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# Airport dominance, route network design and flight delays

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A B S T R A C T

Airlines with a dominant position at the destination airports have little competitive pressure to reduce delays, but they might care about the negative effects that delays generate on their own flights. Using detailed daily flight data for six Spanish airports in 2017–2018 including very precise information on the external factors that generate flight delays, we find that flights operated by network airlines (i.e., airlines that operate a hub-and-spoke network) with a large presence at the destination airports have less delays than flights operated by other airlines. This finding is in line with the literature on congestion internalization, which predicts a negative relationship between airlines' dominance at the destination airports and delays. We also show that flights operated by low-cost airlines (i.e. airlines that operate a point-to-point network) with a dominant presence at destination airports are more likely to exhibit delays. This result could be explained by the route configuration of low-cost airlines and by their relative low number of connecting passengers.

## 1. Introduction

Traffic growth and airport congestion experienced before and after the covid-19 pandemic crisis have produced considerable delay problems in air transportation markets, especially in the US and the European Union (Britto et al., 2012; Calzada and Fageda, 2019; Forbes et al., 2019). Delays generate uncertainty for travelers and force them to incur extra costs to arrive on time. They also affect the number of hours worked in the industry, which has an impact on labor productivity. Market authorities have traditionally used different measures to remedy this situation, including airport charges,[1] regulations to increase transparency, and the establishment of compensation mechanisms for consumers. Airlines also try to avoid delays to improve their reputation with consumers.[2] However, investing in reducing delays is costly and the benefits airlines obtain depend on their market power, route network configuration and airport congestion.

Delays might have several causes. First, they can be related with the intensity of competition and airlines' network configuration. Airlines with market power may have weak incentives to invest to reduce delays, as this might have a limited impact on their demand. However, airlines with a hub-and-spoke network configuration may want to avoid delays due to the propagation effects these can have

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[1] Several studies have advocated for the use of airport pricing to balance the demand and the limited capacity of airports (Daniel, 1995, Brueckner 2002, Lin and Zhang, 2016, Lin, 2019; Lin, 2021).

[2] Mayer and Sinai (2003a) demonstrated that most airlines choose a posted flight duration that is very close to the minimum allowed under federal regulations to minimize wage costs. Lee and Rupp (2007) analyzed the relationship between the pilots' effort and airport delays and found that pilots' wage reduction affects delays.

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in their connecting flights even if they have market power. Second, a relevant fraction of delays is caused by factors external to airlines, such as weather events and mechanical incidences (Bubalo and Gaggero, 2015; Borsky and Unterberger, 2019). Third, delays can be generated by capacity constraints in airports, which appear when these schedule an excessive number of flights at peak times.[3] In addition, in Europe capacity and staff limitations of air traffic control systems (ATC) have been a frequent cause of delays.

Airlines can use various measures to prevent delays. For example, they can increase the number of back-up aircraft in their main airports to respond to unexpected incidences, make a more intensive use of their aircraft and crew, contract more crew and personal to handle luggage and reduce check-in time, increase the speed of delayed flights, use faster and bigger aircraft, and adjust the schedule of their flights to reduce the propagation of delays (Forbes et al., 2019; Brueckner et al., 2020; Chen and Lin, 2021). All these measures help airlines to mitigate delays in their own flights and generate positive externalities for their rivals. However, these actions are expensive, and airlines adopt them only when it is profitable.

The goal of this paper is to analyze the causal relationship between airlines' dominance in the destination airports and delays. Specifically, we examine whether the airlines' share of flights at destination airports and their network configuration affects their incentives to reduce delays. To address these questions, we consider a rich dataset at the daily flight level with information about the delays of all inward flights arriving at six Spanish airports in the period November 2017 to October 2018. Arrival delays are measured as the difference in minutes between the actual and the announced time of the flight. We also use data about the minutes of delays caused by Eurocontrol regulations, adverse weather conditions, and ATC strikes. In the period considered, strikes promoted by air traffic control employees affected many European airports. Moreover, Eurocontrol regulations on airspace congestion, capacity constraints at airports, and weather events affected a large proportion of flights.[4]

We analyze six Spanish airports that are representative of the three main types of airports that can be found in any European aviation market. Madrid is a large hub dominated by network airlines that operate under a hub-and-spoke route structure. Barcelona is a large airport dominated by low-cost airlines that operate point-to-point routes. Finally, Bilbao, Santiago de Compostela, Sevilla and Valencia are small airports that are also dominated by low-cost airlines. This variety of cases is useful to examine how airlines' airport dominance affects their incentives to reduce delays. Another advantage of using this group of Spanish airports is that they are managed by the same operator (AENA), which allow us to study a sample of arrival airports that is homogeneous in terms of the management of flights and slots.

The first contribution of our analysis is to show that flights operated by network airlines (i.e., airlines that operate a hub-and-spoke network) with a dominant position in the destination airports have less delays than flights operated by other airlines. This finding is in line with the literature on congestion internalization, which predicts a negative relationship between airport concentration and delays. In particular, this literature considers that airports with a high airline concentration should experience relatively fewer delays, as airlines with a dominant position in these airports will dedicate resources to reduce the propagation of delays among their own flights (Brueckner, 2002; Daniel, 1995). Our analysis considers a sample of six Spanish airports, and therefore we cannot directly test the relationship between airport concentration and flight delays. However, we find that network airlines with a dominant position at the destination airports incur in relatively less delays than other airlines.

The second contribution of our paper is to examine the relationship between airport dominance by low-cost airlines and flight delays. We show that flights operated by low-cost airlines (i.e. airlines that operate a point-to-point network) with a dominant presence at destination airports are more likely to exhibit delays. We argue that low-cost airlines have relatively less incentives to reduce delays due to the configuration of their routes and to the lower weight of connecting passengers. This finding contributes to the literature that examines the role of airlines network configuration in flight delays and has relevant policy and managerial implications. Indeed, in the last years, low-cost airlines have been increasing their operations in major airports (Dobruszkes et al., 2017; Jimenez and Suau-Sánchez, 2021), which can have positive effects in terms of lower fares and higher traffic. Our analysis demonstrates that a potential negative effect of this process is the reduction of service quality, as airports dominated by low-cost airlines may have on average more delays than hub airports dominated by network airlines.

Another important novelty of our analysis is that we can distinguish between arrival delays generated by any situation and the delays generated by Eurocontrol regulations. We find that delays caused by Eurocontrol regulations (which have a shorter duration and can be recovered by the airlines) are not related to the dominant position of the airlines at the destination airports. In addition, we demonstrate that our main result that airlines dominance at destination airports affects flight delays does not depend on the heterogeneous effects that weather events or strikes may have on the sample of Spanish airports we analyze.

The rest of the paper continues as follows. Section 2 reviews the literature and provides a theoretical background for the paper. Section 3 presents the data. Section 4 describes the empirical strategy used to examine the effects of airport dominance on flight delays. Section 5 presents our main results. Section 6 presents additional analysis about alternative measures of delays and examines the external causes of delays. Moreover, it discusses the endogeneity of some control variables and studies how the market power of the airlines interacts with their fares and delays. Finally, Section 7 concludes.

[3] Many European airports are capacity controlled in terms of the maximum number of available slots per time period and airports participate in scheduling conferences organized by the International Air Transport Association (IATA; Bubalo and Gaggero, 2015). Despite this, before the pandemic crisis airports usually experienced congestion.

[4] The European Organisation for the Safety of Air Navigation (Eurocontrol) coordinates and manage air traffic control in Europe so that it may establish regulations on flights that generate delays coming from different causes like, for example, congestion in the airspace, capacity restrictions at airports or weather events. Notice, for example, that the pilots must wait to the permission of Eurocontrol to take-off.

## 2. Background

This paper contributes to the literature that analyzes how airport concentration determines travel time and delays (Greenfield, 2014; Cao et al., 2017). Brueckner (2002) theoretically and empirically shows that dominant airlines in an airport have incentives to self-internalize airport congestion, as scheduling more flights in the peak-hour can slow down their own flights. This study inspired several empirical papers using data for the US that have analyzed whether airlines with a large presence in an airport make more efforts to internalize congestion. The internalization hypothesis was first confirmed by Mayer and Sinai (2003b), who explains that airlines cluster their flights in short time spans to offer passengers as many connections as possible with short waiting times. They demonstrated that delays decrease with airport concentration, while delays at hub airports are longer than at non-hubs. Ater (2012) offers additional evidence on the internalization hypothesis using data on scheduling at hub airports. He shows that hubbing airlines internalize congestion at concentrated airports by choosing longer departure and arrival banks (waves of departing and arriving flights).

Daniel and Harback (2008), Rupp (2009) and Bilotkach and Lakew (2022), find evidence of no self-internalization, which suggest the need to establish congestion pricing for improving efficiency. Daniel and Harback (2008) examine a group of twenty-seven major U.S. airports and use specification tests to reject the internalization hypothesis at most airports. Rupp (2009) revisits the internationalization hypothesis considering on-time arrival and delays based on actual versus scheduled arrival and departure times (i.e. he considered that passengers are concerned about schedule delays and not so much about excess travel time). He finds that, once this delay measure is taken into account, airlines do not internalize flight congestion costs, since departure and arrival delays are positively correlated with airport concentration.[5] Bilotkach and Lakew (2022) use data on different sources of delays aggregated at the annual level. They find that total delays are positively correlated with airport-level concentration, although the variance of delays at larger airports does fall as concentration increases. They also show that an increase in airport concentration consistently decreases the share of delays that can be deemed endogenous to the airline.

Another strand of literature considers that flight delays is an aspect related to the quality of the service and shows that there is a positive correlation between competition and service quality (Suzuki, 2000; Mazzeo, 2003; Greenfield, 2014; Bubalo and Gaggero, 2015). In this sense, Mazzeo (2003) finds that flight delays are more common and longer in duration in routes where only one airline provides direct service and in airports in which the airline has a large share of the total flights. He concludes that airlines may lack sufficient incentive to provide service quality in markets where they do not face competition. Greenfield (2014) examine the effect of competition on airline on-time performance, using an instrumental variable approach to deal with the endogeneity of market structure. He obtains that competition reduces flight delays.

Bendinelli et al. (2016) try to conciliate these two strands of the literature by presenting a single econometric model to test both the "congestion internalization effect" and the "competition-quality effect". Specifically, they suggest that airlines' internalization of congestion can be explained by their dominant position at the airport level, while their effort to reduce delays (increase quality) can be related to the competition they face at the route level. In their analysis of the Brazilian market, they find evidence of both the internalization and the competition-quality effects. Similar results are found in Miranda and Oliveira (2018) for the Brazilian domestic market. These authors also show the role of airport slots in strengthening the airlines' congestion internalization behavior.[6]

Guo et al. (2018) have proposed a new approach to test the internalization hypothesis. They emphasize that airports' market concentration has two effects on airport delay, one "internalization effect" and one "residual market-power effect". The residual market power effect (as named by Brueckner, 2002) appears when due to the high airport market concentration, dominant airlines can charge higher prices or offer fewer flights. Therefore, even if there is not an internalization effect airport market concentration can lead to a reduction of delays. These authors propose to analyze the internalization hypothesis controlling for both the "competition-quality effect" and for the "residual market-power effect". Specifically, they consider the theoretical prediction that if airlines do internalize airport congestion, airfare prices would be positively correlated with the interactive term of the airline's passenger number at the origin airport and the congestion delay at the airport level. Their analysis concludes that congestion internalization occurs for full-service carriers, but not for low-cost airlines.

A few other papers have analyzed the role of airlines' network configuration in explaining delays. Prince and Simon (2015) analyze whether incumbent airlines improve on-time performance after the entry of low-cost airlines. They obtain that entry of low-cost airlines reduces on-time performance of the incumbent, as airlines prioritize price competition over quality. Gil and Kim (2021) study the effects of the entry of low-cost airlines and of airline mergers in the US market. They obtain that incumbent airlines increase frequency of flights and number of seats when there is more competition and reduce cancellations and departure and arrival delays when there is a threat of entry in a route by low cost airlines. Moreover, airlines react to competition differently at their hubs. An increase in competition results in an increase in flight frequency, the number of seats and aircraft size if there is a threat of a low-cost airline entry in a hub relative to a non-hub airport. Fageda and Flores-Fillol (2016) examined the ways in which airlines adjust frequencies to delays depending on their network types using aggregated data for US. They show that while airlines operating fully connected configurations reduce frequencies in response to delays, airlines operating hub-and-spoke networks increase them, even if

[5] Controlling for hub airports and weather conditions, Rupp (2009) shows that from the carrier perspective, shorter excess travel times occur at highly concentrated airports (internalization of airport congestion). However, he finds the opposite result from the passenger perspective, as departure and arrival delays are more likely at highly concentrated airports.

[6] A positive association between slot controls and flight delays has also been found in Brueckner (2002), Greenfield (2014), Santos and Robin (2010), and Chen and Lin (2021).

**Table 1**
Descriptive statistics by airport

| | Madrid | Barcelona | Small |
|---|---|---|---|
| **Total traffic** | 57,890,057 | 50,172,689 | 22,346,150 |
| **Share main airlines** | 27 % Iberia | 38 % Vueling | 29 % Ryanair |
| | 15 % Air Europa | 15 % Ryanair | 24 % Vueling |
| **Share Iberia group & Ryanair** | 56 % | 57 % | 65 % |
| **Share airlines in alliances** | 64 % | 21 % | 23 % |
| **Share domestic traffic** | 28 % | 27 % | 45 % |
| **Share traffic from other European airports** | 46 % | 59 % | 52 % |
| **Share traffic from non-European airports** | 26 % | 14 % | 3 % |

**Table 2**
Delays by airport

| | All | Madrid | Barcelona | Small |
|---|---|---|---|---|
| **Observations with arrival delays larger than 15 min. All causes of delays (%)** | 24.6 % | 21.6 % | 29.5 % | 22.7 % |
| **Average arrival delays. All causes of delays (in minutes)** | 8.76 | 5.3 | 13.51 | 5.12 |
| **Observations affected by Eurocontrol regulations (%)** | 30.3 % | 22.9 % | 40.9 % | 15.6 % |
| **Average arrival delays due to Eurocontrol regulations (in minutes)** | 3.61 | 2.12 | 5.51 | 2.02 |

this is at the expense of greater congestion at their hub airports. Roucolle et al. (2020) analyzed the impact of network design on excess travel times for the main US carriers between 2008 and 2017. They found that bigger airlines (in terms of the number of city pairs served by the airline) show higher values for excess travel time and delays. However, they did not find one network configuration that is clearly superior to the other in terms of on-time performance. Alderighi and Gaggero (2015) show that airlines participating in global alliances are more prone to cancel flights as they may rely on its partners' network.

Our paper is closer to the scarce literature analyzing flight delays in the European markets. Santos and Robin (2010) examined a group of large European airports in the period 2000–2004 and conclude that airport concentration is an important determinant for delays. Bubalo and Gaggero (2015) analyze whether a higher presence of low-costs airlines at the departing airport reduces the arrival delay of the flights landing. They consider a dataset covering 100 European airports for the period April 2011 to December 2012 and find that on average low-cost airlines contribute to the reduction of the delays of all flights landing at a given airport. Bubalo and Gaggero (2021) study whether differences in the network configuration of European airlines can help to explain arrival delays. They consider 40 European countries in the period between April 2015 and March 2016 and use an index of interconnectedness to assess if airlines' networks are closer to a hub-and-spoke or to a point-to-point system. They show that airlines operating under a hub-and-spoke structure are on average more effective in tackling and reducing delay propagation, especially if flights originate at one of their own hubs.

We contribute to this literature by jointly examining the role of airport dominance and route network configuration in explaining flight delays. Given the small number of destination airports in our sample (data is for arrival delays in inward flights to six airports), we cannot directly test the hypothesis that airport concentration led to less flight delays. However, we examine whether airlines with a dominant position in an airport have more incentives to internalize congestion. We will interpret that a dominant airline contributes to the internalization of congestion if it has relatively less delays than its rivals. We also analyze whether dominant airlines with hub-and-spoke, or a point-to-point network configuration have different incentives to internalize congestion. Finally, an important novelty of our paper is that we use detailed data on external causes of delays, including Eurocontrol regulations, adverse weather events and strikes at the flight level. This information allows us to control for the existence of these external causes of delays, which can differ across airports.

## 3. Data

Our dataset covers the period from November 2017 to October 2018 and includes all inward flights arriving at six Spanish airports, Barcelona, Bilbao, Madrid, Santiago de Compostela, Sevilla and Valencia. The unit of observation is the flight operated by day and time.

We define as a flight one route operated by one airline and offered at a particular time. An example is flight VLG 8301, which covers the route between Amsterdam and Barcelona, is operated by Vueling, and is scheduled at 10.20 h. Flights are operated multiple times in the period we examine, which allows us to analyze the determinants of delays. Our dataset includes information at flight level (e.g. arrival delays, weather, strikes, Eurocontrol regulations), route level (e.g. Herfindahl-Hirschman Index, *HHI*), and airport level (e.g. number of flights by time interval, shares of the airline at the origin and destination airports). Overall, our dataset includes 2,433 flights from 267 different origin airports to the six destination Spanish airports, which add up 324,248 observations with complete data. We next describe our main data sources.

Descriptive data on traffic and airline shares come from the Spanish airport operator (AENA) and refer to 2018. Table 1 shows the statistics of some relevant variables for the three groups of Spanish airports considered in the analysis (Madrid, Barcelona and small airports).

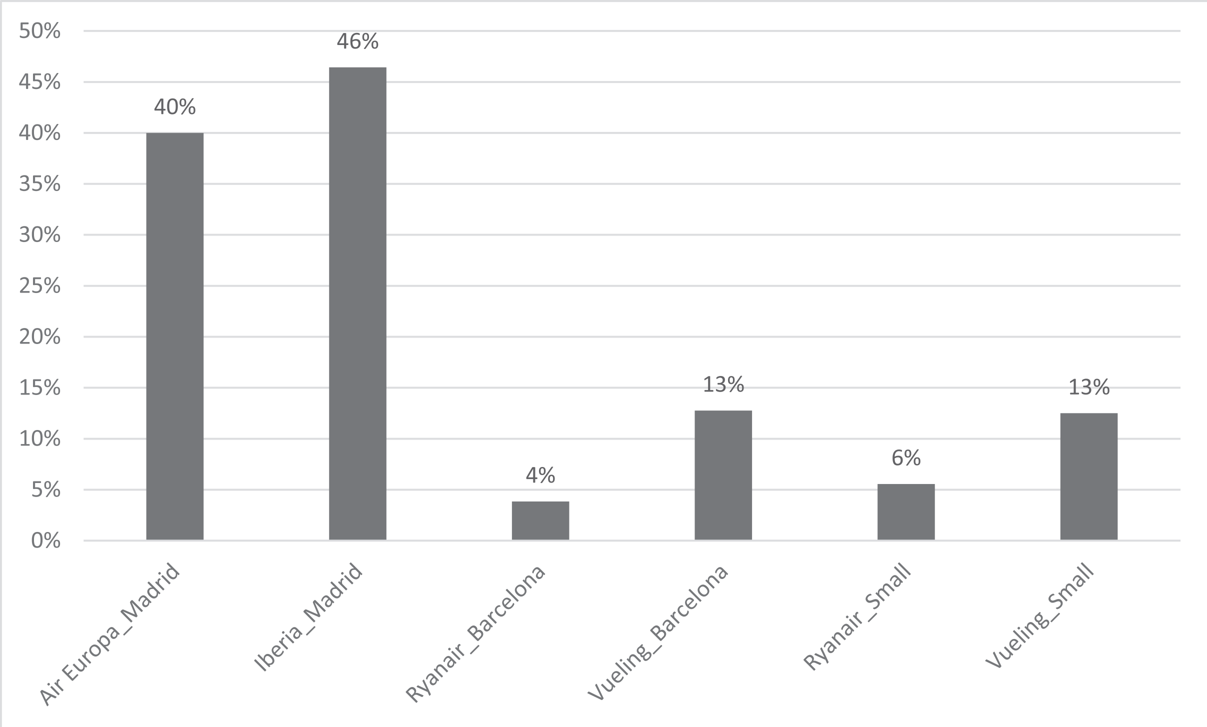


**Fig. 1. Percentage of connecting passengers over total passengers, 2016**
Note: Data come from Official Airlines Guide (OAG) – Traffic analyzer tool.

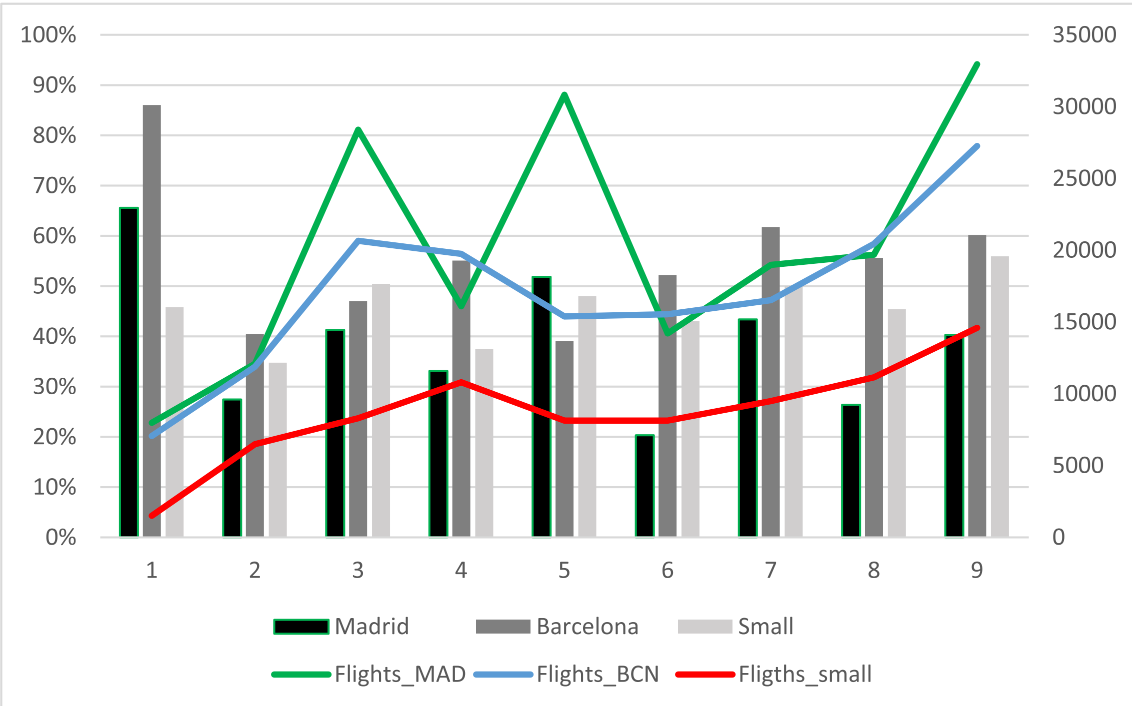


**Fig. 2. Share of the dominant airline, by time interval**
Note: Dominant airlines are Iberia and Air Europa in Madrid, Vueling and Ryanair in Barcelona and in the small airports. Time intervals are: (1) 0–6.59 h.; (2) 7–8.59 h.; (3) 9 h-10.59 h.; (4) 11–12.59 h.; (5) 13 h-16.59 h.; (6) 15 h-16.59 h.; (7) 17 h-18.59 h; (8) 19 h-20.59 h; and (9) 21 h-23.59 h.

In the period examined, Madrid and Barcelona had a traffic of more than 50 million passengers per year. The two airports were close to their maximum capacity, which is 70 million passengers for Madrid and 55 million passengers for Barcelona. Barcelona and Madrid airports have relevant differences. Madrid is a hub airport dominated by two network airlines that operate under a hub-and-spoke route structure: Iberia (a member of Oneworld alliance) and Air Europa (a member of Skyteam alliance). Barcelona is an airport dominated by two low-cost airlines that operate point-to-point routes: Vueling and Ryanair. The four small Spanish airports considered in our analysis had traffic in 2018 that ranged from 7.7 million in Valencia, 6.3 million in Sevilla, 5.5 million in Bilbao and 2.7 million in Santiago. These airports are dominated by two low-cost airlines (Vueling and Ryanair) and serve medium-sized cities with modest tourism activity. Table A1 in the appendix shows the top-10 airports in Europe in terms of traffic in 2018. Madrid Airport was ranked as the fifth largest in terms of traffic, so it can be considered as a major hub. Barcelona Airport was ranked as the sixth largest, being the largest non-hub airport in Europe. The rest of airports in our sample can be considered as small airports.

It is important to clarify that Iberia operates with subsidiaries from Madrid airport including low-cost airlines (Vueling and Iberia Express) and regional carriers (Air Nostrum). As a result, the joint share of the Iberia group and Ryanair in the six destination airports analyzed is greater than 50 %. Network airlines had 64 % of traffic in Madrid, while they only channeled around 20 % of the traffic in Barcelona and in the smaller airports.

Table 1 shows that traffic from non-European destinations is much higher in Madrid than in the other Spanish airports, while the share of domestic traffic is much higher in the smaller airports than in the larger ones. Fig. 1 shows the percentage of connecting passengers over the total number of passengers for the airlines that have a dominant position in the six destination airports. The figure makes evident that Iberia and Air Europa operate under a hub-and-spoke route structure since almost half of their passengers are connecting passengers. In contrast, the weight of connecting passengers is much smaller for Vueling and especially for Ryanair.

Fig. 2 shows that in all Spanish airports, the lowest number of arrivals is in the time interval from 0 h to 6.59 h, while the peak in arrivals is in the interval from 21 h to 23.59 h. Furthermore, the evolution of arrivals in Madrid and in the rest of airports differs importantly. In Madrid, three peak periods concentrate many of the arrivals of dominant airlines. These arrival banks reflect their hub-and-spoke configuration. In contrast, in Barcelona and in the other airports flights arrive progressively throughout the day, and peak periods are less marked. This is the expected arrival pattern in airports dominated by airlines that operate point-to-point networks.

Information on arrival delays comes from Flightstats, a firm specialized in real-time tracking of flight status, departures and arrivals, delays and airport information. Arrival delays are measured as the difference in minutes between the actual and the announced time of the flight, which can be caused by multiple circumstances.[7]

We use different data sources to identify potential causes of delays. Meteorological information is from Weather Underground, a commercial weather service that obtains information from the National Weather Service (NWS) and a wide network of personal weather stations. This firm provides weather reports at airport level, every half hour or every hour, depending on the airport. We used a web crawler to collect weather information and we matched it with our dataset at flight level. For each flight, we consider the weather information that is closest to scheduled departure and arrival times. Thus, the weather information refers to each specific flight by day and time. Table A2 in the appendix provides additional details on the percentage of observations affected by different weather conditions both at origin and at destination airports.

The literature has shown the relevance of adverse weather conditions on delays in the US (Coy, 2006; Borsky and Unterberger, 2019) and in the EU (Bubalo and Gaggero, 2015). These studies indicate that the effects of weather disturbances largely depend on the type and intensity of the event. Moreover, large airports, which usually serve as hubs for large airlines, present longer delays in response to weather shocks. Following Bubalo and Gaggero (2015), our model considers several variables that reflect the weather conditions on origin and destination airports at the hourly level: fair, weather, snow, rain, fog, storm, cloud, and temperature at the origin airport.[8] Notice that only a few papers in the literature such as Bubalo and Gaggero (2015, 2021) and Borsky and Unterberger (2019) consider the meteorological conditions at the specific time of take-off or landing. Most of the literature reviewed in Section 2 use daily or monthly averages of weather status, which are less precise to capture adverse operation conditions.

An important novelty of our paper is that we consider information on flight regulations and delays from the European Organization for the Safety of Air Navigation (Eurocontrol). Eurocontrol is in charge of the coordination and planning of air traffic flow management (ATFM) for all of Europe. Flights are regulated by issuing a calculated take-off time (CTOT) that creates an ATFM 'slot'. The ATFM "slot" establishes that an aircraft can depart during a narrow window of 5 min before and 10 min after the CTOT. ATFM regulations may impose a delay in the departure time, which is measured as the difference in minutes between the airline's requested take-off time (in the flight plan) and the CTOT issued by Eurocontrol. Eurocontrol delays can be due to different causes like capacity limitations in the airspace between the two airports, capacity restrictions at the origin and/or destination airports, weather events and so on. Our dataset contains Eurocontrol information on whether the flight was subject to a regulation, the cause of the regulation, and the minutes of delays that this implied. Tables A3 and A4 in the appendix provides detailed information on the Eurocontrol regulations affecting the period we examine.

[7] Flights cancelled or diverted represent a 0.04% of observations in our sample, and are not considered in the analysis.

[8] The variable of temperature is considered only at the origin airport because temperature mainly affect delays when it is less than 0 degrees. This is a situation that may happen at the origin but not at the (Spanish) destinations.

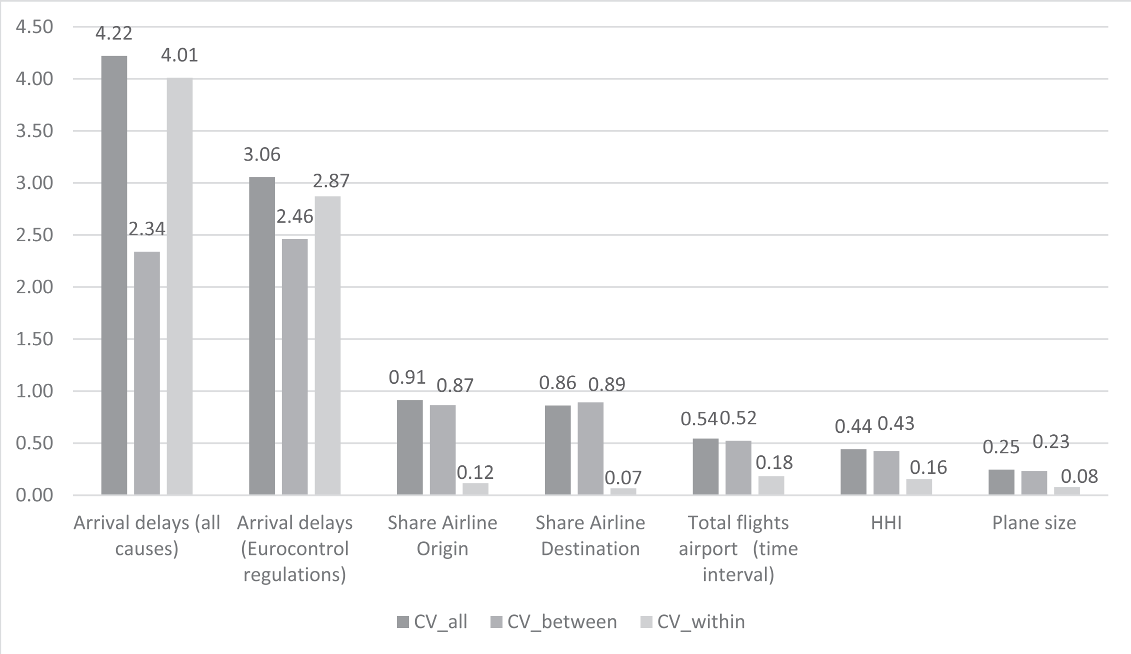


**Fig. 3. Variation Coefficient of selected variables**

Notes: The Variation Coefficient is the ratio between the standard deviation and the mean. While the between variation refers to the variability between flights, the within variation refers to the variability over time within each flight. We consider the mean values of the selected variables: (1) *Arrival Delays* in minutes (all causes): 8.76. (2) *Arrival Delays* in minutes (Eurocontrol regulations):3.61. (3). *Share Airline Origin* in percentage: 27.38 (4). *Share Airline Destination* in percentage: 19.44. (5). *Total Flights Airport* (time interval): 49.44 (6). *HHI* in percentage over 100: 61.92. (7). *Plane size* in number of seats: 189.92.

Our dataset also incorporates information on strikes (air control and airport services) affecting European markets. This information was obtained from the Eurocontrol's Monthly Network Operations Reports. Strikes can affect different zones of air space. In the period we analyze, we identify strikes in France, Greece, and Italy. We assume that strikes in France can directly affect Western European flights, and that strikes in Italy and Greece can directly affect Southern European flights.[9]

Table 2 shows the percentage of observations in our sample subject to a delay. The first two rows of the table present the number of observations in our sample affected by any type of delays larger than 15 min, and the average arrival delay for all flights, which is measured as the difference between the actual and the announced time of the flights. We find that around 24.6 % of total flights were subject to arrival delays exceeding 15 min, and that the average arrival delay for all flights was 8.76 min. This can be considered a large average delay, considering that many flights did not have delays or even had a negative delay when they arrived before the announced time. We also observe relevant differences across Spanish airports. While in Madrid and in the small Spanish airports around 22 % of flights suffered arrival delays (5 min on average), in Barcelona the percentage was 29.5 % (13.5 min on average).

The last two rows of Table 2 show the number of observations affected by Eurocontrol regulations. In this case, the delay is measured as the difference in minutes between the airlines's requested take-off time (in the flight plan) and the actual take-off time issued by Eurocontrol. We find that around 23 % and 15 % of the flights arriving to the Madrid airport and to the small airports, respectively, were affected by Eurocontrol regulations. The percentage increases to the 40 % in the case of Barcelona.[10] In addition, the average length of delays due to Eurocontrol regulations is much shorter than the delays attributed to other causes. Notice that our standard measure of arrival delays and the delays due to Eurocontrol regulation are not directly comparable, as Eurocontrol regulations only considers flights within Europe and reflects the requested take-off time. In this sense, delays due to Eurocontrol regulations only explain part of the delay time that can affect a flight.

The main explanatory variable of our empirical analysis reflects the position that airlines had at the destination airport. The

[9] Strikes in France can affect Marseille or the entire country. Strikes in Marseille were on: 7–9 April, 28–29 April, 5–7 May, 12–14 May, 26–28 May, 9–11 June, 16–18 June, 23–25 June of 2018. Strikes affecting all of France were on: 15–17 November of 2017, 21–23 March of 2018 and 21–23 May of 2018. Strikes in Italy were on: 15 December of 2017, and 8 March, 8 May and 8 June of 2018. Strikes in Greece were on 30 May of 2018.

[10] The large number of regulatory interventions in Barcelona may be explained by different factors. First, Barcelona airport has several nearby airports (Reus, Girona) that could impose restrictions in terms of Air Traffic Control. Second, the two runways of the airport cannot be used independently, in order to minimize noise externalities in neighborhoods near to the airport. Third, the airport operates close to its maximum capacity.

**Table 3**
Number of observations by airlines

| Airline | Total observations | Share over total observations (%) |
|---|---|---|
| Vueling | 84,397 | 25 |
| Ryanair | 60,320 | 18 |
| Iberia | 47,552 | 14 |
| Air Europa | 28,702 | 8 |
| easyJet | 20,864 | 6 |
| Lufthansa | 11,038 | 3 |
| Norwegian | 9,742 | 3 |
| British Airways | 6,049 | 2 |
| Transavia | 5,943 | 2 |
| KLM | 4,697 | 1 |
| Wizz Air | 4,361 | 1 |
| TAP Portugal | 4,111 | 1 |
| SWISS | 3,642 | 1 |
| Brussels Airlines | 2,902 | 1 |
| Air France | 2,882 | 1 |
| American Airlines | 2,869 | 1 |
| Aeroflot | 2,659 | 1 |
| Turkish Airlines | 2,610 | 1 |
| Alitalia | 2,389 | 1 |
| Eurowings | 1,865 | 1 |

variable *Share of the Airline at the Destination Airport* shows the monthly share of flights that the airline had at the destination airports. Information for this variable comes from RDC aviation (Apex schedules) and shows the position that airlines had in these airports. A large share of the airlines in the airport can affect them in different ways. According to the congestion internalization hypothesis, airlines with a large presence at the destination airport are more prone to adjust their operations to avoid negative spillovers caused by delays (Brueckner, 2002). However, a large presence of the airlines at the destination airport reflects market power and can be associated with less incentives to reduce delays (Mazzeo, 2003).

Our model also considers other control variables that are based on supply measures. First, the *Share Airline Airport Origin* shows the monthly share of flights that the airline had in origin airports. The *Hirschman-Herfindalh Index* (HHI) measures the intensity of competition at the route and it is calculated considering the daily flights in the route. The variable *Plane Size* reflects the number of seats of the plane operating the flight. Finally, our regressions include a variable that reflects the total number of flights arriving at the airport in nine-time intervals: 0–6.59 h; 7–8.59 h; 9–10.59 h; 11–12.59 h; 13–14.59 h; 15–16.59 h; 17–18.59 h; 19–20.59 h; and 21–23.59 h.[11] These intervals have been computed using the announced times of the flight.

Fig. 3 shows the Variation Coefficient (VC) for the main variables of our analysis. The VC is calculated as the ratio between the standard deviation of a variable and its mean. The figure presents the variation of the variable *Arrival Delays* and the supply variables (*Share Airline Airport Origin, Share Airline Airport Destination, Total Flights Airport, HHI* and *Plane Size*) *between* flights and the variation over time *within* the same flight. The results indicate that the variable *Arrival Delays* has a very high *between* and *within* variability. In contrast, the supply variables have a much lower variability, which is in line with the aviation studies that consider that airlines first make supply decisions and then adjust fares according to the evolution of their demand.[12] These results suggest that, in the short-term, airlines adjust their demand with the fares rather than with the supply.

It is particularly remarkable the low within variability of the variable *Share of the Airline at the Destination Airport*. Fig. 3 provides clear evidence that in the short period of time we consider the supply was very stable, revealing that the dominance of airports by airlines is in our context essentially a static phenomenon. Taking this into account, our identification strategy is based on the assumption that the airlines' dominance of destination airports is stable over time, and it is not affected by potential delays affecting these airlines.

Table 3 shows the breakdown of observations in our sample by airline. 65 % of the observations refer to the four largest players: Vueling, Ryanair, Iberia and Air Europa (Iberia and Vueling are owned by IAG). Interestingly enough, 56 % of the observations refer to low-cost airlines, 39 % to network airlines and the remaining 5 % to airlines that cannot be classified into either of these two groups (e.g. charter airlines with scheduled flights, regional airlines using small planes). We consider that network airlines are part of an international alliance (Oneworld, Star Alliance or Skyteam) and operate a hub-and-spoke route structure. Moreover, we use the classification of the Civil Aviation Organization to identify low-cost airlines.

[11] In the period examined, there were scheduled arrivals after midnight in all Spanish airports, except for Bilbao. However, very few flights arrived at Spanish airports between 0h and 6.59h, so we consider this range of hours a homogeneous off-peak time interval. The last interval we consider is of three hours, while the rest of the non-night time intervals are of two hours. Most of the few flights that arrive from 0h to 0.59h are intercontinental flights that are not considered in the regressions that include Eurocontrol regulations. Hence, we consider a unique time interval from 21h to 23.59h.

[12] Examples of studies that estimate supply equations for air routes include Schipper et al. (2002), Richard (2003), Fageda and Flores-Fillol (2012) and Brueckner and Luo (2014).

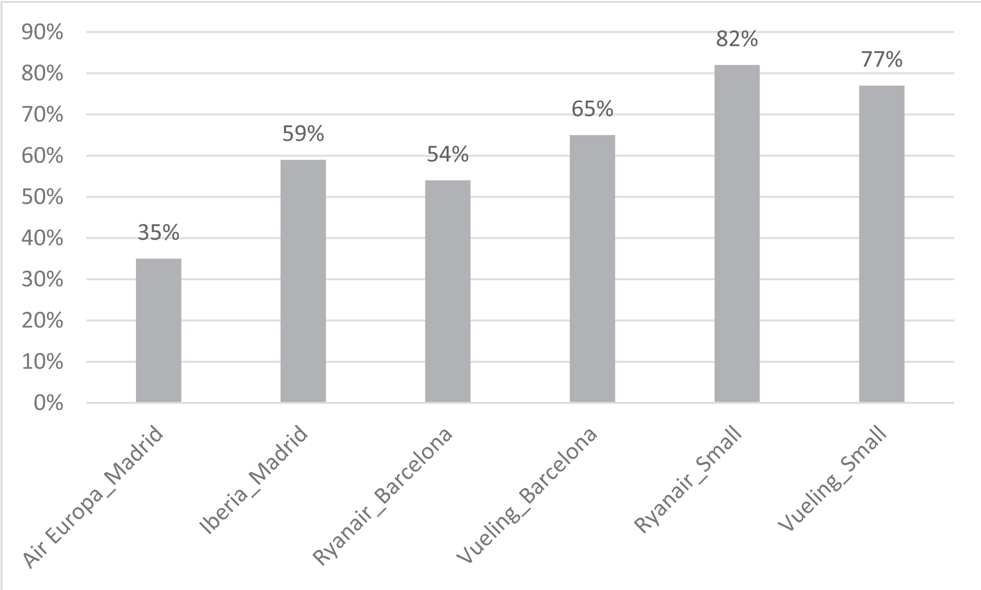


**Fig. 4.** Average route share of dominant airlines

Table A5 in the appendix shows the top-10 airlines in Europe in terms of flights in 2018. Three dominant airlines in our sample (Ryanair, Iberia and Vueling) were among the top-10 airlines in Europe. Ryanair was the largest low-cost airline and Vueling was the fifth one. Iberia was the fifth largest network airline. Our sample includes 177,188 observations of the five largest low-cost airlines in Europe (Ryanair, easyjet, Norwegian, Eurowings and Vueling) and 72,568 observations of the five largest network airlines in Europe (Air France-KLM, Lufthansa, British Airways, SAS and Iberia).

Fig. 4 shows the average route share (in terms of flights) of dominant airlines in the six Spanish airports we analyze. Dominant airlines have an average share of flights in the routes they operate that is over 50 %, except in the case of Air Europa in Madrid where the average share is 35 %. These measures imply that dominant airlines have an important market power in these destination airports, as they operate a large percentage of the routes at these airports and have a large share of the flights at these routes.

Finally, notice that the variables considered in our analysis could be defined in alternative ways. For example, the variables *Share Airline Airport Destination*, *Share Airline Airport Origin* and *HHI* are measured in terms of flights but could be measured in terms of seats. Interesting enough, the correlation between number of seats and number of flights is very high and our results are virtually the same regardless of the definition used. Furthermore, these variables could be measured in terms of airline group or alliance instead of airline, but the correlation between these alternative definitions is also very high and results are qualitatively similar when using one or another.

## 4. Empirical model

Our empirical model examines the relationship between airlines' dominance at the destination airports and arrival delays. Airlines with a large share of the fights at the destination airport could have more flight delays, since they have market power and could be less concerned about the disutility created in passengers. However, according to the congestion internalization hypothesis, network airlines with hubs at destination airports should be concerned about arrival delays because of the negative effects these may have on their other flights. We estimate the following models at daily flight level*:*

$$Arrival\ Delays_{itd} = \alpha + \beta\ Share\ Airline\ Airport\ Destination_{im} + \theta X_{id} + \sum_{t=1}^{8} \lambda_t + \varphi\ Origin\_Airport_r + \delta\ Destination\_Airport_a + \rho_m + \varepsilon_{id} \tag{1}$$

$$Arrival\ Delays_{itd} = \alpha + \beta\ Share\ Airline\ Airport\ Destination_{im} + \theta X_{id} + \sum_{t=1}^{8} \lambda_t + \gamma_i + \rho_m + \varepsilon_{id} \tag{2}$$

where *Arrival Delays*$_{itd}$ reflects the difference in minutes between the actual and the announced time of the flight *i* in the time interval *t* at which the flight arrives (see Fig. 2 for a classification of the intervals), in the day *d*.[13] The variable *Share Airline Airport*

[13] Note that our measure of arrival delay is based on the difference between the actual and announced time of arrival at the gate.

*Destination$_{im}$* measures the airline's share of flights in the destination airports in month *m*.

A potential econometric challenge in the identification of the relationship between airlines' airport dominance and delays is the possibility that these two variables are determined simultaneously. More delays can lead to less demand and this can reduce the share of flights that airlines have at the airport. We consider that this situation does not constitute a severe limitation for our analysis.[14] Notice that while the number of passengers taking a particular flight is affected by demand conditions such as the price and the quality of the service, the supply is a long-term decision that requires more time to adjust. As shown in Fig. 3, the share of flights that airlines had at the destination airports in the period examined has a very low within variability, which reveals the slow adjustment of the supply to the changes in the market. Airlines in Europe typically schedule flights for 6-month periods and maintain their offer regardless of the evolution of the demand within that period. In fact, airlines are very reluctant to discontinue their flights on a route because they can lose their slots (airport usage rights) if they use them less than the 80 % of the allocated time (i.e. "use it or lose it" rule). This regulation is especially important in airports with capacity restrictions such as Barcelona and Madrid.[15] Also notice that the market power of dominant airlines at the six Spanish destination airports is high either if we consider their shares at the airport or at the route level. Therefore, we expect that if delays reduce the number of passengers of these airlines, they will not renounce to their valuable slots.

The estimated models in (1) and (2) include a vector of controls ($X_{id}$) that capture additional route or airport characteristics that might influence flight delays. The controls at the route level include two dummy variables that reflect the effects of strikes: *Strikes Western Europe* is the interaction of the strikes that took place in this period in France and a dummy variable for flights from Western Europe to Spanish airports; and *Strikes Southern Europe* is the interaction of the strikes that took place in Greece and Italy and a dummy variable for flights from Southern Europe to Spanish airports. The *Hirschman-Herfindalh Index* (*HHI*) measures the intensity of competition at the route level and is calculated considering the daily flights on the route. Notice that this variable can be affected by a problem of endogeneity, as the airlines' unobserved effort to reduce delays might depend on route-level competition. In Section 6 we discuss this situation, and we estimate the model with an instrumental variable approach to verify the robustness of our results. Finally, *Plane Size* indicates the number of seats on the plane operating the flight.[16]

As for airport attributes, the variable *Share Airline Airport Origin* is the airline's share of flights in the origin airports. The variable *Total Flight Airport* shows the total number of flights arriving at the airport in different time intervals. Hence, this variable captures congestion at the airport during different periods of the day (Mazzeo, 2003; Bubalo and Gaggero, 2015).

We control for the existence of adverse weather conditions at the flight level including the dummy variables *Snow*, *Rain*, *Fog*, *Storm, Cloud and Fair Weather* (baseline dummy). Following Bubalo and Gaggero (2015), we include separate variables that reflect the weather situation at the precise time of departure and arrival of each flight. Moreover, we consider the variable *Temperature on Origin* to account for the case in which the temperature was below 0 degrees Celsius at departure time, as aircraft de-icing operations can imply some delays.

The model includes several types of fixed effects. First, eight-time interval fixed effects, $\lambda_t$, are included to reflect the times at which the flights arrive at the airport (0 h to 6.59 h ( baseline interval); 7–8.59 h; 9–10.59 h; 11–12.59 h; 13–16.59 h; 15–16.59 h; 17–18.59 h; 19–20.59 h; and 21–23.59 h). We expect early flights to suffer less from delays than subsequent flights, as airport congestion increases throughout the day. We also include month fixed effects, $\rho_m$, to capture seasonal effects that may be common to all flights. Note that each flight code has many observations and the variables of month and time interval may take different values for the same flight code.

Finally, notice that model (1) considers *Origin* and *Destination Airport* fixed effects to account for time-invariant unobservable factors related to the airports, while model (2) includes *Flight* fixed effects $\gamma_i$ to account for time-invariant unobservable factors related with the flight. Model (1) has the advantage of including time-invariant variables. Given that dominance at airports is essentially a static phenomenon in our context, we estimate model (1) with two alternative indicators: the shares of the airlines at the destination airports and dummies for the dominant airlines at the destination airports. Dominant airlines at Madrid airport are Iberia and Air Europa, while dominant airlines at Barcelona and smaller airports are Vueling and Ryanair. Model (2) exploits the within variation of the data, but has the disadvantage that the main explanatory variables we consider have low within variability. Considering this, we will consider that our baseline model is model (1). Finally, we assume the regression error term, $\varepsilon_{it}$, to be iid.

Our estimates may present heteroscedasticity and 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 we may have problems of heteroscedasticity and autocorrelation, which must 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

[14] For a discussion on the endogeneity of market structure regressors in the analysis of flight delays see for example Greenfield (2014) and Bendinelli et al. (2016).

[15] In our sample, Madrid, Barcelona, Bilbao and Valencia are slot coordinated airports where the demand of airlines exceeds the airport capacity for significant periods, a situation that cannot be resolved in the short term. Santiago de Compostela and Sevilla are airports with schedules facilitated where airlines' demand is close to the airport's capacity and where there is a potential risk of saturation at certain times. For more details, see the website of the Spanish agency that coordinate the slots in Spain (AECFA): https://www.slotcoordination.es/csee/Satellite/Slots/en/.

[16] Notice that the variable *Plane Size* could also be affected by an endogeneity bias, as airlines could adjust the size of the aircraft to respond to changes in the demand caused by the delays. However, Table A6 in the appendix shows that a high proportion of flights of the main airlines in our sample are operated with either an A320 or a B737-700. Low-cost airlines operate with one single family of planes and most of their flight are operated with one or as much two models of planes. Moreover, we do not expect relevant changes in the composition of the aircraft fleet in the period we consider. Planes used at each flight are also related with distance since different aircraft models are efficient for specific distance ranges.

**Table 4**
Arrival Delays (all causes), whole sample

| | Airport FE (I) | Flight FE (II) |
|---|---|---|
| **Share airline airport origin** | 0.018 (0.015) | −0.092 (0.0407)** |
| **Share airline airport destination** | 0.095 (0.018)*** | 1.176 (0.151)*** |
| **HHI** | −0.009 (0.018) | 0.004 (0.009) |
| **Total flights airport (time interval)** | 0.089 (0.015)*** | 0.126 (0.018)*** |
| **Plane size** | 0.026 (0.007)*** | 0.034 (0.007)*** |
| **Strike France * Western Europe** | 13.468 (0.865)*** | 13.494 (0.851)*** |
| **Strike Italy/Greece * Southern Europe** | 21.884 (5.021)*** | 22.545 (5.022)*** |
| **Snow on origin** | 35.016 (1.592)*** | 34.770 (1.599)*** |
| **Rain on origin** | 5.517 (0.289)*** | 5.565 (0.278)*** |
| **Fog on origin** | 7.308 (0.633)*** | 7.490 (0.593)*** |
| **Storm on origin** | 34.364 (2.542)*** | 34.551 (2.514)*** |
| **Cloud on origin** | 0.999 (0.181)*** | 1.038 (0.167)*** |
| **Temperature on origin** | 0.090 (0.017)*** | 0.086 (0.016)*** |
| **Snow on destination** | 9.009 (3.065)*** | 9.065 (2.928)*** |
| **Rain on destination** | 9.882 (0.337)*** | 9.941 (0.337)*** |
| **Fog on destination** | 9.617 (1.623)*** | 9.858 (1.433)*** |
| **Storm on destination** | 21.494 (2.096)*** | 21.220 (2.067)*** |
| **Cloud on destination** | 4.695 (0.188)*** | 4.692 (0.185)*** |
| **Madrid** | Base (0) | – |
| **Barcelona** | 8.483 (0.547)*** | – |
| **Bilbao** | 1.363 (1.238) | – |
| **Santiago C.** | 0.253 (1.601) | – |
| **Sevilla** | 2.266 (1.201)* | – |
| **Valencia** | 5.391 (1.181)*** | – |
| **Origin Airport FE** | YES | NO |
| **Destination airport FE** | YES | NO |
| **Time Arrival Interval FE** | YES | YES |
| **Month FE** | YES | YES |
| **Flight FE** | NO | YES |
| **R2** | 0.08 | 0.14 |
| **Observations** | 324,248 | 324,248 |

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the flight level). Statistical significance at 1% (***), 5% (**), 10% (*).

standard errors in clusters by flight to correct for autocorrelation in the error term at cross-sectional and temporal levels.

## 5. Estimation and results

This section analyses the relationship between airlines dominance at destination airports and arrival delays. Column I in Table 4 presents the results of the model with origin and destination airport fixed effects, while column II considers the model with flight fixed effects. The estimates of the two models reveal that the variable *Share Airline Airport Destination* has a positive and statistically significant effect on *Arrival Delays***.** This result implies that the airlines that have a larger share of the flights at the destination airports exhibit more delays and do not contribute to internalize the congestion at the airport. Results for the variable *Share Airline Airport Origin* are less clear-cut, since it is not statistically significant in the regression in column I. The negative coefficient for this variable in the model with flight fixed effects suggests that those airlines with a larger position in the origin airport might have more capacity to adjust to unexpected events and have less delays. This conclusion goes in line with Bubalo and Gaggero (2021), who show that flights operated by network airlines with a hub at the origin airport are less likely to propagate delays.

The variable *Total Number of Flights at the Airport* (by time interval) is positive and statistically significant. This result suggests that a high number of flights at the destination airport in specific time intervals is relevant in explaining delays. Flights that arrive to the airports in periods with more concentration of operations are subject to more delays. Interesting enough, the variable *HHI* that considers the level of competition at the route level is not statistically significant, which contrasts with the literature showing the existence of a competition-quality effect (Mazzeo, 2003; Greenfield, 2014; Bubalo and Gaggero, 2015). We discuss the potential endogeneity of this variable in Section 6. The variable *Plane Size* is significant and positively related with the delays, which implies that flights using bigger airplanes are more likely to experience delays.

The variables reflecting adverse weather conditions at the flight's origin and destination airport show a positive and statistically significant effect. Delays are particularly higher in flights affected by snow and storms at the origin airport or by storms at the destination airport. Moreover, flights affected by strikes exhibit significantly higher delays. Interestingly, column I shows that the dummies for Barcelona, Valencia and Sevilla airports are positive and statistically significant. Given that the reference airport is Madrid, this implies that flights arriving to airports dominated by low-cost airlines have more delays. In this regard, flights to Barcelona airport are on average subject to more delays than those arriving to Madrid airport, as it could be inferred from the descriptive

**Table 5**
Delays, dominance and network type (dependent variable: Arrival Delays – all causes), whole sample

| | Dominance (I) | Dominance & network type (II) |
|---|---|---|
| **Dominant destination airport** | 0.185 (0.581) | −7.063 (1.093)*** |
| **LCC** | – | 1.875 (0.976)* |
| **Dominant destination airport X LCC** | – | 11.001 (1.427)*** |
| **Controls** | ALL | ALL |
| **Origin Airport FE** | YES | YES |
| **Destination Airport FE** | YES | YES |
| **Time Arrival Interval FE** | YES | YES |
| **Month FE** | YES | YES |
| **Flight FE** | NO | NO |
| **N** | 324,248 | 324,248 |
| **R2** | 0.07 | 0.07 |

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the flight level). Statistical significance at 1% (***), 5% (**), 10% (*).

**Table 6**
Delays by airport (dependent variable: Arrival Delays – all causes)

| | Madrid airport | | | Barcelona airport | | | Small airports | | |
|---|---|---|---|---|---|---|---|---|---|
| | Dominance (I) | Airport share (II) | Airport share (III) | Dominance (I) | Airport share (II) | Airport share (III) | Dominance (I) | Airport share (II) | Airport share (III) |
| **Dominant destination airport** | −5.460 (1.125)*** | – | – | 5.989 (1.053)*** | – | – | 2.875 (1.017)*** | – | – |
| **Share airline destination airport** | – | −0.119 (0.039)*** | −0.331 (0.403) | – | 0.204 (0.277)*** | 2.243 (0.324) *** | – | 0.0270** (0.0119) | 0.112 (0.126) |
| **Controls** | All | All | All | All | All | All | All | All | All |
| **Origin airport FE** | YES | YES | NO | YES | YES | NO | YES | YES | NO |
| **Destination airport FE** | YES | YES | NO | YES | YES | NO | YES | YES | NO |
| **Time Arrival Interval FE** | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| **Month FE** | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| **Flight FE** | NO | NO | YES | NO | NO | YES | NO | NO | YES |
| **N** | 123,391 | 123,391 | 123,391 | 139,754 | 139,754 | 139,754 | 61,156 | 61,156 | 61,156 |
| **R2** | 0.05 | 0.05 | 0.11 | 0.09 | 0.09 | 0.14 | 0.06 | 0.05 | 0.12 |

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the flight level). Statistical significance at 1% (***), 5% (**), 10% (*).

data presented in Section 2.

Table 5 repeats the estimation of model (1) but using different indicators to reflect the dominance of airlines at the airport. Column I considers a dummy variable that takes the value of one when the flight is operated by an airline that is dominant at the destination airport. We do not find a significant result for this variable. Column II repeats the previous analysis but considering the airlines' network configuration. Specifically, we add to the model a dummy variable for low-cost airlines, and the interaction of this dummy with the variable of dominance at the destination airports. The results clarify some of the previous findings. First, we find that flights operated by airlines with a dominant position at the destination airport have less delays. Second, low-cost airlines with a dominant position at the destination airports have relatively more delays than the rest of airlines. Table A7 in the appendix shows that similar results are obtained when considering separate sub-samples for international and domestic flights. That is, low-cost airlines with a dominant position at the destination airport have more delays.

We complete our analysis by considering separate regressions for Madrid, Barcelona and for the four smaller airports. The results that we obtain for these airports are heterogeneous, as it could be expected from the different characteristics of the dominant airlines operating on them. Table 6 shows that the variable *Dominant at the Destination Airport* is negative and significant in Madrid (where the dominant airlines has a hub-and-spoke network configuration) and positive and significant in the other airports (where the dominant airlines are low-cost airlines). The regressions considering the variable *Share of the Airline at the Destination Airport* show different results depending on whether they include *Origin* and *Destination Airport* fixed effects or *Flight* fixed effects. Consider first the case with airport fixed effects (specification II). In Madrid, a larger share in the destination airport has a significant negative effect. In Barcelona and in the small airports, a larger share in the destination airports has a positive and significant effect in the delays. Take now the model with flight fixed effects (specification III). The sign of the variable *Share of the Airline at the Destination Airport* is the same as in the regressions with airport fixed effects. However, the only statistical effect that is maintained is that in Barcelona a larger share in the destination airport is positively related with the delays. Regressions with flight fixed effects are more imprecise and give high values for the standard errors. Thus, the non-significance of the airport share variables in Madrid and small airports could be explained by its very low within variation.

Overall, the results of Tables 5 and 6 show that among the six Spanish airports examined, the internalization of congestion occurs only in the case of Madrid airport, which is dominated by two network airlines. In the other five airports, the flights of the low-cost airlines with a dominant position at the airport exhibit more delays that those of their rivals. This result is in line with the findings of Guo et al. (2018), who show that congestion internalization is not observed in the case of low-cost airlines. One potential explanation for this result is that the point-to-point design of low-cost airlines allow them to generate network effects with a lower exposition to congestion, but at the same time they might have less capacity to adjust to delays. Low cost airlines try to gain market power in an origin–destination region by controlling a large fraction of passengers in the region and serving airports that form part of the same market.[17] Their configuration with multiple focus airports close to each other might help them to avoid some of the congestion problems that affect airlines operating hub-and-spoke networks, but this also prevent them to offer the quick responses to delays and unexpected incidences that can offer network airlines.

## 6. Robustness checks

### 6.1. Additional measures of delays

The dependent variable of our previous analysis was *Arrival Delays*, which measures the difference in minutes between the actual and the announced arrival times of the flight. However, delays can be originated at different stages of the flights: departure delay at the origin airport; en-route delay in the air; and arrival delay in the terminal area of the destination airport. The dominant position of the airlines at the destination airports can offer them different mechanisms and incentives to reduce these different types of delays.

Table 7 shows the results of regressions that consider these different measures of delays. Results for *Arrival Delays* are the same than in Tables 4 and 6. *Departure Delay* is the difference between the actual and announced departure time of the flight, while *En-Route Delay* is the difference between the actual and scheduled flight time (in the air). For simplicity, the table just reports the results for our baseline model that includes origin and destination airport fixed effects. Notice that our findings in this table go in the same line with those of Table 4. If anything, we obtain that the variable of *Share of the Airlines at the Destination Airport* is not statistically significant for *En-Route Delays* in Madrid and for *Departure Delays* in small airports. We also find that in the flights to Madrid, the *Share of the Airlines at the Destination Airport* is negatively related with *Departure Delays*, and this effect is maintained with *Arrival Delays*. In the case of Barcelona, the *Share of the Airlines at the Destination Airport* is positively related with the *Departure Delay* and the *En-route Dalays*, and this effect is increased in the case of *Arrival Delays*. Finally, in the case of the small airports, we do not find an effect of this variable in the *Departure Delays*, but we do observe that dominance at the destination airport is positively related with *En-Route* and *Arrival Delays*.

### 6.2. External causes of delays

The previous analysis has shown that the airlines' dominance at the destination airports is a relevant factor for understanding arrival delays. However, it is possible that some external causes of delays such as adverse weather conditions, strikes and air traffic control regulations are more important in some airports than in others. For example, the Barcelona airport has a high proportion of flights subject to Eurocontrol regulations. If dominant low-cost airlines arriving to Spanish airports are more affected by external causes of delays, this could put into question our finding that there is a positive causal relationship between low-cost airlines' dominance at destination airports and delays. To examine this possibility, we perform two robustness checks. First, we repeat the previous analysis but considering as dependent variable the minutes of delays caused by Eurocontrol regulations. And second, we re-estimate our model excluding the observations affected by adverse weather conditions and strikes. As before, to simplify the exposition, we focus in our baseline model with origin and arrival airport fixed effects and we use the *Share of the Airline at the Destination Airport* as the main explanatory variable.

We start by considering as dependent variable the delays caused by the Eurocontrol regulations, that is, the difference in minutes between the airline's requested take-off time (in the flight plan) and the take-off time issued by Eurocontrol. These regressions are useful to identify whether dominant airlines are subject to more delays due to Eurocontrol regulations than the rest of airlines. Table 8 shows the results for each type of airport. In all cases, the variable *Share of the Airline at the Destination Airport* is not statistically significant. Therefore, we can conclude that our finding that flights operated by airlines with a large share in Barcelona and in the small Spanish airports have relatively more delays is not due to the fact that these airlines are more prone to be affected by Eurocontrol

[17] Fu et al. (2019) show that low-cost airlines operating point-to-point networks can generate network externalities in different ways than airlines operating hub-and-spoke networks. Low-cost airlines seek to control a large fraction of the traffic of a region, which allows them to aggregate passengers at focus airports without incurring in the costs of running a hub. In addition, they serve substitute markets out of the same airports. This strategy increases airlines' market power in an origin–destination region and allows them to configure multiple focus airports close to each other. This is not possible in HS airlines, as locating close to each other would reduce traffic volumes at hubs and spokes markets.

**Table 7**
Arrival, departure and en-route delays

| | **All** | | | **Madrid** | | | **Barcelona** | | | **Small** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Ar delay (I)** | **Dep delay (II)** | **En-ro delay (III)** | **Ar delay (IV)** | **Dep delay (V)** | **En-ro delay (VI)** | **Ar delay (VII)** | **Dep delay (VIII)** | **En-ro delay (IX)** | **Ar delay (X)** | **Dep delay (XI)** | **En-ro delay (XII)** |
| **Share airline destination airport** | 0.0952*** | 0.0305* | 0.059*** | −0.119*** | −0.221*** | 0.0498 | 0.204*** | 0.127*** | 0.0419*** | 0.0270** | −0.00240 | 0.059*** |
| | (0.0182) | (0.0169) | (0.0250) | (0.0393) | (0.0300) | (0.102) | (0.0277) | (0.0255) | (0.018) | (0.0119) | (0.0112) | (0.0034) |
| Observations | 325,055 | 307,595 | 303,967 | 123,446 | 114,329 | 117,112 | 140,453 | 135,304 | 133,695 | 61,156 | 57,962 | 53,160 |
| R-squared | 0.090 | 0.084 | 0.505 | 0.084 | 0.076 | 0.579 | 0.113 | 0.106 | 0.704 | 0.090 | 0.083 | 0.318 |
| Controls | ALL | ALL | ALL | ALL | ALL | ALL | ALL | ALL | ALL | ALL | ALL | ALL |
| Origin Airport FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Destination Airport FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Time Arrival Interval FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Month FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Flight FE | NO | NO | NO | NO | NO | NO | NO | NO | NO | NO | NO | NO |

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the flight level). Statistical significance at 1% (***), 5% (**), 10% (*).

**Table 8**
External causes of delays by airports (dependent variable: minutes of delays due to Eurocontrol regulations)

| | Madrid | Barcelona | Small |
|---|---|---|---|
| **Share Airline Destination** | −0.0009 | 0.010 | 0.005 |
| | (0.008) | (0.008) | (0.005) |
| **Controls** | ALL | ALL | ALL |
| **Origin airport FE** | YES | YES | YES |
| **Destination airport FE** | YES | YES | YES |
| **Time Arrival Interval FE** | YES | YES | YES |
| **Month FE** | YES | YES | YES |
| **Flight FE** | NO | NO | NO |
| **N** | 103,156 | 128,659 | 51,584 |
| **R2** | 0.07 | 0.12 | 0.09 |

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the flight level). Statistical significance at 1% (***), 5% (**), 10% (*).

**Table 9**
Delays by airport – flights with fair weather conditions and no strikes (dependent variable: Arrival delays – all causes)

| | Madrid | Barcelona | Small |
|---|---|---|---|
| **Share Airline Destination** | −0.110 (0.040)*** | 0.197 (0.028)*** | 0.059 (0.027)** |
| **Controls** | ALL | ALL | ALL |
| **Origin airport FE** | YES | YES | YES |
| **Destination airport FE** | YES | YES | YES |
| **Time Arrival Interval FE** | YES | YES | YES |
| **Month FE** | YES | YES | YES |
| **Flight FE** | NO | NO | NO |
| **N** | 102,099 | 123,161 | 50,699 |
| **R2** | 0.07 | 0.12 | 0.09 |

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the flight level). Statistical significance at 1% (***), 5% (**), 10% (*).

**Table 10**
Arrival Delays – instrumental variables, whole sample

| | All | Madrid | Barcelona | Small |
|---|---|---|---|---|
| **Share airline airport destination** | 0.143 (0.036)*** | −0.066 (0.014)*** | 0.222 (0.018)*** | 0.0287 (0.009)*** |
| **Observations** | 325,055 | 123,446 | 140,453 | 61,156 |
| **R-squared** | 0.055 | 0.037 | 0.082 | 0.047 |
| **F-test (1st stage)** | 54.146*** | 8056.85*** | 3116.42*** | 1955.34*** |
| **Controls** | ALL | ALL | ALL | ALL |
| **Origin Airport FE** | NO | NO | NO | NO |
| **Destination Airport FE** | YES | YES | YES | YES |
| **Time Arrival Interval FE** | YES | YES | YES | YES |
| **Month FE** | YES | YES | YES | YES |
| **Flight FE** | NO | NO | NO | NO |

Notes: Instrument of HHI is a dummy for routes affected by open skies agreements. Standard errors in parentheses (robust to heteroscedasticity and clustered at the flight level). Statistical significance at 1% (***), 5% (**), 10% (*).

regulations than the rest.

Similarly, it is important to consider the possibility that the flights operated by airlines with a dominant presence in Barcelona and in the small Spanish airports are more exposed to adverse weather events and to ATC strikes. To control for this situation, Table 9 repeats the analysis of Table 6 but for a subsample of fights not affected by these exogenous factors. The results we obtain are qualitatively the same than before, which confirms that our results are not driven by the heterogeneous influence of adverse events.

### *6.3. Endogeneity of control variables*

In this section, we examine the potential endogeneity of the *HHI* control variable. Airlines may have incentives to engage in different types of managerial activities to reduce delays. This unobserved effort may be dependent on route-level competition and thus may correlate with *HHI*. To deal with this potential endogeneity problem, we apply an instrumental variables (IV) procedure in which

**Table 11**
Arrival delays at the airline-route and month levels

| | All | Madrid | Barcelona | Small |
|---|---|---|---|---|
| **Share airline airport destination** | 0.0944*** | −0.277*** | 0.293*** | 0.0385 |
| | (0.0204) | (0.0508) | (0.0600) | (0.0263) |
| **Fares** | −0.00398 | 0.0124 | −0.0358 | 0.0268** |
| | (0.0169) | (0.0201) | (0.0498) | (0.0122) |
| **Observations** | 5,647 | 1,280 | 2,008 | 2,359 |
| **R-squared** | 0.279 | 0.466 | 0.311 | 0.337 |
| **Controls** | ALL | ALL | ALL | ALL |
| **Origin Airport FE** | YES | YES | YES | YES |
| **Destination Airport FE** | YES | YES | YES | YES |
| **Time Arrival Interval FE** | NO | NO | NO | NO |
| **Month FE** | YES | YES | YES | YES |
| **Flight FE** | NO | NO | NO | NO |

Notes: Data aggregated at the route-airline and month levels. Controls include distance, plane size, HHI and share airline airport origin. Standard errors in parentheses (robust to heteroscedasticity and clustered at the airline-route level). Statistical significance at 1% (***), 5% (**), 10% (*).

*HHI* is instrumented with a dummy variable that takes the value of 1 for flights affected by an "open skies agreement".[18] Air traffic relations between countries are typically regulated by bilateral agreements that, among other aspects, impose entry barriers (Bernardo and Fageda, 2017). In the case of the European Economic Area (EEA), flights among country members has been completely liberalized. In addition, the European Union has signed open skies agreements with United States, Morocco, Georgia and Israel to liberalize the air traffic. Considering this, we expect the competition to be stronger for the flights affected by these agreements than for flights regulated by bilateral agreements between countries.

Table 10 shows the results of the analysis with instrumental variables. The F-test of the first stage regression is very high, which confirms that the dummy variable for open skies agreements has a significant (and negative) effect in the HHI variable. Results for the second stage of the IV estimation are qualitatively identical to those in Table 4 and 6, when we consider the full sample and the subsamples of airports. Table A8 in the appendix provides additional evidence that the potential endogeneity of the *HHI* variable does not affect our main results. This table considers a sample of monopoly routes, so that the only source of variability in terms of market power has to do with the share of the airlines in the airports.

Finally, notice that the variable *Total Flights at the Arrival Airport* could also be affected by a problem of endogeneity if unobserved managerial effort to reduce delays is correlated with the periods of congestion at the airport. This variable is defined at a very detailed level (by time interval per day), which makes unfeasible to find good instruments to apply an instrumental variables procedure. This is a limitation of our analysis that must be taken into account.

### *6.4. Delays and fares*

One relevant omitted explanatory variable in our analysis is the fare charged by airlines. Whether for reasons attributable to the airlines or external factors, delays influence fares (Forbes, 2008; Bilotkach and Pai, 2020). Note that our dataset is at the flight level and does not contain price information. However, we have created an aggregated sample at the airline-route and month level that includes information on the average fares posted by airlines and the average arrival delays. Data on airlines' fares has been obtained from RDC aviation.[19]

Table 11 shows the results of the estimation of equation (1) at the airline-route and month level, including a variable for fares. We find that the relationship between delays and the share of the airline at the destination airport is not affected by the consideration of fares as covariate. Note also that our analysis does not show a clear link between delays and fares (only in the case of small airports we find that higher fares are associate with more delays), although this could be due to the limitations of our fare data. In this regard, the fare variable can be endogenous and affect our estimates. Previous analysis of Bilotkach and Pai (2020) have found that airlines delays do not affect airfares in markets where passengers do not have a non-stop flight alternative. Guo et al. (2018) estimate a price equation for the air market considering the reverse causality problem between ticket price and the passenger traffic, as well as delays. As they explain, airlines may adopt a low-price strategy to attract passengers, but this can increase the number of passengers in individual markets, as well as the airport load. As a result, increased traffic volume would increase congestion and delays. To address this problem, the authors use one-year lagged values of airport load, flight delays and their interaction term at both airport and market level.

[18] In a similar approach, Greenfield (2014) uses a five-year sample of panel data to examine how temporal variation in airport-pair market structure (measured by the *HHI* index) impacts airline on-time performance. He employs an IV approach, considering two distinct instruments for *HHI*. First, he uses lagged market structure as an instrument for current market structure. Second, he relies on variation in competition caused by the 2008 merger between Delta Air Lines (DL) and Northwest Airlines (NW).

[19] RDC aviation provides data on the estimated weighted fares that are built using an algorithm that considers as inputs, at the airline-route level, multiple pricing observations for a representative series of flights. These are factored by an airline and route-specific booking algorithm that estimates the number of bookings made at each point in the sales-cycle of the flight. It should be noted that our fare variable refers to round-trip flights for the economy fare class and it includes all government taxes, including airport charges and departure taxes.

## 7. Conclusions

For many years, delays in air transportation have been a considerable source of concern for consumers and sectorial regulators. In this paper we have examined whether airlines with a dominant position at the destination airports experience more delays. On the one hand, dominant airlines might have little incentives to reduce delays because they are less affected by competition. On the other hand, they might have incentives to internalize airport congestion to avoid the negative effects that delays can generate on their other flights and on connecting passengers.

Our paper has examined this question using a very rich dataset on the arrival delays of all inward flights arriving at six Spanish airports in the period Nov 2017–Oct 2018. Our dataset also contains detailed information on the adverse weather conditions, strikes and Eurocontrol regulations affecting these flights. An important source of variability that we have used in our analysis is the fact that Madrid airport is a hub dominated by two network airlines, while Barcelona and the smaller Spanish airports are dominated by two low-cost airlines.

The results of our analysis show that among the six Spanish airports examined, the internalization of congestion occurs only in the case of Madrid airport, which is dominated by two network airlines. In the other five airports, the flights of the low-cost airlines with a dominant position in the airport exhibit more delays that those of their rivals. These findings show that the airlines' efforts to reduce congestion at the destination airports depends on their network configuration. The point-to-point design of low-cost airlines allow them to generate network effects with a lower exposition to congestion, but these airlines might have less capacity to adjust to delays. Low-cost airlines try to gain market power in an origin–destination region by controlling a large fraction of passengers in the region and serving airports that form part of the same market. Their configuration with multiple focus airports close to each other might help them to avoid some of the congestion problems that affect airlines operating hub-and-spoke networks, but also prevent them to offer the quick responses to delays and unexpected incidences that can offer network airlines.

From a policy point of view, our results are especially remarkable for large airports. Although the increasing presence of low-cost airlines at large airports might have positive effects in terms of lower fares and more traffic, it can also entail a reduction in the quality of the service, measured in terms of on-time performance. Our analysis suggests that a greater presence of low-cost airlines in the airport implies more delays. Managers of large airports can try to avoid these negative effects by discouraging the entry of low-cost airlines (for example with an increase of the airport charges) or by the imposition of regulations penalizing delays. In the case of small airports, the presence of low-cost airlines may be desirable, even if that is at the expense of further delays, given the difficulties of attracting network airlines.

Finally, it is worth mentioning two relevant aspects not considered in our analysis. First, in the last years airlines worldwide have increasingly used padding to reduce their delays. This practice consists in extending the announced travel duration beyond the minimum travel time (Baumgarten et al., 2014, Zhang et al., 2018; Forbes et al., 2019; Brueckner et al., 2021a; 2021b). Airlines can use padding to better coordinate their banks of arrival flights to an airport and to avoid consumers' claims after delays. Clearly, this is an aspect that depends on the level of competition at the route level, as airlines might try to reduce the announced duration of flights to attract passengers. Second, a comprehensive method for analyzing the determinants of flight delays should consider delay propagations across linked airports and routes. Delays propagation among airports have been explored in previous studies (Du et al. 2018; Whu and Law, 2019), but few papers have considered this issue in the study of the congestion internalization hypothesis (Chen and Lin, 2021). The structure of our dataset does not allow us to consider padding and the propagation of delays but these relevant aspects should be considered in future studies.

### CRediT authorship contribution statement

**Joan Calzada:** Conceptualization, Data curation, Formal analysis, Investigation. **Xavier Fageda:** Conceptualization, Data curation, Formal analysis, Investigation.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Data availability

Data will be made available on request.

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### Appendix

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**Table A1**
Total traffic by European airports in 2018

| Airport | Total traffic |
|---|---|
| London Heathrow | 80,100,311 |
| Paris Charles de Gaulle | 72,196,444 |
| Amsterdam Schipol | 70,979,498 |
| Frankfurt Main | 69,385,941 |
| *Madrid Barajas* | 56,477,891 |
| *Barcelona El Prat* | 49,594,338 |
| Munich | 46,205,919 |
| London Gatwick | 46,081,327 |
| Rome Fiumicino | 42,894,217 |
| Paris Orly | 33,114,935 |

Note: Data come from Eurostat.

**Table A2**
Percentage of observations affected by different weather conditions

| | Percentage of observations |
|---|---|
| **Fair weather on origin** | 55.0 % |
| **Snow on origin** | 0.7 % |
| **Rain on origin** | 7.6 % |
| **Fog on origin** | 1.9 % |
| **Storm on origin** | 0.2 % |
| **Cloud on origin** | 34.6 % |
| **Temperature on origin (less than0 degrees)** | 0.01 % |
| **Fair weather on destination** | 73.4 % |
| **Snow on destination** | 0.0 % |
| **Rain on destination** | 5.0 % |
| **Fog on destination** | 0.4 % |
| **Storm on destination** | 0.3 % |
| **Cloud on destination** | 21.0 % |

**Table A3**
Descriptive statistics for Eurocontrol regulations

| Cause regulation | Total observations | Share over total observations | Mean delay (minutes) | Main reasons |
|---|---|---|---|---|
| No regulation | 199,851 | 71 % | – | – |
| ATC capacity | 27,684 | 10 % | 8.42 | Traffic congestion, runway configuration, reduced capacity due to technical incidents, late slots |
| Airport capacity | 7,572 | 3 % | 7.06 | Traffic congestion, Works in progress, late slots |
| Strikes | 2,861 | 1 % | 25.44 | ATC industrial action, industrial action non-ATC, strikes |
| Airspace management | 1,302 | 0.5 % | 8.45 | Reduced capacity due to technical incidents |
| Other | 1,548 | 1 % | 10.12 | Runway configuration, radar problems, Instrumental landing system calibration, ATC technical problems |
| Special event | 8,536 | 3 % | 9.47 | ATC system modification |
| ATC issues | 10,176 | 4 % | 13.55 | ATC staffing, ATC equipment, ATC re-routing |
| Environmental issues | 6,779 | 2 % | 10.14 | Night configuration, noise abbatement, runway configuration |
| Weather | 20,613 | 7 % | 17.69 | Low visibility, strong wind, high turbulences, heavy rain, snow, storms |

**Table A4**
Descriptive statistics for Eurocontrol regulations by airport

| Cause regulation/% observations | Madrid | Barcelona | Small |
|---|---|---|---|
| No regulation | 77 % | 59 % | 84 % |
| ATC capacity | 9.51 % | 9.90 % | 9.63 % |
| Airport capacity | 3.64 % | 2.90 % | 0.01 % |
| Strikes | 0.87 % | 1.11 % | 1 % |
| Airspace management | 0.43 % | 0.49 % | 0.43 % |
| Other | 0.55 % | 0.34 % | 1.05 % |
| Special event | 0.41 % | 6.08 % | 0.33 % |
| ATC issues | 0.00 % | 5.18 % | 0.00 % |
| Environmental issues | 0.00 % | 5.18 % | 0.00 % |
| Weather | 4.61 % | 10.75 % | 0.02 % |

**Table A5**
Total flights by operating airline in Europe in 2018

| Airline | Total flights |
|---|---|
| *Ryanair* | 740,964 |
| easyJet | 579,911 |
| Air France-KLM | 520,317 |
| Lufthansa | 505,425 |
| British Airways | 303,386 |
| SAS | 292,451 |
| Eurowings | 240,705 |
| Norwegian | 218,576 |
| *Vueling* | 209,778 |
| *Iberia* | 193,624 |

Note: Data come from RDC aviation.

**Table A6**
Percentage of observations by model of aircraft for main sample airlines

| Airline | Aircraft model | Percentage of flights by model |
|---|---|---|
| Vueling | A320 | 82 % |
| | A321 | 13 % |
| | A319 | 3 % |
| Ryanair | 737–800 | 100 % |
| Iberia | A320 | 32 % |
| | A319 | 26 % |
| | A321 | 25 % |
| | A340 | 8 % |
| | A330-200 | 5 % |
| | A330-300 | 5 % |
| Air Europa | 737–800 | 55 % |
| | E195 | 25 % |
| | A330-200 | 12 % |
| | ATR 72 500 | 4 % |
| Easyjet | A320 | 50 % |
| | A319 | 49 % |
| Lufthansa | A321 | 51 % |
| | A320 | 36 % |
| | A319 | 10 % |
| Norwegian | 737–800 | 97 % |
| British Airways | A320 | 69 % |
| | A321 | 9 % |
| | A319 | 10 % |
| | 767–300 | 6 % |
| Transavia | 737–800 | 86 % |
| | 737–700 | 13 % |

**Table A7**
Delays, dominance and network type (dependent variable: Arrival Delays – all causes), whole sample

| | International flights | | | Domestic flights | | |
|---|---|---|---|---|---|---|
| | Dominance & network type (I) | Airport share (II) | Airport share (III) | Dominance & network type (IV) | Airport share (V) | Airport share (VI) |
| **Dominant destination airport)** | −8.836 (1.267)*** | | – | −11.395 (2.686)*** | | |
| **LCC** | 1.138 (1.140) | | – | −6.111 (2.200)*** | | |
| **Dominant Destination X LCC** | 15.420 (1.626)*** | | – | 19.253 (4.567)*** | | |
| **Share airline airport destination** | – | 0.130 (0.023)*** | 1.318 (0.228)*** | | 0.056 (0.0265)** | 1.005 (0.187)*** |
| **Controls** | ALL | ALL | ALL | ALL | ALL | ALL |
| **Origin airport FE** | YES | YES | NO | YES | YES | NO |
| **Destination airport FE** | YES | YES | NO | YES | YES | NO |
| **Time Arrival Interval FE** | YES | YES | YES | YES | YES | YES |
| **Month FE** | YES | YES | YES | YES | YES | YES |
| **Flight FE** | NO | NO | YES | NO | NO | YES |
| **N** | 223,407 | 223,407 | 223,407 | 100,841 | 100,841 | 100,841 |
| **R2** | 0.08 | 0.07 | 0.13 | 0.08 | 0.06 | 0.13 |

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the flight level). Statistical significance at 1% (***), 5% (**), 10% (*).

**Table A8**
Arrival Delays – monopoly routes

| | All (I) | Madrid (II) | Barcelona (III) | Small (IV) |
|---|---|---|---|---|
| **Share airline airport destination** | 0.038 (0.014)*** | −0.289 (0.162)* | 0.339 (0.149)** | 0.039 (0.019)** |
| **Observations** | 99,055 | 26,946 | 36,100 | 36,009 |
| **R-squared** | 0.101 | 0.130 | 0.119 | 0.047 |
| **Controls** | ALL | ALL | ALL | ALL |
| **Origin Airport FE** | YES | YES | YES | YES |
| **Destination Airport FE** | YES | YES | YES | YES |
| **Time Arrival Interval FE** | YES | YES | YES | YES |
| **Month FE** | YES | YES | YES | YES |
| **Flight FE** | NO | NO | NO | NO |

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the flight level). Statistical significance at 1% (***), 5% (**), 10% (*).

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