The effect of code-share agreements on the temporal profile of airline fares*

Marco Alderighi†
University of Valle d'Aosta
Bocconi University

Alberto A. Gaggero‡
University of Pavia

Claudio A. Piga♯
Keele University
RCEA, Rimini, Italy

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Abstract

This paper aims at investigating how the pricing strategy of European airline carriers is affected by code-share agreements on international routes. Our data cover several routes linking the main UK airports to many European destinations and includes posted fares collected at different days before departure. By analyzing the temporal profile of airline fares, we identify three main results. First, code-share increases fares especially for early bookers. Second, the higher prices in code-shared flights are offered by marketing carriers. Finally, in single operator code-shared flights (unilateral code-share), the pricing profile is flatter than under parallel code-share.

Keywords: Code-share, dynamic pricing, operating carrier, marketing carrier, revenue management.

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† Università della Valle d'Aosta, Grand Chemin 73/75, 11020 Saint Christophe (AO), Italy. Tel +39 0165 066747. Fax +39 0165 066749. E-mail: m.alderighi@univda.it.
‡ *Corresponding author*. Department of Economics and Management, University of Pavia, Via S. Felice 5, 27100 Pavia, Italy. Tel +39 0382 986226. Fax +39 0382 986228. E-mail: alberto.gaggero@unipv.it.
♯ Keele Management School, Keele University, Keele, Staffordshire, ST5 5BG, United Kingdom. E-mail: c.piga@keele.ac.uk.

1. Introduction

Code-share (henceforth CS) agreements are contracts between two carriers in which one airline, acting as Marketing Carrier (MC), is allowed to sell seats on a flight operated by the other airline, acting as Operating Carrier (OC).[1] In recent years, such agreements have become increasingly popular (Brueckner and Whalen, 2000; Brueckner, 2003).

The large expansion of code-sharing agreements is indicative of their mutual advantage for the involved airlines. In addition to providing benefits in the form of cost saving, risk reduction and network expansion, CS is relevant because it can pave the way to more integrated forms of cooperation such as an alliance or even a merger (Brueckner and Pels, 2005; Gaggero and Bartolini, 2012). Indeed, to harmonize the activities of the airlines involved, CS comprises the definition of a set of commercial and operational agreements concerning, amongst others, pricing, seat inventory and frequent flyer programs (Chen and Ross 2000; Iatrou and Alamdari, 2005).

Because these agreements may reduce the functioning of the market, they are often under the scrutiny of antitrust authorities (Gayle, 2007; Gayle and Brown, 2014). In Europe, Article 101 of the European Treaty prohibits agreements between two or more independent market operators, which restrict competition. This Article is similar in spirit to the first Section of the Sherman Act (1890) in the US legislation.[2] Both sets of norms, albeit with minor differences, accept that code-sharing agreements can be allowed in principle, only if they are in favor of consumers, and, more specifically, when the antitrust commission expects that the agreement would not increase fares and/or would not lead to a reduction in the competition.[3] For this reason, code-sharing agreements are evaluated case by case and decisions are taken in terms of the impact on prices or on consumer surplus. Such decisions may also involve the imposition of such remedies as slot conditions or frequency freeze.

The theoretical literature has also highlighted the existence of different factors playing in favor and against code-sharing agreements. Using a simulation analysis Brueckner and Whalen (2000) show that allied partners charge lower fares, thereby increasing consumers' surplus and welfare. Brueckner (2001) uses a hub-and-spoke model to show that both consumer and total surplus rise after the formation of an alliance. He argues that the benefits of alliances arise because of lower fares set by the partner airlines in the interline markets. Park (1997) finds that, depending on the size of the market and on the economies of traffic density, complementary alliances increase economic welfare, while parallel alliances reduce it. Bilotkach (2005) shows

[1]For instance, the flight BA781 operated by British Airways from London Heathrow to Stockholm Arlanda is also sold under the code AY5936 by Finnair. In this example British Airways is the operating carrier, whilst Finnair is the marketing carrier.

[2]In some cases companies are allowed to sign cooperative agreements, which allow firms to collaborate without the risk of the intervention of the antitrust authority. In Europe, airline industry exemptions are called individual or block exemptions; in the US, antitrust immunities. In both legislations, the use of exemptions has been largely decreasing over time.

[3]See for instance Lufthansa/SAS in 1995, British Midland/Lufthansa/SAS in 2001, Lufthansa/SAS/United in 2002, KLM/Northwest in 2002, Lufthansa/Austrian in 2002, British Airways/SN Brussels in 2003, British Airways/Iberia/GB Airways in 2003, Air France/Alitalia in 2004, SAS/Austrian 2005.

that alliances without antitrust immunity are welfare enhancing. While he argues that the impact of alliances with antitrust immunity on welfare is ambiguous, he concludes that alliances increase total welfare, the larger the spoke-to-spoke traffic relative to traffic between hubs of alliance partners. Czerny (2009) demonstrates that interline passengers are better off under code-share agreement, whilst non-interline passengers are worse-off.

Various empirical papers investigate the effects of CS practices, mostly using US data. Park and Zhang (2000) find that consumers were generally made better off by the alliances in the North American aviation markets. Armantier and Richard (2006) examine the influence of the alliance between Continental Airlines and Northwest Airlines on prices; they find evidence of lower prices across markets in which the two airlines establish a code-share agreement. A companion study to Armantier and Richard (2006) is conducted by Gayle (2008), who focuses on the Delta/Continental/Northwest code-share alliance. He also does not find empirical evidence in favor of collusive pricing on the overlapping routes served by these carriers. The conclusion that fares on code-share itineraries are cheaper than in otherwise similar non-code-share itineraries is also reached by Ito and Lee (2007). To sum up, most of the existing literature investigates the role of code-sharing agreements on US routes providing a generally positive influence on consumer welfare.

This paper contributes to the literature on the role of CS in the airline industry in a number of ways; first, it focusses on European airline markets and second, it explores whether different types of code-sharing agreements are likely to affect not only the level of fares, but also their temporal profile. Our data cover several routes linking the main UK airports to some of the largest European destinations and include posted fares collected at different days before departure. As discussed in Gaggero and Piga (2011) and Dobson and Piga (2013), looking at how fares evolve over time is relevant for consumer welfare because different passengers categories (e.g. leisure or business) may be characterized by a different purchasing behavior. In general leisure travelers book in advance and business traveler book late. Thus, also in the occurrence of no impact on the overall welfare, there can still be a significant re-distributive effects. This issue has not been investigated in previous works, because the data structure does not allow to consider it.[4] Moreover, we distinguish the impact of CS on the fare temporal profile studying whether the airline under investigation code-shares its flight or not, is the operating carrier or the marketing carrier, there is a single or multiple operator code-shared flight (e.g. unilateral or parallel operations).

The econometric analysis is conducted by taking into account the antecedent decision by airlines to operate a flight in code-share. First, we estimate the likelihood that two carriers enter

[4]Many studies on airline pricing use DB1B database provided by the US Bureau of Transportation Statistics. This database contains a random draw of 10 per cent of all US airline tickets, collected on a quarterly basis since 1993. In the current study we use posted fares retrieved on a daily basis from the Opodo website. Although the authors acknowledge the advantage of using transaction fares to study the airline pricing behavior in those circumstances in which price-capacity relation is paramount, the DB1B database can be less useful in other cases because it does not comprise the information on the date when the ticket can be booked. Thus, with the DB1B database it is not possible to track the fare changes over time as, instead, we do in our work with posted fares.

a code-share agreement, using a probit procedure. In the second step, we use this information to "correct" the estimates in the carriers' pricing equation (Heckman, 1979; Maddala, 1983; Campa and Kedia, 2002). By analyzing the temporal profile of airline fares, we identify three main results. First, code-share increases fares especially for early bookers. Second, the fare shift in code-shared flights is due to higher prices offered by marketing carriers. Finally, when flights are in unilateral code-share, the pricing profile is flatter than under parallel code-share.

The remainder of paper is structured as follows. The next section surveys the different types of code-share agreements, as well as the reasons generally considered to be effective in inducing an airline to do code-share. Section 3 presents the data. Section 4 discusses the empirical model and estimation. Section 5 concludes.

2. Code-share practices

Code-sharing agreements may differ depending on a number of various dimensions (Heimer and Shy, 2006; Whalen, 2007, Ito and Lee, 2007). For instance, based on the geography of the route, CS may be conducted under "parallel operations" when both airlines operate on the route with their own aircraft and are alternatively the operating or marketing carriers (e.g., Alitalia and Air France on the route Paris-Rome), "unilateral operation" when only one airline is the operating carrier on the route (e.g. Air France runs the route Paris-Genoa and Alitalia is the marketing carrier) and "behind and beyond route", which typically involves routes with more than one leg, operated by different carriers (e.g. Paris-Palermo with one stop-over in Rome, the first leg Paris-Rome is operated by Air France and code-shared by Alitalia, while Rome-Palermo is operated by Alitalia and code-shared by Air France). Because under behind and beyond route airlines complement each other, this category is also identified with the term "complementary" CS.

Code-share agreements may also vary according to the seat inventory clause. If the airlines decide to operate under "free-flow" or "free-sale" agreement, the information on the current seat availability is shared between the airlines and both the OC and the MC are able to sell as many seats as they wish upon availability (Vinod, 2005; Abdelghany et al, 2009). Alternatively, under the "block-space" agreement there is no real time communication between the OC and the MC because the allocation of capacity between the parties is determined in advance, that is, the MC is assigned a pre-determined number of seats to sell (Ito and Lee, 2005). Finally, there can be minor differences in the way the airlines split the revenues and costs (European Commission, 2007; Hu et al, 2013). For instance, under behind and beyond route (i.e., when the journey involves more than one carrier) the default approach is to split the fare according to the weighted mileage. Alternatively, carriers can agree to specify a fixed revenue amount for each leg of the journey. More generally, airlines can make special prorate agreements which can be tailored to the case (Brueckner, 2003a, 2003b). A common form of special prorate agreement is the so-called *net* special prorate agreement, which sets the amount to be paid to the airline carrying the passenger based solely on the booking class of the passenger.

There are various reasons why airlines decide to make code-sharing agreements. A primary motivation is that the marketing carrier can expand its flight offer both in terms of destinations and schedule without incurring the costs and risks of additional investment in capacity; at the same time, the operating carrier is likely to enjoy higher load factors and therefore a higher per-seat yield (Dresner and Windle, 1996; Brueckner, 2001).

Furthermore, CS often involves carriers with usually a strong market position in their own distinct countries of origin; thus, CS may be beneficial to both carriers since they do not need to create an own sales network in the other carrier's country. Such partner's network is expected to generate additional traffic, which will allow the exploitation of economies of scope and density (Brueckner and Spiller, 1994; Caves et al., 1984; Flores-Fillol and Moner-Colonques, 2007).

Code-sharing agreements may create a close link between member companies, which is conducive to tighter forms of cooperation, such as a global alliance or a merger (Brueckner and Pels, 2005; Gaggero and Bartolini, 2012). Indeed, airlines that have formed a global alliance or merged have first started their collaboration by code-sharing their flights (e.g., Air France with Alitalia or British Airways with Iberia).

Previous arguments are positively evaluated by antitrust authorities; however, such other reasons as the creation of a joint dominant position, which are against the interest of consumers because they are meant to weaken competition, may lie behind the airlines' decision towards doing code-share (Bilotkach and Hüschelrath, 2011). Consider the following example: airline A, B and C serve an arbitrary route; A flies in the morning, B in the afternoon and C in the evening. A and C decide to sign a code-share agreement; this gives more time options to passengers choosing A-C rather than B and therefore the product A-C is more likely to be picked, all else being equal.[5] Moreover, if A and C decide to share the same frequent-flyer program, the combination of the two carriers becomes even more attractive, especially for business passengers, and, hence, A-C are more likely to increase their joint market share. In the long run B may decide to exit the route if this market becomes unprofitable. Furthermore, CS may constitute a barrier to entry, as a potential entrant D may be threatened by the coordinated behavior of A and C (Chen and Ross, 2000; Goetz and Shapiro, 2012). A and C will enjoy a joint monopoly position, which may induce higher fares and/or lower flight frequency (Richard, 2003) and which, therefore, may require the intervention of antitrust authorities.

The question whether CS reduces or increases fares is investigated empirically mostly using US data. Armantier and Richard (2006) check whether fares increase or decrease, following the code-sharing agreement between Continental Airlines and Northwest Airlines in 1999.

[5]The point here is that passengers usually buy return tickets. Assume that preferential departure and return schedules are randomly drawn, and there are three time windows (morning, afternoon, evening), then the likelihood that a passenger simultaneously finds a return flight satisfying her/his preferred schedule is 4/9 when two carriers are involved in a code-sharing agreement and only 1/9 without CS. The disproportionate demand for carriers having higher market shares and frequencies is informally referred as 'S-curve'.

They use quarterly data on prices obtained from the US Department of Transportation (DOT) for the period 1998-2001, so that their sample comprises both the ex-ante and ex-post agreement period. They find evidence of lower prices across markets in which Continental Airlines and Northwest Airlines code-share, concluding that code-sharing agreements do not necessarily lead airlines to collude.

Gayle (2008), who also focuses on the US market using DOT data, studies the effect on fares due to the Delta/Continental/Northwest CS alliance. Similarly, to the finding by Armantier and Richard (2006), he does not observe any price increase in the overlapping routes served by these airlines. Park and Zhang (2000) analyze four alliances in North Atlantic aviation markets (British Airways / USAir, Delta / Sabena / Swissair, KLM / Northwest, and Lufthansa / United Airlines) and also provide evidence of fare reductions on the routes served by the allying carriers.

Ito and Lee (2007) consider a sample of US domestic flights which are operated by a single carrier but that also includes information on tickets sold by marketing carriers. In their work they identify the importance of unilateral code-share, which they refer to as "virtual code-share". They find that fares on routes characterized by virtual CS are: *i)* above the fares under parallel CS; *ii)* below the fares of an operating carrier without CS. Their findings suggest that virtual CS tickets are perceived as imperfect substitutes relative to the non-CS tickets. This is because passengers tend to consider the latter as the carrier's brand-name premium product, whilst the former as a less desirable generic product. Therefore, they conclude that virtual CS can be a form of product differentiation to attract high price sensitive consumers. A complementary research question addresses whether CS is associated with traffic increase. The empirical literature on this issue practically unanimously finds evidence of higher passenger volumes subsequent to a code-sharing agreement (Armantier and Richard, 2006; Bamberger et al., 2004; Gayle, 2008; Park and Zhang, 2000).

3. Data

The analysis relies on two main datasets; the first one contains primary data on posted fares, while the second one provides market structure measures derived from secondary data obtained from the UK Civil Aviation Authority (CAA).

Fares are retrieved using a web spider specifically designed to capture the prices posted by an on-line travel agent, Opodo.[6] The fare variable (*Fare*) is the final lowest price in British pounds (taxes and fees included) available at the moment of the query for a round-trip non-changeable and non-refundable ticket of a flight leaving at a given scheduled date and return-

[6]See www.opodo.co.uk, which is owned and managed by Aer Lingus, Air France, Alitalia, Austrian Airlines, British Airways, Finnair, Iberia, KLM, Lufthansa, and the global distribution system Amadeus. Thus, fares listed on Opodo are likely to represent the official prices of each airline. Opodo, however, may not report promotional offers that an airline may post on its own website.

ing one week later. This time framework (week interval) has been chosen in order to avoid such restrictions as the Saturday night stay-over, which may occur for some flights if a shorter interval has been selected.

Our data cover 310 days (from 8 April 2003 to 11 February 2004) and comprise 49 routes (see Table 1) served by 14 full-service carriers (British Airways, Alitalia, Swiss, Aer Lingus, KLM, Lufthansa, Scandinavian Airlines, Air Europa, Air France, Czech Airlines, Tap Portugal, Iberia, BMI British Midlands, Finnair).

For each day and route, the spider collected all the round-trip posted fares that a hypothetical consumer would pay if she booked her ticket 7, 10, 14, 17, 21, 28, 35, 42, 49 and 56 days before the departure date (i.e. booking days). The spider also saved the time of departure and arrival of each flight code.

We define therefore two observations as belonging to the same flight in code-share by observing whether they share the same departure and arrival times, as well as the same origin and destination airports, but have different flight codes specific to each different airline. We collected 7,526 different flight code pairs: 3,223 in CS and 4,303 not in CS.

The UK CAA provides census monthly data for the full set of flights operated between the UK and Continental Europe during the period of analysis. This dataset contains such information as flight frequency, available seats and passenger flows; we use this information to construct a measure of market concentration at route level (*HHI*), as well as a measure of carriers' network size at the endpoints of the route (*Routes*).

Moreover, information contained in the CAA database allows us to distinguish between the operating and marketing carriers on code-shared flights. Indeed, the CAA reports only the statistics for the flights managed by the operating carrier; we can therefore classify in the Opodo dataset whether an observation for a code-shared flight refers to either the operating carrier or the marketing one.

Distances are collected from the World Airport Codes' web site;[7] the daily price of jet fuel is obtained from Thompson Reuters database;[8] Population density is downloaded from Eurostat. More specifically, our data contain the following variables of interest and controls:

- *CS* (Code share) is a dummy variable equal to 1 if the flight is code-shared, 0 otherwise.
- *MC* (Marketing carrier) is a dummy variable equal to 1 if the fare is set by a marketing carrier and 0 if it is set by the operating carrier.
- *Parallel* is a dummy variable equal to 1 if there is a parallel code-sharing agreement and 0 if there is a unilateral code-sharing agreement.
- *BookingDay** indicates the number of days before departure. In the econometric analysis, we will normalize this variable on the unitary interval to facilitate the representation of the results. We use the following transformation: *BookingDay*=(*BookingDay**-7)/(56 -7).

[7]See: http://www.world-airport-codes.com.
[8]See http://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm.

- *Distance* is the route distance in 1,000 kilometers.
- *FuelPrice* is the price of one gallon of jet fuel in dollars.
- *Hub* is a dummy variable equal to 1 if a flight is operated by an airline having a hub at one (or at two) endpoint(s) of the route.
- *Population* is the geometric mean of hundred inhabitants per squared kilometers of the two regions hosting the origin and destination airports. Regions are defined by the EU Nomenclature of territorial units for statistics at the county level (NUTS 2).[9]
- *LCC* is the total number of low-cost carriers operating on the route.
- *AlliedCarriers* is the number of marketing and operating European carriers on the route member of any global alliance (Oneworld, Skyteam, Star Alliance and Wing).
- *Frequency* is the total number of flights offered by the carrier on the route in a month. It includes flights offered as marketing carrier as well as operating carriers. It is often used as a measure of the quality of the flight supply (Brueckner, 2004). However, higher frequencies also imply economies of density (Caves et al., 1984; McShan and Windle, 1989).
- *RouteCityShare* is the share of passengers flying on the route over the total of the city pair.[10]
- *HHI* is the Herfindahl-Hirschman index at route level, computed as the sum of the square of the passenger market shares of each operating carrier providing non-stop service on the route.
- *SameAlliance* is a dummy variable equals 1 if there are at least two operating carriers belonging to the same global alliance on the route.
- *Holiday* is a dummy indicating whether the departure date of the flight falls during a holiday period (i.e., main UK bank holidays and the week before and after Christmas and Easter).
- *Routes* is obtained by computing the total number of international (non-stop) routes that the operating carrier runs from each of the two endpoints of the route, taking the highest value of the two. In the case in which there is a parallel code-sharing agreement, we compute the maximum for each carrier and then we take the average among the carriers.
- *Morning*, *LateMorning*, *Afternoon* and *Evening* are dummy variables equal to 1 if the departure time is respectively in the morning (6.00am-9.59am), late morning (10.00am-1.59pm), afternoon (2.00pm-5.59pm), and evening (6.00pm-1.59pm). *Morning* is set as the omitted category in the regression.

Table 1 reports the main descriptive statistics of the variables used in the analysis. Additional information on data employed in the analysis is provided in the Appendix (Tables A.1

[9] For a definition of NUTS2, see: http://ec.europa.eu/eurostat/web/nuts/overview.

[10] A route is an airport pair, e.g. London Gatwick (LGW) - Rome Fiumicino (FCO), while a city pair is a set of routes linking the airports of two city areas., i.e. London (LON) - Rome (ROM).

and A.2).

4. Descriptive analysis

To gain a better understanding of the structure of our data, and to complement the econometric analysis provided in the next section, we now describe the inter-temporal pricing behavior under different regimes. For each booking day, Table 2 reports the percentage of times that the fare posted by the operating carrier (P_{OC}) is strictly larger or smaller than £5 relative to that of the marketing carrier (P_{MC}); such an amount is deemed to define an economically significant difference.

The same table also reports the proportion of cases when the difference between the two fares is within the +/- £5 range. We observe that the operating carrier is generally cheaper than the marketing carrier. The table shows that, as the departure date approaches, the proportion of cases where the fare posted by the MC is strictly and significantly larger than the fare posted by the OC tends to decrease.

Table 1: Descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max
Fare	68.58	33.10	22.35	431.15
CS	0.36	0.48	0.00	1.00
MC	0.13	0.34	0.00	1.00
Parallel	0.17	0.38	0.00	1.00
*BookingDay**	29.10	14.71	7.00	56.00
Distance	0.80	0.42	0.24	2.42
FuelPrice	0.78	0.05	0.67	0.90
Hub	0.66	0.47	0.00	1.00
Population	0.28	0.19	0.05	0.99
LCC	1.65	0.71	0.00	4.00
AlliedCarriers	1.72	0.72	0.00	4.00
Frequency	388.78	182.67	30.00	824.00
RouteCityShare	0.45	0.22	0.02	0.83
HHI	0.57	0.19	0.31	1.00
Routes	22.70	17.73	2.00	54.00
SameAlliance	0.66	0.48	0.00	1.00
Morning	0.14	0.35	0.00	1.00
LateMorning	0.25	0.43	0.00	1.00
Afternoon	0.27	0.45	0.00	1.00
Evening	0.28	0.45	0.00	1.00
Holiday	0.06	0.24	0.00	1.00

(a) Number of observations: 2,956,562.

Table 2: Price operating carrier - Price marketing carrier (percentage values)

*BookingDay**	(1) $P_{OC} \ll P_{MC}$	(2) $P_{OC} \approx P_{MC}$	(3) $P_{OC} \gg P_{MC}$
7	55	31.37	13.63
10	55.1	33.35	11.55
14	55.17	31.92	12.91
17	54.85	33.26	11.89
21	54.56	33.92	11.52
28	52.87	37.55	9.58
35	49.83	41.9	8.27
42	47.2	44.86	7.94
49	46.22	46.13	7.65
56	45.4	46.8	7.8
Average	51.24	38.8	9.95

(a) Column (1): $P_{OC} \ll P_{MC}$ if $P_{OC} - P_{MC} < -£5$
(b) Column (2): $P_{OC} \approx P_{MC}$ if $-£5 \leq P_{OC} - P_{MC} \leq £5$
(c) Column (3): $P_{OC} \gg P_{MC}$ if $P_{OC} - P_{MC} > -£5$

Figure 1 reports the average fare for each booking day in the full sample and in three sub-samples based on the type of carriers and on the absence/presence of a code-sharing agreement.

The figure shows that the pricing curve generally increases through time, it flattens in the period 10-17 days before departure, and then it continues its positive trend. Apart from this discontinuity, the shape of the pricing curve is very close to an exponential path.[11]

Interestingly, by comparing the operating carrier in CS to the marketing carrier (which, by definition, is also in CS), we observe that the pattern is quite similar, but the fare range is shifted upwards in the case of the marketing carrier. This result provides preliminary evidence, which will receive further attention later in the econometric analysis that, for a given flight, the price posted by the marketing carrier is on average higher than the one posted by the operating carrier, irrespective of the booking day. This finding seems to run contrary to the idea that CS eliminates double marginalization, as often stated in the literature (Brueckner and Whalen, 2000; Brueckner, 2001; Brueckner, 2003; Bamberger et al., 2004; Chen and Gayle, 2007; Ito and Lee, 2007; Gayle, 2013).

[11]We exploit this characteristic in the econometric analysis, where we assume that the relation between fares and time before departure can be approximated by a straight line, after applying the logarithmic transformation.

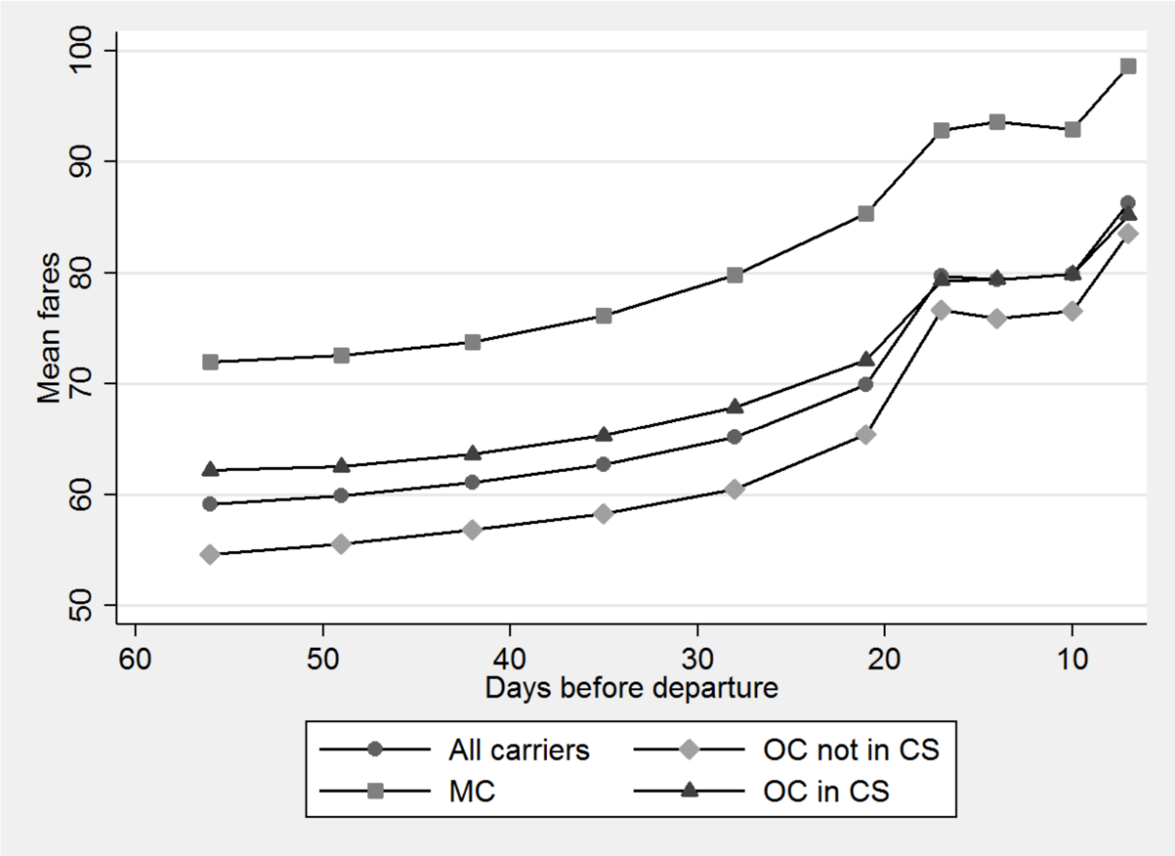

Figure 1: Mean price vs. Days before departure.

5. Econometric analysis

While the previous section has already brought evidence that code-share agreements appear to have significant effects on prices, the econometric analysis can also yield more robust insights on the relationship between code-share and the airlines' inter-temporal pricing behavior. We will do so by distinguishing how the temporal profile varies when, relative to non-CS flights, we consider flights *i*) in CS; *ii*) operated by an OC and/or a MC; *iii*) operated under parallel or unilateral CS.

5.1. Methodology

In order to study the impact of code-share on the temporal profile of fares, i.e. how posted prices vary in accordance to the number of days before departure, we choose to model the temporal profile of fares using a log linear relationship, as suggested by the approximation in Figure 1. Moreover, we normalize the booking day period on the unitary interval, so that all the temporal effects are captured by a single variable, unlike other papers that use separate dummies to measure how fares evolve over time (Bilotkach, 2005; Gaggero and Piga, 2010; Dobson and Piga, 2013). This approach facilitates adding interaction terms between the time variable and other regressors identifying different types of code-sharing agreements and thus simplifies considerably the interpretation of the ensuing results relative to the case where each booking day is represented by a separate dummy variable.

Our econometric analysis also addresses another, more serious econometric aspect. Simply put, the decision to operate a flight in CS is not independent of factors that may affect the setting of fares. Code-sharing agreements do not occur at random and are usually affected by some observable and unobservable characteristics that make the regressors and the error term in the price equation correlated (Brueckner, 2003b). Therefore, we need to correct for the selection bias because, in this case, the use of the standard Ordinary Least Squares (OLS) estimator does not guarantee consistent estimates of the coefficients in the price equation.[12]

More specifically, we consider the following two-stage model: in the first stage, operating carriers choose for which route, if any, they want to be engaged in a code-share agreement; then, in the second stage, operating and marketing carriers set their fares. The setup we analyze corresponds to a two-stage methods for switching regression models, initiated in the seminal work by Heckman (1979), and subsequently discussed and extended in several other works (Maddala, 1983; Winship and Mare, 1992; Kyriazidou, 1997; Puhani, 2000; Campa and Kedia, 2002; Fernandez-Val and Vella 2011). To correct for the selection bias, we implement the procedure described in Campa and Kedia (2002), which can be summarized by the following steps.

Step 1: Use a probit model to estimate the selection variable $Pr(D=1|X_1)=\Phi(\beta_1 X_1)$, where Φ is the cumulative normal distribution, D is a binary choice variable, X_1 is a matrix containing a set of regressors and β_1 is a parameter vector.

Step 2: Calculate the inverse Mills ratio (λ) using the estimated values of the probit model $\lambda = D\phi(\hat{\beta}_1 X_1)/\Phi(\hat{\beta}_1 X_1) - (1-D)\phi(\hat{\beta}_1 X_1)/\left(1-\Phi(\hat{\beta}_1 X_1)\right)$, where ϕ is the density normal distribution.

Step 3: Estimate by OLS the pricing equation including the correction term λ: $Y=\beta_2 X_2 +$

[12] The endogenous causes for the formation of code-share agreements are highlighted by Chen and Gayle (2007).

$\beta_\lambda \lambda + \varepsilon$, where X_2 is a matrix containing a set of regressors including D; β_2 and β_λ are parameters to be estimated, and ε is the error term.

Finally, it is worth mentioning some critical issues. First, we have collected fares only on European routes, although code-sharing agreements also concern intercontinental routes. Thus, our analysis is, therefore, partial since it does not capture the effects of code-sharing agreements (signed on European routes) on intercontinental fares.

Second, data mainly refers to flights originating from UK, most of them, from London. Although traffic from UK to the rest of Europe accounts for about one fifth of international European flights and all main European carriers operate on these routes, our study might not be representative of the whole European airline industry if some carriers should behave differently on continental routes. The need to limit the analysis to flights originating from UK airports is motivated by the need to match data on fares with other flight information, which is only available for the UK.

Third, we have not collected fares charged by low-cost carriers (LCCs). This is not a major concern, as LCCs do not usually enter in code-sharing agreements. Nevertheless, LCCs are accounted for in the analysis by controlling for their presence in the estimation of the code-sharing agreement choice and in the pricing equation.

Fourth, although, the process leading to code-sharing decisions is very complex, in Section 5.2 we will describe some of the determinants of CS at the route level. McMullen and Du (2012) have recently developed a similar approach for the US airline industry. The modelling of the negotiation phase in a more comprehensive way is out of the goal of this paper, since our primary interest is to study the effects of code-sharing agreements on fares.

5.2. Correcting for selectivity

In this subsection, we run a probit model to evaluate the probability for an operating carrier to be engaged in a code-sharing agreement:

$$Pr\left(CS_{fd} = 1 | X_{1fd}, \tau_d\right) = \Phi\left(\beta_1 X_{1fd} + \beta_{1\tau}\tau_d\right), \tag{1}$$

where subscript f defines the flight-code pair of the operating carrier(s) and d the departure date. The dependent variable (CS_{fd}) is a dichotomous variable equal to one if the flight is in CS and zero otherwise. Φ is the cumulative normal distribution. The vector X_{1fd} comprises all the variables presented in the descriptive statistics except the *MC*, *OC* and *Parallel* dummy variables and the set of dummy variables referring to different time windows (*Morning*, *LateMorning*, *Afternoon* and *Evening*) and to holiday periods (*Holiday*). The term τ_d represents the set of month-year dummy variables included to account for a possible common trend in code-sharing agreements. Finally, it is worth noting that we account for the presence of other operating carriers belonging to the same strategic alliance on the route (*SameAlliance*).This variable is included in the selection equation but not in the pricing equation and is therefore used as excluded instrument to allow the economic identification of the model (Wooldridge, 2012).

Because all the variables above are invariant within the booking day series and the time of departure, we only need to estimate the model by considering one observation per flight code pair/date. Standard errors are clustered by route-week to allow the residuals of different flight code pairs (possibly of different airlines) within the same route and week to be correlated. This procedure aims to take into consideration possible shocks that are route-week specific. The results of the probit estimates are reported in Table 3, column (1). Most of the variables are statistically significant.

The coefficient on *SameAlliance* is highly significant indicating a preferential choice of carriers to code-share a route with other operating carriers of the same strategic alliance (if any).[13] The *Hub* variable has a negative sign, indicating that carriers prefer not to provide access to its Hub to competing firms. The negative coefficient of *Population* and the positive one of *Distance* suggest that the airline is more willing to engage in CS on less dense and more distant destinations. A possible explanation is that, under those circumstances, it is more difficult for a carrier to achieve high levels of capacity utilization (Chen and Chen, 2003; Iatrou and Alamdari, 2005).

Moreover, the presence of a *LCC* reduces the likelihood to offer code-sharing agreements, while the presence of carriers involved in some alliance (*AlliedAirlines*), as well as a high flight frequency offered by the carrier on the route (*Frequency*) play in favor of them.[14] The positive coefficient on *RouteCityShare* suggests that operating carriers prefer to limit their code-sharing agreements on those airport-pair (route) within a city pair that is not characterized by a large flow of passengers. These airport-pairs include city airports such as London City, etc. Because these airports usually host high willingness-to-pay travelers, carriers usually prefer to directly manage this type of clients by themselves. Moreover, these airports are less involved in intercontinental flights and, therefore, these flights are less demanded for code-sharing agreements.

Finally, the coefficients on *Routes* is negative and statistically significant. The larger its network at the endpoints, the lower the carriers' interest to offer a code-sharing agreement. A possible explanation is that the OC is less prone to code-share since it wants to keep capacity for offering connecting flights.

[13]As suggested by an anonymous referee, in order to have a more comprehensive description of the code-sharing choice, the model should take into account the fact that parallel code-sharing is often based on reciprocity. The introduction of the *SameAlliance* variable partially account for this aspect.

[14]As noted by another referee, the use of *AlliedCarriers* as a predictor of the decision to code-share might increase the risk of reverse causality, since a carrier that decides to code share with an allied party may then choose to exit the route. We find that this issue is not particularly relevant in our data because exit in such situation rarely occurs in our data (i.e. only on one route).

Table 3: The determinants and price equation of code-share (CS).

	(1)		(2)		(3)		(4)	
Depependent Variable	*CS*		*Log(Fare)*		*Log(Fare)*		*Log(Fare)*	
Constant	-2.061**	(0.994)	3.514***	(0.109)	3.437***	(0.112)	3.583***	(0.107)
CS			0.099***	(0.022)	0.070***	(0.022)	0.072***	(0.023)
MC					0.097***	(0.010)	0.086***	(0.010)
Parallel							-0.041***	(0.014)
Booking day			0.366***	(0.007)	0.367***	(0.007)	0.349***	(0.007)
*BookingDay * CS*			-0.074***	(0.012)	-0.108***	(0.016)	-0.155***	(0.014)
*BookingDay * MC*					0.090***	(0.018)	0.117***	(0.017)
*BookingDay * Parallel*							0.180***	(0.017)
Log(Distance)	0.491***	(0.078)	0.195***	(0.009)	0.199***	(0.010)	0.186***	(0.010)
Log(FuelPrice)	-0.274	(0.249)	0.084**	(0.040)	0.079*	(0.040)	0.082**	(0.038)
Hub	-0.493***	(0.099)	0.107***	(0.012)	0.107***	(0.011)	0.101***	(0.011)
PopulationDensity	-1.998***	(0.250)	-0.380***	(0.017)	-0.380***	(0.017)	-0.380***	(0.017)
LCC	-0.551***	(0.079)	-0.045***	(0.007)	-0.046***	(0.007)	-0.043***	(0.007)
AlliedAirlines	0.179**	(0.084)	-0.009	(0.008)	-0.010	(0.008)	0.000	(0.008)
Log(Frequency)+	0.048	(0.098)	-0.128***	(0.010)	-0.118***	(0.011)	-0.139***	(0.010)
RouteCityShare+	1.514***	(0.316)	-0.049	(0.032)	-0.065**	(0.033)	-0.022	(0.034)
HHI	-1.424***	(0.260)	0.048*	(0.028)	0.038	(0.029)	0.077***	(0.030)
Log(Routes)	-0.772***	(0.050)	0.018***	(0.003)	0.019***	(0.003)	0.019***	(0.003)
SameAlliance	1.703***	(0.120)						
LateMorning			-0.006**	(0.002)	-0.006**	(0.002)	-0.006**	(0.002)
Afternoon			0.003	(0.003)	0.004	(0.003)	0.003	(0.003)
Evening			-0.004	(0.002)	-0.005**	(0.002)	-0.005*	(0.002)
Holiday			0.129***	(0.016)	0.129***	(0.016)	0.130***	(0.016)
Lamda			0.024*	(0.012)	0.022*	(0.013)	0.028**	(0.013)
Day-of-week dummies	No		Yes		Yes		Yes	
Month-year dummies	Yes		Yes		Yes		Yes	
Pseudo-R2 / R2	0.329		0.372		0.384		0.388	
Observations	596,471		2,956,562		2,956,562		2,956,562	

(a) Model (1): Probit estimation. Models (2)-(4): OLS estimation.

(b) Robust - Model (1) -, Bootstrap – Models (2)-(4) - standard errors to heteroscedasticity and serial correlation in parenthesis, clustered by route-week.

(c) *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

(d) Variables denoted by "+" are lagged one month to reduce the risk of endogeneity.

5.3. Pricing equation with code-share

In this subsection, we consider the following econometric model:

$$Y_{cfdt} = \beta_2 X_{2cft} + \beta_{2\rho}\rho_c + \beta_{2\tau}\tau_d + \beta_{2h}\delta_d + \beta_\lambda \lambda_{crd} + \varepsilon_{crdt}, \qquad (2)$$

where c is the carrier, r the route, d the departure date, and t the booking day. The dependent variable (Y_{crdt}) is the logarithm of the fare posted on the internet on a given booking day. λ_{crd} is the correction term as described in the second step of the procedure in subsection 5.1. Because we include an estimated regressor, λ_{crd}, the standard errors for the coefficients are obtained using a bootstrap method. Since the selection equation has been estimated with a lower number of observations, estimated values from (1) for a given flight-code pair and departure date are extended to all the marketing and operating carriers offering the same physical flight as operating carrier or as marketing carrier and to all the booking days of that flight. Moreover ρ_c is the carrier fixed effect, τ_d is the month-year fixed effect and δ_d is day of the weak fixed effect. β_2, β_λ, $\beta_{2\rho}$, $\beta_{2\delta}$ and $\beta_{2\tau}$ are the parameters of the model and ε_{crdt} is the error term, assumed random with zero mean. Furthermore, standard errors are clustered by route-week to allow for the possibility that the residuals of different flight codes operated on the same route during the same week may be correlated. This way of clustering aims to take into consideration that all flights in a route within a week may be subject to the same shock. Moreover, clustering is also required because many regressors have common values across observations.

With the exception of the excluded variable *SameAlliance* employed in the first stage, the matrix X_{2cft} contains all the regressors presented in Table 2, as well as the interaction term of the *BookingDay* variable with *CS*, *MC* and *Parallel*.[15] Thus, equation (2) becomes:

$$\begin{aligned} log(Fare_{cfdt}) = \pi_{00} + \pi_{01}CS_{cfd} + \pi_{02}MC_{cfd} + \pi_{03}Parallel_{cfd} + \\ +\pi_{10}BookingDay_t + \pi_{11}CS_{cfd}\cdot BookingDay_t + \pi_{12}MC_{cfd}\cdot BookingDay_t \\ + \pi_{13}Parallel_{cfd}\cdot BookingDay_t + controls + \varepsilon_{crdt} \end{aligned} \qquad (3)$$

In its essence equation (3) specifies how the temporal slope (π_{0i}) and the intercept (π_{1i}) of a pricing curve vary when we consider flights in CS ($i = 1$); operated by a MC ($i = 2$); running under parallel CS operations ($i = 3$). Table 3 columns (2)-(4) reports the estimates of the pricing equation (3) with different restrictions on the CS coefficients. In column (2) we only consider the *CS* dummy and its interaction with the *BookingDay* variable; in column (3) we also include the *MC* dummy and interaction, and, finally, in column (4) we consider the full

[15] Note that because of the non-linearity of the probit model employed in the first step of the procedure, the model is econometrically (but not economically) identified even if we include *SameAlliance* in estimate of the pricing equation. By doing this, we find that in the four cases, the coefficient is not statistically different from zero at the conventional levels. This suggests that our estimates rely on a valid excluded instrument.

model of equation (3), which also includes the *Parallel* dummy variable and relative interaction.

The coefficient on *BookingDay*, which identifies the slope of the pricing curve, is positive and statistically significant. This result is in line with the expectation of higher fares as the day of departure approaches. The coefficient ranging from 0.349 to 0.367 indicates that on average fares increase by about 0.7% each day.[16] This is amply consistent with findings in the empirical literature on airline pricing (Piga and Bachis, 2007; Gaggero and Piga, 2010, 2011).

For convenience, Table 4 summarizes the intercept and slope parameters and its estimations under different regimes.[17] It appears that fares under CS are higher than in the case of no CS, regardless of the type of carrier: 4.047 versus 3.948. The difference of 0.099 indicates that the fare of an airline under CS is about 10.4% higher than in the absence of CS.[18] Buying a ticket from a MC is, on average, more expensive than from an OC. The intercept of MC is equal to 4.111, which is higher than the intercept of OC, which is equal to 4.015. This finding is in line with what is depicted in Figure 1.

Table 4: Interpretation of the intercept and slope.

Model*	Carrier	Parameters** Intercept/Slope	Estimation Intercept	Slope
(2)	Carrier not in CS	π_{j0}	3.948	0.366
(2)	Carrier in CS	$\pi_{j0} + \pi_{j1}$	4.047	0.292
(3)	OC not in CS	π_{j0}	3.945	0.367
(3)	OC in CS	$\pi_{j0} + \pi_{j1}$	4.015	0.259
(3)	MC	$\pi_{j0} + \pi_{j1} + \pi_{j2}$	4.111	0.457
(4)	OC in unilateral CS	$\pi_{j0} + \pi_{j1}$	4.019	0.194
(4)	OC in parallel CS	$\pi_{j0} + \pi_{j1} + \pi_{j3}$	3.978	0.374
(4)	MC in unilateral CS	$\pi_{j0} + \pi_{j1} + \pi_{j2}$	4.105	0.311
(4)	MC in parallel CS	$\pi_{j0} + \pi_{j1} + \pi_{j2} + \pi_{j3}$	4.064	0.491

* The model number corresponds to the column of Table 3.
** Intercept parameters emerge when j = 0 and slope parameters emerge when j = 1.

The positive coefficients on CS and the negative ones on the interacted term $CS \cdot BookingDay$ indicate that if a flight is in CS, then its temporal profile is on average above and less steep than in the case of flights without CS. Thus, CS fares are larger especially for early

[16] Given that our booking period spans from 7 to 56 days, which correspond to 1 and 0 respectively, a one-day variation is measured as 1/49. Therefore, the bounds of the marginal effect are calculated as 0.349/49=0.0071 and 0.367/49=0.0074.

[17] The pricing profile for the different regimes can be computed using two different ways. A first approach is to rely on the estimates of column (4) and weigh them by the proportion of observations in each regime. An alternative way, which we followed in this work, is to directly use only the estimates presented in columns (2)-(4).

[18] The percentage numbers stem from the formula in Wooldridge (2012): $exp(\pi) - 1$, which computes the marginal effect in percentage terms of a dummy variable when the dependent variable is expressed in logarithmic form; π is the estimated coefficient of the dummy variable.

bookers travelers. Conversely, late bookers, usually business travelers, appear to gain from CS practices since they pay less and also benefit from rising quality provided by a higher number of frequencies. The shift in the temporal profile is compatible with the fact that since the number of potential travelers increases thanks to the additional marketing activity of the MC, as well as to the potential increase in quality, carriers will offer higher fares.

Figure 2 provides a graphical representation of the econometric results: the *Log(Fare)* variable is on the vertical axis and the *BookingDay* variable lies on the horizontal axis. The north-west diagram represents the estimates of column (2) of Table 3. The north-east diagram depicts the situation reported in column (3) of Table 3. The two remaining bottom diagrams stem from column (4) of Table 3, they depict, in the case of unilateral and parallel CS, the pricing profile of respectively the OC (south-west diagram) and the MC (south-east diagram).

Consider the case of an OC in the top right panel of the Figure 2, where the slope of the line is flatter than in the case of the OC not in CS; thus, for the OC the fare difference between code-shared and not-code-shared flights tends to converge to zero, as the departure date approaches. A MC has a similar slope of an OC not in CS but with a higher intercept. These results suggest that because some passengers are brand loyal, code-sharing agreements may be a way to implement a price discrimination strategy, where a brand premium is charged to those booking via the MC. In addition, this pricing strategy has a positive return for both carriers, when travelers are not perfectly informed in the sense that they are not aware of the CS arrangement. Indeed, even price sensitive consumers may be induced to accept the (lower) fare charged by the OC, after they compare it and find a gap with that offered by the MC.

Returning to the summary of estimates in Table 4, both in the case of the OC and in the case of the MC, CS under parallel operations is characterized by a steeper slope relative to the case of CS under unilateral operations: 0.374 versus 0.194 for OC and 0.491 versus 0.311 for MC. For a graphical representation see the bottom diagrams of Figure 2. These results can be somehow related to the work by Ito and Lee (2007), where fares on unilateral CS are generally higher than under parallel CS. However, the authors are not able to control for the evolution of fares as the departure date approaches. As the bottom part of Figure 2 reveals, our results show that the findings of Ito and Lee (2007), in our sample, hold only in the early part of the booking period, whilst during the last month before the flight departure the fares under parallel CS overcome the fares under unilateral CS for both types of partners. Thus, parallel pricing favors early bookers (mostly, leisure travelers) and hurts late bookers, which generally include a greater proportion of business travelers.

As far as the other controls are concerned, *log(Distance)* has its expected positive sign, as longer length of the flight implies higher fuel costs which are transferred on the ticket fare. The coefficient less than one indicates fares increase less than proportionally with distance. This finding confirms the non-linear relationship between fares and distance, already documented in the literature (Gaggero and Piga, 2010). Indeed the specification of distance in log captures the economies of scale of operating longer routes, given that landing and take-off are fuel-intensive operations whose cost can be better spread over longer routes.

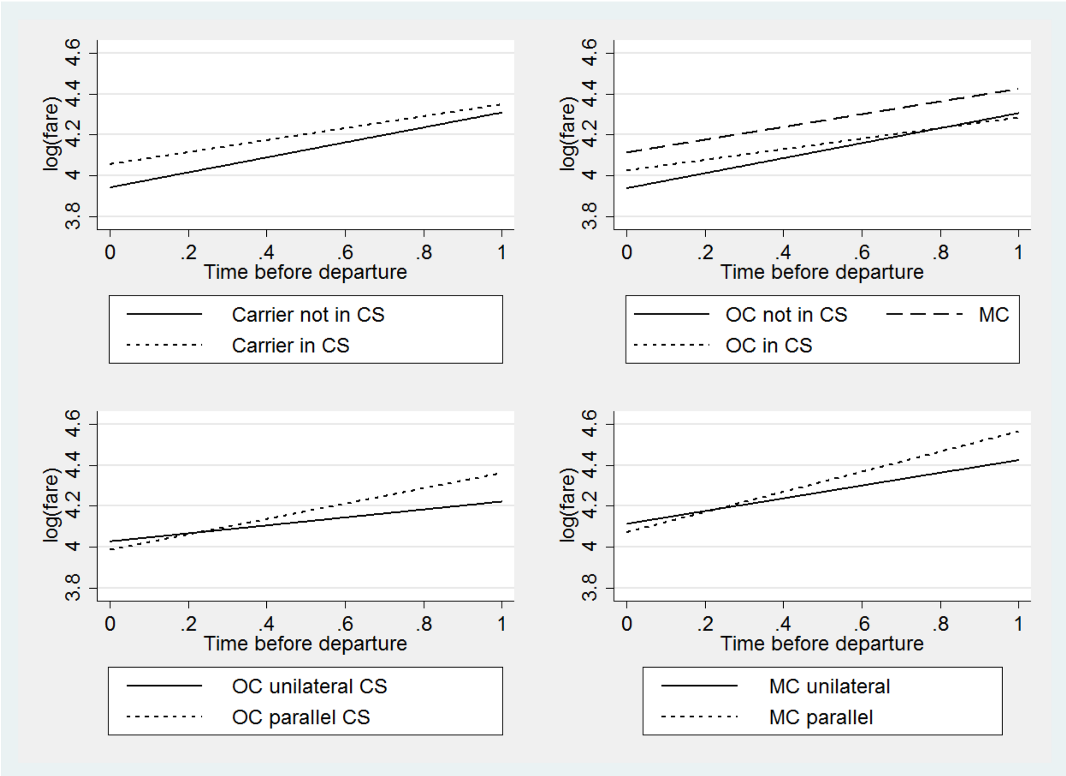

Figure 2: Graphical illustration of the estimates in Table 5.

The price of the jet fuel is also correctly signed, since an increase of its price determines higher operating costs and therefore higher fares. Since the coefficient on *log(FuelPrice)* represents the elasticity of fares to the price of jet fuel, a one-percent increase of jet fuel translates into about 0.8% higher fares. This effect is less than proportional, showing that airlines try to internalize part of the increment in the operating costs.

The *Hub* dummy is also positive and statistically significant, indicating that an airline tends to charge higher fares on routes operated from its hubs (Brueckner and Whalen, 2000; Lederman, 2008). This hub effect is estimated to increase fares by about 11.29%. The extent of market concentration in a route has the expected positive effect on prices (Borenstein, 1989). One standard deviation increase of *HHI* implies higher fares by almost 1.46%. As robustness check, we have also performed the analysis by computing *HHI* at city-pair level obtaining similar results. As expected the presence of a LCC reduces fares by about 4-5%. This is consistent to the results presented in literature (Alderighi et al., 2012). The maximum number of routes at the endpoints (*Routes*) is positive and significant meaning that the larger the network, the higher the implicit cost of capacity and, consequently, the higher the charged prices.

The geometric mean of the population density at the two endpoints has a negative effect on price, as higher densely populated areas are normally served by larger-sized aircraft, which imply lower operating costs transferring in lower fares. For a similar reason, we find that the coefficient of the *Frequency* variable is negative. As noted in Section 3, there is a price reducing effect due to the economies of density and a price enhancing effect due to increasing willingness to pay caused by higher quality. In our analysis, the first effect dominates the second one. The time of departure dummies indicates that late morning, evening and afternoon flights are, respectively, cheaper by about 0.6%, 0.5% and 0.3% than early morning flights.

Finally, the positive and statistically significant sign on *Holiday* is in line with the presumption that flights scheduled to depart during the peaks of the season are more expensive (by about 14%) than flights departing off-peaks.

6. Conclusion

In this paper we have studied the impact of code-share agreements on the temporal profile of fares. By analyzing the temporal profile of airline fares, we identify three main results. First, CS increases fares especially for early bookers. Second, much of the shift in code-shared flights is due to higher prices offered by marketing carriers. Finally, when flights are operated under unilateral code-share, the pricing profile is flatter than under parallel code-share, which implies that early fares are cheaper in the latter.

These findings highlight some welfare implications. The effects of CS do not uniformly apply to all passenger categories. Leisure travelers are damaged especially by unilateral CS: Buying in advance to try to get cheap fares is not so beneficial since carriers apply a flat temporal profile. This empirical result is only apparently in opposition with the theoretical works on pricing under CS, where unilateral CS is usually welfare enhancing since it reduces the double marginalization problem. This theoretical prescription works for (high) business fares, but does not apply to (low) leisure fares that, even in the absence of a code-sharing agreement, are not sensitive to the double marginalization problem. Furthermore, business travelers seem to be less negatively affected by CS especially if they are not too brand sensitive. The OC, near to the departure date, charges fares that are close to the case without CS. For this type of passengers, as theoretical works predict, fares may also decrease. These findings are also in line with the empirical literature reviewed in the first part of the paper.

Because our data are representative of the UK airline market, many routes in the sample (especially those ones not in code-share) are served by the former UK flag carrier, British Airways. Therefore, the results of this analysis reflects, to a large extent, the business strategy of this company, which may differ from those of other airlines.

Finally, it is worth mentioning that many issues are still open to future research. First, code-sharing agreements should be analyzed on a wider number of routes, in order to offer a more comprehensive view of the real effects of code-sharing practices around Europe. Second, since code-sharing agreements also involve intercontinental flights, it could be useful to study the simultaneous impact of code-sharing agreements on international and intercontinental routes. Third, the first-stage of the model (code-sharing decision) could be enriched by providing a more comprehensive model, accounting for a multi-route agreement decisions, reciprocity and other strategic considerations (network complementarities). Finally, it could be beneficial to collect data both on prices and quantity sold in order to have a better understanding of the functioning of the market.

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Appendix

Table A.1: Routes considered in the empirical analysis.

BHX-DUB	LGW-GLA	LHR-FRA
BRS-DUB	LGW-GVA	LHR-GLA
EDI-DUB	LGW-MAD	LHR-GOT
LCY-AMS	LGW-MAN	LHR-GVA
LCY-DUB	LGW-MUC	LHR-HAM
LCY-GVA	LGW-TLS	LHR-LIN
LCY-ZRH	LHR-AGP	LHR-MAD
LGW-AGP	LHR-AMS	LHR-MAN
LGW-ALC	LHR-ARN	LHR-MUC
LGW-AMS	LHR-ATH	LHR-MXP
LGW-BCN	LHR-BCN	LHR-ORK
LGW-BIO	LHR-CDG	LHR-OSL
LGW-BRU	LHR-DUB	LHR-PRG
LGW-CDG	LHR-DUS	LHR-ZRH
LGW-DUS	LHR-EDI	MAN-DUB
LGW-FAO	LHR-FAO	
LGW-FCO	LHR-FCO	

Table A.2: Number of routes offered by carrier with/without code-share.

	Operating carrier not in CS	Operating carrier in CS	Marketing carrier
British Airways	28	4	6
Alitalia	4	0	0
Swiss	4	0	0
Aer Lingus	2	4	1
KLM	2	0	0
Lufthansa	1	2	0
Scandinavian Airlines	1	2	0
Air Europa	1	0	0
Air France	1	0	0
Czech Airlines	1	0	0
Tap Portugal	1	0	0
Iberia	0	3	2
BMI British Midlands	0	0	4
Finnair	0	0	1
TOTAL	36	15	14