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How do airlines react to slot displacements? Evidence from a major airport

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ABSTRACT

The main strategic mechanism developed by the aviation industry to manage airport capacity is IATA's Slot Allocation Process. At airports where such mechanism is in place, airlines need to be assigned slots by an independent slot coordinator to schedule their flights. The slot allocation process involves multiple steps spanning several months of negotiations between airlines and slot coordinators. The most critical step is the initial slot allocation during which the coordinators communicate to airlines whether their slot requests have been accepted or need to be displaced (i.e., moved to a different time of the day). In this article, we use logistic regression models to analyze the reactions of airlines to slot displacement decisions by coordinators and the subsequent need to change their flight schedules. We focus our analysis on Paris Charles de Gaulle (CDG) Airport, one of the busiest worldwide. Our results indicate that even a small displacement (of less than 30 min) can decrease substantially the odds of a flight being scheduled, but that these odds vary widely with the type of airline involved, the time of the day and several other factors. This information could be used by coordinators to make initial slot allocation decisions that take into account their expected flight scheduling implications. Ultimately, this would contribute to more efficient use of the scarce capacity available at congested airports and increased responsiveness to the mobility needs of air passengers.

1. Introduction

Despite some periods of pronounced economic downturn, air passenger traffic has grown globally at an average annual rate of approximately 5.5% between 1970 and 2019 (https://data.worldbank.org/indicator/IS.AIR.PSGR, accessed April 24, 2022). This trend was sharply interrupted in 2020 by the covid-19 pandemic, which practically halted aviation activity almost everywhere in the world. However, most recent forecasts from the main airline and airport associations (IATA and ACI, respectively) point to a resumption of similarly high annual growth rates following the pandemic.[1] This also means that the airport congestion and flight delay problems affecting air transport until recently will certainly be experienced again in the near future.

The main strategic mechanism developed by the aviation industry to manage airport capacity is IATA's Slot Allocation Process (Gillen et al., 2016). This process is now carried out according to the Worldwide Airport Slot Guidelines – WASG (ACI, IATA and WWSAG, 2020), which replaced the 10th edition of the Worldwide Slot Guidelines – WSG (IATA, 2019) after May 31, 2020.[2] A slot is defined in these guidelines as a permission to use "the full range of airport infrastructure necessary to arrive or depart at an airport on a specific date and time". The airports where such permissions are necessary are designated as "slot

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[1] According to these forecasts, aviation activity will be back to pre-covid activity levels in 2025 (ACI, 2022; IATA, 2021). Western Europe is one of the regions where recovery is expected to take longer, whilst the Asia-Pacific region may be back to such levels as early as the end of 2022.

[2] A critical difference between the WSG and the WASG is that the former were prepared by airline representatives (assembled by IATA) and airport coordinators (assembled by the WWASG, the worldwide association of airport slot coordinators), whereas the latter also involved airport representatives (assembled by ACI, the association of airport operators). In this sense, the often-used reference to "IATA's Slot Allocation Process" reflects the historical background of the process (which was conducted initially by IATA alone) but is no longer correct.

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coordinated” or “Level 3”. Such designation must follow a “thorough analysis” that demonstrates “a risk[3] that demand may significantly exceed the capacity of the airport” (WASG, Section 1.5.2). At present (April 2022), 198 airports are classified as Level 3 (in the aviation Summer season). Level 3 airports play a central role in the global air transport system. In fact, although they account for less than 5% of all airports in the world with commercial passenger service, they served about 4.3 billion arriving or departing passengers in 2019, or 47% of the world’s total. In Europe, this percentage was much higher, approximately 70%.

At every Level 3 airport, a slot coordinator is responsible for deciding, based on several criteria, whether a slot request is accepted, rejected or displaced, i.e., assigned to a time different from the one requested by the airline. In this article, we examine the reactions of airlines to the slot displacement decisions of coordinators for Paris Charles de Gaulle (CDG) Airport, one of the busiest worldwide, in the Summer season of 2018. The primary question we want to address is how the magnitude of the displacement assigned to a slot request influenced an airline’s decision of whether to operate the corresponding flight for an upcoming season or drop it from its schedule. Additionally, we want to understand whether and to what extent different attributes of the flight (e.g., peak vs. off-peak hour, full-service vs. low-cost) have an impact on that decision. Since air transport activity (as measured by number of passengers or number of movements) has a demonstrated impact on employment and GDP at the regional and national level (see, e.g., Brueckner, 2003; Percoco, 2010; Allroggen and Malina, 2014; Campante and Yanagizawa-Drott, 2018; Sheard, 2019; and, for recent reviews, Antunes and Martini, 2020; and Zhang and Graham, 2020), answering these questions contributes to shedding light on how displacing slot requests affects economic development.

To address the questions identified above, we have relied on logistic regression analysis, through which we were able to calculate the odds of a flight being operated depending on the displacement assigned to the slot and on the attributes of the flight. In particular, we have found for Paris CDG that even a small displacement of less than 30 min can decrease substantially the odds of a flight actually being operated. However, the change in odds varies widely with the type of airline involved, the time of the day and several other factors. Our findings, while confirming existing notions about the reactions of airlines to slot displacement, also provide relevant quantitative information about them, thus allowing for a more informed discussion of the impacts of slot allocation decisions on airline scheduling decisions.

Our article contributes to the airport capacity management literature and, more specifically, to its airport slot allocation stream, which has been attracting growing interest, particularly during the last 15 years (Dixit and Jakhar, 2021).[4] Subjects such as comparisons between “market-based” and administrative slot allocation processes, and the analysis and optimization of these processes, have been extensively investigated by now (see, e.g., Starkie, 1998; Czerny et al., 2008; Madas and Zografos, 2008; Basso and Zhang, 2010; Verhoef, 2010; Swaroop et al., 2012; Adler et al., 2014; Gillen et al., 2016; Pellegrini et al., 2017; Adler and Yazhemsky, 2018; Ribeiro et al., 2018; and Fairbrother et al., 2020). However, to the best of our knowledge, the topic of this article has not been previously addressed in the literature, primarily because its treatment requires highly detailed information solely available to slot coordinators – information that we were able to obtain for Paris CDG thanks to a collaboration with COHOR (the French slot coordination entity) and ENAC (École Nationale de l’Aviation Civile) involving exchanges of interns, software, and data.

The remainder of this article is structured as follows. First, we outline briefly IATA’s Slot Allocation Process (Section 2) and present and explain the aggregate statistics relevant to this process for Paris CDG in the Summer season of 2018 (Section 3). In Section 4, we provide essential background on the formulation, interpretation, estimation and assessment of logistic regression models, and describe the three model specifications we have analyzed in our study of the reactions of airlines to the displacement of slot requests. The experimental dataset based on which the models were estimated is described in Section 5. The model estimation results are presented and discussed in detail in Section 6. The final section of the article highlights our main conclusions and proposes possible directions for further research.

2. IATA’s slot allocation process

The administrative mechanism known as IATA’s Slot Allocation Process aims at allocating landing and take-off slots to airlines at Level 3 airports “in a neutral, transparent and non-discriminatory manner” (IATA, 2019). This process is carried out bi-annually for the two aviation seasons (Winter and Summer) and involves the six main steps displayed in Fig. 1. The contents of each one of these steps are briefly described below (for details, see Ribeiro et al., 2019, or IATA, 2020).

2.1. Capacity declaration

Airports inform slot coordinators about their declared capacities for an upcoming season approximately one year before that season starts. Different capacities may be declared for different types of movements (e.g., arrivals, departures and total) and for different elements of the airport (e.g., runway system, apron areas and terminal facilities). In particular, these capacities specify the number of slots that can be allocated at each time of the day. A slot (i.e., a permission to land or take off) refers to an expected departure or arrival time and an interval around it. In general, major airports outside the United States define the expected times in terms of 5-min windows (in the US, 1-min windows are used). The interval around the expected time changes across airports. In general, it is [−15, +15] minutes, but at major airports it can shrink to [−5, +10].

2.2. Slot requests

Airlines submit their slot requests to coordinators by the Initial Submission Deadline roughly six months prior to the start of the season. The requests are for series of slots (individual slots can be requested later). A series consists of “at least 5 slots allocated for the same or approximately same time on the same day-of-the-week, distributed

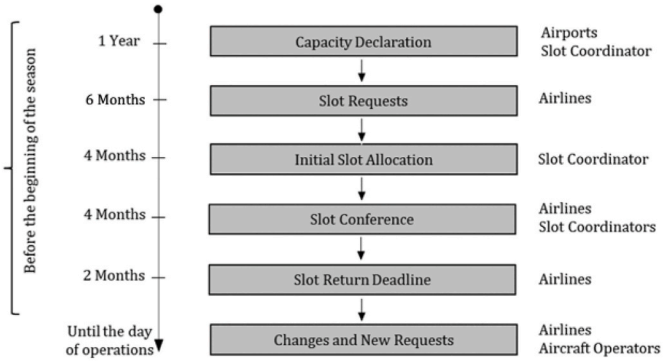

Fig. 1. Slot allocation process steps.

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[3] In practice, risk is not assessed in the same way everywhere. For example, the demand vs. capacity relationship at certain European airports that have been designated as Level 3 is much less strained than at several US airports designated as Level 2 or, even, Level 1 in the United States.

[4] A search of the Web of Science on the 1st of April 2022 with the phrase « slot* and allocation and (“air transport*" or aviation or airport*)» returned 124 journal articles (and reviews) of which 63 have been published in 2017 or later. The total number of citations of these articles was 1,754, with 216 in 2020 and 321 in 2021.

regularly in the same season" (IATA, 2019; ACI, IATA & WWSAG, 2020). The slot requests from the airlines follow the standard code provided in Chapter 6 of the Standard Schedules Information Manual (IATA, 2014). Table 1 lists the flight attributes that must be included in a slot request.

2.3. *Initial Slot Allocation*

This step is also designated as Slot Allocation Listing (SAL). Slot coordinators perform the initial allocation of the slots requested by airlines within approximately one month after receiving the requests. To comply with the capacity declared by airports, some requests may have to be displaced or even rejected. The displacement or rejection of slots is made in accordance with the priority criteria defined in the slot allocation guidelines (WSG until the May 31, 2020, and WSAG after that). According to these criteria, the first slots to be allocated are the historic slots; i.e., series of slots requested by an airline that were used at least 80 percent of the time in the previous equivalent season. After the WASG became effective, all the remaining slot requests are allocated subsequently. According to the WSG, priority was given, first, to requests for change-to-historic series of slots (i.e., to historic slot series for which the airline requests a change, such as retiming or using a different type of aircraft), second, to new-entrant slots (i.e., slots requested by airlines owning less than five slots on the day-of-the-week requested) and, last, to "other" requests (i.e., requests not qualifying for historic, change-to-historic or new entrant designation). However, the WASG modified these priorities and (after May 31, 2020) assigned equal priority to change-to-historic, new entrant and "other" requests, with allocation taking into account several "additional criteria", if two series are equally eligible for the same set of slots.[5]

2.4. *Slot Conference*

The Slot Conferences take place shortly after the Initial Slot Allocation. These are working conferences where delegates of airlines, airports and slot coordinators meet, generally in person, to discuss and possibly modify the initial allocation of slots. Indeed, it is possible for airlines to individually negotiate with the coordinator adjustments to the initial allocation or to exchange slots with other airlines.

Table 1
Flight attributes in slot requests.

Attribute	Definition
Flight number	1 to 9999
Aircraft	IATA code, three characters
Airline	IATA code, three characters
Arrival/ Departure	A if arrival, D if departure
Frequency	Days of the week in which the operation is conducted
Number dow	Number of days of the week in which the operation is conducted
Number weeks	Number of weeks in which the operation is conducted
Period start	First day of operation
Period end	Last day of operation
Previous/Next	Previous or next airport's IATA code, depending on whether the operation is an arrival or a departure
Requested slot	Time requested for the operation, as a four-digit number (e.g., 0600 for 6:00 or 1530 for 15:30)
Seat count	Number of seats of the aircraft
Time historic	Historic time as a four-digit number if the slot is historic, otherwise 9999

2.5. *Slot Return Deadline and Historic Baseline Date (HBD)*

Until the Slot Return Deadline (SRD), which occurs about 2.5 months before the start of the season, airlines may choose to return series and slots that they do not intend to use without being penalized. After that date, coordinators may make additions to the schedule by re-allocating returned slots to waitlisted requests or to newly submitted requests. Approximately 15 days later, by the Historic Baseline Date (HBD), they compile the "baseline" schedule for the upcoming season. This baseline schedule acts as the reference against which the use of each series is measured during the season. Series that achieve an 80% or higher use rate are designated as "historic" at the end of the season.

2.6. *Start of the Season*

During the 2 months remaining until the Start of the Season (SOS) and throughout the season itself, changes to the slot allocation and new requests for individual slots may still be considered provided that slots are still available.

3. Paris Charles de Gaulle Airport

The reactions of airlines to slot displacements will be examined based on data for Paris Charles de Gaulle (CDG) Airport, one of the world's most important hubs. Inaugurated in 1974, it handled 76.2 million passengers in 2019 and ranked as the 2nd busiest airport in Europe and the 9th in the world. Passenger traffic at CDG increased by about 35% between 2009 and 2019 (but, in 2020, dropped by almost 70% to 22.5 million passengers). The airport is designated as Level 3 since 1993 (http://www.cohor.org/en/aeroport-paris-charles-de-gaulle-cdg/, accessed November 12, 2021). The declared capacity of CDG in force since October 2016 is as follows: (1) runways - maximum of 80–120 movements per hour, varying with time of the day, between 06:00 and 21:59 (and of 32–67 between 22:00 and 05:59); (2) terminals - maximum of 4800 (Terminal 1) and 10,600 (Terminal 2) departing passengers per hour.

The slot allocation data for CDG made available by COHOR are summarized in Table 2. In the Summer season of 2018, a total of 347,646 slots were initially requested by airlines. Almost 68% of these slots were historic, and almost 19% were change-to-historic. This means that less than 14% of the slots were requested for flights not offered in the previous equivalent season. The requests made at SAL were placed by 145 airlines (of which 17 low cost). Air France was the airline that requested the highest, by far, number of slots, 171,518 (almost half of the total), of which 15,034 (8.8%) were non-historic. The corresponding figures for the second airline, easyJet, were 23,927 and 1709 (7.1%).

Table 3 describes the evolution of slot allocation at Paris CDG with reference to three of the process's key steps: the Initial Slot Allocation date when the initial Slot Allocation Listing (SAL) is presented by the coordinator; the Historics Baseline Date (HBD); and the Start of the Season (SOS).

Six different descriptive statistics are examined:

- Number of allocated slots – the total number of slots allocated at each step (regardless of when they were allocated). This number went

Table 2
Initial slot requests.

Length of the season (days)	217	
Number of requests	3600	
Number of slots requested	347,646	
Historic slots (F)	234,936	(67.6%)
Change-to-historic slots (CL/CR)	64,783	(18.6%)
New-entrant slots (B)	2073	(0.6%)
Other slots (OS)	45,854	(13.2%)

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[5] The allocation rules under the WASG for these three classes of requests include some more complicated details that are outside the scope of this article. Because of the covid-19 pandemic, these rules have not yet been extensively applied or tested in practice.

Table 3
Evolution of the slot allocation process.

Descriptive statistics	SAL	HBD	SOS
Number. of allocated slots	347,646	316,064	302,494
Number. of withdrawn slots	51,828	18,372	–
Number of allocated SAL slots	347,646	295,818	282,435
Number of displaced SAL slots	23,285	17,676	16,111
Number of displaced and withdrawn SAL slots	5609	1565	–
Number of new allocated slots	0	20,246	4802

from 347,646 at SAL to 302,494 at SOS (an overall reduction of 13%).

- Number of withdrawn slots – the number of slots withdrawn by the airlines at each step. From the 347,646 slots allocated at SAL, 51,828 were withdrawn before HBD (15% of the slots). From the 316,064 slots allocated at HBD (i.e., 347,646 minus 51,828 plus 20,246 new slots allocated between SAL and HDB), 18,372 were withdrawn before SOS (6%) and 4802 added for a total of 302,494 at SOS.
- Number of allocated SAL slots – the number of slots originally allocated at SAL that remained allocated in subsequent steps. At SAL, this number was obviously equal to the "number of allocated slots", but it decreased as the process evolved to become 282,435 at SOS – 81% of the slots allocated initially.
- Number of displaced SAL slots – the number of slots allocated at SAL that were displaced (i.e., were not allocated at the time requested by the airlines). At SAL, 23,285 slots were displaced (7% of the total number of slots allocated). At SOS, only 16,111 of these displaced slots (69% of the 23,285) were still scheduled to take place during the season, as a total of 7174 (31%) of the flights displaced at SAL were cancelled, with 5609 of these cancellations announced during the time between SAL and HBD and another 1565 between HBD and SOS.
- Number of displaced and withdrawn SAL slots – as noted above, the number of slots displaced at SAL that were subsequently withdrawn was 7174 – of which 5609 occurred after SAL and 1565 after HBD.
- Number of new allocated slots – the number of slots allocated after SAL. Between SAL and HBD, 20,246 new slots were added to the 295,818 allocated at SAL (giving a total of 316,064), while 4802 new slots were added between HBD and SOS.

These descriptive statistics indicate that airlines initially requested more slots than they intended to operate, and used the various steps of the process to adjust their schedules. A strategy they apparently followed was to "stretch" the range of dates (flight attribute "number weeks" in Table 1) for some of the slot series requested initially. After the SAL, instead of maintaining the entire series, they broke down the initially requested series into "sub-series" that they truly intended to operate. Furthermore, airlines seemed to react to the displacement of some of their long series of slots by reducing their range, possibly hoping that shorter slot requests might not be displaced. This is apparent in Fig. 2, where the percentage of requests covering the whole season (31weeks) decreased from 84% at SAL to 56% at SOS. In fact, as a result of the breaking down of some series into a set of sub-series, the total number of slot series rose from 12,485 at SAL to 20,708 at SOS.

As shown in Table 3, a large proportion (about 31%) of the 23,285 slots displaced at SAL were subsequently withdrawn before SOS (5609 at HBD and 1565 after that). This proportion was larger than the proportion of withdrawn slots in the total number of slots allocated at SAL (approximately 15%, i.e. 51,828 slots out of the 347,646 slots allocated initially). This clearly indicates that airlines have more readily withdrawn displaced slots than slots allocated at their preferred time. One possible reason for this is that many of the "kept" slots were historic and therefore could not be displaced. Indeed, it seems unlikely that airlines would willingly give up slots they used at least 80% of the time during the previous season.

The main features of the flights scheduled at Paris CDG as of the SOS of the Summer season of 2018 (as many as the number of allocated slots) are described in Table 4. It can be seen that only a small percentage of flights (15%) was operated by low-cost airlines. This is explained to a great extent by the dominance of Air France at this airport (around 50% of the total number of movements). The presence of low-cost airlines was more significant at Paris Orly (ORY) and, especially, at Paris Beauvais (BVA) and Paris Vatry (XCR), where their share exceeded 90%. A substantial proportion of flights connected Paris CDG with Level 3 airports, which are numerous in Europe, handling about 70% of the total number of air passengers as already noted. The number of both short-haul and long-haul flights was large, as Paris CDG is a major hub for domestic, continental and intercontinental travel. Midsize aircraft were clearly prevalent, accounting for more than 85% of the total. Approximately half of the flights were offered in every week of the season, and approximately one third on every day.

4. Logistic regression model(s)

To analyze airline decisions on whether to schedule or withdraw by SOS the flights displaced by the slot coordinator of Paris CDG at SAL, we resort to logistic regression models. These models are used when – as is the case here – the dependent variable is binary or dichotomous (Washington et al., 2003). They have been widely applied in transport research, notably in the analysis of accident data. Most of the first applications in aviation also focused on accidents, e.g. Li and Baker (1995), McFadden (1996, 1997) and Gudmundsson (1999). In more recent times, aviation accidents (and incidents) have continued to be investigated through logistic regression models (Bazargan and Guzhva, 2011; Boyd, 2015; Dai et al., 2021), but several other topics have also been explored, such as air traffic forecasts (Kotegawa et al., 2010; Rajendran et al., 2021), flight cancellations (Xiong and Hansen, 2013), flight rerouting (Evans et al., 2018) and flight delays (Wang and Vaze, 2016; Arora and Mathur, 2020; de Oliveira et al., 2021), among others.

In this section, we first summarize essential knowledge on the formulation and interpretation of logistic regression models, and then on its estimation and assessment. This summary is principally based on Hosmer and Lemeshow (2013). The final part of the section is dedicated to the model specifications we have considered in our analyses.

4.1. Model formulation and interpretation

A logistic regression model expresses the probability of a given binary occurrence,.., to take place ($Y = 1$) as a function of a number of explanatory factors, $X_1, \ldots, X_n$. In our case, this occurrence is the scheduling of a (displaced) flight and the explanatory factor in which we are primarily interested is the displacement of the flight decided by the slot coordinator. Other possible explanatory factors relate to various attributes of the flight. The model can be mathematically formulated as follows:

$$P(Y=1)=\frac{e^{\alpha+\beta_1X_1+\ldots+\beta_nX_n}}{1+e^{\alpha+\beta_1X_1+\ldots+\beta_nX_n}} \tag{1}$$

This model is nonlinear, but can be linearized by applying a logit transformation to the dependent variable (Equation (2)) and then taking logs of both sides (Equation (3)); that is:

$$\frac{P(Y=1)}{1-P(Y=1)}=e^{\alpha+\beta_1X_1+\ldots+\beta_nX_n} \tag{2}$$

It should be noted that the dependent variable in this equation expresses the odds of an event – in our case, the probability of a flight being scheduled against that of being withdrawn.

An insightful way of interpreting the meaning of parameters β_i involves the concept of odds ratio (OR). The odds ratio is the ratio of the odds of an event Y (e.g., scheduling a flight) when factor $X_i = a$ (i.e., the displacement of the slot of that flight is a minutes) and of the odds of that

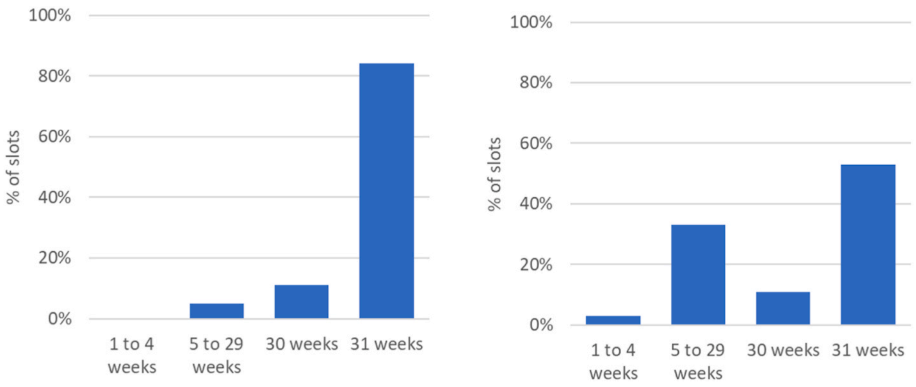

Fig. 2. Length of slot series requested at SAL (left) and of remaining slot series at SOS (right).

Table 4
Descriptive statistics of flights scheduled at SOS.

Total number of flights	302,494	
Flights operated by low-cost airlines	55,742	(15.0%)
Flights to/from other Level3 airports	186,305	(61.6%)
Short-haul flights (<810 nmi)	230,095	(61.9%)
Long-haul flights (>2200 nmi)	82,027	(22.1%)
Flights operated with small aircraft (<100 seats)	28,150	(7.6%)
Flights operated with large aircraft (>300 seats)	20,562	(5.5%)
Whole-season flights	159,899	(52.0%)
Daily flights	101,417	(33.5%)

event when factor $X_i = b$; that is,

$$OR = \frac{\frac{P(Y=1|X_i=a)}{1-P(Y=1|X_i=a)}}{\frac{P(Y=1|X_i=b)}{1-P(Y=1|X_i=b)}} \tag{3}$$

If the probability of event Y is given by Equation (1), then it is easy to show that

$$OR = \frac{e^{\beta_i a}}{e^{\beta_i b}} = e^{\beta_i (a-b)} \tag{4}$$

Or, defining ΔX_i as the difference between a and b ($\Delta X_i = a - b$),

$$OR = e^{\beta_i \Delta X_i} \tag{5}$$

In particular, this signifies that event Y is e^{β_i} times more likely ($\beta_i > 0$) or less likely ($\beta_i < 0$) to occur when factor X_i increases by one unit ($\Delta X_i = 1$).

4.1.1. Numerical example

Assume that the dependent variable Y takes value 1 or 0 depending on whether a flight is scheduled or withdrawn, that variable X_1 represents flight displacement in minutes, and that variable X_2 takes value 0 or 1 depending on whether the flight is made by a full-service or a low-cost airline. Assume, additionally, that β_1 and β_2 are respectively equal to -0.02 and -0.8 (which are similar to the values we have obtained for Paris CDG). This implies that:

(1) A flight is $e^{-0.02\times 5} \approx 0.90$ times less likely of being scheduled when its slot is displaced by 5 min than when it is allocated at the requested time ($\Delta X_1 = 5 - 0$). If the displacement is 30 min or 1 h, then it is 0.55 or 0.30 times less likely, respectively, of being scheduled.
(2) A flight is $e^{-0.8} \approx 0.45$ times less likely of being scheduled when it is operated by a low-cost airline than when it is operated by a full-service airline ($\Delta X_2 = 1 - 0$).

4.2. Model estimation and assessment

Several methods can be applied to estimate the parameters of a logistic regression model. The method we used, maximum likelihood estimation, is the most common one. It relies on the maximization of a function (the likelihood function) that expresses the probability of the observed data in terms of the value of the model's parameters, therefore providing the estimators of these parameters that better fit the observed data. These estimators have, among others, two attractive limiting properties: the first is consistency, i.e., as the sample size increases, the estimator of a parameter converges in probability to the parameter's true value; the second is efficiency, i.e., no consistent estimator is characterized by a lower asymptotic mean squared error.

The assessment of logistic regression models (and, indeed, of any regression models) involves two main issues: the first is the significance of the parameters of the model, i.e., whether there is sufficient evidence that the parameters are different from zero and, therefore, the respective explanatory variables can be expected to actually impact the dependent variable; the second is the goodness-of-fit of the model to the observed data, which largely determines its predictive power.

The significance of a parameter is typically assessed by calculating the respective z value, i.e., the ratio of the estimated value of the parameter divided by the standard error deviation of the estimate. The higher the module of the z-value, the more probable it is that the parameter is different from zero. This probability can be assessed through the respective p-value: if this value is smaller than π (generally a small value, e.g., 0.05 or 0.01), then the parameter is different from zero with a probability of at least (1- π).[6]

The goodness of fit can be assessed through a variety of methods, all of them comparing the observed values of the dependent variable with the values predicted by the model. Amongst the various possible alternatives (see Hosmer and Lemeshow, 2013, Chap. 5), we rely here on the concepts of classification table (or confusion matrix) and "area under the ROC curve", explained below.

A classification table compares the observed values of a dependent variable with the modeled values as shown in Table 5. True positives and true negatives are cases correctly classified (or predicted) by the model. For example, if, in case A, we observe $Y = 1$ and the probability given by the model is $P(Y = 1|A) \geq 0.5$, then we have a true positive; and if, in case B, we observe $Y = 0$ and the model gives $P(Y = 1|B) < 0.5$ then we have a true negative. In turn, false negatives and false positives arise when observed values do not match the modeled values.

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[6] The p-value of a hypothesis test is a complex concept. According to Washington et al. (2003, Chap. 2), it is the smallest level of significance that leads to rejection of the test's null hypothesis – in this case the hypothesis that the parameter is zero. For a thorough discussion of this concept, see Wasserstein and Lazar (2016).

Table 5
Classification table.

Observed value	Modeled value	
	0	1
0	*TN* (number of true negatives)	*FP* (number of false positives)
1	*FN* (number of false negatives)	*TP* (number of true positives)

The information on a classification table can be summarized by a number of performance measures, notably the true positive rate (TPr), the false positive rate (FPr), the accuracy (ACC), the sensitivity (SEN) and the specificity (SPE). The accuracy is the proportion of cases correctly classified by the model, the sensitivity is the proportion of cases correctly classified when $Y = 1$, and the specificity is the proportion of cases correctly classified when $Y = 0$. Mathematically, these measures can be formulated as follows:

$$TPr = \frac{TP}{TP + FP + TN + FN} \tag{6}$$

$$FPr = \frac{FP}{TP + FP + TN + FN} \tag{7}$$

$$ACC = \frac{TN + TP}{TN + TP + FN + FP} \tag{8}$$

$$SEN = \frac{TP}{TP + FN} \tag{9}$$

$$SPE = \frac{TN}{TN + FP} \tag{10}$$

All these measures depend on the cutpoint, c, i.e., the probability considered to distinguish between cases correctly classified by the model and cases incorrectly classified. In the example given above, it was assumed that $c = 0.5$. Instead, we could have used the optimal cutpoint, c^*, which is defined as the probability that maximizes the difference between the true positive rate and the false positive rate; i.e., $c^* = argmax(TPr - FPr)$.

Another, related way of treating classification information involves the concept of ROC curve, initially developed in the context of signal detection theory (ROC stands for receiver operator characteristic). A ROC curve plots the probability of detecting true signal (true positive rate) against that of detecting false signal (false positive rate) for the entire range of possible cutpoints (0–1).

The area under the ROC curve ($AUROC$) must be between 0.5 and 1. The lower value corresponds to the red (dashed) curve in Fig. 3, and indicates that a model is unable to discriminate between true positives and false positives. Values of $AUROC$ between 0.7 and 0.8 (like the one associated with the blue curve in Fig. 3) indicate "acceptable discrimination", and values above 0.8 indicate excellent discrimination (Hosmer and Lemeshow, 2013, Section 5.2.4).

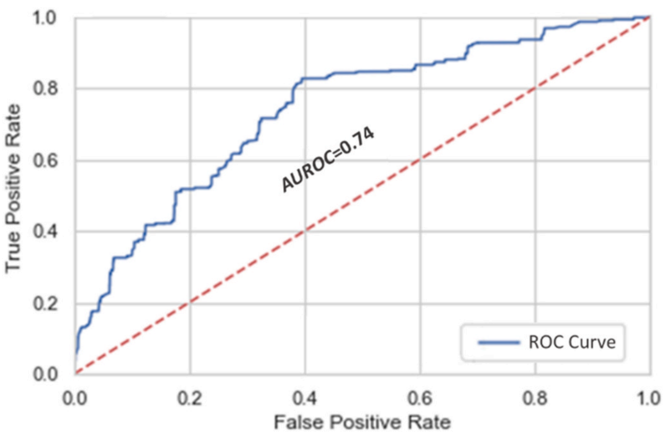

Fig. 3. Examples of ROC curves.

4.3. Model specifications

Based on the general logistic regression model formulation presented in Section 4.1, we considered three different model specifications (Models 1, 2 and 3) to analyze how slot allocation decisions made during the initial slot allocation may influence an airline's choice of scheduling or withdrawing a flight at the start of the season. For all three specifications, the dependent variable is a binary variable that takes value 1 if a requested flight displaced at SAL by the coordinator is scheduled at SOS, and 0 otherwise. The explanatory variables are described in Table 6.

The model specifications are as follows:

- Model 1 considers displacement as the only explanatory variable. It allows an evaluation of whether and to what extent flight displacements, on their own, can explain the scheduling and withdrawal decisions of airlines when flights are displaced.
- Model 2 includes 6 other explanatory variables corresponding to various flight attributes that, according to the literature on the determinants of airline profitability (e.g., Antoniou, 1992; Ginieis et al., 2020; Malighetti et al., 2011; Mantin and Wang, 2012; Scotti and Volta, 2017; and Tsikriktsis, 2007), are likely to influence airline decisions.
- Model 3 includes 5 additional explanatory variables representing flight attributes that, according to our intuition, might also have an impact on airline decisions. Some of these attributes have been studied in the existing literature as possible determinants of airline profitability, but the results were inconclusive.

Table 6
Model specifications and explanatory variables.

Explanatory variable	Type	Description	Model specification		
			1	2	3
displacement	Numeric	Flight displacement (between SAL and SOS) in minutes (multiples of 5).	•	•	•
link_level3	Binary	Equal to 1 if the flight connects CDG to a Level 3 airport, equal to 0 otherwise.		•	•
peak_hour	Binary	Equal to 1 if the flight was requested (at SAL) for a peak hour, equal to 0 otherwise.		•	•
airlines_sametype	Numeric	Number of airlines of the same type (full-service or low-cost) operating in the same market		•	•
airlines_othertype	Numeric	Number of airlines of other type operating in the same market		•	•
flights_sametype	Numeric	Average number of daily flights of the same type (low-cost or full-service) operating in the same market		•	•
flights_othertype	Numeric	Number of daily flights of other type operating in the same market		•	•
seat_count	Numeric	Number of seats of the aircraft making the flight.			•
flight_length	Numeric	Distance in nautical miles between CDG and the flight origin or destination airport.			•
low_cost	Binary	Equal to 1 if the flight is made by a low-cost airline, equal to 0 otherwise.			•
Schengen_flight	Binary	Equal to 1 if the flight connects CDG to a Schengen area airport, equal to 0 otherwise.			•
length_series	Numeric	Number of weeks for which the flight was requested (at SAL)			•

The flight attributes considered in Model 2 are as follows: level of origin or destination airport (Level 3 vs. other); time of arrival or departure of the flight (peak vs. off-peak); and market competition from the same or different types of arlines (full-service or low-cost). For example, flights connecting Paris CDG with Level-3 airports and flights arriving or departing at peak hours (6:00 to 11:59 or 17:00 to 18:59) might be expected to accommodate larger displacements, because, *ceteris paribus*, their load factors would tend to be higher. Indeed, most studies on this matter clearly show that load factor is a positive determinant of airline profits (e.g., Antoniou, 1992; Mantin and Wang, 2012). Furthermore, in both cases (Level-3 airports and peak-hour flights), if an airline gives up a slot, it can likely lose it to a competitor. Regarding competition, a lower number of airlines and flights offered in a given market, should result in higher profits and, consequently, in greater odds of a flight being scheduled despite having been displaced. The question here is whether the relevant competition comes from all types of airlines or only from the same type of airline, and this is why variables distinguishing between full-service vs. low-cost airlines were included in the model.

The additional variables included in Model 3 represent the size of the aircraft making the flight for which the slot is requested, the length of the flight, the type of airline (full-service vs. low-cost); the type of flight (Shengen vs. non-Shengen)[7]; and the length of the slot series. Intuitively, it seems quite likely that such attributes might influence an airline's decision as to whether or not to schedule a displaced flight.

Several other binary variables were considered to further characterize the airline operating the flight, as well as the flight's origin/destination. These were the following: the airline is Air France (or not); the airline is a top-25 airline; the origin/destination of the flight is a French airport; the origin/destination is a top-25 airport; and the origin/destination is a capital city. However, the inclusion of these variables into Model 3 did not improve the goodness-of-fit of the model.

5. Experimental dataset

We describe in this section the process of assembling the experimental dataset used in the estimation of the logistic regression model(s), and present descriptive statistics for the variables included in the dataset. Since the focus of the analyses were the slot requests displaced at SAL, only these requests were considered in the construction of the dataset.

The first step of this construction consisted in preparing a table based on the information we received from COHOR organized by lines and columns, with each line corresponding to a slot request and each column to an attribute of a standard slot request (Table 1). Hence, each line of this table involves multiple flights, operated on multiple days of the season at a specific time of the day. After the SAL, the airlines can (and, as seen earlier, frequently do) split their requests into "sub-requests" that will subsequently be treated independently by the slot coordinator. These requests can also be shortened or extended. In particular, for slots displaced by the coordinator, airlines may decide to only schedule a subset of the flights included in their initial slot requests and withdraw the other flights. For this reason, we prepared a new table considering the slot request data at the flight level. To be able to trace the flights between the SAL and the SOS, we merged them using a unique key to flight attributes: *flightKey* = (*Date*; *Flight number*; *Airline*; *Arrival or Departure*; *Linked airport*). Flight keys that were found both in SAL and SOS correspond to flights that were scheduled by the airlines (despite having been displaced by the coordinator), while flight keys that could only be found at SAL correspond to flights that were withdrawn. Finally, to complete the dataset used in the estimation of the logistic regression models, we added a column to the new table specifying whether the flights were scheduled or withdrawn, and deleted the columns not corresponding to explanatory variables of the model.

The experimental dataset assembled as described above consists of 23,285 flights (lines) with information on the dependent variable (displaced flight scheduled or not) and the 12 explanatory variables of Table 6 for each flight (columns). Out of these flights, 16,160 were eventually scheduled by airlines at SOS, which defines a global scheduling rate of almost 70%.

Descriptive statistics of the explanatory variables are displayed in Table 7 (numeric variables) and Table 8 (binary variables). It can be seen in Table 7 that the average flight displacement was slightly greater than 30 min, and the maximum displacement was 150 min. As shown in Fig. 4, around 50% of the flights was displaced by 15 min or less, and only 10% were displaced by 90 min or more. The analysis of Table 8 and Fig. 5 makes clear that a very high percentage of displaced flights (76%) was concentrated on peak hours.

Focusing on the relationship between scheduling rates and flight displacements, Fig. 6 shows that the proportion of scheduled flights remained quite high, above 70%, when the displacements were less than or equal to 60 min, and that it decreased quickly above that time threshold, being less than 40% when the displacements surpassed 90 min.

Finally, in Fig. 7 we show how scheduling rates vary with binary flight attributes. It can be seen there that flights from/to Level 3 airports and flights (initially) requested for a peak hour are the ones that airlines scheduled proportionally more despite being displaced, being the proportions 75% and 71%, respectively. These proportions decrease to 66% and 60% in the case of flights operated by low-cost airlines and Schengen flights.

6. Model results

The regression results for the three model specifications described in Section 4.3 are presented below and then discussed in detail considering, in particular, their practical implications with respect to slot coordination decisions. These results were obtained after splitting the experimental dataset randomly into two sets, with 70% of the data being used for model estimation (training) and the remaining 30% for model assessment (testing).

6.1. Presentation of results

The main results obtained through the estimation of the three different regression models are presented in Tables 9 and 10 and in Fig. 8: Table 9 shows the parameters of the models and the respective *p*-values; Table 10 the classification tables for the models, based on which it is possible to calculate the respective accuracy (*ACC*), sensitivity (*SEN*) and specificity (*SPE*); and Fig. 9 the ROC curves of the models.

Table 7
Descriptive statistics of the numeric explanatory variables.

Explanatory variable	Mean	Std. dev.	Median	Maximum	Minimum
displacement (min)	32.0	35.0	15	150	5
airlines_sametype	2.2	1.3	2	8	1
airlines_othertype	0.8	1.2	0	6	0
flights_sametype (daily avg.)	7.6	6.3	6	31	1
flights_othertype (daily avg.)	2.6	5.1	0	26	0
seat_count (seats)	190.6	73.5	180	516	0
flight_length (nmi)	1601	1602	794	5793	95
length_series (weeks)	29.4	4.5	31	31	5

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[7] The Shengen area comprises a set of 26 European countries, including France, between which passport and other types of border controls are not (normally) applied (European Commission, 2015). Flights between Paris CDG and any airports in these countries can therefore be viewed as equivalent to domestic flights.

Table 8
Descriptive statistics of the binary explanatory variables.

Explanatory variable	Number of flights	Percentage (%)
link_level3	13,040	56
peak_hour	16,697	76
low_cost	5821	25
Schengen_flight	9860	42

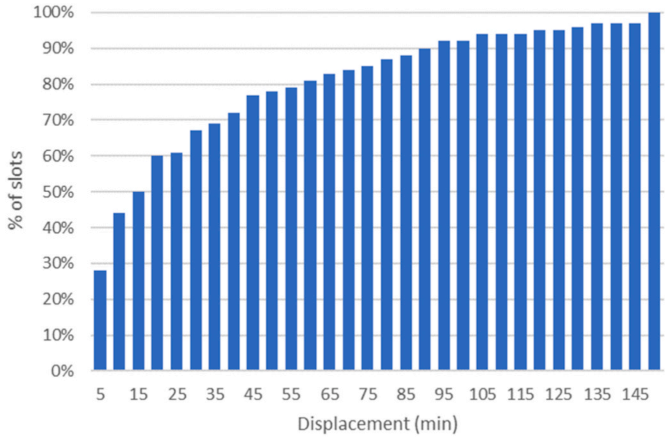

Fig. 4. Cumulative distribution of the displacement variable.

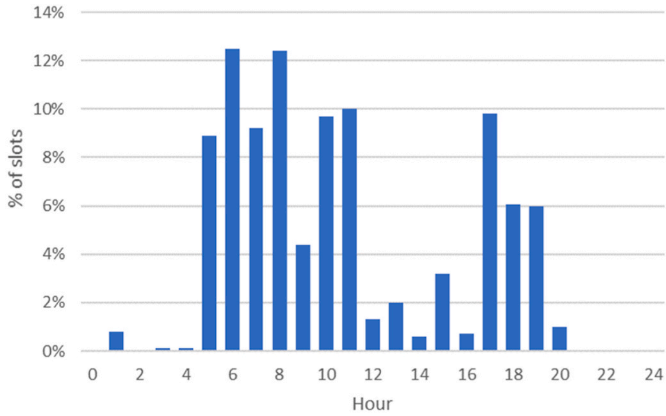

Fig. 5. Distribution of delayed flights over the day.

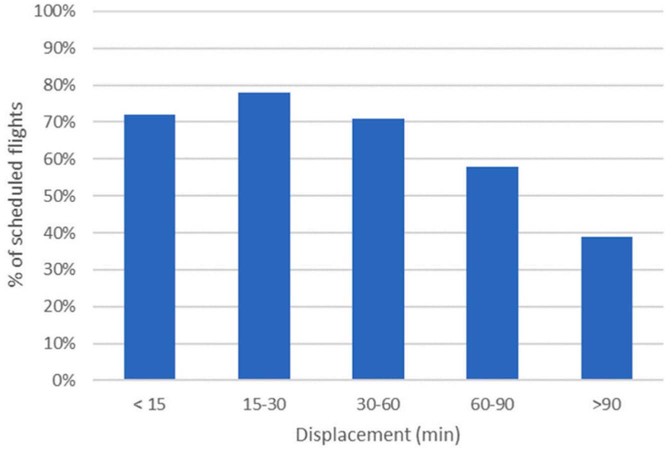

Fig. 6. Proportion of scheduled flights as a function of displacement.

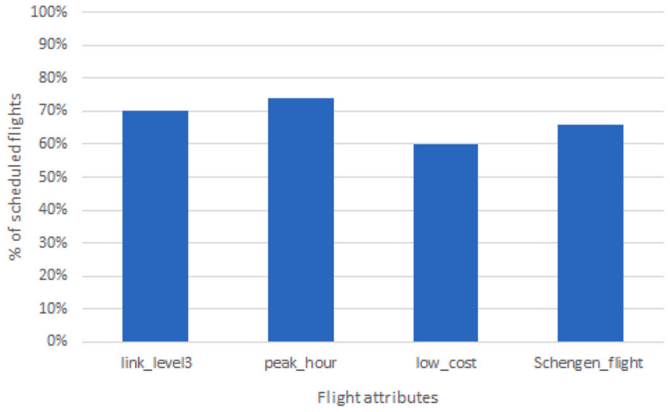

Fig. 7. Proportion of scheduled flights as a function of binary flight attributes.

As shown in Table 9, the estimation of Model 1 yielded a negative regression parameter for the displacement variable (−0.0095), with an extremely low *p*-value ($<$0.00005). This clearly suggests that the larger the displacement the less probable it is that a displaced flight is scheduled (at SOS). However, the fit of the model is quite poor. Based on the classification table (Table 10), it can be seen that, when applied to the testing dataset, Model 1 classified correctly 2479 observed scheduling decisions (out of $950 + 2479 = 3429$) and 1519 withdrawing decisions (out of $1519 + 1862 = 3381$). Therefore, its accuracy is only $ACC = 0.59$ (sensitivity and specificity are, respectively, $SEN = 0.72$ and $SPE = 0.45$). The poor fit of Model 1 is also reflected by the ROC curve displayed in Fig. 8 (top). The *AUROC* is 0.58, thus not reaching the 0.70 threshold that defines an acceptable model fit.

The estimation results for Model 2 are clearly better. The *AUROC* increased to 72% (Fig. 8, middle), which signifies that, unlike Model 1, it is characterized by an acceptable, though not excellent, goodness-of-fit. This is confirmed by the values of the performance measures extracted from the classification table: $ACC = 0.67$, $SEN = 0.68$, and $SPE = 0.65$; that is, 67% of the flights from the testing dataset are now correctly classified, 68% of which are scheduled flights and 65% withdrawn flights. The better performance of Model 2, compared to Model 1, is also apparent in the significance of 5 of the 6 additional explanatory variables considered, which are all characterized by *p*-values well below 0.01 (the variable *flights_othertype* is the one that is not significant, with a *p*-value of 0.66). The regression parameter for *displacement* is negative again, and more negative than in Model 1, that is, the displacement effect is stronger. The parameters of variables *link_level3* and *peak_hour* are both positive, meaning that, as expected, flights connecting to busy airports and peak-hour flights are more likely to be scheduled if displaced than other flights. Regarding the competition variables, the estimation results reveal that the more airlines of the same type (full-service or low-cost) operate in a given market, the more likely it is that a displaced flight is scheduled (the sign of *airlines_sametype* is positive), but this likelihood decreases with the number of flights offered by these airlines (the sign of *flights_sametype* is negative). Instead, if the competition comes from airlines of the other type, then the reaction of airlines is the opposite, i.e., they are less likely to schedule displaced flights (the sign of *airlines_othertype* is negative), and this regardless of the number of competing flights (*flights_othertype* is not significant as mentioned above). This point is discussed further in Section 6.2.2.

Finally, the estimation results for Model 3, where 5 additional explanatory variables are considered, are even better than those for

Table 9
Model parameters and respective ***p***-values.

Variable	Model 1		Model 2		Model 3	
	Parameter	*p*-value	Parameter	*p*-value	Parameter	*p*-value
constant	0.3263	0.0000***	−1.3409	0.0000***	−0.3252	0.0123**
displacement	−0.0096	0.0000***	−0.0178	0.0000***	−0.0187	0.0000***
link_level3	–	–	0.5642	0.0000***	0.7680	0.0000***
peak_hour	–	–	1.5923	0.0000***	1.5562	0.0000***
airlines_sametype	–	–	0.3281	0.0000***	0.4275	0.0000***
airlines_othertype	–	–	−0.1069	0.0000***	−0.0542	0.0054***
flights_sametype	–	–	−0.0173	0.0000***	−0.0849	0.0000***
flights_othertype	–	–	−0.0019	0.6641	0.0071	0.1406
seat_count	–	–	–	–	0.0011	0.0010***
flight_length	–	–	–	–	−0.0004	0.0000***
low_cost	–	–	–	–	−0.8081	0.0000***
Schengen_flight	–	–	–	–	−0.5618	0.0000***
length_series	–	–	–	–	0.0012	0.7070

Confidence level:* $p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Table 10
Classification tables for Models 1, 2 and 3.

Observed value (flights)	Modeled values (flights)					
	Model 1		Model 2		Model 3	
	Withdrawn	Scheduled	Withdrawn	Scheduled	Withdrawn	Scheduled
Withdrawn	1519	1862	2205	1176	2294	1087
Scheduled	950	2479	1095	2334	1066	2363

Model 2, but only slightly so – for example, accuracy increases to $ACC = 0.68$ (from 0.67) and the *AUROC* increases to 0.74 (from 0.72).[8] All explanatory variables included in Model 2 are significant (with, again, the exception of *flights_othertype*, but now with a much lower *p*-value, 0.13), and their parameters kept the same sign and, in general, very similar values. Four of the 5 additional variables are significant. The only one that is not is *length_series* (*p*-value ≈ 0.70). In this case, our intuition that this variable could be important to explain airline decisions was not confirmed.

To conclude this section, it is important to note that the results presented here are specific to Paris CGD and to the Summer season of 2018. This means, in particular, that the observation that variables *flights_othertype* and *length_series* were non-significant cannot be generalized. This is especially so in the case of the latter variable because of the lack of variability that characterizes the length of requested series at CDG in Summer (2018), with more than 80% of the requests being for the full season (31 weeks) – see Table 7.

6.2. Discussion of results

In this section, we discuss in detail the results obtained using Model 3 (i.e., the best fitting model). Specifically, we first examine the effects of slot displacement on the scheduling decisions of airlines, and then the effects of flight attributes considered both individually and in combination.

6.2.1. Effects of displacement

As confirmed by the results presented in the previous section, displacement has a negative effect on the decision of scheduling a flight. A larger slot displacement means that an airline may not be able to capture the same demand from passengers as originally intended. The displacement might also have consequences on a network level and make some planned connections at other airports impossible. When displacements become too large and their consequences too costly, airlines may decide to withdraw some of their flights.

As stated before (Section 4.1), an insightful way of analyzing the effects of the explanatory variables of logistic regression models involves the concept of odds ratio (Equation (3)). This ratio indicates, in the present context, how much less likely a flight is to be scheduled (at SOS) when it is displaced (at SAL) by a slot coordinator than when it is not displaced (i.e., when the flight is scheduled at the time requested by the airline). Table 11 presents the odd ratios obtained using Model 3 for different levels of displacement. For instance, the odds ratio for a 30-min displacement is $OR = exp(-0.0187 \times 30) = 0.570$, i.e, the chances of a flight being scheduled are less than 60%, while a 90-min displacement reduces these chances to less than 20%.

6.2.2. Effects of flight attributes

6.2.2.1. Individual effects. Focusing now on the effects of flight attributes, we present in Table 12 the odds ratios obtained for the binary flight attribute variables considered in Model 3. First, it can be observed that flights connecting Paris CDG with other Level 3 airports are more likely to be scheduled than otherwise. For instance, for two identical flights with the same displacement and attributes except for the variable *link_level3*, the chances of a flight from/to a Level 3 airport being scheduled are more than 2 times higher than those of a flight to another type of airport ($OR = exp(-0.7680) = 2.155$). Similarly, airlines are less likely to withdraw flights requested for peak hours. In this respect, it should be noted that an odds ratio close to 5, like the one characterizing variable *peak_hour*, is, by a large margin, the highest we have obtained in our analyses. With respect to the influence of airline type, we observe that low-cost airlines are clearly more sensitive to displacement than full-service airlines. Indeed, for two otherwise identical flights, the one

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[8] Model 3 was also implemented with displacement as a categorical variable instead of a numerical variable. The intervals for each displacement category were: [15, 30],]30,60],]60, 90] and >90 min. With this characterization of displacement, the estimation results improved yet a little more. In particular, the *AUROC* increased to 0.76. The signs and values of the parameters remained practically the same, which means that the discussion of next section would essentially not change if these results were considered.

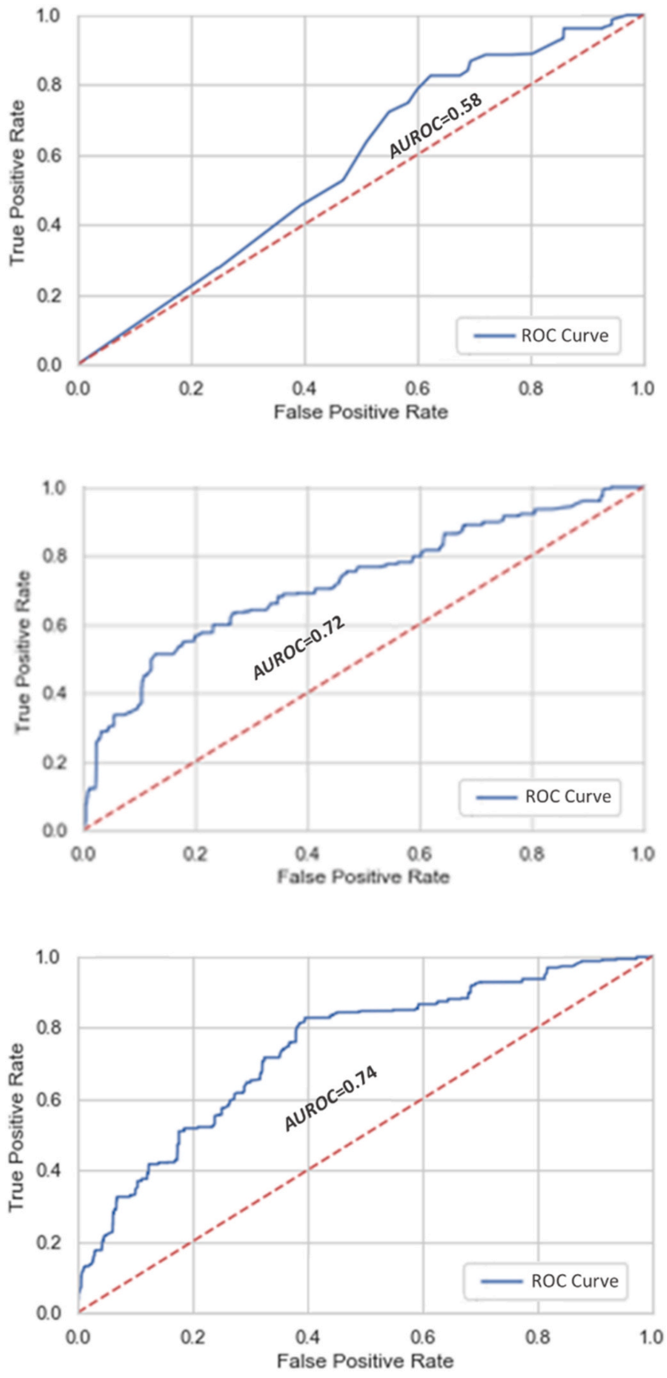

Fig. 8. ROC curves of Model 1 (top), Model 2 (middle) and Model 3 (bottom).

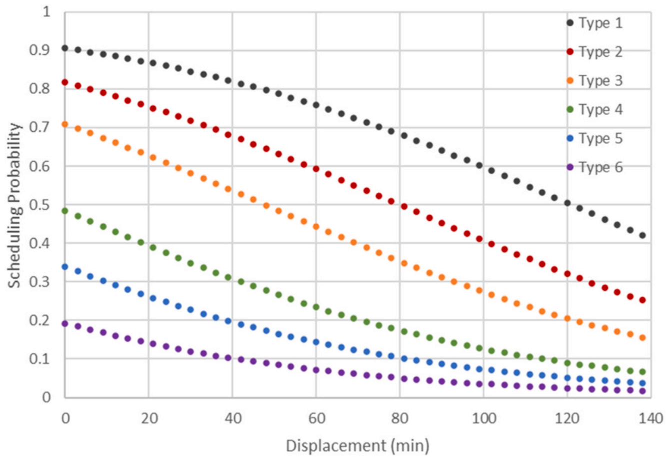

Fig. 9. Flight scheduling probability as a function of slot displacement.

Table 11
Odds ratios for the displacement variables (Model 3).

Displacement (minutes)	Odds ratio
5	0.911
15	0.755
30	0.570
60	0.326
90	0.185

Table 12
Odds ratios for the binary flight attribute variables (Model 3).

Explanatory variable	Odds ratio
link_level3	2.155
peak_hour	4.741
low_cost	0.446
Schengen_flight	0.570

Table 13
Odds ratio for the numeric flight attribute variables (Model 3).

Explanatory variable	Change	Odds ratio
airlines_sametype	+1	1.53
	+3	3.61
airlines_othertype	+1	0.95
	+3	0.85
flights_sametype	+2	0.84
	+5	0.65
seat_count	+100	1.12
	+300	1.39
flight_length	+500	0.82
	+1500	0.55

operated by a low-cost airline is around 45% less likely to be scheduled if displaced than the flight operated by a full-service airline. A possible reason is that slot displacements can make infeasible the tight sequences of flights that low-cost airlines typically include in their schedules (to maximize aircraft utilization). Furthermore, these airlines can more easily change the markets they serve because they operate point-to-point flight networks. Finally, regarding the odds of Schengen and non-Schengen flights, it is observed that the former are around 60% less likely of being scheduled when displaced. This may indicate that non-Schengen flights are more profitable than Schengen ones despite the higher costs they involve in passenger controls and custom formalities.

Similar results for the (significant) numeric flight attribute variables of the model are presented in Table 13. Note that, for some of these variables, a one-unit change may affect airline choices only very marginally, and we therefore analyze larger and more meaningful levels of change (e.g., in the case of variable *seat_count*, 100 and 300 seats instead of 1 seat).

Regarding the competition variables, it can be seen in the table that the presence of another airline of the same type in the same market increases the chances of a flight being scheduled by 1.53, and, if the number of airlines is 3, by 3.6 (i.e., proportionally less). However, these chances drop depending on the number of competing flights, being reduced by a factor of 0.84 if there are 2 such flights, and by a factor of 0.65 if there are 5. In sum, airlines try to schedule their displaced flights when facing competition from similar airlines, particularly if competing airlines are relatively few and the number of competing flights is small. Conversely, if the competition comes from airlines of a different type, the odds that flights are scheduled decrease by a factor of 0.95 or 0.85 (i.e., mildly) depending on the number of airlines being 1 or 3. These results clearly suggest that airlines, in their scheduling decisions, focus primarily on competitors of the same type.

The analysis of Table 13 additionally reveals that flights operated by larger aircraft are more likely to be scheduled when displaced than those operated by smaller ones. For instance, for two otherwise identical flights, the odds of a flight made by a 300-seat aircraft being scheduled are around 1.12 times higher than those made by a 200-seat aircraft. Economies of scale (i.e., lower costs per seat) are a plausible reason for this to happen. In contrast, the longer the flight, the less likely it is to be scheduled when displaced. Indeed, an additional 500 nmi reduces the chances of a displaced flight being scheduled by a factor of 0.82.

6.2.2.2. Combined effects. Thus far, we have focused on the separate effects of flight attributes on the chances of a displaced flight being scheduled. Using Equation (1) with the variables described in Table 6 and the parameter values presented in Table 9 (for Model 3), it is possible to compute the probability that a displaced flight with a given set of combined attributes will be scheduled. To illustrate this, we analyze the effects of different combinations of binary attributes while keeping the numeric attributes equal to their respective median values (see Table 7). Table 14 describes the attributes of a sample of six different flight types. Fig. 9 presents the probability of each type of flight being scheduled as a function of the displacement.

The flights that are least likely to be scheduled if displaced are those of Type 6. We observe that, even for low levels of displacement, such flights are often withdrawn. For instance, considering the smallest possible displacement (5 min), the model predicts that these flights have a probability of only 20% of being scheduled. Conversely, flights of Type 1 have a much higher chance of being scheduled even for high levels of displacement. These flights could be assigned a 120-min displacement, and still have a probability of 50% of being scheduled. The probabilities for the other four types of flights fall somewhere between those two extremes. This analysis could be easily extended to flights with different attributes.

7. Conclusion

We have addressed in this article a topic that, to the best of our knowledge, has not been studied before in the literature: the impact of the allocation decisions of airport slot coordinators on the flight scheduling decisions of airlines. We focused on the case of Paris Charles de Gaulle (CDG) Airport, the busiest in France and one of the busiest worldwide, in the Summer season of 2018. By resorting to logistic regression models, we were able to quantify the odds of a flight being scheduled despite being assigned a displacement at SAL. These odds are a function of the size of the displacement and of a number of key flight attributes. This information may assist coordinators in making allocation decisions that take into account the likely consequences of assigned displacements. This would contribute to more efficient use of the sparse capacity available at congested airports and to increased responsiveness to the mobility needs of air passengers.

In our analyses of Paris CDG, we observed that even small flight displacements frequently led to the withdrawal of flights. In fact, *ceteris paribus*, the chances of a flight displaced by 30 min being scheduled were equal to only about 60% of those of a flight that was not displaced, while a 90-min displacement reduced these chances to less than 20%. The specific attributes of the flight can, however, modify these chances substantially. The time of the day is a particularly important factor in this respect: peak-hour flights were much more likely to be scheduled despite being displaced than off-peak hour flights.

The conclusions we obtained for Paris CDG were generally not surprising and we expect similar qualitative outcomes for other major airports. However, this has yet to be confirmed. Extending our analyses to other airports worldwide is an obvious direction of research to pursue in the future. The same type of logistic regression model can be used for this purpose after adding an explanatory variable describing the airport (or type of airport). However, obtaining access to the necessary data remains the principal challenge in this case. In addition, the data available from some coordinators may not be organized in a way that allows the tracking of slots and flights through the different steps of the slot allocation process (this is, for instance, the case of the Airport of Lisbon).

Table 14
Sample of flight types.

Flight type	Explanatory variable			
	link_level3	peak_ hour	low_cost	Schengen_flight
1	1	1	0	0
2	1	0	0	0
3	1	1	1	1
4	0	0	0	0
5	0	1	1	1
6	0	0	1	1

Another research direction to explore in the future relates to the explanatory variables of the logistic regression model. We recognize that the goodness-of-fit of our two best models, while good, was not excellent. Improvements in this respect may still be possible and the inclusion of new variables in the model should be tested. This comprises, for instance, variables representing the importance of a flight to an airline's network.

A third important research direction would address the utilization of the results of our analyses. In recent years, as stated in the introductory section, significant efforts have been devoted to the development of models aimed to assist coordinators in the allocation of airport slots considering objectives like the minimization of total displacement (i.e., the sum of all slot displacements) and the minimization of the maximum displacement across all flights. A significant improvement to these models would be achieved if the likely implications that the allocation decisions might have on airline scheduling decisions were taken into account. For instance, if a Flight A is less likely to be withdrawn than Flight B, requested for the same time, then it may make sense to displace A rather than B (provided this does not raise issues regarding the fair treatment of airlines). Incorporating effects of this type into the existing slot allocation models would make them more complex, but also more valuable to coordinators concerned with the final impacts of their decisions on passengers, airlines and airports.

Author statement

Lilian Pouget: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Software; Visualization; Writing - original draft; Writing - review & editing.

Nuno Antunes Ribeiro: Conceptualization; Formal analysis; Investigation; Methodology; Validation; Visualization; Writing - review & editing.

Amedeo R. Odoni: Conceptualization; Investigation; Methodology; Supervision; Validation; Writing - review & editing.

António Pais Antunes: Conceptualization; Funding acquisition; Investigation; Methodology; Project administration; Resources; Supervision; Validation; Writing - review & editing.

Declaration of competing interest

None.

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