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“Airline Cooperation Effects on Airfare Distribution: An Auction-model-based Approach”

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Abstract

Airline alliances have a long history yet there is no academic consensus on how they affect price levels and their impact on price dispersion has not yet been studied. We address this question using a novel methodology motivated by the service homogenization and increased price competition in this industry in the recent years. Establishing an equivalence between the online sales process and a reverse English auction, we use methods from auction econometrics to work in a new way with the standard industry data set: using individual ticket sales where only aggregated prices have been used in the past. Applicable to other industries where sellers compete in prices, this approach allows us to reconsider the effect of airline alliances on the distribution of airfares in the US domestic market. We find lower price mean and dispersion in markets where airlines belong to an alliance as a result of the lower variability of costs. The methodology we apply here can be used to study any distribution of individualized prices, which are now prevalent since the advent of the digital economy.

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1 Introduction

Airline cooperation plays a unique and crucial role in the industrial organization of international and domestic air travel. Most airlines cooperate in some manner, varying from a codeshare agreement on a particular market where airlines not operating a flight are allowed to sell tickets on that flight, to the more integrated arrangement of an alliance. There is no consensus among economists on the magnitude or/and the intensity of the effect of cooperation among airlines on prices or welfare. Airlines implement complex pricing practices to better extract consumer's surplus, which blurs studying the impact of cooperation on prices. To address this question, the analysis usually proposed in the literature is somehow incomplete as it mainly focuses on how aggregated prices are affected by cooperation. However, as aggregated figures ignore heterogeneity, their use can create heteroskedasticity which can affect the precision of the measure of impact of cooperation, an issue which is well recognized in most of the literature on airlines.¹

To contribute to the empirical assessment of airline cooperation's impact on prices, we propose an original approach that allows the use of individual transaction prices to estimate the airfare distribution rather than studying aggregated figures. We argue that the internet ticket sales process leads airlines to face Bertrand competition, which is equivalent to a Dutch reverse auction under certain assumptions (see for instance Maskin and Riley (1984), Spulber (1990) or Athey, Bagwell and Sanchirico (2004)). In our model, there is one buyer (the passenger or auctioneer) and multiple sellers (the airlines or bidders) who offer competing prices or fares; these fares are observable by all the sellers who can modify their offer according to their competitors' offer.² The transaction price at which the passenger buys the ticket is equal to the second lowest reservation cost among the competitors, where the reservation cost is the minimum acceptable compensation for the airline.³ This result allows us to interpret the observed airfares as winning bids and to analyze their distribution by methods pertaining to the econometrics of auctions.

The empirical auction literature has developed various methods for the estimation of auction outcomes.⁴ Our contribution relies on applying for the first

¹ For more information on the problem of aggregation see for instance Blundell and Stoker (2005)'s survey or the more recent Stoker (2016) present techniques that allows to attenuate the heterogeneity problems created when using aggregated figures in specific scenarios.

² For each product in our sample, that is an operating carrier and city pair combination, on average 91.3% of the transactions present different prices. If instead we focus on city pairs, independently of the carriers, 62.2% of the transactions present different prices.

³ Note that Klemperer (2004) states that theoretically such a "process corresponds exactly to the standard ascending auction among bidders competing to buy an object." He therefore refers to "ascending auctions" even for reverse auctions. We prefer to use the term "reverse auction" which is more coherent with our context. Note also that we use the term of reservation cost (instead of simply cost) to emphasize that we consider both operating and opportunity costs as explained in Section 3.

⁴ For a recent survey, see Gentry et al. (2018).

time such methods to describe an internet sale process. In the recent years, we have seen a spectacular increase in the number and popularity of search engines, websites and applications that compare prices. On the firm side, we have similarly observed an increase in the deployment and sophistication of yield management or pricing optimization techniques.⁵ More and more sectors see their goods and services traded online, with near-zero cost of price comparison and under heightened price competition. Some examples are car rentals, hotels, trains or more generally any market where firms offer similar products or services and compete exclusively on prices based on private reservation costs, a setup corresponding to a reverse English auction. To present this new approach in a tractable manner, we focus thereafter on symmetric duopoly markets, i.e., markets with two companies that share a similar cost structure and similar product characteristics such as frequencies.

We apply this methodology to revisit the literature studying airline alliance effects on prices, where we make three important contributions. First, we directly work with individual prices while traditionally, the impact of alliances -or cooperative agreements more generally- is estimated in terms of average prices, aggregated over passengers, per airline, per market and per period. Second, our approach allows for a more comprehensive treatment of the price distribution by jointly modeling airfares' mean and the variance. Third, we estimate the impact of alliances on the variability of ticket prices, which has not been considered before, neither by the literature on airline cooperation, nor by the literature studying the effect of competition on airfare dispersion.

An alliance is a partnership agreements between two or more competing firms. There exist a wide range of such agreements in the different sectors of the economy, see for instance the review by Kang and Sakai (2000) on international alliances; our work is focused on airlines alliances. Alliances allow carriers to cooperate, while maintaining certain boundaries and not constituting a merger. Most of the practices that alliance partners can engage in are considered beneficial for consumers: they can market their partners' tickets and collaborate in supplying a product (codeshare), offering a larger network reach (foreign carriers usually cannot operate within the domestic market known as cabotage); they can coordinate their schedules, improving the service quality; and they can share frequent flyer programs and promotional campaigns, providing more value to their customers. Furthermore, an alliance may lead to lower costs due to economies of density, because partners share airport equipment and staff.

Despite the listed benefits, the impact of alliances over consumers in terms of prices is still open to discussion. There is general agreement that airline alliances can reduce prices for international services, as suggested by Park (1997), Brueckner and Whalen (2000), Brueckner (2001), Brueckner et al. (2011) or

⁵ Yield or revenue management is a variable pricing strategy that allows firms to increase revenues in an environment with fixed capacity that has an expiration date (for instance, the takeoff of a plane) and uncertain demand.

Calzaretta et al. (2017). Most of the proposed products on international air markets, namely, connecting flights, combine the services of at least two carriers. For instance, to travel from city A in one country to city C in another country, a stop is required in city B, with the routes AB and BC operated by two different carriers. To the benefit of passengers, the alliance can eliminate the double marginalization problem that appears when each of the carriers prices its service independently from the other. Now, on markets where the alliance partners offer the same service, called overlapping markets, the double marginalization problem does not exist, and airfares may be higher because of the alliance if there are not enough competitors (Brueckner and Singer 2019). As overlapping international markets represent a small percentage of the total number of markets, the social costs of higher prices are in this case largely compensated by the social benefits due to the removal of double marginalization on connecting flights. That is why international alliances are generally approved.

The situation used to be different for U.S. domestic alliances, where carriers are free to provide service between any two cities and their networks can overlap significantly.⁶ The competitive effects of alliances in such markets caused concerns for the relevant authorities, one example being the Continental/Northwest/Delta alliance in 2002. The U.S. Department of Transportation (the DOT) argued that the process of communicating the necessary information to organize the codesharing service would facilitate carriers to collude explicitly or tacitly on prices and/or service in the overlapping markets. Despite these allegations, the Department of Justice allowed the formation of domestic alliances that eventually transformed into mergers, while their impact on airfares in the overlapping domestic markets was still uncertain.

To reassess such decisions, we implement our methodology on the US domestic direct markets operated by legacy carriers during the third quarter of 2015 and 2016. The alliance status of the airlines defines two market types, alliance or non-alliance markets. If the two airlines operating in a market belong to the same alliance, we denote it as an alliance market. These are the overlapping markets of the alliance partners. The market is non-alliance if the two airlines do not belong to the same alliance.

We show that, in the considered duopoly markets, prices are lower and less disperse in alliance markets compared to non-alliance markets; more precisely, prices are 10 percent lower, and standard deviation is 14.4 percent lower. This finding suggests that alliance agreements lead to efficiency gains that are passed on to consumers.

This implies that alliances are welfare improving, as is generally observed in international alliances. A reduction of the price mean is considered to be welfare enhancing for a given quality level. Our methodology allows competition authorities to expand their focus from only the effect of cooperation on the mean

⁶ The number of available slots and their allocation is regulated by the Department of Transportation at only a few airports due to traffic congestion.

of the airfare to also considering the impact on its variance, where variance can be linked to price discrimination but also to cost drivers and to demand uncertainty.^{7, 8}. We also contribute to the literature studying the effect of competition on price dispersion, which up to now has not considered cooperation agreements between competitors except for the recent work by Ciliberto et al. (2019) on codesharing.

Given that this methodology is general, it can be applied to analyze competition and cooperation in other industries. As shown by Kang and Sakai (2000), alliances have been widely implemented in the past. According to KPMG (2017), they are a valuable strategic opportunity for firms: “As critical drivers of growth, strategic alliances should be up there with M&A as a top priority for CEOs.” Some examples from the car industry over the last 20 years are the General Motors-Fiat partnership, or the Fiat – Renault and Daimler -Uber partnerships. (See KPMG, 2017) Thus, our methodology can be a relevant tool to analyze the impact of a cooperation agreements between firms when firms compete mainly in prices.

In the next section, we present the background to our work: our novel estimation approach applied to the standard industry data set (subsection 2.1), and the literature on airline alliances and on the effect of competition on price dispersion (subsection 2.2 and 2.3 respectively), as our methodology allows us to investigate both features of the price distribution simultaneously. In Section 3, we introduce our theoretical model and the econometric specification. Section 4 presents the data set and variables, and Section 5 provides the empirical results. Lastly, Section 6 concludes.

2 Background

2.1 The DB1B dataset

The U.S. Department of Transportation (DOT) publishes a comprehensive price data source, the Airline Origin and Destination Survey (DB1B). This survey is a 10 percent sample of all airline tickets sold in the U.S. domestic market. It provides information on the price paid for each ticket sold (called below the transaction price) for a given market (or city pair) and for given product characteristics. The product characteristics are the attributes that distinguish different types of flights within the same market, namely, the operating airline. Information about the purchasing date and the flight characteristics, such as the scheduled flight date

⁷ We direct the reader to Geradin and Petit (2005) or to Armstrong (2008) for a thorough discussion on the price discrimination theory and its effect on total and consumer welfare.

⁸ There exist other potential sources of price dispersion such as demand uncertainty, costly capacity or peak load pricing. See, for instance, Gale and Holmes (1993), Deneckere, Marvel, and Peck (1996) or Dana (1999), who show that price dispersion can arise as a result of other factors and not be linked to price discrimination.

and time, is not available. Due to this limitation, sometimes other databases aside from the DB1B are considered in the airline literature.

For example, web data-scraping is one way to collect data on posted prices that includes the flight characteristics as well as the date and time at which prices were posted. The structural approach applied to data collected from online sources has great research potential for airline dynamic pricing. See, for instance, Escobari (2012), Lazarev (2013), Williams (2013), Zhang et al. (2018). The main limitation of this approach is that in most of the cases only posted prices are observed, but not the transaction prices and the number of transactions. Moreover, structural models using this kind of data are so far limited to the monopoly case because of the high complexity of modeling competition in a dynamic framework.

Computer reservation systems (CRS), such as Amadeus or Sabre, can provide information on actual transactions, not only on posted prices, including information on the purchasing date. However, only transactions that occur within the system are registered in this dataset. Information from some airlines may be missing in certain markets, with no clear way to model or reconstruct the missing data. CRS data is usually sold at high prices to airlines and not generally accessible to researchers. As far as we know, the only exception is the work done by Sengupta and Wiggins (2012, 2014), Hernandez and Wiggins (2014) and Escobari and Hernandez (2019), who had access to one CRS for most of the carriers and domestic routes within US.

For these reasons, the DB1B remains the main source for analyzing different market and product features of the U.S. domestic airline industry, such as competition, mergers, collusion, entry of low-cost carriers (LCC), hub premium, or loyalty programs, as in Borenstein and Rose (1991), Brueckner and Spiller (1991), Miller (2010), Brueckner, Lee and Singer (2013), Berry, Carnall, and Spiller (1996), and Ciliberto and Williams (2010), respectively. These studies use the average market price or average product price as the dependent variable.

As the database contains many prices with the same market and airline characteristics, the traditional approach in the literature is to either study average prices (over markets and/or airlines) or price dispersion. Our work is the first to propose a joint analysis of the mean price and the price variability through a methodological contribution that allows us to work with individual transaction prices from the DB1B.

2.2 U.S. domestic alliances

The literature on domestic airline alliances exclusively uses the DB1B data set, and the outcome variable is the average (at the market or product level) transaction price. The alliance impact is typically measured by comparing the average prices before and after the alliance formation. Bamberger, Carlton and Neumann (2004) focus their analysis on the Continental/America West and Northwest/Alaska alliances; Armantier and Richard (2006) estimate the effect of

the Continental/Northwest alliance; Gayle (2007) studies the formation of the Continental/Northwest/Delta alliance. While Bamberger, Carlton and Neumann's (2004) results suggest lower prices for alliance markets, the last two studies find the opposite result. All three studies find an increase in traffic volumes. The authors interpret their results as suggesting that alliance partners are successful at expanding their customer base and employing price discrimination strategies. They conclude that, while the airline alliance can lead to higher overall prices, the outcome is not necessarily collusive or universally welfare reducing for consumers.

To evaluate the overall effect of alliances on consumer surplus, Armantier and Richard (2008) propose a structural discrete choice model, which uses individual transaction prices as well as an auxiliary data set to circumvent the limitations of the DB1B. Their analysis demonstrates that, while consumers using direct flights do face higher prices, this is compensated by the overall improvement of service quality as a result of the alliance. This methodology is not as easily accessible as what we propose below, because it is computationally complex and requires detailed data to supplement the DB1B.

Another strand of the literature focuses on the type of cooperation between alliance partners as a product feature. Ito and Lee (2007) distinguish between virtual codeshared products (where one partner operates the flight and the other sells the tickets on that flight) and traditional codeshared products (where both partners are involved in the operation of the flight and both can sell tickets). They report that 85 percent of their sample are virtual codeshare products and they are in direct competition with the airline's own product in 70 percent of the markets. They conclude that alliance products are seen as inferior by consumers in comparison to pure online flights (that is, flights operated and marketed by the same airline) and used by airlines to price discriminate between consumers with different willingness to pay. Gayle (2007) performs a similar exercise, but he focuses on the effect of the presence of traditional and virtual codeshare flights on the average market price; he finds that markets with traditional codesharing products have lower average prices, while markets with virtual codesharing have higher average prices.

While the literature attests that alliances (and more generally cooperation) are a relevant factor influencing prices, the estimated effects on average prices vary according to the employed methodology and the selected data subset. The model that we present in the next section updates this evidence regarding a more recent period in the history of alliances, while complementing the analysis of price means with that of price dispersion.

2.3 Price dispersion in the airline industry

Up to our knowledge, there is no theoretical model analyzing how cooperation affects price dispersion. A large branch of the empirical literature on airline markets has analyzed price dispersion and how it is affected by different market

features or by competition. Alderighi (2010) compiles the main results. As an outcome variable, these studies use aggregated measures of price dispersion such as the Gini coefficient or the coefficient of variation. We are not aware of any study in this literature that analyzes the impact of alliances.

In a seminal paper, Borenstein and Rose (1994) regress the Gini coefficient on factors related to costs. They exploit the difference in the number of carriers across markets to measure competition, and they find a positive effect on dispersion. Gerardi and Shapiro (2009) pursue the same objective by implementing a before-after approach that uses fixed market effects to control for unobservable time-invariant market characteristics. They find the opposite result – a negative effect of competition on price dispersion. Dai, Liu and Serfes (2013) find that the relationship between competition and price dispersion may be non-monotonic. Despite the methodological differences, the three studies used the DB1B database. Gaggero and Piga (2011) and Siegert and Ulbricht (2014) use web-scraping to collect posted price data for the European market. They find a negative correlation between competition and posted price dispersion, although the latter shows that this correlation is positive when price dispersion is measured at the market level rather than the flight level.

Using other types of price dispersion measures, Bachis and Piga (2011), Mantin and Koo (2009) and Hernandez and Wiggins (2014) find that price dispersion decreases with the level of competition. Gillen and Mantin (2009) and Sengupta and Wiggins (2014) find that competition does not generally affect price dispersion. Recently Chandra and Lederman (2018) find that the relationship depends on consumer heterogeneity and can be U-shaped. Overall, it appears that there is no clear consensus on the effect of competition on the variability of prices, or what measure of dispersion is most suitable.

We find it to be an important omission that none of the aforementioned studies analyze the impact of cooperation on price dispersion, despite the alliance and codesharing literature demonstrating that cooperation certainly has a significant effect on price means. Only Ciliberto et al. (2019) show that the presence of codesharing agreements reduces price dispersion. Our study includes cooperation measures over market with similar competition levels and establishes a link between the literature on price dispersion and that on alliances.

3 A model of airline competition

In this section, we detail the assumptions that allow us to establish the observational equivalence of competition in the airline market with an auction model. We discuss the underlying determinants of costs; we outline the derivation of the maximum likelihood estimation (MLE); we describe how to estimate the distribution of prices and how cooperation, alliances in particular, affect it.

3.1 Overview

We propose a competitive framework aimed to depict appropriately the current economic environment faced by airlines. The recent trends in the industry, specifically service homogenization, the large use of internet price search engines and high consumer price sensitivity, motivate our assumption that, in the short run, airlines proposing similar quality levels compete in prices given existing capacities.⁹ The airline industry benefits from one of the most sophisticated inventory and price management systems: all the global distribution systems and many consulting firms propose tools and big data solution to monitor and responds to pricing of competing carriers.¹⁰ Airlines can observe their competitors' prices and modify their behavior accordingly. In our data sample, the US domestic flights during the third quarter of 2008-2019, 91.3% of the transactions for an average route and operator present different fares.

Following the rationale of Klemperer (2004), we argue that this large variety of fares can be modelled if each ticket sale is viewed as a reverse¹¹ English auction. Consider two airlines with different minimum prices at which they are willing to provide the service, what we call their reservation cost. The reservation cost comprises the operating cost as well as the opportunity cost of the service. The operating cost covers the explicit costs to provide the service on a market.¹² The opportunity cost is the value an airline places on selling a ticket now, relative to an uncertain sale of a ticket with a potentially higher price closer to the departure date.

The airline with the lower reservation cost has a competitive advantage -- it can provide the service at a lower price than its competitor. The profit-maximizing strategy of this airline is to offer a price that is not unnecessarily low; it "wins" the sale at the highest price (or bid) that guarantees a sale. In other

⁹ We leave aside entry and exit issues, which are studied by Berry (1992). However, we control for the potential bias that this could represent by sensitivity checks that include origin and destination level fixed effects.

¹⁰ For instance "Sabre AirVision Fares Optimizer empowers airlines to strategically adjust their fares based on real-time market data. It recommends pricing structures based on customer segmentation and competitor price checks" <https://www.sabre.com/insights/releases/sabre-launches-industry-first-pricing-technology-to-deliver-on-an-end-to-end-dynamic-pricing-strategy/#:~:text=As%20part%20of%20our%20commitment,and%20well%20into%20the%20future.&text=Sabre%20AirVision%20Fares%20Optimizer%20empowers,on%20real%2Dtime%20market%20data>, last accessed december 2020.

¹¹ In a reverse auction, the auctioneer is a buyer and the participants are sellers who compete by offering prices (their bids) at which they are willing to provide the service. During an open auction of this kind, known as an English auction, competitors can observe each other's bids (just as they do in our price competition set-up) and react to them.

¹² Operating costs are defined by the International Civil Aviation Organization to include aircraft or direct operating costs such as fuel, aircraft servicing costs such as handling, traffic service costs such as meals or flight attendance, booking and sales costs and other costs such as advertising or general administrative expenses.

words, the most competitive airline makes a sale by offering a bid that slightly undercuts the reservation cost of its competitor.¹³

The airlines observe their competitor's bids, while they do not observe their competitor's costs. Each airline bid depends on the competitor's bids, and the airlines privately know reservation cost. The reservation cost of any airline, at any point in time, can be split into two parts with respect to its statistical nature and its relevance for the airlines. In the language of statistics, there is a deterministic component that is common and observed by all competitors. For example, the fuel cost to cover the distance between the ends of a market. There is also a random component that is private knowledge and has private relevance to the cost of an airline, for example, the opportunity cost for each airline at a given moment of time. Therefore, we consider that:

Assumption 1: *The random component of reservation costs is an independent private value.*

Auctions are repeated among players with capacity constraints and an ideal model should account for these interactions; however, the DB1B dataset does not provide any information on the acquisition date which impedes analyzing such dynamics. We treat the individual ticket sales as realizations of independent auction games. Therefore, the private random component of each airline in each sale is drawn anew from a probability distribution that is independent and identical across airlines and across sales. This simplification with respect to reality allows us to treat transaction prices individually via a methodology based on Paarsch (1997)'s approach for estimating auction outcomes that as we will explain in the next subsection.

Our last assumption allows us to model price variability within a market using market characteristics. The DB1B prices exhibit significant variability driven by the unavailable flight characteristics and purchasing date, and the literature has treated this issue by averaging prices at the market level. We conjecture that flight characteristics and purchasing dynamics are endogenous to the market fundamentals. Unlike previous work, we propose to model this variability by making the following assumption:

Assumption 2: *Market characteristics are determining factors of flight characteristics and advance purchasing dynamics, and thus, of price variability within a market.*

For example, in a large metropolitan market we would expect multiple flights due to the large and diverse population compared to smaller metropolitan areas

¹³ Our model is in line with the widely-spread yield management method of bid price control. In practice, there are several techniques that the airline can use to increase their revenue, some of which involve the estimation of a marginal cost of each seat on a plane, at each moment in time. One such method is bid price control, where this marginal cost is used as a bid -- an optimum cut-off required to accept a booking. These bids correspond to reservation cost in our model, below which airlines are unwilling to sell tickets. Bid prices are dynamically adjusted over time to reflect the changing reservation cost under dynamic demand. This practice has been analyzed in the operations management literature by Talluri and Van Ryzin (1998) and Adelman (2007), among others.

with smaller frequencies; as a result, price variability would be higher because different flights have different operating costs. Higher or more diverse population income would affect the advance purchasing patterns. For instance, more last-minute business travels would cause the opportunity costs to increase significantly. Thus, the market features, in terms of income and size, determine the unobserved flight features and the advance purchasing patterns over time. This rationale allows us to model the variability of airfares as a function of the market features.

A limitation of the model is that the following two scenarios are not considered due to data limitations. First, our setting implies that both airlines have available seats on their flights. If a flight is fully booked, the airline with free capacity can act as a monopoly and in this sense the proposed model cannot work. This limitation of the model should be alleviated by the limited number of sales under this scenario that implies a 100% load factor. Second, travellers with willingness to pay comprised between the competitor's reservation costs, will not make a transaction. Given richer data, an auction model that includes these special cases could be identified and estimated (Athey, Haile, Econometrica 2002).

3.2 The model

In this section, we pattern the equilibrium bidding strategy in a reverse English auction under the independent private values paradigm. We identify the players and describe each player's own information, available strategies and rewards; finally, we characterize the equilibrium. We consider exclusively duopolies for the sake of simplicity.¹⁴

Suppose that a single buyer (namely, the consumer or the traveler) wishes to purchase one ticket in a market with two players (that is, the sellers or the airlines). Each player has a reservation cost to provide the ticket, which we denote c . The strategies available to the sellers are their bids (announced, posted or offered price) as a function of the reservation cost. The game proceeds as follows. The consumer only cares about prices and compares the airlines' offers.¹⁵ The players fully observe, and can react to, each other's prices. Whenever it is profitable for them to do so, they can undercut the price of the competitor to win the sale. Each player is willing to lower one's price up to $p = c$, but not lower. The winner is the player with the lowest reservation cost who undercuts slightly the opponent with the highest reservation cost. *The resulting transaction price corresponds to the highest reservation cost among the two players.*

¹⁴ Scenarios with more than two players imply asymmetry of the players, as usually only two of them will be in an alliance. Asymmetry would add significant complexity to the analysis without broadening the contribution of the methodology.

¹⁵ For example, consumers may use one of many and very popular websites offering search and comparison services, such as Kayak, Expedia, Orbitz and Travelocity, that allow consumers to enter their trip parameters and obtain a price ranking.

To estimate this model, we implement the MLE methodology for auction data proposed by Paarsch (1997). Given the equilibrium of the game, the observed transaction price is a function of the reservation cost: It is the highest reservation cost from two independent and identical reservation cost draws. Let us assume that the reservation cost has a cumulative distribution F and a respective density f in \mathbb{R}^* . Moreover, we assume that the reservation cost follows a logarithmic normal distribution with mean μ and standard deviation σ , its natural logarithm being a normally distributed variable.¹⁶

Denoting by $o(d)$ the city at origin (destination, respectively), a market is defined as a directional city pair od .¹⁷ The likelihood of an observation i in the market od is the occurrence probability that an airline sells ticket i at a price p_{iod} for a travel from o to d . For clarity of the exposition, the exact derivation of the likelihood, which is standard, is left for Appendix A. The likelihood of a single price observation is written as:

$$L_{iod} = 2F(p_{iod} | \mu_{od}, \sigma_{od}) f(p_{iod} | \mu_{od}, \sigma_{od}) \quad (1)$$

The MLE approach yields estimates for the distribution parameters (μ_{od} , and σ_{od}) such that the resulting price distribution approximates the observed sample of individual observations as close as possible.

The task is now to estimate the parametric effect of variables of interest (notably the presence of alliances) on the distribution of reservation costs. Through the distributional relationship between the reservation cost and the transaction price, we derive how these variables ultimately affect the transaction price distribution. To do so, we discuss in the next subsection how the distribution parameters are identified and estimated.

3.3 Model Specification

Let X_{od} be a vector of N variables relevant to the market od . These deterministic market factors affect the mean and standard deviation of the reservation cost distribution according to

$$\mu_{od} = X_{od}' \alpha , \quad (2)$$

$$\sigma_{od} = X_{od}' \beta , \quad (3)$$

where α and β are the N -parameter vectors of the underlying reservation cost distribution to be estimated.

¹⁶ The advantage of the logarithmic-normal distribution is that it allows us to interpret the coefficients of all the continuous explanatory variables as elasticities, as the explanatory variables themselves are transformed by taking their natural logarithm. This approximation is valid whenever the effects are relatively small, as is the case for our results.

¹⁷ The directional definition provides the basis for the delineation of relevant market in many studies. See Gayle (2007) and Berry and Jia (2010) or Luttmann (2018). There exist a 10,4% difference on average fares between directions on the city pairs in our sample.

Our main interest is how these market factors affect the actual transaction prices. As already discussed, the observed transaction price has a distribution that is a function of the underlying reservation cost, that is, the highest out of two reservation cost draws. Let us denote the corresponding mean and standard deviation of the price distribution as m_{od} and s_{od} , respectively. Then, following the derivation in Nadarajah and Kotz (2008), we can express the parameters of the price distribution in terms of those of the reservation cost distribution.¹⁸ The mean of the transaction price, m_{od} , is a combination of μ_{od} , and σ_{od} , the mean and standard deviation of the reservation cost distribution. The price standard deviation, s_{od} , is simply the scaled standard deviation of the reservation cost. The marginal effects of the set of variables X_{od} on m_{od} and s_{od} , denoted below as a and b , respectively, can then be simply calculated using the marginal effects α and β of the reservation cost distribution as:

$$m_{od} = \mu_{od} + \frac{\sigma_{od}}{\sqrt{\pi}} = X'_{od} \left(\alpha + \frac{\beta}{\sqrt{\pi}} \right) = X'_{od} a \quad (4)$$

$$s_{od} = \sigma_{od} \sqrt{\frac{\pi-1}{\pi}} = X'_{od} \beta \sqrt{\frac{\pi-1}{\pi}} = X'_{od} b \quad (5)$$

where π represents the number pi.

Looking at Equation (4), we can infer that the average transaction price is larger than the average reservation cost. However, we cannot conclude if the impact of the n^{th} variable in X_{od} will be larger over transaction prices than over reservation costs. The ranking depends on the signs and relative magnitude of α_n and β_n coefficients. If they have the same sign, then the impact on the mean price, a_n , is larger than the impact on the reservation cost. If they have different signs, the overall effect depends on their relative magnitude and significance. It may be the case that both α_n and β_n are significant but of opposite sign, and a_n is insignificant.¹⁹

According to Equation (5), the variables X_{od} have a smaller impact on the price standard deviation, s_{od} , than on the reservation cost standard deviation, σ_{od} , since $\sqrt{\frac{\pi-1}{\pi}} < 1$. The distribution of prices presents a lower standard deviation because observed prices are reservation costs that are selected in a “directional” way -- we take the highest from two.

4 Data and explanatory variables

¹⁸ The exact forms of the different moments of the distribution of order statistics have been known for a while and are available in many good reference books such as David and Nagaraja (2003).

¹⁹ Coefficients in vectors b and β share the same statistical significance. The significance of coefficients in vector a is calculated by representing them as a combination of two randomly distributed normal variables (α and β).

We exploit the DB1B data for the third quarter of 2008-2019, and we select all markets satisfying three conditions. First, we exclusively consider duopolies where only two airlines operate. Duopolies represent 33% of the observed markets and 18.2% of the passengers during the period 2008-2019. The data cleaning process is explained in Appendix B. Second, all the proposed flights must be direct flights. Our methodology requires that the airlines propose equivalent products and compete exclusively on prices, therefore we restrict our analysis to firms with similar size imposing that market shares do not exceed 60%. Furthermore, our analysis concerns only markets where major legacy carriers operate. We do not consider LCCs and markets where they operate. The cost structure of LCCs is different from that of legacy carriers, and moreover, they do not enter alliances, which makes them an unsuitable group to use for comparison.²⁰

In our definition of an alliance, we follow Ito and Lee (2007). Carriers are alliance partners if passengers on one of the alliance carriers can earn elite-qualifying frequent flyer miles on flights marketed or operated by the other alliance partner and vice versa. The alliance presence is defined at the market level. The market can either be an alliance market ($Alliance_{od} = 1$) if both carriers are in the same alliance, or a non-alliance market ($Alliance_{od} = 0$) if the carriers are not in an alliance together. In this sense, we do not model explicitly the exact type of cooperation products or level of coordination (flight scheduling, sharing equipment and personnel, revenue sharing or else) that occurs within alliance markets. Table 1 shows the evolution of alliances among US legacy carriers over the last decade.²¹

Following Brueckner, Lee and Singer (2013) we include as legacy carriers American Airlines(AA), Continental (CO), Delta (DL), Midwest (YX), Northwest (NW), United (UA), and US Air (US). Over the duration of the sample, several mergers led to an increase in concentration and only 4 legacy carriers remain: AA, AS, DL and US. This leads to a decrease in cooperation, both in the number of alliances and in the number of codeshared tickets. We observe that passengers flying with codesharing tickets have decreased drastically since the departure of US Airways from Star Alliance. Codeshared passengers represented on average 3.4% before 2014 on the DB1B database while they only represent 0.2% afterwards.

Among the considered alliances, only the AA/AS alliance remains active in the US domestic market in 2021. While most of the passengers in the US domestic market keep flying in airlines belonging to an international alliance (namely, American, Delta or United Airlines) the interaction between the members of each international alliance, in the form of domestic alliances, have decreased

²⁰ Regional-legacy carrier agreements are not considered to be alliances but rather an integrated service. As is standard in the literature, we recode tickets sold by regional carriers as the legacy partner.

²¹ We also considered connecting markets, however alliance presence in such markets is negligible in the US domestic market since 2011.

drastically. Table 2 presents the evolution of duopoly market passengers in allied and non-allied markets. As you can see, this number is very low after the economic crisis in 2009 until 2014, and then starts to decrease again in 2017.

Table 1
Alliances Evolution

Carriers	Begin	End
Alaska/American	1999	-
Alaska/Continental	March 1999	CO merged with UA October 2009
Alaska/Northwest	August 1999	NW merged with DL January 2010
United/US Airways	January 2003	US moved to Oneworld March 2014
Continental/Delta	June 2003	CO merged with UA October 2009
Continental/Northwest	June 2003	CO merged with UA October 2009
Alaska/Delta	November 2004	Ends in May 2017

An underlying assumption of our model is a stable market structure. For this reason, we find that data from years with mergers is less suitable because firms' costs and objectives are changing. The results presented here are based on a sample for 2015 and 2016, however the results are robust if we consider different subsamples or if we include more years in the dataset as presented in subsection 5.2.

4.1 Explanatory variables

Our explanatory variables X_{od} include market, origin and destination characteristics and are obtained from the DB1B and the U.S. Census Bureau. These variables affect the operating and/or opportunity costs in a deterministic (non-random) manner. The complete list of variables and their definition is displayed in Table 3. *Distance* is a product-level variable that is measured in number of miles flown between the origin and destination airports, including the outbound and inbound flights. The distance impacts the level of operating costs, as longer distances require more fuel to reach the destination. Distance can also affect the opportunity cost of a ticket, as it affects substitution with land travel.

Table 2
Alliances Evolution on Direct Duopolies

Number of passengers		
Year	Duopoly markets	Duopoly allied markets
2008	38,099	13,044
2009	48,215	15,358
2010	50,743	9,828
2011	27,922	8,776
2012	30,566	4,353
2013	26,887	5,853
2014	20,79	12,376
2015	31,709	16,995
2016	25,076	18,466
2017	41,506	5,002
2018	61,136	2,367
2019	65,77	3,455

Our demographic measures -- *Population* and *Income* -- are measured at the origin and destination cities. Higher income cities have both richer leisure travelers who do not need to plan in advance and more business travelers who book tickets in the last days before departure. We therefore expect high income to lead to a higher average and a lower variability for the reservation cost. *Population*, on the other hand, is a measure of market size and could be associated with lower operating costs, as larger scale operations are more efficient. However, the effect of *Population* over the reservation cost is not clear since a larger population can also imply higher opportunity costs, as more buyers are expected to arrive closer to the departure date. We construct four variables that describe the market in relation to the network. *Origin volume* and *Destination volume* measure the total number of domestic ticket sales at the origin and destination of the market, respectively, to passengers traveling to any point in the airport's network. To quantify the market's centrality in the network, we build two variables; *Origin markets* and *Destination markets*. Origin markets counts the number of cities directly accessible from the origin, while Destination markets counts the number of cities from which one can fly to the destination. The centrality in a network affects operating costs through scope economies and the alternative use of resources (planes, personnel) in adjacent markets.

As a further measure of the importance of the origin and destination we include the variables *Origin hub* and *Destination hub*. The hub variables are defined at the airport level and measure the number of connecting domestic passengers. The large scale of operations at hub airports may reduce operating costs, but costs may also fluctuate more as the airline allocates aircraft capacity among connecting passengers from different origins and destinations.

We include a dummy controlling for the presence of codesharing passengers. Codesharing may affect to both cost and prices although it is not clear the effect

direction (see for instance Zou and Chen 2017 for a discussion on possible effects). Finally, we use a dummy variable to indicate the alliance presence, which we discuss in more detail in the next subsection.

Table 3
List of variables and their definition

Variable	Description
<i>Distance</i>	The roundtrip distance between the two city endpoints of the market measured in miles.
<i>Origin population</i>	The origin city's population.
<i>Destination population</i>	The destination city's population.
<i>Origin income</i>	The origin city's median income (GDP) in US dollars.
<i>Destination income</i>	The destination city's median income (GDP) in US dollars.
<i>Origin volume</i>	Number of domestic passengers departing from the origin.
<i>Destination volume</i>	Number of domestic passengers departing from the destination.
<i>Origin markets</i>	Number of markets accessible from the origin.
<i>Destination markets</i>	Number of markets accessible from the destination.
<i>Origin hub</i>	Number of domestic passengers connecting at the origin airport.
<i>Destination hub</i>	Number of domestic passengers connecting at the destination airport.
<i>Alliance</i>	Dummy equal to 1 if the two carriers operating on the market are in an alliance.
<i>Codeshare</i>	Dummy equal to 1 if at least one passenger use codeshared tickets between the carriers on a market.

4.2 Alliance presence

The literature on the impact of airline alliances has approached the estimation of their effect in two ways. Ito and Lee (2007) look at the prices of different types of alliance products within the same market. Gayle (2007) and Bamberger, Carlton and Neumann (2004), on the other hand, look at the effect of introducing an alliance product in a given market. In our methodology, we compare prices across markets (*cross-sectionally*), rather than before and after the agreement, to estimate how the presence of the agreement affects them.

Ex-ante, it is not obvious how the alliance presence could affect the level and variability of the reservation cost, as there are several potential effects working in opposite directions. On the one hand, alliances are allowed to share certain

operating costs such as personnel and airport facilities, which could reduce operating costs. On the other hand, the ability to coordinate schedules and to sell tickets on a competitor's flights can make price discrimination more profitable, affecting the opportunity cost and how it evolves over time. The *Alliance* variable thus measures the overall effect of the alliance on the reservation cost's mean and standard deviation.

An important assumption in our approach is that, after controlling for all observed variables, alliance markets must be comparable to non-alliance markets. In other words, there are no unobservable factors that make the alliance more profitable in the specific markets where the alliance operates. If this were not true, the estimated alliance effect would also contain the effect of the unobserved factors, hence it would be biased. To avoid this problem, Brueckner (2003) uses a model with entry. Another more direct approach that is used by Brueckner and Whalen (2000) and Ito and Lee (2007) is to introduce fixed effects, which we consider in Subsection 5.2.

4.3 Summary statistics

Table 4 presents the summary statistics distinguishing between alliance and non-alliance markets for 2015 and 2016. As our dataset is based on directional city

pairs, summary statistics are weighted by the volume of passengers.²² Overall, there do not seem to be significant differences in market characteristics between alliance and non-alliance markets. The only exception is that alliance markets present longer distances, given the presence of several markets between the east and west coast. The same magnitudes are observed if the full sample, 2008-2019, is considered.

Although the variables are presented here in levels, for the estimation they are transformed by taking their natural logarithm. This transformation allows us to interpret the coefficients of all continuous variables as elasticities. In other words, each estimated coefficient represents the percentage change in the mean μ_{od} or the standard deviation σ_{od} of the reservation cost given one percent change in the relevant variable. The Alliance coefficient, however, is a dummy, and its interpretation is slightly different; we multiply the estimated coefficient by 100 to obtain the percentage change of the mean or standard deviation of the reservation cost when Alliance = 1. This interpretation is also relevant for the price mean and standard deviation, m_{od} and s_{od} , respectively. The effects of the explanatory variables on m_{od} and s_{od} are derived using Equations (4) and (5).

Table 4
Average values by alliance presence

	Alliance	Non-Alliance
Price (\$)	497.84	539.85
Distance (Miles) ²³	4059	2058
Origin population	3,340,968	5,615,129
Destination population	4,798,379	4,518,930
Origin income (\$)	74,643	65,753
Destination income (\$)	61,728	61,497
Origin volume	5,241,427	6,268,399
Destination volume	7,130,162	5,302,370
Origin markets	105	137
Destination markets	91	129
Origin hub	1,248,352	921,801
Destination hub	3,445,245	1,377,329
Codeshare	0.179	0
Alaska Airlines	4,049	946
American Airlines	1,759	12,381
Delta Airlines	2,413	8,285
United Airlines	0	10,685

²² The data cleaning process explained in Appendix B leads to a database where not all our markets are present in both directions in our database. For instance, we impose that the two carriers present in the market must cumulate 95% of the market share, which could be satisfied in one direction and not necessarily in another one. Same results are obtained if we restrict the sample to city pairs where both directions are observed.

²³ As our dataset considers only roundtrip passengers, both the price and distance reflect the full price and full distance (outbound and inbound flight).

5 Empirical results

In subsection 5.1, we present the estimation results from equations (2) - (5) using the full set of covariates measuring the market characteristics. Our main results are presented in sub-section 5.2, where we control for unobserved origin or destination factors not included among our explanatory variables by re-estimating our model with fixed effects. These results indicate that omitted variable bias is a valid concern and that fixed effect estimation is preferred. Finally, in subsection 5.3 we present the results for the coefficient of variation.

5.1 Estimation with market covariates

Table 5 contains the results from the estimation of equations (2), (3), (4) and (5). The results indicate that the *Alliance* variable has a negative significant effect on both the mean and standard deviation of the reservation cost. This translates to negative effects on the mean and standard deviation of the transaction prices. We revisit this result in the next section, where for robustness we re-estimate the model with fixed effects. Below, we comment on the coefficients on the market covariates.

Distance has a positive impact on the mean of the reservation costs, which is due to the cost of fuel and other operating expenses. At the same time, higher distance is associated with lower varied reservation costs. This finding could be explained considering the option to substitute air travel with land travel. It is likely that airlines need to provide a larger variety of fares in shorter trips in order to be able to attract tourist demand that is sensitive to surface transportation competition.

The demographic variables population and income are associated with higher reservation cost and transaction price means. Both variables are likely to generate a higher chance of last-minute ticket purchases, which increases the opportunity costs of ticket sales. Bigger cities are also associated with more products in terms of flight characteristics, and therefore price variability.

The origin and destination volume are associated with a lower reservation cost and transaction price means, which is likely due to economies of density and scale. Destination volume is also associated with a lower reservation cost and transaction price variance. The variables related to network centrality, the hub and destination markets at origin and destination, are all associated with a higher reservation cost and transaction price, possibly due to the high opportunity cost of equipment, time slots for landing and take-off, and staff. However, airports with a larger number of connecting passengers show more variability while markets with more connections have less variability in their reservation cost and transaction price.

Table 5
MLE estimation results

	Reservation cost		Transaction price	
	μ_{od}	σ_{od}	μ_{od}	σ_{od}
Alliance	-0.188*** (0.008)	-0.025*** (0.006)	-0.202*** (0,008)	-0,021*** (0,005)
Distance	0.136*** (0.006)	-0.012*** (0.004)	0.130*** (0,005)	-0,010*** (0,003)
Origin population	0.118*** (0.007)	0.007* (0.004)	0.122*** (0,007)	0.006 (0,003)
Dest. Population	0.148*** (0.006)	0.006 (0.004)	0.151*** (0,006)	0.005** (0,004)
Origin income	0.172*** (0.024)	-0.015 (0.017)	0.164*** (0,024)	-0.013 (0,014)
Destination income	0.183*** (0.026)	0.020 (0.020)	0.194*** (0,026)	0.016 (0,017)
Origin volume	-0.176*** (0.011)	-0.007 (0.008)	-0.180** (0,011)	-0.006 (0,006)
Destination volume	-0.247*** (0.010)	-0.021*** (0.007)	-0.259*** (0,010)	-0,017*** (0,006)
Origin markets	0.053*** (0.013)	-0.028*** (0.007)	0.038*** (0,010)	-0.023*** (0,006)
Destination markets	0.062*** (0.006)	-0.034*** (0.004)	0.042*** (0,005)	-0,028*** (0,003)
Origin hub	0.032*** (0.003)	0.006*** (0.002)	0.036*** (0,003)	0.005** (0,002)
Destination hub	0.044*** (0.003)	0.008*** (0.002)	0.049*** (0,003)	0.007*** (0,002)
Codeshare	0.175*** (0.013)	0.022** (0.010)	0.188*** (0.012)	0.018** (0.008)
Dummy 2016	-0.045*** (0.005)	-0.059*** (0.004)	-0.078*** (0.005)	-0.047*** (0.003)
Constant	1.980*** (0.416)	0.776** (0.320)	2.418*** (0,454)	0.641 *** (0,264)
Likelihood	-59,704.74		-59,704.74	
Number of observations	40,504		40,504	

Note: Standard error are given in parentheses. The symbols */**/** indicate statistical significance at the 5/1/0.1 % level, respectively.

Finally, codesharing presents a positive effect both on the reservation cost and transaction prices. The positive effect on transaction prices thanks to codesharing agreements have been already illustrated in the theoretical and

empirical literature (see for instance Alamdari(2005), Adler and Hanani (2016) or Zou and Chen (2017)). There are few studies on the impact of codesharing on operating cost and they find weak evidence (Chua et al. 2005 or Goh and Yong 2006). As detailed on the next section, the impact of codesharing is reduced when fixed effects are included.

5.2 Estimation with fixed effects

In this subsection, we propose to control for unobserved origin and destination factors that may correlate with *Alliance* and could bias its effect by re-estimating our model with origin and destination fixed effects. The estimated effects of the *Alliance* and *Codeshare* variable on the reservation cost and the transaction price are reported in Table 6.

The results indicate that omitted variable bias is a valid concern. *Alliance* does not have a significant impact on the mean of the reservation cost. The effect of *Alliance* on the standard deviation of the reservation cost is instead more negative, -17.5 percent. These results suggest that alliance partners manage to reduce cost fluctuation although this does not come with a decrease in the average costs. Due to data limitations it is beyond our scope to model how exactly this is achieved, but some potential explanations could be harmonizing the demand forecasts, physical resources and operations scheduling. The lower cost variance has a negative and significant effect on the mean and standard deviation of the transaction: -10.2 percent and -14.4 percent. In other words, prices are lower and less varied in alliance markets because of the lower variance of costs.

On the other hand, *Codeshare* presents a positive effect on both reservation cost (+8.61 percent) and transaction prices (+4.7 percent). Still, the cumulated effect of both cooperation variables remains negative and the results for the *Alliance* variable are not affected if codeshared markets are excluded.

These result also holds if other periods are considered although the size of the impact varies across the years. For robustness, we run our model over 2008-2019 excluding years were mergers were taking place (2010, 2014 and 2017) and including interactions of *Alliance* and codeshare with a time trend. *Alliance* does not have a significant impact on prices or reservation costs at the beginning of the sample though it has a negative and significant impact (-0.006*** for prices) when interacted with the time trend. Codesharing presents a positive and significant effect at the beginning of our sample (0.186***) and a negative trend across time (-0.018***). With respect to dispersion, both reservation costs and transaction prices start with a small positive effect in 2008 though the effect becomes negative due to a negative trend. These results must be interpreted with caution as both codesharing and alliances are decreasing in importance across time in the US domestic market.

Table 6
***Alliance* effect on the reservation and transaction price distributions**

	Reservation cost		Transaction price	
	μ_{od}	σ_{od}	m_{od}	s_{od}
Alliance	-0.003 (0.059)	-0.175*** (0.042)	-0.102* (0.050)	-0.144*** (0.035)
Codesharing	0.0861*** (0.020)	-0.070*** (0.015)	0.047** (0.015)	-0.058*** (0.013)

Note: Standard error are given in in parentheses; Origin and Destination fixed effects are controlled for, but estimates have been suppressed in the table. The symbols */**/** indicate statistical significance at the 5/1/0.1 % level, respectively. N is the number of observations.

5.3 Coefficient of variation

As argued in the introduction, the coefficient of variation (CV) is a standard metric for price dispersion in the literature. To be consistent with previous work, we present here the effect of Alliance on the CV of prices. The reservation cost and transaction price are transformed by the natural logarithm in our estimation; then, we construct the CV of transaction prices using properties of moment generating functions. The complete derivation of Equation (6) is presented in Section C of the Appendix. Note that, in the end, the CV of prices is only a function of the standard deviation of the log-reservation cost, σ , specifically:²⁴

$$CV = \left(\frac{\exp(\sigma^2) \Phi(\sqrt{2}\sigma)}{2 \left(\Phi\left(\frac{\sigma}{\sqrt{2}}\right) \right)^2} - 1 \right)^{1/2} \quad (6)$$

Since *Alliance* is an indicator rather than a continuous variable, its marginal effect is obtained as the difference between the CV when *Alliance* is one and zero, that is to say:

$$\Delta CV (Alliance) = CV (Alliance = 1) - CV (Alliance = 0) \quad (7)$$

For testing the significance of the alliance effect, we use the estimated standard deviation of the log-reservation cost evaluated at either *Alliance*=1 and *Alliance*=0 and at the sample mean values for all other covariates.

Table 7 contains the estimated CVs, both for the model with covariates and the model with fixed effects. *Alliance* is associated with a decrease in CV, regardless of whether the model is estimated with or without the fixed effects. A negative impact is also found for codesharing similarly to the work by Ciliberto et al. (2009). The cooperation among airlines affects price dispersion, which should not be omitted when analyzing the relationship between competition and price

²⁴ In the formula, exp(.) indicates the exponential function and $\Phi(\cdot)$ is the cumulative distribution of the standard normal function.

Table 7
Alliance effect on the coefficient of variation of transaction prices

Model	N	$CV(Alliance=1)$	$CV(Alliance=0)$	$\Delta CV(Alliance)$
Covariates	40,504	0.289***	0.312***	-0.023***
Fixed Effects	40,504	0.175***	0.331***	-0.157***

Note: Standard error are given in in parentheses; Origin and Destination fixed effects are controlled for, but estimates have been suppressed in the table. The symbols */**/** indicate statistical significance at the 5/1/0.1 % level, respectively. N is the number of observations.

dispersion. The literature has not found a clear relationship between competition and price dispersion. In our sample, we should not observe price dispersion differences due to competition since all the markets have two competitors with similar market shares nevertheless we can observe the impact of cooperation. In this sense our work is a new step contributing to the work by Liu and Serfes (2006) and Chandra and Lederman (2018) that try to reconcile the conflicting results in the earlier literature.

6 Conclusion

Airline markets have gone through many transformative changes in the last couple of decades. Low-cost carriers expanded their services and made standard the “no frills” type of service, decreasing the importance of service quality and increasing the homogenization of the product. The spread of the Internet as a sales channel has been another challenge for the industry; consumers’ search and comparison costs became negligible using online travel agents and price comparison sites. Furthermore, the various economic crisis made all travelers, and particularly business travelers, very sensitive toward prices. We are motivated by these recent changes in the industry to propose a new estimation method that models ticket sales as an auction process. This approach, which is the main novelty of the paper, is applicable to any online sales process based on price competition.

We apply this model to revisit the analysis of airline alliances, a form of cooperation in airline markets that has caused much controversy. Our novel approach allows us to work with the individual data observations of the DB1B and to simultaneously explore the effect of alliances on price means and price variability, the latter being completely novel to the alliance literature. Our results indicate that alliances are associated with both lower prices and lower price dispersion, and that they achieve this through a decrease in the fluctuation of their reservation costs.

These results contrast with previous results in the alliance literature by Gayle (2008) and Armantier and Richard (2006), which were relevant to the post-alliance formation period of the late 1990s and early 2000s. This difference could

be well explained by the emerging competition from LCC and by the fact that alliance partners responded by improving their efficiency.

Our results shed a new light on the debate of the impact of competition on price dispersion. Indeed, the literature studying this issue presented in Subsection 2.2 has not found a clear conclusion. Our analysis shows that markets with similar levels of competition present lower dispersion levels due to the presence of cooperation, in the form of alliances. Still, more work is required to obtain a clearer picture on the mechanism behind these results. While the large number of recent mergers in the United States have decreased the importance of alliances, the proposed methodology could be applied to analyze the impact of cooperation in other sectors or other types of cooperation in the airline sector. In the case of airlines, codesharing has been a frequent issue of concern for competition authorities. Diverse types of alliance or cooperation agreements are present in a wide range of industries, such as Financial services, Pharmaceuticals, Automobile or Software.²⁵

Beyond the question of the impact of alliances in airline markets, we believe that our approach based on the econometrics of auction models can be easily applied to facilitate the analysis of any issue of interest in markets where competition is based on prices and when the analyst is interested in both price levels and dispersion.

²⁵ Kang and Sakai (2000) present a review of international strategic alliances between 1990 and 2000 by sector and by country or region.

Appendix A

Order statistics and the maximum likelihood derivation

To estimate a model using the maximum likelihood approach, we need to specify the distribution by which our data is generated. In the framework that we propose, the price is an order statistic of the reservation cost; it is the highest reservation cost from two randomly drawn reservation costs. Order statistics and their distribution are important elements of auction models, where the winner is chosen based on a ranking of the bids, and the bids are usually a monotonic function of the underlying random costs or valuations. For a detailed exposition on the derivation of order statistics, see Paarsch and Hong (2006), particularly Appendices 1 and 2 in their book. Here, we will explain intuitively how the distributions are derived in our model.

Both carriers l and m offer the same service and draw their reservation costs, c_l and c_m , from the same distribution $F(c)$. A price observation takes the value p in two distinct cases: in the case where player l makes the sale, and in the case where player m makes the sale.

Let us take the last case, where player m makes the sale, which is an outcome of two independent events happening simultaneously. Given the strategies of the players to lower their offers/bids until it is no longer profitable, we know that the “loser”, carrier l , which has the higher reservation cost, will have reservation cost $c_l = p$ exactly. At the same time, the “winner”, carrier m , or the carrier with the lower reservation cost, must have $c_m < c_l = p$. These are two independent events, and therefore, the probability of observing price equal to p is the product of the probabilities of the two events:

$$P(p|m \text{ wins}) = P(c_m < c_l)P(c_l = p) \quad (\text{A1})$$

The probability of the first event is the sum of all probabilities for which $c_m < c_l = p$. With a continuous distribution, this is the cumulative density $F(p)$. The probability of the second event is exactly the density of the distribution at p : $f(p)$. Hence, we have:

$$P(p|m \text{ wins}) = F(p)f(p) \quad (\text{A2})$$

Similarly, due to the symmetry of the players, the case of observing p when player l wins has the following probability:

$$P(p|l \text{ wins}) = F(p)f(p) \quad (\text{A3})$$

Then, the unconditional event of observing the price p is the sum of the cases where l wins and m wins:

$$P(p) = 2F(p)f(p) \quad (\text{A4})$$

Appendix B

Data cleaning

We start with the full data available for the 2008 third quarter including all origin and destinations within United States. We consider exclusively round-trip passengers. Carriers with less than 15 passengers are deleted, since these probably reflect coding errors. We also remove tickets with prices lower than 50 USD and higher than 3000 USD. Most of these happen to be tickets at zero USD, representing frequent flyer purchases. We also focus on markets with more than nine passengers per quarter, as that is equivalent to one passenger per day given that the sample represents 10 percent of the quarterly ticket sales.

Another modification of the data set comprises grouping airports in the same metropolitan area.²⁶ The six groups of airports are: Dallas-Fort Worth International and Love Field in Dallas, TX; Baltimore/ Washington International, Dulles, and National in Washington, DC; Midway and O'Hare in Chicago, IL; Kennedy, LaGuardia, and Newark in New York, NY; Los Angeles, Burbank, and Long Beach in Los Angeles, CA; San Francisco, Oakland, and San Jose in San Francisco, CA. For example, Chicago Midway and Chicago O'Hare International will represent the same market. Again, this is a standard treatment in the literature (Berry and Jia (2010)). Note this modification affects only approximately 15 percent of our observations, as we are working with duopoly markets that are usually markets less central to the network. Following Evan and Kessides (1993, 1994), we count carriers as operating in each market if their sales represent at least 1 percent of observations in the data, equivalently 1 percent of total sales. Regional "feeder" or "commuter" carriers are recoded as their major carrier partner. The full table can be provided upon request.

We study exclusively direct duopoly markets, i.e., markets with only two operating airlines. In any market, we might observe unusual choices by travelers using long paths (two or three connecting airports) due to capacity constraints in the supply or to random events such as bad weather conditions, technical issues on a plane or strikes. Therefore, we include in our database markets where a third airline exist with a market share smaller than 5% or markets where less than 5% of the passengers use alternative routes (for instance, flying with 3 coupons), although these passengers are excluded from our analysis. Once our sample is restricted to duopoly markets, we exclude all markets where an LCC is present.

²⁶ Note that not all the metropolitan areas that are usually considered in the literature are included in our database such as Miami or Houston.

Appendix C

Coefficient of Variation Derivation

The coefficient of variation (*CV*) is defined as the variable's standard deviation divided by the variable's mean. In our case, we are interested on the transaction price p with mean, m , and standard deviation s . The *CV* can be expressed as:

$$CV = \frac{s}{m} = \left(\frac{E[p^2] - E[p]^2}{E[p]^2} \right)^{1/2} = \left(\frac{E[p^2]}{E[p]^2} - 1 \right)^{1/2} \quad (C1)$$

Our model analyzes the logarithm of the reservation costs in duopoly markets. We call $\log(c_l)$ and $\log(c_m)$ the logarithms of the reservation costs of our two competitors, airlines l and m , respectively. The logarithm of the transaction price is the highest of the two reservation costs, $\log(p) = \max(\log(c_l), \log(c_m))$.

With the moment generating functions obtained from Nadarajah and Kotz (2008) for the max/min of two random variables, we can compute:

$$E[p] = E[e^{\log(p)}] = 2e \left(\mu + \frac{\sigma^2}{2} \right) \Phi \left(\frac{\sigma}{\sqrt{2}} \right) \quad (C2)$$

$$E[p^2] = E[e^{\log(p)} e^{\log(p)}] = E[e^{2\log(p)}] = 2e(2\mu + 2\sigma^2) \Phi \left(\frac{2\sigma}{\sqrt{2}} \right) \quad (C3)$$

which implies that:

$$CV = \left(\frac{E[p^2]}{E[p]^2} - 1 \right)^{1/2} = \left(\frac{e(\sigma^2) \Phi \left(\frac{2\sigma}{\sqrt{2}} \right)}{2 \left(\Phi \left(\frac{\sigma}{\sqrt{2}} \right) \right)^2} - 1 \right)^{1/2} \quad (C4)$$

References

- Adelman, Daniel. 2007. 'Dynamic Bid Prices in Revenue Management'. *Operations Research* 55 (4): 647–61. <https://doi.org/10.1287/opre.1060.0368>.
- Adler, Nicole, Eran Hanany, 2016, Regulating inter-firm agreements: The case of airline codesharing in parallel networks, *Transportation Research Part B: Methodological*, Volume 84, Pages 31-54, ISSN 0191-2615, <https://doi.org/10.1016/j.trb.2015.12.002>.
- Alderighi, Marco. 2010. 'Fare Dispersions in Airline Markets: A Quantitative Assessment of Theoretical Explanations'. *Journal of Air Transport Management*, Selected papers from the 48th Congress of the European Regional Science Association, 16 (3): 144–50. <https://doi.org/10.1016/j.jairtraman.2009.07.004>.
- Alamdari, F., Iatrou, K., 2005. The empirical analysis of the impact of alliances on airline operations. *J. Air Transp. Manag.* 11 (3), 127e134.
- Armantier, Olivier, and Oliver Richard. 2006. 'Evidence on Pricing from the Continental Airlines and Northwest Airlines Code-Share Agreement'. *Advances in Airline Economics* 1: 91–108.
- . 2008. 'Domestic Airline Alliances and Consumer Welfare'. *The RAND Journal of Economics* 39 (3): 875–904. <https://doi.org/10.1111/j.1756-2171.2008.00042.x>.
- Armstrong, M. (2006). Recent Developments in the Economics of Price Discrimination. In R. Blundell, W. Newey, & T. Persson (Eds.), *Advances in Economics and Econometrics: Theory and Applications*, Ninth World Congress (Econometric Society Monographs, pp. 97-141). Cambridge: Cambridge University Press. doi:10.1017/CBO9781139052276.006
- Athey, Susan, Bagwell, Kyle and Sanchirico, Chris, (2004), Collusion and Price Rigidity, *Review of Economic Studies*, 71, issue 2, p. 317-349 <https://doi.org/10.1111/0034-6527.00286>
- Bachis, Enrico, and Claudio A. Piga. 2011. 'Low-Cost Airlines and Online Price Dispersion'. *International Journal of Industrial Organization* 29 (6): 655–67. <https://doi.org/10.1016/j.ijindorg.2011.02.006>.
- Bamberger, Gustavo E., Dennis W. Carlton, and Lynette R. Neumann. 2004. 'An Empirical Investigation of the Competitive Effects of Domestic Airline Alliances*'. *The Journal of Law and Economics* 47 (1): 195–222. <https://doi.org/10.1086/386274>.
- Berry, Steven. 1992. 'Estimation of a Model of Entry in the Airline Industry'. *Econometrica* 60 (4): 889–917.
- Berry, Steven, Michael Carnall, and Pablo T. Spiller. 1996. 'Airline Hubs: Costs, Markups and the Implications of Customer Heterogeneity'. *National Bureau of Economic Research*. <http://www.nber.org/papers/w5561>. DOI 10.3386/w5561

- Berry, Steven, and Panle Jia. 2010. 'Tracing the Woes: An Empirical Analysis of the Airline Industry'. *American Economic Journal: Microeconomics* 2 (3): 1–43. <https://doi.org/10.1257/mic.2.3.1>.
- Blundell, Richard, and Thomas M. Stoker. 2005. 'Heterogeneity and Aggregation'. *Journal of Economic Literature* 43 (2): 347–91. <https://doi.org/10.1257/0022051054661486>.
- Borenstein, Severin, and Nancy L. Rose. 1991. 'Competition and Price Dispersion in the US Airline Industry'. National Bureau of Economic Research. <http://www.nber.org/papers/w3785>.
- . 1994. 'Competition and Price Dispersion in the U.S. Airline Industry'. *Journal of Political Economy* 102 (4): 653–83. <https://doi.org/10.1086/261950>.
- Brueckner, Jan K. 2001. 'The Economics of International Codesharing: An Analysis of Airline Alliances'. *International Journal of Industrial Organization* 19 (10): 1475–98. [https://doi.org/10.1016/S0167-7187\(00\)00068-0](https://doi.org/10.1016/S0167-7187(00)00068-0).
- . 2003. 'International Airfares in the Age of Alliances: The Effects of Codesharing and Antitrust Immunity'. *Review of Economics and Statistics* 85 (1): 105–18. <https://doi.org/10.1162/003465303762687749>.
- Brueckner, Jan K., Darin Lee, and Ethan S. Singer, 2011. Alliances, code-sharing, antitrust immunity and international airfares: do previous patterns persist? *Competition Law and Economics*, Vol. 7, pp. 573-602.
- Brueckner, Jan K., Darin Lee, and Ethan S. Singer. 2013. 'Airline Competition and Domestic US Airfares: A Comprehensive Reappraisal'. *Economics of Transportation* 2 (1): 1–17. <https://doi.org/10.1016/j.ecotra.2012.06.001>.
- Brueckner, Jan K., and W. Tom Whalen. 2000. 'The Price Effects of International Airline Alliances'. *The Journal of Law & Economics* 43 (2): 503–46. <https://doi.org/10.1086/467464>.
- Brueckner, Jan K., and Ethan Singer. 2019. "Pricing by International Airline Alliances: A Retrospective Study." *Economics of Transportation* 20 (December): 100139. <https://doi.org/10.1016/j.ecotra.2019.100139>.
- Brueckner, Jan, and Pablo Spiller. 1991. 'Competition and Mergers in Airline Networks'. *International Journal of Industrial Organization* 9 (3): 323–42.
- Calzaretta, Robert J. , Yair Eilat and Mark A Israel, 2017. "Competitive Effects Of International Airline Cooperation," *Journal of Competition Law and Economics*, Oxford University Press, vol. 13(3), pages 501-548.
- Chandra, Ambarish, and Mara Lederman. 2018. 'Revisiting the Relationship between Competition and Price Discrimination'. *American Economic Journal: Microeconomics* 10 (2): 190–224. <https://doi.org/10.1257/mic.20160252>.
- Chua, Chew Lian, Hsein Kew, and Jongsay Yong. 2005. "Airline Code-Share Alliances and Costs: Imposing Concavity on Translog Cost Function Estimation." *Review of Industrial Organization* 26 (4): 461–87. <https://doi.org/10.1007/s11151-005-0223-6>.

- Ciliberto, Federico, and Jonathan W. Williams. 2010. 'Limited Access to Airport Facilities and Market Power in the Airline Industry'. *Journal of Law and Economics* 53 (3): 467–495.
- Ciliberto, Federico, Eddie Watkins, and Jonathan W. Williams. 2019. "Collusive Pricing Patterns in the US Airline Industry." *International Journal of Industrial Organization* 62 (January): 136–57. <https://doi.org/10.1016/j.ijindorg.2018.07.008>.
- Dai, Mian, Qihong Liu, and Konstantinos Serfes. 2013. 'Is the Effect of Competition on Price Dispersion Nonmonotonic? Evidence from the U.S. Airline Industry'. *The Review of Economics and Statistics* 96 (1): 161–70. https://doi.org/10.1162/REST_a_00362.
- Dana, James D. 1999. 'Using Yield Management to Shift Demand When the Peak Time Is Unknown'. *The RAND Journal of Economics* 30 (3): 456. <https://doi.org/10.2307/2556058>.
- David, Herbert A., and H. N. Nagaraja. 2003. *Order Statistics*. 3 edition. Hoboken, N.J: Wiley-Interscience.
- Deneckere, Raymond, Howard P. Marvel, and James Peck. 1996. 'Demand Uncertainty, Inventories, and Resale Price Maintenance'. *The Quarterly Journal of Economics* 111 (3): 885–913. <https://doi.org/10.2307/2946675>.
- Escobari, Diego. 2012. 'Dynamic Pricing, Advance Sales and Aggregate Demand Learning in Airlines'. *The Journal of Industrial Economics* 60 (4): 697–724.
- Escobari, Diego, and Manuel A. Hernandez. 2019. "Separating Between Unobserved Consumer Types: Evidence from Airlines." *Economic Inquiry* 57 (2): 1215–30. <https://doi.org/10.1111/ecin.12736>.
- Evans, William N., and Ioannis N. Kessides. 1993. 'Localized Market Power in the U.S. Airline Industry'. *The Review of Economics and Statistics* 75 (1): 66–75. <https://doi.org/10.2307/2109627>.
- . 1994. 'Living by the "Golden Rule": Multimarket Contact in the U. S. Airline Industry'. *The Quarterly Journal of Economics* 109 (2): 341–66. <https://doi.org/10.2307/2118466>.
- Gaggero, Alberto A., and Claudio A. Piga. 2011. 'Airline Market Power and Intertemporal Price Dispersion'. *The Journal of Industrial Economics* 59 (4): 552–577.
- Gale, Ian L., and Thomas J. Holmes. 1993. 'Advance-Purchase Discounts and Monopoly Allocation of Capacity'. *The American Economic Review*, 135–146.
- Gayle, Philip G. 2007. 'Is Virtual Codesharing a Market Segmenting Mechanism Employed by Airlines?' *Economics Letters* 95 (1): 17–24. <https://doi.org/10.1016/j.econlet.2006.09.007>.
- Gayle, Philip G. 2008. 'An Empirical Analysis of the Competitive Effects of the Delta/Continental/Northwest Code-Share Alliance'. *The Journal of Law and Economics* 51 (4): 743–66. <https://doi.org/10.1086/595865>.
- Gentry, Matthew L., Timothy P. Hubbard, Denis Nekipelov, and Harry J. Paarsch. 2018. 'Structural Econometrics of Auctions: A Review'. *Foundations and*

- Trends[®] in Econometrics 9 (2–4): 79–302.
<https://doi.org/10.1561/0800000031>.
- Geradin, Damien, and Nicolas Petit. 2005. 'Price Discrimination under EC Competition Law: The Need for a Case-by-Case Approach'. College of Europe DP 7 (05).
<http://www.coleurop.eu/content/gclc/documents/GCLC%20WP%2007-05.pdf>.
- Gerardi, Kristopher S., and Adam Hale Shapiro. 2009. 'Does Competition Reduce Price Dispersion? New Evidence from the Airline Industry'. *Journal of Political Economy* 117 (1): 1–37. <https://doi.org/10.1086/597328>.
- Gillen, David, and Benny Mantin. 2009. 'Price Volatility in the Airline Markets'. *Transportation Research Part E: Logistics and Transportation Review* 45 (5): 693–709. <https://doi.org/10.1016/j.tre.2009.04.014>.
- Goh Mark, Jongsay Yong, 2006, Impacts of code-share alliances on airline cost structure: A truncated third-order translog estimation, *International Journal of Industrial Organization*, Volume 24, Issue 4, Pages 835-866, ISSN 0167-7187, <https://doi.org/10.1016/j.ijindorg.2005.09.012>.
- Hernandez, Manuel A., and Steven N. Wiggins. 2014. 'Nonlinear Pricing Strategies and Competitive Conditions in the Airline Industry'. *Economic Inquiry* 52 (2): 539–61. <https://doi.org/10.1111/ecin.12045>.
- Ito, Harumi, and Darin Lee. 2007. 'Domestic Code Sharing, Alliances, and Airfares in the U.S. Airline Industry'. *The Journal of Law and Economics* 50 (2): 355–80. <https://doi.org/10.1086/511318>.
- Kang, Nam-Hoon, and Kentaro Sakai. 2000. 'International Strategic Alliances: Their Role in Industrial Globalisation'. OECD Science, Technology and Industry Working Papers 2000/05. <https://doi.org/10.1787/613723204010>.
- Klemperer, Paul. 2004. *Auctions: Theory and Practice*. Princeton, NJ: Princeton University Press.
- Lazarev, John. 2013. 'The Welfare Effects of Intertemporal Price Discrimination: An Empirical Analysis of Airline Pricing in US Monopoly Markets'. working paper. http://www.johnlazarev.com/Lazarev_JMP.pdf.
- Luttmann, Alexander. 2018. 'Evidence of Directional Price Discrimination in the U.S. Airline Industry'. *International Journal of Industrial Organization*, March. <https://doi.org/10.1016/j.ijindorg.2018.03.013>.
- Mantin, Benny, and Bonwoo Koo. 2009. 'Dynamic Price Dispersion in Airline Markets'. *Transportation Research Part E: Logistics and Transportation Review* 45 (6): 1020–29. <https://doi.org/10.1016/j.tre.2009.04.013>.
- Maskin, Eric and Riley, John, (1984), Optimal Auctions with Risk Averse Buyers, *Econometrica*, 52, issue 6, p. 1473-1518
<https://doi.org/10.2307/1913516>
- Miller, Amalia R. 2010. 'Did the Airline Tariff Publishing Case Reduce Collusion?' *The Journal of Law & Economics* 53 (3): 569–86. <https://doi.org/10.1086/605294>.

- Nadarajah, S., and S. Kotz. 2008. 'Exact Distribution of the Max/Min of Two Gaussian Random Variables'. *IEEE Transactions on Very Large Scale Integration (VLSI) Systems* 16 (2): 210–12. <https://doi.org/10.1109/TVLSI.2007.912191>.
- Paarsch, Harry J. 1997. 'Deriving an Estimate of the Optimal Reserve Price: An Application to British Columbian Timber Sales'. *Journal of Econometrics* 78 (2): 333–57. [https://doi.org/10.1016/S0304-4076\(97\)00017-1](https://doi.org/10.1016/S0304-4076(97)00017-1).
- Paarsch, Harry J., and Han Hong. 2006. *An Introduction to the Structural Econometrics of Auction Data*. Cambridge, MA: MIT Press.
- Park, Jong-Hun. 1997. 'The Effects of Airline Alliances on Markets and Economic Welfare'. *Transportation Research Part E: Logistics and Transportation Review* 33 (3): 181–95. [https://doi.org/10.1016/S1366-5545\(97\)00013-6](https://doi.org/10.1016/S1366-5545(97)00013-6).
- Sengupta, Anirban, and Steven N. Wiggins. 2012. 'Comparing Price Dispersion on and off the Internet Using Airline Transaction Data'. *Review of Network Economics* 11 (1). <https://doi.org/10.1515/1446-9022.1244>.
- . 2014. 'Airline Pricing, Price Dispersion, and Ticket Characteristics on and off the Internet'. *American Economic Journal: Economic Policy* 6 (1): 272–307.
- Siegert, Caspar, and Robert Ulbricht. 2020. "Dynamic Oligopoly Pricing: Evidence from the Airline Industry." *International Journal of Industrial Organization* 71 (July): 102639. <https://doi.org/10.1016/j.ijindorg.2020.102639>.
- Spulber, Daniel F. 1990. "Auctions and Contract Enforcement." *Journal of Law, Economics, & Organization* 6 (2): 325–44.
- Spulber, Daniel, (1995), Bertrand Competition When Rivals' Costs Are Unknown, *Journal of Industrial Economics*, 43, issue 1, p. 1-11
- Stoker, Thomas M. 2016. "Aggregation (Econometrics)." In *The New Palgrave Dictionary of Economics*, 1–11. London: Palgrave Macmillan UK. https://doi.org/10.1057/978-1-349-95121-5_2620-1.
- Talluri, Kalyan, and Garrett Van Ryzin. 1998. 'An Analysis of Bid-Price Controls for Network Revenue Management'. *Manage. Sci.* 44 (11): 1577–1593. <https://doi.org/10.1287/mnsc.44.11.1577>.
- Kevin R. Williams, 2020. "Dynamic Airline Pricing and Seat Availability," Cowles Foundation Discussion Papers 2103, Cowles Foundation for Research in Economics, Yale University..
- Zhang, Yahua, Breno Sampaio, Xiaowen Fu, and Zhibin Huang. 2018. "Pricing Dynamics between Airline Groups with Dual-Brand Services." *Transportation Research Part A: Policy and Practice* 112 (June): 46–59. <https://doi.org/10.1016/j.tra.2018.01.006>.
- Zou, Li, and Xueqian Chen. 2017. "The Effect of Code-Sharing Alliances on Airline Profitability." *Journal of Air Transport Management* 58 (January): 50–57. <https://doi.org/10.1016/j.jairtraman.2016.09.006>.

