Transportation Research Part A 116 (2018) 201–219

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Airport slots and the internalization of congestion by airlines: An empirical model of integrated flight disruption management in Brazil

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ARTICLE INFO

JEL classification:
D22
L11
L93

Keywords:
Airlines
Airports
Slots
Congestion externalities
Econometrics

ABSTRACT

This paper examines the relationship between the control of airport slots by major airlines and their incentives to engage in service quality. We investigate a set of airline strategies regarding possible practices of slot hoarding and slot concentration through mergers aiming at erecting airport barriers to entry. We develop an econometric model of flight disruptions by allowing an integrated management of flight delays, cancellations, aircraft size, price and passengers per flight. We consider the case of the domestic airline industry in Brazil. We find evidence of the internalization of congestion externalities by dominant carriers. We also have some evidence of schedule padding, a strategic trade-off between delays and cancelations, and slot hoarding following a merger. Our results suggest that carriers intensify the internalization of congestion externalities when slot flight concentration increases.

1. Introduction

The present paper empirically investigates some of the determinants of passenger service quality in the airline industry, with a special emphasis on the role of airport slots. Airport authorities and regulators typically impose takeoff and landing slots to mitigate flight disruptions through the restriction of runway operations during peak-hour periods. As a consequence, a slot system constitutes a way to distribute scarce airport capacity among interested airlines via slot allocation rules. The failure of the slot system may discourage carriers to utilize the available airport infrastructure in an optimal way since the flight cap restrictions may allow incumbent airlines to systematically cancel unprofitable flights while still keeping the ability to deter the entry of potential rivals at the congested airport.

Airport slots represent a key issue to the perceived quality performance of airlines in major cities around the world. For example, in 2012, the US Government Accountability Office (GAO) released a study investigating the main slot-controlled airports in the United States, including Reagan National (Washington DC) and the three main airports in New York (LaGuardia, JFK and Newark), which were among the 30 worst in the country with respect to service quality levels.[1] The study cited evidence that the existing slot allocation rules led to inefficiencies and underutilization at the affected airports by stressing that flights tended to work with emptier and smaller airplanes, while keeping higher daily frequencies than a non-slot-controlled airport (a "slot hoarding" behavior, also known as "slot babysitting"). In the UK, in 2016, the government announced its support for an extra runway at London/Heathrow

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[1] "*Slot-Controlled Airports - FAA's Rules Could Be Improved to Enhance Competition and Use of Available Capacity*" Government Accountability Office Report - Report to the Committee on Commerce, Science, and Transportation, U.S. Senate. GAO-12-902, September 2012.

https://doi.org/10.1016/j.tra.2018.06.008
Received 11 January 2018; Received in revised form 20 April 2018; Accepted 12 June 2018

Airport aimed at improving the service levels of the airport. This followed years of intense criticism with respect to its recurring high flight delays and lack of resilience under unforeseen disruptive circumstances.[2] In 2015, more than 25% of all take-offs and landings at the airport operated with a delay of more than 15 min outside their scheduled arrival times.[3] In China, in 2015 the Civil Aviation Administration of China (CAAC) announced a regulatory reform over its slot allocation mechanism to reduce the competitive advantage of state-owned carriers and to enhance the access of private airlines to some highly demanded time periods. In 2017, the CAAC also announced a tightening in the slot capacity at the congested Beijing Capital International Airport to improve overall on-time performance.[4]

This paper develops an econometric model of flight disruptions to inspect the efficacy of airport slot rules in avoiding airline service quality deterioration under airport congestion.[5] The main objective of the research is to investigate the congestion internalization behavior of major airlines and the possible role of airport slots. We supplement the empirical analysis with econometric models of aircraft size and price to obtain a broader picture of the congestion internalization problem. We extend the literature on the congestion internalization behaviors of major airlines to examine the possible impact of airport slots (Daniel, 1995; Brueckner, 2002; Mayer and Sinai, 2003a, Santos and Robin, 2010; Ater, 2012; Bendinelli, Bettini and Oliveira, 2016). In particular, we test if the presence of a flight cap constraint produces an effect of either aligning or misaligning the incentives of carriers towards a more efficient flight disruption management. To the best of our knowledge, our study is the first to examine the possible association between slot flight concentration to few airlines, the odds of flight delays and cancellations and the possible effects on the internalization of some of the associated external costs of congestion by carriers.

We consider the case of the Brazilian air transport industry from 2002 to 2013. We study the slot-controlled São Paulo/Congonhas Airport, CGH. CGH is well-known for its time-sensitive, business-related traffic since it is located close to downtown São Paulo. The slot system at the airport has been regulated by the National Civil Aviation Agency (ANAC) and consists of grandfathering combined with a use-it-or-lose-it rule. Since a slot reform in 2007, the airport has operated under a stricter runway hourly capacity regime. We examine the influence of the tightening of the flight cap system on the flight disruption management of dominant airlines. The airport has been dominated by two major carriers, Tam and Gol, which account for 93% of all flights. In contrast, in the studied period, the episodes of flight delays and flight cancellations have dropped by 50% and 69%, respectively.[6] We aim to disentangle the effects of the 2007 regulatory reform that resulted in an hourly slot cap reduction of approximately 16% from the effects of an acquisition of a carrier with a major stake of slots at the airport (Varig airlines) by one of the dominant carriers (Gol airlines). Our contribution lies in the utilization of an econometric model that allows integrated approaches of airline disruption management with endogenous flight delay, flight cancellation, aircraft size, price and passenger output decisions. We therefore aim at uncovering key factors that influence service quality management and market power of major carriers, by investigating a set of airline behavioral patterns and strategies regarding possible practices of slot hoarding and slot concentration through mergers, and the consequent erection of airport barriers to entry. Our model also tests for the effects of the increasingly common practice of schedule padding practices in the industry.

This paper is divided as follows. Section 2 presents the discussion of the literature on flight disruptions and the economic impacts of airport slots. Section 3 presents the empirical model. Section 4 presents the estimation results and discussions, which is followed by the conclusions.

2. Airline flight disruptions and the effect of airport slots

An important set of airports throughout the world operate under explicit rules restricting their allowed number of hourly takeoffs and landings.[7] Airport authorities and/or airline regulators have imposed flight caps at major airports aimed at reducing flight delays, enhancing safety and improving the airport's overall performance during peak hours. Since these airports typically constitute key nodes of existing air transportation networks, the adequate disruption management at slot-controlled airports is vital to avoid major impacts on the airport delays experienced in the entire airspace systems of many countries. The implementation of slot regulations has important side effects of restricting the ability of airlines to freely allocate flights and manage operations, limiting passenger choice at the most-desired times and hampering competition and access to essential facilities at key airports. However, so far, few existing empirical studies have investigated the role of such relevant airport operational restrictions on the incentives that carriers have to engage in quality service related to on-time performance.

2.1. The empirical literature of flight disruptions

The econometric literature of the causes of flight disruptions has been primarily concerned with flight delays and less with flight cancellations. The empirical literature has considered two testable hypotheses. The first hypothesis regards the congestion

[2] "*Government decides on new runway at Heathrow*" - October, 25, 2016, available at www.gov.uk; "*BAA airports market investigation - A report on the supply of airport services by BAA in the UK*" - UK Competition Commission March, 19, 2009.

[3] "*Capacity crisis at UK airports revealed by delays league*" - The Telegraph, September, 14, 2017.

[4] "*China reforming slot-assignment process at some major airports*" - Reuters, Dec, 7, 2015; "*Airport plans may leave delays in the past*" - China Daily, Sept, 9, 2017.

[5] We define "flight disruption" as a situation where a scheduled flight is either cancelled or delayed for fifteen minutes or more.

[6] Source: Active Scheduled Flight Report (VRA), National Civil Aviation Agency - 2002–2013.

[7] According to the United States Government Accountability Office, more than 150 airports were slot-controlled in the world in 2012. "*Slot-Controlled Airports - FAA's Rules Could Be Improved to Enhance Competition and Use of Available Capacity*" - GAO-12–902, September 2012.

internalization behavior in which the dominant carrier(s) of an airport would address congestion by internalizing its associated congestion costs (Daniel, 1995; Brueckner, 2002). Some of the empirical papers that test and find evidence of the internalization hypothesis are Mayer and Sinai (2003a), Santos and Robin (2010) and Ater (2012). The second hypothesis present in the literature regards the competition-service quality relationship (Mazzeo, 2003; Rupp, Owens and Plumly, 2006; Greenfield, 2014, among others), in which additional competition would force airlines to improve their service quality to passengers. The papers in this strand of the literature test if route concentration worsens on-time performance and if an increase in competition would consequently reduce flight delays. Bubalo and Gaggero (2015) and Bendinelli, Bettini and Oliveira (2016) provide formal tests of both hypotheses in the same econometric framework. We build on the contributions of the above literature of flight disruptions, in particular the findings related to the congestion internalization of airlines concomitant with service quality competition. We therefore aim at extending the previous literature to assess the possible moderation effects of slot concentration in few airlines on the identified congestion internalization behavior. We suspect that slot concentration is a potentially relevant driver of the congestion internalization practices of major carriers mainly because it may be related to their perception of property rights over the airport - a hypothesis that has not been investigated so far in the literature.

2.2. Impacts of airport slots

Santos and Robin (2010) list slot coordination as one of the main determinants of delays in European airports, along with factors such as market concentration, hub airport and hub airlines. Mayer and Sinai (2003a) find a small congestion externality effect in their empirical model of flight delays. They suggest that this result may be driven by the performance of the slot-restricted airports in their sample and conclude that flight delays would increase if the FAA removed the flight caps at those airports. Bubalo and Gaggero (2015) study the impact of low cost carriers (LCCs) on flight delays and conclude that they have lower wait times for take-off and landing at airports. They also produce a positive externality for the remaining airlines and thus improve overall on-time performance. Santos and Robin (2010) investigate the determinants of flight delays and test the effect of different airport slot coordination levels. They find that delays at origin airports are highest for fully coordinated airports, lower for schedule facilitated ones, and lowest for non-coordinated ones. They find mixed results for destination airports. Rupp and Holmes (2006) estimate a model of flight cancellations and find that having a slot-controlled airport as origin and/or destination of a route is associated with significantly higher cancellation rates. Vaze and Barnhart (2012) find that small reductions in the total number of allocated airport slots would substantially reduce flight delays. Swaroop et al. (2012) suggest that a more extensive use of slot controls in major airports would improve passenger welfare in the US airline market. They also suggest that if the slot caps at the slot-controlled airports in US airline industry were further tightened, it would potentially reduce two-thirds of the total nationwide delays.

Sieg (2010) analyzes the grandfather rights with a theoretical model. He concludes that airports prefer such a use-it-or-lose-it rule to unconditional property rights, and suggests that the use-it-or-lose-it rule increases slot use when air transportation demand is low. Fukui (2010, 2012, 2014) inspects the possible anti-competitive consequences of airport slots with special focus on the effects of secondary markets for slots. Fukui (2010) investigates airport slot trading at US slot-constrained airports to assess whether the strategic behavior of major carriers may have impeded effective functioning of slot markets and finds mixed results. Fukui (2012) investigates the potential slot hoarding behavior and uncovers evidence that carriers have hoarded underutilized slots at the US airports LaGuardia and O'Hare. Fukui (2014) studies the UK airline industry to analyze the effect of slot trading on route-level competition, and finds evidence of increased mutual forbearance between carriers implied by the bilateral nature of slot trading.

Mayer and Sinai (2003a) suggest that the imposition of either a Pigouvian tax or a system of flight caps on airport takeoffs and landings that do not take into account the network benefits of hubbing would not be optimal. In contrast, as the congestion internalization suggests, the high airport share market during peak times would allow dominant hub carriers to naturally internalize an appreciable portion of congestion costs. Brueckner (2009), Verhoef (2010), Sieg (2010), and others study the issue of congestion pricing and airport slots using theoretical models. Brueckner (2009) compared price and quantity-based approaches to the management of airport congestion by considering the possibility of congestion internalization by carriers. He finds that a slot system in which an airport authority allocates a fixed number of slots produces an efficient outcome as long as the number of slots is optimally chosen. Verhoef (2010) studies the regulation of two Cournot airline duopolists and found that slot trading is an ineffective policy when the market power distortion outweighs the congestion distortion.

As far as we are aware, no paper has studied the efficacy of an actual regulatory reform of the slot regulation system on the incentives airlines have towards improved service quality. Reforms of airport slot regulations are rare but may have important consequences over the performance of the entire air transportation system. For example, in early 2000s in the US airline market, new exemptions were granted to the High Density Rule of the New York City area airports. The partial liberalization allowed several additional flights at LaGuardia and JFK operated by new entrants and to small communities across the country. However, the new measures had the unintended consequence of an abrupt increase in flight delays at LaGuardia that ultimately forced the FAA to retighten the slot controls at that airport in 2001.[8] We also have not found empirical studies that address the potential relationship between slot concentration and the service quality provided by major carriers. In principle, slot dominance by few airlines may hinder competition and potentially stimulate more frequent flight disruptions if the competition-service quality hypothesis prevails. Additionally, studies have apparently neglected the possibility of indirect effects produced by regulatory reforms of slots (i.e., flight cap tightening (reduction) or loosening (increase) of airport slots) on carrier behavior regarding flight disruptions. One such behavior

[8] Source: United States Government Accountability Office (2012), op. cit.

would be the internalization of congestion suggested by the literature. The slot control rules may not only constitute entry barriers to competition. They may also change the behavior of incumbents regarding the property rights (or the perception of them) over the airport and, as a consequence, may realign their incentives related to service quality. Therefore, we believe that not accounting for the intervening effects of slot regulations on the relationship between slot concentration and the incentives carriers have in avoiding flight disruptions (such as delays and cancellations) may cause misspecification bias in the empirical analysis.

2.3. Integrated flight disruption management

There is ample anecdotal evidence that carriers engage in a joint decision-making process of flight delays/flight cancellations rather than making independent decisions. In fact, carriers may trade-off between delays and cancellations when implementing their disruption management strategy. For example, in the European market, Ryanair has recently announced it was considering the cancellation of between 40 and 50 flights per day for more than a month in order to improve its overall on-time performance.[9] Some existing papers in the literature have employed models of integrated flight disruption management by airlines. Regarding the possible integrated decision-making of flight delays/flight cancellations, Rupp and Holmes (2006) provide evidence linking flight cancellations with airline revenue since carriers apparently have control over cancellations. They show that flight cancellations are less likely on Thursdays, Fridays, Sundays and for the last flight of the day. Therefore, they provide evidence suggesting that flight cancellations are not random events but may be strategically implemented by airlines to avoid operating flights with low load factors. The authors claim that in some cases flight cancellations and flight delays behave as substitute goods by which airlines have to cancel a flight to avoid additional delays. In contrast, in other circumstances, delays and cancellations can be treated as complementary goods when they have common sources that have to be managed by airlines. Rupp, Holmes and DeSimone (2005) describe a trade-off between cancellations and delays during irregular airport operations and employ a nested logit specification to model for airline choice between both types of flight disruptions. Xiong and Hansen (2013) investigate airline flight cancellation decisions in the US domestic air transport industry. Besides identifying the main determinants of flight cancellations, their model also captures the influence of flight delays on the flight cancellation decisions of carriers and thus sheds light on the trade-off between their respective costs. Marla et al. (2016) develop an enhanced airline schedule recovery model that integrates flight planning into the disruption management of airlines. Their model allows for flight speed changes by carriers to trade-off flight delays and fuel burn. This allows for a reduction in total recovery costs and passenger-related delay costs compared to the existing approaches.

Another commonly observed tool of flight disruption management utilized by airlines is schedule padding. Padding is part of the scheduling strategy of carriers in which they allow for a slack added to planned flight times. By padding the schedule, carriers aim to enhance on-time performance through higher resilience to flight delays and possibly also to flight cancellations. As an illustration, in 2017, the top five airlines in the US market were believed to practice schedule padding rates between 2.7% and 6.4% of their average domestic schedule flight time.[10] A couple of the limited econometric papers that address the issue of airline schedule padding in the literature are Mayer and Sinai (2003b) and Forbes et al. (2017).

2.4. Schedule optimization, congestion management, and the impacts of mergers

There are several studies in the literature dealing with key concepts used in the present paper. This literature focus on topics such as schedule optimization, congestion management, and the impacts of mergers and acquisitions on the performance in airline markets, among others. First, regarding the research on airport congestion management, there are studies of congestion internalization through pricing, peak period pricing, marginal cost pricing, slot trading as Madas and Zografos (2010), Vaze and Barnhart (2012), Zografos et al. (2012), Corolli et al. (2014), Jacquillat and Odoni (2015), Pyrgiotis and Odoni (2015), Zografos et al. (2017), Zografos et al. (2018).

Second, with respect to the schedule optimization models and approaches for allocating airport capacity at a single airport or network of airports, we may refer to Brueckner (2009), Verhoef (2010), Zhang and Zhang (2010), Castelli et al. (2011), Czerny and Zhang (2011), Czerny and Zhang (2014), Wan, Jiang and Zhang (2015), Kidokoro and Zhang (2017), Lin and Zhang (2017). Some of these studies deal with schedule optimization trade-offs, such as slot scheduling efficiency versus fairness, scheduling efficiency versus slot acceptability, etc.

Finally, it is important to mention the empirical studies on the assessment of impacts of mergers/acquisitions on various operational, service and competition aspects of the airline markets. Among the recent papers, we have Kwoka and Shumilkina (2010), Bilotkach et al. (2013), Dobson and Piga (2013), Fageda and Perdiguero (2014), Hüschelrath and Müller (2014), Chen and Gayle (2018).

3. Research design

3.1. Application

We consider the Brazilian airline industry in the 2002–2013 period and the case of the slot controlled Congonhas Airport (CGH)

[9] See "*Ryanair to Cancel Up to 50 Flights Per Day 'to Improve Punctuality'*" - Reuters, Sep, 15 2017.
[10] See "*Which Airlines Pad Their Schedules the Most?*" - The Wall Street Journal, June, 28 2017.

located in downtown São Paulo. Traditionally, the typical passenger at CGH was business-related and highly time sensitive, since the airport is located close to downtown São Paulo and some of the richest demand generation zones of the metropolitan region. Until recently, CGH was the only slot airport in the country. According to the terminology of the International Air Transport Association (IATA), CGH is nowadays a "Level 3 Airport", i.e. an airport with either a shortage of infrastructure capacity, or where authorities impose any operational constraint that prevents it to meet existing demand. The National Civil Aviation Agency (ANAC) is the appointed slot coordinator of CGH, with the role of allocating slots to airlines and to general aviation aiming at managing its declared capacity. The regulatory framework under which CGH currently operates regarding demand/congestion management consists of a use-it-or-lose-it rule in which, to keep their grandfather rights, airlines must comply with allowances for maximum flight delays and cancellations rates of 20% and 10%, respectively. Since 2014, aimed at improving the utilization of runway capacity at the airport, ANAC has increased the number of maximum hourly takeoff and landing slots at CGH at the busiest times from 30 to 33 per hour. The first round of slot allocations after the new declared capacity happened in late 2014, with 100% of the new slots prioritized to smaller carriers Azul and Avianca.[11]

The Brazilian air transportation industry has grown considerably in the sample period, from 31 million domestic passengers in 2002 to 90 million in 2013.[12] The average price dropped 40% from BRL 546 in 2002 to BRL 327 in 2013 (see footnote [12]). In the mid-2000s, due to rapid growth and the lack of airport infrastructure, the air transportation system in the country suffered from substantial congestion problems. The period between 2006 and 2007 is known in the country as the "air blackout" years, marked by two tragic commercial aircraft accidents, operational slowdowns by air traffic controllers - namely work-to-rule procedures that in some cases resembled strike actions - which, along with airport congestion and poor airline disruption management, provoked recurring episodes of massive flight disruptions.[13] One of the airports that suffered the most from flight disruptions in the period was São Paulo/Congonhas (CGH), which had its slot-constrained status formally established by the National Civil Aviation Agency (ANAC) in 2006. Table 1 presents the evolution of flight disruptions in Brazil by contrasting CGH airport ("CGH routes", i.e., airport-pairs that contain CGH as one of the endpoints) with the remaining airports ("non CGH routes") of the country. The time period from 2002 to 2013 has been split on three sub-periods, considering the "air blackout" years (2006–2007) separately.

In Table 1, we notice that the proportion of disrupted flights in the country considerably increased in the mid 2000s from around a third in the 2000–2005 period to more than forty percent in the 2006–2007 period, as shown in the Column named "Total Disruptions (DEL + CAN)".[14] Total disruptions declined to < 30% by the end of the sample in the 2008–2013 period. When considering the whole period, there was a drop in total disruptions of 6.2% for CGH routes and 3.2% for non CGH routes. On average, the CGH routes are typically associated with higher total disruptions than the non CGH routes. However, this effect is not always clear when considering the disaggregation of flight disruptions into flight delays and flight cancellations. For example, in the "air blackout" months of the 2006–2007 period during which the non CGH routes experienced delays and cancelations of 25.5% and 16.5% respectively, the CGH routes had lower delay rates (25.0%) and higher cancellation rates (21.6%). In the subsequent period (2008–2013), an opposite situation was observed in which the CGH routes had higher delay rates (19.8%) and lower cancellation rates (8.5%).

After an airplane crash at CGH in 2007 (the July 17, 2007 TAM Flight 3054 crash), the aviation authorities introduced an important slot reform on the airport. Many operating restrictions were imposed such as a perimeter rule, a transfer of some flights to São Paulo/Guarulhos International Airport (GRU), a temporary ban on flight connections and several safety measures regarding the terminal, runway and air traffic control. The most important measure related to the management of operations at the airport was a slot cap reduction in the allowed flight movements per hour to alleviate congestion. The slot mechanism at the airport is an administrative allocation system that has been regulated by the National Civil Aviation Agency (ANAC). It consists of grandfather rights with use-it-or-lose-it rules that impose maximum levels of flight delays (20%) - the "80/20" rule - and, since 2014, also of flight cancellations (10%). From the slot reform in 2007 until late 2014, the airport has operated under a declared runway capacity of 30 scheduled flights per hour.[15]

Fig. 1 allows a better visualization of the possible effects of the implementation of the slot reduction on the CGH airport. In Fig. 1, it is possible to see the evolution of hourly scheduled flights, slot concentration and flight disruptions at the airport.

As seen in Fig. 1, we can see the evolution of the hourly scheduled flights at the airport extracted at the annual daily 75th percentile over the 2004–2013 period. It also depicts the evolution of the proportion of disrupted flights (delays, cancellations and delays plus cancellations). Finally, Fig. 1 also contains the concentration of flights measured by the Herfindahl-Hirschman index at slot-constrained hours at the airport (slot flights HHI).[16] Note that in the peak of the "air blackout" period (2007), even though 26% of flights were cancelled, 28% of the flights remained delayed by more than 15 min. It is important to emphasize, however, that the analysis of Fig. 1 does allows us determine if the flight delays or cancelations were due to issues at CGH or at the other airport of the flight.[17] Also in Fig. 1, we can observe that the number of scheduled flights at the 75th percentile hour at the airport dropped

[11] See IATA's Worldwide Slot Guidelines, Edition 8.1 (2018), and the list of current IATA Level 2 and Level 3 airports at www.iata.org.

[12] Source: National Civil Aviation Agency, Air Transport Yearbook, 2012 and 2013 editions.

[13] See details in Oliveira et al. (2016).

[14] We aimed at assessing the probability of a passenger to experience any sort of flight disruption. By considering two mutually exclusive events, namely a situation of a "delayed flight" (DEL) and of a "cancelled flight" (CAN), then the probability that DEL or CAN will occur is the sum of the probability of each event. Based on addition rules for probability, we therefore sum up DEL and CAN percentages to produce Total Disruptions percentages.

[15] Airport Capacity Declaration, 2014 - São Paulo/Congonhas - National Civil Aviation Agency (ANAC).

[16] See the description of variables in the empirical model for details.

[17] We aim at performing such analysis in our econometric model of flight disruptions (in Section 3.3), by isolating the *ceteris paribus* effect of slot concentration at CGH on the odds of flight delays and cancellations.

Table 1
Flight disruptions in Brazil - CGH vs remaining airports.
Source: National Civil Aviation Agency, Active Scheduled Flights Report with own calculations, 2000–2013.[a]

Period	Delays (DEL)		Cancellations (CAN)		Total Disruptions (DEL + CAN)	
	CGH routes	non CGH routes	CGH routes	non CGH routes	CGH routes	non CGH routes
(1) 2000–2005	17.1%	15.8%	17.4%	14.4%	34.5%	30.2%
(2) 2006–2007	25.0%	25.5%	21.6%	16.5%	46.6%	42.0%
(3) 2008–2013	19.8%	18.2%	8.5%	8.7%	28.3%	27.0%
Diff.						
(2)-(1)	***7.9%***	***9.7%***	***4.1%***	***2.1%***	***12.0%***	***11.8%***
(3)-(2)	***−5.2%***	***−7.3%***	***−13.1%***	***−7.7%***	***−18.2%***	***−15.0%***
(3)-(1)	***2.8%***	***2.4%***	***−9.0%***	***−5.7%***	***−6.2%***	***−3.2%***

[a] The primary measurement units of the reported percentages in periods (1), (2) and (3) of Table 1 are the proportion of delayed flights (DEL) and the proportion of cancelled flights (CAN). Both proportions were extracted calculating the number of delayed and cancelled flights over the total flights, on routes that have CGH as one of the endpoint airport ("CGH routes") and on the remaining routes of the domestic scheduled air transport system ("non CGH routes"). The differences reported in (2)-(1), (3)-(2) and (3)-(1), named "Diff." represent the percentage change among the figures of periods (1), (2) and (3).

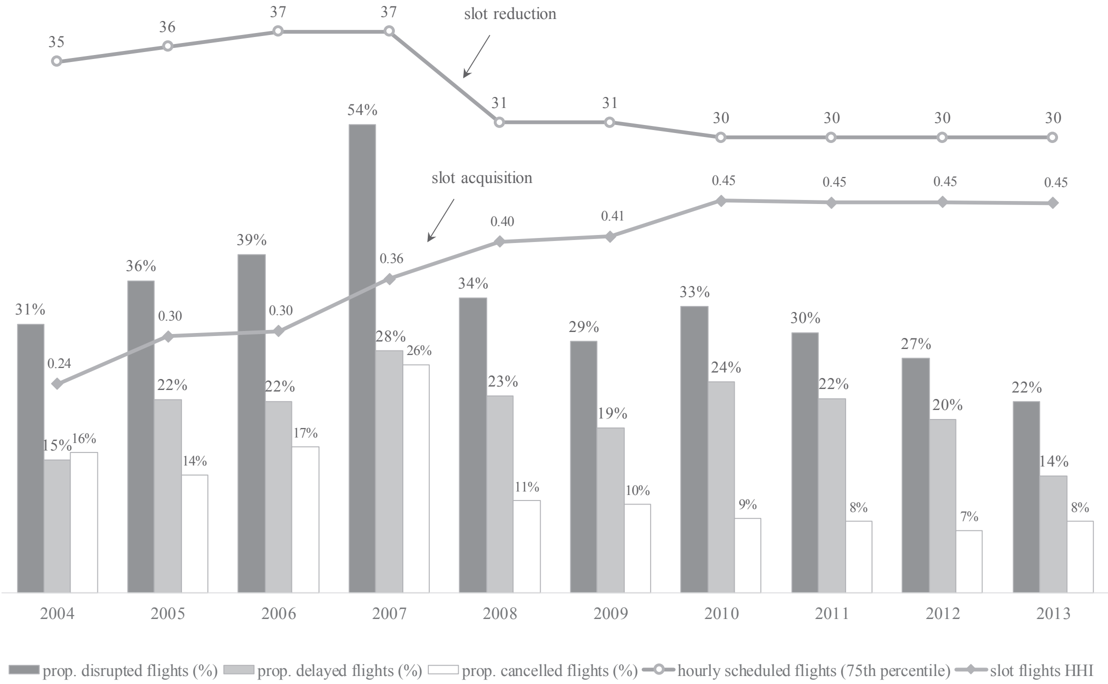

Fig. 1. Hourly scheduled flights, slot concentration and flight disruptions at CGH airport.
Source: National Civil Aviation Agency, Active Scheduled Flights Report, Air Transportation Market Statistical Database - Monthly Traffic Report, with own calculations, 2004–2013. See the description of variables in the empirical model for details.

approximately 16% from 37 (2007) to 31 (2008). The hourly movement at the airport has then followed a flat pattern since 2010.[18]

With respect to the concentration of slot flights in few airlines, CGH has been traditionally dominated by two major carriers: Varig and Tam in the early 2000s, and Tam and Gol since the mid 2000s. For the 2008–2013 period, Tam and Gol's operations account for 93% of all flights at the airport. In April 2007, Gol announced the acquisition of Varig. The merger has allowed Gol to gain access to a major stake of slots at CGH. Prior to the acquisition, Gol had an average of 939 weekly slots at CGH and its rival TAM had 1412 slots.[19] With the acquisition of Varig, Gol added an average of 470 new weekly slots, and therefore matched Tam's 45% market share of slots at CGH. As we can observe in Fig. 1, the concentration of slot flights at the airport has consequently increased 88% from 0.24

[18] Although the hourly capacity of CGH was publicly declared by the government to be 30 flights per hour in late 2007, the obtained data reveals a pattern of gradual transition to the new upper bound, being therefore fully enforced only from 2009. In 2014, ANAC has again expanded the declared capacity of the airport, from 30 to 32 and 33 flights per hour, depending on the specific hour of the operating day.

[19] Source: Active Scheduled Flight Report (VRA), National Civil Aviation Agency - 2007q1, with own calculations.

in 2004 to 0.45 in 2013.

In parallel to the events of slot reduction and slot acquisition of the late 2000s at CGH, the operational performance indicators of the airport seem to have improved considerably since its worst moment in 2007. Indeed, the proportion of delayed flights plunged by half from 28% (2007) to 14% (2013), and the proportion of canceled flights declined more than two-thirds from 26% (2007) to 8% (2013).[20] These figures constitute relative reductions of 50% in flight delays and 69% in flight cancellations, which suggest that the notable events that occurred at the airport may have had a role in contributing to them. We consider the case that either the slot reform, the Gol-Varig merger, or both events may have produced effects that ultimately allowed a much better operational performance of the carriers at the airport. Therefore, our challenge in the empirical modeling is to disentangle the effects of both events on the service quality indicators of flight delays and cancellations of major carriers at CGH. We also examine their average prices and aircraft size to inspect issues related to market power formation and slot hoarding behavior.

3.2. Data

Our data set consists of the panel data of domestic directional city-pairs in Brazil from January 2002 to December 2013. Only passenger flights are considered in the data set. In our analysis, a route is defined as a domestic directional city-pair. In case of multiple airports in a region, we group the related airports in the same area. We include in the sample only routes that have state capitals and/or the country's capital as the two endpoints. The main data source is publicly available from the National Civil Aviation Agency (ANAC), which provides information on all scheduled flights in the country in the Active Scheduled Flight Report (VRA). That online database contains detailed records regarding flight level data of carriers, airport-pairs, flight numbers, scheduled and actual departure and arrival times, and the justification code reported for each delayed and cancelled flight. We aggregate the original VRA data of more than 10 million flight-level daily observations to form a city-pair/month data set. Additionally, we restrict our attention to the major carriers in the period, namely, the full-service carriers Tam and Varig and the hybrid low cost carrier Gol.

We also utilize ANAC's Microdata of Commercial Air Fares Database, an online data set that contains information of all domestic and international fares (both monetary values and the number of tickets sold) in the country on a carrier/airport-pair/month basis. In that data set, all possible itineraries (direct and indirect flights) are accounted for in the same airport-pair market. Since we consider city-pair markets, we aggregate that information to form observations at the city-pair level. The sources of socio-economic data are the Brazilian Institute of Geography and Statistics (IBGE) and the Brazilian Central Bank.

3.3. Econometric model

Our econometric modelling builds on the empirical specification of the previous studies of flight delays found in the literature, as Mayer and Sinai (2003a), Mazzeo (2003), Rupp (2009), Santos and Robin (2010), Zou and Hansen (2014), among others. In this literature, a flight delays metric is typically regressed against some proxies for flight operations, market competition and airport dominance, such as route and airport concentration, hub airport's size and slot restrictions. As the vast majority of papers deal with panel data, most models contain a set of controls for unobserved effects at the route level and time. In our specification, we consider four categories of variables, named "flight operations & costs", "disruption management", "competition & dominance", and "slot concentration" - the latter constituting our main research focus. We examine each set of variables in detail below. Eq. (1) presents our empirical model of flight disruption in the Brazilian airline industry. Note that the categories of regressors are grouped in brackets in the equation.

$$\begin{aligned}\mathrm{ODDSDIS_{kt}} = {} & (\beta_1 \mathrm{flights_{kt}} + \beta_2 \mathrm{pax\ per\ flight_{kt}} + \beta_3 \mathrm{maxcities\ served_{kt}}) + (\beta_4 \mathrm{delay/cancel\ mgmt_{kt}} + \beta_5 \mathrm{schedule\ padding_{kt}} \\ & + \beta_6 \mathrm{maxcity\ prop\ disrupt_{kt}}) + (\beta_7 \mathrm{codeshare\ majors_{kt}} + \beta_8 \mathrm{city{-}pair\ HHI_{kt}} + \beta_9 \mathrm{maxcity\ HHI_{kt}}) \\ & + (\beta_{10} \mathrm{slot\ fligths\ HHI_{kt}} + \beta_{11} \mathrm{slot\ flights\ HHI_{kt}} \times \mathrm{slot\ acquisition_{kt}} + \beta_{12} \mathrm{slot\ flights\ HHI_{kt}} \times \mathrm{slot\ reduction_{kt}}) + \gamma_k \\ & + \gamma_t + u_{kt},\end{aligned} \tag{1}$$

where k denotes the route, i.e. the non-directional city-pair ($k = 1, \ldots\ldots, 181$ routes), and t denotes the time period ($t = 1, \ldots, 144$ months). The components of Eq. (1) are the following:

- *ODDS DIS*$_{kt}$ is the log odds of flight disruption, i.e., the logarithm of the ratio of the probability of the event of a flight being disrupted to that of the alternative event of the flight not being disrupted. We therefore have *ODDS DIS*$_{kt}$ = ln [*prop disrupted flights*$_{kt}$/(1 − *prop disrupted flights*$_{kt}$)], where the variable *prop disrupted flights*$_{kt}$ is the proportion of scheduled non-stop flights of major carriers reported with either delays or cancellations over the total scheduled non-stop flights on city-pair k and time t. Only flight arrival delays of more than fifteen minutes are computed. We also consider the alternative metrics *ODDS DEL*$_{kt}$ and *ODDS CAN*$_{kt}$ to denote, respectively, the log odds of flight delays - use of *prop delayed flights*$_{kt}$ instead of *prop disrupted flights*$_{kt}$ - and flight cancellations - use of *prop cancelled flights*$_{kt}$.[21]

To inspect the effect of airport slots on other factors we also utilize the following variables as alternative regressands in Eq. (1):

[20] Source: Active Scheduled Flight Report (VRA), National Civil Aviation Agency - 2007q1, with own calculations, 2002–2013 period.
[21] Source: National Civil Aviation Agency, Active Scheduled Flight Report - VRA, with own calculations.

- *aircraft size*$_{kt}$ is the average number of seats of the airplanes operated by major carriers on all scheduled non-stop flights of city-pair k and time t (see footnote [21]).
- *yield*$_{kt}$ is the average price per kilometer of major carriers on city-pair k and time t. This variable includes all air tickets sold by major carriers in all flight itineraries in the city-pair travel market at time t.[22] This variable was inflation-adjusted to produce constant monetary values.

We therefore estimate five different equations, using the following regressands: (1) *ODDS DIS*$_{kt}$, (2) *ODDS DEL*$_{kt}$, (3) *ODDS CAN*$_{kt}$, (4) *aircraft size*$_{kt}$, and (5) *yield*$_{kt}$.

Regressors: flight operations & costs

- *flights*$_{kt}$ is the total number of scheduled non-stop flights of major carriers on city-pair k and time t (see footnote [21]). This variable is intended to capture the effect of routes with high flight frequency that possibly have low aircraft turn times and more flights during peak periods, which make them vulnerable to disruptions.
- *pax per flight*$_{kt}$ is the total number of passengers on the flight segments of city-pair k and time t divided by the number of scheduled non-stop flights of major carriers.[23] This variable is aimed at capturing the effect of routes associated with flight connections. *Ceteris paribus*, the higher the number of connecting passengers, the higher the number of passengers per flight. As a consequence, these routes may be exposed to delays, a the airline may hold a plane for passengers arriving on delayed connecting flights.
- *max cities served*$_{kt}$ is the maximum number of destinations served, computed between both endpoint cities of city-pair k and time t. It includes only destinations served by major carriers with non-stop flights from these cities. This variable is designed to capture the hubbing activity of major carriers (hub size with respect to the number of served cities), as in Mayer and Sinai (2003a), among others (see footnote [21]).

Regressors: disruption management

- *delay/cancel mgmt*$_{kt}$ is an umbrella term that accounts for the possible integrated flight delays/flight cancellation approach in the flight disruption management of the major airlines - as suggested in Rupp et al. (2005). This variable is computed in different ways depending on the version of Eq. (1) being estimated: it is equal to *prop cancelled flights*$_{kt}$ in the right-hand side of *ODDS DEL*$_{kt}$ equation; equivalently, it is equal to *prop delayed flights*$_{kt}$ in the *ODDS CAN*$_{kt}$ equation; finally, it is equal to *prop disrupted flights*$_{kt}$ in the *aircraft size*$_{kt}$ and *yield*$_{kt}$ equations. See details in the discussion of the *ODDS DIS*$_{kt}$ variable above (see footnote [21]).
- *schedule padding*$_{kt}$ is a proxy for the possible schedule padding practices of major airlines. With schedule padding, carriers add an extra time - a slack - to their planned flight times, targeting at an enhanced on-time performance through higher resilience of schedules to unpredictable flight disruptions. As Mayer and Sinai (2003a), we compute a “minimum feasible travel time” metric, defined as the shortest observed travel time on a given non-stop route of city-pair k at time t. Our schedule padding metric is therefore the mean difference between the scheduled travel time of each planned non-stop flight, and the computed minimum feasible travel time on city-pair k at time t.[24] In the Appendix, we discuss the consistency of our schedule padding metric to the terminology used in the empirical framework of Mayer and Sinai (2003a).
- *max city prop disrupt*$_{kt}$ is the maximum proportion of disrupted flights - either delayed or cancelled - of all carriers between the origin and destination endpoint cities of city-pair k and time t. It accounts for time-varying unobservables at the city level that could be related to flight disruptions. More than being a regressor, *max city prop disrupt*$_{kt}$ is an important control variable in our empirical framework. If a subset of the national air transport network is subject to delay propagation, then delays may cascade from one airport to another - Mayer and Sinai (2003a), Rupp and Holmes (2006) - a phenomenon that may affect a great amount of flights of a city. By accounting for the overall level of flight disruptions, *max city prop disrupt*$_{kt}$ is therefore intended to at least partially control for the unobserved airline responses to cascading delays and therefore helps avoiding omitted variables bias in the estimation. The variable is also intended to control for overall delays incurred by unfavorable weather conditions - mainly related to rain and fog - observed on a subset of days of a month in the endpoint cities (see footnote [21]).

Regressors: competition & dominance

- *codeshare majors*$_{kt}$ is a dummy variable to account for a codeshare agreement in which the major carriers TAM and Varig had joint operations on city-pair k and time t. The 2003–2005 codeshare agreement was the only relevant alliance among airlines in the

[22] Source: National Civil Aviation Agency, Microdata of Commercial Air Fares Database; the number of routes that had the yield information in that report for the sample period was 172 (out of 182) and therefore some missing data was generated for this variable. The reason for the missing data was that prior to 2010, the regulator collected price data only for a subset of routes, including most of the densest airport-pairs in the country. The missing data generation process is therefore related to low-density routes in the domestic aviation market. As the slot-constrained Congonhas Airport (CGH) is mostly associated with dense route markets, we then consider that the possible problem of sample selection is not a major concern in our framework

[23] Sources: National Civil Aviation Agency, Air Transportation Market Statistical Database - Monthly Traffic Report, and Active Scheduled Flight Report - VRA, with own calculations.

[24] This variable has the total number of scheduled flights of all carriers on a city as the denominator. Source: National Civil Aviation Agency, Active Scheduled Flight Report - VRA, with own calculations.

sample period.[25] Codeshare partners may perform considerable changes in their operations to better coordinate schedules and therefore to maximize the benefits of the agreement that may be ultimately beneficial to passengers. On the other hand, with an increased market power allowed by the alliance, airlines may have lower incentives to keep service quality levels and higher incentives to increase prices. With this variable, we aim at controlling for the presence of the allied carriers in the market during the codeshare period, and therefore at inspecting the existence of such effects in our sample.

- *city-pair HHI*$_{kt}$ is the Herfindahl-Hirschman index of concentration of revenue passengers of city-pair k and time t. To extract this variable, we use the city-pair level market shares of all participating carriers and then calculate the city-pair concentration. This variable aims at capturing the effect of airline market dominance, i.e. market concentration at the route level.[26]
- *max city HHI*$_{kt}$ is the maximum Herfindahl-Hirschman index of concentration between the endpoint cities of city-pair k and time t. First, we extract the city Herfindahl-Hirschman index of concentration, calculated by summing the squared market share of revenue passengers of each carrier at the city level. Second, we extract the maximum computed index between the two endpoint cities. This variable aims at capturing the effect of overall dominance of the available airports of a city (see footnote [26]).

Regressors: slot concentration

- *slot fligths HHI*$_{kt}$ is a metric of concentration of slot flights in few airlines. It is the Herfindahl-Hirschman index of concentration (based on the usual market shares calculation) of flights at slot-constrained hours of city-pair k and time t. It is designed to capture internalization effects, restricted to the time of day when the airport is most congested. To extract this variable, we defined "slot-constrained hours" by considering the full clock hours at São Paulo/Congonhas airport (CGH) at which the number of scheduled flights (arrivals plus departures) was either equal or higher than the official declared runway capacity in the period. That computation was performed on a daily basis. We then summed the number of flights of every participating carrier during these slot-constrained hours for each city-pair k and time t. Finally, we computed the market shares of flights of all carriers at the slot hours and then calculated the slot flights concentration levels.[27]
- *slot acquisition*$_{kt}$ is a proxy for the effect of the acquisition of Varig airlines by Gol airlines since April 2007. It is calculated as the mean number of weekly flights of Varig at slot-constrained hours[28] on city-pair k and time t. That mean is computed for the three months immediately before the merger. The mean is invariant to time but varies over city-pairs, being assigned with values for periods after the acquisition and with zero for periods before that event. The higher the value, the higher the number of Varig's slots acquired by Gol due to the merger.[29] *slot acquisition*$_{kt}$ is aimed to capture the market power effects of the merger on the incentives regarding the internalization of congestion by carriers. In principle, an acquisition of a carrier with many slots may increase the perception of property rights over the airport and therefore may have an impact on the possible congestion internalization behavior (see footnote [15]).
- *slot reduction*$_{kt}$ is a proxy for the slots reduction - slot reform - undertaken by the regulator since August 2007. This variable calculated as the difference between the number of weekly flights at slot-constrained hours (see footnote [27]) on city-pair k and time t, and the (fixed) average number of weekly slot flights that prevailed on the city-pair in the three months immediately before the slot reform. This variable is assigned with zero for periods before the slot reform. The higher the value, the higher the associated slot "tightening" effect. *slot reduction*$_{kt}$ is therefore designed to capture the effects of the reduction in total available slots at CGH on the behavior of the dominant carriers. It allows to inspect if the loss of some flights in the most desired hours of the airport since the reform would result in a diminished perception of property rights by those carriers regarding the airport. Also, the reform may have resulted in the erection of entry barriers that enhanced the market power of dominant carriers.[30]
- *slot flights HHI*$_{kt}$ × *slot acquisition*$_{kt}$ is an interaction term of *slot flights HHI*$_{kt}$ and *slot acquisition*$_{kt}$. The idea of this variable is that the strength of the internalization effects captured by the *slot fligths HHI*$_{kt}$ variable is made stronger or weaker when slots are acquired via merger.
- *slot flights HHI*$_{kt}$ × *slot reduction*$_{kt}$ is an interaction term of *slot flights HHI*$_{kt}$ and *slot reduction*$_{kt}$. The purpose of this variable is to control for the fact that the strength of the internalization effects captured by the *slot fligths HHI*$_{kt}$ variable is made stronger or weaker when the slot cap is lowered.

[25] Source: Secretariat for Economic Monitoring (SEAE) of the Ministry of Finance.

[26] Source: National Civil Aviation Agency, Monthly Traffic Report, with own calculations.

[27] Sources: National Civil Aviation Agency - VRA Report, and an airport capacity study commissioned by the Brazilian government (2010) "*Study of the Air Transport Sector in Brazil*" (text in Portuguese) - Brazilian Development Bank, Jan, 25, 2010, available at www.bndes.gov.br, with own calculations. Note that, in our computation of slot concentration, the values of slot flights HHI may differ across the routes of CGH airport. Although we define a fixed number of slot-constrained hours at that airport, each route has a different number and composition of flights/carriers operated during those slot-constrained hours. As a result, the number of slot flights of each carrier, and also the associated slot flights market share, are allowed to present variation across city-pairs - and across time - in our empirical framework.

[28] See the definition of "slot-constrained hours" above.

[29] Note that we utilize the period before the merger only to extract the three-months mean, but actually assign non-zero values to this variable in the period after the merger. The reason for that procedure is that we aimed at reproducing the most accurate portrait of the acquired firm on the occasion of merger (and before its restructuring) to the future periods of the sample. Also note that the Brazilian antitrust authority, the Administrative Council for Economic Defence (CADE), did not required slot divestiture as a precondition for the merger to be allowed.

[30] Source: National Civil Aviation Agency, Active Scheduled Flight Report - VRA, with own calculations. Note that in the present case we are unable to investigate the effects of airport pricing of aircraft takeoff and landing slots because no schemes of airport congestion charges were in force in the sample period in Brazil. We therefore are unable to capture any slot pricing effects on the mitigation or internalization of congestion by existing or prospective users.

Table 2
Descriptive statistics of the model variables set.

Variable	Unit	Nr. Observ.	Mean	Std. dev.	Min	Max
prop delays	proportion	19,506	0.233	0.147	0.000	0.968
prop cancellations	proportion	19,506	0.080	0.109	0.000	1.000
prop disruptions	proportion	19,506	0.313	0.172	0.000	1.000
aircraft size	nr of seats (mean)	19,506	159.419	22.421	50.000	285.000
yield	local currency	13,201	0.871	0.722	0.099	8.638
flights	nr of flights	19,506	244.082	362.527	1.000	3375.000
pax per flight	nr of passengers	19,506	106.811	26.438	21.146	226.636
max cities served	nr of cities (mean)	19,506	13.729	5.781	1.000	25.333
schedule padding	nr of minutes (mean)	19,486	13.420	6.564	0.000	40.000
max city prop disrupt	proportion	19,506	0.341	0.110	0.075	0.931
codeshare majors	dummy	19,506	0.180	0.384	0.000	1.000
city-pair HHI	index [0, 1]	19,506	0.476	0.147	0.205	1.000
max city HHI	index [0, 1]	19,506	0.396	0.072	0.230	1.000
slot flights HHI	index [0, 1]	19,506	0.079	0.199	0.000	1.000
slot acquisition	nr of flights (mean)	19,506	2.838	16.819	0.000	169.556
slot reduction	nr of flights (mean)	19,506	2.710	16.244	0.000	312.765

Note that both *slot flights* HHI_{kt} × *slot* $acquisition_{kt}$ and *slot flights* HHI_{kt} × *slot* $reduction_{kt}$ are representative of possible moderation effect induced by the events of slot acquisition and slot reduction. Such moderation effects may impact the relationship between slot flight concentration (*slot flights* HHI_{kt}) and flight disruptions (*ODDS* DIS_{kt}), and between slot flight concentration and the other considered regressands. In this sense, by considering those interaction variables in the model we allow for testing if notable changes in flight caps of a slot-constrained airport produce an effect of either aligning or misaligning the incentives of carriers towards a more efficient flight disruption management at the airport. Also note that the main challenge of such approach is the procedure of disentangling the effects of events that occurred almost simultaneously, namely the slot acquisition in April 2007 and slot reduction in August 2007. We aim at identifying those effects through the computations of the variables described above, in which enough inter-route variability - and time variability, in the case of *slot flights* HHI_{kt} × *slot* $reduction_{kt}$ - is allowed in both variables.

Fixed effects and disturbances

- γ_k are the city-pair fixed effects; γ_t are time fixed effects (two-way fixed effects model); the β's are unknown parameters; u_{kt} is the associated error term.

Henceforth, we omit indexes *k* and *t*. Table 2 presents descriptive statistics of the main variables of our empirical model.

In Table 2, it is possible to observe that, in our sample, the mean proportion of delayed flights (*prop delays*) is almost three times higher then the mean proportion of cancelled flights (*prop cancellations*) - i.e. 0.233 against 0.080. Also, in Table 2, the mean *slot flights HHI* is 0.079, which appears to be much lower than the city-pair HHI, equal to 0.476. In fact, this result is due to the fact that the sample includes several city-pairs that do no have the slot-controlled CGH airport in at least one of the endpoint cities. For the 3024 observations in which a flight frequency from/to CGH exists in the sample, we have that, whereas the *city-pair HHI* is equal to 0.399, the mean *slot flights HHI* is 0.487, i.e. 22% higher than the mean city-pair concentration in that case. Note that the Pearson correlation between both variables is 0.299. Also in Table 2, we can observe that in the sample, the mean schedule padding is equal to 13.42 min.

Finally, it is important to discuss the statistics of the variable *max cities served*. This variable is pertinent in our case as it is related to the potential impacts of slot controls on the accessibility of small communities to São Paulo city via the utilization of regional airports. In our sample, the mean maximum number of served cities between origin and destination is 13.729, as it can be observed in Table 2. However, if we restrict our analysis to the number of cities served only to/from CGH airport, the sample mean is increases to approximately 22. More importantly, the evolution of that indicator shows a drop of more than half from 39 in 2002 to 17 in 2013. The sharp decrease in the number of served cities by CGH airport is a clear indication that the concomitant slot flights increase in concentration at the airport in the period - showed in Fig. 1 - may have produced negative consequences with respect to not only to market access to new entrants without historic slot holdings but also to small communities across the country.

3.4. Estimation strategy

In estimating the empirical models specified in Section 3.3, it is important to consider a multiple regression estimation method that accounts for the common econometric problems of heteroscedasticity, autocorrelation and endogeneity. Particularly with respect to endogeneity, the commonly used Ordinary Least Squares estimator (OLS) is inconsistent and should be avoided. We consider regressors *flights*, *pax per flight*, *delay/cancel mgmt* (*prop delayed flights*, *prop cancelled flights*, and *prop disrupted flights*), *city-pair HHI* and *max city HHI* as endogenous variables. To address the issue of endogeneity, the potential instrumental variables methods that were considered to estimate Eq. (1) were the Two Stage Least Squares (2SLS), the Two-Step Feasible Efficient Generalized Method of Moments Estimator (2SGMM) and the Limited Information Maximum Likelihood estimator (LIML). The method employed to run our main regressions was the 2SGMM. The main results were not changed when we employed 2SLS, which is a special case of the GMM estimator class. Additionally, we employed LIML in our robustness check experiments. We utilize the version of the estimator that produces standard errors that are robust and efficient to autocorrelation and arbitrary heteroscedasticity. We employ the Newey-West procedure to adjust the standard error estimates.[31]

To accomplish estimation, we need instrumental variables that are both valid and relevant. See Baum et al. (2003) for a discussion. We consider the following instrumental variables in our identification approach. First, we use structural instruments associated with the following demand shifters of origin and the destination cities: gross domestic products (GDP), population, employment rate, Gini income inequality, number of bank agencies, total amount of bank deposits, total credit and loans. The data sources were the Brazilian Institute of Geography and Statistics (IBGE) and the Brazilian Central Bank. The first two metrics have yearly periodicity and therefore required interpolation to produce monthly series. We utilize the following versions of each instrumental variable: minimum, maximum, geometric mean, and the product ("gravity") between the values of the endpoint cities of each market.[32] We also interacted these variables with a dummy variable assigned with one from August 2007. That dummy variable is related to the reduction of slots since that period. As discussed before, the slot reform was notably motivated by an exogenous event - the aircraft accident of July 2007 at CGH airport. We therefore considered that dummy variable as non-correlated with the error term in our models.

We also utilized the methodology of Hausman (1996) to generate additional instruments. The identifying assumption of the Hausman-type instruments is that the panel structure of the data allows for the use of variables constructed with values from other routes to instrument the endogenous variables related to a given route in the same period. We thus assume that variables extracted for other routes may be correlated with variables extracted for a given route and be uncorrelated with the error term. See applications to the airline industry in Piga and Bachis (2006), Mumbower et al. (2014) and Bendinelli et al. (2016). We utilize the Hausman-type variables: aircraft size, slot flights concentration, route share of passengers of the largest carrier, maximum disruption at the city level, maximum city concentration at the endpoint cities, maximum number of served cities, passengers per flight, proportion of delays, cancellations and disruptions of major carriers and of the whole market, proportion of disruptions caused by airport operations/flight connections and bad weather, route level concentration of passengers, schedule padding, difference between average flight speed and planned flight speed, and the number of weekly flights of major carriers and the fringe carriers.

To examine the quality of our instrumentation methodology, we conducted several statistical tests of the validity and relevance of the instrumental variables. We present the results of all of these tests at the bottom of the result table in Section 3. We utilized Hansen J tests to check the validity of the over-identifying conditions and Kleibergen-Paap rk LM underidentification tests to check the relevance of the instruments set. We also report the minimum F-Statistic of excluded instruments estimated in the first stage of each regression. As we will see in the robustness check section, we further challenged our instrumentation approach by utilizing a reduced set of overidentifying restrictions set. We obtained evidence suggesting the orthogonality and relevance of the proposed set of instrumental variables from the analysis of all hypothesis tests and checks.

4. Discussion of results

Table 3 presents the estimation results for the following specifications: (1) *ODDS DIS*, (2) *ODDS DEL*, (3) *ODDS CAN*, (4) ln *aircraft size* and (5) ln *yield*. As previously discussed, all results were obtained utilizing a two-way fixed effects estimator.

With respect to the flight operations and cost controls, the variable *flights* is statistically significant and positively associated with major airlines' flight disruptions in general (Column 1), and with their flight delays and cancellations (Columns 2 and 3). Additionally, more flights (and also more passengers per flight) are associated with lower yields, possibly due to economies of traffic density, as indicated by Column (5). These results suggest that consumers in markets with higher flight frequency benefit from both lower average times between flights and lower airfares. On the other hand, they also face higher chances of both sorts of flight disruptions. The indicator of hubbing activity (*max cities served*) is statistically significant at the 1% level in explaining flight disruptions (Column 1), but only through flight delays and not cancellations (Columns 2 and 3). In contrast, *max cities served* is associated with lower yields (Column 5), which suggests that airlines exploit some cost economies of hubbing.

Regarding the disruption management variables, we find evidence of a strategic trade-off between flight delays and cancellations in the integrated management of major airlines' operations. In fact, the results point to negative and statistically significant coefficients for both the *prop cancelled flights* variable in the flight delays equation (Column 2) and of the *prop delayed flights* variable in the flight cancellations equation (Column 3). As discussed earlier, this trade-off relationship between delays and cancellations was suggested and modeled by Rupp and Holmes (2006) and Rupp et al. (2005), but it has not yet been confirmed in empirical tests in the literature. Regarding the *schedule padding* variable, the results point to a statistically significant reduction of airline disruptions in all Columns (1) to (3). In contrast, we do not find evidence that keeping a slack in planned schedules produces an increase in the operating costs that is passed through to prices, since the coefficient of the *schedule padding* variable in the yield equation (Column 5) is not statistically significant.

Another estimation result is that flight disruption costs are apparently passed through to prices - the estimated coefficient of *prop disrupted flights* is positive and statistically significant in Column (5). This result is in contrast with Forbes (2008), who finds that prices fall in response to longer flight delays at the slot constrained LaGuardia Airport in the early 2000s. In that case, the author claims that the implied decrease in passenger service quality of flight delays has a negative effect on price, and particularly in

[31] Bartlett kernel function with a bandwidth of round ($T^{1/4}$), $T = 144$.

[32] In some cases, GDP per capita and population density (population per squared kilometer) were also used in combination or substitution for GDP and population.

Table 3
Estimation results.

Variables	(1) *ODDSDIS*	(2) *ODDSDEL*	(3) *ODDSCAN*	(4) ln aircraft size	(5) ln yield
Flight operations & costs					
flights	0.5271^{**}	0.4657^{**}	0.6075^{***}	0.0150	-0.2587^{**}
pax per flight	−0.0319	0.1063	0.1256	0.0876^{***}	-0.1712^{**}
max cities served	0.2849^{***}	0.2636^{***}	0.0816	0.0152	-0.1280^{***}
Disruption management					
delay/cancel mgmt:					
prop cancelled flights		-0.2916^{**}			
prop delayed flights			-0.5791^{***}		
prop disrupted flights				0.0393	0.2419^{***}
schedule padding	-0.0259^{**}	-0.0282^{**}	-0.0408^{**}	0.0130^{***}	0.0095
max city prop disrupt	0.5960^{***}	0.5306^{***}	0.7873^{***}		
Competition & dominance					
codeshare majors	−0.0649	−0.1070	0.2712^{***}	-0.0522^{***}	0.1170^{*}
city-pair HHI	0.6052^{***}	0.6364^{***}	0.4881^{**}	0.0163	−0.1447
max city HHI	-0.4816^{***}	-0.6196^{***}	-0.7359^{***}	0.1035^{**}	0.3088^{***}
Slot concentration					
slot flights HHI	-0.0340^{**}	-0.0398^{**}	0.0121	0.0035	0.0227^{***}
slot flights HHI × slot acquisition	-0.0234^{**}	−0.0109	−0.0051	-0.0033^{***}	0.0115^{**}
slot flights HHI × slot reduction	0.0153^{**}	0.0108	0.0191^{**}	0.0004	−0.0044
Fixed effects					
city-pair fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*
time fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*
Adjusted R-squared	0.5718	0.5885	0.4037	0.7290	0.9295
RMSE stat	0.6014	0.6007	0.9453	0.0777	0.1935
KP underidentif stat	51.0324	28.7892	30.6681	11.9755	25.8049
KP underidentif p-value	< 0.0001	0.0171	0.0007	0.0351	0.0401
Min F Stat 1st stage	12.7986	2.7799	8.1475	2.6427	2.0418
Mean F Stat 1st stage	29.0229	16.6265	18.7395	23.4202	12.0699
J test stat	14.3474	13.1323	8.6289	0.9438	13.5981
J test p-value	0.3498	0.5161	0.4722	0.9182	0.4801
Nr observations	19,467	19,419	16,166	19,506	13,201

Notes: Results produced by the two-step feasible efficient generalized method of moments estimator (2SGMM); statistics efficient for arbitrary heteroscedasticity and autocorrelation. P-value representations: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

competitive markets. In contrast, our data sample contains several routes marked by low levels of competition. It seems that in our case, the upward cost effect of flight disruptions on prices more than compensates the possible downward effect caused by perceived lower quality of disrupted flights. The economic rationality behind our welfare-reducing outcome of lower passenger service quality concomitant to price increase is therefore related to a cost effect, rather than a product quality effect, of delays and cancellations in concentrated airline markets. This result is in accordance with the empirical findings of Zou and Hansen (2014).

With respect to the competition and dominance variables, we have the following results. First, regarding the codeshare agreement observed in the period (*codeshare majors*), the estimated effect is statistically significant only in the models of cancellations and aircraft size (Columns 3 and 4). Second, consistent with the competition-quality hypothesis (Mazzeo, 2003; Greenfield, 2014; Bendinelli et al., 2016), we have strong evidence that market concentration (*city-pair HHI*) is positively associated with flight disruptions. This effect is observed in all results from Columns (1) to (3), and therefore is related to both flight delays (Column 2) and cancellations (Column 3). However, this behavior does not enable them to change their prices, since the coefficient of the *city-pair HHI* variable in Column (5) is not statistically significant. Finally, the results of the *max city HHI* variable point to evidence favorable to the hypothesis of internalization of congestion externalities of Brueckner (2002), Mayer and Sinai (2003a) and Ater (2012). In fact, the results of Columns (1) to (3) show evidence that with higher airport (and city) concentration, there are statistically significant reductions in both delays and flight cancellations. These results suggest that bigger carriers have more efficient management of scheduling and operations to reduce flight disruptions than smaller carriers. Consistent with the congestion internalization theory and the fact that bigger carriers exert greater dominance of scarce airport facilities (runway, apron, gates, check-in counters, etc.), we infer that the average yield of these carriers increase with airport concentration, as seen in Column (5). This effect is often associated with "hub premiums" and with airport dominance by one or a few airlines. Similar evidence has been obtained since Borenstein (1989) and Evans and Kessides (1993), such as in Hofer et al. (2008), Oliveira and Huse (2009), Ciliberto and Williams (2010), and others.

4.1. Slot concentration

Our main results are related to the variable *slot flights HHI* and its interactions. First, with respect to the direct effect of that variable, we find enough evidence that slot concentration allows carriers to increase yields, which is an intuitive result that can be seen in Column (5). However, the coefficients of *slot flights HHI* in Columns (1) and (2) are negative and statistically significant, indicating a relevant drop in flight disruptions caused by lower odds of flight delays. These results suggest that the control of runway congestion via the system of takeoff and landing slots at CGH airport has produced opposing but intrinsically consistent effects on the welfare of consumers. There are higher prices along with the benefit of more intense internalization of congestion costs by dominant carriers. Those contrasting outcomes resemble the effects of hub airport domination found in the previous literature (Brueckner, 2002; Mayer and Sinai, 2003a) and that are confirmed by the results of our *max city HHI* variable above.[33] It is important to note that the results of *slot flights HHI* must be regarded as a *ceteris paribus* effect on the estimated hubbing activity controls (*pax per flight* and *max cities served)* and to market and city concentration (*city-pair HHI* and *max city HHI)*. Therefore, we suggest the interpretation that a concentration of slot flights has an effect of strengthening the mitigation of flight delays and overall flight disruptions allowed by airport concentration. Therefore, it allows the consolidation of the internalization of the external costs of airport congestion by dominant carriers. In this sense, we infer that in the present case of a market with two dominant carriers under airport regulation marked by grandfathering combined with use-it-or-lose-it regulation, airport concentration apparently has not been enough *per se* to allow for the full internalization of congestion costs. Additionally, with an isolated positive effect on prices (Column 5), we have evidence that slots concentration allows airlines to pass through at least some of the internalized costs to air ticket fares, as indicated by the positive coefficient of *slot flights HHI* in Column (5).[34]

Thus, the possible inefficiencies generated by the increase in prices due to a greater concentration of slots are partially offset by the economic efficiency from the internalization of the external costs of congestion and reduction in the level of flight delays. The suggestive interpretation would be that a greater concentration of slots enhances the perceived property rights of dominant airlines at the airport, which enhances their disruption management at the airport and ultimately benefits the consumer. The welfare benefits may especially be the highest for business travelers who are typically highly time-elastic and have higher willingness to pay for the service, as is the case of CGH airport and of some other slot-constrained airports around the world.

Our results suggest that the slot constraint solution to manage airport congestion can produce beneficial results, even in the presence of hubbing activity and high airport concentration. Mayer and Sinai (2003a) acknowledge that congestion controls may be a welfare-enhancing solution in airports with low concentration and no single dominant hub carrier, small capacity, and large local demand.[35] In the present case there are two dominant carriers, and, consistent with Brueckner (2009), we have evidence that a quantity-based approach to the management of airport congestion (like the imposition of airport slots) may reinforce the behavior of congestion internalization by carriers. Therefore, the slot mechanism has apparently aligned the incentives of carriers towards a more efficient flight disruption management with the goals of the regulator. Consequently, slot flight concentration may be welfare enhancing when the perceived property rights of airlines regarding the airport are augmented. In contrast, Daniel (2014) shows that the airport authority is only able to induce dominant carriers to fully internalize if it is capable of fully determining the specific times when major and fringe carriers operate, which is clearly not the case at CGH airport. One of the main limitations of our work is therefore that we cannot identify if the particular slot mechanism at CGH was able to produce an outcome that resembles full internalization of congestion by carriers.

4.2. Slot acquisition vs slot reduction

With respect to the estimation of the interaction variables *slot flights HHI* × *slot acquisition* and *slot flights HHI* × *slot reduction* it is possible to infer some important results. Regarding the merger-related variable *slot acquisition*, we have evidence that the acquisition of an airline with the possession of slots by a major carrier may have played a role to the internalization of congestion at the airport. Indeed, the estimated coefficients of variable *slot flights HHI* × *slot acquisition* in Column (1) is statistically significant, indicating that the merger that involved the acquisition of a considerable number of slots affected the incentives of dominant carriers regarding their service quality at the airport. This result may indicate that slot transfers originated from mergers may not be an activity of public concern at least regarding the management of flight disruptions, which may improve with mergers. However, we have evidence that the average aircraft size has reduced since the estimated coefficient of the same variable in Column (4) is negative and statistically significant at 1% level. This result is consistent with the slot hoarding behavior of dominant carriers ("slot baby-sitting"), which is a situation when carriers employ smaller aircraft to fill as many slots as possible with flights and avoid the reallocation of slots to smaller air carriers. Additionally, there is evidence of a positive price effect (Column 5), possibly due to either the higher costs associated with slot hoarding and/or the consequential increase in market power stemming from that behavior. Since the *slot acquisition* variable has a negative and statistically significant moderating effect on the overall flight disruptions level (Column 1), we therefore infer that the uncovered slot hoarding practices apparently have not encouraged an inefficient use of slots at the airport but, on the contrary, may have engendered quality improvement.

Regarding the effect of the *slot reduction* variable, we have evidence of a statistically significant effect of the 2007 slot reform on

[33] The effects of variables *slot flights HHI* and *max city HHI* are not always the same across the results in Table 3. Contrary to slot concentration, overall airport dominance apparently does produce a decreasing influence on flight cancelations and has a positive effect on the average size of aircraft.

[34] Other possible interpretations of such pricing behavior allowed by slot flights concentration would be the increase in quality of service (peak hours, fewer delays, etc.) and the associated costs, and also the higher market power (dominance of essential resources). However, we suggest that all these effects are already controlled by the passenger-related HHI measures (*city-pair HHI* and *max city HHI*). Therefore, we leave the result of *slot flights HHI* with the direct interpretation of an extra congestion internalization behavior by carriers.

[35] They illustrate the point using the slot-constrained LaGuardia airport.

Table 4
Robustness checks results.

	(1)	(2) Instrumental variables	(3)	(4)	(5) Specification	(6)
Checks	*Main Model (Table 3)*	*Half overidentifying restrictions set*	*Full overidentifying restrictions set*	*Half overidentifying restrictions set*	*Dropped max city prop disrupt prop cancelled flights prop delayed flights*	*Dropped max city prop disrupt prop cancelled flights prop delayed flights*
Estimator	2SGMM	2SGMM	LIML	LIML	2SGMM	LIML
ODD DIS						
city-pair HHI	0.6052***	0.6625***	0.7382***	0.6999***	0.6661***	1.0698***
max city HHI	−0.4816***	−0.5241***	−0.6061**	−0.5608**	−0.3718***	−0.6967**
slot flights HHI	−0.0340**	−0.0360**	−0.0413*	−0.0371*	−0.0353**	−0.0485*
slot flights HHI × slot acquisition	−0.0234**	−0.0267**	−0.0268*	−0.0272*	−0.0289***	−0.0465**
slot flights HHI × slot reduction	0.0153**	0.0187**	0.0152	0.0181*	0.0174**	0.0273**
ODD DEL						
city-pair HHI	0.6364***	0.7274***	0.9706***	0.8916***	0.6323***	1.0339**
max city HHI	−0.6196***	−0.6946***	−0.9454**	−0.8638**	−0.5225***	−0.9207**
slot flights HHI	−0.0398**	−0.0451**	−0.0541**	−0.0529**	−0.0454**	−0.0647**
slot flights HHI × slot acquisition	−0.0109	−0.0152	−0.0208	−0.0207	−0.0113	−0.0226
slot flights HHI × slot reduction	0.0108	0.0149	0.0140	0.0177	0.0099	0.0142
ODD CAN						
city-pair HHI	0.4881**	0.7100**	0.6405**	0.7515**	0.6659**	0.7765**
max city HHI	−0.7359***	−0.9931**	−0.8583**	−1.0190**	−1.0245***	−1.1714**
slot flights HHI	0.0121	0.0083	0.0077	0.0082	0.0421	0.0379
slot flights HHI × slot acquisition	−0.0051	−0.0075	−0.0056	−0.0074	0.0011	−0.0034
slot flights HHI × slot reduction	0.0191**	0.0206**	0.0159	0.0182	0.0174	0.0185
ln *aircraft size*						
city-pair HHI	0.0163	0.0038	0.0234	0.0038	0.0163	0.0234
max city HHI	0.1035**	0.1318	0.0988*	0.1318	0.1035**	0.0988*
slot flights HHI	0.0035	0.0043	0.0030	0.0043	0.0035	0.0030
slot flights HHI × slot acquisition	−0.0033***	−0.0036**	−0.0035***	−0.0036**	−0.0033***	−0.0035***
slot flights HHI × slot reduction	0.0004	0.0010	0.0003	0.0010	0.0004	0.0003
ln *yield*						
city-pair HHI	−0.1447	−0.2195**	−0.3329*	−0.3422**	−0.1447	−0.3329*
max city HHI	0.3088***	0.3762***	0.5111**	0.5280***	0.3088***	0.5111**
slot flights HHI	0.0227***	0.0249***	0.0277**	0.0281**	0.0227***	0.0277**
slot flights HHI × slot acquisition	0.0115**	0.0139**	0.0146*	0.0153*	0.0115**	0.0146*

(continued on next page)

Table 4 (*continued*)

	(1)	(2) Instrumental variables	(3)	(4)	(5) Specification	(6)
Checks	*Main Model (Table 3)*	*Half overidentifying restrictions set*	*Full overidentifying restrictions set*	*Half overidentifying restrictions set*	*Dropped max city prop disrupt prop cancelled flights prop delayed flights*	*Dropped max city prop disrupt prop cancelled flights prop delayed flights*
Estimator	2SGMM	2SGMM	LIML	LIML	2SGMM	LIML
slot flights HHI × slot reduction	−0.0044	−0.0047	−0.0021	−0.0024	−0.0044	−0.0021

Notes: Results produced by the two-step feasible efficient generalized method of moments (2SGMM) and the limited-information maximum likelihood (LIML) estimators; statistics robust to heteroskedasticity and autocorrelation. P-value representations: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

the odds of flight cancellations (Column 3). Since it provides a positive coefficient of an interaction variable (*slot flights HHI* × *slot reduction*), it must be interpreted as a moderating effect on the direct relationship between slot concentration and flight disruptions. This implies that the public policy measures of arbitrary slot cap reductions by the authorities may have produced a misalignment of the incentives of major airlines towards an efficient disruption management and inhibited some of the internalization of congestion. We interpret this result as representing a situation in which the perceived property rights of airlines over the airport have been reduced by the loss of some flights in the most desired hours since the reform. Additionally, it may be the case that the entry barriers created by the slot reform enhanced the market power of dominant carriers, which consequentially induced higher rates of strategic flight cancellations. However, with respect to flight delays (Column 2), the estimated moderating effect was not statistically significant.

The empirical model of Eq. (1) may be used to study many other relationships regarding the behavioral patterns and strategies of airlines in congested airports. In particular, we suggest that it could incorporate the concept of flight speed changes of Marla, Vaaben and Barnhart (2016) to investigate the effect of flight planning on the disruption management of airlines. Other possibilities are conceivable, with respect to the investigation of the market determinants of slot hoarding, aircraft size, slot concentration, etc., and the impacts of late returns of unwanted slots, among others.

5. Robustness checks

We systematically checked the robustness of our empirical model. In Table 4, we present the results of a set of experiments aimed at inspecting the sensitivity of results of Table 3 to changes in the estimation approach. The experiments are motivated by the recommendations of Angrist and Pischke (2008) to assess the risks of false positive findings. Table 4 presents the results of these experiments for each considered regressand and for the main regressors, namely *city-pair HHI*, *max city HHI*, and *slot flights HHI* and its interactions.

For comparison reasons, the results of Table 3 are reproduced in Table 4, Column (1), whereas the other columns present the alternative results. First, in Columns (2), (3) and (4), we inspect the sensitivity of results to changes in the instrumental variables estimation. We employ different identification approaches, considering reduced number of excluded instruments and/or an alternative instrumental variables estimator. We challenge our instrumentation approach by employing only half of the original overidentifying restrictions set in these specifications. With respect to the alternative estimation method, we employ the Limited Information Maximum Likelihood estimator (LIML). Second, in Columns (5) and (6), we drop three key disruption management variables - namely, *max city prop disrupt*, *prop delayed flights* and *prop cancelled flights* - to inspect the sensitivity of results to changes in model specification.

The results of all the robustness checks indicate that most estimates of Table 3 are not affected by the proposed specification changes. One exception is the result of variable *slot flights HHI* × *slot reduction*, which, contrary to Column (1), becomes not statistically significant in some robustness checks (Columns 2–6) in the *ODDS DIS* and *ODDS CAN* equations. The same happens with the results of *max city HHI* in the *ln aircraft size* equation. In those cases, we must interpret that, contrary to Table 3, the possible effects of these variables are statistically non-significant in the indicated equations.

A final robustness check was to challenge our definition of schedule padding. As Mayer and Sinai (2003a), we consider the minimum observed travel time on a given nonstop route in a given month - i.e., the "minimum feasible travel time" - as a reference to calculate schedule padding. In that procedure, we assume the unimpeded block time to be the lowest block time of all flights of a nonstop route within a month. In the robustness check, we change that definition in two ways: first, we consider the 5th percentile values of block times instead of the lowest values as in Mayer and Sinai (2003a); and second, we consider the corresponding year, instead of the month, in the computation. With those procedures, we therefore develop and experiment with an alternative measure of schedule padding.[36] The results of that robustness check can be found in the Appendix. Again, the proposed changes did not affect the main results of Table 3.

6. Conclusion

The present paper developed an econometric model of flight disruptions that investigated the congestion internalization behavior of major airlines and the possible role of airport slots. In particular, we considered the case of the domestic airline industry in Brazil with special interest in the slot-constrained airport São Paulo/Congonhas (CGH). We found evidence of the internalization of congestion externalities by dominant carriers. Moreover, a more intense competition in the city-pair markets tended to reduce both flight delays and cancellations, thus providing evidence in favor of the competition-service quality hypothesis of the literature. Additionally, carriers strategically manage (trade-off) flight delays and cancellations and employ schedule padding. Flight disruptions costs are apparently passed through to the consumers' prices.

The main results of our empirical model suggest that airport slots may have a role in strengthening congestion internalization behavior in the airline industry. We estimate that slot flights concentration has allowed some further internalization of congestion costs by dominant carriers, which is a *ceteris paribus* effect that is not directly associated with either hubbing activity or airport concentration. We also provide evidence that a merger that involved the acquisition of a considerable number of slots induced a slot hoarding behavior by dominant carriers. However, the slot hoarding practices have not been effective in misaligning the incentives

[36] We thank an anonymous reviewer for suggesting this analysis.

towards the internalization of airport congestion. Additionally, in 2007, the regulators reduced the hourly slot cap at the airport, which has apparently produced a moderating effect on the congestion internalization behavior related to flight cancellations. From a policy perspective, our results overall suggest that a traditional scheme of slot allocation through grandfathering combined with a use-it-or-lose-it rule would be sufficient for stimulating the internalization of at least some of the still uninternalized congestion externalities. Our findings, however, are limited by the fact that the sample utilized in the present paper comprises only a single slot airport and its dominant carriers. We therefore recommend that future studies focus on the development of samples with a higher diversity of slot airports and airlines, comprising different conditions of airport concentration, aiming at better inspecting, and perhaps generalizing, the relationship between airport slots concentration and the incentives for congestion internalization in this industry.

Acknowledgements

The authors wish to thank the São Paulo Research Foundation (FAPESP) - grants n. 2013/14914-4 and 2015/19444-1; the National Council for Scientific and Technological Development (CNPq) - grants n. 301654/2013-1, n. 301344/2017-5 and PIBIC; and CAPES Institutional Postgraduate degree funding. They also wish to thank William Bendinelli, Daniel Pamplona, Renan Oliveira, Humberto Bettini, Cláudio Jorge P. Alves, Carlos Müller, Rogéria Arantes, Giovanna Ronzani, José Guerreiro Fregnani, Jan Brueckner, the anonymous reviewers, and the participants of the 2016 Symfposium on Air Transport Economics, São José dos Campos. All of the mistakes are ours.

Appendix A

We define "schedule padding" as the extra time added by the airline to the scheduled arrival time of a flight, aimed at reducing the risk of that flight being publicly declared delayed by the authorities. We therefore have the following expression:

$$\text{schedule padding} \equiv \text{scheduled arrival time - earliest feasible arrival time,} \tag{A1}$$

where *schedule padding* is measured in time units. By summing *scheduled departure time* to both sides of (A1) and rearranging terms we may reach:

$$\text{schedule padding} = (\text{scheduled arrival time - scheduled departure time}) + (\text{earliest feasible arrival time - scheduled departure time}). \tag{A2}$$

With (A2) it is easy to obtain expression (A3):

$$\text{schedule padding} = \text{scheduled travel time - minimum feasible travel time,} \tag{A3}$$

where *scheduled travel time* = *scheduled arrival time* − *scheduled departure time*, and *minimum feasible travel time* = *earliest feasible arrival time* − *scheduled departure time*. (A3) allows to relate our definition of schedule padding to the concept of *minimum feasible travel time*, defined as "the shortest observed travel time on a given nonstop route in a particular month" (Mayer and Sinai, 2003a,b, p. 1201). Additionally, it is relatively straightforward to show how our *schedule padding* metric relates to the authors' concept of excess *time*. In fact, Mayer and Sinai (2003a,b) define *excess time* in the following way:

$$\text{excess travel time} \equiv \text{actual travel time - minimum feasible travel time.} \tag{A4}$$

By summing *scheduled travel time* to both sides of (A4) and rearranging terms we may reach:

$$\text{excess travel time} \equiv (\text{actual travel time - scheduled travel time}) - (\text{scheduled travel time - minimum feasible travel time}), \tag{A5}$$

and therefore we have:

$$\text{excess travel time} = \text{actual delay - schedule padding,} \tag{A6}$$

where *actual delay* is the difference between actual travel time and scheduled travel time, being thus an official metric of flight delays, but, as Mayer and Sinai (2003a,b) emphasize, is subject to airlines' manipulation by "adjusting their schedule times to compensate for expected delays". With (A6), we show that our concept of schedule padding is consistent with, and directly related, to the definition of excess travel time of the authors.

Important to note that Mayer and Sinai (2003a,b)'s procedure of netting out the minimum feasible travel times (A4) is actually equivalent to discounting the effect of schedule padding on flight delays, as can be viewed in (A6). In other words, to investigate the determinants of flight delays in the US airline market, Mayer and Sinai (2003a,b) focus on excess times instead of actual flight delays, and therefore eliminate schedule padding from their analysis. In our framework, we do not eliminate schedule padding but keep it as a control to understand its effects on the many dimensions of airline decision making regarding operations, costs and prices.

Appendix B

See Table 5.

Table 5
Robustness check - alternative schedule padding metric.

Variables	(1) *ODDSDIS*	(2) *ODDSDEL*	(3) *ODDSCAN*	(4) ln aircraft size	(5) ln yield
Flight operations & costs					
flights	0.4783**	0.4759**	0.5714***	0.0167	−0.2522**
pax per flight	−0.0692	0.1046	0.1189	0.0888***	−0.1752**
max cities served	0.2749***	0.2628***	0.0728	0.0180	−0.1258***
Disruption management					
delay/cancel mgmt:					
prop cancelled flights		−0.3086**			
prop delayed flights			−0.5548***		
prop disrupted flights				0.0346	0.2477***
schedule padding (***alternative***)	−0.0525***	−0.0657***	−0.0474**	0.0105***	0.0151*
max city prop disrupt	0.5995***	0.5356***	0.7787***		
Competition & dominance					
codeshare majors	−0.0653	−0.1077	0.2723***	−0.0504***	0.1100*
city-pair HHI	0.5958***	0.6572***	0.4969**	0.0170	−0.1371
max city HHI	−0.4752***	−0.6318***	−0.7609***	0.0897*	0.3030***
Slot concentration					
slot flights HHI	−0.0335**	−0.0400**	0.0123	0.0034	0.0223***
slot flights HHI × slot acquisition	−0.0221**	−0.0119	−0.0039	−0.0029***	0.0113*
slot flights HHI × slot reduction	0.0142*	0.0118	0.0180**	0.0002	−0.0043
Fixed effects					
city-pair fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*
time fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*
Adjusted R-squared	0.5723	0.5900	0.4035	0.7290	0.9294
RMSE stat	0.6011	0.5996	0.9454	0.0777	0.1936
KP underidentif stat	52.3774	29.6111	31.3665	11.6639	25.9006
KP underidentif p-value	< 0.0001	0.0134	0.0005	0.0397	0.0391
Min F Stat 1st stage	12.9983	2.7508	8.5245	3.3387	2.2390
Mean F Stat 1st stage	29.9575	17.1920	19.2099	24.9565	12.6992
J test stat	12.9694	12.3987	8.8118	1.1169	13.1831
J test p-value	0.4502	0.5743	0.4548	0.8916	0.5122
Nr observations	19,467	19,419	16,166	19,506	13,201

Notes: Results produced by the two-step feasible efficient generalized method of moments estimator (2SGMM); statistics efficient for arbitrary heteroscedasticity and autocorrelation. P-value representations: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. See Section 5 for a description of the alternative schedule padding metric.

References

Angrist, J.D., Pischke, J.S., 2008. Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University Press, Princeton.
Ater, I., 2012. Internalization of congestion at US hub airports. J. Urban Econ. 72 (2), 196–209.
Baum, C.F., Schaffer, M.E., Stillman, S., 2003. Instrumental variables and GMM: estimation and testing. Stata J. 3 (1), 1–31.
Bendinelli, W.E., Bettini, H.F., Oliveira, A.V., 2016. Airline delays, congestion internalization and non-price spillover effects of low cost carrier entry. Transport. Res. Part A: Policy Pract. 85, 39–52.
Bilotkach, V., Fageda, X., Flores-Fillol, R., 2013. Airline consolidation and the distribution of traffic between primary and secondary hubs. Region. Sci. Urban Econ. 43 (6), 951–963.
Borenstein, S., 1989. Hubs and high fares: dominance and market power in the US airline industry. RAND J. Econ. 344–365.
Brueckner, J.K., 2002. Airport congestion when carriers have market power. Am. Econ. Rev. 92 (5), 1357–1375.
Brueckner, J.K., 2009. Price vs. quantity-based approaches to airport congestion management. J. Public Econ. 93 (5), 681–690.
Bubalo, B., Gaggero, A.A., 2015. Low-cost carrier competition and airline service quality in Europe. Transp. Policy 43, 23–31.
Castelli, L., Pellegrini, P., Pesenti, R., 2011. Airport slot allocation in Europe: economic efficiency and fairness. Int. J. Revenue Manage. 6 (1–2), 28–44.
Chen, Y., Gayle, P., 2018. Mergers and product quality: evidence from the airline industry. Int. J. Ind. Organ (future edition).
Ciliberto, F., Williams, J.W., 2010. Limited access to airport facilities and market power in the airline industry. J. Law Econ. 53 (3), 467–495.
Corolli, L., Lulli, G., Ntaimo, L., 2014. The time slot allocation problem under uncertain capacity. Transport. Res. Part C: Emerg. Technol. 46, 16–29.
Czerny, A.I., Zhang, A., 2011. Airport congestion pricing and passenger types. Transport. Res. Part B: Methodol. 45 (3), 595–604.
Czerny, A.I., Zhang, A., 2014. Airport congestion pricing when airlines price discriminate. Transport. Res. Part B: Methodol. 65, 77–89.
Daniel, J.I., 1995. Congestion pricing and capacity of large hub airports: a bottleneck model with stochastic queues. Econometr.: J. Econometr. Soc. 327–370.
Daniel, J.I., 2014. The untolled problems with airport slot constraints. Econ. Transport. 3 (1), 16–28.
Dobson, P.W., Piga, C.A., 2013. The impact of mergers on fares structure: evidence from European low-cost airlines. Econ. Inq. 51 (2), 1196–1217.
Evans, W.N., Kessides, I.N., 1993. Localized market power in the US airline industry. Rev. Econ. Stat. 66–75.
Fageda, X., Perdiguero, J., 2014. An empirical analysis of a merger between a network and low-cost airlines. J. Transp. Econ. Policy 48 (1), 81–96.
Forbes, S.J., 2008. The effect of air traffic delays on airline prices. Int. J. Ind. Organ. 26 (5), 1218–1232.
Forbes, S., Lederman, M., Yuan, Z., 2017. Do Airlines Pad Their Schedules? Working Paper.
Fukui, H., 2010. An empirical analysis of airport slot trading in the United States. Transport. Res. Part B: Methodol. 44 (3), 330–357.
Fukui, H., 2012. Do carriers abuse the slot system to inhibit airport capacity usage? Evidence from the US experience. J. Air Transp. Manage. 24, 1–6.
Fukui, H., 2014. Effect of slot trading on route-level competition: evidence from experience in the UK. Transport. Res. Part A: Policy Pract. 69, 124–141.
Greenfield, D., 2014. Competition and service quality: new evidence from the airline industry. Econ. Transport. 3 (1), 80–89.

Hausman, J.A., 1996. Valuation of new goods under perfect and imperfect competition. In: Gordon, Robert J., Bresnahan, Timothy F. (Eds.), The Economics of New Goods. University of Chicago Press, Chicago, pp. 207–248.
Hofer, C., Windle, R.J., Dresner, M.E., 2008. Price premiums and low cost carrier competition. Transport. Res. Part E: Logist. Transport. Rev. 44 (5), 864–882.
Hüschelrath, K., Müller, K., 2014. Airline networks, mergers, and consumer welfare. J. Transp. Econ. Policy 48 (3), 385–407.
Jacquillat, A., Odoni, A.R., 2015. An integrated scheduling and operations approach to airport congestion mitigation. Oper. Res. 63 (6), 1390–1410.
Kidokoro, Y., Zhang, A., 2017. Airport congestion pricing and cost recovery with side business. Transport. Res. Part A: Policy Pract.
Kwoka, J., Shumilkina, E., 2010. The price effect of eliminating potential competition: evidence from an airline merger. J. Ind. Econ. 58 (4), 767–793.
Lin, M.H., Zhang, Y., 2017. Hub-airport congestion pricing and capacity investment. Transport. Res. Part B: Methodol. 101, 89–106.
Madas, M.A., Zografos, K.G., 2010. Airport slot allocation: a time for change? Transp. Policy 17 (4), 274–285.
Marla, L., Vaaben, B., Barnhart, C., 2016. Integrated disruption management and flight planning to trade off delays and fuel burn. Transport. Sci. 51 (1), 88–111.
Mazzeo, M.J., 2003. Competition and service quality in the U.S. airline industry. Rev. Ind. Organ. 22 (4), 275–296.
Mayer, C., Sinai, T., 2003a. Network effects, congestion externalities, and air traffic delays: or why not all delays are evil. Am. Econ. Rev. 93 (4), 1194–1215.
Mayer, C., Sinai, T., 2003b. Why do Airlines Systematically Schedule their Flights to Arrive Late? Working Paper.
Mumbower, S., Garrow, L.A., Higgins, M.J., 2014. Estimating flight-level price elasticities using online airline data: a first step toward integrating pricing, demand, and revenue optimization. Transport. Res. Part A: Policy Pract. 66, 196–212.
Oliveira, A.V.M., Huse, C., 2009. Localized competitive advantage and price reactions to entry: full-service vs. low-cost airlines in recently liberalized emerging markets. Transport. Res. Part E: Logist. Transport. Rev. 45 (2), 307–320.
Oliveira, A.V.M., Lohmann, G., Costa, T.G., 2016. Network concentration and airport congestion in a post de-regulation context: a case study of Brazil 2000–2010. J. Transp. Geogr. 50, 33–44.
Piga, C., Bachis, E., 2006. Hub premium, airport dominance and market power in the European airline industry. Riv. Polit. Econ. 11–54.
Pyrgiotis, N., Odoni, A., 2015. On the impact of scheduling limits: a case study at Newark liberty international airport. Transport. Sci. 50 (1), 150–165.
Rupp, N.G., 2009. Do carriers internalize congestion costs? Empirical evidence on the internalization question. J. Urban Econ. 65 (1), 24–37.
Rupp, N.G., Holmes, G.M., 2006. An investigation into the determinants of flight cancellations. Economica 73 (292), 749–783.
Rupp, N.G., Holmes, G.M., DeSimone, J., 2005. Airline schedule recovery after airport closures: empirical evidence since September 11th. South. Econ. J. 71 (4), 800–820.
Rupp, N., Owens, D., Plumly, L., 2006. Does competition influence airline on-time performance. Adv Airline Econ. 1, 251–272.
Santos, G., Robin, M., 2010. Determinants of delays at European airports. Transport. Res. Part B: Methodol. 44 (3), 392–403.
Sieg, G., 2010. Grandfather rights in the market for airport slots. Transport. Res. Part B: Methodol. 44 (1), 29–37.
Swaroop, P., Zou, B., Ball, M.O., Hansen, M., 2012. Do more US airports need slot controls? A welfare based approach to determine slot levels. Transport. Res. Part B: Methodol. 46 (9), 1239–1259.
Vaze, V., Barnhart, C., 2012. Modeling airline frequency competition for airport congestion mitigation. Transport. Sci. 46 (4), 512–535.
Verhoef, E.T., 2010. Congestion pricing, slot sales and slot trading in aviation. Transport. Res. Part B: Methodol. 44 (3), 320–329.
Wan, Y., Jiang, C., Zhang, A., 2015. Airport congestion pricing and terminal investment: effects of terminal congestion, passenger types, and concessions. Transport. Res. Part B: Methodol. 82, 91–113.
Xiong, J., Hansen, M., 2013. Modelling airline flight cancellation decisions. Transport. Res. Part E: Logist. Transport. Rev. 56, 64–80.
Zhang, A., Zhang, Y., 2010. Airport capacity and congestion pricing with both aeronautical and commercial operations. Transport. Res. Part B: Methodol. 44 (3), 404–413.
Zografos, K.G., Androutsopoulos, K.N., Madas, M.A., 2018. Minding the gap: optimizing airport schedule displacement and acceptability. Transport. Res. Part A: Policy Pract (future edition).
Zografos, K.G., Madas, M.A., Androutsopoulos, K.N., 2017. Increasing airport capacity utilisation through optimum slot scheduling: review of current developments and identification of future needs. J. Sched. 20 (1), 3–24.
Zografos, K.G., Salouras, Y., Madas, M.A., 2012. Dealing with the efficient allocation of scarce resources at congested airports. Transport. Res. Part C: Emerg. Technol. 21 (1), 244–256.
Zou, B., Hansen, M., 2014. Flight delay impact on airfare and flight frequency: a comprehensive assessment. Transport. Res. Part E: Logist. Transport. Rev. 69, 54–74.