WP 27_14

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THE EFFECT OF CODE-SHARE AGREEMENTS ON THE TEMPORAL PROFILE OF AIRLINE FARES

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

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February 2014

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 largest 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, when flights are in unilateral code-share, the pricing profile is flatter than under parallel code-share.

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

* We thank Ricardo Flores-Fillol, Gianmaria Martin, Maurizio Conti, Robert Windle, participants to the 2013 ATRS conference in Bergamo, to the 2014 SIEPI workshop in Naples and seminar participants in Bergamo for helpful comments. All remaining errors are ours.

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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. They are a result of the liberalization process which characterizes the airline sector worldwide (Brueckner and Whalen, 2000; Brueckner, 2003).

The large expansion of CS 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 tighter business cooperations such as an alliance or even a merger (Brueckner and Pels, 2005; Gaggero and Bartolini, 2012). This is because, 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, 2010). In Europe, Article 101 of the European Treaty prohibits agreements between two or more independent market operators which restrict competition. This Article is close to the first Section of the Sherman Act (1890) in the US legislation.[2] Both sets of norms, albeit with minor differences, accept that CS agreements should be allowed, although sometimes by imposing some remedies (e.g. slot conditions or frequency freeze) only if they are in favor of consumers, and, more specifically, when the antitrust commission expects that fares do not increase and/or there is not a reduction in the competition.[3] For this reason, CS agreements are evaluated case by case and decisions are taken in terms of the impact on prices or on consumer surplus.

The theoretical literature has also highlighted the existence of different factors playing in favor and against CS 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 that alliances

[1]For instance, the Heathrow-Madrid flight BA7056 operated by British Airways is also sold under the code IB3164 by Iberia. In this example British Airways is the operating carrier, whilst Iberia 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.

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 CS 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 CS 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 their data structure does not allow to take it into account. 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, runs CS under parallel or unilateral 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 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. By analyzing the temporal profile of airline fares, we identify three main results. First, code-share 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 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

CS 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-share 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).

CS 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 they 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. 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 collusive 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-share agreement between Continental Airlines and Northwest Airlines in 1999. 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-share 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 code-share 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 code-share are: (i) above the fares under parallel code-share; (ii) below the fares of an operating carrier without code-share. 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 code-share can be a form of product differentiation to attract high price sensitive consumers.

A complementary research question addresses whether code-share is associated with traffic increase. The empirical literature on this issue practically unanimously finds evidence of higher passenger volumes subsequent to a CS 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).

Table 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	

Fares were retrieved using a web spider specifically designed to capture the fares posted by an on-line travel agent, Opodo.[4] We collect fares on 49 routes (see Table: 1) with a total of 1023 operated flights. There are 475 flights in codeshare and 548 flights without agreements.

For each day between 8 April 2003 and 11 February 2004 and for each flight code pair, 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. We will refer to these dates as booking days. In order to avoid such restrictions as the Saturday night stay-over, the return leg was set one week after the outgoing flight. 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.

The UK CAA provides census monthly data for the full set of flights operated between the UK and Continental Europe during the period April 2003-February 2004. 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, as well as the number of max/min routes operated by the carrier at the endpoints of each route. 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;[5] the daily price of jet fuel is obtained from Thompson Reuters data base;[6] Population density by NUTS-3 regions is downloaded from Eurostat.

Table 2 reports the main descriptive statistics of the variables used in the whole analysis. A full list carriers and number of routes in this sample they operate, differentiating whether in code-share or not, is provided in the Appendix (Table 7).

[4]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 may however not report promotional offers that an airline may post on its own website.

[5]See: http://www.world-airport-codes.com.

[6]See http://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm.

Table 2: Descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max
Price (in £)	68.58	33.10	22.35	431.15
BookDay	0.55	0.30	0.00	1.00
Marketing carrier	0.13	0.34	0.00	1.00
Parallel	0.66	0.48	0.00	1.00
Morning (6am-10am)	0.19	0.39	0.00	1.00
Late morning (10am-2pm)	0.25	0.43	0.00	1.00
Afternoon (2pm-6pm)	0.27	0.45	0.00	1.00
Evening (6pm-0am)	0.28	0.45	0.00	1.00
Distance (in 1000 Km)	0.80	0.42	0.24	2.42
Fuel price (100$ per gallon)	0.78	0.05	0.67	0.90
Hub	0.66	0.47	0.00	1.00
Population density (geom. mean endpoints)	0.28	0.19	0.05	0.99
HHI route	0.57	0.19	0.31	1.00
Business pax share	0.33	0.17	0.00	1.00
Code-share	0.26	0.44	0.00	1.00
Pax shr route/citypair	0.45	0.22	0.02	0.83
Max # routes at endpoints	22.70	17.73	2	54
Min # routes at endpoints	4.15	4.42	1	18
Number of allied airlines	1.72	0.72	0.00	4.00

4. Descriptive analysis

To gain a better understanding of the structure of our data, and to complement the econometric analysis in the next section, we now show some descriptive statistics on inter-temporal pricing under CS.

For each booking day, Table 3 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 also 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 increase.

Table 3: Price operating carrier - Price marketing carrier

Booking day	$P_{oc} - P_{mc} < -£5$	$-£5 \leq P_{oc} - P_{mc} \leq £5$	$P_{oc} - P_{mc} > £5$
7	55.00%	31.37%	13.63%
10	55.10%	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%	41.90%	8.27%
42	47.20%	44.86%	7.94%
49	46.22%	46.13%	7.65%
56	45.40%	46.80%	7.80%
Average	51.24%	38.80%	9.95%

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 CS agreement.

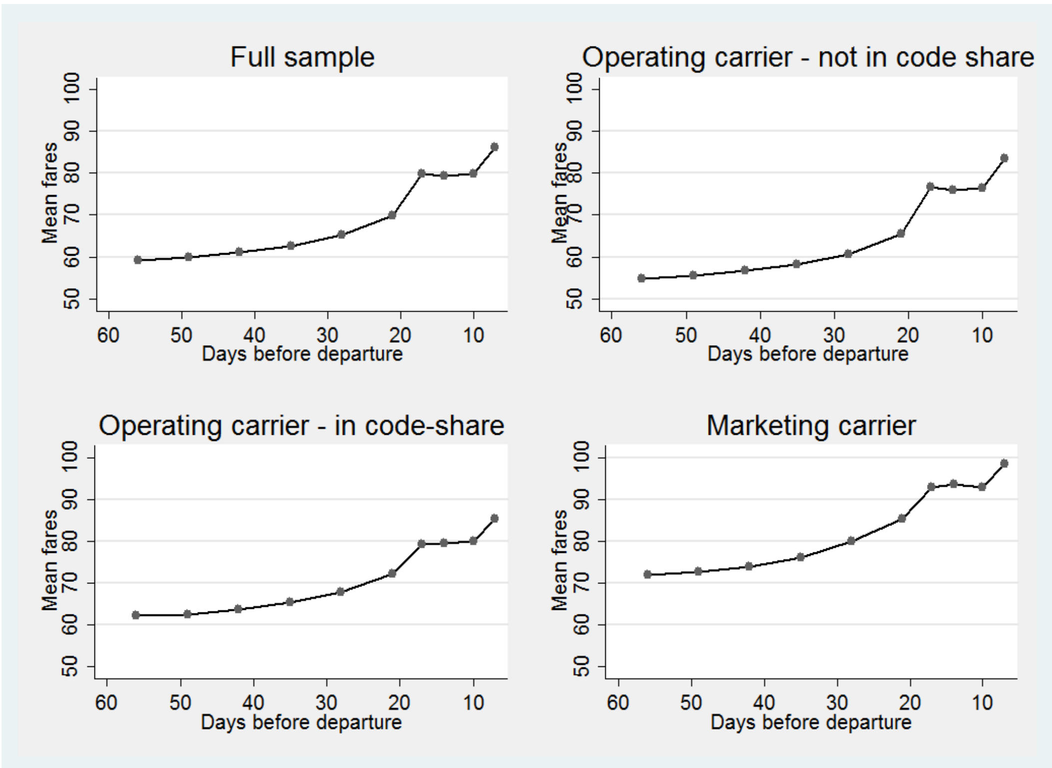

Figure 1: Mean price vs. Days before departure.

The figure shows that the pricing curve generally increases through time, it flattens in the period 20-10 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.[7]

Interestingly, by comparing the two bottom diagrams, which respectively refer to the operating carrier in CS and to the marketing carrier (which by definition is 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; Gayle, 2013; Ito and Lee, 2007).

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 MC; *iii*) running under parallel or uni-lateral 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 CS 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

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

setting of fares. Code-share agreements do not occur at random and are usually affected by some observable and unobservable characteristics which 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.[8] More specifically, an airline faces a sequential decision: in the first stage the carrier chooses whether to engage into a code-share agreement; then, in the second stage, it sets the fares. The setup we analyze corresponds to the classical econometric selection model, first discussed in the seminal work by Heckman (1979), and subsequently in several other works (Puhani, 2000; Baffoe-Bonnie, 2004). To correct for the selection bias, we implement the procedure described in Greene (2003, p. 978):

Step 1: Use a probit model to evaluate the factors affecting an airline's decision to engage in a CS agreement : $p = \Pr(Y_1 \mid X_1) = \Phi(X_1' \hat{\beta}_1)$, where Φ is the cumulative normal distribution.

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

Step 3: Estimate by OLS the pricing equation including the correction term λ : $y_2 = x_2' \hat{\beta}_2 + \lambda(x_1' \hat{\beta}_1) + v_2$.

5.2. Correcting for selectivity

In this subsection we run a probit model to evaluate the probability for an operating carrier to operate a flight in CS:

$$\Pr(\mathrm{CS}_{fcrt} = 1 \mid X, Z, V, \tau) = \Phi(X'_{rt}\alpha + Z'_{crt}\beta + V'_{fcrtt}\gamma + \tau_t) \tag{1}$$

where subscript f defines the flight code, c the carrier, r the route, and t is the date of the flight, set daily. The dependent variable is a dichotomous variable equal to one if the flight is in code-share and zero otherwise. Φ is the cumulative normal distribution. The vector X_{rt} comprises variables which are common to all flights of a given route, namely, the share of passengers traveling on the route relative to the passengers traveling on the corresponding city pair (*Pax shr route/citypair*), lagged one month to reduce simultaneity issues; the number of allied airlines in the route (*Allied airlines*) and the geometric mean of the population density at the two endpoints of the route (*Pop density*).[9]

The vector Z_{crt} aims to control for airline-specific factors: we consider the two end-

[8]The importance of endogenizing the formation of code-share agreements is highlighted by Chen and Gayle (2007).
[9]Population density for each end-point of the route is obtained from the Eurostat database combining information on the number inhabitants and geographical area sizes (in squared kilometers) at NUTS2 level.

points of the route and pairwise take the maximum and minimum number of routes that the operating carrier runs from the endpoints of the observed route (*Max # routes at endpoints* and *Min # routes at endpoints*, respectively). Variables specific of the flight code are gathered in V_{fcrt}, which comprises a set of dummies to control for day of the week when the flight is scheduled to take-off. V_{fcrt} also includes three dummy variables (*Late morning*, *Afternoon* and *Evening*) equal to one if the flight is scheduled to depart respectively in the late morning (10am-2pm), afternoon (2pm-6pm) and evening (6pm-12midnight). The reference category is therefore set to define flights departing in the early morning (6am-10am). Finally, the term τ_t represents the set of monthly dummy variables.

Because all the variables above are invariant within the booking day series, we only need to estimate the model by considering one observation per flight. Standard errors are clustered by route and month to allow the residuals of different flight codes (possibly of different airlines) within the same route and month to be correlated. This procedure aims to take into consideration possible shocks that are route-month specific.

The results of the probit estimates are reported in Table 4. Overall the estimates indicate that the airline is more willing to engage in CS whenever it is more difficult for a flight to achieve high levels of capacity utilization (Chen and Chen, 2003; Iatrou and Alamdari, 2005). *Pop density* has a negative effect on the likelihood of adopting code-share. In denser routes the airline does not need to sign a code-share agreement because the potential demand guarantees traffic volumes sufficient to yield high enough occupancy rates for the flight. On the contrary in thinner routes, the need to maintain a certain quality of service, and hence to guarantee an adequate frequency of flights, increases the risk of flights leaving with a high level of spare capacity, which is reduced by CS agreements where the OC can tap into the customers' basis of the partner airline.

The positive coefficient on *Pax shr route/citypair* suggests that a dominant position of the operating carrier on the market (which is given by the city pair) increases the likelihood of doing CS. This may occur because in this situation the airline is probably operating under spare capacity and CS may represent an effective tool to fill it.

The coefficients on *Max # routes at endpoints* and *Min # routes at endpoints* are both negative and statistically significant. As they capture the extent of the OC's own network, these variables measure the possibility of using such routes to feed the route under consideration. An already highly developed network (higher values of *Max # routes at endpoints* and of *Min # routes at endpoints*) implies a lower incentive for the OC to sign a CS agreement because it is more likely that the concerned route may gain traffic from connecting flights. Indeed, the higher magnitude in absolute term of *Min # routes at endpoints* relative to *Max # routes at endpoints* indicates that the need of a partner airline to complement the OC's network becomes weaker if both endpoints of the route are already well-served by the observed OC. This is because the OC is capable to fill the aircraft using its own connections at both airports.

As expected, the number of allied airlines on the route is positive, but statistically insignificant. The positive coefficients on *Late morning* and *Afternoon* indicate that an airline prefers to code-share the flights scheduled to depart in the central part of the day (between 10am and 6pm) relative to the *Early morning* category (6am-10am), whilst the latter are more likely to be in CS than flights departing in the evening.

Table 4: The determinants of code-share.

	(1)	(2)	(3)	(4)	(5)
Population density	-3.739***	-2.405***	-3.091***	-3.112***	-3.127***
	(0.702)	(0.393)	(0.403)	(0.437)	(0.439)
Max # routes at endpoints		-0.016***	-0.012***	-0.012***	-0.012***
		(0.003)	(0.004)	(0.004)	(0.004)
Min # routes at endpoints		-0.172***	-0.200***	-0.201***	-0.204***
		(0.027)	(0.030)	(0.030)	(0.031)
Pax shr route/citypair (-1m)			2.402***	2.388***	2.427***
			(0.368)	(0.382)	(0.384)
Nbr of allied airlines				0.023	0.014
				(0.116)	(0.114)
Late morning (10am-2pm)					0.103***
					(0.032)
Afternoon (2pm-6pm)					0.139***
					(0.028)
Evening (6pm-0am)					-0.055*
					(0.029)
Day-of-the-week dummies	No	No	No	No	Yes
Monthly dummies	No	No	No	No	Yes
Observations	130,776	130,776	130,776	130,776	130,776

(a) Probit estimation. Dependent variable CS equal one if the flight is in code-share and zero otherwise.
(b) Robust standard errors to heteroscedasticity and serial correlation in parenthesis, clustered by route-month.
(c) *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

5.3. Pricing equation with code-share

We consider the following econometric model, which relates the posted fares (p) to code-share practices, time of purchase before departure, route and flight code characteristics:

$$\begin{aligned}\log(p_{fcrt}) = {} & \alpha_0 + \alpha_1 CS_{fcr} + \alpha_2 MC_{fcr} + \alpha_3 Parallel_{fcr} + \beta_0 BookDay_t + \\ & \beta_1 CS_{fcr} * BookDay_t + \beta_2 MC_{fcr} * BookDay_t + \\ & \beta_3 Parallel_{fcr} * BookDay_t + \mu_1 Morning_f + \mu_2 Afternoon_f + \\ & \mu_3 Evening_f + \nu_1 \log(Distance)_r + \nu_2 \log(Fuel_t) + \nu_3 Hub_{cr} + \\ & \nu_4 PopDensity_{rt} + \nu_5 HHI_{rt-30} + \lambda_{rt} + \rho_c + \delta_t + \sigma_{fcrt}\end{aligned} \tag{1}$$

where f is the flight code, c the carrier, r the route. Time t defines the booking day, i.e. those days prior to the take-off date in which the fare is posted on the internet. For each f we collect fares 7, 10, 14, 17, 21, 28, 35, 42, 49 and 56 days before the departure. The dependent variable is the logarithm of the fare posted on the internet on a given booking day. The variables *CS*, *MC* and *Parallel* are three dummies: the first is equal to one in case of code-share flight, the second is equal to one if the airline is the marketing carrier, the third is equal to one if CS on the route is conducted under parallel operations.

BookDay considers the aforementioned series of days prior to departure when the fare is collected. The variable is normalized between zero and one, with one corresponding to the latest day of fare collection, namely day 7, and zero the earliest, namely day 56.

The logarithm of route distance and the logarithm of the daily price of the jet fuel are standard controls for the operating costs. *Hub* is a dummy variable equal to one if the airline has a hub at one end-point of the route, and *PopDensity* is the geometric mean of the population density at the two endpoints of the route. *HHI* is the route Herfindahl-Hirschman index, obtained using the market share from the number of passengers flying on a route. This variable aims to control for degree of competitive pressure in the route. In order to mitigate the possible endogeneity concerns, due to the simultaneous determination of price and quantity, we lag *HHI* by one month. The usual set of dummies (*Late morning*, *Afternoon* and *Evening*) to identify the departure time is also included.

The Heckman correction term for sample selection described in the previous section is represented by λ. The carrier fixed effect is identified by the parameter ρ_c, and δ_t is the time fixed-effect, represented by the day of the week when the flight is scheduled to depart. Finally, σ_{fcrt} is the regression error, assumed random with zero mean.

In its essence equation (2) specifies how the temporal slope (β) and the intercept (α) of a pricing curve vary when we consider flights i) in CS; ii) operated by an OC or a MC; iii) running under parallel or unilateral CS operations.

Because we include an estimated regressor, λ, the standard errors for the coefficients are obtained using a bootstrap method. 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. For instance, in a given week a special event (e.g. a football final, a national holiday, a festival or a concert) may cause an excess of demand on routes where one endpoints is the city where the event takes place.[10]

[10] Clustering is also required because many regressors have common values across observations.

Table 5: The price equation with code-share (CS) - Dep var *log(Price)*.

	(1)	(2)	(3)	(4)
Constant	2.563***	2.457***	2.288***	2.347***
	(0.075)	(0.069)	(0.065)	(0.099)
Code-share		0.108***	0.084***	0.087***
		(0.015)	(0.015)	(0.015)
Marketing carrier			0.145***	0.142***
			(0.013)	(0.013)
Parallel CS				-0.092
				(0.064)
BookDay	0.335***	0.361***	0.360***	0.236***
	(0.007)	(0.008)	(0.008)	(0.010)
BookDay * Code-share		-0.070***	-0.098***	-0.105***
		(0.013)	(0.016)	(0.016)
BookDay * Marketing carrier			0.077***	0.082***
			(0.017)	(0.017)
BookDay * Parallel code-share				0.192***
				(0.011)
log(Distance)	0.204***	0.210***	0.242***	0.241***
	(0.011)	(0.011)	(0.010)	(0.010)
log(Fuel price)	0.110**	0.101*	0.118**	0.118**
	(0.053)	(0.053)	(0.053)	(0.053)
Hub	0.021**	0.028***	0.032***	0.033***
	(0.009)	(0.009)	(0.008)	(0.008)
Population density	-0.338***	-0.327***	-0.292***	-0.294***
	(0.025)	(0.025)	(0.025)	(0.025)
Herf. index (-1m)	0.360***	0.350***	0.320***	0.320***
	(0.026)	(0.026)	(0.027)	(0.027)
Late morning (10am-2pm)	-0.018***	-0.019***	-0.018***	-0.017***
	(0.003)	(0.003)	(0.003)	(0.003)
Afternoon (2pm-6pm)	-0.019***	-0.021***	-0.019***	-0.020***
	(0.003)	(0.003)	(0.003)	(0.003)
Evening (6pm-0am)	-0.007***	-0.009***	-0.011***	-0.011***
	(0.003)	(0.002)	(0.002)	(0.002)
Heckman's lamda	-0.080***	-0.069***	-0.058***	-0.058***
	(0.004)	(0.004)	(0.004)	(0.004)
R^2	0.369	0.373	0.383	0.388
Observations	2,956,562	2,956,562	2,956,562	2,956,562

(a) Bootstrap standard errors in parenthesis, clustered by route-week.
(b) *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.
(c) All models include airline and day-of-the week fixed effects.

Table 5 reports the estimates of the pricing equation (2) with different restrictions on the CS coefficients. In column (1) we do not differentiate for CS agreements; in column (2) we add the *Code-Share* dummy and its interaction with the *BookDay* variable; in column (3) we also include the *MC* dummy and interactions, and, finally, in column (4) we consider the full model of equation (2), which also includes the *Parallel* dummy and relative interaction.

The coefficient on *BookDay*, 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 0.236 to 0.361 indicates that on average fares increase by 0.48% - 0.74% each day.[11] 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 6 summarizes the intercept and slope parameters and its estimations. As far as the intercept is concerned, it appears that fares under CS are higher than in the case of no CS, regardless of the type of carrier: 2.565 versus 2.457. The difference of 0.108 indicates that the fare of an airline under CS is about 10.96% higher than in the absence of CS.[12] The MC is on average more expensive than the OC (MC intercept equal to 2.517, which is higher that OC intercept equal to (2.372): this finding is in line with what is depicted in Figure 1.

Table 6: Interpretation of the intercept and slope.

Model*	Carrier	Parameters** Intercept/Slope	Estimation Intercept	Slope
(2)	Carrier not in CS	π_0	2.457	0.361
(2)	Carrier in CS	$\pi_0 + \pi_1$	2.565	0.291
(3)	OC in CS	$\pi_0 + \pi_1$	2.372	0.262
(3)	MC	$\pi_0 + \pi_1 + \pi_2$	2.517	0.339
(4)	OC in unilateral CS	$\pi_0 + \pi_1$	2.434	0.131
(4)	OC in parallel CS	$\pi_0 + \pi_1 + \pi_3$	2.343	0.323
(4)	MC in unilateral CS	$\pi_0 + \pi_1 + \pi_2$	2.576	0.213
(4)	MC in parallel CS	$\pi_0 + \pi_1 + \pi_2 + \pi_3$	2.484	0.406

* The model number corresponds to the column of Table 5.

** Intercept parameters emerge when $\pi = \alpha$ and slope parameters emerge when $\pi = \beta$.

[11] 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 0.236*1/49=0.0048=0.48% and 0.362*1/49=0.0074=0.74%.

[12] The percentage numbers stem from the formula in Wooldridge (2012): $100(\exp(\hat{\beta})-1)\%$, which computes the marginal effect in percentage terms of a dummy variable when the dependent variable is expressed in logarithmic form; $\hat{\beta}$ is the estimated coefficient of the dummy variable.

The larger coefficients on *Code-share* and the smaller on the interacted term *BookDay* * *Code-share* 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 bookers travelers. Conversely, late bookers, usually business travelers, appear to gain from CS practices since they may 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 offers a graphical representation of the econometric results: on the Y-axis we report the logarithm of fare and on the X-axis the booking days. The north-west diagram represents the estimates of column (2) of Table 5. The north-east diagram depicts the situation reported in column (3) of Table 5. The two remaining bottom diagrams stem from column (4) of Table 5, they depict, in the case of unilateral and parallel code-share, the pricing profile of respectively the OC (south-west diagram) and the MC (south-east diagram).

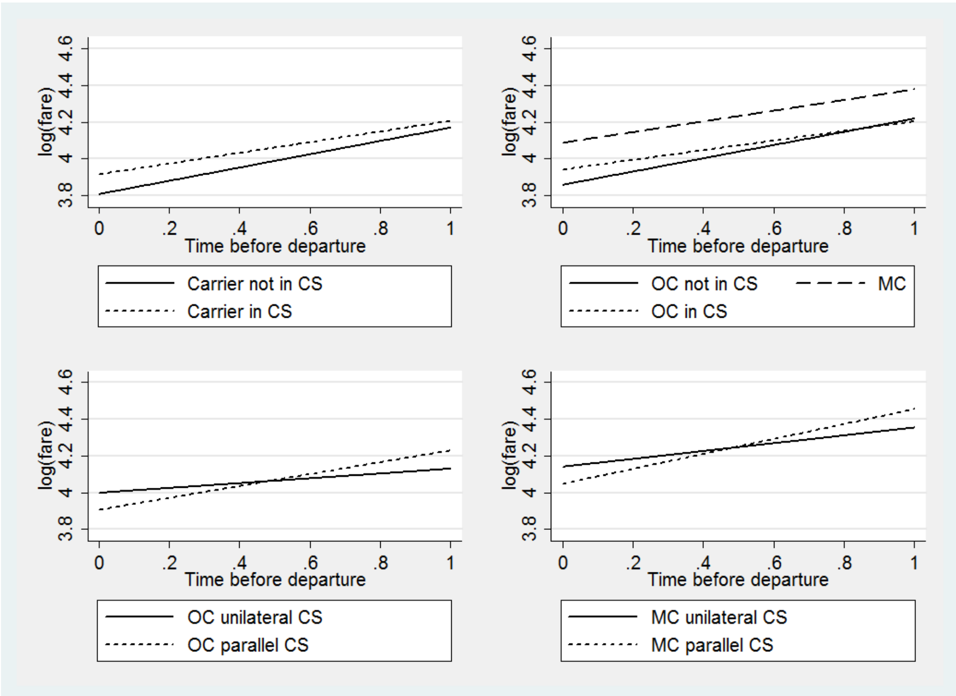

Figure 2: Graphical illustration of the estimates in Table 5.

Consider the case of an OC in the top right panel of the Figure 2 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 take-off day approaches. If the airline considered is the MC, the slope of the line is similar to that of an OC not in CS, but the former line is well above the latter, in line with the statistics reported in Table 3.

These results suggest that because some passengers are brand loyal, CS 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 returns 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 significant gap with that offered by the MC.

Returning to the estimates in Table 6, both in the case of the OC and of the MC, CS under parallel operations is characterized by a steeper slope relative to the case of CS under unilateral operations: 0.323 versus 0.131 for OC and 0.406 versus 0.213 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) hold only in the early part of the booking period, whilst during the last month before the take-off the fares under parallel CS overcome the fares under unilateral CS for both types of partners. Thus, parallel pricing favors leisure travelers and damages business ones.

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.

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 v_2 represents the elasticity of fares to the price of jet fuel, 0.36 means that a one-percent increase of jet fuel translates into a 0.10%-0.12% higher fares. This effects 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 1.55%.

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 6.08%.

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. Finally, the time of departure dummies indicates that afternoon, late morning and evening flights are, respectively, cheaper by about 2%, 1.8% and 1.1% than early morning flights.

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 by CS especially under unilateral CS. Buying in advance to try to get cheap fares is not so beneficial since carriers apply a flat temporal profile under unilateral CS. 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 which, even in the absence of a CS 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.

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Appendix: number of routes by carriers with/without code-share

Table 7: Number of routes offered by carrier with and 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