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How do global airline alliances affect flight frequency? Evidence from Russia[☆]

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ABSTRACT

This paper analyzes the effects on flight frequency of two alliances that came about in the Russian airline market in recent years: between Aeroflot and SkyTeam in 2006, and between S7 and oneworld in 2010. We use a difference-in-differences (DID) model to identify the effects of these alliances on flight frequencies. The integration of S7 into oneworld provides evidence that the alliance resulted in reduced flight frequencies on routes where S7 overlapped with its new partners, but that it resulted in increased frequencies on routes where there was no overlap, especially in the case of so-called *thin* routes. Regarding the integration of Aeroflot into SkyTeam, we find that the alliance led to increased flight frequencies on routes where Aeroflot and its new partners had previously been competing. The fact that Aeroflot is a state-owned airline with a strong position in the Russian market might explain this expansion after the alliance. We also find that the alliance increased the frequencies on thin routes where there was no overlap.

1. Introduction

Airline alliances have shaped the air transport market over the past three decades.[1] Alliances are voluntary agreements between airlines that contain different features affecting pricing and marketing collaboration, mutual recognition of frequent-flyer programs, code-sharing, cooperative schedule planning, or the joint use of airport services like ground handling and catering.[2] The economic literature has debated at length the effects of alliances on fares, traffic and consumer welfare. Consumers can benefit from such agreements through reductions in the cost of connecting flights and the expansion of airlines to reach more destinations (Bruckner and Whalen, 2000; Bilotkach, 2005; Flores-Fillol and Monquer-Colonques, 2007). Nonetheless, alliances can generate negative effects in the routes in which their members were initially competing, if they gain sufficient market power and are able to increase their prices and reduce flight frequencies (European Commission, 2010; Bilotkach and Hüschelrath, 2013).

This paper analyzes the effects on flight frequencies of two alliances that came about in the Russian airline market in recent years[3]: the alliance between Aeroflot and SkyTeam that took place in 2006, and the alliance between S7 and oneworld that became effective in 2010. SkyTeam and oneworld are two of the major global airline alliances. At the beginning of 2020, SkyTeam included 19 carriers from five continents, flew to more than 1030 destinations in about 170 countries and operated more than 15,440 flights daily (Mazareanu, 2020; SkyTeam press release, 2020). Meanwhile, oneworld had 14 members and 30 affiliated airlines, served about 1100 airports in more than 180 territories with approximately 14,000 daily departures (oneworld press release, 2020).

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[1] Alliances became common in the 1990s, after KLM and Northwest Airlines signed a large-scale code-share agreement in 1989 (Wickson, 2017). In the following years several new global alliances were created, the largest being Star Alliance (created in 1997), oneworld (created in 1999) and SkyTeam (created in 2000).

[2] Airlines within an alliance can attain greater degrees of cooperation on specific routes when they are granted antitrust immunity (ATI) by competition authorities. In these cases, they cooperate not only with frequencies, but also with prices. Furthermore, joint ventures allow partners to share costs on particular routes. The integration of Aeroflot and S7 into international alliances implied a lesser level of cooperation.

[3] Russia has one of the largest air transport markets in Europe. At the end of 2019, it was the 7th European market in terms of seat capacity after the United Kingdom, Germany, Spain, Italy, France, and Turkey (Sinitsky, 2019). According to the IATA, it was one of the markets with the greatest expansion.

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Since the seminal paper by Brueckner (2001), two different effects of airline alliances have been identified in terms of prices and quantities. In inter-line routes (i.e., flights with at least one stop where passengers change plane en route) alliances eliminate the double marginalization and reduce transaction costs for connecting flights, which generates a "market expansion effect" that increases traffic.[4] In inter-hub routes (i.e., non-stop flights that connect the hub airports of the different alliance partners), alliances may have negative consequences for passengers, depending on the initial level of competition between the alliance partners. In the inter-hub routes in which alliance's partners where initially overlapping, the alliance can reduce competition, leading to higher fares and less traffic. However, this "competition effect" can be compensated by a "market expansion effect" when the alliance generates a sufficiently large increase in the number of interline passengers (connection passengers). In inter-hub routes without overlapping, the "competition effect" does not exist and the alliance can only generate a "market expansion effect".

The objective of this paper is to analyze the effect of the alliance of Aeroflot in Skyteam and of S7 in oneworld in the flight frequencies of the inter-hub routes affected by these agreements. Specifically, we want to examine whether in inter-hub routes with overlapping the "market expansion effect" was relatively more important than the "competition effect" and there was an increase of flight frequencies. Indeed, the increase in the share of connecting passengers could lead airlines to offer more frequencies and to optimize the bank of arrival flights in their hubs to minimize missed connections. For similar reasons, inter-hub routes without overlapping should experience an increase of frequencies.

Recent theoretical and empirical literature has examined the effects of alliances in the frequencies of inter-line routes. Regarding theoretical studies, Czerny et al. (2016) show that airline collaboration can increase frequency supply by eliminating airlines' strategic reduction of frequencies. Czerny et al. (2021) show that allied carriers are more inclined to expand networks and/or increase frequency supply than independent carriers, and that antitrust immunity can eliminate double marginalization and create incentives to extend networks. Brueckner and Flores-Fillol (2020) show that when airlines frequencies are aligned (zero layover costs) alliances lead to a higher frequency as double marginalization is eliminated. However, alliances can reduce frequencies when airlines have different types of consumers (high-cost layover time) and initially offer different frequencies. There is also a large empirical evidence supporting the idea of a market expansion effect of alliances in these routes (Brueckner and Whalen, 2000; Brueckner, 2003; Whalen, 2007; Brueckner et al., 2011; Calzaretta et al., 2017; Brueckner and Singer, 2019; Fageda et al., 2019, 2020).[5]

The literature is much less conclusive on the potential effects of alliances in inter-hub routes. On the one hand, Oum et al. (1996), Park and Zhang (1998), Brueckner and Whalen (2000), Gayle and Brown (2014) and Fageda et al. (2019) do not find evidence of anti-competitive effects. On the other hand, Gillespie and Richard (2012), Alderighi et al. (2017) and Brueckner and Singer (2019) find that alliances reduce competition, while Bilotkach and Hüschelrath (2013) obtain mixed results. This study contributes to the literature on inter-hub routes by showing that the impact of alliances on frequencies depends on the characteristics of the airlines participating in the agreement, and on the types of routes that they supply.

Our paper uses a dataset of international flights from European countries to Russian cities from 2002 to 2019. The period covered is sufficiently long to include periods "before" and "after" the creation of the two alliances, so that we can identify changes in the routes affected in comparison to routes not affected. We have monthly data for 1213 different routes that add up 54,208 observations. This contains information on 88 airlines operating in the Russian market. Moreover, we consider 187 non-Russian airports located in 173 cities across 42 European countries and 71 airports located in 68 Russian cities.

We implement a difference-in-differences (DID) model to examine the effects of the alliances. Specifically, we compare the difference in flight frequencies on the inter-hub routes affected by the alliances (our treatment group) before and after the cooperation agreements came into effect, relative to the difference for routes not affected by alliances (control group) between the same two periods. At this point, it is important to clarify that one difficulty in identifying the causal effect of the alliances is that the airlines participating on them might choose their partners for strategic reasons. Thus, for example, they can look for airlines that complement their networks and that facilitate their expansion plans. The endogeneity in the alliance formation could impose an estimation bias that must be taken into account in the interpretation of results.

We find evidence that the integration of S7 into oneworld alliance reduced flight frequencies on the routes for which S7 overlapped with their new partners. However, our results also show an increase in the flight frequencies on routes without overlapping, specifically in the case of thin routes. This suggests that for this alliance the competition effect could be larger than the market expansion effect in overlapping inter-hub routes, and that there was a positive market expansion effect in non-overlapping routes that generated an increase in frequencies. Moreover, our results for thin routes imply that these types of routes can benefit more from the reorganization of operations and from the increase of density economies.

Regarding the integration of Aeroflot into SkyTeam, we find that the alliance increased flight frequencies on routes where Aeroflot and its new partners previously competed. We also find that the alliance increased frequencies on thin routes without overlapping. As in the case of S7, this effect could be explained by the complementarities between the airline and its new partners, and by elimination of the double marginalization for connecting flights.

Overall, our results suggest that the complementarities of the airlines participating in an alliance might have a relevant effect on flight frequencies.[6] While overlapping inter-hub routes are affected by a competition and a market expansion effect, non-overlapping routes benefit from a market expansion effect that increases the number of connecting passengers and can increase flight frequencies. Another relevant result of our analysis is that the participation of SkyTeam and oneworld in the alliances had different effects on the frequencies that they offer in inter-hub routes. Aeroflot is a state-owned airline that might have as an objective to increase the Russian consumers well-being.[7] Hence, the competition effect in routes operated by Aeroflot may be weak. Furthermore, Aeroflot is much bigger than S7 so that the market expansion effect may be stronger in routes operated by Aeroflot. Finally, it must be mentioned that the decision of Aeroflot and S7 to participate in different global alliances respond to their different interests and that this can explain why they reconfigured their commercial offer differently after the alliances.

[4] Examples of relevant theoretical works on airline alliances include Park (1997), Park and Zhang (1998), Park et al. (2001), Hassin and Shy (2004), Bilotkach (2005, 2007), Heimer and Shy (2006), Zhang and Zhang (2006), Flores-Fillol and Moner-Colonques (2007) and Brueckner and Proost (2010).

[5] Bilotkach (2019) reviews this literature and shows that most papers focus on the effects of alliances on prices and on traffic. See also Zhang and Czerny (2012) for an analysis of the previous studies on airline alliances.

[6] Alliances select new partners considering the complementarity of their routes and manage their routes internalizing their interests (Lordan et al., 2015). In the case of inter-line routes, they reduce double marginalization and favor increased traffic (Brueckner and Singer, 2019). When they have many overlapping routes (parallel alliances), they can reduce frequencies to relax competition (Bamberger et al., 2004).

[7] In 2020, the Russian Government owned 51% of Aeroflot through the Federal Agency for State Property Management. The rest of the shares were in the hands of public investors.

The rest of the paper is organized as follows. Section 2 presents some general characteristics of the Russian air market and describes the two alliances we study. Section 3 describes the data used in the analysis, and Section 4 explains our empirical strategy. In Section 5, we report the main results of the empirical analysis and finally, Section 6 summarizes our conclusions.

2. The Russian market and the alliances

The Russian air passenger market has been relatively underdeveloped for years, with low passenger volumes and limited entry of foreign airlines (Chsherbakov and Gerasimov, 2019). In part, this has been attributed to the substantial number of technological, structural, and administrative barriers to market entry that existed in Russia at the beginning of the 21st century (Lykyanov et al., 2018). Since the collapse of the Soviet Union, all bilateral agreements with the largest European countries had solely involved Aeroflot, the major state-owned airline. However, in 2010 the government liberalized international air travel, mainly on routes that connected with European countries (Tasun, 2015). Between 2010 and 2013, a "second" and then a "third" designated air carriers started to operate on most of the routes connecting Russia with European countries.[8] An "open skies" policy is currently active at the airports of Vladivostok (since 2011), Sochi (since 2014), Kaliningrad (since 2015), and Saint Petersburg (2020). Since the early 2000s, air traffic has growth at an annual rate of 10%, reflecting the liberalization of the market and the internationalization of the Russian economy. This process has developed in parallel with the expansion of the European market, both in terms of traffic and the number of routes operated (Calzada and Fageda, 2019).

Market concentration has increased to a considerable degree in the last years. While in 2004, around 99% of both the domestic and international passenger traffic was operated by 85 airlines, in 2019 that traffic was operated by just 35 airlines. In the same period, the market share of the top five airlines increased from about 49% to 67%, and the market share of the 15 largest airlines increased from 70% to 73%. In 2020, the five biggest airlines in Russia, by passenger traffic, were Aeroflot, S7 Airlines, Rossiya, Ural Airlines and Pobeda (Russian Aviation Insider, 2020). Aeroflot is Russia's largest state-owned airline and the biggest airline in terms of passenger traffic, carrying 37.2 million passengers, in 2019. The second largest airline in the country is the privately owned S7, which carries 14 million passengers per year. The third largest is Rossiya Airlines (75% owned by Aeroflot) that in 2019 served 11.6 million passengers. The fourth is Ural Airlines that served 9.6 million passengers in 2019. In fifth place, Pobeda (another Aeroflot subsidiary) raised its passenger numbers to almost 9.6 million.[9] Note that neither Rossiya airlines nor Pobeda are members of the SkyTeam alliance even though they are subsidiaries of Aeroflot. Fig. 1 shows the evolution of the annual passenger traffic for Aeroflot and S7 since 2013. Aeroflot has remained the market leader with a permanent rise in the number of passengers.

The integration in global alliances have been an important factor for the internationalization of the Russian market. Aeroflot initiated negotiations to become a member of the SkyTeam alliance in 2001, and its participation in the alliance started on April 14, 2006. Launched in 2000, SkyTeam includes 19 airlines from five continents. At the beginning of 2020, this alliance connected more than 1036 destinations in around 170 countries and operated more than 15,445 flights daily, with 676 million annual passengers (SkyTeam press release, 2020). The agreement between Aeroflot and SkyTeam was intended to increase the number of flights operated jointly between the partners, while maintaining their own route network. Each SkyTeam member was a natural leader in its region, so Aeroflot was well positioned to strengthen the role of Moscow as the main entry point into Russia (Vasilchenko, 2010). Aeroflot helped SkyTeam to cover new markets in the Commonwealth of Independent States and Eastern Europe. In turn, the alliance allowed Aeroflot to expand into Europe, Africa, and north and south America, as well as to open up to the Middle East market.

The integration of S7 into oneworld took place on November 15, 2010. The oneworld alliance became operational in 1999 and currently includes 14 members, as well as Fiji Airways as a regional partner, and 30 affiliated airlines on six continents. In 2019, oneworld carried more than 550 million passengers per year. Initial information on the negotiations between S7 Airlines and oneworld appeared in the summer of 2007. Vladislav Filev, general director of S7, explained that the integration of the airline into a global alliance was inevitable for such a large network carrier as S7 Airlines (Aviation news journal ATO. ru).

3. The data

Our empirical analysis considers a dataset of international flights between European and Russian cities, from 2002 to 2019. Data availability determines the timeframe of our analysis, which is sufficiently long to include several periods before and after the alliance agreements. The dataset includes 54,208 observations at the route level.

Data on air services supply comes from RDC aviation (Apex schedules). In particular, we have information on the number of flights provided by airlines at the route level on a monthly basis. Information on the gross domestic product per capita at the country level has been retrieved from the World Bank (World Bank Development Indicators), and data for population at the urban level has been obtained from the United Nations (World Urbanization Prospects). Data for income and population is annual.

The sample covers 88 airlines, including network, regional and low-cost carriers. The carriers of primary interest are European members of oneworld (Air Berlin, British Airways, Finnair, Iberia and S7 Airlines) and SkyTeam (Aeroflot, Air Europa, Air France, Alitalia, Czech Airlines, KLM and TAROM), which scheduled flights to Russia in the period we examine. Most of the airlines belonging to these alliances are former flag carriers of their countries.

Our analysis also considers 187 non-Russian airports located in 173 cities in 42 countries (countries from the European Economic Area plus Switzerland, United Kingdom, the former Yugoslavia and several countries in the CIS). As destinations, we consider 71 international Russian airports located in 68 cities. Moscow-Domodevodo (DME) and Moscow-Sheremetyevo (SVO) are hubs for oneworld and SkyTeam, respectively. Novosibirsk-Tolmachevo (OVB) is also a hub for S7, although this airport is not a destination for international flights from European countries.

Table 1 provides traffic statistics for the four largest airports in Russia, including three airports in Moscow (Sheremetyevo, Domodedovo and Vnukovo) and Saint Petersburg. We show the information for 2005, which is the year before the integration of Aeroflot in Skyteam, and for 2009, which is the year before the integration of S7 in oneworld. For comparison reasons, we also include information for 2019, which is the last year in our dataset. Aeroflot has a dominant position at Moscow Sheremetyevo with a share well above 50% in all considered years. S7 has a strong position at Moscow Domodedovo with a share that is in all years above 25%.

The presence of Aeroflot and S7 in Moscow Vnukovo and Saint Petersburg airports was irrelevant in the years before the alliance agreements. The presence of these airlines increased over time in Saint

[8] An agreement was reached with Italy for the Moscow-Rome and Moscow-Milan routes, and with France for the Moscow-Paris and Moscow-Nice routes. Niki (an Austrian airline) also entered the Russian market via an intergovernmental agreement between Russia and Austria. The second designated carrier was introduced on the Moscow-Prague route in 2014 and on the Moscow-Helsinki route in 2013.

[9] Low-cost carriers (LCCs) have a small, but increasing, presence in the country (Sinitsky, 2019). In 2019, the share of LCCs reached almost 10% of domestic seats and 6% of international seats.

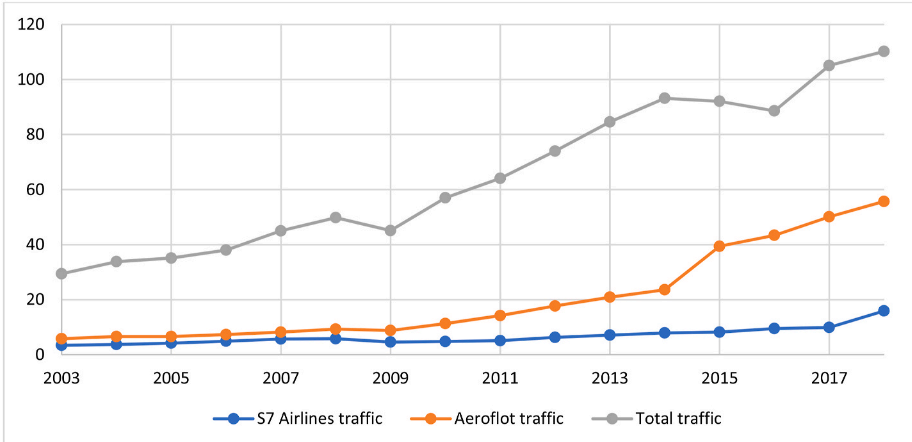

Fig. 1. S7 Airlines, Aeroflot and total Russian-based airline traffic (in millions of passengers)
Source: Our own elaboration based on the annual reports of S7 Airlines, Aeroflot and the Russian Federal Air Transport Agency.

Table 1
Traffic indicators of the largest airports in Russia.

	2005			2009			2019		
	Total flights	Share Aeroflot	Share S7	Total flights	Share Aeroflot	Share S7	Total flights	Share Aeroflot	Share S7
Moscow (SVO)	65,918	56%	0%	71109	62%	0%	177068	83%	0%
Moscow (DME)	47,248	0%	28%	79142	0%	26%	86528	0%	44%
Moscow (VKO)	17,016	0%	0%	41087	0%	0%	69269	0%	0%
Saint Petersburg (LED)	25,776	4%	1%	38426	8%	3%	51233	15%	12%

Petersburg, but it is still very modest in comparison to the dominant role of Aeroflot in Moscow Sheremetyevo and of S7 in Moscow Domodedovo. Moreover, the total number of flights in Saint Petersburg is lower than in the two major airports of Moscow. These data imply that Saint Petersburg is not a hub airport of any of the Russian airlines involved in alliances. Taking this into account, our analysis of the effect of the alliances on the flight frequencies of inter-hub routes will only consider as treated the routes having Sheremetyevo and Domodedovo airports as endpoints.

Table 2 shows the list of the inter-hub routes considered in our analysis. Column 3 shows the airline that uses each endpoint airport as a hub, while column 4 shows the airlines that are effectively operating the route. Thus, carriers that are no listed in column 4 are alliance partners that have a hub in the airport but that do not provided service on the route.

Most of the routes linking hubs in the SkyTeam alliance are operated by both alliance partners during the whole period we consider. This is the case of the routes that link Amsterdam, Paris CDG, Rome FCO, Milan MXP and Prague to Moscow SVO. The exceptions are the route Bucharest to Moscow SVO where Aeroflot operates as a monopoly in most of years/months, and the route Madrid to Moscow SVO where Aeroflot operates as a monopoly in the entire period. For the oneworld alliance, only the routes from Madrid and Dusseldorf to Moscow DME are operated by both alliance partners in much of the considered period. In this regard, it is remarkable to mention the exit by S7 in the route Madrid-Moscow DME. On the other routes, either S7 or its partner is offering flights (in some cases discontinuously). Note that S7 is a smaller airline than Aeroflot and several of its oneworld partners (Air Berlin, Finnair) are also relatively small airlines.

In addition to these routes, our dataset includes 952 non-alliance routes connecting European airports, 818 of which do not have one of the two major airports in Moscow as their endpoint. Many different types of carriers provide services in these non-alliance routes.

Finally, Fig. 2 shows the evolution of the frequencies on the routes affected by the alliances in the period we study. In the case of S7, the figure shows a growth in frequencies before the alliance in 2010 and an important decrease in frequencies afterwards. The figure also shows a pre-trend growth on the routes affected by the SkyTeam alliance. The increase in frequencies on those routes is maintained after the alliance is in force.

4. Empirical model

The objective of this paper is to examine the impact of the integration of Aeroflot into the SkyTeam alliance and of the integration of S7 into the oneworld alliance, on the flight frequencies offered on inter-hub routes. We consider that a route is affected by an alliance when it has as its endpoints primary hubs of the non-Russian airlines participating in the alliances and the hubs of Aeroflot and S7. A similar approach to identify routes affected by alliances have been used in Park and Zhang (1998), Gillespie and Richard (2012), Bilotkach and Hüschelrath (2013) and Fageda et al. (2019, 2020).

In order to examine the effect of the alliances we implement a difference-in-differences (DID) model that considers the integration of Aeroflot and S7 in the alliances as a shock in the market. More specifically, the DID regression allows us to compare the difference in the flight frequencies on the routes affected by the alliances (the treated routes) before and after the agreements took place, relative to routes not affected by the alliances (control routes) in the same two periods.

DiD analysis is a common methodology used in the treatment evaluation framework (Angrist and Pischke, 2009; Gertler et al., 2016). The identification strategy in a DID consist in comparing the results for two groups of observations: one group affected by the treatment/shock at some point during the considered period, and a control group not affected by the treatment/shock. In our context, we have a panel dataset that includes routes affected by alliances (treated routes) and routes not affected by alliances (control routes). Hence, the DID variable in our analysis is a dummy variable that takes a value of one for routes affected by alliances since the period in which these took place. Therefore,

Table 2
Routes inter-hub affected by alliances.

Route	Alliance	Hub/airline	Airlines within alliances offering flights
Amsterdam to Moscow SVO	SkyTeam	Amsterdam/KLM, Moscow SVO/Aeroflot	Aeroflot & KLM (all periods)
Bucharest to Moscow SVO	SkyTeam	Bucharest/Tarom, Moscow SVO/Aeroflot	Aeroflot until Feb. 2014, Aeroflot & Tarom since Mar. 2014 until Dec. 2016, Aeroflot since Jan 2017
Paris CDG to Moscow SVO	SkyTeam	Paris CDG/Air France, Moscow SVO/Aeroflot	Aeroflot & Air France (all periods)
Rome FCO to Moscow SVO	SkyTeam	Rome FCO/Alitalia, Moscow SVO/Aeroflot	Aeroflot & Alitalia (all periods)
Madrid to Moscow SVO	SkyTeam	Madrid/Air Europa, Moscow SVO/Aeroflot	Aeroflot (all periods)
Milan MXP to Moscow SVO	SkyTeam	Milan MXP/Alitalia[2], Moscow SVO/Aeroflot	Aeroflot & Alitalia (all periods)
Prague to Moscow SVO	SkyTeam	Prague/Czech airlines, Moscow SVO/Aeroflot	Aeroflot & Czech airlines (all periods)[4a]
Dusseldorf to Moscow DME	oneworld	Dusseldorf/Air Berlin[3], Moscow DME/S7	Discontinuous service of Air Berlin and S7[4b]
Helsinki to Moscow DME	oneworld	Helsinki/Finnair, Moscow DME/S7	Discontinuous service of S7
London LHR to Moscow DME	oneworld	London LHR/British Airways, Moscow DME/S7	British Airways (all periods)[4c]
Madrid to Moscow DME	oneworld	Madrid/Iberia, Moscow DME/S7	Iberia & S7 until Jul-2017, only Iberia since Aug. 2, 017[4c]
Berlin TXL to Moscow DME	oneworld	Berlin TXL/Air Berlin[3], Moscow DME/S7	Air Berlin until 2015, S7 since 2016[4b]

Notes: 1) By discontinuous service, we mean that the route is operated in some but not all months of the year. 2) Hub of Alitalia until march 2008.3) Air Berlin ceased operations in October 2017.4) Non-alliance partners offering services: 4a. Smartwings offer flights since 2015, 4 b. Discontinuous service of Germania, Germanwings, Lufthansa and Transaero, 4c. Discontinuous service of Transaero.

controlling for all relevant observable characteristics of the routes, we can identify changes in flight frequencies on treated routes compared to changes in flight frequencies on control routes.[10]

Our analysis focuses on the total flight frequencies (across all carriers) in nonstop routes connecting European and Russian cities. Taking this into account, we estimate the following two equations at the route level *i* for year *y* and month *m*:

$$\text{Flight\_frequency}_{\text{iym}} = \beta_0 + \beta_1\text{Alliance}_{\text{iym}} + \beta_2\text{No\_overlap}_{\text{iym}} + \beta_3\text{Alliance x No\_overlap}_{\text{iym}} + \beta\text{X}_{\text{iy}} + \delta_{\text{i}} + \lambda_{\text{y}} + \gamma_{\text{m}} + \varepsilon_{\text{iym}} \tag{1}$$

$$\text{Flight\_frequency}_{\text{iym}} = \beta_0 + \beta_1\text{SkyTeam}_{\text{iym}} + \beta_2\text{oneworld}_{\text{iym}} + \beta_3\text{No\_overlap}_{\text{iym}} + \beta_4\text{SkyTeam x No\_overlap}_{\text{iym}} + \beta_5\text{oneworld x No\_overlap}_{\text{iym}} + \beta\text{X}_{\text{iy}} + \delta_{\text{i}} + \lambda_{\text{y}} + \gamma_{\text{m}} + \varepsilon_{\text{iym}} \tag{2}$$

have different objectives. Equation (1) examines the overall effect of alliances in the Russian market. In this equation, the variable *Alliance* identifies the inter-hub routes affected by both the integration of Aeroflot into SkyTeam and that of S7 into oneworld.

The aim in equation (2) is to disentangle a potential differential effect of the integration of Aeroflot into Skyteam and of S7 into oneworld. Hence, the equation considers two dummy variables *SkyTeam* and *oneworld*. *SkyTeam* takes the value 1 after April 2006 for inter-hub routes of Skyteam partners, while *oneworld* take the value 1 after November 2010 for inter-hub routes of oneworld partners.

The dependent variable in models (1) and (2) is *Flight Frequency*, which is the number of flights offered by airlines on each route *i*. Flight frequency is considered to be the main indicator of service quality in aviation, as it determines the schedule delay cost experienced by consumers (the difference between the actual and desired time of departure). Our data do not show variations in the size of the aircraft used on either the treated or control routes in the period considered. Hence, flight frequency is also a strong indicator of the seats capacity offered by airlines in each route. In fact, the results we obtain are essentially identical whether we use the total number of flight frequencies or total seat capacity as the dependent variable.

The main explanatory variable in the two equations is a dummy variable (the DID indicator) that takes the value 1 after the month and year in which the route was affected by an alliance. The two equations

The two models also include the variable *No Overlap*, which takes the value 1 when the route presents no network overlap between Aeroflot and a SkyTeam partner, or between S7 and a oneworld partner. This variable takes a value of 0 when there is overlap. The models also include the interactions between the variables *Alliances* and *No Overlap*. Considering this, the un-interacted coefficient of *Alliances* shows the effect of alliances on routes with an overlap on flight frequencies, while the coefficient of the interaction between *Alliances* and *No Overlap* shows how this effect is altered on routes without an overlap.

As explained in the introduction, the existence of a “competition effect” that reduces the number of flight frequencies could be relevant on routes in which the new and the existing members of the alliance were operating before the agreement. The alliances could facilitate frequency coordination, leading airlines to offer fewer flights and set higher prices. By contrast, the "market expansion effect" could be present both on routes with and without overlapping of the partner airlines, as alliances can increase the volume of connecting passengers. Taking this into account, the sign of the variable *Alliance* can be positive or negative, depending on the net effect of the competition and market

[10] Examples of recent studies that apply the DiD in the transportation sector include Aguirre et al. (2019), Bernardo and Fageda (2017), Conti et al. (2019), Haojie Li et al. (2012), Jiménez et al. (2018), Oum et al. (2019) and Wolff (2014).

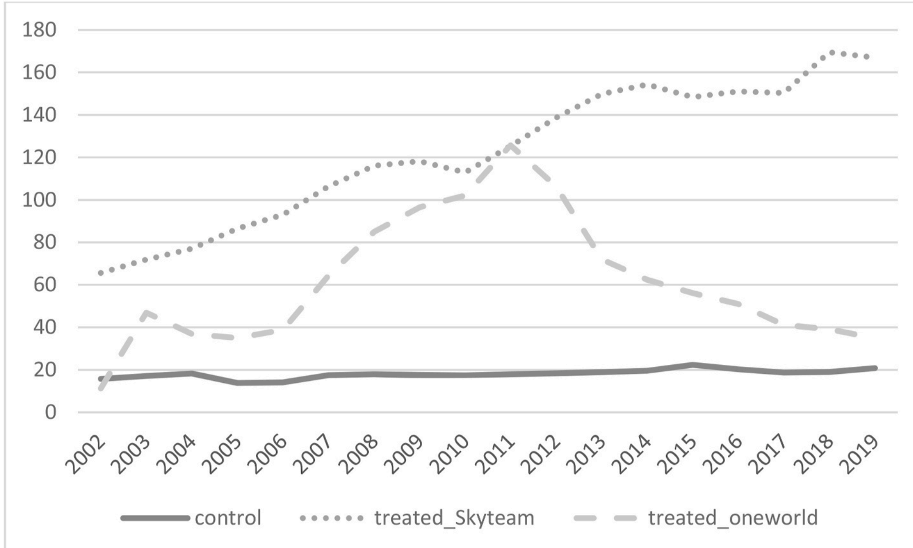

Fig. 2. Mean flight frequency over time.

expansion effects, and the sign of the interaction between the variables *Alliances* and *No overlap* should be positive, as in this case there is not a competition effect.

The estimated model also includes a vector of controls (X_{it}) that reflect additional aspects that might influence the number flights offered on the route. In aviation studies, it is commonly assumed that airlines first make supply decisions and then they adjust fares according to the evolution of demand. Hence, fares are not considered to be an explanatory variable in supply equations. By contrast, demand shifters (population, income, distance) and the intensity of competition are typically considered major determinants for airlines' supply choices. Examples of studies that estimate supply equations for air routes using a similar approach as in our model include Schipper et al. (2002), Richard (2003), Bettini and Oliveira (2008), Fageda and Flores-Fillol (2012), Fageda (2014), Calzada and Fageda (2019) and Brueckner and Luo, (2014).

Air transportation demand is usually modelled as a gravity equation in which passenger volumes depend positively on the income and population at both endpoints of the route, and negatively on the distance.[11] Given the strong positive correlation between demand and supply, our model includes as controls the key variables usually considered in gravity models for demand functions. Specifically, it includes as regressors the weighted mean population of the origin and the destination cities of the routes (*Population*), and the weighted mean gross domestic product per capita of the origin and the destination countries of the route (*Income*). Weights are based on population of each origin and destination on the route. Flight frequencies should be higher on routes with high demand that connect larger and richer endpoints. Thus, we expect a positive effect of population and income on flight frequencies.

Our model also includes two variables that capture the intensity of competition at the route level. It is well established in the literature, both theoretically and empirically that airlines compete in frequencies (eg; Berry and Jia, 2010 Bilotkach et al., 2010; Brueckner, 2004; Brueckner and Flores-Fillol, 2007; Brueckner and Luo, 2014; Schipper et al., 2007; Brueckner and Flores-Fillol, 2020; Czerny et al., 2021). Considering this, our model includes as a control the Hirshman-Herfindal Index (*HHI*), which is based on the sum of squared shares of the seats across airlines offering flights on each route. Furthermore, we include a dummy variable that takes the value 1 on those routes and periods in which LCCs are offering services. We use the list of LCCs provided by the International Civil Aviation Organization (ICAO).[12] We expect that the routes with stronger competition (i.e., low HHI and presence of LCCs) will exhibit more frequencies.

Finally, notice that we estimate a route fixed-effects model that identifies changes from one period to another, as this is the most appropriate method to evaluate the effect of alliances (Verbeek, 2000). Consequently, the model includes route fixed effects (δ_i), year fixed effects (λ_y) and month fixed effects (γ_m). The model is based on the within transformation of the variables as deviations from the average. Thus, it allows us to compare changes in outcomes between routes affected and those not affected by alliances. Furthermore, the route fixed effects control for omitted and time-invariant variables that correlate with the variables of interest. The year fixed effects control for yearly effects common to all routes and the month fixed effects controls for seasonal variations over the year. Finally, ε_{ym} is the error term.

All continuous variables are expressed in log values, as is typical in gravity models (Grosche et al., 2007; Wadud, 2011; and Chang, 2014). Log values reduce the difference between the number of flights across routes and also diminish the influence of outliers and allow for interpretation of the coefficients of alliance variables as percentages. Table 3 shows the descriptive statistics of the variables used in the empirical analysis.

5. Estimation and results

We first estimate our model for the entire sample and then we estimate it for so-called *dense* routes (those with more flights than the sample mean) and for *thin* routes (those with fewer flights than the sample mean). These separate estimations are useful to examine for which type of routes alliances had a stronger net impact. In a theoretical and econometric analysis, Fageda et al. (2019) show that thin routes have a higher potential to profit from density economies after an alliance; whereas dense and congested routes would benefit less from the reorganization of operations between airlines.

As a robustness check, we also run a regression using a matching sample. In this case, to identify the causal effect of the alliances on frequencies, we consider comparable routes affected and not affected by the alliances. It could be that routes affected by the alliances (the treated

[11] See a review of gravity models applied to aviation markets in Grosche et al. (2007), Wadud (2011), and Chang (2014).

[12] According to the ICAO Glossary, an LCC is "an air carrier that has a relatively low-cost structure in comparison with other comparable carriers and offers low fares and rates".

Table 3
Descriptive statistics of the variables used in the empirical analysis.

Variable	Time period and data source	Mean	Standard error	Min. Value	Max. Value
Flight frequency: number of flights per month	2002–2019 RDC aviation (Apex schedules)	33.24	45.1	1	1,051
Population: thousands of inhabitants per year	2002–2019 United Nations (World Urbanization Prospects)	6,871.6	4,521.0	42	14,895
Income: euros per capita per year	2002–2019 The World Bank (World Bank Development Indicators)	12,773.1	6,823.7	1,414.6	78,789.9
HHI: concentration index - monthly seats	2002–2019 RDC aviation (Apex schedules)	0.84	0.27	0	1
Low cost: dummy variable	2002–2019 RDC aviation (Apex schedules), ICAO	0.07	0.26	0	1
Alliance: dummy variable	2002–2019 RDC aviation (Apex schedules)	0.025	0.156	0	1
Oneworld: dummy variable	2002–2019 RDC aviation (Apex schedules)	0.007	0.085	0	1
SkyTeam: dummy variable	2002–2019 RDC aviation (Apex schedules)	0.017	0.132	0	1

Table 4
Results of the estimates – flight frequency.

	All sample		Dense routes		Thin routes		Matched sample	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Population	1.261 (0.290)***	1.252 (0.289)***	2.047 (1.304)	2.120 (1.295)*	0.859 (0.255)***	0.863 (0.255)***	13.413 (20.843)	15.693 (19.268)
Income	−0.043 (0.095)	−0.047 (0.094)	0.153 (0.142)	0.152 (0.137)	−0.107 (0.091)	−0.114 (0.091)	−0.022 (0.257)	−0.185 (0.247)
HHI	−1.211 (0.046)***	−1.209 (0.046)***	−0.733 (0.068)***	−0.722 (0.066)***	−0.972 (0.045)***	−0.973 (0.045)***	−1.100 (0.156)***	−1.058 (0.154)***
Low Cost	0.006 (0.044)	0.005 (0.044)	0.019 (0.037)	0.017 (0.037)	0.028 (0.042)	0.023 (0.042)	−0.036 (0.082)	−0.056 (0.084)
Alliance	−0.016 (0.111)	–	0.065 (0.100)	–	−0.122 (0.174)	–	−0.223 (0.118)*	–
oneworld	–	−0.366 (0.123)***	–	−0.282 (0.039)***	–	−0.375 (0.121)***	–	−0.6259 (0.114)***
SkyTeam	–	0.178 (0.093)**	–	0.238 (0.086)***	–	0.140 (0.079)*	–	0.012 (0.092)
No Overlap	−0.046 (0.037)	−0.058 (0.037)	−0.0039 (0.030)	−0.016 (0.027)	−0.016 (0.039)	−0.025 (0.039)	−0.208 (0.096)**	−0.277 (0.093)***
Alliance X No overlap	0.074 (0.097)	–	−0.103 (0.071)	–	0.303 (0.085)***	–	0.181 (0.139)	–
oneworld X No Overlap	–	0.171 (0.158)	–	0.063 (0.104)	–	0.176 (0.075)**	–	0.333 (0.186)*
SkyTeam X No Overlap	–	0.075 (0.080)	–	−0.085 (0.055)	–	0.211 (0.091)**	–	0.184 (0.123)
Intercept	−6.957 (2.484)	−6.834 (2.474)	−15.43 (11.52)	−16.05 (11.46)	−3.359 (2.085)*	−3.322 (2.083)	−118.057 (190.248)	−137.431 (175.996)
R^2	0.306	0.308	0.38	0.329	0.177	0.178	0.479	0.508
Number of observations	54,149	54,149	15,499	15,499	38,700	38,700	3690	3690

Note: Standard errors in parenthesis (robust and clustered at the route level). All regressions include route, year and month fixed effects. Statistical significance at 1% (***), 5% (**), 10% (*).

routes) correlate strongly with the explanatory variables. To account for this possibility, we apply a propensity score matching procedure and re-estimate equations (1) and (2) with the routes that have common support. See the Appendix for a detailed explanation of the process we follow to obtain the matching sample.

The estimates may present heteroscedasticity and both temporal and cross-sectional autocorrelation problems. We apply the Breusch-Pagan/Cook-Weisberg test for heteroscedasticity and the Wooldridge test for autocorrelation in panel data. Both tests show that there could be problems of heteroscedasticity and of autocorrelation, which need to be addressed. Hence, the standard errors are robust to heteroscedasticity. Following Bertrand et al. (2004), we allow for an arbitrary variance–covariance structure by computing the standard errors in clusters by route to correct for autocorrelation in the error term both at the cross-sectional and temporal levels.

Table 4 shows the results of our estimates. Columns I and II report the estimates for the entire sample. While column I presents the results of the estimation of equation (1), column II shows the estimates of equation (2), where the separate effects of the alliances of Aeroflot and S7 are identified. Meanwhile, columns III and IV show the results for dense routes, columns V and VI those for thin routes, and columns VII and VIII for the matched sample.

Regarding the control variables, we find the expected positive effect for the *Population* variable, although it is not statistically significant in the regression that uses the matched sample. This is not surprising, as the variation in population is much smaller in this reduced sample. In contrast, we do not find evidence of a relevant effect of the *Income* variable, which could be explained by us having used income at the country level rather than at the city level (information at the city level is not available for the entire sample). As expected, the *HHI* variable is negative and statistically significant in all regressions, meaning that airlines offer lower frequencies on routes that are more concentrated. Finally, we do not find a significant impact of the *Low-Cost Airlines* variable. This result can be explained by the modest presence of this type of airlines on the routes that link Russian and European airports.

Results for the un-interacted variable *Alliance* that measures the net result of the competition and market expansion effects of alliances on overlapping routes are ambiguous. The estimate of this variable is only statistically significant (with a negative sign) in the regression that uses the matched sample of treated and control routes. This suggests the existence of a negative effect of alliances on frequencies. In particular, the matching analysis shows that flight frequency is reduced by about 22% on routes affected by alliances in comparison to control routes with similar characteristics.

When we examine the separate effects of the alliances, we find clearly different results for the alliance of Aeroflot with SkyTeam and for the alliance of S7 with oneworld. First, there is a strong negative effect of the alliance of S7 with oneworld on routes with an overlap. Indeed, the un-interacted variable of *oneworld* is negative and statistically significant in all the regressions. The magnitude of the impact is very high, ranging from −28% to −62% lower frequencies on routes affected by this alliance. The largest point estimated is obtained with the matching estimation of column VIII.

Results for the integration of Aeroflot into the SkyTeam alliance are less conclusive. First, we find a positive and significant effect of the alliance when we consider the entire sample (column II), for dense (column IV) and for thin routes (column VI). However, the variable *SkyTeam* is not statistically significant in the regression that uses the matched sample (column VIII). One explanation for this result is the difficulty in finding adequate control routes for routes affected by the alliance, which can reduce the efficiency of the estimators.

Results for no-overlap routes, not affected by the "competition effect", are different. The interaction of the variables *Alliances* and *No Overlap* are no significant when we consider all the sample (column I), dense routes (column III), and the matched sample (column VII), but is positive and significant for no-overlap thin routes (column V). This positive effect on thin routes is confirmed when we consider separately the effects of the alliances with SkyTeam and oneworld (column VI). This suggest that alliances could led to an increase of connecting traffic on thin routes, incentivizing the increase of frequencies.

Overall, we find a positive and significant effect of the alliance of Aeroflot with SkyTeam on the frequencies on routes with an overlap. However, it is important not to infer general causal effects from these results, as airlines might prefer to reach agreements with those alliances that generate more complementarities. Indeed, in the case of Aeroflot, one strategic motivation for this agreement could have been to expand to other markets, and therefore there are other factors in addition to the alliances that can explain the increase in frequencies. Furthermore, results with the matched sample are not conclusive. In contrast, we find clear evidence of a negative causal impact of the alliance of S7 with SkyTeam on overlap routes.

The Aeroflot-Skyteam results are consistent with alliance theory when applied to inter-hub routes that have potential to generate more connecting traffic. In this case, the market expansion effect can dominate the competition effect, and lead to an increase of frequencies. In contrast, S7 is a relatively small carrier that relied on relatively small oneworld alliance partners such as Air Berlin and Finnair. In this case, the capacity of the alliance for building connecting traffic may have been more limited. With the market expansion effect being smaller, the competition effect of the alliances could dominate, leading to lower frequencies.

6. Conclusions

This paper has investigated the impact of the alliance of Aeroflot with SkyTeam in 2006 and of S7 Airlines with oneworld in 2010.[13] Our objective has been to analyze the effects of these alliances on the flight frequencies of the routes that connect airports that function as hubs for the alliance members.

We consider that alliances can generate two types of effects on the frequencies of inter-hub routes. First, on the routes in which alliance's partners overlap before the alliance, alliances can produce an adverse "competition effect" leading to higher fares and less frequencies. Second, alliances can produce a positive "market expansion effect" when they generate an increase in the number of connecting passengers that leads to an increase of frequencies. On inter-hub routes with airline overlapping, the positive "market expansion effect" can compensate the adverse "competition effect", when the increase in the number of connecting passengers is sufficiently large. On inter-hub routes without overlapping, the elimination of the double marginalization and the coordination between airlines can produce a reduction of fares and an increase of connection possibilities that generate a "market expansion effect" and an increase of flight frequencies.

Our analysis shows that the integration of S7 into the oneworld alliance generated an important reduction of flight frequencies on inter-hub routes where S7 and their partners had initially overlapped. Alliances generate economies of density in the operations and additional cost savings for airlines. However, they also facilitate the coordination of partner airlines and increase their market power. In this case, we find that the competition effect was larger than the market expansion effect and generated a reduction in flight frequencies. In contrast, there was an increase in the flight frequencies on routes without overlapping, specifically in the case of thin routes.

In the case of the alliance of Aeroflot with SkyTeam, we found evidence of an increase of flight frequencies on overlapping routes. This result can reflect the continuous expansion that has characterized this airline in the last two decades, and also the complementarities with its new partners. We also show that this alliance increased the flight frequencies on thin routes with no overlap. As in the case of the S7 alliance, this result can be explained by the increase of connecting passengers that resulted after the cooperation between airlines.

Overall, our paper shows that there is not a clear causal effect of the alliances on flight frequencies, and that their effects depend on the characteristics of the participating airlines. In the Russian market, while the alliance between S7 and oneworld had a significant negative effect on flight frequencies, the alliance between the Aeroflot and SkyTeam had a much more neutral (or even positive) impact. These different effects may be explained by the size and type of ownership of the two Russian airlines. Aeroflot is a state-owned airline with a leading position in the Russian market that may have used the alliance to expand operations in international markets. Its vast network of routes and destinations also implies a high potential to increase connecting traffic for the alliance members. In contrast, S7 is a much smaller private airline with fewer options for complementarity with its European partners and with less potential to benefit from an increase in the connecting traffic.

With an increasing number of global alliances and the coronavirus pandemic, the aviation market is becoming more concentrated. In this context, aviation market authorities should be more vigilant of the implications of alliances at the route level. Alliances can increase connectivity and market efficiency, but can also lead to fare increases and to less frequencies on some routes.

[13] An interesting extension of this research will be to study the effects of the new Aeroflot hub at Krasnoyarsk, which was scheduled to open in the summer of 2020 and will allow connections with alliance partners in Asia and the Americas. It will compete with the current S7 Airlines hub in Novosibirsk, Siberia.

Appendix

Columns VII and VIII in Table 4 show the results of the matching procedure used to mitigate possible bias in the selection of treated and control routes. Specifically, we pair routes that are affected by alliances (treated routes) with routes unaffected by them (control routes) that have similar values for all the covariates in the baseline year.

Following, Rosenbaum and Rubin (1983) we follow a two step matching procedure. The first step consists in using a logit model to estimate the probability of a route of being affected by an alliance, conditional on the preexisting characteristics that may differ between groups. For this estimation, we use 2005 as the baseline year, as this is the year before Aeroflot reached an agreement with SkyTeam. The dependent variable in the logit model we estimate is a dummy variable that takes the value one for treated routes (routes affected by alliances). The explanatory variables are controls included in equations (1) and (2). Specifically, the matching equation that we estimate for route i is as follows:

$$\mathrm{D^{treated}}_{\mathrm{i}} = \beta_1 \mathrm{Population_i} + \beta_2 \mathrm{Income_i} + \beta_3 \mathrm{HHI_i} + \beta_4 \mathrm{Low - cost_i} + \varepsilon c \tag{3}$$

The second step, consist in matching routes in the treated and control groups with respect to their propensity scores, using the first nearest neighbor algorithm. This algorithm matches treated routes with the control routes that has the closest propensity score. Finally, we drop all routes for which there is no common support and re-estimate equations (1) and (2) using the sample of matched routes.

Table 1A shows the results of the first step of the matching procedure. All explanatory variables have a significant influence on the probability of being treated. In this regard, treated routes have richer and more populated endpoints than control routes. They are also less concentrated and with a higher presence of low-cost airlines. Table 2A shows that in the matched sample differences between treated and control routes are substantially reduced.

Table 1A
Determinants of the probability of being treated

Population	0.0005 (0.00008)***
Income	0.00012 (0.000014)***
HHI	−2.454 (0.317)***
Low-cost	0.789 (0.472)*
Intercept	−7.156 (0.901)***
R^2	0.26
Observations	2354

Notes: Standard errors in parentheses (robust to heterocedasticity). Statistical significance at 1% (***), 5% (**), 10% (*).

Table 2A
Mean T-tests of variables used in the empirical analysis in 2005

Sample	All sample			Matched sample		
	Control	Treated	T-test	Control	Treated	T-test
Population	5659.59	9506.89	−10.57***	9625.068	9405.046	3.721***
Income	7646.13	10890	−5.368***	8942.62	9924.13	−1.589
HHI	0.821	0.576	8.987***	0.581	0.610	−0.597
Low-cost	0.024	0.123	−6.315***	0.155	0.137	0.363
Observations	2233	121	–	103	109	–

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