.

[16] The first departure date in the sample is October 1, 2004. Please refer to the appendix for further discussion on the data.

## B.2. Empirical Results

*B.1. Residual Variation Analysis at route-carrier-departure date level*

This estimation methodology uses a two-step regression methodology. In the first stage the prices (in logs) are regressed on the ticket characteristics and the residuals obtained in the online and offline markets individually. In the second stage we construct measures of dispersion (SD and CV) based on these residuals which are then regressed on market structure variables like market share of carrier, HHI, average population and per capita income, absolute temperature difference and average distance across the two endpoints on the route, and most importantly a control variable indication whether the measure of dispersion belongs to the online or offline market.

Each observation measures SD or CV of the residuals calculated from the first stage regression (discussed above) for the online and offline markets individually. This methodology uses 29546 observations calculated at route-carrier-departure date level. Of these, 18838 observations (roughly 64 percent) represent the offline market while the remaining 36 percent of observations represent the online market. This implies that for a particular route-carrier-departure date combination we do not observe online transactions, or we observe only a single transaction such that the SD (and hence the CV) is reported as missing and not included in the analysis. Further, of the 29546 observations 1136 observations have a zero SD (CV). This accounts for roughly 4 percent of the observations. In this route-carrier-departure date level analysis, bias resulting from censored observations can be argued to be minimal. We, however, present results of Tobit model estimation to address this concern.

Tables 2 and 3 present the OLS and Tobit estimation results for the route-carrier-departure date combination analysis. The variable online represents the electronic market corresponding to the measure of dispersion. Both OLS and Tobit estimates, strongly suggest that the price dispersion is significantly lower in the online markets as compared to the offline markets, though the estimates of 2SLS regressions are not statistically significant. The remaining specifications however, strongly suggest a negative correlation between dispersion and online markets, consistent with the standard theoretical predictions.

The results also suggest that increased market share and concentration reduce dispersion, consistent with the findings of Borenstein and Rose (1994). Increased average population and per capita income increases dispersion. The presence of low cost carrier suggests a weak decrease in dispersion while presence of Southwest airlines on a route tends to increase dispersion, probably by increasing competition on the route.

*B.2. Residual Variation Analysis at route-carrier-advance level*

In this section we discuss results of the residual variation analysis where the residuals are now constructed at the route-carrier-advance level. Travelers flying on a certain date buy their tickets in different time intervals – some buy them weeks ahead before the planned departure while some the day before. This methodology attempts to measure the dispersion among tickets which share the same time window in respect to the number of days prior to actual departure tickets are purchased.

Similar to section B.1, we have two observations for SD (CV), for each individual market (online/offline) respectively. This methodology results in 26012 observations, of which 15135 (58 percent) observations corresponds to the offline market while the remaining 10877 (42 percent) observations to the online market. Of this total number of observations, we have 3050 (11.7 percent) observations where the SD (CV) is calculated to be zero. This suggests that the PD and CV variables have a censored distribution, that is, they are left censored at zero.

The problem of left censored observation is more prominent in the current methodology as compared to the previous one (route-carrier-departure where the measure of dispersion was calculated at the route-carrier-departure date level. The existence of a censored dependent variable results in non-normal error distribution, thereby violation one of the classical assumptions of ordinary least squares (OLS), making the OLS estimates biased (Greene (1997), Ghose and Yao (2006)). Following Ghose and Yao (2006) we use a censored regression model such as the Tobit model, to undermine the existence of the censored observations.

Tables 4 and 5 present the results from both the Least squares and the Tobit model estimations. The results are qualitatively similar to those in Tables 2 and 3. The results suggest that dispersion measured at route-carrier-advance level, the online markets exhibit a significantly lower dispersion than the traditional markets. The relationship between dispersion and market structure variables, namely market share of the carrier on a route and HHI are same as in Tables 2 and 3, and consistent with the findings in the existing airline literature. Compared to previous results, the effects of the presence of low cost carriers and Southwest airlines on the route are statistically insignificant in most of the specifications. The results also tend to lend weak support to the hypothesis that both average population and per capita income across the two end-points on a route increases dispersion on a route. Routes with dominant tourist traffic exhibits more dispersion.

In sum, results suggest that dispersion is lower in the online markets as compared to the more traditional one, when dispersion is measured at the departure date. The dispersion, however, when measured by coefficient of variation is statistically insignificant and tends to weaken our results based on the standard deviation of the residuals. To explore this issue, further, we adopt a new methodology in the next section.

### *B.3. Measuring Dispersion at Product Level*

In the residual variation analysis, we tried to measure dispersion net of the ticket characteristics. An alternative approach to measure the dispersion is to measure it at the product level. As discussed in length in section II, airlines offer a variety of tickets with varying combinations of restrictions. The different restrictions primarily consist of refundability, advance purchase requirements, travel and stay restrictions. Ghose and Yao (2006) focus their analysis on homogenous goods. To parallel their analysis, we allocate the tickets into different 'bins' where a 'bin' refers to a specific combination of the different restrictions mentioned above including whether the ticket involved travel in a first or a business class. Using the travel class and the observed restrictions on the tickets, we allocate the tickets into 28 different bins. Each of these bins exhibits the same combination of restrictions and travel class, such that we can define each of these bins as a different product.[17]

[17] For a more detailed definition of the bins please refer to the appendix.

Further, we categorize these 28 bins into four broad *categories*, without loss of generality.[18] Simplifying the product categories into four broad categories merely makes the computation less cumbersome. The primary focus of this categorization is to establish product heterogeneity, and broadly categorizing the bins into four broad categories do not attenuate the empirical findings.

Based on these four major product categories, we construct measures of dispersion, namely SD, CV and PD, both at route-carrier-departure date-category level and also at route-carrier-departure date-issue date-category level. The results from these two approaches are discussed below.

*B.3a. Measuring dispersion at route-carrier-departure date-category level*

In Tables 6 and 7 we confine our analysis at route-carrier-departure date-category level. This approach results in 42015 observations of which 31692 (75 percent) corresponds to offline observations and 10323 observations to the online market. Of these 8100 observations (19.2 percent) for PD and CV takes a value of zero giving the Tobit estimation results greater weightage. For a single observation for a certain route-carrier-departure date-category, the range will be calculated as zero as compared to missing such that we observe more observations for the estimations with price difference as the dependent variable, 53133.

Compared to the approach of residual variation analysis, analysis at the product (category) level necessitates the inclusion of some additional variables. In addition to the variables used in the earlier regression, we include a variable QTY that measures the total

[18] We performed similar calculations with the individual bins. The results are qualitatively similar to that of the 'category' results.

number of tickets that have been bought in a product category for a particular route-carrier-departure date. This variable is included to control for a product's popularity, since previous work has found that price dispersion differs with difference in popularity level. DAY is the average number of days in advance tickets are bought for a certain departure date within a product category. This is included to control for differences in demand. Airlines typically exhibit stochastic peak load pricing, where high priced tickets are sold in the last few days prior to departure. We would expect, price dispersion to be lower in a certain route-carrier-departure date-product category if more of the tickets are bought far from the actual travel date.

We also include several other variables to control for the quality of tickets or a certain product category, which are not used in defining the category. STAY measures the average number of days of stay that are included in the itineraries. The variable SAT is the share of tickets in a certain product category that involved a Saturday night stay-over. Previous studies have shown that itineraries that include a Saturday night stay (Sengupta and Wiggins (2006)) or require a Saturday night stay-over (Stavins (2001)) lowers the ticket prices. In this spirit, we would think, that an increased share of tickets involving a Saturday stay on average would reduce dispersion. Similarly, higher share of round-trip tickets (RTRIP) sold in a product category would be expected to decrease dispersion while a higher share of direct itineraries (DIRECT) that require no change of planes, may be expected to increase dispersion. PRICE is the average price of tickets that are sold in a particular category.

Tables 6 and 7 represent the estimation results from OLS and Tobit estimations. The results are robust to the measures of dispersion and strongly suggest that price dispersion is lower in the online channel as compared to the offline. The results are robust to all the measures of dispersion. The coefficient of variation measure of dispersion is also negative and statistically significant as compared to the statistically insignificant estimates found previously in the residual variation analysis. The robust lower dispersion in the online markets is also enforced by the Tobit estimates too in Table 7. These results strengthens our hypothesis that even after controlling for ticket characteristics (product heterogeneity) and market structure variables, tickets bought on the internet, on average, exhibit lower dispersion than those bought in the offline market.

The results also suggest that increased market share and competition on route increases dispersion, consistent with the findings in previous studies. The effects of the new variables are as expected. Higher share of tickets requiring tickets to be bought more days in advance typically reduces dispersion. This is probably because that ticket with advance purchase requirements is relatively cheaper such that dispersion is less. Increase in the quantity of a particular category of tickets (more popular) results in higher dispersion. The results also suggest that as more people buy their tickets earlier the dispersion rises. This is probably due to the higher prices that people pay when they buy their tickets close to the departure date as compared to the discounted fares that people pay when they plan their trip in advance. Increased share of tickets involving Saturday stay reduces dispersion and so does increased share of roundtrip tickets which have been found to be considerably less expensive than the one way tickets.[19] Increase in the average prices for a certain product category are positively correlated with the measure, though the estimates are economically close to zero when coefficient of variation or the

[19] Sengupta and Wiggins (2006) reports a 12 percent difference between one way and roundtrip fares, controlling for other factors.

absolute price difference is used as the measure of dispersion. The results from the Tobit model are not very different, though the effects of hub and slot variables switch signs among the two estimating models.

*B.3b. Measuring dispersion at route-carrier-advance-category level*

In previous sub-section we analyzed dispersion for tickets bought for a certain departure date. In this section we construct measures of dispersion for route-carrier-advance-category combination, where advance measures the number of days prior to actual departure a ticket is purchased. As mentioned earlier, this methodology analyzes dispersion for tickets that share similarity with respect to the number of days before actual departure they were purchased.

This methodology results in 32489 observations. For the dispersion measure, percentage price difference, singleton observation in route-carrier-advance-category combination yields a dispersion of zero, which are otherwise discarded for SD and CV. This yields a higher number of observations when PD is used as the measure of dispersion, which in this case equals 43570 observations.

Table 8 and Table 9 provides the estimation results for OLS (and IV) and Tobit (and IV Tobit) models. The results are similar to the other specifications discussed above. The main variable of interest, online, is still negative and statistically significant, as in other specifications. The online coefficient is negative and statistically significant for all specification with marginal difference between the ordinary and the IV estimates. Measuring dispersion at the route-carrier-advance-category level corroborates with all of our previous findings, online market displays lower variation in prices compared to the offline markets.

The results also suggest that increased market share increases dispersion while decrease in market concentration reduces dispersion. The presence of a hub (of the operating carrier) or slot restricted airport at the end-point on a route both contributes to increased dispersion on the route. Increased number of days of stay associated with the itineraries increases dispersion. Categories that include a higher share of Saturday stay-over itineraries on average exhibit lower dispersion. This is consistent with our prior as tickets which involve Saturday stay-over are cheaper than those which do not leading to lower dispersion.[20] This result also holds true for higher share of roundtrip tickets in a certain product category. Higher share of itineraries that do not involve a change of flight are associated with higher prices and consequently higher dispersion.

In summary, Table 8 and Table 9 provide strong empirical evidence to our central hypothesis that online markets exhibit lower dispersion as compared to the offline markets. This result is robust, to the different specifications used and the different methodologies adopted to segment the data.

## VII. Conclusion

Previous studies had documented lower dispersion in the online markets. Most of these studies use posted internet prices as a proxy for internet prices. Posted prices may tend to overestimate the magnitude of dispersion, since these are not transaction prices and may have been lowered if no transaction took place at the posted price. Ghose and Yao (2006) using contemporaneous online and offline transaction for hardware and office

[20] See Sengupta and Wiggins (2006)

supplies, document a near zero dispersion in the online markets. This study parallels Ghose and Yao (2006) to empirically compare the dispersion in the online and offline markets for airline tickets. This paper finds evidence of significant lower dispersion in the online markets, but fails to lend support for a near zero dispersion in this market. This may be associated with the complicated pricing strategy by the carriers. The airlines provide a variety of tickets with varying restrictions, both online and offline. The customers have individual preferences for these products in both the markets. This may serve as plausible explanation for the absence of near zero dispersion since even controlling for all ticket and route characteristics; there remains the possibility of an adverse selection problem. Nonetheless, this paper is one of the few handfuls of studies to use contemporaneous online and offline transaction data and quantify the magnitude of dispersion. The empirical evidence conforms to the theoretical predictions, that increased information reduces dispersion. Online markets exhibit lower dispersion than the offline markets, but does not approach to zero as some previous studies document. The results are robust to the different specifications used and the different methodologies adopted to segment the data.

REFERENCES

Bailey, Joseph. 1998. "Intermediation and Electronic Markets: Aggregation and Pricing in Internet Commerce," *Ph.D. Dissertation, Technology, Management and Policy, Massachusetts Institute of Technology, Cambridge, MA*.

Bakos, Yannis. 1997. "Reducing Buyer Search Costs: Implications for Electronic Marketplaces," *Management Science,* 43 (12): 1676-1692.

J.Bailey and Y.Bakos. 1997. "An Exploratory Study of the Emerging Role of Electronic Intermediaries'," *International Journal of Electronic Commerce* 1-3,7-20.

Baye, Michael R. and John Morgan. 2001. "Information gatekeepers on the Internet and the competitiveness of homogeneous product markets," *The American Economic Review*, 91 (3): 454-474.

Baye, Michael R. and John Morgan. 2004, "Price Dispersion in the Lab and on the Internet: Theory and Evidence," *Rand Journal of Economics*, 35(3): 448-466.

Baye, Michael R., John Morgan, and Patrick Scholten. 2004. "Price Dispersion in the Small and in the Large: Evidence from an Internet Price Comparison Site," *Journal of Industrial Economics*, 52(4):463-496.

Baye, Michael R., John Morgan, and Patrick Scholten. 2004. "Persistent Price Dispersion in Online Markets," In: D. Jansen (Eds.), *The New Economy*. University of Chicago Press.

Borenstein. Severin and Rose. Nancy. 1994. "Competition and Price Dispersion in the U.S. Airline Industry," *Journal of Political Economy*, 102(4):653-683.

Brynjolfsson, Erik and Michael Smith. 2000. "Frictionless Commerce? A Comparison of Internet and Conventional Retailers," *Management Science,* 46 (4): 563-585.

Clay, Karen, Ramayya Krishnan, and Eric Wolff. 2001. "Prices and Price Dispersion on the Web: Evidence from the Online Book Industry," *The Journal of Industrial Economics*, 49 (4): 521-539.

Clemons, Eric, Il-Horn Hann, and Lorin Hitt. 2002. "Price Dispersion and Differentiation in On-Line Travel: An Empirical Investigation," *Management Science*, 48(4), 534-549.

Ghose, Anindya and Yuliang, Yao. 2006. “Goodbye Price Dispersion? New Evidence from Transaction Prices in Electronic Markets,” SSRN Working Paper, November 2006.

Lee, Darin and Prado, Maria. 2005. “The Impact of Passenger Mix on Reported “Hub Premiums” in the US Airline Industry,” *Southern Economic Journal*, 72 (2): 372-394.

Pan, Xing, Brian T. Ratchford, Venkatesh Shankar. 2002. “Can Price Dispersion in Online Markets be Explained by Differences in e-tailer Service Quality?” *Journal of the Academy of Marketing Science,* 30(4): 443-456.

Pan, Xing, Ratchford, Brian T., and Shankar Venkatesh. 2003a. “Why Aren’t the Prices of the Same Item the Same at Me.com and You.com?: Drivers of Price Dispersion Among E-Tailers,” *Working Paper, University of Maryland, College Park, MD 20742. July 2003*.

Pan, Xing, Ratchford, Brian T., and Shankar Venkatesh. 2003b. “A Model of Retail Competition in Service and Price: Pure Play Internet vs. Bricks-and-Mortar Retailer.” *Working Paper, Indiana University, Bloomington, IN 47405*.

Pan, Xing, Ratchford, Brian T., and Shankar Venkatesh. 2004. “Price Dispersion on the Internet: A Review and Directions for Future Research.” *Journal of Interactive Marketing,* 18 (4): 116-135.

Smith, Michael, Joseph Bailey, and Erik Brynjolfsson. 2000. “Understanding Digital Markets: Review and Assessment,” In Erik Brynjolfsson and Brian Kahin, editors, *Understanding the Digital Economy*. MIT Press, Cambridge, MA.

Stavins, Joanna. 2001. “Price Discrimination in the Airline Market: The Effect of Market Concentration.” *Review of Economics and Statistics*. 83 (1): 200-202.

## Appendix:

Data description, construction of variables and expected effects:

We sketch below a detailed description of the variables used and how they were constructed. The final data set used for the analysis has been comprised from three different data sets. The first data set includes contemporaneous online and offline transaction data from the fourth quarter of 2004. However, our period includes some of the peak travel period, particularly Thanksgiving, Christmas and New Years. To sidestep the problems of pricing during these peak travel periods, we dropped transactions for travel during the Thanksgiving week. We also kept transaction which included departure and return within the 22nd of December, 2004. Thus we do not include itineraries involving travel during the last week of the year, since pricing can be different for these periods.

This transaction data comes from one of the major computer reservation systems. Unfortunately, due to confidentiality reasons, they did not provide us with the ticket restrictions. To overcome this limitation, we collected computer reservation system data by gathering the same from one of the local travel agents. The travel agents systems can access historical data for a year. However, due to the time difference between the actual period for which we had data and the data that we could collect, we could obtain a subset of the prices and their characteristics that were offered for the last quarter of 2004, since much of the data was taken out from the reservation systems in a random manner. We matched our transaction data to the travel agents data to obtain the restrictions on the individual tickets. To overcome, the data limitation problem arising from the sub-set of the data that we could collect, we adopted a matching rule. If the two prices from the data sets matched within a 2 percent range, we assigned it as a match. We are thereby assuming, that for a ticket priced at $150 will be qualitative similar to one priced at $147 or $153. We however, took full precaution that the other matching criteria like carrier, booking class and coach class, the day of the week of travel (in case we matched it with a ticket that has a travel day restriction) and the advance purchase requirement were matched in both the data sets.

Following Borenstein (1989) and Borenstein and Rose (1994), we include itineraries which has at most of one break (stop-over) in either direction. The prices are for roundtrip fares. For the one-way itineraries the fares are multiplies by two. We exclude all itineraries which are open-jaw and circular trip tickets. This study includes tickets which are operated by American Airlines, Continental, Delta, Northwest, US Airways, United Airlines, Frontier, Air Tran, Spirit, Alaska, American Mid-west, Sun Country, Frontier Airlines and American Trans Air.

| Table A1<br>List of City Pairs Used | |
|---|---|
| **Routes** | **Routes** |
| | |
| Atlanta (ATL)-Boston (BOS) | Chicago (ORD) – Orange County (SNA) |
| Atlanta (ATL)-Cincinnati (CVG) | Chicago (MDW) – Detroit (DTW) |
| Atlanta (ATL)- Fort Lauderdale (FLL) | Cleveland (CLE) – Chicago (MDW) |
| Atlanta (ATL)-Dulles, DC (IAD) | Cleveland (CLE)– Chicago O' Hare (ORD) |
| Atlanta (ATL)-Houston (IAH) | Cincinnati (CVG)–O' Hare (ORD) |
| Atlanta (ATL)-Los Angeles (LAX) | Columbus (CMH) – La Guardia (LGA) |
| Atlanta (ATL)-La Guardia (LGA) | Dallas (DFW) – Atlanta (ATL) |
| Atlanta (ATL)- Orlando (MCO) | Dallas (DFW) – Denver (DEN) |
| Atlanta (ATL)- Memphis (MEM) | Dallas (DFW) – Washington (IAD) |
| Atlanta (ATL) – Miami (MIA) | Dallas (DFW)- Houston (IAH) |
| Atlanta (ATL)-New Orleans (MSY) | Dallas (DFW) – Los Angeles (LAX) |
| Atlanta (ATL) – Chicago O' Hare (ORD) | Dallas (DFW) – Long Beach (LGB) |
| Atlanta (ATL)- Philadelphia (PHL) | Dallas (DFW) – Kansas City (MCI) |
| Atlanta (ATL)-Tampa (TPA) | Dallas (DFW) – Chicago (ORD) |
| Baltimore (BWI) – Atlanta (ATL) | Dallas (DFW) – Phoenix (PHX) |
| Baltimore (BWI) – Cleveland (CLE) | Denver (DEN) – Atlanta (ATL) |
| Baltimore (BWI) – Dallas (DFW) | Denver (DEN) – Boston (BOS) |
| Baltimore (BWI)- Fort Lauderdale (FLL) | Denver (DEN) – Washington (DCA) |
| Baltimore (BWI) – Los Angeles (LAX) | Denver (DEN) – Newark (EWR) |
| Baltimore (BWI)- Orlando (MCO) | Denver (DEN) – Houston (IAH) |
| Boston (BOS) – Baltimore (BWI) | Denver (DEN) – New York (LGA) |
| Boston (BOS)- Charlotte (CLT) | Denver (DEN) – Kansas City (MCI) |
| Boston (BOS)- Washington (DCA) | Denver (DEN) – Orlando (MCO) |
| Boston (BOS) – Dallas (DFW) | Denver (DEN) – Portland (PDX) |
| Boston (BOS) – Detroit (DTW) | Denver (DEN) – Philadelphia (PHL) |
| Boston (BOS) – Los Angeles (LAX) | Denver (DEN) – Phoenix (PHX) |
| Boston (BOS) – Philadelphia (PHL) | Denver (DEN) – St. Louis (STL) |
| Boston (BOS) – Pittsburgh (PIT) | Denver (DEN) – Tampa (TPA) |
| Boston (BOS) – Fort Myers (RSW) | Detroit (DTW) – Atlanta (ATL) |
| Boston (BOS) – Tampa (TPA) | Detroit (DTW) – Baltimore (BWI) |
| Charlotte (CLT) – Orlando (MCO) | Detroit (DTW) – Dallas (DFW) |
| Chicago (ORD) – Boston (BOS) | Detroit (DTW) – Newark (EWR) |
| Chicago (ORD) – Baltimore (BWI) | Detroit (DTW) – Fort Lauderdale (FLL) |
| Chicago (ORD) – Charlotte (CLT) | Detroit (DTW) – Las Vegas (LAS) |
| Chicago (ORD) – Denver (DEN) | Detroit (DTW) – Orlando (MCO) |
| Chicago (ORD) – Washington (IAD) | Detroit (DTW) – Chicago (ORD) |
| Chicago (ORD)- New York (LGA) | Fort Lauderdale (FLL) – Boston (BOS) |

| Table A1<br>List of City Pairs Used | |
|---|---|
| **Routes** | **Routes** |
| | |
| Chicago (ORD) – Miami (MIA) | Fort Lauderdale (FLL)- Chicago (ORD) |
| Chicago (ORD) – Minneapolis (MSP) | Hartford (BDL) – Washington (DCA) |
| Chicago (ORD) – New Orleans (MSY) | Hartford (BDL) – Chicago O' Hare (ORD) |
| Chicago (ORD) – Omaha (OMA) | Honolulu (HNL) – Los Angeles (LAX) |
| Chicago (ORD) – Ft. Myers (RSW) | Houston (IAH) – New Orleans (MSY) |
| Chicago (ORD) – San Diego (SAN) | Houston (IAH) – Chicago (ORD) |
| Las Vegas (LAS) – Burbank (BUR) | New York (LGA) – Cincinnati (CVG) |
| Las Vegas (LAS) – Los Angeles (LAX) | New York (LGA)- Dallas (DFW) |
| Las Vegas (LAS) – Chicago (ORD) | New York (LGA) – Detroit (DTW) |
| Long Beach (LGB) – Dallas (DFW) | New York (LGA)- Houston (IAH) |
| Los Angeles (LAX) – Denver (DEN) | New York (LGA) – Palm Beach, FL (PBI) |
| Los Angeles (LAX) – Detroit (DTW) | Oakland (OAK) – Denver (DEN) |
| Los Angeles (LAX) – Houston (IAH) | Oakland (OAK) – Seattle (SEA) |
| Los Angeles (LAX)- Miami (MIA) | Ontario (ONT) – Denver (DEN) |
| Los Angeles (LAX)- Chicago (ORD) | Orlando (MCO) – Washington (DCA) |
| Los Angeles (LAX) – Philadelphia (PHL) | Orlando (MCO) – Dallas (DFW) |
| Los Angeles (LAX) – Reno (RNO) | Orlando (MCO)- New York (LGA) |
| Los Angeles (LAX) – Tampa (TPA) | Palm Beach (PBI) – Boston (BOS) |
| Miami (MIA) – New York (LGA) | Philadelphia (PHL) – Chicago (ORD) |
| Miami (MIA) – Boston (BOS) | Philadelphia (PHL) – Palm Beach (PBI) |
| Miami (MIA)- Newark (EWR) | Phoenix (PHX) – Minneapolis (MSP) |
| Milwaukee (MKE) – Minneapolis (MSP) | Phoenix (PHX) – Ontario (ONT) |
| Minneapolis (MSP) – Denver (DEN) | Pittsburgh (PIT) – New York (LGA) |
| Minneapolis (MSP) – Dallas (DFW) | Pittsburgh (PIT) – Chicago (ORD) |
| Minneapolis (MSP) – Detroit (DTW) | Portland (PDX) – Las Vegas (LAX) |
| Minneapolis (MSP) – Los Angeles (LAX) | Portland (PDX) – Los Angeles (LAX) |
| Minneapolis (MSP) – New York (LGA) | Portland (PDX) – Oakland (OAK) |
| Minneapolis (MSP) – Chicago (MDW) | St. Louis (STL) – Los Angeles (LAX) |
| Newark (EWR) – Minneapolis (MSP) | Sacramento (SMF) – Los Angeles (LAX) |
| Newark (EWR) – Chicago (ORD) | Salt Lake City (SLC) – Denver (DEN) |
| Newark (EWR) – Atlanta (ATL) | San Francisco (SFO) – Boston (BOS) |
| Newark (EWR) – Boston (BOS) | San Francisco (SFO) – Dallas (DFW) |
| Newark (EWR) – Los Angeles (LAX) | San Jose (SJC) – Denver (DEN) |
| New Orleans (MSY) – New York (LGA) | Tampa (TPA) – New York (LGA) |
| New York (JFK) – Los Angeles (LAX) | Washington (DCA) – Atlanta (ATL) |
| New York (LGA) – Boston (BOS) | Washington (DCA) – Dallas (DFW) |
| New York (LGA) – Cleveland (CLE) | Washington (DCA)-La Guardia (LGA) |
| New York (LGA) – Charlotte (CLT) | Washington (DCA)- Chicago (ORD) |

**Table A2: Definition of 'Bins' and Corresponding Categories**

| Bin# | Category* | NRF | AP=0 | 0<AP<7 | 7<=AP<14 | 14<=AP<21 | 21<=AP<30 | AP=30 | Travel-restriction | Min/Max stay-restriction | First-class | Full coach Y-class | Business class |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | | |
| 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 2 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 3 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 4 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 5 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 6 | 2 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 2 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 2 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 9 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 10 | 2 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 11 | 2 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 12 | 3 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 13 | 3 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 14 | 3 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 15 | 4 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 16 | 4 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 17 | 4 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 18 | 4 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 19 | 4 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 20 | 4 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 |
| 21 | 4 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 22 | 4 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 23 | 4 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 24 | 4 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 25 | 4 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| 26 | 4 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| 27 | 4 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| 28 | 4 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |

Note: AP=0 includes tickets which do not have any advance purchase requirements
0<AP<7: includes 1/3/5 day advance purchase requirement
7<=AP<14 requirement includes 7/10 day advance purchase requirement
14<=AP<21 includes 14-day advance purchase requirement
21<=AP<30 includes 21 day advance purchase requirement
AP=30 includes 30-day advance purchase requirement
(*) These 4 categories constitute 94% of all transactions

## Table 1. Descriptive Statistics

| Variable Description | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Round-trip fare | 476.950 | 470.80 | 61.99 | 4647.99 |
| Days prior to departure ticket purchased | 15.230 | 19.78 | 0.000 | 202.000 |
| Saturday stay-over | 0.169 | 0.375 | 0.000 | 1.000 |
| Online | 0.122 | 0.327 | 0.000 | 1.000 |
| Direct flight | 0.989 | 0.103 | 0.000 | 1.000 |
| Roundtrip | 0.723 | 0.447 | 0.000 | 1.000 |
| Absolute temperature difference | 15.295 | 10.914 | 0.001 | 46.000 |
| HUB | 0.745 | 0.435 | 0.000 | 1.000 |
| Slot constrained airport | 0.266 | 0.442 | 0.000 | 1.000 |
| Low cost carrier on route | 0.468 | 0.499 | 0.000 | 1.000 |
| Southwest Airlines | 0.062 | 0.242 | 0.000 | 1.000 |
| Distance | 955.993 | 632.834 | 185.000 | 2704.000 |
| Average population* | 2004479 | 1601511 | 233014.6 | 5974809 |
| Average per capita income* | 36523.14 | 3332.794 | 23808.000 | 45046.490 |
| Market share | 0.551 | 0.253 | 0.000 | 1.000 |
| HHI | 0.539 | 0.191 | 0.189 | 1.000 |

*In thousands
**Source**: Ticket characteristic and fare data comes from one of the major CRS.
Market level data including market share and HHI is calculated using Department of Transportation's T-100 database.
List of hub airports is gathered from Air Traveler's (http://www.faqs.org/faqs/travel/air/handbook/part2/section-13.html)
For data descriptions please refer to the Appendix.

**Table Ia: Average Dispersion of Residuals based on Route-Carrier-Departure Date**

| | Standard Deviation of Residuals | Coefficient of Variation of Residuals | Absolute Difference in Residuals |
|---|---|---|---|
| Offline Market | 0.219 | 3.061 | 10.964 |
| Online Market | 0.133 | 0.512 | 0.707 |

**Table Ib: Average Dispersion of Residuals based on Route-Carrier-Number of Days Prior to Departure Ticket Purchased**

| | Standard Deviation of Residuals | Coefficient of Variation of Residuals (=SD/mean) | (Maximum-Minimum)residual/Expected Value(residuals) |
|---|---|---|---|
| Offline Market | 0.098 | -1.35 | -0.57 |
| Online Market | 0.055 | 0.750 | 1.22 |

**Table Ic: Average Dispersion of Roundtrip Fares based on Route-Carrier-Departure Date-Product Category**

| | Standard Deviation of Residuals | Coefficient of Variation of Residuals (=SD/mean) | (Maximum-Minimum)residual/Expected Value(residuals) |
|---|---|---|---|
| Offline Market | 69.58 | 0.422 | 1.21 |
| Online Market | 17.17 | 0.176 | 0.274 |

**Table Id: Average Dispersion of Roundtrip Fares based on Route-Carrier-Departure Date-Product Category**

| | Standard Deviation of Residuals | Coefficient of Variation of Residuals (=SD/mean) | (Maximum-Minimum)residual/Expected Value(residuals) |
|---|---|---|---|
| Offline Market | 28.51 | 0.209 | 0.533 |
| Online Market | 7.30 | 0.90 | 0.160 |

**Table 2. Linear Regressions of Measures of Dispersion of Residuals Calculated at Route-Carrier-Departure Date Level**

| | (1) SD) (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| **Market Structure Variables:** | | | | | | |
| Market share | 0.064 | 0.023 | 43.001 | 47.599 | 0.611 | 0.509 |
| | (17.23)** | (2.66)** | (2.38)* | (1.14) | (54.14)** | (21.40)** |
| HHI | -0.069 | -0.012 | -46.101 | -38.407 | -0.584 | -0.472 |
| | (13.99)** | (1.09) | (1.91) | (0.73) | (37.21)** | (15.26)** |
| HUB | 0.002 | 0.000 | 14.324 | 12.587 | 0.022 | 0.019 |
| | (0.83) | (0.11) | (1.23) | (1.04) | (2.57)* | (2.17)* |
| Slot constrained airport | 0.064 | 0.023 | 43.001 | 47.599 | 0.611 | 0.509 |
| | (17.23)** | (2.66)** | (2.38)* | (1.14) | (54.14)** | (21.40)** |
| **Internet Variables:** | | | | | | |
| Online | -0.081 | -0.08 | -6.038 | -6.095 | -0.308 | -0.312 |
| | (55.81)** | (54.98)** | (0.86) | (0.86) | (46.84)** | (46.98)** |
| **Other Route Specific Characteristics:** | | | | | | |
| Low cost carrier on route | -0.005 | -0.004 | -2.946 | -2.537 | 0.016 | 0.019 |
| | (3.45)** | (2.50)* | (0.38) | (0.32) | (2.87)** | (3.36)** |
| Southwest Airlines | 0.016 | 0.012 | 10.555 | 10.218 | 0.043 | 0.032 |
| | (6.44)** | (4.62)** | (0.85) | (0.79) | (4.95)** | (3.53)** |
| **Other Route Level Variables:** | | | | | | |
| Absolute Temperature | 0.002 | 0.001 | 1.16 | 1.249 | 0.008 | 0.008 |
| Difference (Log) | (3.29)** | (3.02)** | (0.5) | (0.54) | (5.08)** | (5.07)** |
| Average population (Log) | 0.011 | 0.011 | -3.33 | -2.525 | 0.087 | 0.085 |
| | (10.27)** | (9.60)** | (0.62) | (0.45) | (22.56)** | (21.39)** |
| Average per capita | 0.05 | 0.041 | 8.357 | 10.508 | 0.598 | 0.573 |
| Income (Log) | (6.00)** | (4.73)** | (0.2) | (0.25) | (20.98)** | (19.72)** |
| Distance (log) | 0.003 | 0.004 | 0.226 | -0.679 | -0.001 | 0.001 |
| | (2.35)** | (2.87)** | (0.04) | (0.11) | (0.14) | (0.24) |
| **Carrier Fixed Effects (American Airlines omitted):** | | | | | | |
| Continental | 0.000 | 0.000 | 13.125 | 12.875 | 0.004 | 0.002 |
| | (0.17) | (0.13) | (0.92) | (0.91) | (0.36) | (0.22) |
| Delta | -0.028 | -0.026 | -5.662 | -5.988 | -0.112 | -0.109 |
| | (11.77)** | (10.92)** | (0.5) | (0.52) | (13.44)** | (12.92)** |
| Northwest | -0.019 | -0.015 | -13.455 | -14.835 | -0.194 | -0.179 |
| | (6.54)** | (4.66)** | (0.93) | (0.97) | (18.77)** | (16.48)** |

**Table 2, Continued**

| | (1) SD (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| United Airways | -0.005 | -0.003 | -6.343 | -5.739 | -0.124 | -0.119 |
| | (2.60)** | (1.58) | (0.63) | (0.56) | (17.13)** | (16.33)** |
| US Air | -0.032 | -0.03 | -37.532 | -38.737 | -0.182 | -0.177 |
| | (10.51)** | (9.43)** | (2.50)* | (2.52)* | (17.57)** | (16.80)** |
| HP | -0.025 | -0.027 | -13.156 | -10.623 | -0.195 | -0.204 |
| | (5.74)** | (6.00)** | (0.63) | (0.49) | (13.44)** | (13.76)** |
| FL | -0.144 | -0.16 | 7.635 | 8.41 | -0.469 | -0.505 |
| | (14.62)** | (15.56)** | (0.16) | (0.17) | (21.46)** | (21.85)** |
| F9 | -0.053 | -0.058 | -2.171 | -0.229 | -0.257 | -0.27 |
| | (15.48)** | (15.88)** | (0.13) | (0.01) | (21.71)** | (22.07)** |
| NK | -0.07 | -0.075 | -2.058 | -0.287 | -0.319 | -0.329 |
| | (14.02)** | (14.56)** | (0.09) | (0.01) | (19.20)** | (19.56)** |
| SY | -0.073 | -0.088 | 11.352 | 13.16 | -0.218 | -0.251 |
| | (9.69)** | (10.93)** | (0.31) | (0.34) | (8.95)** | (9.92)** |
| HA | -0.055 | -0.048 | -5.294 | -1.283 | -0.414 | -0.402 |
| | (2.73)** | (2.37)* | (0.05) | (0.01) | (6.23)** | (6.02)** |
| TZ | -0.08 | -0.079 | 0.693 | 0.726 | -0.547 | -0.543 |
| | (6.01)** | (5.91)** | (0.01) | (0.01) | (13.80)** | (13.66)** |
| AS | -0.071 | -0.063 | -17.973 | -16.814 | -0.337 | -0.319 |
| | (13.09)** | (11.32)** | (0.68) | (0.62) | (17.83)** | (16.45)** |
| YX | -0.008 | -0.039 | 29.561 | 29.747 | 0.05 | -0.018 |
| | (0.56) | (2.46)* | (0.41) | (0.39) | (1.13) | (0.39) |
| Constant | -0.487 | -0.4 | -36.863 | -71.346 | -6.947 | -6.675 |
| | (5.29)** | (4.22)** | (0.08) | (0.15) | (22.17)** | (20.88)** |
| Departure date fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 29546 | 29546 | 29546 | 29546 | 21472 | 21472 |
| R-squared | 0.16 | 0.15 | 0.01 | 0.01 | 0.38 | 0.38 |

**Note:** Absolute value of t statistics in parentheses; * significant at 5%; ** significant at 1%; Source: Please refer to Table 1

**Table 3. Tobit Regressions of Measures of Dispersion of Residuals Calculated at Route-Carrier-Departure Date Level**

| | (1) SD) (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| **Market Structure Variables:** | | | | | | |
| Market share | 0.071 | 0.028 | 175.225 | 308.995 | 0.746 | |
| | (18.47)** | (3.12)** | (7.29)** | (5.67)** | (56.93)** | (22.91)** |
| HHI | | | | | | |
| | -0.075 | -0.015 | -138.359 | -265.322 | -0.715 | -0.554 |
| | (14.67)** | (1.31) | (4.34)** | (3.86)** | (39.56)** | (15.89)** |
| Slot constrained airport | 0.002 | -0.001 | -19.11 | -19.972 | 0.02 | -0.001 |
| | (0.61) | (0.33) | (1.26) | (1.27) | (2.09)** | (1.43) |
| **Internet Variables:** | | | | | | |
| Online | -0.084 | -0.084 | -49.658 | -51.854 | -0.354 | -0.359 |
| | (56.35)** | (55.51)** | (5.41)** | (5.62)** | (46.93)** | (47.12)** |
| **Other Route Specific Characteristics:** | | | | | | |
| Low cost carrier on route | -0.005 | -0.004 | 22.329 | 19.858 | 0.022 | 0.027 |
| | (3.14)** | (2.17)* | (2.22)* | -1.95 | (3.57)** | (4.27)** |
| Southwest Airlines | 0.016 | 0.011 | -13.81 | -3.207 | 0.041 | 0.026 |
| | (5.99)** | (4.16)** | -0.85 | -0.19 | (4.15)** | (2.51)* |
| **Other Route Level Variables:** | | | | | | |
| Absolute Temperature | 0.002 | 0.001 | 2.909 | 3.602 | 0.009 | 0.01 |
| Difference (Log) | (3.18)** | (2.90)** | (0.98) | (1.2) | (5.12)** | (5.17)** |
| Average population (Log) | 0.012 | 0.012 | 9.261 | 13.297 | 0.099 | 0.097 |
| | (10.61)** | (9.93)** | (1.33) | (0.84) | (22.90)** | (21.83)** |
| Average per capita | 0.056 | 0.047 | 146.621 | 181.228 | 0.68 | 0.648 |
| Income (Log) | (6.52)** | (5.21)** | (2.77)** | (3.33)** | (21.22)** | (19.84)** |
| Distance (log) | 0.002 | 0.003 | -33.004 | -39.071 | -0.009 | -0.008 |
| | (1.81) | (2.37)** | (4.10)** | (4.64)** | (1.75) | (1.5) |
| **Carrier Fixed Effects (American Airlines omitted):** | | | | | | |
| Continental | 0 | 0 | 42.915 | 41.141 | 0.001 | -0.001 |
| | (0.07) | (0.04) | (2.36)* | (2.26)* | (0.12) | (0.09) |
| Delta | -0.028 | -0.026 | -15.098 | -21.49 | -0.116 | -0.111 |
| | (11.53)** | (10.66)** | (1.01) | (1.43) | (12.43)** | (11.84)** |
| Northwest | -0.02 | -0.015 | -43.94 | -62.689 | -0.213 | -0.195 |
| | (6.64)** | (4.72)** | (2.35)* | (3.16)** | (18.51)** | (16.06)** |
| United Airways | -0.006 | -0.004 | -13.008 | -16.043 | -0.131 | -0.125 |

**Table 3, Continued**

| | (1) SD (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| | (2.82)** | (1.78) | (1.00) | (1.22) | (16.29)** | (15.31)** |
| US Air | -0.034 | -0.032 | -31.023 | -42.98 | -0.208 | -0.202 |
| | (10.72)** | (9.62)** | (1.59) | (2.15)* | (17.82)** | (17.06)** |
| HP | -0.025 | -0.027 | 38.607 | 54.796 | -0.206 | -0.215 |
| | (5.62)** | (5.90)** | (1.43) | (1.97)* | (12.53)** | (12.82)** |
| FL | -0.185 | -0.202 | -255.233 | -208.363 | -0.753 | -0.8 |
| | (16.75)** | (17.62)** | (3.48)** | (2.76)** | (24.34)** | (24.98)** |
| F9 | -0.053 | -0.058 | 41.849 | 64.053 | -0.258 | -0.274 |
| | (15.01)** | (15.48)** | (1.98)* | (2.83)** | (19.22)** | (19.74)** |
| NK | -0.073 | -0.078 | -24.352 | -3.869 | -0.347 | -0.358 |
| | (14.09)** | (14.64)** | (0.76) | (0.12) | (18.16)** | (18.54)** |
| SY | -0.076 | -0.092 | 11.196 | 62.49 | -0.226 | -0.27 |
| | (9.68)** | (10.96)** | (0.23) | (1.21) | (8.04)** | (9.22)** |
| HA | -0.057 | -0.049 | -95.218 | -97.767 | -0.459 | -0.439 |
| | (2.73)** | (2.36)* | (0.69) | (0.71) | (6.10)** | (5.79)** |
| TZ | -0.086 | -0.085 | 11.927 | 9.302 | -0.659 | -0.654 |
| | (6.25)** | (6.15)** | (0.15) | (0.11) | (13.95)** | (13.80)** |
| AS | -0.072 | -0.064 | -34.464 | -51.582 | -0.349 | -0.323 |
| | (12.84)** | (11.05)** | (1.00) | (1.45) | (16.44)** | (14.84)** |
| YX | -0.004 | -0.036 | -15.456 | 69.712 | 0.1 | 0.008 |
| | -0.28 | (2.24)* | (0.16) | (0.68) | (2.02)* | (0.16) |
| Constant | -0.561 | -0.47 | -1,712.22 | -2,089.78 | -7.978 | -7.649 |
| | (5.89)** | (4.79)** | (2.94)** | (3.49)** | (22.65)** | (21.28)** |
| Departure date fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 29546 | 29546 | 29546 | 29546 | 21472 | 21472 |

**Note:** Absolute value of t statistics in parentheses; * significant at 5%; ** significant at 1%; Source: Please refer to Table 1

**Table 4. Linear Regressions of Measures of Dispersion of Residuals Calculated at Route-Carrier-Advance Level**

| | (1) SD) (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| **Market Structure Variables:** | | | | | | |
| Market share | 0.054 | -0.005 | 6.107 | 16.85 | 0.554 | 0.371 |
| | (13.36)** | (0.51) | (1.72) | (1.99)* | (51.38)** | (16.24)** |
| HHI | -0.045 | 0.009 | -0.167 | -9.273 | -0.574 | -0.38 |
| | (8.53)** | (0.75) | (0.04) | (0.86) | (38.20)** | (12.76)** |
| HUB | 0.009 | 0.01 | -2.845 | -3.117 | 0.003 | 0 |
| | (3.63)** | (3.77)** | (1.28) | (1.34) | (0.39) | (0.02) |
| Slot constrained airport | 0.054 | -0.005 | 6.107 | 16.85 | 0.554 | 0.371 |
| | (13.36)** | (0.51) | (1.72) | (1.99)* | (51.38)** | (16.24)** |
| **Internet Variables:** | | | | | | |
| Online | -0.056 | -0.055 | -1.016 | -1.107 | -0.311 | -0.318 |
| | (38.37)** | (37.82)** | (0.79) | (0.86) | (49.72)** | (50.10)** |
| **Other Route Specific Characteristics:** | | | | | | |
| Low cost carrier on route | 0.001 | 0.002 | 1.341 | 1.144 | 0.033 | 0.038 |
| | (0.34) | (1.09) | (0.93) | (0.77) | (6.10)** | (6.88)** |
| Southwest Airlines | 0.007 | 0.004 | -0.141 | 0.44 | 0.009 | -0.01 |
| | (2.62)** | (1.31) | (0.06) | (0.18) | (1.08) | (1.19) |
| **Other Route Level Variables:** | | | | | | |
| Absolute Temperature | 0.002 | 0.002 | 0.449 | 0.501 | 0.009 | 0.009 |
| Difference (Log) | (3.56)** | (3.01)** | (1.02) | (1.13) | (6.09)** | (6.06)** |
| Average population (Log) | 0.008 | 0.006 | 1.073 | 1.389 | 0.09 | 0.086 |
| | (6.86)** | (5.36)** | (1.06) | (1.33) | (24.30)** | (22.42)** |
| Average per capita | 0.092 | 0.08 | 35.347 | 37.544 | 0.56 | 0.515 |
| Income (Log) | (10.27)** | (8.78)** | (4.49)** | (4.69)** | (20.49)** | (18.38)** |
| Distance (log) | 0.018 | 0.02 | -1.494 | -1.885 | 0.033 | 0.036 |
| | (13.03)** | (13.96)** | (1.22) | (1.5) | (7.69)** | (8.15)** |
| **Carrier Fixed Effects (American Airlines omitted):** | | | | | | |
| Continental | -0.007 | -0.006 | -0.837 | -0.932 | 0.008 | 0.006 |
| | (2.14)* | (2.00)* | (0.31) | (0.34) | (0.84) | (0.57) |
| Delta | -0.038 | -0.036 | 2.265 | 1.882 | -0.101 | -0.095 |
| | (15.90)** | (14.89)** | (1.07) | (0.88) | (12.60)** | (11.64)** |
| Northwest | -0.008 | -0.001 | -0.189 | -1.557 | -0.179 | -0.152 |
| | (2.69)** | (0.33) | (0.07) | (0.54) | (18.14)** | (14.54)** |
| United Airways | -0.001 | -0.001 | 1.4 | 1.276 | -0.106 | -0.099 |

**Table 4, Continued**

| | (1) SD (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| | (0.69) | (0.24) | (0.75) | (0.67) | (15.39)** | (14.12)** |
| US Air | -0.044 | -0.041 | -0.114 | -0.737 | -0.218 | -0.207 |
| | (13.25)** | (12.12)** | (0.04) | (0.25) | (21.93)** | (20.47)** |
| HP | -0.04 | -0.049 | 3.66 | 5.408 | -0.166 | -0.184 |
| | (9.06)** | (10.54)** | (0.93) | (1.32) | (11.99)** | (12.91)** |
| FL | -0.108 | -0.128 | 3.341 | 7.065 | -0.485 | -0.548 |
| | (10.86)** | (12.25)** | (0.38) | (0.77) | (23.00)** | (24.50)** |
| F9 | -0.046 | -0.057 | 2.003 | 4.217 | -0.281 | -0.306 |
| | (12.69)** | (14.43)** | (0.63) | (1.2) | (24.78)** | (25.91)** |
| NK | -0.047 | -0.057 | 2.462 | 4.373 | -0.256 | -0.274 |
| | (9.61)** | (11.15)** | (0.57) | (0.98) | (16.04)** | (16.89)** |
| SY | -0.065 | -0.09 | 2.912 | 7.487 | -0.204 | -0.265 |
| | (8.09)** | (10.08)** | (0.41) | (0.95) | (8.78)** | (10.88)** |
| HA | -0.074 | -0.074 | -3.637 | -3.334 | -0.518 | -0.501 |
| | (5.63)** | (5.57)** | (0.31) | (0.28) | (8.10)** | (7.74)** |
| TZ | -0.042 | -0.042 | -0.297 | -0.186 | -0.403 | -0.396 |
| | (3.02)** | (3.04)** | (0.02) | (0.02) | (10.66)** | (10.40)** |
| AS | -0.072 | -0.066 | -1.08 | -2.028 | -0.486 | -0.455 |
| | (12.07)** | (10.74)** | (0.21) | (0.37) | (26.91)** | (24.44)** |
| YX | 0.067 | 0.029 | 0.906 | 7.676 | 0.056 | -0.063 |
| | (3.77)** | (1.54) | (0.06) | (0.46) | (1.35) | (1.42) |
| Constant | -0.942 | -0.814 | -379.401 | -404.344 | -6.148 | -5.656 |
| | (9.69)** | (8.20)** | (4.42)** | (4.63)** | (20.50)** | (18.40)** |
| Days prior to departure ticket purchased fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 26012 | 26012 | 26012 | 26012 | 21472 | 21472 |
| R-squared | 0.27 | 0.26 | 0.01 | 0.01 | 0.55 | 0.54 |

**Note:** Absolute value of t statistics in parentheses; * significant at 5%; ** significant at 1%; Source: Please refer to Table 1

**Table 5. Tobit Regressions of Measures of Dispersion of Residuals Calculated at Route-Carrier-Advance Level**

| | (1) SD) (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| **Market Structure Variables:** | | | | | | |
| Market share | 0.068 | 0.007 | 49.371 | 97.104 | 0.628 | 0.422 |
| | (15.30)** | (0.63) | (9.25)** | (7.65)** | (53.86)** | (17.38)** |
| HHI | -0.055 | 0.004 | -41.767 | -92.961 | -0.644 | -0.415 |
| | (9.48)** | (0.29) | (6.02)** | (5.77)** | (39.84)** | (13.08)** |
| HUB | 0.009 | 0.01 | -14.137 | -13.791 | 0.002 | -0.003 |
| | (3.31)** | (3.33)** | (4.33)** | (4.03)** | (0.26) | (0.35) |
| Slot constrained airport | 0.068 | 0.007 | 49.371 | 97.104 | 0.628 | 0.422 |
| | (15.30)** | (0.63) | (9.25)** | (7.65)** | (53.86)** | (17.38)** |
| **Internet Variables:** | | | | | | |
| Online | -0.063 | -0.062 | -11.06 | -11.471 | -0.339 | -0.347 |
| | (38.96)** | (38.44)** | (5.85)** | (6.04)** | (50.30)** | (50.69)** |
| **Other Route Specific Characteristics:** | | | | | | |
| Low cost carrier on route | 0.002 | 0.003 | 4.194 | 2.844 | 0.037 | 0.043 |
| | (0.97) | (1.7) | (1.97)* | (1.3) | (6.57)** | (7.48)** |
| Southwest Airlines | 0.004 | 0.001 | 8.64 | 11.761 | 0.009 | -0.013 |
| | (1.43) | (0.19) | (2.47)* | (3.26)** | (0.99) | (1.46) |
| **Other Route Level Variables:** | | | | | | |
| Absolute Temperature | 0.002 | 0.002 | 0.578 | 0.731 | 0.01 | 0.011 |
| Difference (Log) | (3.44)** | (2.94)** | (0.9) | (1.14) | (6.25)** | (6.28)** |
| Average population (Log) | 0.01 | 0.008 | 5.048 | 5.95 | 0.097 | 0.093 |
| | (7.81)** | (6.42)** | (3.40)** | (3.88)** | (24.72)** | (22.91)** |
| Average per capita | 0.104 | 0.092 | 105.479 | 113.879 | 0.589 | 0.538 |
| Income (Log) | (10.54)** | (9.15)** | (9.02)** | (9.58)** | (20.30)** | (18.11)** |
| Distance (log) | 0.019 | 0.021 | -9.848 | -10.983 | 0.031 | 0.033 |
| | (12.25)** | (13.07)** | (5.52)** | (5.98)**) | (6.82)** | (7.13)** |
| **Carrier Fixed Effects (American Airlines omitted):** | | | | | | |
| Continental | -0.008 | -0.008 | 1.399 | 0.96 | 0.004 | 0.001 |
| | (2.45)* | (2.33)* | (0.36) | (0.24) | (0.43) | (0.1) |
| Delta | -0.042 | -0.039 | 2.033 | 0.436 | -0.108 | -0.101 |
| | (15.65)** | (14.67)** | (0.65) | (0.14) | (12.72)** | (11.69)** |
| Northwest | -0.011 | -0.003 | -5.171 | -10.674 | -0.192 | -0.162 |
| | (3.22)** | (0.96) | (1.3) | (2.55)* | (18.40)** | (14.66)** |
| United Airways | -0.004 | -0.003 | -3.368 | -4.468 | -0.112 | -0.103 |

**Table 5, Continued**

| | (1) SD (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| | (1.84) | (1.32) | (1.23) | (1.6) | (15.28)** | (13.85)** |
| US Air | -0.049 | -0.046 | -2.602 | -4.574 | -0.237 | -0.225 |
| | (13.53)** | (12.49)** | (0.62) | (1.08) | (22.44)** | (20.98)** |
| HP | -0.049 | -0.058 | 9.192 | 15.337 | -0.171 | -0.189 |
| | (9.81)** | (11.09)** | (1.6) | (2.55)* | (11.59)** | (12.47)** |
| FL | -0.154 | -0.176 | -29.929 | -12.671 | -0.637 | -0.708 |
| | (12.76)** | (13.93)** | (2.07)* | (0.84) | (25.48)** | (27.00)** |
| F9 | -0.046 | -0.058 | 3.085 | 11.99 | -0.28 | -0.307 |
| | (11.61)** | (13.26)** | (0.66) | (2.31)* | (23.11)** | (24.32)** |
| NK | -0.058 | -0.068 | -4.76 | 2.786 | -0.265 | -0.284 |
| | (10.45)** | (11.80)** | (0.72) | (0.41) | (15.43)** | (16.26)** |
| SY | -0.069 | -0.096 | 26.341 | 47.326 | -0.197 | -0.265 |
| | (7.69)** | (9.59)** | (2.60)** | (4.16)** | (7.90)** | (10.16)** |
| HA | -0.089 | -0.088 | 0.083 | -2.217 | -0.551 | -0.528 |
| | (5.85)** | (5.74)** | (0.01)\ | (0.12) | (7.75)** | (7.34)** |
| TZ | -0.054 | -0.055 | -31.679 | -31.45 | -0.457 | -0.45 |
| | (3.56)** | (3.58)** | (1.73) | (1.72) | (11.13)** | (10.87)** |
| AS | -0.079 | -0.072 | 3.704 | -2.146 | -0.499 | -0.462 |
| | (11.88)** | (10.57)** | (0.5) | (0.28) | (26.05)** | (23.41)** |
| YX | 0.072 | 0.031 | 22.303 | 55.068 | 0.085 | -0.053 |
| | (3.71)** | (1.52) | (1.03) | (2.37)* | (1.92) | (1.12) |
| Constant | -1.102 | -0.973 | -1,170.52 | -1,258.02 | -6.527 | -5.993 |
| | (10.25)** | (8.87)** | (9.16)** | (9.67)** | (20.52)** | (18.36)** |
| Days prior to departure ticket purchased fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 26012 | 26012 | 26012 | 26012 | 21472 | 21472 |

**Note:** Absolute value of t statistics in parentheses; * significant at 5%; ** significant at 1%; Source: Please refer to Table 1

## Table 6. Linear Regressions of Measures of Dispersion Calculated at Route-Carrier-Departure Date-Category Level

| | (1) SD) (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| **Market Structure Variables:** | | | | | | |
| Market share | 10.463 | 20.117 | 0.032 | -0.011 | 0.097 | 0.005 |
| | (4.02)** | (2.72)** | (7.70)** | (0.93) | (12.13)** | (0.25) |
| HHI | -24.761 | -33.658 | -0.046 | 0.01 | -0.133 | -0.026 |
| | (7.69)** | (4.09)** | (8.79)** | (0.76) | (13.31)** | (1.07) |
| HUB | -5.38 | -6.559 | 0.005 | 0.01 | 0.02 | 0.032 |
| | (4.36)** | (4.41)** | (2.58)** | (4.14)** | (5.16)** | (6.72)** |
| Slot constrained airport | -4.089 | -4.581 | 0.007 | 0.007 | 0.021 | 0.023 |
| | (2.79)** | (2.98)** | (3.06)** | (2.90)** | (4.53)** | (4.69)** |
| **Internet Variables:** | | | | | | |
| Online | -11.885 | -12.097 | -0.045 | -0.044 | -0.133 | -0.13 |
| | (11.04)** | (11.13)** | (25.82)** | (25.02)** | (40.90)** | (39.59)** |
| **Other Characteristics** | | | | | | |
| Average number of days in advance ticket | -0.173 | -0.171 | -0.001 | -0.001 | -0.001 | -0.001 |
| purchased within a category | (6.10)** | (6.05)** | (11.94)** | (12.01)** | (10.84)** | (10.92)** |
| Total quantity bought in a category | 0.237 | 0.221 | 0.001 | 0.001 | 0.008 | 0.008 |
| | (7.65)** | (6.69)** | (12.78)** | (13.23)** | (75.10)** | (72.15)** |
| Mean price of tickets in a category | 0.153 | 0.153 | 0 | 0 | 0 | 0 |
| | (88.12)** | (86.71)** | (5.51)** | (6.09)** | (2.45)* | (1.75) |
| Average stay of itineraries in a category | 4.752 | 4.679 | 0.012 | 0.012 | 0.037 | 0.037 |
| | (15.86)** | (15.39)** | (24.36)** | (24.58)** | (46.40)** | (46.46)** |
| Share of roundtrip tickets in a category | -27.642 | -27.81 | -0.051 | -0.051 | -0.155 | -0.155 |
| | (14.15)** | (14.18)** | (16.17)** | (16.11)** | (24.13)** | (24.18)** |
| Share of Saturday night stay tickets in a category | -11.006 | -10.812 | -0.03 | -0.031 | -0.057 | -0.058 |
| | (15.27)** | (14.73)** | (26.17)** | (26.39)** | (59.70)** | (59.50)** |
| Share of direct flight tickets in a category | 12.807 | 10.491 | 0.018 | 0.03 | 0.062 | 0.091 |
| | (3.15)** | (2.38)* | (2.82)** | (4.18)** | (6.26)** | (7.79)** |
| **Other Route Specific Characteristics:** | | | | | | |
| Low cost carrier on route | -4.473 | -4.575 | -0.007 | -0.007 | -0.02 | -0.018 |
| | (4.79)** | (4.87)** | (4.92)** | (4.38)** | (6.60)** | (6.02)** |
| Southwest Airlines | -3.477 | -3.307 | -0.017 | -0.018 | -0.037 | -0.041 |
| | (2.08)* | (1.96)* | (6.15)** | (6.70)** | (6.91)** | (7.53)** |
| **Other Route Level Variables:** | | | | | | |
| Absolute Temperature | -0.383 | -0.37 | 0.002 | 0.002 | 0.005 | 0.005 |
| Difference (Log) | (1.27) | (1.22) | (4.00)** | (4.07)** | (4.99)** | (5.07)** |

**Table 6, Continued**

| | (1) SD) (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| Average population (Log) | 3.358 | 3.701 | 0.004 | 0.003 | 0.012 | 0.01 |
| | (5.06)** | (5.18)** | (3.39)** | (2.65)** | (5.56)** | (4.29)** |
| Average per capita | 1.403 | 3.392 | -0.011 | -0.018 | -0.03 | -0.046 |
| Income (Log) | (0.28) | (0.64) | (1.32) | (2.10)* | (1.82) | (2.74)** |
| Distance (log) | 8.68 | 8.103 | 0.016 | 0.018 | 0.049 | 0.054 |
| | (9.67)** | (8.22)** | (11.18)** | (11.24)** | (17.35)** | (17.32)** |
| **<u>Carrier Fixed Effects (American Airlines omitted):</u>** | | | | | | |
| Continental | -6.736 | -6.365 | -0.024 | -0.026 | -0.072 | -0.077 |
| | (4.02)** | (3.75)** | (8.84)** | (9.34)** | (13.27)** | (13.85)** |
| Delta | -13.964 | -14.379 | -0.045 | -0.043 | -0.12 | -0.117 |
| | (10.02)** | (10.09)** | (20.16)** | (18.88)** | (26.42)** | (25.33)** |
| Northwest | -7.576 | -8.4 | -0.018 | -0.015 | -0.049 | -0.042 |
| | (4.23)** | (4.46)** | (6.12)** | (4.80)** | (8.45)** | (6.96)** |
| United Airways | -0.7 | -0.778 | -0.003 | -0.001 | -0.029 | -0.027 |
| | (0.57) | (0.62) | (1.41) | (0.7) | (7.35)** | (6.73)** |
| US Air | -3.001 | -4.05 | -0.013 | -0.009 | -0.066 | -0.057 |
| | (1.68) | (2.10)* | (4.59)** | (2.97)** | (11.58)** | (9.42)** |
| HP | -18.345 | -17.238 | -0.056 | -0.058 | -0.141 | -0.148 |
| | (6.22)** | (5.63)** | (11.71)** | (11.69)** | (14.88)** | (15.04)** |
| FL | -18.371 | -16.092 | -0.091 | -0.102 | -0.171 | -0.191 |
| | (2.17)* | (1.87) | (6.70)** | (7.34)** | (7.81)** | (8.55)** |
| F9 | -21.774 | -21.128 | -0.041 | -0.043 | -0.106 | -0.109 |
| | (8.80)** | (8.38)** | (10.39)** | (10.58)** | (13.90)** | (14.15)** |
| NK | -11.921 | -10.915 | -0.028 | -0.032 | -0.098 | -0.104 |
| | (3.46)** | (3.10)** | (5.12)** | (5.55)** | (9.31)** | (9.73)** |
| SY | -33.043 | -30.259 | -0.096 | -0.108 | -0.195 | -0.218 |
| | (5.56)** | (4.83)** | (10.00)** | (10.70)** | (10.25)** | (11.06)** |
| HA | -35.85 | -36.485 | -0.063 | -0.055 | -0.122 | -0.108 |
| | (2.43)* | (2.46)* | (2.65)** | (2.31)* | (2.61)** | (2.28)* |
| TZ | -18.935 | -20.295 | -0.057 | -0.051 | -0.127 | -0.114 |
| | (1.73) | (1.85) | (3.23)** | (2.89)** | (4.41)** | (3.94)** |
| AS | -20.321 | -21.747 | -0.066 | -0.057 | -0.132 | -0.114 |
| | (5.82)** | (5.89)** | (11.67)** | (9.57)** | (11.94)** | (9.79)** |
| YX | -13.411 | -7.408 | -0.038 | -0.068 | -0.062 | -0.124 |
| | (1.26) | (0.64) | (2.21)* | (3.66)** | (1.95) | (3.61)** |
| Constant | -151.043 | -169.15 | 0.053 | 0.098 | -0.007 | 0.109 |
| | (2.69)** | (2.93)** | (0.58) | (1.05) | (0.04) | (0.6) |
| Departure Date Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 6, Continued**

| | (1)<br>SD)<br>(OLS) | (2)<br>SD<br>(IV) | (3)<br>CV<br>(OLS) | (4)<br>CV<br>(IV) | (5)<br>PD<br>(OLS) | (6)<br>PD<br>(IV) |
|---|---|---|---|---|---|---|
| Category Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 42015 | 42015 | 42015 | 42015 | 53133 | 53133 |
| R-squared | 0.32 | 0.32 | 0.16 | 0.16 | 0.37 | 0.36 |

**Note:** Absolute value of t statistics in parentheses; * significant at 5%; ** significant at 1%; Source: Please refer to Table 1

**Table 7. Tobit Regressions of Measures of Dispersion Calculated at Route-Carrier-Departure Date-Category Level**

| | (1) SD) (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| **Market Structure Variables:** | | | | | | |
| Market share | 20.932 | 37.133 | 0.047 | 0.008 | 0.141 | 0.06 |
| | (6.64)** | (4.19)** | (9.21)** | -0.57 | (11.74)** | (1.94) |
| HHI | -39.513 | -53.833 | -0.066 | -0.013 | -0.193 | -0.071 |
| | (10.16)** | (5.46)** | (10.39)** | -0.78 | (12.91)** | (2.04)* |
| HUB | -5.38 | -7.38 | 0.006 | 0.01 | 0.038 | 0.048 |
| | (3.67)** | (4.17)** | (2.45)* | (3.48)** | (6.69)** | (6.96)** |
| Slot constrained airport | -2.849 | -3.734 | 0.01 | 0.01 | 0.041 | 0.039 |
| | (1.64) | (2.06)* | (3.54)** | (3.23)** | (6.04)** | (5.52)** |
| **Internet Variables:** | | | | | | |
| Online | -24.265 | -24.627 | -0.062 | -0.062 | -0.185 | -0.183 |
| | (18.48)** | (18.58)** | (29.20)** | (28.54)** | (37.43)** | (36.60)** |
| **Other Characteristics** | | | | | | |
| Average number of days in advance ticket | -0.277 | -0.274 | -0.001 | -0.001 | -0.001 | -0.001 |
| purchased within a category | (7.77)** | (7.69)** | (12.43)** | (12.48)** | (10.21)** | (10.30)** |
| Total quantity bought in a category | 0.327 | 0.299 | 0.001 | 0.001 | 0.006 | 0.006 |
| | (9.05)** | (7.75)** | (12.87)** | (12.96)** | (43.80)** | (41.82)** |
| Mean price of tickets in a category | 0.167 | 0.166 | 0 | 0 | 0 | 0 |
| | (80.81)** | (79.40)** | (8.38)** | (8.77)** | (1.85) | (2.26)* |
| Average stay of itineraries in a category | 8.912 | 8.787 | 0.018 | 0.018 | 0.1 | 0.101 |
| | (25.03)** | (24.30)** | (30.63)** | (30.60)** | (79.41)** | (79.01)** |
| Share of roundtrip tickets in a category | -43.165 | -43.481 | -0.075 | -0.075 | -0.287 | -0.289 |
| | (18.51)** | (18.57)** | (19.69)** | (19.65)** | (31.94)** | (32.05)** |
| Share of Saturday night stay tickets in a category | -23.916 | -23.594 | -0.05 | -0.05 | -0.289 | -0.29 |
| | (26.68)** | (25.88)** | (33.90)** | (33.84)** | (93.99)** | (93.96)** |
| Share of direct flight tickets in a category | 15.965 | 12.046 | 0.021 | 0.031 | 0.089 | 0.117 |
| | (3.12)** | (2.18)* | (2.52)* | (3.51)** | (4.99)** | (5.86)** |
| **Other Route Specific Characteristics:** | | | | | | |
| Low cost carrier on route | -2.591 | -2.763 | -0.005 | -0.004 | -0.018 | -0.017 |
| | (2.35)* | (2.49)* | (2.78)** | (2.37)* | (4.32)** | (3.84)** |
| Southwest Airlines | -13.234 | -12.989 | -0.029 | -0.031 | -0.077 | -0.082 |
| | (6.49)** | (6.32)** | (8.86)** | (9.27)** | (9.76)** | (10.23)** |
| **Other Route Level Variables:** | | | | | | |
| Absolute Temperature | -0.204 | -0.178 | 0.002 | 0.002 | 0.006 | 0.006 |
| Difference (Log) | (0.57) | (0.5) | (3.94)** | (4.04)** | (4.23)** | (4.43)** |

**Table 7, Continued**

| | (1) SD) (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| Average population (Log) | 3.305 | 3.907 | 0.004 | 0.003 | 0.006 | 0.006 |
| | (4.18)** | (4.60)** | (2.75)** | (2.31)* | (1.95) | (1.73) |
| Average per capita | 1.808 | 5.191 | -0.01 | -0.016 | -0.021 | -0.034 |
| Income (Log) | (0.3) | (0.82) | (0.97) | (1.53) | (0.92) | (1.41) |
| Distance (Log) | 10.499 | 9.503 | 0.018 | 0.020 | 0.052 | 0.054 |
| | (9.78)** | (8.08)** | (10.37)** | (10.14)** | (12.62)** | (12.16)** |
| **<u>Carrier Fixed Effects (American Airlines omitted):</u>** | | | | | | |
| Continental | -12.745 | -12.13 | -0.032 | -0.034 | -0.11 | -0.114 |
| | (6.38)** | (5.99)** | (9.82)** | (10.15)** | (14.12)** | (14.40)** |
| Delta | -16.738 | -17.452 | -0.05 | -0.048 | -0.154 | -0.151 |
| | (10.17)** | (10.35)** | (18.57)** | (17.54)** | (24.03)** | (23.26)** |
| Northwest | -4.683 | -6.079 | -0.014 | -0.012 | -0.051 | -0.046 |
| | (2.21)* | (2.74)** | (4.12)** | (3.19)** | (6.26)** | (5.43)** |
| United Airways | -1.039 | -1.136 | -0.003 | -0.002 | -0.029 | -0.026 |
| | (0.71) | (0.77) | (1.45) | (0.82) | (5.17)** | (4.50)** |
| US Air | -2.764 | -4.563 | -0.013 | -0.01 | -0.061 | -0.055 |
| | (1.29) | (1.97)* | (3.82)** | (2.64)** | (7.46)** | (6.31)** |
| HP | -31.019 | -29.055 | -0.074 | -0.076 | -0.198 | -0.199 |
| | (8.52)** | (7.70)** | (12.57)** | (12.35)** | (13.95)** | (13.62)** |
| FL | -111.26 | -107.513 | -0.242 | -0.251 | -0.544 | -0.564 |
| | (7.26)** | (6.95)** | (9.96)** | (10.27)** | (9.18)** | (9.46)** |
| F9 | -23.858 | -22.722 | -0.044 | -0.045 | -0.107 | -0.108 |
| | (8.06)** | (7.54)** | (9.16)** | (9.23)** | (9.42)** | (9.38)** |
| NK | -13.118 | -11.381 | -0.03 | -0.032 | -0.075 | -0.078 |
| | (3.12)** | (2.65)** | (4.36)** | (4.63)** | (4.61)** | (4.74)** |
| SY | -49.948 | -45.219 | -0.121 | -0.132 | -0.287 | -0.308 |
| | (6.78)** | (5.83)** | (10.13)** | (10.51)** | (9.84)** | (10.21)** |
| HA | -50.656 | -51.524 | -0.084 | -0.076 | -0.239 | -0.217 |
| | (2.93)** | (2.97)** | (2.96)** | (2.67)** | (3.41)** | (3.09)** |
| TZ | -37.308 | -39.587 | -0.085 | -0.08 | -0.23 | -0.22 |
| | (2.69)** | (2.84)** | (3.78)** | (3.55)** | (4.66)** | (4.44)** |
| AS | -46.184 | -48.511 | -0.106 | -0.098 | -0.238 | -0.218 |
| | (10.09)** | (10.11)** | (14.39)** | (12.63)** | (13.46)** | (11.82)** |
| YX | -9.319 | 0.65 | -0.034 | -0.062 | -0.094 | -0.154 |
| | (0.73) | (0.05) | (1.64) | (2.74)** | (1.98)* | (3.03)** |
| Constant | -195.658 | -227.004 | -0.008 | 0.026 | -0.119 | -0.067 |
| | (2.92)** | (3.30)** | (0.07) | (0.23) | (0.46) | (0.26) |
| Departure Date Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 7, Continued**

| | (1) SD) (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| Category Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 42015 | 42015 | 42015 | 42015 | 53133 | 53133 |

**Note:** Absolute value of t statistics in parentheses; * significant at 5%; ** significant at 1%; Source: Please refer to Table 1

**Table 8. Linear Regressions of Measures of Dispersion Calculated at Route-Carrier-Advance-Category Level**

| | (1) SD) (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| **Market Structure Variables:** | | | | | | |
| Market share | 21.346 | -9.616 | 0.034 | -0.049 | 55.237 | 3.222 |
| | (7.08)** | (1.18) | (7.73)** | (4.05)** | (10.21)** | (0.23) |
| HHI | -41.272 | -22.329 | -0.054 | 0.029 | -88.021 | -56.512 |
| | (11.02)** | (2.40)* | (9.87)** | (2.08)* | (13.01)** | (3.53)** |
| HUB | 7.361 | 10.977 | 0.01 | 0.019 | 23.801 | 30.568 |
| | (5.22)** | (6.77)** | (4.86)** | (7.84)** | (9.08)** | (10.08)** |
| Slot constrained airport | 8.897 | 11.959 | 0.015 | 0.019 | 30.096 | 35.417 |
| | (5.15)** | (6.55)** | (6.01)** | (6.98)** | (9.34)** | (10.40)** |
| **Internet Variables:** | | | | | | |
| Online | -20.288 | -19.877 | -0.038 | -0.037 | -49.105 | -48.407 |
| | (18.52)** | (18.04)** | (23.56)** | (22.70)** | (24.63)** | (24.17)** |
| **Other Characteristics** | | | | | | |
| Total quantity bought in a category | -0.04 | -0.025 | 0 | 0 | 0.89 | 0.918 |
| | (2.65)** | (1.62) | (1.68) | (3.30)** | (28.22)** | (28.44)** |
| Average stay of itineraries in a category | 2.519 | 2.821 | 0.012 | 0.013 | 10.259 | 10.626 |
| | (7.33)** | (8.06)** | (24.31)** | (25.09)** | (20.49)** | (20.95)** |
| Share of roundtrip tickets in a category | -44.157 | -42.938 | -0.025 | -0.023 | -201.958 | -200.993 |
| | (16.43)** | (15.89)** | (6.41)** | (5.78)** | (37.92)** | (37.67)** |
| Share of Saturday night stay tickets in a category | -6.827 | -7.558 | -0.029 | -0.031 | -15.845 | -16.352 |
| | (9.10)** | (9.83)** | (26.62)** | (27.44)** | (26.99)** | (27.29)** |
| Share of direct flight tickets in a category | 15.742 | 23.838 | 0.017 | 0.04 | 24.887 | 40.225 |
| | (3.68)** | (4.96)** | (2.66)** | (5.68)** | (3.87)** | (5.23)** |
| **Other Route Specific Characteristics:** | | | | | | |
| Low cost carrier on route | -6.082 | -5.947 | -0.002 | -0.001 | -16.553 | -16.509 |
| | (5.60)** | (5.41)** | (1.55) | (0.74) | (8.15)** | (8.04)** |
| Southwest Airlines | -11.667 | -11.927 | -0.006 | -0.008 | -19.926 | -20.508 |
| | (6.13)** | (6.19)** | (1.96)* | (2.75)** | (5.61)** | (5.69)** |
| **Other Route Level Variables:** | | | | | | |
| Absolute Temperature | 0.098 | -0.026 | 0.003 | 0.003 | 0.993 | 0.843 |
| Difference (Log) | (0.27) | (0.07) | (6.37)** | (6.11)** | (1.53) | (1.29) |
| Average population (Log) | 3.84 | 2.276 | 0.006 | 0.004 | 8.058 | 5.406 |
| | (4.93)** | (2.74)** | (5.45)** | (3.11)** | (5.55)** | (3.51)** |
| Average per capita | 23.167 | 17.206 | 0.067 | 0.054 | 65.906 | 56.813 |
| Income (Log) | (3.84)** | (2.79)** | (7.54)** | (5.91)** | (5.94)** | (5.04)** |

**Table 8, continued**

| | (1) SD) (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| Distance (Log) | 35.73 | 38.082 | 0.018 | 0.023 | 65.673 | 69.571 |
| | ((36.31)** | (35.01)** | (12.47)** | (14.25)** | (36.37)** | (35.27)** |
| **Carrier Fixed Effects (American Airlines omitted):** | | | | | | |
| Continental | -6.762 | -7.733 | -0.023 | -0.026 | -16.68 | -18.534 |
| | (3.28)** | (3.71)** | (7.58)** | (8.43)** | (4.35)** | (4.79)** |
| Delta | -15.227 | -14.28 | -0.031 | -0.029 | -37.117 | -35.639 |
| | (9.46)** | (8.77)** | (13.29)** | (12.09)** | (12.25)** | (11.67)** |
| Northwest | 1.623 | 4.324 | -0.01 | -0.004 | -2.459 | 2.095 |
| | (0.75) | (1.92) | (3.28)** | (1.11) | (0.6) | (0.5) |
| United Airways | 7.316 | 6.742 | -0.009 | -0.008 | 3.265 | 2.253 |
| | (5.08)** | (4.60)** | (4.16)** | (3.73)** | (1.22) | (0.83) |
| US Air | -14.412 | -11.646 | -0.019 | -0.013 | -40.558 | -35.999 |
| | (6.62)** | (5.17)** | (6.00)** | (3.97)** | (10.18)** | (8.77)** |
| HP | -21.292 | -27.576 | -0.037 | -0.049 | -53.022 | -63.364 |
| | (6.45)** | (7.87)** | (7.71)** | (9.43)** | (8.68)** | (9.85)** |
| FL | -6.59 | -14.373 | -0.05 | -0.072 | -5.807 | -16.402 |
| | (0.79) | (1.66) | (4.02)** | (5.67)** | (0.43) | (1.19) |
| F9 | -16.54 | -20.814 | -0.049 | -0.058 | -35.26 | -41.877 |
| | (5.88)** | (7.06)** | (11.86)** | (13.40)** | (6.84)** | (7.84)** |
| NK | -9.056 | -13.748 | -0.017 | -0.027 | -15.648 | -22.816 |
| | (2.59)** | (3.80)** | (3.22)** | (4.96)** | (2.48)* | (3.51)** |
| SY | -22.784 | -33.325 | -0.067 | -0.097 | -44.48 | -61.075 |
| | (3.59)** | (4.81)** | (7.22)** | (9.52)** | (3.78)** | (4.86)** |
| HA | -34.563 | -35.976 | -0.06 | -0.053 | -71.69 | -73.542 |
| | (3.13)** | (3.23)** | (3.70)** | (3.25)** | (3.52)** | (3.58)** |
| TZ | -2.958 | 0.872 | -0.055 | -0.046 | -8.757 | -2.182 |
| | (0.26) | (0.08) | (3.26)** | (2.69)** | (0.47) | (0.12) |
| AS | -28.753 | -26.123 | -0.063 | -0.052 | -63.104 | -58.329 |
| | (6.67)** | (5.82)** | (9.98)** | (7.78)** | (7.68)** | (6.85)** |
| YX | 24.294 | 6.511 | -0.017 | -0.072 | 43.053 | 14.888 |
| | (1.92) | (0.48) | (0.94) | (3.57)** | (1.98)* | (0.64) |
| Constant | -331.197 | -268.179 | -0.77 | -0.665 | -770.399 | -675.75 |
| | (5.03)** | (4.00)** | (7.95)** | (6.72)** | (6.35)** | (5.50)** |
| Days in Advance Ticket Purchased Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Category Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.27 | 0.26 | 0.20 | 0.19 | 0.31 | 0.31 |
| Observations | 32489 | 32489 | 32489 | 32489 | 43570 | 43570 |

**Note:** Absolute value of t statistics in parentheses; * significant at 5%; ** significant at 1%; Source: Please refer to Table 1

**Table 9. Tobit Regressions of Measures of Dispersion Calculated at Route-Carrier-Advance-Category Level**

| | (1) SD) (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| **Market Structure Variables:** | | | | | | |
| Market share | 39.762 | 10.607 | 0.056 | -0.03 | 102.34 | 44.67 |
| | (10.34)** | (1.03) | (9.83)** | (1.96) | (11.41)** | (1.99)* |
| HHI | -66.19 | -49.706 | -0.083 | 0.004 | -169.607 | -136.029 |
| | (13.91)** | (4.22)** | (11.74)** | (0.25) | (15.25)** | (5.31)** |
| HUB | 12.322 | 15.737 | 0.016 | 0.025 | 43.136 | 50.613 |
| | (6.98)** | (7.77)** | (6.23)** | (8.35)** | (10.37)** | (10.55)** |
| Slot constrained airport | 10.051 | 13.006 | 0.018 | 0.021 | 39.588 | 45.367 |
| | (4.72)** | (5.80)** | (5.62)** | (6.33)** | (7.93)** | (8.65)** |
| **Internet Variables:** | | | | | | |
| Online | -34.996 | -34.594 | -0.057 | -0.056 | -85.492 | -84.661 |
| | (24.98)** | (24.58)** | (27.18)** | (26.48)** | (25.94)** | (25.60)** |
| **Other Characteristics** | | | | | | |
| Total quantity bought in a category | -0.061 | -0.047 | 0 | 0 | 0.611 | 0.642 |
| | (3.46)** | (2.58)** | (0.09) | (1.52) | (14.44)** | (14.71)** |
| Average stay of itineraries in a category | 8.515 | 8.805 | 0.021 | 0.021 | 54.989 | 55.403 |
| | (19.77)** | (20.09)** | (31.89)** | (32.31)** | (60.38)** | (60.19)** |
| Share of roundtrip tickets in a category | -61.919 | -60.704 | -0.051 | -0.048 | -251.303 | -250.029 |
| | (19.06)** | (18.60)** | (10.30)** | (9.74)** | (33.11)** | (32.90)** |
| Share of Saturday night stay tickets in a category | -24.972 | -25.662 | -0.055 | -0.057 | -153.987 | -154.549 |
| | (24.80)** | (24.96)** | (36.71)** | (37.05)** | (74.90)** | (74.87)** |
| Share of direct flight tickets in a category | 20.733 | 28.326 | 0.02 | 0.045 | 62.606 | 79.766 |
| | (3.67)** | (4.51)** | (2.41)* | (4.81)** | (4.96)** | (5.56)** |
| **Other Route Specific Characteristics:** | | | | | | |
| Low cost carrier on route | -4.632 | -4.542 | 0 | 0.001 | -16.424 | -16.385 |
| | (3.45)** | (3.34)** | (0.03) | (0.67) | (5.20)** | (5.14)** |
| Southwest Airlines | -19.629 | -19.803 | -0.014 | -0.016 | -49.449 | -49.978 |
| | (8.07)** | (8.05)** | (3.81)** | (4.42)** | (8.55)** | (8.55)** |
| **Other Route Level Variables:** | | | | | | |
| Absolute Temperature | 0.571 | 0.444 | 0.004 | 0.004 | 2.095 | 1.932 |
| Difference (Log) | (1.29) | (1.00) | (6.48)** | (6.31)** | (2.02)* | (1.85) |
| Average population (Log) | 5.207 | 3.685 | 0.008 | 0.005 | 9.782 | 6.847 |
| | (5.34)** | (3.56)** | (5.41)** | (3.47)** | (4.27)** | (2.83)** |
| Average per capita | 50.983 | 45.447 | 0.103 | 0.089 | 142.013 | 132.657 |
| Income (Log) | (6.78)** | (5.92)** | (9.12)** | (7.75)** | (8.09)** | (7.46)** |

**Table 9 Continued**

| | (1) SD) (OLS) | (2) SD (IV) | (3) CV (OLS) | (4) CV (IV) | (5) PD (OLS) | (6) PD (IV) |
|---|---|---|---|---|---|---|
| Distance(Log) | 40.464 | 42.745 | 0.021 | 0.026 | 88.427 | 92.787 |
| | (33.01)** | (31.54)** | (11.21)** | (12.53)** | (30.92)** | (29.82)** |
| <u>**Carrier Fixed Effects (American Airlines omitted):**</u> | | | | | | |
| Continental | -13.904 | -14.796 | -0.034 | -0.037 | -38.877 | -40.973 |
| | (5.45)** | (5.75)** | (8.74)** | (9.42)** | (6.53)** | (6.81)** |
| Delta | -25.197 | -24.24 | -0.045 | -0.042 | -72.311 | -70.366 |
| | (12.52)** | (11.91)** | (14.88)** | (13.84)** | (15.20)** | (14.67)** |
| Northwest | 0.273 | 2.824 | -0.014 | -0.007 | -6.113 | -1.085 |
| | (0.1) | (1.02) | (3.41)** | (1.6) | (0.98) | (0.17) |
| United Airways | 5.526 | 4.887 | -0.013 | -0.012 | 4.862 | 3.713 |
| | (3.13)** | (2.72)** | (4.73)** | (4.33)** | (1.18) | (0.89) |
| US Air | -19.545 | -16.878 | -0.025 | -0.019 | -54.532 | -49.382 |
| | (7.19)** | (6.01)** | (6.16)** | (4.49)** | (8.59)** | (7.57)** |
| HP | -35.641 | -41.807 | -0.056 | -0.067 | -89.734 | -101.459 |
| | (8.37)** | (9.28)** | (8.80)** | (10.02)** | (8.86)** | (9.56)** |
| FL | -82.318 | -89.469 | -0.149 | -0.173 | -187.157 | -198.743 |
| | (5.65)** | (6.04)** | (7.29)** | (8.27)** | (5.48)** | (5.76)** |
| F9 | -20.857 | -24.979 | -0.058 | -0.067 | -51.452 | -58.787 |
| | (5.88)** | (6.73)** | (10.85)** | (12.05)** | (6.14)** | (6.80)** |
| NK | -21.007 | -25.479 | -0.033 | -0.043 | -37.195 | -44.747 |
| | (4.51)** | (5.30)** | (4.78)** | (6.05)** | (3.33)** | (3.93)** |
| SY | -34.588 | -44.451 | -0.087 | -0.119 | -84.865 | -103.304 |
| | (4.23)** | (5.00)** | (7.15)** | (8.90)** | (4.30)** | (4.93)** |
| HA | -54.142 | -55.965 | -0.089 | -0.082 | -141.569 | -143.953 |
| | (3.63)** | (3.72)** | (3.98)** | (3.62)** | (3.88)** | (3.92)** |
| TZ | -6.746 | -3.144 | -0.064 | -0.055 | -24.934 | -17.787 |
| | (0.47) | (0.22) | (3.00)** | (2.54)* | (0.81) | (0.57) |
| AS | -40.091 | -37.779 | -0.081 | -0.068 | -87.255 | -82.072 |
| | (7.21)** | (6.54)** | (9.74)** | (7.93)** | (6.59)** | (6.00)** |
| YX | 34.727 | 18.262 | -0.01 | -0.067 | 62.041 | 30.92 |
| | (2.27)* | (1.1) | (0.43) | (2.67)** | (1.82) | (0.85) |
| Constant | -681.146 | -621.546 | -1.202 | -1.097 | -1,780.65 | -1,683.10 |
| | (8.28)** | (7.45)** | (9.76)** | (8.75)** | (9.28)** | (8.69)** |
| Days in Advance Ticket Purchased Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Category Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 32489 | 32489 | 32489 | 32489 | 43570 | 43570 |

**Note:** Absolute value of t statistics in parentheses; * significant at 5%; ** significant at 1%; Source: Please refer to Table 1


Figure 1a: Average Daily Dispersion in Roundtrip Fares Measured by Standard Deviation of Roundtrip Fares

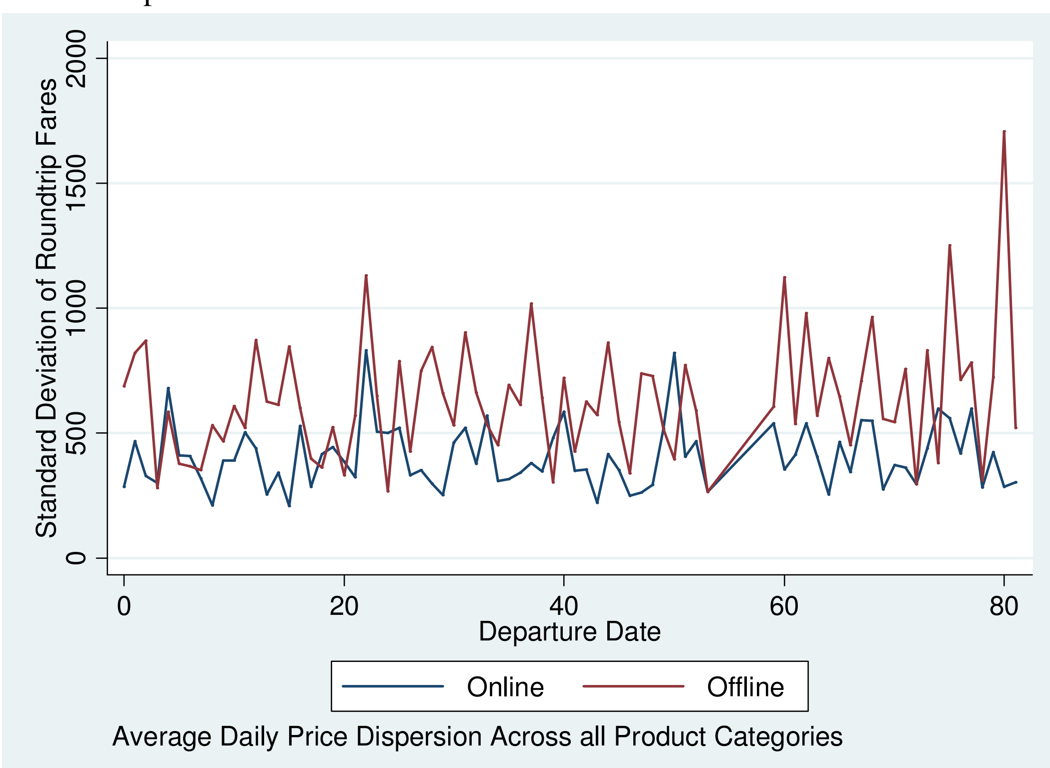


Figure 1b: Average Average Daily Dispersion in Roundtrip Fares Measured by Standard Deviation of Roundtrip Fares Averaged Over All Product Categories

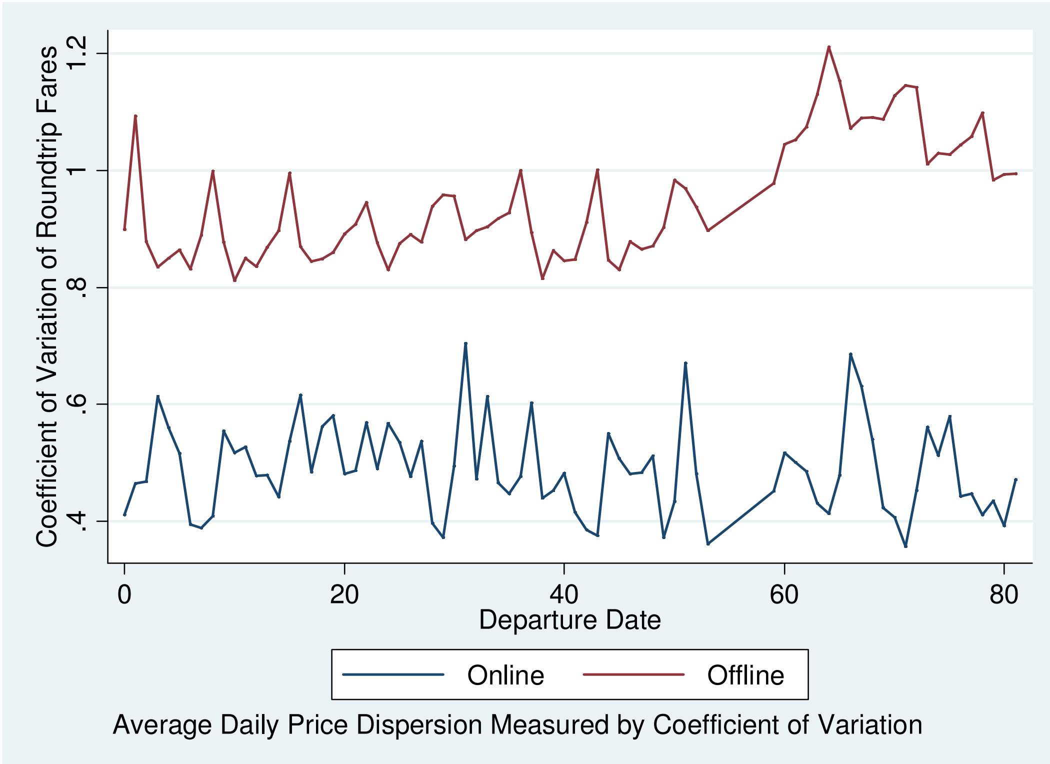


Figure 2a: Average Daily Dispersion in Roundtrip Fares Measured by Coefficient of Variation of Roundtrip Fares

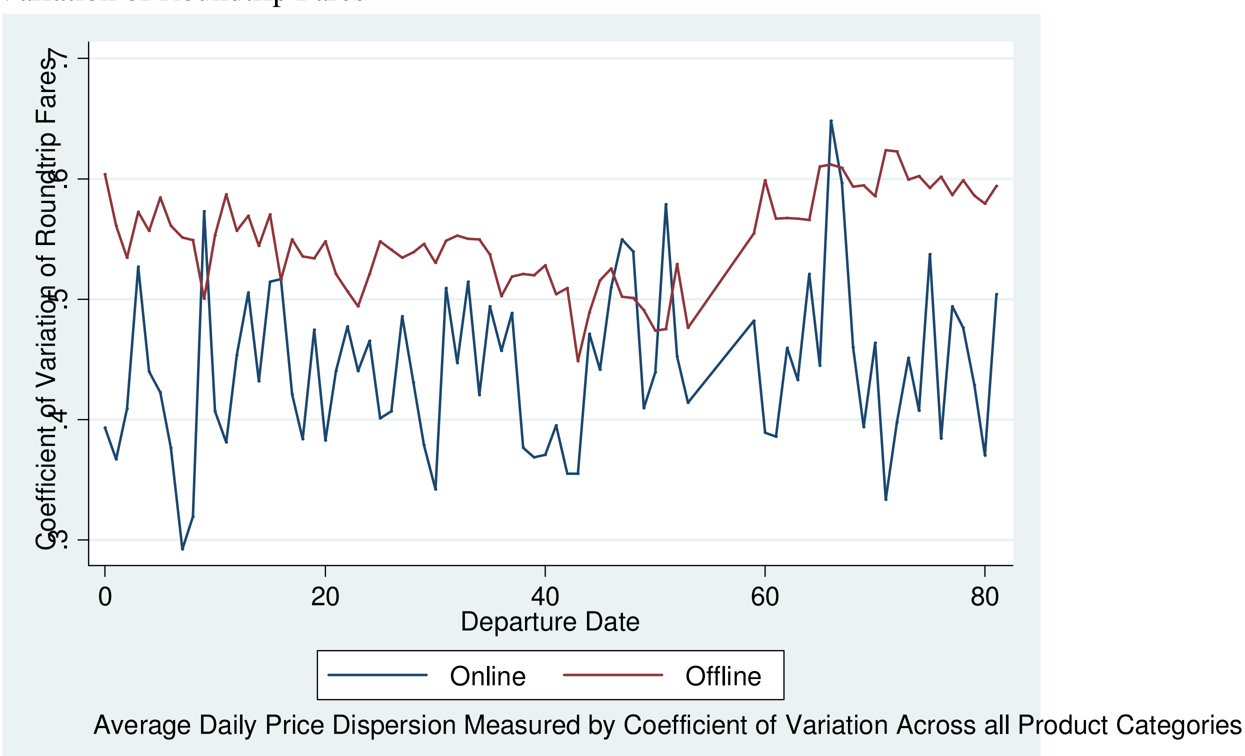


Figure 2b: Average Average Daily Dispersion in Roundtrip Fares Measured by Coefficient of Variation of Roundtrip Fares Averaged Over All Product Categories

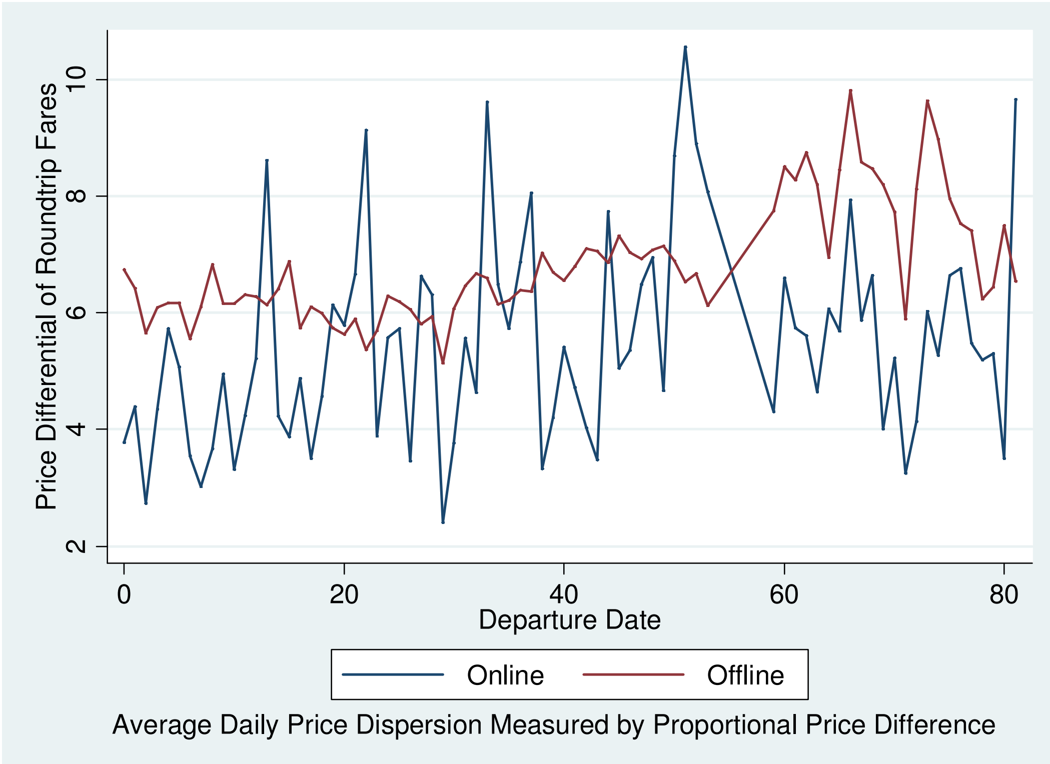


Figure 3a: Average Daily Dispersion in Roundtrip Fares Measured by Proportional Price Difference of Roundtrip Fares

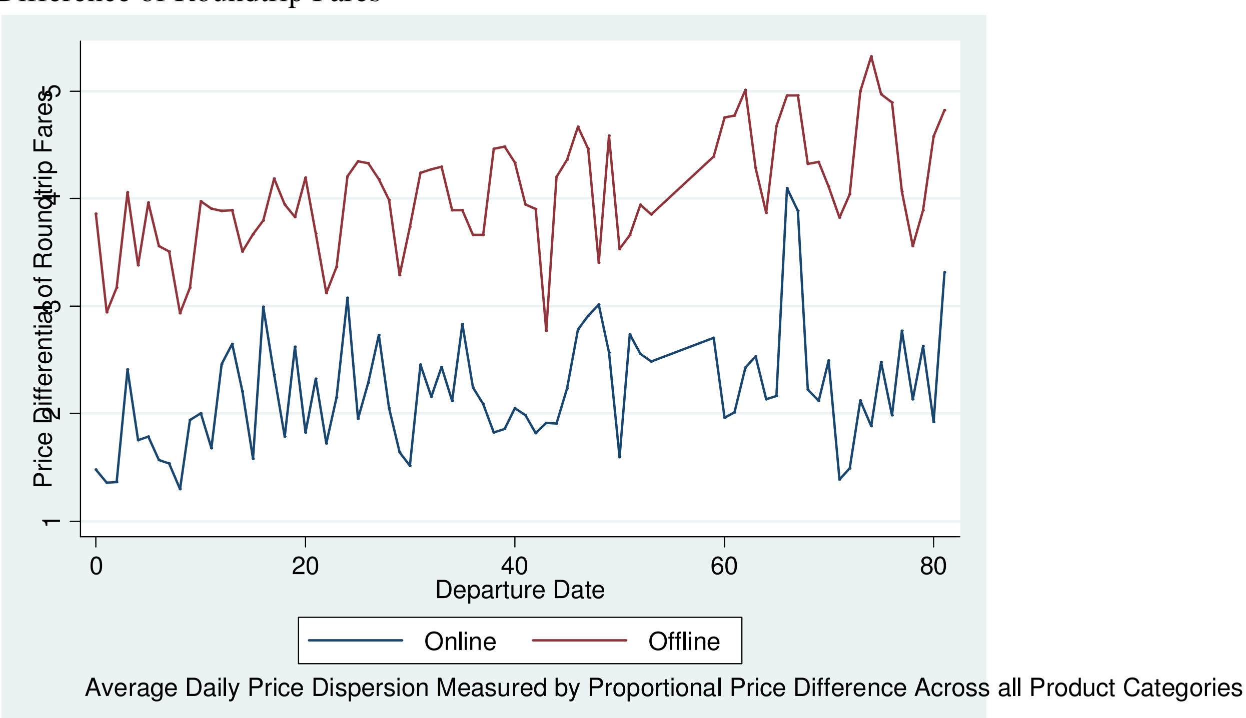


Figure 3b: Average Average Daily Dispersion in Roundtrip Fares Measured by Proportional Price Difference of Roundtrip Fares Averaged Over All Product Categories