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An empirical analysis of the dynamic pricing practices of legacy carriers and low-cost carriers across US domestic routes

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Abstract

In airline ticket pricing, customers who buy their ticket far in advance of the departure date are often rewarded with a discount, the advance purchase discount (APD), while late bookers have to pay a premium, the late purchase premium (LPP). In this paper I study the effects of carrier type and route competition on airline pricing dynamics over the advance booking period by focussing on APDs and LPPs. I make use of an extensive dataset concerning the flights on 22 October 2018 of the 100 busiest routes in the US domestic market. The price trend of each carrier on a route is estimated by a hyperbolic function and examined using fixed effects regressions. I find that legacy carriers grant higher APDs and set higher LPPs than low-cost carriers. I do not find statistical evidence that legacy carriers change their pricing dynamics between routes with and without competition from low-cost carriers. Neither do I find enough evidence to claim that airlines adjust their pricing dynamics based on the number of competitors or flights.

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1. Introduction

In the past decades, flight fares of airlines have been thoroughly studied with data made available by the US Department of Transportation. By examining the monthly data that airlines are obliged to disclose, researchers have learned a lot about carriers' pricing behavior. Such analyses of the monthly average fare of a flight is referred to as the static literature on airline pricing. A more in-depth examination of the development of fares over time has only been recently possible since the rise of online seat reservation systems, which allowed fares to be retrieved day by day. A new strand of literature emerged, the dynamic literature, which tries to explain the fluctuations of fares over the time period leading up to the date of flight, known as the advance booking period. Despite the extensive static literature on fares there is limited empirical understanding of the pricing dynamics in the advance booking period.

From the static literature fares are known to depend on the carrier's business model. Low-cost carriers (LCCs) use their low operating costs as main competitive advantage to offer cheap tickets, whereas the more expensive legacy carriers try to stand out in superior customer service (Belobaba et al., 2015). It is valuable to know that legacy carriers ask higher fares than LCCs on average, but at what moment can price conscious travelers buy the cheapest tickets for each carrier type? The dynamic literature shows that customers who book early are rewarded with a discount, the advance purchase discount (APD), while late bookers often have to pay a premium (Gerardi and Shapiro, 2009), which I will refer to as the late purchase premium (LPP). By the comparison of the results of Alderighi et al. (2014) and Escobari (2012) it looks like the timing of a ticket purchase is more important for legacy carriers. They seem to offer higher APDs, but also set higher LPPs. Yet, a direct comparison of the pricing dynamics of both carriers is absent from the literature.

Another important determinant of airline pricing in the static literature is the competition structure on a route. Carriers drastically lower their average fares in response to the presence of a LCC, while legacy competition barely affects price levels (Brueckner et al., 2013). However, the static literature does not provide any evidence whether the drop in average fares is caused by a permanent reduction over the entire advance booking period or a temporary one only during specific time periods. This would be valuable information for customers, as they might only benefit from competition in some booking periods. For example, in a case study on Ryanair, the largest European LCC, more competitors on a route does not lead to lower permanent fares, but induces Ryanair to grant higher APDs instead (Malighetti et al., 2009). The goal of this paper is to empirically investigate the static relations between fares, carrier types and competition in a dynamic context. Therefore, I will try to answer the following research question: what are the dynamic pricing practices of legacy carriers and low-cost carriers and how are they affected by route competition?

The focus of this study is on the leisure segment (Economy seats) within the 100 busiest routes of the US domestic market (based on passenger counts). I make use of an extensive dataset concerning flights on Monday 22 October 2018, including all daily fares over the 103 days before the flight. The fares of a flight fluctuate around a static level over the advance booking period. I approach dynamic pricing by examining APDs and LPPs relative to the static fare level. In the comparison between the pricing dynamics of various carriers I focus merely on the fluctuations around the static level as if each static fare level is the same. The total dispersion in fares as a consequence of APDs and LPPs is referred to as the temporal price dispersion.

The dynamic literature points out that in most cases, the fare trend in the advance booking period is resembled by a hyperbola (Malighetti et al., 2009; Escobari, 2012; Alderighi et al., 2014). The hyperbolic price equation of Malighetti et al. (2009) includes both the APD and the LPP as parameters. The APD is measured as a decrease in fares that is directly proportional to the number of advance booking days, while the LPP is approximated by the high fare levels during the last days before the flight. Using non-linear least squares, I fit the hyperbolic function to the data for each carrier on a route. Subsequently, I place the dynamic pricing parameters as dependent variables in a series of fixed effect regressions to see how the use of APDs/LPPs varies among carrier types and competition structures.

First of all, I find support in favor of the positive temporal profile of fares in most of the cases (fares increase as time to departure decreases). The hyperbolic model is a significantly accurate fit for two-thirds of the carriers on the average route. Second, I find statistical evidence that legacy carriers grant higher APDs and set higher LPPs than LCCs. Whereas the static literature reveals a higher static fare level of legacy carriers, I show a larger temporal price dispersion of legacy carriers compared to LCCs. Third, the pricing dynamics of legacy carriers do not differ between routes with and without LCC competition. The total price curve is shifted downwards like the static literature predicted, but no temporary price reductions are granted. Fourth, I do not find enough evidence to state that carriers change their dynamic pricing practices based on the number of competitors or flights. This implicates that the fare reductions in response to competitive pressure as observed in the static literature are time invariant.

This study is a first attempt to take what is known about fares of legacy carriers and LCCs from the static literature and examine it in a dynamic context. I contribute to the existing literature by comparing the pricing dynamics of a wide range of carriers and in various competition structures across US routes. Whereas numerous studies focus mostly on APDs (Malighetti et al., 2009; Alderighi et al., 2014), I also give ample attention to LPPs, resulting in a better understanding of how carriers alter *both* ends of the distribution in fares as a dynamic pricing practice. Furthermore, I go one step further than Malighetti et al. (2009) by interpreting the effect of competition on dynamic pricing in terms of prices instead of parameter values. The remainder of this paper is structured as follows. Section 2 further describes the static and dynamic literature, and explains my approach to dynamic pricing. In section 3, I combine the theories from both strands of literature to build my hypotheses. In section 4, I explain how the data is retrieved, I introduce the explanatory variables and control variables, and present descriptive statistics. The used empirical research method is demonstrated in section 5. In section 6, I present the results of the parameter estimation and regressions followed by comments on the main findings in section 7. In section 8, I go over the limitations of this study and provide recommendations for further research into this topic. Finally, in section 9 I conclude with a brief summary.

2. Theoretical framework

The theoretical framework is divided into static and dynamic literature. The former only encompasses insights about quarterly or monthly average fares, whereas the latter studies the pricing dynamics in the advance booking period on a daily basis. The pricing dynamics determine the price trend of airline tickets prior to the date of flight. In the first subsection I make a distinction between low-cost carriers and legacy carriers. I explain their influence on ticket prices on a static level. In the second subsection I introduce the concept of yield management, the system behind airline pricing dynamics. From these theories I derive two important instruments for the practice of dynamic pricing. My approach to dynamic pricing revolves around these instruments, as I explain in the last paragraph. In the next section I will link the theories of the static and dynamic literature to build my hypotheses of how both carrier types behave in the dynamic context.

2.1 Legacy carriers and low-cost carriers

In the airline industry, two types of carriers can be distinguished based on their operating model: legacy carriers and low-cost carriers (LCCs). Legacy carriers, also referred to as traditional carriers, try to fly via connecting airports (hubs) where they have terminal and time slot dominance. This way, they are able to fly at convenient times, but their planes are forced to wait at the hubs for a relatively long time. The type of plane is fitted especially for the length of the flight, yet the wide range of aircraft types increases maintenance costs. Legacy carriers also tend to offer more complimentary services, such as preferred seats, frequent-flyer loyalty programs and physical customer service, resulting in extra administration costs and higher wages. All these extra costs are reflected in a relatively high ticket price. This makes legacy carriers arguably more appealing to less price sensitive travelers and business people. LCCs, on the other hand, try to minimize costs where possible to offer cheap tickets to leisure customers. They usually fly directly to their destination (point-to-point), and often to secondary airports, in order to enjoy shorter ground time. Furthermore, LCCs fly in the same type of aircrafts mostly on continental routes, customer service is handled online and on-board meals are left out, all to offer the lowest price (Belobaba et al., 2015).

The introduction of LCCs in the seventies had a dramatic impact on ticket prices in the US. The revolution was led by Southwest Airlines, marked by higher traffic levels and lower fares on operating routes. This effect has been observed not only for the actual routes of entry, but also for competitive routes to adjacent airports (Dresner et al., 1996). Goolsbee and Syverson (2008) showed that even the threat of Southwest entering a route substantially depresses fares of other airlines. These different forms of competition from Southwest saved US air travelers already \$12.9 billion in 1998, estimated Morrison (2001). On the contrary, the effectiveness of legacy competition on fares has declined since 2000, and evaporated to a very slight effect by the beginning of 2008. Controlling for cost and product quality differences across carriers, Brueckner et al. (2013) look at three different types of routes: primary, adjacent and connecting. They find a dramatic reduction of fares by LCC competition, ranging from up to 33% on primary routes, to 20% on adjacent routes and 12% on connecting routes. In contrast, the effect of legacy competition is at most 5.3% on primary routes and negligible in the other cases. The study by Brueckner et al. (2013) and others of its kind use data from a 10% quarterly sample of all airline tickets from the US Department of Transportation (database DB1B). The robustness of the results can be checked by various sensitivity analyses and the different traffic volumes during a quarter are taken into account by weighted models. However, this data is not detailed enough to gain a more in-depth look on how ticket prices of the same flight develop over the advance booking period and how that differs per carrier type and competition structure. With the rise of online passenger reservation systems and comparison sides that list all the available flights, ticket characteristics and fares, the airline industry is now more transparent than ever before. By using web scraping tools researchers are able to collect the data needed to shed more light on the dynamic pricing practices.

2.2 Yield management

The strand of research that focusses on dynamic pricing is called Yield Management (YM). It refers to a set of pricing strategies to optimize profits when customers are heterogeneous, demand is uncertain, and capacity is hardly modifiable (Alderighi et al., 2014). These characteristics create the potential for very large swings in the opportunity cost of sale, because the opportunity cost of sale is a potential foregone subsequent sale (McAfee & te Velde, 2006). In theory, this entails the trade-off between accepting a booking request now at a low price or refusing it in the expectation that tomorrow a potential customer will be willing to pay a higher price. In practice, airlines group seats into different booking classes and implement YM by assigning specific fares and a specific number of seats to each class (Alderighi et al., 2014). The fares and seats allocated to each class are modified by airlines over time according to capacity-based and time-based pricing policies. The former revolves around the flight's occupancy rate and the latter around the time left to departure. Most capacity-based theories point towards a positive relationship between fares and flight occupation (Dana, 1999; Escobari and Gan, 2007; Deneckere and Peck, 2012, Escobari, 2012; Alderighi et al., 2014). This means that tickets become more expensive as the plane fills up. Alderighi et al. estimate that capacity-based theories account for about two-thirds of changes in prices, and one-third is a pure time effect.

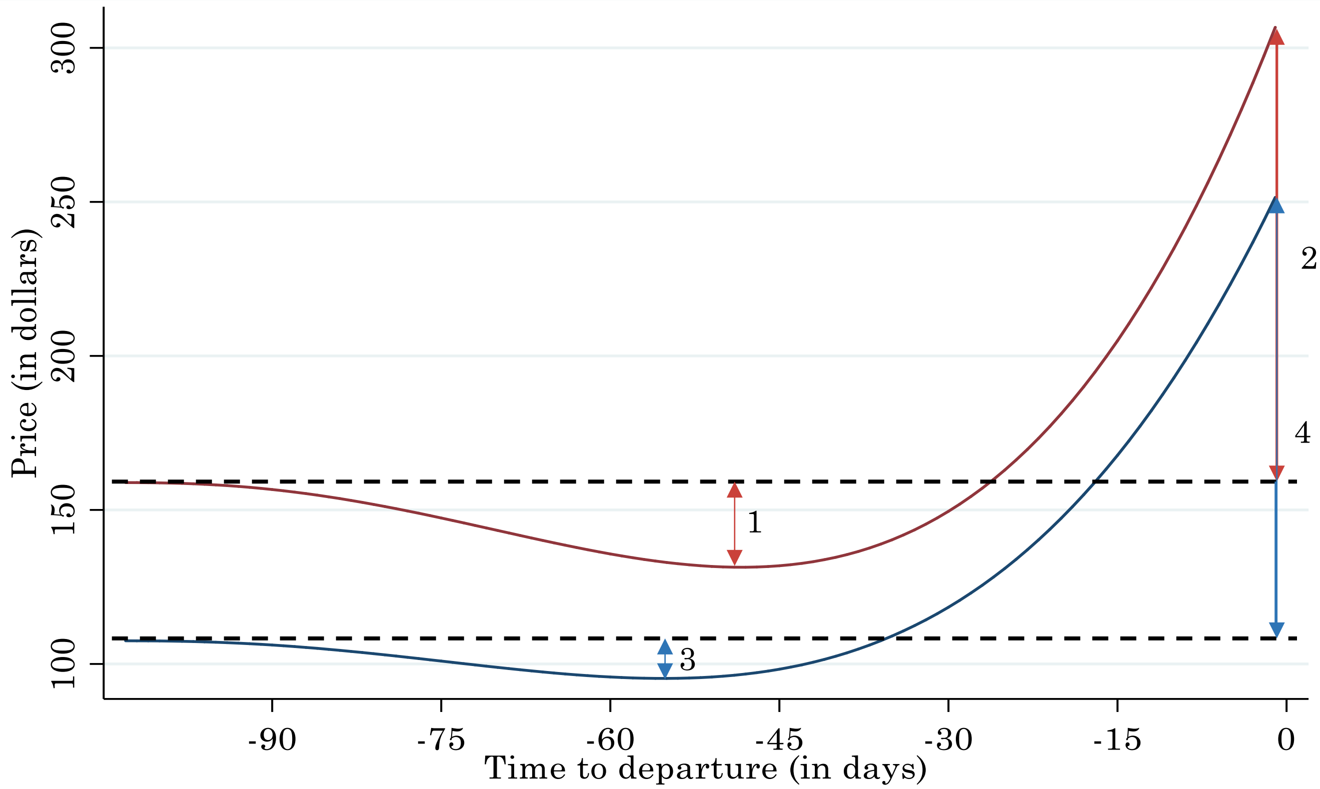
There has been a long debate among economists about the temporal profile of fares. Gallego and van Ryzin (1994) argue that the option value of waiting for the arrival of a customer with a high willingness to pay falls as the departure date approaches, and so should the prices. This argument is supported by the clearance sales practices, as observed by Moller and Watanabe (2010). Fare reductions in the periods immediately preceding departure would attract potential customers to sell the last available seats. However, when a carrier establishes a reputation of constantly offering last-minute deals, customers could anticipate and delay their purchases (McAfee and te Velde, 2007). This is in no interest of any airline, instead it would be better to spread the demand to divert it from peak to off-peak periods.

According to Gale and Holmes (1992), this can be done by offering fare reductions in the periods far from the departure date. These advance purchase discounts (APD) thus advocate a positive temporal profile in the advance booking period. The rising trend in fares over time is supported by the latest studies, which have found a temporal profile that resembles a hyperbola in the 1-2 months before departure. Escobari (2012) finds this pattern for US legacy carriers and Alderighi et al. (2014) do the same for Ryanair, Europe's largest LCC. Interestingly, the difference is that for Ryanair, the LCC, fares start rising sooner and more equally than those of the American legacy carriers. This indirect empirical comparison reveals a vague distinction between the two carrier types. Moreover, it highlights the missing links between the static and dynamic literature, as a direct comparison between the pricing dynamics of legacy carriers and LCCs is still to be made in the literature.

Besides demand management, APDs can be viewed as an instrument for price discrimination. Advance-purchase requirements are one of the types of restrictions on tickets that allows airlines to distinguish between consumer types. Price-inelastic consumers with a high value of time, for example business people, are willing to pay more for a ticket when they make their purchase close to the date of departure. By making use of APDs, airlines are able to separate this type of consumers from price-sensitive leisure travelers and charge both types a different fare (Gerardi and Shaprio, 2009). Gerardi and Shapiro (2009) show that for US legacy carriers, the dispersion in fares is stronger in markets of low competition, as increased market power implies more margin to set fares. Fiercer competition especially lowers the fares at the top of the distribution of tickets. This effect is stronger in the case of competition from LCCs, like we saw with the average fares. Studies on Ryanair find that the effect of competition does not manifest itself at the top range of fares, but at the bottom range instead (Malighetti, 2009; Alderighi et al., 2014). Ryanair grants higher APDs on routes with more competitors. A theoretical explanation for the difference in response to competition between LCCs and legacy carriers is absent from the literature.

All in all, two important instruments of airlines to practice dynamic pricing can be derived from the literature. On the one end, customers who book early are rewarded with a discount, the advance purchase discount (APD). On the other end, customers who book late have to pay a premium, which I call the late purchase premium (LPP). Hence, APDs are likely to cause the bottom range in the distribution of fares, while LPPs account for the upper range of fares. My approach to dynamic pricing revolves around APDs and LPPs, which I will elaborate on with the help of figure 1. Figure 1 displays the price trends of two different carriers over the advance booking period. Imagine that the fares of a flight fluctuate around a static fare level, denoted with the black horizontal dotted lines. In this paper I always interpret APDs (numbers 1 and 3) and LPPs (numbers 2 and 4) relative to this static fare level. When I compare the pricing dynamic of two carriers, I only look at the fluctuations around the static price level as if both static price levels are the same. In this case the APDs of carrier *Red* are higher than carrier *Blue* (1>3), and so are the LPPs (2>4). In sum the price dispersion of carrier *Red* is larger. I call the difference between the top and bottom fares in the advance booking period the temporal price difference, which can be interpreted as a measure for dynamic pricing intensity. Due to restrictions in the availability of data on capacity utilization, less focus will be put on the distinction between the capacity and time aspects of dynamic pricing. I can still examine the temporal profile in detail, but I am not able to say whether the changes in fares are due to capacity-based or time-based policies.

Figure 1. Illustration of APDs and LPPs for two different carriers



3. Hypotheses

In this section I develop my hypotheses around APDs and LPPs, taking what is known about legacy carriers and LCCs from the static literature to the dynamic context. In the first subsection I formulate my first hypothesis regarding how dynamic pricing relates to the business model of an airline. In the second section I formulate the other two hypotheses about the relation between dynamic pricing and the competition structure on a route.

3.1 Effects of carrier types

From the static literature we know that legacy carriers set higher average fares than LCCs as a result of the higher costs associated with their business model. Alongside this static price difference a distinction in dynamic pricing practices can be observed between the two carrier types. In the comparison between the results of Alderighi et al. (2014) and Escobari (2012) the fares of Ryanair, the LCC, fluctuate less than those of the American legacy carriers in the advance booking period. The LCC lets its fares rise sooner and more equally, indicating that its dynamic pricing policy involves less use of APDs and LPPs. As a result, the temporal price dispersion in the advance booking period is lower for the LCCs than the legacy carriers. A theoretical explanation for this specific dissimilarity in price dispersion is nonexistent in the dynamic literature. By looking at other studies on airline price dispersion, I might find the cause.

In numerous studies, airline price dispersion is reasoned to be the result of price discrimination. Carriers lower their fares on moments on which price sensitive customers (e.g. leisure travelers) are likely to buy their ticket, for example early in the advance booking period (Gerardi and Shapiro, 2009), on weekend days (Puller and Taylor, 2012), and in evenings (Escobari et al., 2018). Conversely, carriers set higher fares intended for price insensitive customers (e.g. business travelers) close to departure, on working days and during office hours. A heterogeneous mixture of leisure and business travelers is optimal for such price discriminatory tactics (Gerardi and Shapiro, 2009). My conjecture is that legacy carriers serve a more balanced mixture of price sensitive and price insensitive customers, while the customer base of LCCs is more homogeneous and predominately consists of price sensitive travelers. Subsequently, legacy carriers are more able to price discriminate and their temporal price dispersion over the advance booking period is higher. Note that this explanation differs from the prime cause of higher average fares of legacy carriers in the static literature, i.e. higher costs. I will test the following hypothesis to see whether legacy carriers do, in fact, make more use of APDs and LPPs:

Hypothesis 1a: Legacy carriers offer higher APDs than LCCs.

Hypothesis 1b: Legacy carriers set higher LPPs than LCCs.

3.2 Effects of competition

Besides comparing the dynamic pricing practices of different types of carriers within the same markets, it is interesting to see whether the pricing behavior of the same carrier varies between markets. First, I look at the type of competition and second, I examine the intensity of competition.

The static literature shows that the effect of competition on fares is greatly dependent on the type of competitor. Brueckner et al. (2013) find that legacy carriers strongly compete with LCCs, adjusting their fares downwards. However, in competition among legacy carriers there is less pressure to set low fares. The question arises whether the reduction in average fares comes from a permanent reduction or a temporary one only in some periods of the advance booking period. Although this question has not yet been addressed before, the existing dynamic literature offers some clues in favor of temporary fare reductions. For example, Ryanair grants higher APDs on routes with more competitors (Malighetti et al., 2009; Alderighi et al., 2014). More competitive pressure thus seems to encourage airlines to offer higher APDs in order to attract customers. My conjecture is that this is especially true in the case of LCC competition. As a large portion of LCC customers are leisure travelers, LCC competition especially threatens the price sensitive customer base of legacy carriers. In response to the presence of a LCC on a route, I expect legacy carriers to grant higher APDs in order to keep being appealing to leisure travelers. At the top range of fares, I expect the legacy carriers to struggle to profit from the higher willingness-to-pay of late bookers, since price discrimination tactics are harder to implement with competitive pressure from LCCs (Gerardi and Shapiro, 2009). This would result in lower LPPs on routes with LCC competition. I will test the following hypothesis to find out whether legacy carriers change their dynamic pricing practices between routes with (mixed competition) and without (uniform competition) LCC presence:

Hypothesis 2a: Legacy carriers in uniform competition offer lower APDs than in mixed competition.

Hypothesis 2b: Legacy carriers in uniform competition set higher LPPs than in mixed competition.

A higher intensity of competition induces carriers to set lower average fares, according to the static literature (Brueckner et al., 2013). Again, it is unclear whether airlines respond by permanent or temporary price reductions within the advance booking period. Competition intensity is often measured as the number of competitors operating on the same route. More competitors on a route intensifies competition at the bottom range of fares (Alderighi et al., 2014), and limits price discrimination in the upper range of fares (Gerardi and Shapiro, 2009). Hence, my conjecture is that a higher number of competitors leads to higher APDs and lower LPPs. Another, less common, way to measure the intensity of competition is the total number of daily departures. More flights means more substitution options for customers which gives more incentives for carriers to lower their fares, but it is questionable whether it is as important as the number of competitors. Is a route with many different carriers that only fly once a day more competitive than one where a few carriers fly very frequently? I will test the following hypothesis to examine both measures of the competition intensity:

Hypothesis 3a: As the competition on a route intensifies, APDs increase.

Hypothesis 3b: As the competition on a route intensifies, LPPs decrease.

4. Data

This section is divided into three subsections. First, I discuss the data sources used in this study. Second, I define the carrier type, competition and control variables. The motivation and justification for the use of these variables are explained in the methodology section. Third, I present descriptive statistics, which give preliminary evidence about the accuracy of hypothesis 1 and 2.

4.1 Data collection

The first two datasets regarding ticket prices are retrieved and merged by my supervisor Yannis Kerkemezos. The first data source is matrix.itasoftware.com, a website that compares ticket prices and other flight characteristics for the US domestic market. Flight information is collected using a web scraping tool on the 100 busiest routes, based on the total passenger count flown from one airport to another. Only one-way passenger flights that depart on 22 October 2018 appear in this sample, including multiple flights of the same carrier on different times. The two different directions of the same route are considered as separate markets. The web scraping tool gathered the lowest daily fare for each of these flights, starting from 103 days before departure until the day before. Information about flights by Southwest had to be retrieved from its own website, the second data source. This was done following the same method as described above. All the seats are in the Economy class, unless this class was already sold out. It should always be kept in mind that I focus merely on the leisure segment and the data is measured from an airport-pair approach. Competition from adjacent airports is not taken into account as opposed to the city-pair approach (Morrison, 2001), which I will further explain in the limitations section. The last two datasets are used to control for route specific effects that might influence ticket prices. The third data source is the US Census Bureau, an organization which collects data about US citizens. From their database I retrieved population estimates per metropolitan area for 2018. I did the same for per capita income estimates for 2017 (the most recent year), which I collected from the US Bureau of Economic Analyses. This fourth data source is an agency of the Department of Commerce and gathers data about the US domestic economy.

4.2 Carrier type, competition and control variables

Legacy carriers that operate on the examined routes are Alaska, American, Delta, Hawaiian, Mokulele and United. The LCCs are Frontier, JetBlue, Southwest and Spirit. In order to identify the type of carrier, the dummy *LCC* is created, which takes the value 1 for low-cost carriers, and equals 0 for legacy carriers. Two market structures emerge with distinct competition characteristics: routes with legacy carriers competing only with one another, and mixed competition between legacy carriers and LCCs[1]. The dummy variable *LCC_presence* marks the presence of a LCC competitor on a route. Next, the total number of carriers operating on a route are counted (indicated as $ncar_j$), as well as the total number of

[1] There are no routes within the dataset where there is purely LCC versus LCC competition.

departures on 22 October 2018 (indicated as $tdep_j$). The individual flight frequency of carriers is stated as $tdep_{ij}$. The route control variables include *route_length*, the duration of the flight in minutes, *origin_income* and *destination_income*¸ the income per capita of departure and destination metropolitan areas respectively, and lastly *origin_population* and *destination_population*, the population estimates of departure and destination metropolitan areas respectively.

4.3 Descriptive statistics

The summary statistics of the various competitors and markets are shown in table 1. T-tests point out that all the means are significantly different from each other at the 1% level. If I compare the average number of carriers operating on route, I see this is the highest for legacy carriers in legacy competition, followed by legacy carriers in mixed competition and then LCCs. I find the same pattern for flight frequency: legacy carriers only competing with each other depart on average 24 times a day in total, legacy carriers in mixed competition fly almost as frequently, and LCCs fly less than half as much. An equal trend is also evident for fares. In legacy competition, legacy carriers set their prices about 11 dollars higher than in mixed competition. The gap between prices of legacy carriers and LCCs in mixed competition is larger, namely 42 dollars. Both of the observations regarding fares are in line with the static literature, which states that the fares of legacy carriers are higher without LCC competition, and a lot higher than those of LCCs.

Table 1. Summary statistics

	Legacy carriers, uniform competition		Legacy carriers, mixed competition		Low-cost carriers	
Variable	Mean	**Std. Dev.**	Mean	**Std. Dev.**	Mean	**Std. Dev.**
Ncar	2.885	**0.992**	2.421	**0.920**	2.025	**0.766**
Tdep	24.032	**6.467**	21.221	**11.395**	8.452	**3.219**
Fare	174.983	**95.496**	163.821	**87.916**	121.861	**67.242**
No. Of Obs.	49,851		136,899		52,554	

The standard deviations of fares in table 1 tell us that fares vary the most around their mean for legacy carriers and less for LCCs. This could be a sign that the temporal price dispersion is higher for legacy carriers in favor of hypothesis 1. However, these deviations are the sum of devations over time and across routes. To get a better understanding of how fares evolve over time, fares are plotted over the advance booking period by fractional polynomial plots in figures 2 and 3. The flatter slopes of LCCs compared to legacy carriers in figure 2 give prelimary evidence for hypothesis 1; LCCs make less use of APDs and LPPs. Figure 3 reveals that the shape of the curve of legacy carriers in uniform competition is very similar to those in mixed competition, indicating that the fare reduction due to LCC competition is probably permanent instead of temporary. This contradicts hypothesis 2; legacy carriers in uniform competition grant higher APDs and set lower LPPs.

Figure 2. Price trend for legacy carriers and LCCs in mixed competition

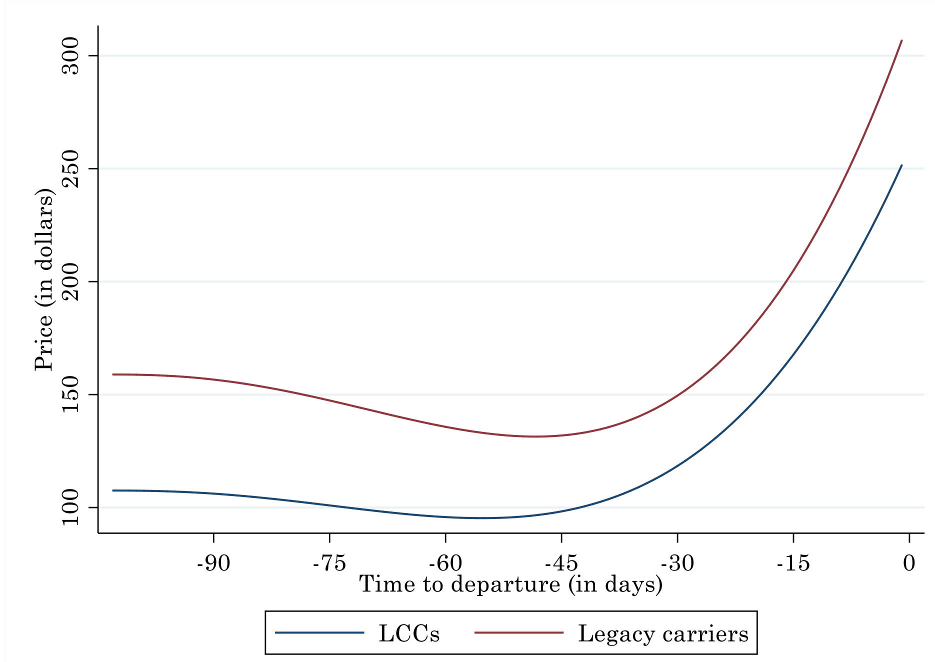
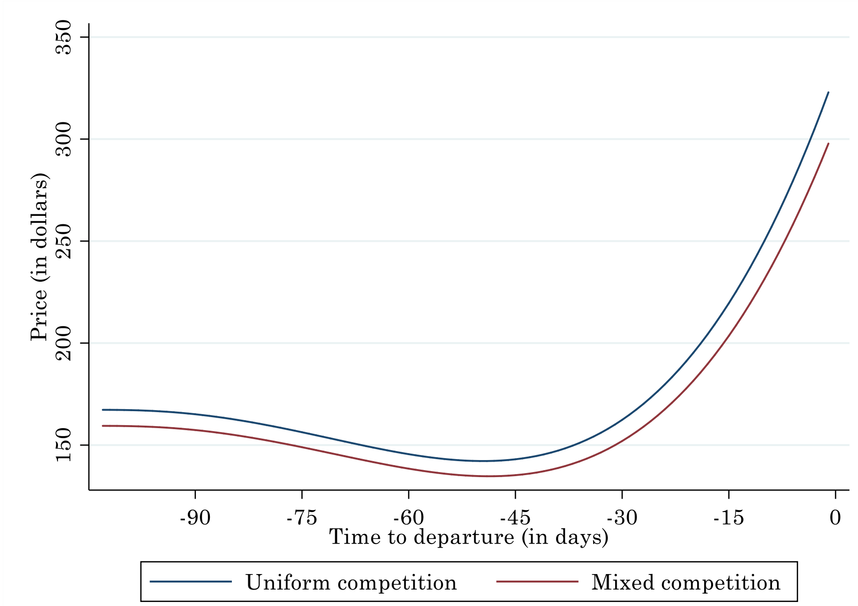


Figure 3. Price trend for legacy carriers in uniform and mixed competition



5. Methodology

The methodology I take to study dynamic pricing consists of three phases. First, the course of fares over the advance booking period is fitted in a hyperbolic function. The two determinants of dynamic pricing, namely APDs and LPPs, are resembled by parameters ß and α of this function respectively. I present this model in the first subsection. In the second phase the estimated parameters are used as dependent variables in regressions to test the hypotheses. I specify these regressions in the second subsection. In the third phase the outcomes of the regression analyses are converted from parameter values to fares, reversing the process of phase 1. This way the effect of carrier type and competition structure on dynamic pricing is expressed in terms of fares instead of parameter values, allowing for a more meaningful interpretation of the results. I will do this in the results section.

5.1 Parameter estimation

In all of the non-parametric fits of prices over time (figures 2 and 3) fares tend to follow a kind of U-shaped pattern over the three months before the flight. Fares start to rise monotonically between 8-6 weeks in advance, giving shape to a hyperbola in the mid to late booking period. The same trend is discovered by Escobari (2012) and Alderighi et al. (2014). Overall, the trend is closer resembled by a hyperbolic shape than a parabolic shape since the decline in prices in the early booking period is relatively small. A hyperbolic function seems to be the better fit to the data, therefore I search for a hyperbolic model as basis to catch the pricing dynamics in the advance booking period. By optimizing multiple theoretic relations that influence airline pricing (like demand functions and capacity constraints), Malighetti et al. (2009) come to an adjusted form of the standard hyperbolic function to estimate fares in their Ryanair case study. Moreover, they incorporate APDs and LPPs in this function as two separate parameters. Since these are the two key determinants of dynamic pricing of interest in this study, this model is especially suited for my approach. I use the aforementioned arguments as justification to apply the hyperbolic model of Malighetti et al. (2009), which is written down as:

$$p_{ijt} = \frac{1}{\alpha \cdot (1 + \beta \cdot t)} + \mu + \varepsilon_{ijt}$$

p_{ijt} is the flight price of carrier i on route j on t days before the flight date. Parameter α reflects the LPP, indicating the high price levels during the last days before the flight. A low α stands for a high LPP, which means that an airline drives up its fares drastically to exploit the higher willingness to pay of last-minute bookers. Parameter ß reflects the APD, indicating a decrease in fares that is directly proportional to the number of advance booking days. A low ß stands for a low APD, i.e. a steady upwards price trend as the flight date approaches. Conversely, a high ß represents an APD that is higher and lasts for a longer time. μ is a constant and should be interpreted as the static fare level on which the dynamic practices build. For each carrier on a route I estimate these three parameters. I save the α and ß to examine the use of APDs and LPPs. I am not interested in the constant, because I want to leave out the static price level in order focus solely on the dynamic aspect, as discussed in section 2.2. A graphical example of the hyperbolic function can be found in the appendix.

All parameters are computed on route carrier level. Route carrier level looks at the average of all the daily flights by an airline on a route. Estimation is done through the nonlinear ordinary least squares method after taking the natural logarithm of both sides of the equation. By taking the natural logarithm I make sure that the prices (dependent variable) and residuals are normally distributed. Histogram plots of both can be found in the appendix. After the parameter estimation is carried out, a few modifications are made to the data before regressions are run in phase 2. Only when *both* α and β of a route carrier are significant, they will be taken into account for the testing of the hypotheses. This way, I make sure that I only incorporate route carriers in my analyses of which the fares are accurately described by the hyperbolic base model. Route carriers with fare trends that deviate from the hyperbolic model are beyond the scope if this study; a limitation I will elaborate on later. Additionally, duplicate parameter estimates are removed to prevent that route carriers with more daily flights have more impact in the regression analyses. Lastly, outliers resulting from ineffective parameter estimation ($\alpha>0.02$; $\beta>3$) are removed to prevent that they will bias the ordinary least squares regressions.

5.2 Regression analyses

I use the dynamic pricing parameters α and β as dependent variables in regressions to see how APDs and LPPs are influenced by various business models and market conditions. For every hypothesis test I carry out at least two regressions, one with α as response variable and the other with β as response variable. All of the regressions are linear and with route or carrier fixed effects to isolate the causal relations of interest. In the model subscripts, i and j denote carrier and route respectively. Furthermore, I use a separate regression model for each hypothesis instead of a single all-encompassing model, because the studied effects are highly dependent on the context. Three different subgroups can be distinguished: LCCs, legacy carriers in mixed competition and legacy carriers in uniform competition. For the first hypothesis I am only interested in the first two subgroups[2], and I only want to use *route* fixed effects as I will later explain. For the second hypothesis I am only interested in the second two subgroups, and I only want to use *carrier* fixed effects. For the third hypothesis I am interested in all subgroups, but the effect and significance of competition appears to be different for every subgroup to the extent that dummy variables for each group are not an adequate solution. Meeting all these different demands in a single model would require a long list of very specific variables, diminishing the explanatory power of every individual variable.

In order to see how the parameters differ between the two types of carriers, the dummy variable *LCC* is used as explanatory variable in the following model:

[2] In the comparison between LCCs and legacy carriers, I exclude legacy carriers in uniform competition, because the goal here is to compare the two different carrier types in the same markets.

$$\alpha_{ij} = \gamma_0 + \gamma_1 * \mathrm{LCC} + \delta_j + \varepsilon_{ij}$$

$$\beta_{ij} = \gamma_0 + \gamma_1 * \mathrm{LCC} + \delta_j + \varepsilon_{ij}$$

If I find a positive effect of *LCC* on α and negative effect on β, this means that $\alpha_{leg} < \alpha_{LCC}$ ($\mathrm{LPP}_{leg} > \mathrm{LPP}_{LCC}$) and $\beta_{leg} > \beta_{LCC}$ ($\mathrm{APD}_{leg} > \mathrm{APD}_{LCC}$). If both results are significant, I cannot reject hypothesis 1. I choose the fixed effects model to control for route specific effects. Route fixed effects allows me to control for the fact that a carrier may behave differently in different markets. This time-invariant effect is captured in δ_j . I do not include carrier fixed effects, because this would account for much of the variation in behavior between different carriers. There would be little variation left for the dummy variable *LCC* to make a distinction between legacy carriers and LCCs. Control variables could be added to counter potential omitted variable bias that is specific to an airline without removing the major part of the variation. An example of this bias is a temporary discount, offered only a few times during the year, that is accidentally in effect during the 22nd of October 2018 and resulting in lower fares than usual. However, I do not know whether this or other sporadic events took place. I will discuss this shortcoming in the limitations section.

To examine whether legacy carriers behave differently in markets with and without LCC competition, *LCC_presence* is the explanatory dummy variable in the following model:

$$\alpha_{ij} = \gamma_0 + \gamma_2 * \mathrm{LCC}_{\mathrm{presence}} + \gamma * \mathrm{X}_j + \delta_i + \varepsilon_{ij}$$

$$\beta_{ij} = \gamma_0 + \gamma_2 * \mathrm{LCC}_{\mathrm{presence}} + \gamma * \mathrm{X}_j + \delta_i + \varepsilon_{ij}$$

If I find a positive and significant effect of *LCC_presence* on both parameters, this means that α and β are higher in markets of mixed competition than in uniform competition. In that case LPPs are lower and APDs are higher for legacy carriers in mixed competition, and hypothesis 2 cannot be rejected. This time I do use carrier fixed effects to filter out the differences between carriers, so I end up with an effect for legacy carriers in general. These are denoted by δ_i. For the same reason as before I do not apply fixed effects to control for route characteristics. Fixed effects would take into account the major proportion of individual route variation, which I need to measure the difference between mixed and uniform markets. However, it is likely that some route characteristics may influence both *LCC_presence* and dynamic pricing practices, causing omitted variable bias. Existing literature on the topic points out that route length, origin/destination income per capita and origin/destination population are important determinants of prices (Alderighi et al., 2014; Brueckner et al., 2013, Malighetti et al., 2009). These five variables are added to the model summed up as X_j in the equation above.

The effect of competition intensity on dynamic pricing is tested with $ncar_j$ and $tdep_j$ as explanatory variables in the final model:

$$\alpha_{ij} = \gamma_0 + \gamma_3 * \mathrm{ncar}_j + \gamma_4 * \mathrm{tdep}_j + \gamma_5 * \mathrm{tdep}_{ij} + \gamma * \mathrm{X}_j + \delta_i + \varepsilon_{ij}$$

$$\beta_{ij} = \gamma_0 + \gamma_3 * \mathrm{ncar}_j + \gamma_4 * \mathrm{tdep}_j + \gamma_5 * \mathrm{tdep}_{ij} + \gamma * \mathrm{X}_j + \delta_i + \varepsilon_{ij}$$

A positive and significant effect of $ncar_j$ and $tdep_j$ on both parameters would indicate that I cannot reject hypotheses 3, stating that higher competition intensity leads to higher APDs and lower LPPs. $tdep_{ij}$ is included as a control variable, because it is positively correlated with the total flight frequency and according to Malighetti et al. (2009) negatively correlated with β. Other control variables are carrier fixed effects (δ_i) and route control variables (X_j). As discussed at the beginning of this paragraph I will carry out the last set of regressions for each subgroup of carriers individually to prevent any bias.

6. Results

In this section I discuss the results for each phase of the methodology. In the first subsection I explain to what extent the hyperbolic model succeeded in capturing the true development of fares. In the second subsection I go over the outcomes of the regression analyses and consequently review the hypotheses. Furthermore, I express the results in terms of fares instead of parameters values for a more precise and meaningful interpretation; the last step in the methodology.

6.1 Parameter estimation

Distributions of parameters α and β that are significant can be found in the appendix. Overall, 81% of the parameters are realistically estimated, and if only the significant ones are considered I end up with 67% of the original data. This means that, on average, roughly 1/5-1/3 of carriers operating on a route do not pursue pricing policies that can be approximated by a hyperbolic function. Instead of a price trend that rises at an increasing rate over the advance booking period, those carriers either display a price trend that is rising at a decreasing rate or one that is decreasing over the time to departure. These alternative pricing practices are beyond the scope of this study, as I will further discuss in the discussion and limitations section. If I compare the predicted fares from the hyperbolic model for randomly chosen route carriers with the real fares, I notice three consistent dissimilarities: 1) the dynamics in the early booking period are evened out, 2) the steep rise in fares in the late booking period is stronger and delayed by about a week, and 3) the top fares in the last three days are overestimated. These are the consequences of fitting fares that are not strictly increasing all the time in a hyperbolic function. These inaccuracies do not form a drawback for the test of my hypotheses, because every hypothesis revolves around the comparison between two contexts (LCCs versus legacy carriers; uniform versus mixed competition; low versus high competition), which are both approached from the same methodology. However, considerations are made for relating the results of the models to reality.

6.2 Regression analyses

The outcomes of the first two regressions regarding hypothesis 1 are shown in table 2. Dummy variable *LCC* has significant positive influence on parameter α and significant negative influence on parameter β. In other words, LCCs set lower LPPs and lower APDs than legacy carriers. This means hypothesis 1 cannot be rejected, which essentially states that the temporal price dispersion of LCCs is smaller than legacy carriers.

Table 2. Results for hypothesis 1

	α	β
LCC	0.000520***	-0.158392***
	(0.000182)	(0.055010)
Constant	0.002750***	0.586324***
	(0.000088)	(0.026609)
No. of Obs.	215	215
Adj. R-squared	0.044	0.060

All specifications include route fixed effects. Robust standard errors clustered by route in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

I put the parameter values from table 2 in the hyperbolic function to predict the fares for legacy carriers (denoted by the coefficient of the constants) and LCCs (coefficient of the constants plus the coefficients of *LCC*). Recall that the constant of the price function, μ, represents the static fare level on which airlines build their dynamic pricing practices. By setting μ equal to zero for both types of carriers, I leave out the static fare level in order to focus solely on the dynamic aspect. Plots of the predicted fares over the advance booking period are presented in figure 4. These predicted fares are all significant at the 5% level, but still deviate from the real fares due to the shortcomings of the hyperbolic model as discussed in section 6.1. I will now compare my estimations to the non-parametric fits of the raw data of figure 2 to give an indication at what points the hyperbolic model differs from reality. To facilitate the comparison, I let both curves of figure 1 start at the same fare level while keeping their shapes intact and turn this level into the new horizontal axis where price is equal to zero. The result is shown in figure 5. To sum up, figure 4 shows the significantly predicted pricing dynamics of legacy carriers and LCCs controlled for route characteristics according to the hyperbolic model, while figure 5 shows the observed pricing dynamics of both types of carriers from the data.

The total *predicted* temporal price dispersion is between 200 and 250 dollars, while the *observed* price dispersion lies between 125 and 175 dollars, a 75 dollar overestimation. Figure 4 shows that legacy carriers let their fares rise relatively slowly until 7 days before departure. At that point the negative price difference between legacy carriers and LCCs has reached 5.30 dollars. Thereafter fares of legacy carriers increase much faster, overtaking those of LCCs two days before departure and ending up with a positive difference of 15.06 dollars. Figure 5 shows that the observed peak difference in APDs occurs sooner at about 45 days before departure. Moreover, the observed maximum APD difference is approximately 20 dollars, while the difference in observed LPPs is only around 10 dollars.

Figure 4. Predicted price dynamics of legacy carriers and LCCs in mixed competition

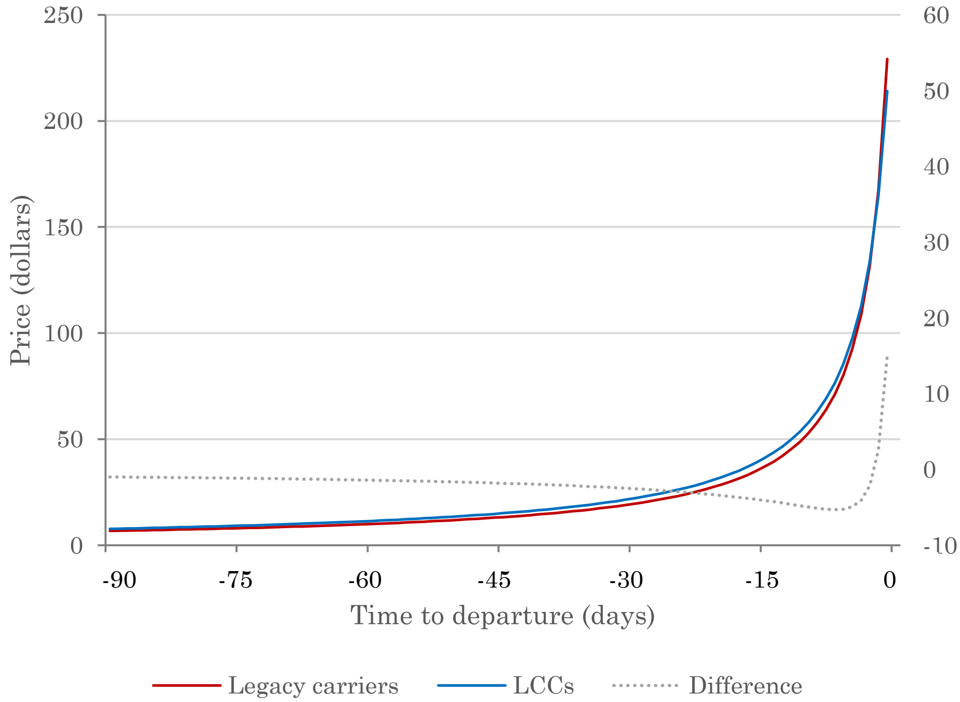


Figure 5. Non-parametric fit of price dynamics of legacy carriers and LCCs in mixed competition

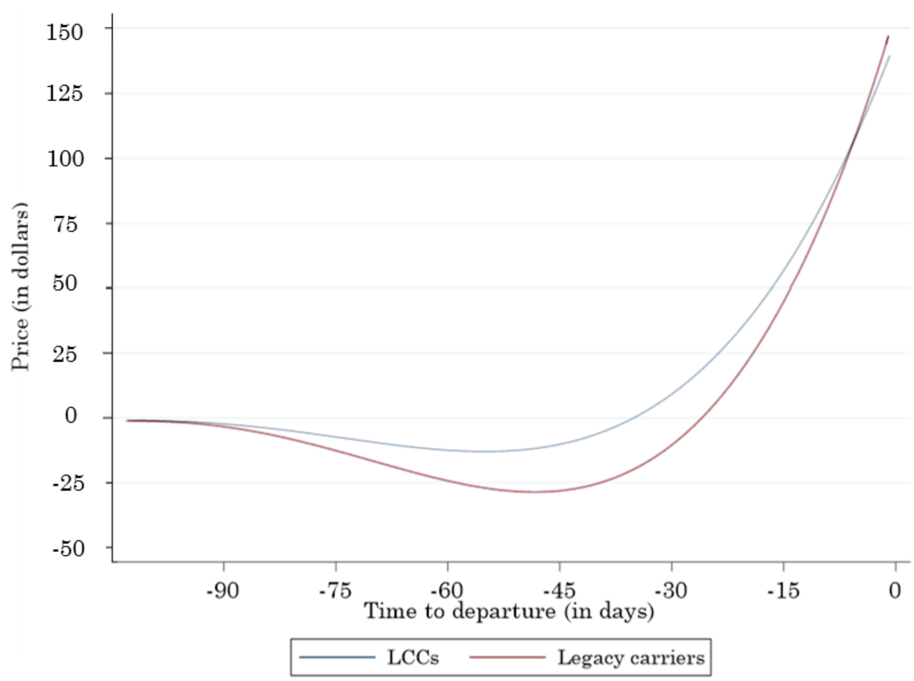


Table 3 shows the results of the second pair of regressions. The coefficient of *LCC_presence* takes on the values I expected, pointing towards lower LPPs and higher APDs of legacy carriers in markets with LCC competition. However, the effect is far from significant, which can be related to the small graphical difference in the non-parametric curves of figure 2. Hypothesis 2 is rejected; I do not find evidence that legacy carriers adjust their pricing dynamics based on the presence of a LCC on a route.

Table 3. Results for hypothesis 2

	α	β
LCC presence	0.000282	0.126611
	(0.000367)	(0.107402)
Flight length	-5.81E-11***	-1.56E-08
	(9.80E-12)	(1.00E-08)
Origin income	2.48E-09	5.67E-06***
	(7.44E-09)	(3.88E-06)
Destination income	4.10E-09	2.76E-06
	(6.77E-09)	(3.88E-06)
Origin population	1.79E-11	8.94E-09
	(2.53E-11)	(8.18E-09)
Destination population	4.39E-11	7.94E-09
	(4.02E-11)	(7.88E-09)
Constant	0.001902	-0.01739
	(0.001129)	(0.524848)
No. of Obs.	147	147
Adj. R-squared	0.010	0.036

All specifications include carrier fixed effects. Robust standard errors clustered by carrier in parenthesis. *** $p<0.01$, ** <0.05, * $p<0.1$

Table 4 shows the results of the last regressions regarding hypotheses 3. The coefficients of $ncar_j$ express the same pattern for all three subgroups, namely that both LPPs and APDs decrease as the number of competitors increases. This result is in favor of hypothesis 3b; LPPs do decrease as a result of increased competition, but contradicts hypothesis 3a; APDs do not increase with higher levels of competition. Instead the temporal price dispersion declines at both the bottom (APDs) and top ranges (LPPs) of fares. However, the effect is significant at the 10% level for LCCs and legacy carriers in uniform competition only, which I interpret as a high likelihood of occurrence for these subgroups but not a certainty. With each competitor in the market the temporal price dispersion of LCCs is likely to shrink by 6.09 dollars. Unfortunately, I cannot reliably predict any fares for legacy carriers in uniform competition, because the coefficient of the constant is not significant. The coefficients for legacy carriers in mixed competition are also far from significant, indicating that they do not change their pricing dynamics depending on route competition.

The signs of the coefficients of $tdep_j$ are the same for LCCs and legacy carriers in mixed competition, indicating lower LPPs and higher APDs. Yet, these coefficients are not significant, so I cannot say that pricing policies are more favorable for travelers on routes where there are a lot of daily flights by LCCs and legacy carriers. I observe a different effect for legacy carriers in uniform competition; their temporal price dispersion becomes significantly *higher* with higher total flight frequency. In contrast to number of competitors, APDs and LPPs are higher when the total number of daily departures is higher. All in all, I reject hypothesis 3, stating that APDs go up and LPPs go down as competition intensifies.

Table 4. Results for hypothesis 3

	Legacy carriers, uniform competition		Legacy carriers, mixed competition		Low-cost carriers	
	A	**β**	A	**β**	A	**β**
Number of competitors	0.0002821*	**-0.1073792***	0.0001118	**-0.017869**	0.0004132**	**-0.0805233***
	(0.000469)	**(0.0577366)**	(0.000227)	**(0.0524123)**	(0.0001939)	**(0.0436364)**
Total flight frequency	-0.0003229***	**0.0380262*****	0.0000389	**0.0057144**	0.000029	**0.0003085**
	(0.0000804)	**(0.0104174)**	(0.0000252)	**(0.0074227)**	(0.0000234)	**(0.0046529)**
Individual flight frequency	0.0000379	**-0.0131038**	0.0000168	**0.021734****	-0.000169**	**0.0241772***
	(0.0000616)	**(0.0141078)**	(0.0000385)	**(0.0094898)**	(0.0000749)	**(0.0123621)**
Flight length	-3.25E-10***	**1.16E-08**	2.06E-11	**4.96E-10**	-2.07E-10***	**-5.29E-09**
	(7.26E-11)	**(1.44E-08)**	(5.96E-11)	**(1.67E-08)**	(5.15E-11)	**(1.15E-08)**
Origin income	4.99E-08***	**-4.51E-06**	-5.40E-09	**6.26E-06**	-9.09E-09	**5.10E-06**
	(1.27E-08)	**(3.57E-06)**	(1.91E-08)	**(4.59E-06)**	(1.47E-08)	**(3.25E-06)**
Destination income	5.67E-08***	**-4.65E-06**	-4.94E-09	**2.16E-06**	1.78E-08	**-7.88E-06****
	(1.92E-08)	**(4.06E-06)**	(1.39E-08)	**(5.11E-06)**	(1.66E-08)	**(3.15E-06)**
Origin population	1.08E-10***	**6.20E-09**	-5.16E-11	**-6.41E-09**	-2.82E-12	**7.20E-09**
	(2.46E-11)	**(7.28E-09)**	(3.46E-11)	**(1.11E-08)**	(3.50E-11)	**(9.85E-09)**
Destination population	1.41E-10***	**5.77E-09**	-1.45E-11	**-5.98E-09**	5.90E-11	**5.96E-09**
	(6.39E-11)	**(1.30E-08)**	(4.64e-11)	**(1.18E-08)**	(4.42E-11)	**(9.57E-09)**
Constant	0.0014673	**0.3994078**	0.0023364*	**-0.281284**	0.0042534***	**0.7123024****
	(0.0023168)	**(0.5491445)**	(0.0012425)	**(0.3901926)**	(0.0014739)	**(0.3240227)**
No. of Obs.	36	**36**	111	**111**	103	**103**
Adj. R-squared	0.420	**0.218**	0.016	**0.067**	0.161	**0.122**

All specifications include carrier fixed effects. Robust standard errors clustered by route in parenthesis.
*** p<0.01, ** <0.05, * p<0.1

7. Discussion

In this section I present explanations for my results and reflect on the existing literature. First and foremost, the use of a hyperbolic function to approximate the dynamic pricing behavior proves broadly accurate for at least two-thirds of carriers operating on a route on average. The general trend of fares over the advance booking period displayed by the non-parametric fits of the data is well resembled by the predicted price curves, and the p-values of the parameters are significant. Hence, the larger part of airlines implements a positive temporal profile of fares, which is also found by Escobari (2012) and Alderighi et al. (2014). However, the non-parametric fits of the data point out that fares are actually not strictly increasing over the entire advance booking period. In line with Alderighi and Escobari, but contrary to Malighetti et al. (2009) I observe a small decline in fares 3-2 months before the flight. The restriction of the hyperbolic model for fares only to increase over time, is a substantial oversimplification of reality. Moreover, for the other one-third of the route carriers a negative temporal profile cannot be ruled out. It is possible that carriers sometimes offer fare reductions briefly before the flight date to sell the last available seats (Moller & Watanabe, 2010).

Alongside the higher average fares of legacy carriers over LCCs found by Brueckner et al. (2013), I find that the temporal price dispersion of legacy carriers is higher. Legacy carriers set relatively high APDs and LPPs, which makes the dispersion between the lowest and highest fare larger than for LCCs. As I reasoned in the hypothesis section, I think this can be explained by a more extensive use of price discrimination by legacy carriers. In short, APDs are granted for price sensitive (leisure) travelers and LPPs are set to profit from price insensitive (business) travelers. A heterogeneous mixture of both types of travelers is optimal for such price discriminatory tactics (Gerardi and Shapiro, 2009). My conjecture is that legacy carriers serve a more balanced mixture of price sensitive and price insensitive customers, while the customer base of LCCs is more homogeneous and predominately consists of price sensitive travelers. Therefore, legacy carriers can price discriminate more effectively, resulting in a higher temporal price dispersion. Conversely, LCCs focus on a steady low price trend as main competitive advantage to attract customers.

From the static literature it is known that legacy carriers compete stronger with LCCs on the leisure segment than with other legacy carriers. Like Brueckner et al. (2013) and Alderighi et al. (2004), I observe a decrease in fares in markets with LCC competition, but this difference is time invariant. In other words, legacy carriers do not grant higher APDs or lower their LPPs due to the pressure of an LCC competitor. It looks like these temporary reductions in fares are not worthwhile and they react by lowering their fares every day. The static literature also predicts that average fares go down as the competition on a route intensifies (Brueckner et al., 2013). If we look at higher competition intensity in terms of number of carriers, APDs and LPPs *both* go down as the number of competing airlines increases. Prices in the early booking period and in the last few days prior to departure move towards each other, reducing the temporal price dispersion. In sum, I predict the total pricing curve is shifted down (static level) and fluctuates less (dynamic level). Hence, the lowest fares do decrease, but not as much as the top fares, in line with Gerardi and Shapiro (2009). They argue that more competitors on a route means less power for carriersto price discriminate, resulting in a lower price dispersion. Business travelers who often purchase their ticket close to departure and pay top fares benefit more than leisure travelers. This is in contrast with Ryanair's practice to grant higher APDs on more competitive routes (Malighetti et al., 2009; Alderighi et al., 2014).

Among legacy carriers in uniform competition the flattening out of pricing dynamics is also more prominent on routes where total flight frequency is low. I expected that more daily flights would always lead to more competitive pressure, because it means more substitution options for travelers. Instead, many competitors operating on the same route with a low total flight frequency are the conditions by which competition among legacy carriers is the fiercest. This situation marks a fragmented market where flight slots are divided over many carriers and airport dominance of individual carriers is limited. Remember that legacy carriers try to fly via airports where they have some dominance, so they can claim convenient flying times and gates (Belobaba et al., 2015). My conjecture is that on routes where only legacy carriers operate, the limited airport dominance is translated to less power to implement heavy price discrimination. The legacy carriers are forced to implement a steady price trend, marked by the lower APDs and LPPs.

8. Limitations

There are several limitations to my research that need acknowledging. The first limitations relate to the data. Although the detailed dataset with daily fares of multiple carrier types is a novelty of this study, all the data concern departures on the 22nd of October 2018 only. This was a Monday, but it could be that pricing dynamics alter based on the day of the week. Moreover, from my own experience, it is a commonly used practice for airlines to offer discounts on specific destinations for a short period of time. I do not know whether any of such temporary offers were in effect over the examined time period. Fares of multiple departure dates should be gathered to see whether my results hold for other days of the week, holidays and other months of the year. For instance, in anticipation of a holiday or the summer vacation airlines might change their pricing dynamics in favor of the increased volume of leisure travelers.

Secondly, I only investigate the hundred busiest routes. The similar characteristics make it easier to compare these routes, but with it there comes a limited variation in competition structure. My dataset does not include any routes where there is only one operating carrier and also contains relatively few duopoly markets. A more diverse dataset in terms of traffic quantities would better highlight any competition effects. Besides, an airport pair approach is taken to collect the data instead of a city pair approach. The latter also takes competition from flights to adjacent airports into consideration. For example, I could have underestimated the impact of LCC competition, since especially LCCs use to fly to secondary airports of big metropolitan areas instead of the primary ones.

Thirdly, the lack of data on available passenger seats makes it impossible to split up pricing dynamics into a pure time and capacity effect. Alderighi et al. (2014) shows that the capacity effect plays a dominant role in the explanation of ticket prices over time. Observed LPPs could be the response to a peak in demand in the last days before departure instead of a temporal price discrimination tactic. Yet, I do not know the influence of varying customer demand on pricing dynamics.

The second set of limitations is related to the choices I have made in my methodology. By estimating the dynamic pricing parameters α and β on route carrier level, I group the data on multiple daily flights by the same carrier. This gives me more extensive data to reliably estimate the parameters, but an examination of individual flights would allow for a more detailed analysis. I do not control for the time of the departures, neither for the fact that the number of competitors differs between time slots. I have tried to run the hyperbolic model on flight level, but that resulted in significant parameters in only 46% of the cases compared to 67% on route carrier level. With data available from only a single day of departures I have chosen for more reliable results instead of more detailed ones.

Lastly, the use of a strict hyperbolic model to fit the data is an oversimplification of the real pricing dynamics. As a consequence, deviations of predicted fares from the actual ones occur or route carriers are excluded from the analysis entirely as discussed in section

6.1. A more complete functional form that also allows fares to decrease over the advance booking period would be a more accurate reflection of reality. An example of such a function is presented by Malighetti et al. (2009):

$$p_{ijt} = \frac{1}{\alpha \cdot (1 + \beta \cdot t + \gamma \cdot t^2 + \theta \cdot \sqrt{t})}$$

9. Conclusion

In this study I investigate how the dynamic pricing policies of legacy carriers and LCCs differ from each other and whether they are affected by different forms of competition across routes. The research question is: what are the dynamic pricing practices of legacy carriers and low-cost carriers and how are they affected by route competition? In order to address this research question I focus on Economy seats of flights on Monday 22 October 2018 for the 100 busiest routes of the US domestic market (based on passenger counts). The fares of a flight fluctuate around a static level over the advance booking period according to the theories of yield management. The literature points out that carriers reward customers who book early with a discount, the advance purchase discount (APD), while late bookers often have to pay a premium, the late purchase premium (LPP). I approach dynamic pricing by examining APDs and LPPs relative to the static fare level. In the comparison between the pricing dynamics of various carriers I focus merely on the fluctuations around the static level as if each static fare level is the same. The total dispersion in fares as a consequence of APDs and LPPs is referred to as the temporal price dispersion.

First, I approximate the fare trend of all individual carriers on route by a hyperbolic function over the 103 days prior to departure using non-linear least squares estimation. I find that at least two-thirds of the carriers on the average route implement a fare trend that resembles a hyperbola as the date of flight approaches, supporting the positive temporal profile of fares. The hyperbolic model includes the APD and LPP as two separate parameters. The APD is measured as a decrease in fares that is directly proportional to the number of advance booking days, while the LPP is approximated by the high fare levels during the last days before the flight. Second, I run fixed effects regressions with the dynamic pricing parameters as dependent variables to study the influence of carrier types and market structures on the use of APDs/LPPs. I find that legacy carriers set significantly higher APDs and LPPs than LCCs. Alongside the higher average fares of legacy carriers predicted by the static literature, the temporal price dispersion of legacy carriers is higher. My second finding is that legacy carriers do not change their dynamic pricing policies based on the presence of a LCC competitor in the market. Neither do I find enough statistical evidence to claim that carriers adopt different pricing tactics on routes with more competitors or flights. I find weak evidence of lower temporal price dispersion in more fragmented markets for some subgroups of carriers. All in all, the fare reductions in response to more competition found by the static literature prove to be mainly permanent instead of during specific periods in the advance booking period.

This study is a first attempt to take what is known about fares of legacy carriers and LCCs from the static literature and examine it in a dynamic context. I contribute to the existing literature by analyzing the pricing dynamics of a wide range of carriers and in various competition structures across US routes. While this paper represents a first step in this direction, more research needs to be conducted on the temporal setting of the flight, such as the time of day and day of the week. Also, the comparison of alternative temporal pricing functions, especially ones that allow for last-minute price reductions, might be the subject of future analyses.

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Appendix

Figure A1: Illustration of α and β for two different carriers with constant μ equal to zero

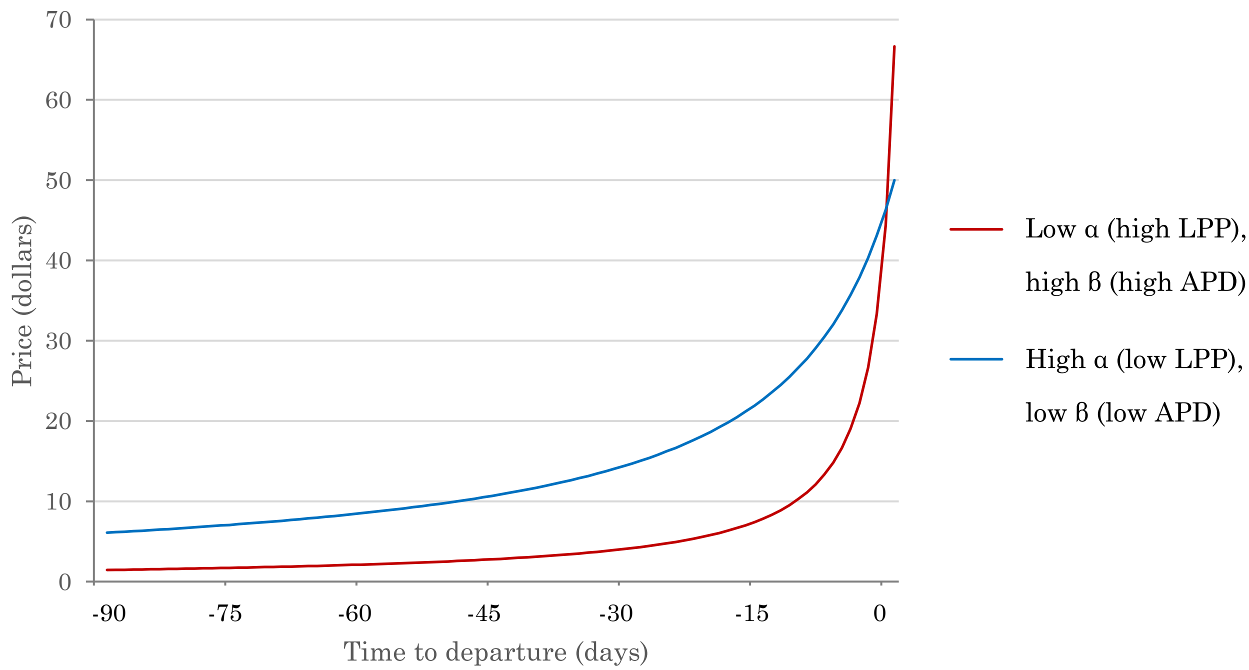

Figure A2: Histogram plot of natural logarithm of prices

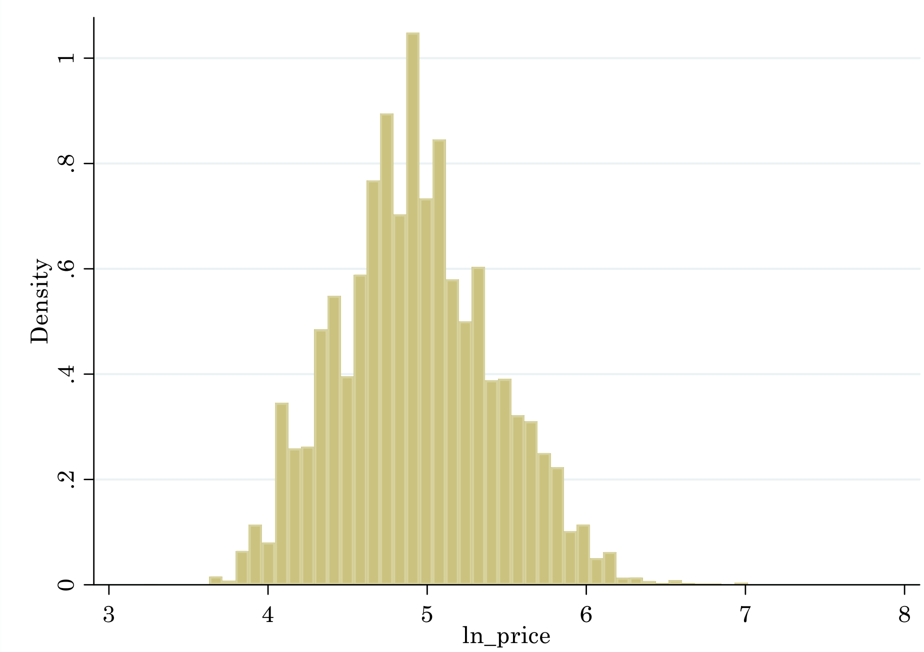

Figure A3: Histogram plot of residuals of parameter estimation

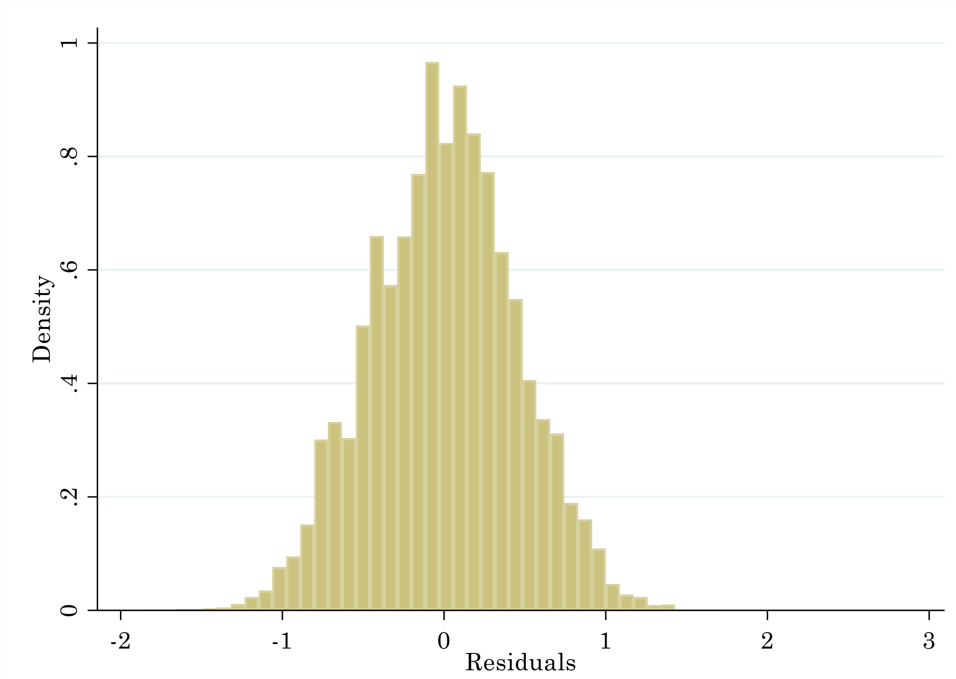

Figure A4: Histogram plot of significantly estimated values of parameter α

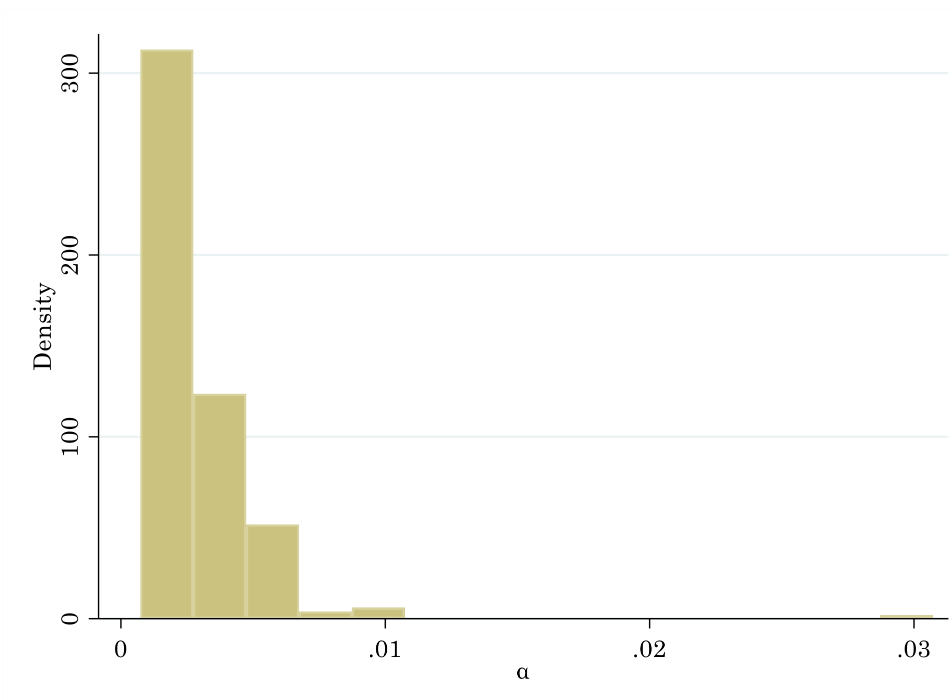

Figure A5: Histogram plot of significantly estimated values of parameter ß