IDENTIFYING AIRLINE PRICE DISCRIMINATION AND THE EFFECT OF COMPETITION

MATTHEW S. LEWIS*

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Abstract

Empirical studies exploring the relationship between competition and price discrimination don't generally consider the role of product differentiation or the asymmetric adoption of discrimination across firms. Using a customized empirical approach to examine the use of Saturday-night-stayover discounts in the U.S. airline industry, I show that discounts are used more often when facing competitors that offer differentiated products but less often when competing with firms that don't use discounts. Legacy carriers rarely use discounts when competing with Southwest or other low-cost carriers, but the presence of competing legacy carriers sometimes enhances the use of discounts.

Keywords: price discrimination, competition, airlines

I Introduction

Theoretical models of both second-degree price discrimination (Stole, 1995; Dai et al., 2014) and third-degree price discrimination (Holmes, 1989; Stole, 2007) have shown that an increase in competition can lead to an increase or a decrease in the amount of discrimination. Empirical studies have also extensively examined this relationship across a variety of markets and settings—sometimes finding that discrimination increases with competition (as in Borenstein (1991), Stavins (2001), Busse and Rysman (2005), Borzekowski et al. (2009), and Seim and Viard (2011)) and other times finding that competition reduces discrimination (Gerardi and Shapiro, 2009; Gaggero and Piga, 2011; Lin and Wang, 2015).

While the theoretical literature offers many valuable insights, it has primarily focused on symmetric equilibria arising from competition between symmetric (or symmet-

*John E. Walker Department of Economics, Clemson University, 228 Sirrine Hall, Box 341309, Clemson, SC 29634-1309, mslewis@clemson.edu

rically differentiated) firms. Similarly, existing empirical studies have generally examined how the (symmetric) discriminatory pricing strategies of all firms in the market are affected by the presence of additional competitors, but have not carefully investigated differences in discriminatory pricing or the heterogeneous effects of competition across firms. In practice, however, competing firms often face different costs, sell different products, and utilize different discriminatory pricing strategies. Of the few theoretical papers that consider discrimination with firm and consumer heterogeneity (Dogan et al., 2010; Shulman and Geng, 2013; Lin, 2017), most find that equilibria do exist in which one firm discriminates and the other firm does not. In this paper I explore the importance of such asymmetries through an empirical investigation of Saturday-night-stayover discounts, which are frequently used in the U.S. domestic airline market by legacy carriers (American, United, and Delta) but not by low-cost carriers (Southwest, JetBlue, etc.).

As in the broader literature, empirical studies of discrimination in airline markets have focused largely on the symmetric effects of competition. In addition, the data limitations faced by many of these studies make it difficult to control for unobserved cost differences when measuring the extent of price discrimination or identify the relationship between competition and discrimination. Borenstein and Rose (1994), Gerardi and Shapiro (2009), Dai et al. (2014), and others rely on price data from the Airline Origin and Destination Survey (DB1B) produced by the U.S. Bureau of Transportation Statistics. These data include a 10% sample of all tickets sold, but only report the quarter of travel, making it impossible to control for underlying cost differences between flights. As a result, these studies generally relate the degree of dispersion in prices (charged by a carrier on a route in a quarter) to the level of concentration on the route, but are unable to clearly separate price discrimination from cost-based price variation. Gaggero and Piga (2011) use more-detailed data from routes between the UK and Ireland, but adopt a similar approach to examine ticket price dispersion.

A second set of papers, including Stavins (2001), Giaume and Guillou (2004), Hernandez and Wiggins (2014), and He (2016), use itinerary-specific fare quote data to examine how concentration on the route affects the price differences associated with specific ticket restrictions (e.g., advance purchase or Saturday-night stayover restrictions) or fare classes.[1] Observable market and flight characteristics are used to control for cost-based factors that contribute to price differences across itineraries. However, given the unpredictable nature of flight-specific demand, substantial cost variation is likely to occur even across flights with the same observable characteristics. As a result, the findings of such studies may still be biased if unexplained cost differences are correlated with the price differences airlines attach to ticket restrictions on specific flights.

In this study I overcome these issues by using a customized data collection strategy to compare fares quoted to passengers staying over Saturday night with fares quoted to passengers not staying over Saturday night for travel on the *exact same pair of flights*.[2] Since the opportunity cost at a particular time of selling a seat on a particular flight is the same regardless of who purchases the seat, this comparison controls for all the unobserved factors affecting costs. Any remaining price differences can, therefore, be entirely attributed to price discrimination.

The findings establish several interesting new empirical facts that enhance the current understanding of airline price discrimination. First, legacy carriers are roughly three to five times more likely to use Saturday-night-stayover discounts on routes where they do not compete with Southwest. The presence of other low-cost carriers (like JetBlue) have a similar though slightly smaller effect, but competition from ultra-low-cost carriers (like Spirit or Frontier) have little impact on legacy carrier discounting behavior. Second, Saturday-night-stayover discounts are larger and more frequent when the competitors offer a different type of service (nonstop vs one-stop) than when they offer the same service type as the legacy carrier. Third, the presence of additional legacy carriers on a route does not reduce the use of Saturday-night-stayover discounts as much as competition from Southwest or LCC carriers, and in some cases competition from other legacy carriers increases the likelihood of discrimination.

The results also contribute new evidence to the broader literature on price discrim-

[1] Puller and Taylor (2012) identify price discrimination using a similar approach but they do not investigate how competition impacts discrimination.

[2] The same pair of flights can't actually represent both a round-trip itinerary with Saturday-night stayover and also one without, but using an approach similar to Lewis (forthcoming) I demonstrate how this comparison can be made by examining differences in the aggregate fares of different pairs of round-trip itineraries formed using the same underlying flights.

ination with asymmetric firms. While theoretical models with asymmetric firms often have equilibria in which one or both firms price discriminate, airlines rarely discriminate on routes where legacy and low-cost carriers are both present. Moreover, in terms of the use of Saturday-night-stayover discounts, the number of competitors on the route may not be as important as whether those competitors also utilize Saturday-night stayover discounts. This can explain why discounts are used less when competing against Southwest or other LCC carriers (that never offer Saturday-night-stayover discounts), but are sometimes used more frequently when competing against legacy carriers (that may also be using discounts). Finally, the results demonstrate that differentiation alters the effect of competition on discrimination. Legacy carriers' use of Saturday-night-discounts is most strongly influenced by Southwest, whose characteristics most-closely resemble the large legacy carriers, and is least impacted by ultra-low-cost carriers, who offer a very different type of product to customers. Similarly, there is significant quality differentiation between nonstop vs one-stop flights, and the use of discrimination is more strongly influenced by competition from carriers offering similar flights (of the same service type) than from those offering more differentiated flights (of a different service type).

With regard to some types of competition, my findings correspond with the conclusions of Gerardi and Shapiro (2009) and Gaggero and Piga (2011) that additional competition (among similar firms) tends to reduce the degree of price discrimination. However, they also complement those of Chandra and Lederman (2018) and Dai et al. (2014) suggesting a more nuanced relationship in which competition can sometimes have the opposite effect. Moreover, my analysis contributes a new source of evidence to the literature, leveraging unique data and a new empirical approach that isolates discrimination by eliminating cost-based price differences. By more extensively incorporating product heterogeneity into the empirical analysis the results also help to clarify the conditions under which competition reduces or enhances discriminatory activity in this market.

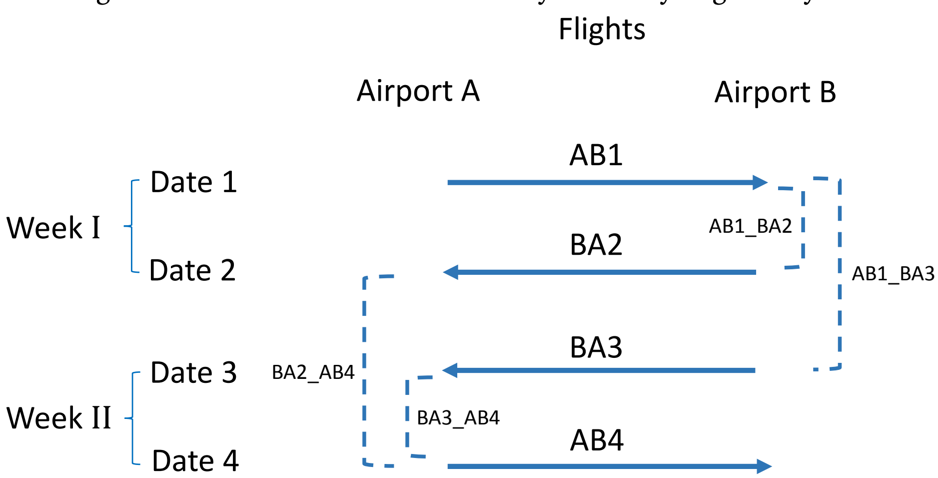
II Measuring Price Discrimination

Itineraries are said to include a Saturday-night-stayover when the passenger stays at their destination for a period that includes at least one Saturday night. In this study I use the term Saturday-night-stayover discount to refer to the purely discriminatory difference in fares charged for itineraries with and without a Saturday-night-stayover that cannot be explained by differences in the airline's underlying costs. The opportunity costs of selling a seat on any particular flight can depend on many factors that are not observable to researchers and are difficult to control for. However, at any point in time the opportunity cost of selling that seat should be the same regardless of the passenger purchasing the ticket or the itinerary it is used to construct. As a result, when the same seats on the same flights are offered concurrently at different fares depending only on the itineraries in which they appear, this can be interpreted as resulting from price discrimination.

My analysis empirically identifies the presence and magnitude of Saturday-night-stayover discounts by comparing the fare at which a seat is offered when part of an itinerary includes a Saturday-night stayover vs the fare at which the exact same seat is offered when it's itinerary does not include a Saturday-night stayover. The methodology is similar to that used by Lewis (forthcoming) to identify and study directional price discrimination. To illustrate, consider the round trip itineraries constructed from a set of four possible flights between airports A and B. The first two flights take place on Dates 1 and 2, respectively, in Week 1, and the other two flights occur on Dates 3 and 4 in Week 2. Using the origin, destination, and travel date of each flight, an itinerary including a flight from A to B on Date 1 and from B to A on Date 2 can be represented by AB1_BA2. Let the price of this itinerary be represented as P_{AB1_BA2}.[3] Figure 1 depicts these four flights and identifies each of the possible round-trip itineraries using dotted lines to connect their two component flights. Notice that the four depicted flights can be combined to form two itineraries (AB1_BA3 and BA2_AB4) that each include a Saturday-night stayover, but can also be combined to form two itineraries (AB1_BA2 and BA3_AB4) that do not include a Saturday-night stayover. As a

[3]To emphasize, two itineraries that both include AB1 (such as AB1_BA2 and AB1_BA3) both share the exact scheduled flight (e.g., Delta flight 455 from SFO to ORD on Tuesday April 3rd departing at 11:45AM), not just flights between the same airports on the same day.

Figure 1: Flights and Itineraries Used to Identify Saturday-Night-Stayover Discounts



result, comparing the sums of the prices of these two pairs of itineraries provides a measure of the Saturday-night stayover discount:

$$\textit{Saturday-Night Stayover Discount} = \frac{(P_{AB1\_BA2} + P_{BA3\_AB4}) - (P_{AB1\_BA3} + P_{BA2\_AB4})}{2}. \tag{1}$$

The primary advantage of this approach is that eliminates the need to identify or control for potentially-unobserved cost differences by using basic fare-quote data to compare prices offered at the exact same moment for travel on the exact same flights.

III Data

III.1 Route and Airport Market Shares

Market structure information is obtained from the 2018 U.S. Department of Transportation's Origin and Destination Survey Database (DB1B) which contains a 10 percent sample of all tickets sold on domestic routes. Defining a route as a unique origin and destination airport pair, I collect the number of nonstop and one-stop tickets sold by each airline on each route during the year and use these to determine which airlines offer service on each route and whether they offer a non-stop flight or not.[4] This information is used to construct measures of the number of (nonstop or one-stop) competitors on each route.[5] I also construct a measure of airport presence for each airline by collecting the total number passengers whose round-trip itineraries originate from that airport.[6]

III.2 Airfare Quotes

The airfare price quotes used to measure price discrimination are collected from a major airfare aggregator website. The aggregator obtains fare information from a global distribution system (GDS) that disseminates the latest fare information provided by airlines to the Airline Tariff Publishing Company (ATPCO). For each quoted itinerary, the data include the fare, ticketing carrier, operating carrier, origin and destination airports, the flight times and dates, and the date and time when the price was quoted. My analysis will focus only on coach-class (economy) fares.[7]

Of the top 10,000 most frequently traveled domestic routes, fare quotes are collected for a sub-sample of 3633 routes. While the number of passengers traveling varies widely across sampled routes, the more infrequently traveled routes are undersampled. Figure 2 reports a frequency histogram of U.S. domestic routes by DB1B passengers traveled and indicates how many routes of each size appear in the fare quote sample. Since the DB1B data is designed to provide a 10 percent sample of all tickets sold, the actual number of passengers that traveled on each route during 2018 is roughly 10 times the number of DB1B passengers reported.

My analysis focuses on fare quotes of the three major legacy carriers–American,

[4]To prevent data errors from impacting my measures of airline presence, an airline is only considered to offer nonstop service on a route if at least 3 percent of the tickets sold by the airline on the route are nonstop and also the airline sells at least 1 percent of all nonstop tickets sold on the route. Similarly, an airline is considered to offer one-stop service if it sells at least one percent of all one-stop tickets on the route.

[5]Counts of competitors only consider the 11 major domestic airlines operating during my sample period: American, Delta, United, Southwest, JetBlue, Alaska, Spirit, Frontier, Hawaiian, Allegiant, and Sun Country.

[6]In the DB1B database this corresponds to a count of the itineraries (or passengers in the DB1B "ticket" data tables) sold by the airline that originate from that airport.

[7]For airlines like American, United, Delta, Alaska, and JetBlue that offer both economy and basic economy fares, the basic economy fares are dropped from the analysis. Fares for airlines like Frontier and Spirit are used despite the fact that the amenities included in these fares are most similar to basic economy fares on other airlines. However, since my analysis relies entirely on within-carrier differences in fares, cross-carrier differences in amenities should have no impact on the results.

Figure 2: Distribution of Routes by Passenger Volume: All Routes and Sampled Routes

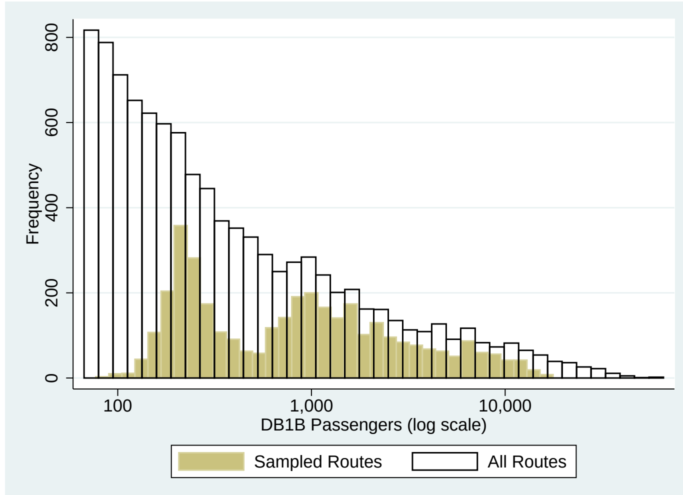


Table 1: Sampled Fares by Round-Trip Itinerary Type

	Mean	Std. Dev.	10th Percentile	90th Percentile	# of obs
Itinerary with Sat.-Night Stayover	$500	$186	$320	$705	298,765
Itinerary without Sat.-Night Stayover	$524	$189	$348	$722	298,765
Nonstop Itinerary	$454	$183	$279	$682	56,777
One-Stop Itinerary	$518	$187	$344	$717	540,753
Advanced Purchase under 21 days	$543	$213	$348	$766	270,635
Advanced Purchase 21 days or more	$486	$159	$327	$752	326,895
All Fares	$512	$188	$335	$714	597,530

Delta, and United–since these are the carriers that extensively engage in itinerary-based price discrimination. Other airlines including Southwest, Alaska, JetBlue, Spirit and Frontier price their flights on a one-way basis, so all round-trip fares are the sum of two one-way fares and are not affected by Saturday-night-stayovers or other itinerary characteristics. Table 1 reports summary statistics of the sampled legacy-carrier fare quotes for different types of itineraries.

The identification approach described in the previous section requires the observation of contemporaneous price quotes for four different round-trip itineraries on each route, as depicted in Figure 1. For all collected fares, Dates 1 and 3 are Tuesdays and Dates 2 and 4 are Thursdays, so observed round trip itineraries that do not include a Saturday-night

Table 2: Example Construction of Saturday-Night Stayover Discount

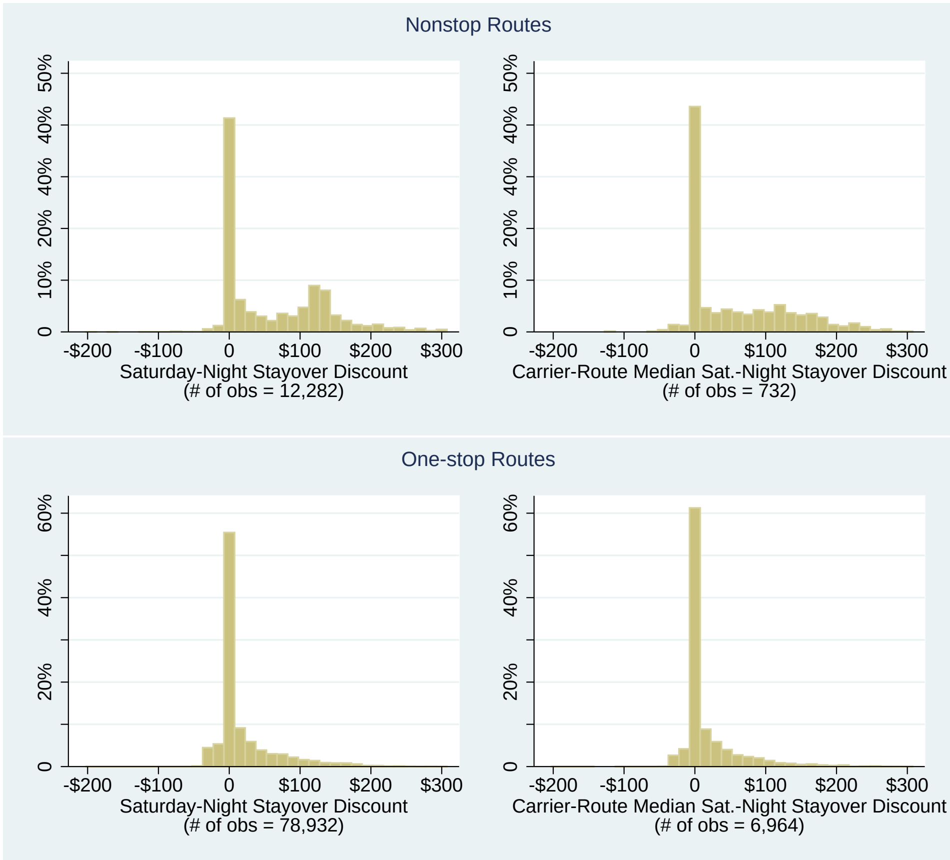
Delta Air Lines nonstop between Cincinnati, OH (CVG) and Newark, NJ (EWR)				
Itinerary	Outbound Departure Time	Inbound Departure Time	Round-Trip Airfare	Sat. Night Stayover
1: CVG to EWR	June 18 5:19 PM	June 20 7:57 PM	\$551	N
2: CVG to EWR	June 18 5:19 PM	June 25 7:57 PM	\$355	Y
3: EWR to CVG	June 20 7:57 PM	June 27 5:19 PM	\$435	Y
4: EWR to CVG	June 25 7:57 PM	June 27 5:19 PM	\$477	N
Implied Sat.-Night Stayover Discount $\left(\frac{(P_1+P_4)-(P_2+P_3)}{2}\right)$:			\$119	

stayover are always Tuesday-to-Thursday trips and itineraries that include a Saturday-night stayover are Tuesday-to-Tuesday or Thursday-to-Thursday trips. Since the data collection is focused on identifying the impact of Saturday-night stayovers, the construction of Saturday-night stayover discounts uses pairs of round-trip itineraries that differ only in the length of the stayover. In particular, the two flights in each direction (AB1 & AB4 and BA2 & BA3) used to construct the discount are chosen to have the same departure times and connecting airports (if a stopover exists). Table 2 provides an example of how the Saturday-night stayover discount is calculated based on Equation 1 for a particular set of flights.

All quotes on a given route (by all airlines) are collected on the same day and for the same travel dates. However, each possible combination of 4 round-trip itineraries results in a different calculated Saturday-night stayover discount. Since airlines typically fly multiple flights per day on a route, this generates over 91,000 unique observations across the three legacy carriers on the 3633 sampled routes. Figure 3 presents histograms of the distribution of observed Saturday-night stayover discounts as well as of the median Saturday-night stayover discount observed within each carrier on each route. The distributions of discounts are reported separately for nonstop and one-stop routes to highlight that discounts are more frequent and larger on nonstop routes. While over half of all observations exhibit no Saturday-night stayover discount, others reveal substantial discounts. Discounts of over \$100 arise in 36% of the observations from nonstop routes and 7% of observations from one-stop routes.

It is generally accepted within the industry that airlines offer lower prices for itineraries

Figure 3: Histograms of Saturday-Night Stayover Discounts for Nonstop and One-Stop Routes



with Saturday-night stayovers, suggesting a positive Saturday-night stayover discount, however, the data appear to contain some negative discount values. Although it may be possible for travelers staying over Saturday night to have a less elastic demand on a few routes, it seems more likely that these negative discount values are the result of measurement error.[8] Positive discount values are much more frequent and are observed over a much wider range of magnitudes. In contrast, negative discounts tend to be quite small and become almost nonexistant at values larger than $35. An examination of the Saturday-night stayover discounts implied by fare quotes from other airlines further supports the measurement error explanation. Airlines such as Alaska and JetBlue and other low-cost carriers are known to use one-way pricing platforms that don't allow for Saturday-night stayover discounts,

[8]Note that negative Saturday-night stayover discounts would also encourage customers to arbitrage by booking two one-way flights rather than the round trip, while positive discounts are not subject to arbitrage.

and yet the fare quote data for these airlines also contain a nontrivial number of nonzero values.[9] The observed discounts for these carriers, however, are symmetrically distributed around zero reflecting the fact that they do not actually engage in itinerary-based pricing. Moreover, when measurement error does generate nonzero Saturday-night stayover discount values for these low-cost carriers (positive or negative) they are almost always smaller than $35 in magnitude.[10] To limit the influence of possible measurement error, my analysis will consider discounts of larger than $35 as exhibiting a Saturday-night stayover discount and observations with a smaller measured discount as having no stayover discount. Altering this threshold does not have a substantial impact on the findings.

The dates of travel and the date on which quotes are requested both vary across the routes in the sample. As a result, the time between the day of the price quote and the first day of travel ranges from 2 days to 42 days with a mean of 22 days. Since the use of Saturday-night stayover discounts may differ for tickets purchased further in advance of travel, my empirical analysis includes a control for the degree of *advance purchase*.

IV Analysis: Price Discrimination and Competition

Given that airlines utilize Saturday-night stayover discounts on some routes but not others, my empirical analysis investigates how the nature of competition on a route impacts both the decision use this form of price discrimination as well as the size of the discount offered. A two-level hurdle model is estimated, with the first part modeling the probability of offering a Saturday-night stayover discount and the second part modeling the magnitude of the discount, if offered. Unlike the more restrictive Tobit model (Tobin, 1958), the hurdle model (Cragg, 1971) allows market factors to differentially influence the decision to discriminate and the amount of discrimination.

[9] Southwest Airlines is the only carrier whose fares do not appear on the airfare aggregator website, so they cannot be included in the comparison analysis.

[10] Such measurement error may be related to the occasional misclassification of basic economy vs. economy fares. Basic economy fares are designated in the data and are not included in the analysis, but it could be possible that some itineraries were incorrectly labeled as economy despite actually including a basic economy flight. Since the price difference between basic economy and economy fares tend not to be larger than $35 this may explain why measurement error in the Saturday-night stayover discount would mostly be limited to smaller magnitudes.

My empirical analysis will be based on the following lognormal hurdle model:

$$P(d = 0|\boldsymbol{x}) = 1 - G(\boldsymbol{x\gamma}) \tag{2}$$

$$\log(d)|(\boldsymbol{x}, d > 0) \sim \mathrm{Normal}(\boldsymbol{x\beta}, \sigma^2) \tag{3}$$

where d represents the Saturday-night stayover discount and $\boldsymbol{x}$ represents a vector of airline and market characteristics. In Cragg's (1971) implementation, Equation 3 represents a model of the latent discount that would be offered (whether it is observed or not), as long as the error terms associated with Equations 2 & 3 are independent. This interpretation is not critical to my analysis, however, as one can alternatively view the estimates of Equation 3 as describing how the size of the discount varies with airline and market characteristics, conditional on a discount being offered. This conditional interpretation allows Equations 2 & 3 to be separately estimated even without assuming independently distributed errors.

My primary focus is on establishing how competition impacts discrimination, so $\boldsymbol{x}$ includes a series of indicator variables capturing the presence of competing airlines on the route. Competitors are categorized as either national legacy carriers (American, Delta, and United), low-cost carriers (JetBlue, Alaska, and Hawaiian), or ultra-low-cost carriers (Spirit, Frontier, Allegiant, Sun Country), with the exception of Southwest Airlines whose presence is accounted for separately because it shares some characteristics with both legacy and low-cost carriers and appears to uniquely impact the decision of legacy carriers to price discriminate. Although the distinct nature and increasing importance of ultra-low-cost carriers (or ULCCs) has been widely acknowledged within the industry (Boyd, 2018; Silk, 2019), most academic studies have continued to group these with other low-cost carriers (LCCs). My categorization is similar to Bachwich and Wittman (2017), who provide evidence that ULCCs utilize different pricing strategies and have distinctly lower costs per mile than airlines like Alaska and JetBlue.[11] For each of these category types, the $\boldsymbol{x}$ vector includes a separate variable indicating whether at least one competing carrier of that type offers nonstop service on the route. Similar variables indicating whether competitors of each of type

[11]While Alaska and Hawaiian Airlines are often considered legacy carriers because they have operated since the regulation era, they have adopted many of the practices of low-cost carriers, including one-way pricing (with round trips fares equaling the sum of two one-way fares), and their costs are more similar to other LCCs than to the larger national legacy carriers (Bachwich and Wittman, 2017).

offer one-stop service on the route are also included.[12]

Unobserved factors affecting the potential profitability of price discrimination on a given route may also influence airlines' entry decisions. As a result, estimation must account for the potential endogeneity of competition measures in both levels of the hurdle model. Fortunately, the scale of an airline's operations at the endpoint airports of a route heavily (and exogenously) influences the likelihood that the airline will provide service on the route. Following previous studies examining airline price discrimination and competition, including Borenstein and Rose (1994), Gerardi and Shapiro (2009), Hernandez and Wiggins (2014), and Chandra and Lederman (2018), I utilize an instrumental variables strategy based on airport presence.

Hurdle models of the form specified above are typically estimated using a Probit estimator for Equation 2 and an OLS estimator for Equation 3. However, given the nonlinear nature of the Probit model and the fact that many of the endogenous variables in my context are discrete indicators of market presence, incorporating instrumental variables into this specification becomes problematic. To overcome these complications I instead adopt a linear probability model, specifying $G(\boldsymbol{x}\gamma) = \boldsymbol{x}\gamma$. While linear probability models have some undesirable characteristics (e.g., predicted probabilities can lie outside the unit interval), Wooldridge (2010, pp. 454-457) and Angrist and Pischke (2009, pp. 101-107) argue that this approach generally offers a good approximation of response probability, particularly in models with discrete explanatory variables. Moreover, linear probability models can accommodate the use of instrumental variables, even with discrete endogenous regressors. The log-normal specification of Equation 3 similarly results in a linear model that can be estimated using a standard instrumental variables approach.

The main empirical analysis focuses on the median Saturday-night stayover discount offered by each carrier on each route. Consequently, the first component of the

[12]Previous studies, including Borenstein and Rose (1994) and Gerardi and Shapiro (2009), find that price discrimination is influenced by the total number of competitors on a route (rather than simply the existence of at least one competitor). However, after dividing carriers into four different types (Legacy, Southwest, LCC, ULCC) I find they rarely face more than one competitor of a given type on a route. Therefore, my main specifications are based on type-specific competition indicators. Nevertheless, alternative specifications including the number of competitors of each type are also estimated, and the results are qualitatively similar to the competition indicator specifications.

hurdle model examines factors affecting the likelihood that an airline offers Saturday-night stayover discounts (of at least $35) for the majority of its itineraries on a given route, and the second component describes how these factors influence the median size of an airline's discounts on the route if a majority of their itineraries exhibit a discount (of at least $35). Using the median discount helps to mitigate the impact of the occasionally mismeasured fares discussed in Section III, and also generates dependent variables that vary at the same carrier-route level as the competition measures and other independent variables. In addition, the decision to adopt Saturday-night Stayover discounts or not appears to be determined at the route level. In the data, over 91% of carriers on nonstop routes and 87% of carriers on one-stop routes use discounts (of at least $35) for either all of their observed itineraries or on none of their itineraries on the route.

Both equations of the model include a number of control variables to better explain variation in price discrimination across routes and carriers. For example, longer flights often use larger planes with more seats which may impact the airline's ability to price discriminate. To control flexibly for distance I include indicators categorizing routes into four different distance intervals. In addition, Gerardi and Shapiro (2009) and others have shown price discrimination to be more extensive on routes between big cities (that tend to have both business and leisure travelers) and less extensive on "leisure routes" that almost exclusively cater to more elastic leisure travelers. I control for such differences using a big city route indicator identifying routes between any two of the largest 35 metropolitan areas in the country[13], and a leisure route indicator identifying when travelers on a route disproportionately (i.e., over 75%) originate from one of the two endpoints. On most routes a relatively equal number of round-trip travelers originate from each endpoint. However, on routes dominated by leisure travel, such as routes into Las Vegas or routes involving airports in Florida, very few travelers on the route originate their round-trip itinerary from the tourist destination airport.[14]

[13]The largest metropolitan statistical areas are identified based on their population in the 2010 U.S. Census. Routes in or out of Miami, Tampa, San Diego, Orlando, and Las Vegas are not included as big city routes (despite being among the 35 largest metro areas) because these are popular tourist destinations and are likely to predominantly serve leisure travelers.

[14]While other studies have identified leisure routes using data on endpoint city accommodation earnings (Borenstein, 1989; Gerardi and Shapiro, 2009), the measure I adopt takes direct advantage of the particular air travel patterns observed on leisure routes rather than relying on supplemental data sources that indirectly

Price quote data for some routes were collected further in advance of the travel date than on other routes. Since the mix of business and leisure travelers shopping for flights may change as the travel date approaches, the incentive to utilize Saturday-night stayover discounts may also change. To account for this both equations also include an indicator variable for whether the price quotes were obtained more than 21 days prior to departure. Continuous measures of advanced purchase and alternative advanced-purchase indicators were also considered, but did not add additional explanatory power or meaningfully alter the other coefficient estimates.

Finally, the underlying level of fares on the route may impact both the airline's decision to offer a Saturday-night stayover discount as well as the size of the discount they choose to offer. Moreover, due to potential measurement error in the data, my empirical analysis only considers observed fare differences as Saturday-night stayover discounts when they exceed \$35.[15] If less expensive routes are more likely to have actual Saturday-night stayover discounts that are smaller than \$35, then these routes will exhibit a lower apparent frequency of price discrimination. To account for these issues when analyzing price discrimination, the log of the underlying fare level (for travel with a Saturday-night stay) is included in $\boldsymbol{x}$ as a control variable in both equations of the hurdle model. Table 3 lists and defines each of the variables present in the main specification of the model.

The use of instrumental variables should ensure that the estimated effects of competition are not biased by omitted variables. Nevertheless, to examine the robustness of the estimates to unobserved route heterogeneity, I consider adding one additional control variable: the log of the total number of passengers (both nonstop and one-stop) traveling between the endpoint cities of the route. Routes with more passengers are more likely to have a larger number of carriers and also may have greater passenger heterogeneity (making price discrimination more profitable). Unfortunately, this variable also has the potential to be endogenous to the extent that the use of price discrimination impacts the number of people that choose to travel on the route. Therefore, while I exclude the measure from my main specification, I also provide alternative specifications that include this control.

capture traveler volumes.

[15]The justification for this \$35 cutoff is discussed in Section III.2.

Table 3: Variable Definitions

Dependent Variables:	
Discount Present$_{cr}$	$= 1$ if Median Saturday-night stayover discount for carrier c on route r is greater than \$35.
ln(Discount)$_{cr}$	Log of the median Saturday-night stayover discount for carrier c on route r (when median discount is greater than \$35).
Competition Indicators:	
WN Nonstop$_r$	$= 1$ Southwest operates nonstop service between the two endpoint cities of the route.†
WN Onestop$_r$	$= 1$ Southwest operates one-stop service between the two endpoint cities of the route.†
Legacy Nonstop$_{cr}$	$= 1$ at least one competing legacy carrier operates nonstop service on the route.
Legacy Onestop$_{cr}$	$= 1$ at least one competing legacy carrier operates one-stop service on the route.
LCC Nonstop$_r$	$= 1$ at least one low-cost carrier operates nonstop service on the route.
LCC Onestop$_r$	$= 1$ at least one low-cost carrier operates one-stop service on the route.
ULCC Nonstop$_r$	$= 1$ at least one ultra-low-cost carrier operates nonstop service on the route.
ULCC Onestop$_r$	$= 1$ at least one ultra-low-cost carrier operates one-stop service on the route.
Control Variables:	
Leisure Route$_r$	$= 1$ if route is classified as a leisure route.
Big-City Route$_r$	$= 1$ if route connects two large cities.
ln(Median Price)$_{cr}$	Log of the median price charged by carrier c on route r (for itineraries with a Saturday-night stayover).
Adv. Purchase Under 21 Days$_r$	$= 1$ if the price quote was observed within 21 days of departure.
Distance Categories$_r^i$	A set of four indicator variables ($i = 1$ to 4) dividing routes into four route-length categories based on distance from origin to final destination (with 1 being the shortest).‡

† In multi-airport cities, Southwest may be viewed as a competitor to a legacy carrier even if it operates out of different a airport. To account for this I consider competition from Southwest to be present on the route if Southwest flies between any airports in the endpoint cities of the route.

‡ Distance category 1 includes routes of less than 1000 miles, category 2 between 1000 and 2000, category 3 between 2000 and 3000, and category 4 over 3000 miles.

IV.1 Construction of Instrumental Variables

Instrumental variables are needed to control for the potential endogeneity of the presence of competitors on the route. Following previous studies my instruments rely on the fact that airlines are more likely to offer service on a particular route when they have a significant presence at each of the route's endpoint airports. A multi-step process is used to construct appropriate instruments. First, for each airline, I estimate the probability that the airline provides service on each potential route as a function of their endpoint airport presence. Then I use these airline-specific estimated probabilities to construct a predicted probability for each of the competition indicators appearing in the model.

In the first step, a logistic regression is estimated separately for each carrier $c \in$ {AA, DL, UA, WN, AS, B6, HA, F9, G4, NK, SY} and each service type $s \in$ {nonstop, one-stop}. The probability of offering service on a route r is modeled as a function of the carrier's endpoint presence[16], the endpoint presence of other major carriers $k \in$ {AA, DL, UA, WN}, and

[16]The two variables used to measure endpoint airport presence are:

Total Endpoint Passengers$_{rc}$**:** The sum of the number of passenger enplanements (on flights to any destination) on carrier c from either one of the two endpoint airports of route r.

Geo. Mean Endpoint Passengers$_{rc}$**:** The geometric mean across the two endpoint airports of route r of the number of passengers enplanements (to any destination) on carrier c.

The first variable captures the overall number of customers that carrier serves at the endpoints, while the second variable contributes additional information on the balance of customers across the endpoints. Since these two variables are somewhat correlated, only the second is interacted with route distance indicators when predicting the carrier's probability of serving the route.

other route characteristics, as follows:

$$
\begin{aligned}
&P(\text{Service Offered}_{src}) = \\
&\quad \alpha_1^{sc}\text{Total Endpoint Passengers}_{rc} + \sum_{k\neq c} \alpha_{k1}^{sc}\text{Total Endpoint Passengers}_{rk} \\
&\quad + \sum_{i=1}^{4} \alpha_2^{isc}(\text{Geo. Mean Endpoint Passengers}_{rc} \times \text{Distance Category}_{ir}) \\
&\quad + \sum_{k\neq c}\sum_{i=1}^{4} \alpha_{k2}^{isc}(\text{Geo. Mean Endpoint Passengers}_{rk} \times \text{Distance Category}_{ir}) \\
&\quad + \sum_{i=1}^{4} \alpha_3^{isc}(\text{Big-City Route}_{r} \times \text{Distance Category}_{ir}) \\
&\quad + \sum_{i=1}^{4} \alpha_4^{isc}(\text{Leisure Route}_{r} \times \text{Distance Category}_{ir}) \\
&\quad + \sum_{i=1}^{3} \alpha_5^{isc}\text{Distance Category}_{ir} + \epsilon_{src}. \qquad (4)
\end{aligned}
$$

The logistic regression is estimated using only route-carrier observations in which the carrier is active in both endpoint airports of the route, since this is necessary to offer service on the route. Consequently, the predicted probability measure is assigned a value of zero for the remaining observations in which the airline is not present in both endpoint airports.

In the second step, the predicted probabilities for each airline on each route are used to construct a measure of the probability of facing competition. For each type of service (nonstop or one-stop), the predicted probability of at least one competing legacy carrier operating on the route is constructed as one minus the product of the predicted probabilities that each of the other legacy carriers does not serve the route.[17] Similarly, the estimates are used to construct the predicted probability of at least one LCC operating on the route and the predicted probability of at least one ULCC operating on the route.

[17] This calculation of the probability of at least one competitor is somewhat simplified in that the probabilities of each carrier operating on the route are treated as if they were independent. However, this independence only applies to the unexplained component of each airline's entry probability because the endpoint airport presence of rival carriers is considered when predicting the probability of serving a route in Equation 4. In other words, the calculation accounts for some strategic interaction, like the relative reluctance of an airline to enter a route that another airline is likely to serve (because that airline has a large presence at both endpoints). Regardless, the validity of the instrumental variable strategy is not impacted by the use of an imperfect measure of the probability of facing competition.

These competitor-type presence probabilities and the predicted probability of Southwest serving the route are then used as instruments for the endogenous competition indicators (listed in Table 3) when estimating both Equations 2 & 3 of the hurdle model, as suggested by Heckman (1978, pp. 946-947). As the histograms in Appendix Figures A1 & A2 illustrate, estimated presence probabilities are distinctly higher for routes where a competitor is actually present. Moreover, the predicted probabilities for each competitor type vary independently and correlate strongly presence of that particular competitor type, allowing the effects of each of the endogenous competition indicators to be separately identified. Conditional first-stage F-statistics computed following the Sanderson and Windmeijer (2016) procedure for each endogenous variable fail to identify any weak instruments, and Kleibergen-Paap F statistics jointly testing all instruments also reject the presence of weak instruments in all specifications except those estimating Equation 3 for nonstop flights, which have a particularly small sample size. A complete presentation of first stage F tests are presented in Appendix Table A1.[18]

IV.2 Identification

My analysis considers how the use of Saturday-night stayover discounts by a legacy carrier changes when competing carriers are also serving the route. The instrumental variables are constructed using the predicted probabilities that competing carriers will serve the route, which are a function of the endpoint airport presence of these competing carriers. As a result, the analysis exploits variation across routes in the endpoint airport presence of competing carriers to identify how competition on a route impacts price discrimination. Identification rests on the assumption that, after controlling for route length and traveler profile (big-city, leisure, etc.), the presence of competing airlines at a pair of airports is not meaningfully influenced by (or correlated with) unexplained variation in the use of Saturday-night stayover discounts on the route between these airports. This type of assumption is relatively common within the empirical literature on airline competition and is

[18]Formal critical values for weak instruments test based on the Sanderson-Windmeijer F-statistic or the Kleibergen-Paap F statistic have not been derived for cases with multiple discrete endogenous variables and correlated heteroskedastic errors, but values smaller than 10 are generally thought to indicate that instruments are potentially weak.

motivated by the fact that airport presence is determined based on the general profitability of all potential routes out of the airport and will not be meaningfully influenced by the pricing strategy being used by competing carriers on any one particular route.

When examining discrimination by legacy carrier X, the predicted probability of a competing carrier Y serving the route primarily depends on carrier Y's presence at the endpoint airports of the route. However, as expressed in Equation 4, I also allow the endpoint airport presence of other carriers (including carrier X) to influence carrier Y's decision to serve a route. Therefore, the instrument could exhibit some correlation with the second-stage error term if legacy carrier X's use of price discrimination is influenced by the magnitude of their own presence at the endpoint airports of the route. For example, business travelers and frequent flyers are common targets for price discrimination and may also be attracted to airlines that offer many flights out of their home airport. To account for such potential demand-side effects of airport presence, I adopt an approach similar to Borenstein (1989) and include in some specifications of Equations 2 & 3 a measure of the carrier's total number of endpoint airport passenger originations.[19]

Some other studies, including Gerardi and Shapiro (2009) and Chandra and Lederman (2018), that have examined airline price discrimination and competition have utilized panel data and have included route fixed effects to further control for unobservable factors that may be correlated with both competition and the degree of price dispersion. My analysis is cross-sectional, so route fixed effects cannot be used. The tradeoff, however, is that the customized fare quote data I use offers a cleaner measure of the use of a specific form of price discrimination. Comparing prices offered at the same time for prices on the exact same flights eliminates price differences resulting from unobserved cost heterogeneity. In contrast, the price dispersion measures used in most panel studies compare prices offered at different times or for travel on different flights, introducing additional variation

[19]Borenstein (1989) argues that an airline's attractiveness to frequent flyers on a particular route may depend on the airline's total originations out of the endpoints airports, where originations are travelers starting their itinerary at the airport. In contrast, when constructing instruments, Borenstein (1989) argues that the costs of serving a route are more likely to be low when the airline flies a large number of passengers (originating or connecting) out of *both* endpoint airports. For this reason, when modeling the probability of serving a route I primarily rely on the geometric mean of passenger enplanements, where enplanements includes both originating and connecting passengers boarding a flight.

that complicates empirical identification.

IV.3 Estimation and Results

Before discussing estimates from the empirical model, it is helpful to present a simple comparison of means highlighting the disparate effects of competition. Across the carrier-route pairs for which nonstop or one-stop fares are observed in my sample, Table 4 considers various subsamples facing different numbers and types of competing carriers. For each subsample, the table reports the number of observations and the share of observations for which the median Saturday-night stayover discount is greater than $35 (i.e., share of observations where $\textit{Discount Present}_{cr} = 1$). The comparisons reveal very large differences in the use of discounts. For example, legacy carriers offering nonstop flights use Saturday-night stayover discounts on 79.5% of routes where they are the only nonstop carrier but use the discounts on only 11.9% of routes where they face nonstop competition from Southwest. A somewhat similar pattern is observed on one-stop flights, though discounts are used less frequently than on nonstop flights. Interestingly, discounts are also relatively infrequent when facing competition from LCCs, but not when facing competition from ULCCs, suggesting that the distinction between LCCs and ULCCs may be important in this context.

The differences in prevalence of discounting revealed in Table 4 are compelling, but it is important to account for other confounding market factors that may vary across subsamples. The double-hurdle model specified in Section IV can more accurately identify the impact of competition on discounting, while controlling for market factors and resolving the potential endogeneity of competition on the route. Both equations of the model are estimated using two-stage least squares with the instruments described in Section IV.1.

Estimation results for the first equation of the model, describing the likelihood of utilizing Saturday-night stayover discounts, are reported in Table 5. Results for the nonstop fare sample appear in Columns 1 through 3 and those for the one-stop sample are in Columns 4 through 6. Columns 1 & 4 present a basic specification that includes only the (instrumented) competition measures. Columns 2 & 5 represent the main specification of the model, adding the control variables discussed in Section IV and carrier fixed effects.

Table 4: Competition and the Frequency of Saturday-night Stayover Discounts

	Number of Observations	Fraction of Routes with Discount
Nonstop Fares:		
No nonstop competition	263	79.5%
Nonstop competition from Southwest only	109	11.9%
Nonstop competition from LCC only	30	20.0%
Nonstop competition from ULCC only	45	68.9%
Nonstop competition from legacy carriers only	74	74.3%
All observations	732	46.7%
One-stop Fares:		
One-stop competition from Southwest (but no LCC or ULCC)	2167	6.7%
One-stop competition from LCC (but no Southwest or ULCC)	475	12.2%
One-stop competition from ULCC (but no Southwest or LCC)	255	42.0%
One-stop competition from legacy carriers only	2312	32.7%
Competing legacy carriers offer nonstop flights (no Southwest, LCC, or ULCC competition)	443	58.2%
All observations	6964	17.8%

Notes: Observations represent a unique carrier-route pair. The "Fraction of Routes with Discount" is the mean of $\textit{Discount Present}_{cr}$ across carriers and routes within the specified subsample. Competition categories specified in the table are not necessarily mutually exclusive (or comprehensive). One-stop fare categories are not defined conditional on presence or absence of one-stop legacy competitors because legacy competition exists on 96% of observed one-stop routes.

Finally, Columns 3 & 6 provide an alternative specification that includes two additional variables: the log of the total number of passengers (both nonstop and one-stop) traveling between the endpoint cities of the route and the sum of the carrier's passenger originations from the route's two endpoint airports. Although the first variable is potentially endogenous, its inclusion in the model serves as a robustness check to assure that unobserved volume-related route heterogeneity is not substantially impacting the estimates of interest. The second variable captures possible demand-side effects of airport presence that might otherwise lead unobserved heterogeneity in the use of discounts to be correlated with the instrumental variables.[20]

The estimates from the nonstop fare sample imply that legacy carriers are 61 percentage points less likely to offer Saturday-night stayover discounts on nonstop flights when Southwest also offers nonstop flights on the route and are 46 percentage points less likely when at least one LCC (other than Southwest) serves the nonstop route. In contrast, the presence of ULCCs or additional legacy competitors on the nonstop route do not have a sizable or statistically significant impact on the likelihood of offering discounts. The nonstop carrier may also face competition from additional carriers that don't offer nonstop service but do offer one-stop flights on the route, however these competitors do not appear to significantly impact the use of Saturday-night stayover discounts on nonstop flights.[21]

A similar pattern emerges when examining legacy carriers that only offer one-stop flights (i.e., no nonstop flights). Saturday-night stayover discounts on these flights are around 25 percentage points less likely when Southwest offers a competing one-stop flight and are 19 percentage points less likely when an LCC offers a one-stop flight but are not impacted by the presence of ULCCs. Competition from legacy carriers offering one-stop flights on the route also has a negative impact on discounting, but the effect is significantly smaller than for competition from LCCs or Southwest. Competition from nonstop carriers has a very different effect. The one-stop legacy carrier is 14 percentage points less likely to offer discounts when competing with a nonstop flight offered by Southwest but is 23

[20]Section IV.2 offers a description of this variable and discusses the motivation for its inclusion.

[21]The possible exception is the presence of one-stop competition from other legacy carriers, which is sometimes associated with a marginally significant increase in the likelihood of using Saturday-night stayover discounts.

Table 5: Equation 2 Estimates: Probability of Offering Saturday-Night Stayover Discount

	Nonstop Fares			One-stop Fares		
	(1)	(2)	(3)	(4)	(5)	(6)
WN Nonstop	-0.704^{***}	-0.613^{***}	-0.492^{***}	-0.111^{***}	-0.140^{***}	-0.236^{***}
	(0.053)	(0.058)	(0.074)	(0.021)	(0.023)	(0.030)
WN Onestop	0.004	-0.048	-0.002	-0.251^{***}	-0.246^{***}	-0.298^{***}
	(0.055)	(0.058)	(0.060)	(0.015)	(0.016)	(0.019)
Legacy Nonstop	-0.064	-0.093	-0.001	0.257^{***}	0.226^{***}	0.160^{***}
	(0.047)	(0.050)	(0.060)	(0.020)	(0.022)	(0.026)
Legacy Onestop	0.129	0.182	0.303^{*}	-0.115^{***}	-0.084^{*}	-0.079^{*}
	(0.111)	(0.109)	(0.145)	(0.032)	(0.033)	(0.035)
LCC Nonstop	-0.420^{***}	-0.462^{***}	-0.367^{***}	0.046	0.026	-0.035
	(0.096)	(0.095)	(0.091)	(0.033)	(0.033)	(0.035)
LCC Onestop	-0.076	-0.041	0.059	-0.202^{***}	-0.191^{***}	-0.219^{***}
	(0.087)	(0.087)	(0.100)	(0.020)	(0.022)	(0.023)
ULCC Nonstop	-0.234^{*}	-0.186	-0.124	-0.056	-0.049	-0.084
	(0.095)	(0.112)	(0.113)	(0.044)	(0.048)	(0.049)
ULCC Onestop	0.112	0.093	0.067	0.054	0.049	0.023
	(0.089)	(0.113)	(0.106)	(0.039)	(0.043)	(0.043)
Leisure Route		-0.092	-0.045		-0.022	-0.036^{*}
		(0.076)	(0.075)		(0.017)	(0.017)
Big-City Route		0.080^{*}	0.133^{**}		0.042^{*}	-0.001
		(0.037)	(0.043)		(0.020)	(0.020)
Distance Category 2		-0.066	-0.066		-0.016	-0.022
		(0.044)	(0.042)		(0.018)	(0.018)
Distance Category 3		-0.048	-0.052		-0.038	-0.050^{*}
		(0.079)	(0.074)		(0.022)	(0.022)
Distance Category 4		-0.076	-0.039		-0.076^{***}	-0.109^{***}
		(0.093)	(0.088)		(0.023)	(0.024)
ln(Median Price)		0.081	0.037		0.118^{***}	0.143^{***}
		(0.068)	(0.065)		(0.024)	(0.024)
Adv. Purchase < 21 Days		0.003	0.056		0.031^{*}	0.008
		(0.034)	(0.036)		(0.013)	(0.013)
Endpoint Origination Share			0.526^{***}			0.008
			(0.144)			(0.037)
ln(Total Passengers on City Route)			-0.057			0.061^{***}
			(0.031)			(0.010)
N	732	732	732	6963	6963	6963

Robust standard errors (in parentheses) are clustered to allow correlation across carriers within a route.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Equation 3 Estimates: Magnitude of Saturday-Night Stayover Discount (if Offered)

	Nonstop Fares			One-stop Fares		
	(1)	(2)	(3)	(4)	(5)	(6)
WN Nonstop	-0.688^{*}	-0.834^{*}	-0.914^{*}	0.418^{**}	0.376^{**}	0.213
	(0.279)	(0.329)	(0.442)	(0.137)	(0.129)	(0.158)
WN Onestop	0.003	−0.052	−0.105	-0.290^{***}	-0.276^{***}	-0.401^{***}
	(0.099)	(0.114)	(0.161)	(0.064)	(0.067)	(0.074)
Legacy Nonstop	-0.308^{*}	−0.270	−0.239	0.162^{**}	0.265^{**}	0.116
	(0.123)	(0.144)	(0.158)	(0.062)	(0.084)	(0.099)
Legacy Onestop	0.053	−0.044	−0.197	−0.352	-0.324^{*}	-0.484^{**}
	(0.211)	(0.260)	(0.455)	(0.183)	(0.164)	(0.186)
LCC Nonstop	-1.311^{**}	-1.575^{***}	-1.555^{**}	−0.240	−0.084	−0.290
	(0.418)	(0.471)	(0.485)	(0.261)	(0.226)	(0.214)
LCC Onestop	0.394	0.162	0.082	0.141	−0.202	-0.270^{*}
	(0.209)	(0.210)	(0.320)	(0.134)	(0.135)	(0.131)
ULCC Nonstop	−0.275	−0.368	−0.406	−0.183	−0.177	−0.309
	(0.273)	(0.371)	(0.394)	(0.179)	(0.200)	(0.199)
ULCC Onestop	0.200	0.214	0.217	0.143	0.139	0.123
	(0.273)	(0.371)	(0.376)	(0.167)	(0.178)	(0.171)
Leisure Route		0.017	−0.024		0.079	0.042
		(0.230)	(0.234)		(0.068)	(0.068)
Big-City Route		0.061	0.007		−0.035	-0.200^{*}
		(0.134)	(0.129)		(0.082)	(0.099)
Distance Category 2		−0.040	−0.027		0.013	−0.002
		(0.112)	(0.122)		(0.052)	(0.052)
Distance Category 3		−0.105	−0.075		−0.060	−0.058
		(0.232)	(0.249)		(0.079)	(0.077)
Distance Category 4		0.394	0.436		0.210^{*}	0.180
		(0.275)	(0.292)		(0.103)	(0.102)
ln(Median Price)		0.130	0.102		0.417^{***}	0.456^{***}
		(0.188)	(0.195)		(0.092)	(0.092)
Adv. Purchase < 21 Days		0.161^{*}	0.132		−0.007	−0.073
		(0.078)	(0.100)		(0.053)	(0.052)
Endpoint Origination Share			0.232			0.014
			(0.313)			(0.102)
ln(Total Passengers on City Route)			0.068			0.134^{**}
			(0.114)			(0.045)
N	342	342	342	1239	1239	1239

Robust standard errors (in parentheses) are clustered to allow correlation across carriers within a route.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

percentage points more likely to offer discounts when competing with the nonstop flight of a legacy carrier. Overall, the estimates from Equation 1 reveal that the presence of additional competitors on a route can increase or decrease the likelihood that legacy carriers use Saturday-night stayover restrictions, and that the direction and magnitude of the effect depends on the type of competitor faced (legacy, LCC, ULCC, or Southwest) as well as the relative quality of the competitor's flight offering (nonstop or one-stop).

The second equation of the double-hurdle model captures how competition and other market factors influence the size of the Saturday-night stayover discounts airlines choose to offer, on routes where they are offered. Coefficient estimates for this equation are reported in Table 6. The estimates for nonstop routes are somewhat imprecise (due in part to the smaller sample size), but competition from Southwest and LCCs again have the largest impact. The presence of nonstop competition from Southwest reduces the size of Saturday-night stayover discounts on nonstop fares by nearly 57% (coefficient = -0.83), and the presence of at least one LCC reduces the size of discounts by 79% (coefficient = -1.58).[22] Legacy carriers offering only one-stop flights use discounts that are 20% to 24% smaller when facing one-stop competition from either Southwest or an LCC. In contrast one-stop carriers that face nonstop competition from either Southwest or another legacy carrier tend to offer discounts that are 30% and 45% larger, respectively.

For additional clarity on identification, reduced form regressions are also estimated for each instrumental variables model in Tables 5 & 6. The coefficient estimates from these reduced form models, presented in Appendix Tables A4 & A5, are nearly identical to those in Tables 5 & 6, implying that the predicted-probability instruments only influence price discrimination through actual presence on the route. In other words, the exclusion restriction required for IV estimation appears to hold, dispelling any potential identification concerns discussed in Section IV.2. Even when Equations 2 & 3 are estimated using Ordinary Least Squares, the coefficient estimates, presented in Appendix Tables A6 & A7, are quite similar to the IV results, offering additional support to our findings and suggesting that endogeneity may not be a primary concern when examining the impacts of competition on price discrim-

[22]Percentage effects for competition indicator variables are all calculated as $e^{\beta} - 1$ using the corresponding regression coefficient, β.

ination.[23] The general consistency in results across OLS, reduced form, and IV estimation further reinforces the robustness of the empirical analysis.

Perhaps the most interesting insights of the analysis arise when comparing the estimated effects of competition from different competitor types. Several broad empirical facts emerge when considering these results collectively.

1. *For both service types (nonstop or one-stop), discounts are smaller and less likely to occur when the legacy carrier faces competition (for the same service type) from Southwest or from LCCs than when they do not. Competition from ULCCs does not impact legacy carrier discounting behavior.*

2. *Discounts are larger and more frequent when facing competition offering a different service type than when the competitor offers the same service type. This comparison holds true regardless of the type of competitor being considered (legacy, LCC, or Southwest).*

3. *Competition from other legacy carriers offering the same service type does not reduce the use of discounts as much as competition from Southwest or LCC carriers. Discounts are often larger or more frequent (or both) when facing competition from other legacy carriers offering a different service type.*

Overall, these empirical patterns suggest that use of Saturday-night stayover discounts may be influenced less by the number of competitors on the route and more by whether those competitors utilize Saturday-night stayover discounts. Southwest and other LCCs never use Saturday-night stayover discounts, and legacy carriers are much less likely to offer such discounts when facing these types of competitors. In contrast, discounts are used more heavily when competing against other legacy carriers than other carrier types, likely because those carriers often use discounts themselves. In fact, when multiple legacy carriers compete on a route they adopt the same discounting strategy over 80% of the time (i.e., either all the legacy carriers use Saturday-night stayover discounts or none do).[24] While I do not explicitly model the response of firms to rivals' pricing strategies, the empirical findings suggest that legacy carriers tend to use Saturday-night stayover discounts when competition is absent or when their competition also uses discounts, but they are less likely to offer

[23]The largest differences between OLS and IV estimates appear when estimating Equation 3 for nonstop flights, where sample sizes are particularly small and weak instruments are of particular concern (see Appendix Table A1).

[24]This holds true regardless of whether Southwest or LCCs are also present on the route, though legacy competitors collectively choose to offer discounts much less often when Southwest or LCCs are present.

discounts when facing competitors that don't use discounts. In other words, although the asymmetric use of price discrimination by competing firms can occur in equilibrium in some theoretical settings (e.g., Dogan et al., 2010; Shulman and Geng, 2013; Lin, 2017), this is relatively uncommon in domestic airline markets.

Competitors' use of discounts also appears to have a stronger influence when the competing products are more homogeneous. Airline characteristics are one important dimension of differentiation. Legacy carriers offer extensive nationwide route networks, robust loyalty programs, and a variety of other amenities, while LCCs have smaller route networks, limited loyalty programs, and fewer amenities. ULCCs typically operate only on selected routes, offer very few amenities, and rely more heavily on *a la carte* pricing. Southwest began as an LCC but in recent years has taken on many of the characteristics of the legacy carriers and is now likely the closest competitor to the remaining legacy carriers.[25] Therefore, in terms of airline characteristics, Southwest is the closest competitor to the legacy carriers, with LCCs being second-closest and ULCCs being the most differentiated. This same pattern is reflected in the results from Tables 5 & 6, which reveal that competition from Southwest has the strongest impact on legacy carriers' use of discounts, while competition from LCCs has a similar but smaller effect, and ULCCs have no noticeable impact.

Flights are also differentiated by whether they are nonstop or one-stop, and competition from carriers offering the same service type tends to have a stronger influence than competition of a different service type. The results from Table 5 show that nonstop legacy carriers are much less likely to use discounts when Southwest or an LCC compete with nonstop service than when they compete with one-stop service. Similarly, discounts on one-stop flights are less common when Southwest or an LCC also offer one-stop service rather than non-stop service. The same relative pattern appears in the response to competition from other legacy carriers, with discounts being used less when facing legacy competition of the same service type than when facing legacy competition of a different service type.

[25]Over the last ten years Southwest has revamped its frequent flyer program, increased the number of long-haul flights (and even international flights), and "has undertaken a new focus on courting business travelers, including expanding to the big-city airports those flyers prefer."(Mutzabaugh, 2014) These are all criteria used by the IATA (International Air Transport Association) to distinguish traditional/legacy carriers and low cost carriers.

Previous studies, including Borenstein and Rose (1994) and Gerardi and Shapiro (2009), have found the total number of competitors on a route (rather than simply the existence of at least one competitor) to be an important determinant of price discrimination. My specification captures how discrimination is influenced by the number of competitor types, but does not capture the impact of additional competitors within a specific type. With four different types (Legacy, Southwest, LCC, ULCC), carriers in my data typically don't face more than one competitor of a given type on a route.[26] Nevertheless, I also estimate alternative specifications including the number of competitors of each type and present the results in Appendix Tables A2 & A3. The results are qualitatively similar to those in Tables 5 & 6, and the three broad empirical facts highlighted above are robust to this change in specification.

IV.4 Discussion and Comparison with Previous Findings

My analysis offers new evidence and explores new aspects of the relationship between price discrimination and competition. These contributions are facilitated by a unique quote-based empirical design that offers several advantages over the approaches of previous studies. First, most previous studies measure market structure using either a Herfindahl-Hirschman Index or an overall count of the number of competitors on the route and, therefore, are unable to identify the importance of differentiation based on airline type or service type.[27] Second, many of these studies examine dispersion in prices across different flights or across tickets purchased on different days rather than a specific, well-defined discriminatory pricing strategy. Focusing on Saturday-night stayover discounts yields a more precise measure that is comparable across carriers and routes and that facilitates more detailed analysis. Unlike most studies, I am able to identify and separately examine the decision to use discounts as well as the chosen magnitude of the discounts offered. In addition, since Southwest and other LCCs are known to have nationwide policies that do not incorporate Saturday-night stayover discounts, their decisions not to discriminate are exogenous to the conditions on

[26] Carriers face two competitors of the same type less than 6% of the time on nonstop routes and less than 29% of the time on one-stop routes.

[27] Some studies, like Gerardi and Shapiro (2009) estimate specifications using separate counts for the number of legacy carriers and low-cost carriers, but these measures are still assumed to have the same impact on pricing across all carrier types and service types.

any particular route and, therefore, their competitive impact on others can be evaluated differently. Finally, while price dispersion measures may inadvertently include some cost-related price variation, my quote-based empirical strategy eliminates all unobservable cost differences that could potentially bias inference on the impacts of competition.

The findings offer some interesting contrasts with those from previous empirical studies. A number of studies of the airline industry, including Gerardi and Shapiro (2009) and Gaggero and Piga (2011), have found that price discrimination falls with additional competition. My analysis reveals this same pattern for competitors that offer reasonably close substitutes, particularly those engaged in less discrimination themselves. On the other hand, discrimination is not impacted by highly differentiated competitors and can even become more likely when facing competitors that also frequently engage in discrimination.

The notion that price discrimination can increase with competition is not new. Borenstein and Rose (1994) suggest this possibility in airline markets, and Stole (2007) uses the (symmetric) framework of Holmes (1989) to demonstrate that additional competition can increase third-degree price discrimination when consumers who have a more elastic demand for the product are also more willing to substitute across providers in response to price differences.[28] Such a situation is certainly plausible in the airline market, if leisure travelers who are more likely to stay over Saturday night to receive a discounted price are also less brand-loyal and more willing to switch airlines to get a lower price. Despite this, relatively few empirical studies of airline pricing have uncovered robust evidence that additional competition is associated with greater discrimination.[29] Using a small sample of fare-level data including information on ticket restrictions, Stavins (2001) finds that routes with higher HHI have larger Saturday-night stayover discounts and greater advanced-purchase discounts.[30] Others conclude that competition increases ticket price dispersion under certain conditions. For example, Chandra and Lederman (2018) find that the upper end of Air

[28]Some models of second-degree price discrimination also predict that, under some circumstances, the curvature in the price schedule can increase as competition increases. See for example: Stole (1995); Dai et al. (2014); Boik and Takahashi (2020).

[29]The findings of Borenstein and Rose (1994) suggested this relationship, but Gerardi and Shapiro (2009) later showed that their result was likely a consequence of omitted variable bias.

[30]However, Stavins (2001) acknowledges that her results should be treated with caution given that fares are only observed from 12 routes and concentration varies little across the routes.

Canada's fare distribution is more disperse on routes where they face competition, while the lower end of the distribution is less disperse. Alternatively, Dai et al. (2014) provide evidence that carriers exhibit greater overall price dispersion on duopoly routes than on monopoly routes.

My analysis of Saturday-night stayover discounts suggests that competition increases discrimination only when competing products are somewhat differentiated and the competing firm is also likely to use discrimination. This arises when legacy carriers face competition from other legacy carriers offering flights of a different service type. For all other types of competitive interaction, the patterns suggested by studies such as Stavins (2001) and Dai et al. (2014) do not arise in my data.

One possible rationalization for these findings can be demonstrated using the theoretical framework of Stole (2007) and Holmes (1989). The fact that most types of additional competition result in lower fare dispersion suggests that even less-elastic business travelers are willing to substitute between carriers enough to cause markups to fall and fare dispersion to compress. However, business travelers may be less likely than leisure travelers to view a one-stop flight as a sufficient substitute for a nonstop flight. In that case, when a legacy carrier offering nonstop service faces new competition from different legacy carrier offering only one-stop service, the residual demand elasticity of leisure travelers will increase much more than the residual demand elasticity of business travelers, resulting in higher fare dispersion as the nonstop carrier reduces Saturday-night stayover fares (intended for leisure travelers) more than unrestricted fares (intended for business travelers).

Additionally, the reduction in Saturday-night stayover discounting resulting from competition with non-legacy carriers (Southwest, LCCs, and ULCCs) can also be explained by considering the non-legacy competitors to be restricted from using Saturday-night stayover discounts due to nationwide company pricing policies. Using the generalized framework of Corts (1998), it is straightforward to show that the dispersion in a firm's equilibrium prices across customer types will be smaller when facing a competitor that does not price discriminate than when facing a competitor that also price discriminates.[31]

[31]More specifically, I am considering the case considered by Corts (1998) in which firms exhibit best re-

Unfortunately, it is more difficult analyze non-legacy carriers' decisions to adopt nationwide policies preventing itinerary-based discrimination (like Saturday-night stayover discounts) because it reflects a response to conditions encountered across a large number of markets and because few theoretical studies directly model the asymmetric adoption and use of price discrimination by heterogeneous firms. Of the few that do, the setting considered in Dogan et al. (2010) most closely resembles that of the airline industry. They specify a spatial model of differentiated product competition in which one firm also has a distinct quality advantage over its rival. The firms have the option to engage in (second-degree) discrimination across two consumer types.[32] Interestingly, some predictions of Dogan et al. (2010) are consistent with my empirical findings while others appear contradictory. In particular, the high-quality firm in the model never price discriminates when their low-quality rival is not discriminating, and, empirically, legacy carriers rarely discriminate when competing with a non-discriminating rival (like Southwest or an LCC). On the other hand, the general use of Saturday-night stayover discounts by legacy carriers but not LCCs is harder to reconcile with the overarching conclusion of Dogan et al. (2010) that low-quality firms are more likely to discriminate even when their rival high-quality firms are not.[33] In some ways, the use of discounts by legacy carriers but not LCCs more closely matches the theoretical predictions of Lin (2017). Lin shows that high-quality firms will be more likely than low-quality firms to discriminate using add-ons and offers supporting empirical evidence that higher quality hotels are more likely to charge separately for internet service. Nevertheless, more theoretical research on the asymmetric use of price discrimination by heterogeneous competitors could help rationalize how Saturday-night stayover discounts are used and clarify why we observe such different usage patterns across different product markets.

sponse symmetry, which most closely matches discrimination between business and leisure travelers. The fully symmetric models of Holmes (1989) and Stole (2007) represent special cases of the Corts (1998) model.

[32]In the model discrimination takes place in the form of rebates (with one consumer group having a lower redemption cost), but these could be recast to represent Saturday-night stayover discounts (with leisure travelers having a lower inconvenience cost of staying over Saturday night).

[33]Dogan et al. (2010) provide suggestive evidence in support of their prediction from the market for computer printers, where market-leading and higher-priced brands offer fewer rebates. It should be noted that the decision of an airline not to use Saturday-night stayover discounts (across all its flights) is very different from the decision of whether to use discounts in a particular market.

V Conclusions

The focus of much of the existing literature on the general relationship between competition and price discrimination overlooks important nuances that arise in markets with product differentiation and firm heterogeneity. My detailed examination of price discrimination in airline markets offers new evidence illustrating how these factors can alter the effects of competition on price discrimination. In particular, competition from more similar products tend to have the largest influence on the use of discrimination, and airlines are much less likely to discriminate when competing carriers are not price discriminating. Additional insights on the modern competitive landscape of U.S. airlines are also revealed, such as the unique position of ultra-low costs carriers and their relatively minor influence on legacy carrier pricing. These empirical findings highlight the need for additional theoretical work examining how product differentiation alters the impact of competition on price discrimination and considering settings in which some firms discriminate while others do not.

My study also demonstrates how customized data collection can facilitate an alternative approach to identifying price discrimination in airline markets while controlling for unobserved cost variation. While the price dispersion measures used by many studies offer, at best, and aggregated measure of discriminatory price variation, this approach allows for the identification of specific discriminatory strategies. Variations on this method can be used to examine different forms of discrimination in this and other quoted-price markets, helping to evaluate the robustness of previous dispersion-based studies.

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Figure A1: Histograms of Predicted Probabilities of Nonstop Competitor Presence

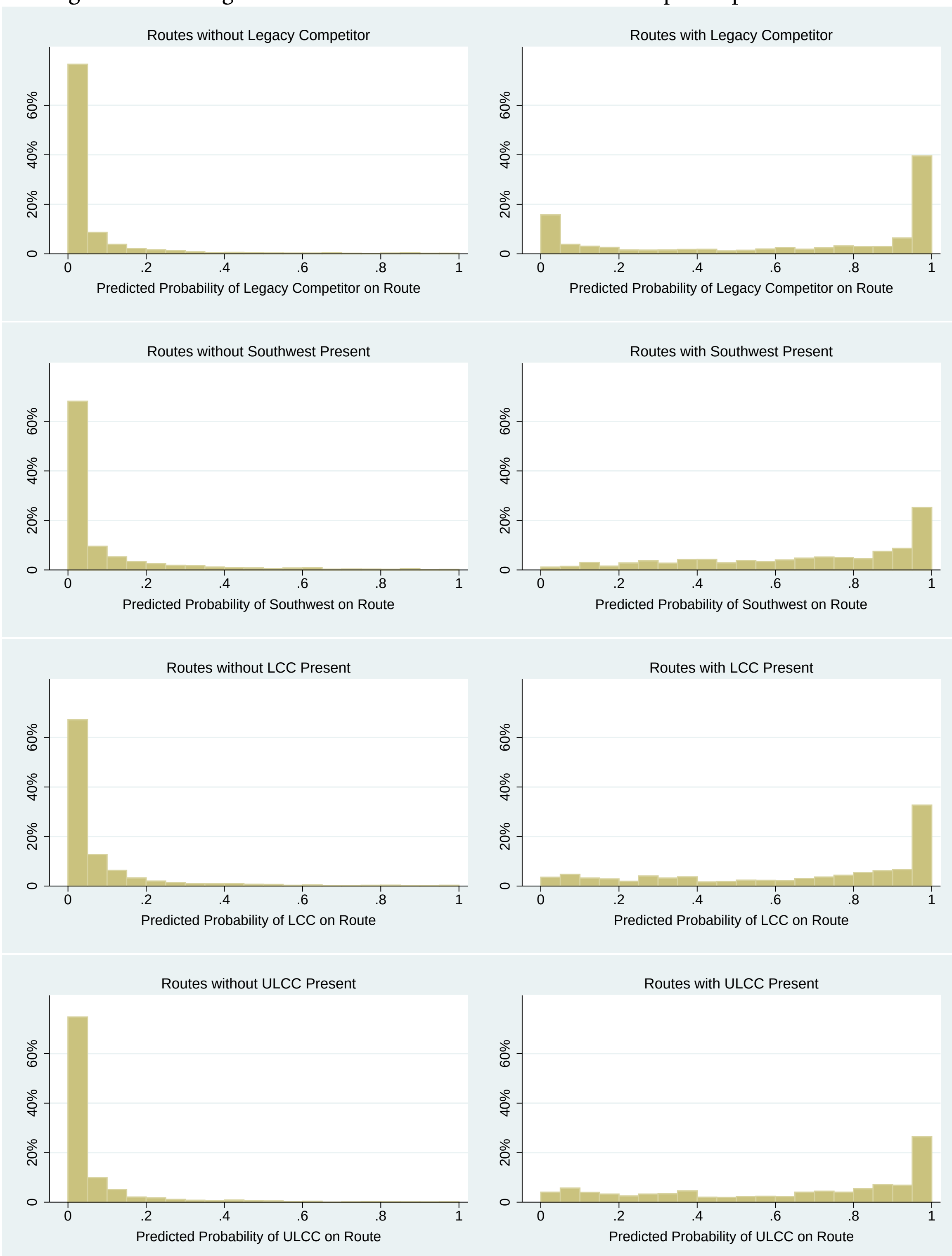

Figure A2: Histograms of Predicted Probabilities of One-Stop Competitor Presence

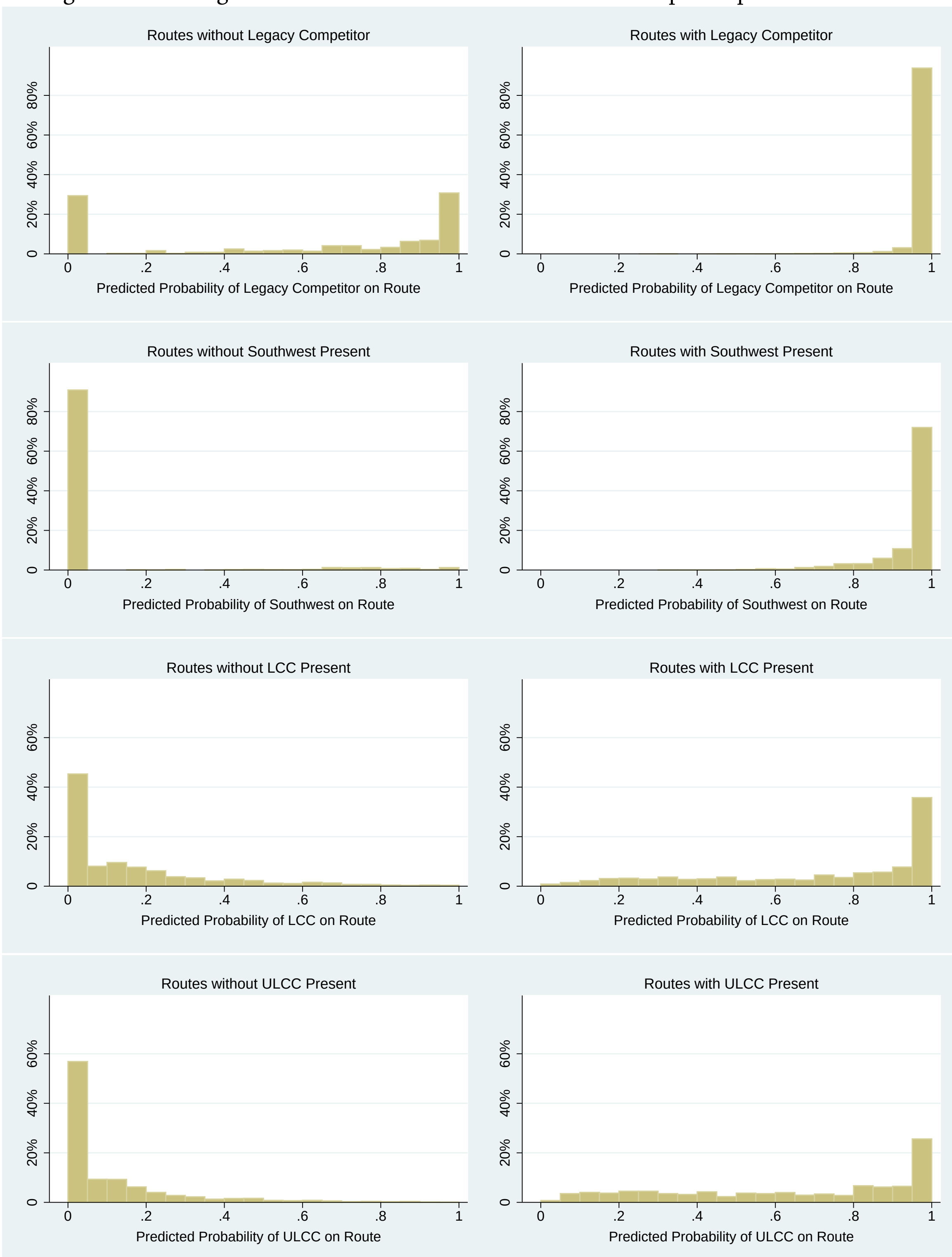

Table A1: First Stage Weak Instruments Test Statistics for Tables 5 & 6

Probability of Offering Discount (Table 5)

	Nonstop Fares			One-stop Fares		
	(1)	(2)	(3)	(4)	(5)	(6)
Sanderson-Windmeijer Partial F stats:						
WN Nonstop	525.1	370.5	120.3	1735.6	1635.3	927.3
WN Onestop	768.9	707.6	577.0	5487.6	5768.4	4227.3
Legacy Nonstop	812.4	593.9	315.3	4219.5	2380.9	1663.1
Legacy Onestop	280.3	213.4	93.5	2355.7	2298.4	2326.0
LCC Nonstop	308.1	255.4	229.6	1615.8	1483.0	1390.8
LCC Onestop	140.4	141.8	79.3	1647.4	1620.0	1644.5
ULCC Nonstop	161.4	91.0	82.9	584.9	446.4	441.5
ULCC Onestop	142.6	97.6	90.4	485.2	380.9	383.5
Cragg-Donald F stat	21.9	18.0	10.9	283.1	230.8	231.7
Kleibergen-Paap F stat	19.6	10.4	8.7	42.9	39.2	39.1
# of obs	732	732	732	6964	6964	6944

Magnitude of Discount if Offered (Table 6)

	Nonstop Fares			One-stop Fares		
	(1)	(2)	(3)	(4)	(5)	(6)
Sanderson-Windmeijer Partial F stats:						
WN Nonstop	50.5	39.4	17.2	201.1	179.2	138.1
WN Onestop	375.3	252.2	36.6	651.7	623.7	658.1
Legacy Nonstop	165.9	161.2	142.0	810.3	329.0	275.5
Legacy Onestop	108.7	65.5	17.4	406.5	413.7	302.8
LCC Nonstop	47.9	36.0	32.1	775.6	531.8	461.6
LCC Onestop	74.8	54.4	15.9	304.1	255.5	214.3
ULCC Nonstop	56.3	28.3	22.8	143.2	99.5	112.6
ULCC Onestop	49.4	31.5	30.0	143.5	115.0	103.5
Cragg-Donald F stat	7.2	5.6	1.9	46.8	42.6	39.8
Kleibergen-Paap F stat	6.0	4.1	1.7	11.6	13.4	16.6
# of obs	342	342	342	1240	1240	1240

Notes: This table presents a selection of first stage F statistics for each of the models estimated in Tables 5 & 6. The Sanderson and Windmeijer (2016) partial F statistics presented here test whether the instruments can independently identify each of the endogenous variables, while the Cragg-Donald F statistic and its robust version, the Kleibergen-Paap F statistic, jointly test for the presence of weak instruments. Formal critical values for these weak instruments tests have not been derived for cases with multiple discrete endogenous variables and correlated heteroskedastic errors, but values smaller than 10 are generally thought to indicate that instruments are potentially weak.

Table A2: Alternative Equation 2 Estimates: Probability of Offering Saturday-Night Stayover Discount

	Nonstop Fares			One-stop Fares		
	(1)	(2)	(3)	(4)	(5)	(6)
WN Nonstop	-0.746^{***}	-0.631^{***}	-0.507^{***}	-0.093^{***}	-0.122^{***}	-0.226^{***}
	(0.052)	(0.059)	(0.070)	(0.020)	(0.022)	(0.030)
WN Onestop	0.031	-0.035	-0.018	-0.254^{***}	-0.249^{***}	-0.305^{***}
	(0.055)	(0.058)	(0.059)	(0.016)	(0.016)	(0.019)
# of Legacy Nonstop	0.037	0.013	0.054	0.205^{***}	0.175^{***}	0.124^{***}
	(0.049)	(0.052)	(0.053)	(0.017)	(0.018)	(0.020)
# of Legacy Onestop	0.004	0.040	0.102^{*}	0.014	0.033^{*}	0.019
	(0.043)	(0.048)	(0.048)	(0.013)	(0.013)	(0.014)
# of LCC Nonstop	-0.334^{**}	-0.386^{***}	-0.289^{**}	0.084^{**}	0.063^{*}	0.011
	(0.102)	(0.102)	(0.098)	(0.029)	(0.029)	(0.031)
# of LCC Onestop	-0.120	-0.083	-0.006	-0.188^{***}	-0.177^{***}	-0.212^{***}
	(0.090)	(0.099)	(0.107)	(0.018)	(0.019)	(0.021)
# of ULCC Nonstop	-0.202^{*}	-0.100	-0.035	-0.028	-0.024	-0.074
	(0.085)	(0.099)	(0.106)	(0.038)	(0.041)	(0.043)
# of ULCC Onestop	0.102	0.021	-0.023	0.017	0.015	0.010
	(0.072)	(0.084)	(0.083)	(0.029)	(0.032)	(0.032)
Leisure Route		-0.102	-0.089		-0.024	-0.035^{*}
		(0.081)	(0.076)		(0.017)	(0.017)
Big-City Route		0.054	0.107^{**}		0.040^{*}	-0.005
		(0.038)	(0.039)		(0.020)	(0.020)
Distance Category 2		-0.045	-0.053		-0.034	-0.036^{*}
		(0.043)	(0.041)		(0.018)	(0.018)
Distance Category 3		-0.011	-0.002		-0.060^{**}	-0.066^{**}
		(0.074)	(0.068)		(0.022)	(0.022)
Distance Category 4		-0.011	0.012		-0.092^{***}	-0.116^{***}
		(0.098)	(0.093)		(0.023)	(0.024)
ln(Median Price)		0.127	0.066		0.142^{***}	0.161^{***}
		(0.069)	(0.065)		(0.024)	(0.024)
Adv. Purchase < 21 Days		-0.015	0.029		0.030^{*}	0.006
		(0.034)	(0.033)		(0.013)	(0.013)
Endpoint Origination Share			0.618^{***}			-0.000
			(0.132)			(0.038)
ln(Total Passengers on City Route)			-0.038			0.063^{***}
			(0.026)			(0.010)
N	732	732	732	6963	6963	6963

Robust standard errors (in parentheses) are clustered to allow correlation across carriers within a route.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Alternative Equation 3 Estimates: Magnitude of Saturday-Night Stayover Discount (if Offered)

	Nonstop Fares			One-stop Fares		
	(1)	(2)	(3)	(4)	(5)	(6)
WN Nonstop	-0.588^{*}	-0.668	-0.635	0.477^{***}	0.426^{***}	0.316^{*}
	(0.292)	(0.352)	(0.425)	(0.130)	(0.123)	(0.148)
WN Onestop	0.012	-0.011	-0.012	-0.284^{***}	-0.258^{***}	-0.345^{***}
	(0.114)	(0.124)	(0.138)	(0.061)	(0.063)	(0.070)
# of Legacy Nonstop	-0.336^{**}	-0.268	-0.259	0.151^{***}	0.251^{***}	0.170^{*}
	(0.124)	(0.155)	(0.160)	(0.044)	(0.057)	(0.072)
# of Legacy Onestop	0.074	0.027	0.039	-0.025	-0.050	-0.093
	(0.098)	(0.127)	(0.172)	(0.049)	(0.054)	(0.057)
# of LCC Nonstop	-1.354^{**}	-1.604^{**}	-1.581^{**}	-0.031	0.173	0.079
	(0.455)	(0.512)	(0.515)	(0.243)	(0.219)	(0.216)
# of LCC Onestop	0.516^{*}	0.328	0.339	0.106	-0.261	-0.323^{*}
	(0.220)	(0.248)	(0.334)	(0.137)	(0.139)	(0.136)
# of ULCC Nonstop	0.022	0.019	0.034	-0.058	0.008	-0.080
	(0.271)	(0.375)	(0.405)	(0.190)	(0.213)	(0.213)
# of ULCC Onestop	-0.102	-0.137	-0.146	0.026	-0.012	-0.020
	(0.256)	(0.347)	(0.357)	(0.155)	(0.170)	(0.165)
Leisure Route		-0.051	-0.059		0.060	0.035
		(0.238)	(0.234)		(0.069)	(0.069)
Big-City Route		0.012	0.019		-0.091	-0.194^{*}
		(0.123)	(0.120)		(0.078)	(0.091)
Distance Category 2		-0.065	-0.066		0.022	0.017
		(0.115)	(0.119)		(0.052)	(0.052)
Distance Category 3		-0.014	-0.013		-0.041	-0.023
		(0.226)	(0.228)		(0.077)	(0.077)
Distance Category 4		0.421	0.436		0.218^{*}	0.218^{*}
		(0.277)	(0.289)		(0.100)	(0.099)
ln(Median Price)		0.104	0.081		0.485^{***}	0.498^{***}
		(0.176)	(0.179)		(0.090)	(0.089)
Adv. Purchase < 21 Days		0.129	0.137		-0.020	-0.063
		(0.078)	(0.084)		(0.051)	(0.051)
Endpoint Origination Share			0.143			0.038
			(0.331)			(0.102)
ln(Total Passengers			-0.001			0.094^{*}
on City Route)			(0.088)			(0.042)
N	342	342	342	1239	1239	1239

Robust standard errors (in parentheses) are clustered to allow correlation across carriers within a route.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4: Reduced-Form Equation 2 Estimates: Probability of Offering Saturday-Night Stay-over Discount

	Nonstop Fares			One-stop Fares		
	(1)	(2)	(3)	(4)	(5)	(6)
Prob. of WN Nonstop	-0.659^{***}	-0.548^{***}	-0.446^{***}	-0.080^{***}	-0.121^{***}	-0.180^{***}
	(0.057)	(0.063)	(0.068)	(0.017)	(0.020)	(0.023)
Prob. of WN Onestop	-0.055	-0.099	-0.006	-0.260^{***}	-0.251^{***}	-0.283^{***}
	(0.053)	(0.056)	(0.058)	(0.015)	(0.016)	(0.017)
Prob. of Legacy Nonstop	-0.035	-0.069	0.054	0.229^{***}	0.188^{***}	0.172^{***}
	(0.050)	(0.051)	(0.055)	(0.018)	(0.018)	(0.020)
Prob. of Legacy Onestop	0.137	0.168	0.293^{**}	-0.106^{**}	-0.061	-0.068^{*}
	(0.112)	(0.100)	(0.106)	(0.033)	(0.033)	(0.034)
Prob. of LCC Nonstop	-0.491^{***}	-0.534^{***}	-0.429^{***}	0.051	0.010	-0.030
	(0.095)	(0.090)	(0.091)	(0.027)	(0.027)	(0.029)
Prob. of LCC Onestop	-0.023	0.014	0.096	-0.192^{***}	-0.172^{***}	-0.201^{***}
	(0.082)	(0.078)	(0.075)	(0.019)	(0.020)	(0.021)
Prob. of ULCC Nonstop	-0.107	-0.138	-0.075	-0.040	-0.052	-0.069
	(0.077)	(0.089)	(0.091)	(0.036)	(0.038)	(0.038)
Prob. of ULCC Onestop	0.065	0.131	0.088	0.065^{*}	0.080^{*}	0.054
	(0.075)	(0.095)	(0.092)	(0.032)	(0.034)	(0.035)
Leisure Route		-0.065	-0.020		-0.030	-0.036^{*}
		(0.072)	(0.071)		(0.016)	(0.016)
Big-City Route		0.084^{*}	0.139^{***}		0.049^{**}	0.014
		(0.040)	(0.039)		(0.018)	(0.018)
Distance Category 2		-0.080	-0.054		-0.032	-0.032
		(0.043)	(0.042)		(0.017)	(0.017)
Distance Category 3		-0.201^{**}	-0.136		-0.073^{***}	-0.070^{**}
		(0.075)	(0.072)		(0.021)	(0.021)
Distance Category 4		-0.115	-0.032		-0.111^{***}	-0.110^{***}
		(0.088)	(0.086)		(0.020)	(0.020)
ln(Median Price)		0.137^{*}	0.104		0.138^{***}	0.141^{***}
		(0.066)	(0.065)		(0.023)	(0.023)
Adv. Purchase < 21 Days		-0.008	0.038		0.034^{**}	0.009
		(0.035)	(0.036)		(0.012)	(0.013)
Endpoint Origination Share			0.514^{***}			0.173^{***}
			(0.139)			(0.042)
ln(Total Passengers			-0.072^{***}			0.041^{***}
on City Route)			(0.019)			(0.006)
N	732	732	732	6963	6963	6963

Robust standard errors (in parentheses) are clustered to allow correlation across carriers within a route.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5: Reduced-Form Equation 3 Estimates: Magnitude of Saturday-Night Stayover Discount (if Offered)

	Nonstop Fares			One-stop Fares		
	(1)	(2)	(3)	(4)	(5)	(6)
Prob. of WN Nonstop	-0.512^{**}	-0.518^{**}	-0.508^{**}	0.453^{***}	0.394^{**}	0.335^{*}
	(0.176)	(0.176)	(0.177)	(0.124)	(0.124)	(0.133)
Prob. of WN Onestop	0.008	−0.027	−0.018	-0.285^{***}	-0.255^{***}	-0.376^{***}
	(0.093)	(0.103)	(0.110)	(0.064)	(0.068)	(0.072)
Prob. of Legacy Nonstop	−0.170	−0.126	−0.082	0.131^{**}	0.161^{**}	0.121
	(0.103)	(0.122)	(0.128)	(0.047)	(0.053)	(0.067)
Prob. of Legacy Onestop	0.010	−0.076	−0.068	-0.376^{*}	-0.300^{*}	-0.406^{*}
	(0.219)	(0.220)	(0.223)	(0.178)	(0.152)	(0.159)
Prob. of LCC Nonstop	-0.875^{**}	-0.988^{***}	-0.973^{***}	−0.192	−0.118	−0.204
	(0.286)	(0.286)	(0.291)	(0.250)	(0.221)	(0.208)
Prob. of LCC Onestop	0.413^{*}	0.277	0.282	0.187	−0.083	−0.193
	(0.192)	(0.163)	(0.167)	(0.129)	(0.118)	(0.117)
Prob. of ULCC Nonstop	−0.165	−0.267	−0.258	−0.222	−0.203	−0.266
	(0.195)	(0.268)	(0.273)	(0.164)	(0.179)	(0.172)
Prob. of ULCC Onestop	0.127	0.207	0.207	0.141	0.155	0.096
	(0.185)	(0.279)	(0.280)	(0.153)	(0.163)	(0.157)
Leisure Route		−0.037	−0.037		0.035	0.022
		(0.210)	(0.216)		(0.064)	(0.063)
Big-City Route		−0.061	−0.057		−0.071	-0.181^{*}
		(0.098)	(0.105)		(0.081)	(0.086)
Distance Category 2		−0.105	−0.101		−0.033	−0.040
		(0.095)	(0.096)		(0.048)	(0.047)
Distance Category 3		−0.248	−0.240		-0.141^{*}	−0.112
		(0.203)	(0.206)		(0.065)	(0.066)
Distance Category 4		0.238	0.259		0.052	0.071
		(0.226)	(0.233)		(0.085)	(0.086)
ln(Median Price)		0.122	0.110		0.512^{***}	0.540^{***}
		(0.166)	(0.175)		(0.086)	(0.086)
Adv. Purchase < 21 Days		0.163^{*}	0.170^{*}		0.018	−0.051
		(0.076)	(0.077)		(0.048)	(0.049)
Endpoint Origination Share			0.164			0.137
			(0.292)			(0.127)
ln(Total Passengers on City Route)			−0.004			0.102^{***}
			(0.032)			(0.029)
N	342	342	342	1239	1239	1239

Robust standard errors (in parentheses) are clustered to allow correlation across carriers within a route.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6: OLS Equation 2 Estimates: Probability of Offering Saturday-Night Stayover Discount

	Nonstop Fares			One-stop Fares		
	(1)	(2)	(3)	(4)	(5)	(6)
WN Nonstop	-0.588^{***}	-0.527^{***}	-0.474^{***}	-0.073^{***}	-0.096^{***}	-0.120^{***}
	(0.037)	(0.039)	(0.041)	(0.011)	(0.013)	(0.015)
WN Onestop	-0.016	-0.038	0.025	-0.223^{***}	-0.214^{***}	-0.236^{***}
	(0.044)	(0.045)	(0.048)	(0.013)	(0.013)	(0.015)
Legacy Nonstop	-0.068	-0.060	0.036	0.210^{***}	0.181^{***}	0.159^{***}
	(0.036)	(0.036)	(0.039)	(0.015)	(0.015)	(0.016)
Legacy Onestop	0.104^{*}	0.096	0.129^{*}	-0.068^{**}	-0.039	-0.050^{*}
	(0.051)	(0.051)	(0.052)	(0.022)	(0.022)	(0.023)
LCC Nonstop	-0.435^{***}	-0.464^{***}	-0.352^{***}	-0.024	-0.041^{*}	-0.062^{**}
	(0.064)	(0.062)	(0.064)	(0.021)	(0.020)	(0.021)
LCC Onestop	0.005	0.019	0.060	-0.115^{***}	-0.101^{***}	-0.110^{***}
	(0.045)	(0.045)	(0.045)	(0.014)	(0.014)	(0.015)
ULCC Nonstop	-0.039	-0.000	0.019	-0.011	-0.014	-0.029
	(0.055)	(0.056)	(0.055)	(0.023)	(0.024)	(0.024)
ULCC Onestop	-0.058	-0.061	-0.051	0.017	0.023	0.017
	(0.049)	(0.054)	(0.052)	(0.020)	(0.020)	(0.020)
Leisure Route		-0.139	-0.085		-0.028	-0.033^{*}
		(0.071)	(0.072)		(0.016)	(0.016)
Big-City Route		0.056	0.117^{**}		0.029	0.008
		(0.034)	(0.037)		(0.018)	(0.019)
Distance Category 2		-0.062	-0.045		-0.032	-0.034^{*}
		(0.037)	(0.036)		(0.017)	(0.017)
Distance Category 3		-0.041	-0.021		-0.064^{**}	-0.066^{***}
		(0.064)	(0.061)		(0.020)	(0.020)
Distance Category 4		-0.055	0.005		-0.112^{***}	-0.120^{***}
		(0.081)	(0.079)		(0.020)	(0.020)
ln(Median Price)		0.142^{*}	0.086		0.135^{***}	0.141^{***}
		(0.065)	(0.064)		(0.023)	(0.023)
Adv. Purchase < 21 Days		-0.023	0.037		0.017	0.005
		(0.033)	(0.034)		(0.012)	(0.013)
Endpoint Origination Share			0.590^{***}			0.038
			(0.130)			(0.037)
ln(Total Passengers on City Route)			-0.050^{**}			0.023^{***}
			(0.018)			(0.006)
N	732	732	732	6963	6963	6963

Robust standard errors (in parentheses) are clustered to allow correlation across carriers within a route.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A7: OLS Equation 3 Estimates: Magnitude of Saturday-Night Stayover Discount (if Offered)

	Nonstop Fares			One-stop Fares		
	(1)	(2)	(3)	(4)	(5)	(6)
WN Nonstop	-0.282^{*}	-0.258	-0.255	0.282^{**}	0.267^{**}	0.196^{*}
	(0.132)	(0.147)	(0.146)	(0.094)	(0.091)	(0.092)
WN Onestop	-0.124	-0.182^{*}	-0.178	-0.253^{***}	-0.233^{***}	-0.312^{***}
	(0.079)	(0.087)	(0.094)	(0.051)	(0.054)	(0.060)
Legacy Nonstop	-0.309^{**}	-0.274^{**}	-0.236^{*}	0.180^{***}	0.234^{***}	0.153^{**}
	(0.097)	(0.105)	(0.105)	(0.044)	(0.049)	(0.057)
Legacy Onestop	0.027	-0.000	-0.007	-0.228^{*}	-0.151	-0.213^{*}
	(0.093)	(0.094)	(0.097)	(0.097)	(0.094)	(0.099)
LCC Nonstop	-0.677^{***}	-0.874^{***}	-0.862^{***}	-0.050	-0.045	-0.158
	(0.195)	(0.224)	(0.227)	(0.208)	(0.190)	(0.188)
LCC Onestop	0.327^{**}	0.280^{**}	0.279^{*}	0.082	-0.095	-0.134
	(0.110)	(0.102)	(0.108)	(0.096)	(0.088)	(0.086)
ULCC Nonstop	-0.155	-0.134	-0.136	0.007	0.064	-0.007
	(0.143)	(0.172)	(0.174)	(0.093)	(0.103)	(0.106)
ULCC Onestop	0.123	0.086	0.090	0.029	0.005	-0.021
	(0.120)	(0.141)	(0.142)	(0.079)	(0.084)	(0.085)
Leisure Route		-0.100	-0.103		0.033	0.012
		(0.220)	(0.225)		(0.063)	(0.063)
Big-City Route		-0.018	-0.016		-0.038	-0.149
		(0.098)	(0.106)		(0.080)	(0.090)
Distance Category 2		-0.047	-0.044		-0.004	-0.013
		(0.090)	(0.091)		(0.047)	(0.047)
Distance Category 3		-0.121	-0.116		-0.074	-0.069
		(0.162)	(0.164)		(0.064)	(0.064)
Distance Category 4		0.274	0.302		0.155	0.137
		(0.228)	(0.234)		(0.084)	(0.085)
ln(Median Price)		0.111	0.089		0.475^{***}	0.501^{***}
		(0.172)	(0.180)		(0.088)	(0.088)
Adv. Purchase < 21 Days		0.148	0.157		-0.026	-0.072
		(0.078)	(0.080)		(0.050)	(0.051)
Endpoint Origination Share			0.205			0.001
			(0.289)			(0.100)
ln(Total Passengers on City Route)			0.004			0.084^{**}
			(0.038)			(0.030)
N	342	342	342	1239	1239	1239

Robust standard errors (in parentheses) are clustered to allow correlation across carriers within a route.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$