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Dynamic pricing and market segmentation responses to low-cost carrier entry

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ABSTRACT

This paper develops an empirical model of online airfares to inspect the impact of the entry of a low-cost carrier (LCC). We utilize a database collected from the website of an online travel agent in Brazil. We test whether incumbents reshape their airfare temporal profiles in an attempt to attract the price-sensitive passengers who constitute the target market of the newcomer. Our results suggest that LCC entry partially spoils the existing market segmentation schemes of incumbents, forcing them to revise their distribution management strategy, simplify their fare structure and migrate from a non-monotonic to a weakly monotonic price curve.

1. Introduction

Airline dynamic pricing has traditionally been associated with the notion of proactive management of fare offerings by airlines as a flight departure nears - the average "temporal profile" of airfares over the reservation period. One of the most recognized motivations for dynamic pricing in the air travel industry is profit maximization through market segmentation. Airlines segment customers by carefully customizing their products - flight attributes, price, associated restrictions and ancillaries - to induce not only self-selection but also a "self-revelation" of individual preferences and, ideally, of each individual's willingness to pay. The most traditional scheme of airline market segmentation considers the timing of flight/fare searches by passengers to be a mechanism for such revelation. Different price curve patterns may emerge according to the different patterns of booking arrival requests by the passenger segments identified in the market. Additionally, the effectiveness of carriers' yield management systems in avoiding revenue dilution through passenger buy-down behavior dictates the relative success of the overall market segmentation approach.

Thus far, the literature on airline dynamic pricing has virtually ignored the important issue of how incumbent airlines adjust their temporal profiles when exposed to competition from low cost carriers (LCCs). Although the impact of LCCs on the *aggregate* prices of incumbents is well documented by the literature, including Windle and Dresner (1999), Morrison (2001), Hofer et al. (2008), Goolsbee and Syverson (2008) and Brueckner et al. (2013), among others, few studies

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have considered the consequences of LCC entry on the *dynamic pricing* of incumbents. Most studies of airline dynamic pricing focus on the temporal profiles of low cost carriers *per se* - such studies include Alderighi et al. (2015b), Bilotkach et al. (2015) and Gaggero and Piga (2011). Two of the few exceptions are Mantin and Koo (2009) and Alderighi et al. (2015a). Mantin and Koo (2009) develop an econometric model of dynamic price dispersion and find evidence of an intensification in the "high-low" pricing strategy to respond to the LCCs and thus an increase in airfare volatility in the market from full-service carriers (FSCs). Alderighi et al. (2015a) utilize data collected from an online travel agency to investigate how the temporal profile of FSC prices is affected by code-sharing agreements, controlling for the total number of low cost carriers operating on the route in their Heckit specification. They estimate that the presence of an LCC reduces not only the fares of incumbent airlines by 4–5% but also the likelihood of offering code-sharing agreements. Although these papers have investigated the temporal profiles of major incumbents facing LCC competition, they have not addressed the issue of how temporal profiles may be adjusted by carriers in response to such increased competition. Our main contribution is to specify and estimate an econometric model of dynamic airline pricing that aims to empirically examine the possible changes in the temporal profiles of fares after the entry of an LCC rival. We test whether incumbents reshape their airfare temporal profiles in an attempt to attract the price-sensitive passengers who constitute the target market of the newcomer. In addition to the price responses to entry, we consider the possibility of reactions in another important dimension of airline competition: the management of distribution channels. Specifically, we test whether incumbents increase the availability of their airfares on an online travel agent (OTA) to intensify competition with the LCC for the early-booking price-sensitive passengers in that sales channel.

Our econometric approach utilizes an original database of airfares collected from the website of an important OTA player in Brazil. The database comprises the domestic airport-pairs of the São Paulo Multiple Airports Region in Southeast Brazil - the most populous metropolitan area and the largest aviation market in the country. As a case study, we investigate the impact of the entry of the LCC Azul Airlines at a secondary airport in the region on the airfares of the two dominant carriers in the domestic market, Tam and Gol airlines. The LCC had rapidly expanded in the region, increasing from 0.66 million enplanements in 2009 to 3.61 million in 2012 and reaching a 15.7% market share. We utilize a Heckit estimation approach to correct for sample selectivity issues that may arise due to the unobserved interaction between yield management and distribution management strategies. We also investigate whether the entry of the LCC produces any effect on the incumbents' distribution management strategies to allow the incumbents to better face the enhanced competition on that sales channel.

The remainder of this paper is organized as follows: Section 2 presents the theoretical framework, with a description of relevant issues related to airline fare distribution and availability in the modern air transport industry. We also present a literature review of airline dynamic pricing and price responses to LCC entry, along with our proposed conceptual model. Section 3 presents our research design, with a description of the application, the data set, the development of our empirical model and the estimation strategy employed. Section 4 presents the estimation results, along with some robustness checks and the discussion of the limitations of the study. The final section contains the concluding remarks.

2. Distribution management and dynamic pricing in the airline industry

In this section, we present a brief description of relevant issues regarding the distribution and pricing management in the airline industry (2.1). Additionally, we survey the literature related to airline dynamic pricing and price responses to LCC entry (2.2 and 2.3). And finally, we present a conceptual model of airfare determinants that constitute the guidance framework for our empirical strategy (2.4).

2.1. Airline strategic distribution management and airfare availability

Traditionally, the industry classifies the distribution of airline tickets into two categories: *direct channels* - such as airline-owned websites and call centers - and *indirect channels* - such as brick-and-mortar travel agencies, travel management companies, online travel agents (OTAs) and metasearch websites. See Although the "airline dot com" is possibly the fastest growing sales channel for carriers - see Alamdari and Mason (2006) -, third-party distributors still account for approximately 50–60% of their bookings.[1] In the United States - one of the largest online travel market in the world, with more than 150 billion dollars in revenues - the brands Expedia, Priceline, Orbitz, and Travelocity account for 44% of the flight bookings.[2] One of the most important benefits of OTAs and metasearch sites is that they potentially *reduce entry barriers* by providing information to consumers about most alternatives available in the market. The consequent reduction in search costs may therefore enhance market contestability by facilitating the entry of new airlines and inhibiting incumbents from exerting market power and increasing fares.

With respect to the online availability of fares, a progressive movement of carriers towards a more strategic use of their distribution channels has created a multiplicity of market situations. For example, whereas OTAs produce their screen results primarily by collecting the fare data through Global Distribution Systems (GDSs) such Amadeus and Sabre, the airlines' own websites are directly connected to their host systems. In principle, these differences may dictate the relative availability of

[1] "*The real NDC: Decoding the planned (r)evolution in airline distribution by IATA and airlines*" - tnooz, Jan 17, 2013.

[2] "*Competitive Landscape Of The U.S. Online Travel Market Is Transforming*" - forbes.com, Apr 8, 2014, and "*Benefits of Preserving Consumers' Ability to Compare Airline Fares*" - Charles River Associates, Prepared for Travel Technology Association, May 19, 2015.

fares and flights to the consumer in the different sales channels. In recent times, however, GDSs have created "dynamic availability" tools that gives airlines full distribution control, aiming to enable airlines to effectively manage availability not only by point of sale but also by distribution channel, which we define here as "distribution management". In parallel, many OTAs have gained access to the airlines' websites via a direct link that bypasses the GDSs and their implied fees; this feature aims to enhance consumer visibility for the airlines' fare products in times characterized by unbundling and pressure to generate ancillary revenue. Meanwhile, the New Distribution Capability (NDC) Program launched by IATA, which aims to improve communications between airlines and third-party distributors, has gradually become a reality - see Westermann (2013) and Wittman and Belobaba (2016). Ultimately, the availability of discounts by OTAs may therefore be a function of their ability to negotiate "full-content agreements" with airlines. In certain cases, aggregators have access to airlines' standard inventories but not to the lowest classes in their inventories.

Passengers across the world are increasingly accustomed and adapted to the common situation in which fare search results differ substantially across air travel websites. One possible reason for such differences are variations in the search algorithms and, more broadly speaking, in the search technology employed by the different aggregators, for example, regarding utilization or not of "fare caching" devices. Moreover, in addition to the "airline-site-only" web fares, it is also possible that private contracts between suppliers and vendors may establish preferential - and faster - access to discounted fares. For example, in case of consumer cross-shopping between channels, the airline website may automatically detect the internet traffic sources and display specific results to different prospective passengers. Most of these features may have a relevant influence on the search results of third-party vendors but typically constitute a set of unobservables for any industry analysis.

2.2. Airline dynamic pricing

Isler and D'Souza (2009) refer to dynamic pricing as an online price-quoting mechanism that utilizes the available information about a customer to estimate her willingness to pay prior to displaying an airfare offering. In fact, the yield management systems of airlines in the modern air transport industry were specifically designed to accomplish effective dynamic pricing in that sense. The most widely known mechanism for segmentation employed by carriers is based on the timing of flight/fare searches by passengers. More precisely, the moment of the arrival of the request for seat availability in yield management systems is the fundamental information that supports this typical passenger segmentation/price discrimination strategy. If late bookers have higher willingness-to-pay than early bookers, then the moment of flight/fare search provides enough information to allow for an efficient segregation of more price-elastic passengers from more price-inelastic passengers. The theoretical strand of the literature concerned with this intertemporal price discrimination (IPD) problem is known as *time-based theories* - see Alderighi et al. (2015b). In fact, it is enough that the market is formed by two consumer segments with high and low price elasticities – for example, leisure and business passengers - and monotonic decreasing and increasing booking request arrival rates, respectively, over the reservation period for the resulting price curve to produce a traditional monotonic price increase temporal profile. Fig. 1 presents examples of temporal price profiles consistent with possible arrival patterns of the two market segments. The subjacent economic model employed in the different diagrams of Fig. 1 is the traditional markup price model. We therefore have an illustration of possible temporal price curve shapes by simulating hypothetical booking request arrivals. The "strictly monotonic case", which is characterized by ever-increasing airfare and the monotonic evolution of the proportion of price inelastic passengers from 0 to 1, is depicted in the first diagram of Fig. 1 (top left).

It is also possible to observe in Fig. 1 that the strictly monotonic temporal profiles of prices over the reservation periods may present interesting variations depending on the pattern of booking arrivals of the different passenger segments. For example, inverted-L or S-shaped price curves, shown at the top middle and top right of Fig. 1, are consistent with monotonic patterns of request arrivals but represent non-linear curves. In contrast, the diagrams at the bottom of Fig. 1 show possible cases of non-monotonic arrival processes. For example, a U-shaped price curve is expected when the less price-inelastic passenger segment initially constitutes the majority of booking arrivals, then declines in size as time evolves, and finally becomes the majority once again at the end of the reservation period. A J-shaped price curve is suggestive of the same pattern but with more asymmetric behavior of the booking arrivals, as depicted at the bottom middle diagram. Evidence of non-monotonic temporal profiles are provided by Alderighi and Piga (2010) and Alderighi et al. (2015b) (U-shaped curves), and Gaggero and Piga (2010) and Bergantino and Capozza (2015) (J-shaped curves). These price dynamics are consistent with market segmentation strategies that segregate the "middle bookers" from the more recognized "early bookers" and "late bookers". Finally, the bottom right diagram of Fig. 1 presents a "roller coaster" price situation in which, for example, a fraction of price-sensitive consumers may be captured by last-minute deals.

Another strand of the literature on dynamic pricing is related to the assumption that airlines set fares aiming to efficiently allocate capacity in an environment where demand is uncertain and capacity is costly and perishable - capacity-based theories, or theories of scarcity pricing -, as in Puller et al. (2009) and Alderighi et al. (2015b).

2.3. Price responses to LCC entry

The literature related to price responses to LCC entry is extensive and has its roots in Windle and Dresner (1995), Dresner et al. (1996) and Windle and Dresner (1999), among others. Morrison (2001) estimates that direct airport-pair competition

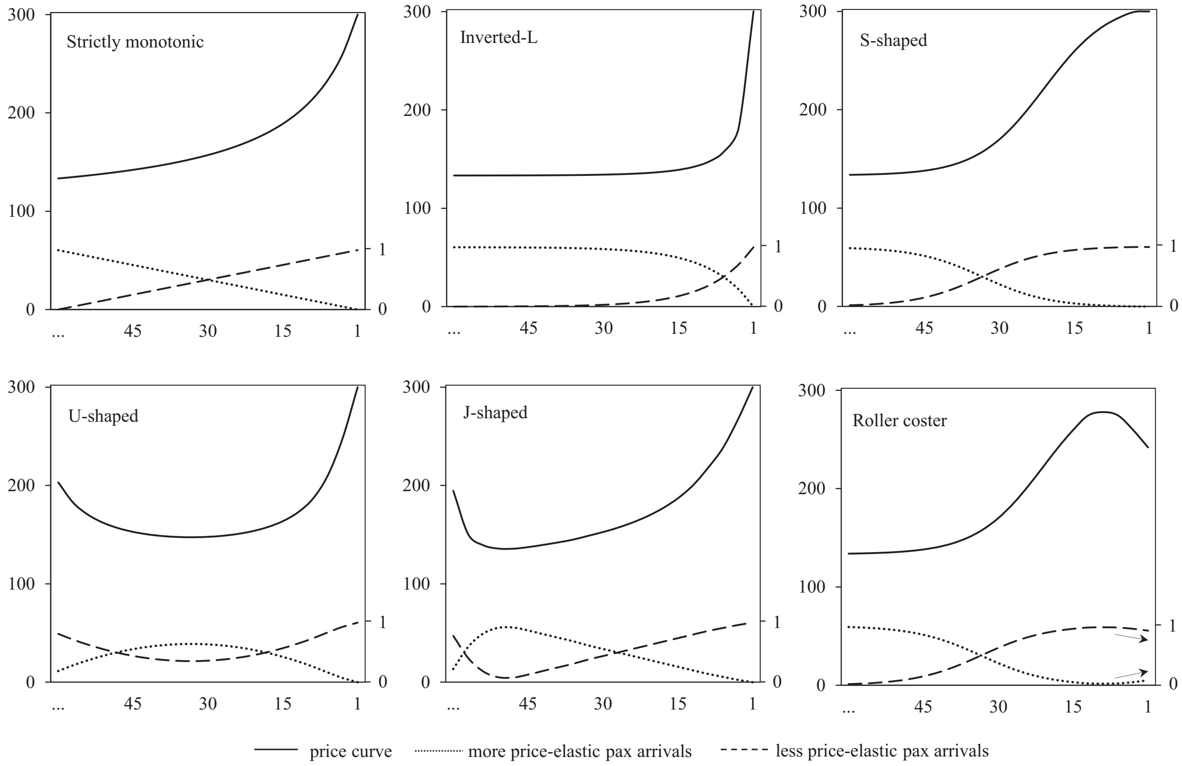

Fig. 1. Price curves associated with hypothetical booking request arrivals of two passenger segments. Vertical axes: price (left) and proportion of booking arrivals (right); horizontal axis: days before departure (booking days). The price curves were obtained by simulating artificial data for the booking arrivals of two theoretical segments: "more price-elastic pax" and "less price-elastic pax". The patterns of arrivals are artificially constructed to allow for easy visualization of patterns. for example, in the "Strictly monotonic" diagram we have linear arrivals with ever-descending participation of the more-price elastic passenger segment in the booking arrivals. In any case, the booking arrivals are normalized to sum 1 (100%) on each arrival day. The resulting price curve is a weighted average of segment-specific price constructed based on the markup pricing rule. Assumptions: markup pricing ($P = marginal\ cost/(1 + average\ price\ elasticity^{-1})$); marginal cost = 100; price elasticities: -4 (more price-elastic pax) and -1.5 (less price-elastic pax).

with Southwest Airlines produced a 46.2% drop in rivals' prices. He also estimates the impact of adjacent competition with the LCC to be a price decrease of approximately 15–26%. Oliveira and Huse (2009) examine the Brazilian airline industry and decompose the fare reactions to LCC entry according to flight distance and the number of seats supplied by the entrant. They find price reductions in the range of 22–26% for routes as short as 350 km and no price reactions on routes with distances greater than or equal to 1250 km. Hofer et al. (2008) examine the relation between LCC competition and price premiums, i.e., price markups enabled by the domination and concentration of routes and airports. The authors estimate that the price premiums of major legacy carriers in the absence of LCC competition are approximately one-third higher than they are in the presence of LCC competition. Goolsbee and Syverson (2008) find that incumbents cut fares significantly when threatened by Southwest's entry and estimate a preemptive price decrease of 17%. Brueckner et al. (2013) are the first to distinguish nonstop markets from connecting markets when estimating the impact of LCCs on fares.[3]

In contrast to the abundance of literature regarding the impact of LCCs on the average prices of major airlines, the literature on incumbents' adjustments to their temporal profiles when exposed to such competition is rather scarce. Mantin and Koo (2009) estimate a model of dynamic price dispersion measured by a power divergence statistic as a function of demand, route characteristics and competition variables using a sample of daily airfares collected from the website of an online travel agency (OTA). Their competition variables are the Herfindahl–Hirschman index (HHI) and the LCC passenger market share on the route. They find a positive and statistically significant effect of the presence of LCCs on price dispersion in the market, which supports the hypothesis that full-service carriers (FSCs) adopt a more aggressive "high-low" pricing strategy in response to LCCs. They also perform weekly breakdowns of their analysis and suggest that the competition for price-sensitive consumers that arrive early in the booking period and constitute the target market of LCCs may provoke such changes in the dynamic pricing strategies of FSCs.

[3] For recent discussions on the impact and behavior of LCCs in airline markets, see Prince and Simon (2014), Bendinelli et al. (2016), Halpern et al. (2016), Fichert and Klophaus (2016), Costantino et al. (2016), and Hsu et al. (2016).

2.4. Conceptual model

Fig. 2 depicts our conceptual model of airfare determinants, which is the basis for our empirical strategy. It contains relevant concepts found in the surveyed literature and discussed in the preceding sections. We observe in Fig. 2 that emphasis is given to the *dynamic pricing* process, which in this case consists of a feedback loop between the concepts of "airline pricing power" and "yield management". The tools available for such interaction are "price discrimination" (different prices targeted at different passenger segments) and "scarcity pricing" (different prices according to the availability of seats), as discussed in 2.1 and 2.2. We insert the concept of "LCC competition" - namely, the competitive impact of the entry of an LCC, as discussed in 2.3 - as a perturbation in the model to allow for an investigation of its impacts on dynamic pricing and airfare availability. The arrows in Fig. 1 mean the relationship of causality between the related variables, and may be either unidirectional or bidirectional. For example, in our setting, the presence of an LCC operator ("LCC competition") provokes changes in the demand of the different passenger segments ("demand by passenger segment"), as the entry of a new LCC operator typically induces competition for the price-sensitive segments of demand.

Fig. 2 shows a number of important market factors that can similarly affect the dynamic pricing formation of airlines. First, we have "seat capacity" and "operating costs" as relevant elements from the supply side. Second, we have demand drivers and passenger segment-specific characteristics that allow for market segmentation efforts; these are denoted by "demand by pax segment". Third, we include the "market structure" concept, which indicates the intensity of market competition, with particular emphasis on the direct and indirect effects of LCC competition. Fourth, we have the different ticket sales channels available to the airlines - the "distribution channels" - which include their own websites and indirect channels such as OTAs and metasearch sites. Note that we allow for the occurrence of "distributions costs" that may eventually impact flight/airfare availability.

Regarding the impact of the entry of an LCC on the pricing process of airlines, we propose two hypotheses, as discussed below. The first hypothesis is related to the dynamic pricing responses to entry. When challenged by the entry of a low cost rival, an incumbent airline may price-respond by rolling out new fare structures to achieve better positioning with respect to the target consumer of the newcomer. Many studies have analyzed the impact of the insertion of simplified fare structures and the consequences of restriction-free pricing (RFP), including Cary (2004), Ratliff and Vinod (2005) and Cooper et al. (2006). Furthermore, incumbents may actively adjust the probability distribution of fares along the booking process - and more intensively revise such adjustments - keeping the fare structure as a given.[4] In this case, a yield management system properly configured with "competitive awareness" attributes produces immediate tactical responses to specific fare actions of rivals. In particular, to engage in more intense head-on competition with the newcomer, incumbents may increase the probability of displaying low fares to the more price-sensitive passenger. In a competitive environment marked by simplified fare structures and a lack of substantial fare restrictions, the incumbents may engage in deeper advance-purchase discounts and therefore migrate from airfare temporal profiles consistent with the U-shaped or J-shaped price curve patterns of Fig. 1 and move towards a less sophisticated market segmentation strategy. A shift towards a more traditional monotonically increasing price curve pattern may therefore be the outcome of the resulting intensification of rivalry in the market. We therefore have the following hypothesis:

H_1 (*Dynamic pricing responses to entry*). The entry of an LCC forces the incumbent airlines to respond by changing their price evolution over the ticket reservation period in such a way to have different price responses to entry on different booking days.

The testable implications of H_1 are therefore related to the shape of the price curve of incumbent carriers after the exposure to new LCC competition. An empirical model that estimates the evolution of the price of incumbents before and after entry will therefore be able to capture the potential differences in price responses to entry according to the booking day. Hypothesis $\underline{\mathbf{H_1}}$ may therefore be formally investigated by the application of empirical tests of the differences in price response intensities over the booking periods. Note that in Fig. 2 we display "$\underline{\mathbf{H_1}}$" three times, meaning that our setting conceives the competitive responses by incumbents as producing booking day-specific changes in prices mainly through the following sequence of interactions between concepts: "LCC competition" induces higher competition for "demand by pax segment", which in turn translates into revisions in the "dynamic pricing" of carriers that are implemented via their "yield management" systems and notably their "price discrimination" capabilities.

Our second hypothesis is related to the strategic distribution management responses to entry. In any online flight search, the probability that a query from a prospective consumer will result in a particular offering from the airline is clearly a function of the availability of flights on the particular desired departure day. Given the existence of flights, availability is further restricted by aircraft load factor - i.e., seat scarcity - which is controlled by the seat inventory control technologies of the airline's yield management system. In addition to these factors, we consider a third component: the strategic distribution management of carriers. In particular, we consider the possibility that when responding to LCC entry, incumbent airlines may, for example, increase the number of fare classes and the availability of restricted airfares on third-party distributors to intensify

[4] We believe that revisions in the setup of probability distributions over time may intensify and change because carriers are now more aware of the competition and therefore are obliged to perform more complex price monitoring of the market, for example, by creating web robot devices to gather data from competitors.

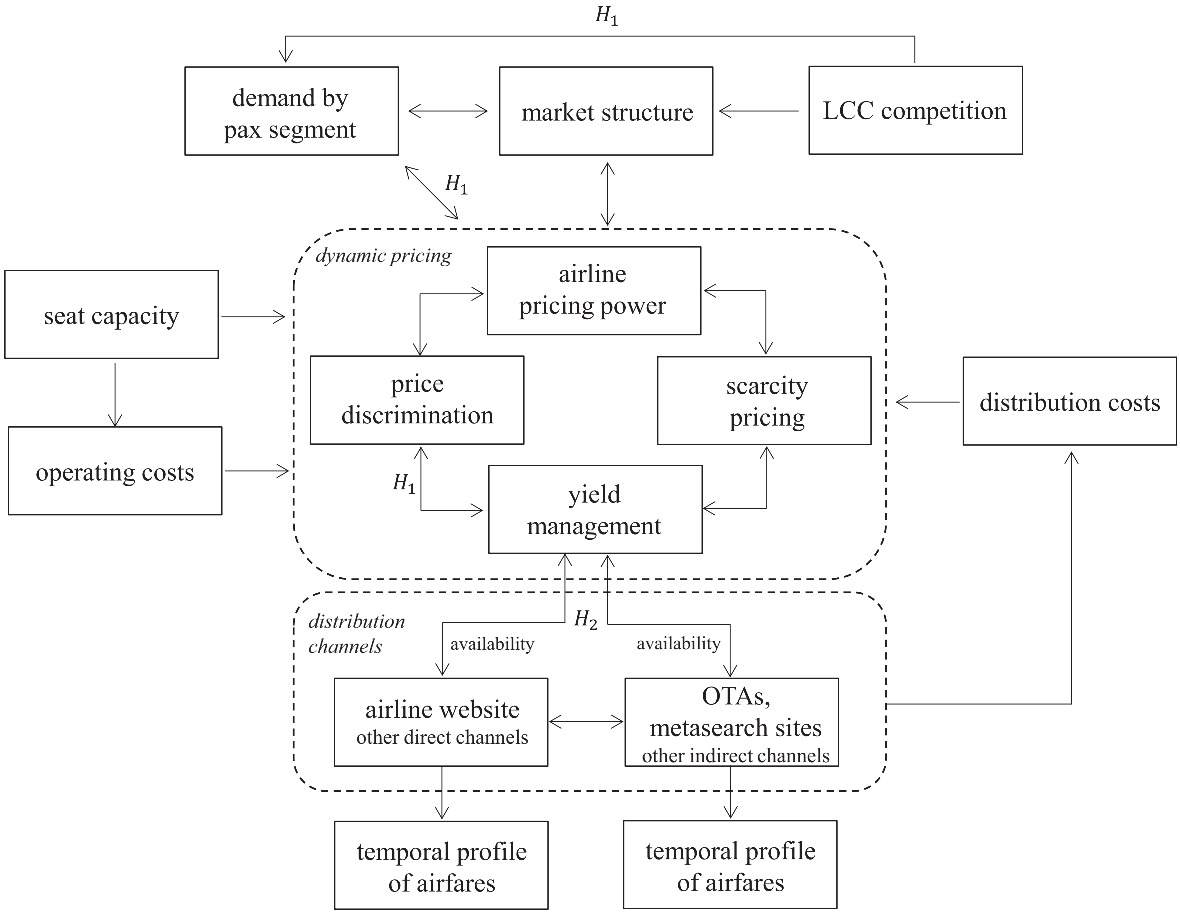

Fig. 2. Conceptual model of airfare determinants of major carriers.

competition with the LCC for price-sensitive consumers on those sales channels. Such a strategy may attract more internet traffic to their own websites, if the target consumers are inclined to cross-shop. We therefore suspect that the entry of an LCC may not be neutral with respect to airfare availability on different distribution channels but rather may be a result of the strategic nature of the airline-GDS-aggregator relation. Bilotkach et al. (2013) claim that airlines favor offering relatively low levels of content to travel agents as an attempt to confine their lowest fares to their own websites rather than making those tickets available through intermediaries. Cary (2004) suggests that innovations in forecasting methods would permit automatic categorization of flight requests and selling channels and thus allow yield management systems to select the most appropriate demand function and thereby optimize revenues in a more disaggregate way. Kimes (2010) explains that in the hospitality industry, hotels can control the availability of certain rates to specific distribution channels, for example, with web-fare exclusive deals. This differential pricing by distribution channel certainly constitutes the basis for an effective channel management strategy because it is capable of addressing channel-specific demands and price elasticities. Arguably, channel-specific availability strategies implemented by airlines are now as common as those implemented by hotels. However, as discussed earlier, airlines have developed new capabilities that allow them to display exclusive fares on their own websites. Airlines have also formed partnerships with third-party vendors that allow them to bypass the full content agreements between airlines and GDSs, which require airlines to provide the same fare content through GDS that is provided through all other channels. Concurrently, the GDSs have created advanced tools for more channel-oriented revenue management, allowing airlines to control distribution of their seat inventory through preferential availability and to reduce non-revenue generating requests from OTAs and metasearch sites.[5] Our second hypothesis is therefore the following:

H_2 (*Strategic distribution management responses to entry*). The entry of an LCC forces the incumbent airlines to respond by changing the evolution of their airfare availability on the OTA over the ticket reservation period, in such a way to have different responses in airfare availability on different booking days.

[5] For example, Amadeus' Availability Management© and Availability Calculator©, www.amadeus.com.

The testable implications of H_2 may be addressed by a probability model - a probit, for example - that estimates the evolution of airfare availability of incumbents on the OTA, both before and after entry. Such a model is able to capture the potential differences in responses to entry related to the airfare availability of incumbents on the OTA on the different booking days. Hypothesis $\underline{\mathbf{H_2}}$ may therefore be investigated by recurring to empirical tests of the before/after differences in mean airfare availability over the booking period.

3. Research design

3.1. Application

We consider Brazilian domestic routes of the São Paulo Multiple Airports Region in Southeast Brazil. Table 1 presents statistics for this extended metropolitan region, which is the most populous conurbation in the country, with 32.19 million people.[6] São Paulo is the biggest aviation market in the country, with 22.98 million enplanements in 2012, accounting for 25.9% of total domestic enplanements. Due to its economic strength - the region concentrates roughly a third of the country's GDP - the propensity to fly in this area is considerably higher than the national average of 0.46 air trips per capita/year, with a rate of 0.71 in 2012.[7] The catchment area of the São Paulo Multiple Airports Region comprises downtown Congonhas Airport (CGH), São Paulo/Guarulhos International airport (GRU) and secondary airports Campinas/Viracopos (VCP). The latter airport is within a radius of 95 km (59 miles) from São Paulo city and is located in the northwest of the extended metropolitan region, respectively.[8] The major carriers operating in the area are Tam and Gol airlines, which in 2008 controlled 95.6% of the air travel market with 12.02 million enplanements. On December, 15, 2008, a new carrier began operations in the market: Azul Airlines.[9] Launched as an LCC alternative, this newcomer was founded by David Neeleman, a Brazilian-American businessman who had already created other low-fare airlines in Canada and the U.S., including JetBlue, the prominent LCC based in New York.

Since its inception in late 2008, Azul designated the secondary airport VCP as its hub and expanded quickly by stimulating latent demand and capturing passengers from its major rivals based at the primary airports CGH and GRU. In 2009, compared with the major incumbents, the newcomer had an average yield that was 14.5% lower, an operating cost per RPK that was 6.9% lower, and - according to an extensive airport survey of passengers taken in July and August of the same year - an average airfare that was between 25% and 40% lower.[10] The LCC ended its first full year of operations with nearly 700,000 passengers and more than quintupled this number between 2009 and 2012 (i.e., increasing from 0.66 million enplanements in 2009 to 3.61 million in 2012), attaining a 15.7% market share in a four-year period. Due to the economic boom in Brazil during this period and the resulting increase in overall air travel demand in the region, the incumbent carriers also observed growth in their enplanements. In Table 1, we can see a traffic gain by incumbent carriers from 12.53 in 2009 to 16.59 in 2012, which represents a reasonable growth rate of 9.8% per year but is slow-paced compared with the newcomer's compound annual growth rate (CAGR) of 76.1% in the same period. Consequently, the market share of incumbents experienced a sharp drop, falling from 87.7% to 72.2% in just a few years. It is also possible to observe in Table 1 that the secondary airport VCP experienced notable growth, with 2.92 additional enplanements, which was leveraged by the LCC expansion path and allowed the São Paulo Metropolitan Airports Area to increase faster than the entire country, growing by 17.2% in the 2009/2012 period. Since 2011, Azul has become the third largest airline in Brazil, with 9.2% of enplanements, through an ever-increasing path that reached 21.0% in 2015.[11]

3.2. Data collection

Our econometric framework utilizes primary data on online fares collected using a "web robot" device in a fashion similar to that of Alderighi et al. (2015b), Bilotkach et al. (2015), and Bachis and Piga (2011), among others.[12] Our web robot was linked to the website of OTA Submarino Viagens. OTAs have been present in the Brazilian air travel market since the late 1990s, when Despegar.com opened a branch in the country under the name Decolar.com. In addition to Decolar, the websites

[6] Source: Brazilian Institute of Geography and Statistics (IBGE), with authors' own calculations.

[7] Source: Brazilian Institute of Geography and Statistics (IBGE), with authors' own calculations, National Civil Aviation Agency, Air Transportation Demand and Supply, and own calculations (2012). GDP figures of 2010.

[8] Among the available secondary airports, so far only VCP has played a major role as an alternative to CGH and GRU. Although Azul launched some few flights in and out of SJK in 2010, the airline quitted operations at the airport in 2014.

[9] That date (December, 15, 2008) marked the carrier's first flights in the domestic market. Its first served cities were Porto Alegre (South of Brazil) and Salvador (Northeast), both from São Paulo/Campinas Airport (VCP). The airline obtained its air operator's certificate a month earlier, after which it started selling flights. Typically, the carrier announces to start a domestic route from fifteen days to two months before the first flight. For a list of route entries by the carrier in the sample period and their respective starting dates, see the Appendix A.

[10] Sources: National Civil Aviation Agency, 2009 Statistical Yearbook, and 2009 survey of The Institute of Economic Research Foundation - FIPE (2009), with authors' own calculations.

[11] National Civil Aviation Agency, Air Transportation Demand and Supply, available at www.anac.gov.br.

[12] A web robot - also called web spider, crawler, among other names - is a software designed to automatically monitor, identify and retrieve relevant information from web sites aiming at indexing, storing and building databases. Examples of web robots are the web search engines and the devices produced by market research companies to study customer profile and trends in geographic markets. For a discussion, see "*Top 50 open source web crawlers for data mining*", available on bigdata-madesimple.com.

Table 1
São Paulo multiple airports area - air travel evolution.

Year	LCC		Incumbents		Total			
	Pax (million)	Share (%)	Pax (million)	Share (%)	Secondary Airport Pax (million)	Primary Airports Pax (million)	Metropolitan Area Pax (million)	Country Pax (million)
2008	0.01	*0.0*	12.02	*95.6*	0.45	12.10	12.57	50.12
2009	0.66	*4.6*	12.53	*87.7*	1.32	12.95	14.28	57.13
2010	1.73	*9.5*	14.47	*79.7*	2.53	15.62	18.17	70.15
2011	2.88	*13.6*	15.80	*74.3*	3.58	17.57	21.25	82.08
2012	3.61	*15.7*	16.59	*72.2*	4.24	18.66	22.98	88.72
2012–2009	2.95		4.07		2.92	5.70	8.70	31.59
% Growth	*446.5*		*32.5*		*220.7*	*44.0*	*60.9*	*55.3*
% CAGR	*76.1*		*9.8*		*47.5*	*12.9*	*17.2*	*15.8*

Source: National Civil Aviation Agency, Air Transport Statistical Database, and own calculations (2008–2012). CAGR stands for compound annual growth rate.

ViajaNet and Submarino Viagens are the main OTA players. In 2016, Submarino Viagens was acquired by the largest tour operator in Latin America, CVC Operadora.

We considered one-way nonstop flights that had either São Paulo's Congonhas (CGH) or São Paulo's Guarulhos International (GRU) as the origin endpoint airports and traveled to destination airports in cities across all Brazilian regions.[13] We programmed the web robot to collect one-way fares at five data collection points within the reservation period of each flight, gathering price information for 7, 10, 30, 45, and 60 days prior to the departure date (henceforth called the "booking days"). Each air travel query performed by the web robot returned a set of available fares for all existing flights on the airport-pair on the chosen date of departure and related information regarding departure and arrival times, number of stops, and operating carrier. Whenever the OTA's website displayed a cluster of flights associated with the same quoted fare, the robot's algorithm disaggregated it into separate data points and assigned the corresponding retrieved fare to each individual flight. The data collection period of fares was July, 14, 2008 to April, 13, 2010, for flights available from July, 21, 2008 to June, 12, 2010.

Because our main objective is to inspect the competitive behavior of incumbent carriers with respect to the entry of the LCC Azul at the VCP Airport, we focused on retrieved data related to the two major airlines in the country, Tam and Gol.[14] Our final dataset has 96,824 price quotes, with flight information for the 35 densest domestic airport-pairs of the 78 existing routes with nonstop flights available from the city of São Paulo. The dataset includes 25 domestic destinations available from São Paulo. The sample of routes are representative of 24.4 million passengers, representing roughly one-fifth of total domestic passengers in the country and 88.7% of São Paulo outbound traffic in the studied period. The number of post-entry observations in the sample is 38,912, i.e., 40.19% of total sample.

We structure our dataset such that each observation is a unique combination of incumbent carrier, booking date and departure date. For each departure date, we pick a summary statistic of the price quote distribution, i.e., the portfolio of available flights on the OTA screen. Our dataset is therefore centered on the evolution of the key summary statistics of price distribution (mean, but also minimum, 25th percentile, median, 75th percentile and maximum) with respect to a future departure date. Our methodological procedure assumes that when booking a flight on the OTA's website, consumers view the different flight alternatives displayed on the OTA screen as substitutable for each other and thus the probability of a given quote being selected may be impacted by the price of alternative displayed flights. Because the OTA primarily displays available flights within a given departure date, we believe that considering the full distribution of flights within the time span of an entire operating day is a reasonable procedure for performing our empirical analysis. For a more disaggregated approach using the flight level as the panel identifier, see, for example, Alderighi et al. (2015b).[15]

[13] We follow Escobari and Gan (2007) and Escobari (2012), which also restrict the analysis to one-way nonstop flights. With this simplifying procedure, we avoid having to taking into consideration the interdependency of demand - and price discrimination strategies of carriers - regarding nonstop, with-stops, one-way and round-trip passenger categories.

[14] We do not consider other airlines in the analysis because they were rather small players to be considered in our inspection of strategic responses to new entry of dominant incumbents. Avianca Brazil - named Oceanair at that time - and Webjet Airlines had 2% market share each in 2008. Another operating carrier was Trip, a regional airline with 1% market share. Webjet was eventually acquired by Gol, in 2011, and Trip by Azul, in 2012. Source: National Civil Aviation Agency, Statistical Yearbooks.

[15] Note that, apart from the mean prices, different flight codes may alternate across booking days as representatives of each summary statistic in our setting. For example, on booking day 60 the minimum price may be associated with one flight code whereas on booking day 45, that statistic may be related to another flight code of the same airline on the same route. By this methodological procedure, we aggregate our analysis to the route/airline level and not the route/airline/flight-code level. To deal with possible bias due to the possible omission of unobserved perceived quality of the representative flight-code, we provide flight-specific and booking day-specific controls, as we will see in the next section.

3.3. Econometric model

In our conceptual model, we propose Hypothesis H_1, which posits that incumbent carriers may engage in dynamic pricing responses to LCC entry. Eq. (1) presents our empirical model of airfare temporal profiles to test that hypothesis:[16]

$$\begin{aligned}\ln \text{price}_{irdt} &= \beta_1 \ln \text{fuel unit cost}_{ird_m} + \beta_2 \ln \text{frequencies HHI}_{rd} + \beta_3 \text{ proportion of closed fares}_{irdt} \\ &+ \sum_t \theta_t \mathbb{1}_{\{booking\,day\,t\}} + \sum_t \theta_t^{lcc} \mathbb{1}_{\{LCC\,entry_{rd}\}} \mathbb{1}_{\{booking\,day\,t\}} + \gamma_{i,r} + \gamma_{d_{a,h}} + \gamma_{d_{dow}} + \gamma_{t_{dow}} + \gamma_{d_{hs}} + \gamma_{d_y} + \gamma_{d_{hol}} + \gamma_{t_{hol}} + u_{irdt},\end{aligned} \tag{1}$$

where i is the incumbent airline, r is the route, d is the departure date, and t is the booking day. We therefore have:

- price_{irdt} is the price of incumbent airline i on airport-pair r, departure date d and booking day t, $t = \{1, 3, 5, 7, 10, 30, 45, 60\}$. We consider $price_{irdt}$ being set as the minimum, 25th percentile, median, mean, 75th percentile and maximum displayed by the OTA for a departure date d for given i, r and t. Source: web robot collected sample, with authors' own calculations. Prices were inflation-adjusted to produce constant monetary values.
- $\text{fuel unit cost}_{ird_m}$ is a proxy for the average fuel costs incurred by carriers on a route-level basis. It is the geometric mean of the jet fuel daily price traded in the origin and destination regions of the route. Source: Weighted-Average Weekly Prices of Oil Derivatives Traded by Producers and Importers (Report), National Agency of Petroleum, Natural Gas and Biofuels (ANP), Brazil. Prices were inflation-adjusted to produce constant monetary values. This variable is also found in Alderighiet al. (2015a);
- $\text{frequencies HHI}_{rd}$ is the Herfindahl-Hirschman index of flight concentration on airport-pair r on departure day d. It is calculated as the sum of the squared market shares in direct flight frequencies of all carriers operating in the route market. It is a proxy for the market structure of the route on departure day d, as in Bergantino and Capozza (2015). Carriers typically perform major changes in their flight schedules twice a year to account for the high and low seasons. In contrast, the Herfindahl-Hirschman index in our model has a day subscript because carriers have different timetables for different days within a week. Apart from that source of daily variation in the HHI, our sample contains timetable variations from tactical adjustments in the flight scheduling over the year - a practice that has become very common after the deregulation measures of the early 2000 s. Source: National Civil Aviation Agency's Active Scheduled Flight Report (VRA), with authors' own calculations.[17]
- $\text{proportion of closed fares}_{irdt}$ is a proxy for capacity scarcity of airline i on route r, departure date d and booking day t. It is the proportion of price quotes that disappear from the OTA screen considering the full portfolio of quotes displayed at any time for the route. It is the ratio of closed fares and total fares, with the denominator being calculated by extracting the maximum amount of fares of airline i made available by the OTA for route r and departure date d considering the entire booking period. Other approaches for capacity scarcity/utilization may be found in Puller et al. (2009) and Alderighi et al. (2015b).
- $\mathbb{1}_{\{booking\,day\,t\}}$ is a set of dummy variables that indicates booking day t and therefore controls for the intertemporal price evolution of carriers; the associated coefficients of these dummies are θ_t, $t = \{7, 10, 30, 45, 60\}$ and imply a set of empirical tests of price dynamics in the booking process.
- $\mathbb{1}_{\{LCC\,entry\,on\,rd\}}$ is a dummy variable that indicates that the incumbent airlines on airport-pair r of the existing primary airports suffer from the adjacent competition of the LCC established at the secondary airport. In Eq. (1), these variables appear interacted with the set of dummies expressed by $\mathbb{1}_{\{booking\,day\,t\}}$ to produce a booking day-specific effect of adjacent competition with an LCC. The empirical tests associated with the coefficients of such interactions (θ_t^{lcc}) constitute our most important methodological step in the analysis of the IPD patterns of airlines.
- $\gamma_{i,r}$ is the incumbent airline/airport-pair fixed effect; $\gamma_{d_{a,h}}$ represents the airport of departure/hour of departure dummies; $\gamma_{d_{dow}}$ and $\gamma_{t_{dow}}$ are dummies for the day of week of departure and the day of week of the price quote; $\gamma_{d_{hol}}$ and $\gamma_{t_{hol}}$ are dummies that control for holiday periods at the departure date and the price quote date; $\gamma_{d_{hs}}$ is a high season dummy, to account for departures in the summer period; γ_{d_y} is a dummy for the year, to control for departures in the second year of the sample; β_1, β_2, β_3, θ_t and θ_t^{lcc} are the unknown parameters; and u_{irdt} is the associated error term. We highlight that

[16] As Cameron and Trivedi (2005) describes, estimation of the coefficient of any regressor that is invariant to the panel individuals' identity is not possible as it is absorbed into the individual-specific effect. In our case, an individual is defined as an airline/route and, for example, the effects of a time-invariant cost shifter such as flight distance variable is automatically accounted by the estimated fixed effects. See Evans and Kessides (1993) for a classic discussion. Such a limitation of fixed-effects estimation has the consequence of restricting the specification to models with relatively few explanatory variables. Additionally, the data used in empirical studies of airline online prices typically have daily periodicity, which hinders finding regressors with such high frequency that concomitantly have within-individual variability. The limited specification problem is also present in Escobari (2012), Alderighi et al. (2015b), Bergantino and Capozza (2015), among others.

[17] We think that the city pair level is the relevant definition for analyzing competition in airline markets. Consistent with a city-pair setting, we follow Morrison (2001) and disaggregate our data at the airport-pair level but control for adjacent airport-pair phenomena. The main phenomenon in our data sample is the entry of the new LCC Azul. Our HHI measure is an airport-to-airport measure. We think that our LCC entry dummies account for changes in the status of rivalry due to an intensification of competition on adjacent airport-pairs, a procedure that eventually reinforces the role of competition at the city-pair level. We are aware that when the LCC enters an adjacent market, the calculated HHI at the city-pair level declines and therefore the two metrics - ie., the city-pair HHI and the entry dummies - are strongly correlated. In our sample, the Pearson correlation coefficient between $\mathbb{1}_{\{LCC\,entry\,on\,rd\}}$ and $frequencies\,HHI_{rd}$ extracted at the city-pair level is -0.6347. As our time span is not long (2 years and 2 months), we did not have means of dealing with such multicollinearity in a satisfactory way and therefore consider it one of the limitations of our approach. We thank one of the anonymous reviewers for suggesting we emphasize this point.

the dummies related to flight departures - i.e., the airport of origin, the day of the week and hour of flight departure - account for the specific attributes of the flight code selected to compute the respective summary statistic. For example, the hour of departure is related to the perceived quality of flights associated with peak and off-peak periods. If in our database a given flight code is associated with the minimum price on a given booking day, than the average unobserved effects related to its departure time are controlled with that dummy. That procedure allows us to consider the idiosyncrasies of flight codes even in our airline/route aggregate dataset.

To empirically inspect the impact of LCC entry on the dynamic pricing of incumbents, we utilize formal hypothesis tests over the estimated coefficients of the sets of dummy variables $\mathbb{1}_{\{booking\,day\,t\}}$ and $\mathbb{1}_{\{LCC\,entry\,on\,rd\}}$. In particular, empirical evidence regarding changes in the shape of the price curve of incumbent carriers after exposure to new LCC competition may be analyzed via the coefficients of $\mathbb{1}_{\{LCC\,entry\,on\,rd\}}$.

3.4. Sample selection

As suggested in the discussion of our conceptual model, the probability that a consumer searching for online fares will obtain a given offering is not randomly assigned but rather determined by structural and relevant industry factors. Sample selection is therefore a potential problem in our data collection procedure. Among the airline institutions that may have an impact on our sample selection, we highlight the role of airline scheduling and distribution management. First, with respect to scheduling, when carriers perform their network management, they must establish the number of flight frequencies along a week of operations according to expected demand and operating costs. Because airlines do not operate daily flights on every route, our methodological procedure of daily collection is conditioned by unobserved airline decision-making factors regarding direct flight availability.

Second, with respect to airline distribution, airlines enter into individual agreements with travel distribution players regarding permission to access airlines' seat inventory content. Our Hypothesis H_2 addresses the issue of strategic channel management responses to entry. For example, many airlines in Brazil provide direct links to their inventories for online travel agencies. Additionally, several industry participants report that airlines restrict at least the last four seats in each cabin to their direct channel to avoid possible oversale situations. The strategic motivation for airfare availability on the various distribution channels is a non-observed component in our analysis and may ultimately produce non-randomly selected samples in our data collection. Other internet technology issues may also be sources of sample selection problems, such as the fare-caching devices of OTAs that aim to reduce the time it takes to display the search result to the consumer; the logic of the OTA algorithm for finding low fares and the limits of possible displayed results; and possible out-of-service periods caused by OTA site overloads due to a high number of simultaneous requests. We therefore acknowledge that the frictions and bargaining characteristics of airline-GDS-OTA interaction may lead to sample selectivity issues in the data collection performed by our web robot on the OTA's website, with the direct consequence of non-random data. Such selection issues may produce inconsistent estimation of our dynamic pricing model and thus structurally motivate a potential estimation bias in the evolution of the collected prices over the observed booking periods.

To account for sample selectivity in our sample of airfare search results collected by the web robot, we utilize the Heckit procedure, in which a selection decision equation is first estimated using a probit model. In our case, "selection" comprises the "joint decision" of the airline and OTA to display the full content associated with each booking query from the web robot. We therefore assume that for each data collection point, the data sample obtained by the web robot is subject to such selection. In the second step, the Heckit procedure involves the inclusion of observed factors that determine the selection in the estimating equation by an inverse Mills ratio variable as a regressor. Our specification of the first-stage probit model considers an auxiliary dataset of 286,590 observations containing a balanced panel of incumbent carrier/airport-pairs for all possible departure dates within the collection timeframe and for each date of query. See Alderighi et al. (2015a) for an application of the Heckit model to the airline industry. The probit specification contains the following variables:

- $Pr(OTA\,results)$ is the regressand, a dummy variable that considers the OTA screen results after a query of one-way flights by the web robot. Pr(.) denotes probability. This variable is assigned a value of 1 if the OTA displays any nonstop flight result for each combination of departure date/query date/airline/airport-pair. As discussed above, not all routes have daily flight operations and therefore the web robot retrieved no result whenever no direct flight was found on the specific query date, with the regressand therefore being assigned a value of 0.
- *total seats*: total seats supplied by the incumbent on the route on the day of departure. We inserted this variable into the model in a quadratic way. We also inserted it interacted with LCC presence.
- $\mathbb{1}_{\{booking\,day\,t\}}$ and $\mathbb{1}_{\{LCC\,entry\,on\,rd\}}$ are as described above.
- airline-route specific-effects, departure & booking day of week dummies, departure & booking month dummies, and departure & booking holiday dummies.

Table 2 presents descriptive statistics of the main variables utilized in the first and second stages of the Heckit model.

Table 3 presents an idea of the temporal profile of the posted fares of the incumbent carriers in our data sample. Figures are disaggregated into routes with and without the presence of the LCC and according to the airfare distribution - minimum,

Table 2
Descriptive statistics - variables of the empirical model.

		Nr observations	Mean	Std. dev.	Min	Max
Price	Inflation-adjusted (BRL)	96,824	541.09	273.68	74.47	2918.87
Fuel unit cost	Inflation-adjusted (BRL)	96,824	1.88	0.49	1.38	2.96
Frequencies HHI	Index [0,1]	96,824	0.52	0.15	0.27	1.00
Proportion of closed fares	Fraction [0,1]	96,824	0.15	0.24	0.00	0.93
LCC entry	Dummy	96,824	0.40	0.49	0.00	1.00
OTA results	Dummy	286,590	0.55	0.50	0.00	1.00
Total seats	Thousands	286,590	0.77	1.12	0.00	7.80

25th percentile, median, 75th percentile and maximum. From Table 3, it is possible to obtain our first insights about the effects of adjacent LCC competition: the presence of the LCC apparently provokes an overall price reduction across all prices, ranging from −4.0% to −26.2% depending on the booking day. Table 3 suggests that the effect of LCC entry on airfare becomes more intense as the booking becomes earlier in a more monotonically shaped price curve.

3.5. Estimation strategy

We consider the variables *frequencies HHI* and *proportion of closed fares* as endogenous in our empirical framework and therefore must employ an instrumental variables estimator. Our identification strategy employed "BLP Instruments" to obtain a consistent estimation of Eq. (1). In a single-product context, BLP instrumentation (Berry et al., 1995) considers own and rival competitors' characteristics. We considered metrics related to the airline's flight frequencies and available seats as potential own-product characteristics but recognized the possibility that these variables may also be endogenous. We therefore focused on the characteristics of the rival incumbent airline as instruments. To reduce potential identification problems, we utilized lagged versions of these metrics - lags of 90 and 105 days. We therefore employed as instruments the following characteristics of the rival incumbent in the market: the number of available seats, the share of flight frequencies, the maximum number of airfares displayed by the rival incumbent within the booking period, the interactions of the maximum number of airfares with the dummies for holidays, high season periods and peak-hour flights. To enhance the statistical relevance of the instrument set, we also lagged versions of the HHI index measured in terms of flight frequencies and available seats. We employed tests of validity and relevance of instrumental variables to challenge our instrumentation approach. With respect to the validity of the full set of over-identifying conditions, we utilized Hansen's J test. With respect to the relevance of the proposed set of instruments, we employed the Kleibergen-Paap rk LM underidentification test (KP). Finally, we also tested for weak identification using the Cragg-Donald Wald F statistic and the Kleibergen-Paap rk Wald F statistic (Weak CD and Weak KP, respectively). The results of all tests on the quality of the instruments are reported in the tables of Section 4. All tests generated evidence supporting the orthogonality and relevance of the proposed set of instrumental variables.

We implemented tests of autocorrelation and heteroscedasticity in the residuals of Eq. (1). With respect to autocorrelation, we implemented a Cumby-Huizinga test for several order specifications, previously having accounted for heteroscedasticity and endogeneity. These tests indicated the presence of autocorrelation. With respect to heteroscedasticity, we implemented the Pagan-Hall, White/Koenker and Breusch-Pagan/Godfrey/Cook-Weisberg tests, employing alternative specifications of levels, squares, cross-products of regressors and fitted values of the regressand. All these tests strongly reject the null of homoscedastic disturbances. We therefore employed the procedure of Newey-West to adjust the standard error estimates.

Our Heckit model contains a first stage in which a random effects probit estimator is applied to the auxiliary dataset of balanced panel data, as discussed earlier. This model has the sample selection variable $Pr(OTA\ results)$ as the regressand. The estimation method employed in the second stage is the two-step feasible efficient generalized method of moments estimator

Table 3
Descriptive statistics - price dynamics in the sample.

Booking days	Minimum fare			25th percentile fare			Median fare			75th percentile fare			Maximum fare		
	LCC entry		*Var%*	LCC entry		*Var%*	LCC entry		*Var%*	LCC entry		*Var%*	LCC entry		*Var%*
	No	*Yes*		*No*	*Yes*		*No*	*Yes*		*No*	*Yes*		*No*	*Yes*	
7	549.76	453.30	*−17.5*	570.81	465.51	*−18.4*	613.07	537.67	*−12.3*	651.87	623.33	*−4.4*	673.16	645.92	*−4.0*
10	544.52	444.21	*−18.4*	564.78	454.60	*−19.5*	607.00	519.74	*−14.4*	642.48	599.54	*−6.7*	661.35	620.07	*−6.2*
30	517.64	387.76	*−25.1*	534.71	397.23	*−25.7*	576.26	447.19	*−22.4*	609.88	508.45	*−16.6*	625.10	524.17	*−16.1*
45	513.36	384.70	*−25.1*	528.34	392.80	*−25.7*	568.26	435.18	*−23.4*	599.00	486.96	*−18.7*	614.60	498.71	*−18.9*
60	519.18	386.05	*−25.6*	533.28	393.30	*−26.2*	569.70	431.93	*−24.2*	597.53	480.15	*−19.6*	612.10	490.67	*−19.8*
Var%															
(7)/(10)	*1.0*	*2.0*		*1.1*	*2.4*		*1.0*	*3.4*		*1.5*	*4.0*		*1.8*	*4.2*	
(10)/(30)	*5.2*	*14.6*		*5.6*	*14.4*		*5.3*	*16.2*		*5.3*	*17.9*		*5.8*	*18.3*	
(30)/(45)	*0.8*	*0.8*		*1.2*	*1.1*		*1.4*	*2.8*		*1.8*	*4.4*		*1.7*	*5.1*	
(45)/(60)	*−1.1*	*−0.4*		*−0.9*	*−0.1*		*−0.3*	*0.8*		*0.2*	*1.4*		*0.4*	*1.6*	
(7)/(60)	*5.9*	*17.4*		*7.0*	*18.4*		*7.6*	*24.5*		*9.1*	*29.8*		*10.0*	*31.6*	

(2SGMM) with standard errors robust and efficient to arbitrary heteroscedasticity and autocorrelation. This model has $price_{irdt}$ as the regressand and has the specification dictated by Eq. (1). We utilize a panel bootstrap procedure (Cameron and Trivedi, 2005) to correct the standard errors of the second-stage regression of the Heckit model to account for the presence of the estimated inverse Mills ratio among the regressors.

4. Results

Table 4 presents the estimation results of the OTA airfare availability probit model - the first step in our Heckit sample selection procedure.

We observe in Column (1) of Table 4 that the availability of fares on the OTA website for routes on which the LCC is absent increases as the departure becomes closer. In fact, the estimated results of the variables *booking day 10* to *booking day 60* show not only that the signs of the estimated coefficients are negative but also that their estimated intensity is weakened as the booking period ends, falling from a statistically significant −0.10 (*booking day 60*) to a statistically not significant −0.01 (*booking day 10*). The base case of the dummies is *booking day 7*. These results suggest that when incumbent airlines are not confronted with competition from the LCC, they tend to resort more intensively to the OTA as an alternative distribution channel at the end of the booking period, i.e., when they are better informed about the actual evolution of their booking curves. If observed sales are lower than forecasted, the seat inventory control systems may, for example, adjust the booking limits of existing fare classes to open up more restricted fare products. The less flexible fare products will then be more frequently visible to the OTA booking queries on the GDS or directly on the carrier's server, which ultimately enhances the airfare availability of the OTA to both the consumer and our web robot. In this sense, the OTA becomes a relatively more important distribution channel to carriers as the booking period ends.

The results of Table 4 also allows for making inferences regarding Hypothesis $\underline{\mathbf{H_2}}$ of our conceptual model, in which the entry of an LCC forces the incumbent airline to engage in different responses in airfare availability on the OTA according to the booking day. We observe in Table 4 that the incumbents considerably change their attitude towards the OTA when they are exposed to LCC entry. Indeed, the estimated coefficients of the set of dummies related to the adjacent LCC presence interacted with booking days show that airlines increase their airfare availability on the OTA in earlier booking periods. For example, the estimated coefficient of the variable *LCC entry x booking day 60* is 0.11, indicating an increase of approximately 11% in the probability that the OTA will display airfare results for a given query of the web robot. This is suggestive of a much higher availability on the OTA sixty days prior to the departure date than for the base case, specifically, 0.21 higher (0.11 + 0.10) than the same estimated probability in the case of no adjacent LCC. This result is indicative of the strategic movement of incumbents against the newcomer in an effort to capture the highly price-sensitive early-booking passengers who constitute the target market of the LCC. Note that the higher availability is quickly dissipated, as the estimated coefficients

Table 4
Estimation results - selection model - OTA screen results.

	(1) Pr(OTA results)	(2) Pr(OTA results)	(3) Pr(OTA results)	(4) Pr(OTA results)
Total seats	0.04***	0.15***	0.14***	0.18***
Total seats squared		−0.02***	−0.02***	−0.03***
LCC entry × total seats			0.01**	0.01
Booking day 7 (*base case*)				
Booking day 10	−0.01	−0.01	−0.01	−0.01
Booking day 30	−0.05***	−0.05***	−0.05***	−0.07***
Booking day 45	−0.07***	−0.07***	−0.07***	−0.10***
Booking day 60	−0.10***	−0.10***	−0.10***	−0.13***
LCC entry × booking day 7	−0.14***	−0.16***	−0.17***	−0.21***
LCC entry × booking day 10	−0.12***	−0.14***	−0.15***	−0.18***
LCC entry × booking day 30	−0.03**	−0.05***	−0.05***	−0.06***
LCC entry × booking day 45	0.03***	0.01	0.01	0.01
LCC entry × booking day 60	0.11***	0.09***	0.08***	0.11***
Airline-route random effects	*No*	*No*	*No*	*Yes*
Departure & booking day of week dummies	*Yes*	*Yes*	*Yes*	*Yes*
Departure & booking month dummies	*Yes*	*Yes*	*Yes*	*Yes*
Departure & booking holiday dummies	*Yes*	*Yes*	*Yes*	*Yes*
Pseudo R squared statistic	0.06	0.06	0.06	0.13
Log-likelihood function	−184,781	−184,608	−184,605	−171,382
Wald statistic	24,806	25,153	25,158	19,652
AIC statistic	369,656	369,312	369,309	342,864
BIC statistic	370,153	369,819	369,826	343,392
Number of observations	286,590	286,590	286,590	286,590

Notes: Results in Columns (1)–(3) are produced by a maximum-likelihood probit model and those in Column (4) are produced by a random effects probit model; intercept, estimates of control variables (departure & booking date dummies) and random effects omitted; p-value representations: ***p < 0.01, **p < 0.05, *p < 0.10.
*** p < 0.01.
** p < 0.05.

of *LCC entry x booking day n*, n = 10, ...,60, in Column (1) not only decrease for booking days closer to departure but also change sign from booking day 30. This latter result is driven by the dynamics of the rivalry with the LCC newcomer: given the possibility of stronger competition for the early booker, it is possible that the deeper discounts are sold out more rapidly. The direct consequence is that the OTA availability decreases quickly and becomes even lower than in the situation of no adjacent LCC presence, as shown by the negative estimates - for example, the estimated coefficient of *LCC entry x booking day 7* is −0.14.

With respect to the variable *total seats*, as expected a priori, the results of Column (1) exhibit a positive relation with the availability of airfares on the OTA. Consistent with our conceptual model, the higher the seat capacity, the higher the availability dictated by the yield management systems. From a distribution management perspective, we may derive the following interpretation: the greater the number of available seats for the airline on the route on a given day, the higher the pressure to sell empty seats and therefore the higher the incentive to more intensively utilize the OTA as a distribution channel. It is important to note that all results in Column (1) can be interpreted as *ceteris paribus* to the respective dummies for departure and booking day of week, departure and booking month, and holiday periods over the departure and booking dates. Columns (2), (3) and (4) of Table 4 present a set of robustness checks for the results of the specification in Column (1). The results of these robustness checks indicate that most regressors remain statistically significant in all specifications and, more importantly, that our empirical analysis of the OTA availability of the airfare of incumbent airlines is not affected.

Table 5 contains the estimation results of the pricing model. In the first two columns of Table 5, we investigate the evolution of median fare over the booking periods. In Column (1), it is possible to observe that competition with the LCC prompts a price drop of approximately 6.8%, i.e., the estimated coefficient of LCC entry in this specification is equal to −0.07. These results are in line with Morrison (2001), who estimated a statistically significant price decrease due to adjacent competition with the LCC Southwest Airlines in the US market in 2000. However, the magnitude of price responses of our model is much lower than the author's estimates of −26.4%. We believe the lower estimates in our study may be a consequence of the sample, which covers a period wherein the LCC under analysis was a startup and thus was smaller than Southwest Airlines in 2000. Additionally, we think that in our case, the secondary airport operated by the LCC is relatively farer away from most relevant zones of traffic origin and destination - 59 miles from São Paulo city's downtown - and with higher access times and disutility associated with the flights of the newcomer from the point of view of many consumers. It is important to note that our empirical analysis presented above is the first to investigate and confirm the findings of the author regarding the case of dynamic pricing by incumbent airlines.

We stress that column (2) contains our preferred model, as it presents a more flexible specification than Column (1), accounting for booking day-specific effects of LCC presence, i.e., the interactions between *booking days* and *LCC entry*. The evidence presented by Column (2) shows that when incumbent airlines are not facing competition from the LCC, they apparently do not set the fares to increase monotonically over the booking period. In fact, the results for the dummy variable *booking day n*, n = 10, ..., 60, are suggestive of a U-shaped pattern of mean prices. Bachis and Piga (2011), Alderighi and Piga (2010) and Alderighi et al. (2014) also find U-shaped temporal profiles of fares. These results are indicative of the exertion of market power by dominant carriers to exploit either the bounded rationality or risk aversion - or both characteristics - of passengers that arrive early in the booking period (Bergantino and Capozza, 2015). In this sense, a U-shaped price evolution is representative of the attempt by carriers to enhance IPD by further segmenting the market into two categories of price-sensitive passengers in addition to the "late bookers", namely, "early bookers" and "middle bookers".

In line with the results of Table 4, the results of Column (2) also point to a dramatic change in behavior by the incumbent airlines when facing competition from the LCC. This finding is consistent with our Hypothesis $\underline{\mathbf{H_1}}$, in which the entry of an LCC produces booking day-specific price responses. Indeed, the estimated coefficients of the interaction *LCC entry x booking day n*, n = 10, ..., 60, show tough and previously nonexistent competition for the early booker, with an estimated 14.8% decrease in fares for advanced purchases two months before departure - i.e., an estimated coefficient of -0.16. Fig. 3 depicts the evolution of the estimated effect on fares considering the model in Column (2) for cases with and without the adjacent LCC presence. We observe in Fig. 3 that a much more intense competition for the early booker is triggered by the entry of the LCC on adjacent routes; the difference between the estimated coefficients of the cases with and without the LCC presence on booking day 60 is statistically significant and equal to -0.10, which is representative of a 9.0% price drop. Additionally, as a consequence, prices start to follow a more delineated S-shaped curve pattern. We believe this pattern may be interpreted in light of the characteristics of the OTA's business model of providing only low restricted fares, which limits the IPD on the OTA website on the last days of the booking period. Indeed, although there is a higher chance of bookings by business travelers during the last booking days - which may pressure prices upwards - the type of restrictions typically associated with the OTA's airfares make them less attractive to these travelers, which in turn may keep prices relatively stable.

Regarding the other results of Column (2), we have that the estimated coefficients of ln *fuel unit cost*, ln *frequencies HHI* and *proportion of closed fares* were all positive and statistically significant, which is in accordance with the *ex ante* expectations. Also, the results of all columns of Table 5 are indicative of the statistical significance of the coefficient of the *inverse mills ratio*, and thus confirming that sample selection is a relevant issue in our econometric model of online fares.

4.1. Robustness checks

To check the validity and sensitivity of our results, we implemented three sets of experiments. First, we inspected whether similar patterns of price evolution can be observed considering not only the median prices of Columns (1) and (2), but also other

Table 5
Estimation results - Heckit model - airline prices.

	(1) ln $price_{p50}$	(2) ln $price_{p50}$	(3) ln $price_{mean}$	(4) ln $price_{min}$	(5) ln $price_{p25}$	(6) ln $price_{p75}$	(7) ln $price_{max}$	(8) ln $price_{p50}$		(9) ln $price_{p50}$
ln fuel unit cost	0.05***	0.04***	0.03*	0.06***	0.07***	0.03**	0.02***	0.05***		0.03***
ln frequencies HHI (*endogenous*)	0.91***	0.92***	0.88***	0.62***	0.60***	0.83***	0.84***	0.79***		0.27***
Proportion of closed fares (*endogenous*)	0.36***	0.37***	0.50***	1.48***	1.26***	0.46***	0.22***	0.19***		0.04***
Booking day 7 (*base case*)								<u>Tam</u>	<u>Gol</u>	
Booking day 10	−0.02***	−0.01***	−0.01***	−0.02***	−0.01***	−0.02***	−0.02***	−0.01	−0.02***	−0.01***
Booking day 30	−0.13***	−0.07***	−0.07***	−0.07***	−0.07***	−0.07***	−0.08***	−0.03***	−0.08***	−0.03***
Booking day 45	−0.14***	−0.07***	−0.07***	−0.07***	−0.07***	−0.08***	−0.08***	−0.02***	−0.08***	−0.03***
Booking day 60	−0.14***	−0.06***	−0.06***	−0.05***	−0.06***	−0.07***	−0.08***	−0.01	−0.08***	−0.03***
LCC entry	−0.07***									
LCC entry x booking day 7		0.05***	0.07***	0.06***	0.02**	0.10***	0.09***	0.08***	0.09***	0.01*
LCC entry x booking day 10		0.02***	0.04***	0.03***	−0.01	0.07***	0.06***	0.07***	0.06***	−0.01**
LCC entry x booking day 30		−0.11***	−0.09***	−0.07***	−0.11***	−0.08***	−0.08***	−0.05***	−0.08***	−0.06***
LCC entry x booking day 45		−0.14***	−0.12***	−0.07***	−0.11***	−0.12***	−0.13***	−0.05***	−0.13***	−0.08***
LCC entry x booking day 60		−0.16***	−0.14***	−0.08***	−0.13***	−0.14***	−0.16***	−0.08***	−0.16***	−0.09***
ln competitors' prices (*endogenous*)										0.64***
Inverse mills ratio	−0.06***	−0.08***	−0.08***	−0.09***	−0.10***	−0.06***	−0.05***	−0.09***		−0.05***
Constant	6.84***	6.82***	6.77***	6.26***	6.33***	6.79***	6.87***	6.76***		2.54***
Airline-route fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Departure airport-hour dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Departure & booking day of week dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Departure & booking holiday dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
High season & year dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Adjusted R squared statistic	0.61	0.62	0.63	0.62	0.62	0.57	0.57	0.57	0.57	0.88
RMSE statistic	0.30	0.30	0.29	0.32	0.31	0.32	0.32	0.32	0.32	0.17
F statistic	1178.01	1180.95	1223.77	1173.96	1199.25	984.29	989.79	989.79	989.79	5165.80
Underidentification test - KP statistic	419.37	419.97	419.97	199.60	176.15	224.07	1651.13	1651.13	1651.13	125.88
Weak identification test - CD statistic	235.32	235.79	235.79	60.82	66.06	112.46	1351.67	1351.67	1351.67	39.27
Weak identification test - KP statistic	153.91	154.13	154.13	51.45	61.17	77.82	498.83	498.83	498.83	25.08
Overidentification test - J statistic	0.01	0.02	1.00	1.06	0.60	0.10	0.14	0.14	0.14	0.76
Number of observations	96,824	96,824	96,824	96,824	96,824	96,824	96,824	96,824	96,824	96,824

Notes: Results produced by the two-step feasible efficient generalized method of moments estimator (2SGMM); statistics robust to heteroscedasticity; first-stage results produced with the probit model of Table 4, Column (4); standard errors of the estimated coefficients were bootstrapped with a panel bootstrap procedure to account for the two-stage nature of the Heckit method (see Cameron and Trivedi, 2005); the reported intercept is the average value of the fixed effects; fixed effects omitted; OLS, RMSE and F statistics reported for the equivalent OLS estimation; p-value representations: ∗∗∗p < 0.01, ∗∗p < 0.05, ∗p < 0.10.

*** p < 0.01.

** p < 0.05.

* p < 0.10.

sample moments of the dataset. We thus considered the mean, the minimum, the 25th percentile, the 75th percentile and the maximum airfares of the observations as the regressands. These variables are denoted, respectively, by ln $price_{mean}$, ln $price_{min}$, ln $price_{25}$, ln $price_{75}$, and ln $price_{max}$. The estimation results are displayed in Table 4, Columns (3) to (7). Estimated price responses to entry ranged from 3.4% to 7.4% when contrasting the situations with and without LCC entry for booking day 60. The most important results found in Column (2) are confirmed by these experiments. Our second robustness check consisted of an alter-

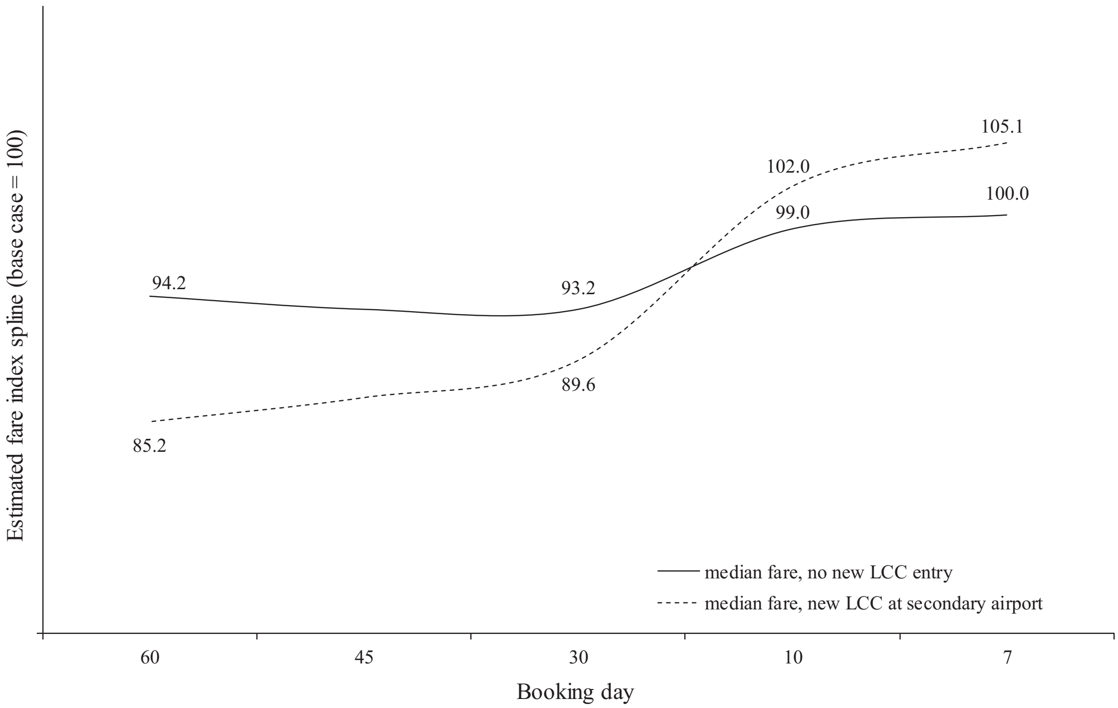

Fig. 3. Estimated dynamic pricing of incumbent airlines - median fare.

native empirical model in which the price responses were disaggregated by carrier, which allows for an inspection if the two incumbents use the same strategy when confronted with LCC entry. This model has the same specification of Eq. (1) with the exception of the *LCC entry* $\times$ *booking day dummies*, which were further interacted with incumbent-specific dummies. We present the results of such experiment in Column (8) of Table 5. The estimation results revealed that, consistent with the fact that Gol was an established LCC, that carrier had stronger price responses to entry than full-service incumbent Tam. These results confirm the findings of the previous literature on asymmetric price responses of incumbents facing new entry - Oliveira and Huse (2012). The main conclusions of the more aggregated analysis of Table 5 are again not changed.

The final robustness check was an effort to control for the strategic interaction among airlines when setting their dynamic pricing in the market. Studies that include competitor price information as an explanatory variable typically estimate reaction functions based on oligopoly theoretical models. Although we do not use such an approach, we believe that it could be an interesting robustness check.[18] To accomplish that, we considered the prices of all rival airlines that were available on the OTA for the triple route/departure date/booking day. In Column (9) of Table 5, we present the estimation results considering the incumbent-specific median competitors' price as an additional regressor - namely, variable ln *competitor's price*. We utilized the instrumentation approach discussed before to address the endogeneity issue related to this regressor. The results of Column (9) indicate a clearly statistically significant strategic interaction between carriers. Moreover, it may be interpreted as a *ceteris paribus* effect, i.e. after controlling for the effects of market structure (ln frequencies HHI) and the other regressors. The sign and statistical significance of all variables in the model are not changed in this robustness check. As far as we are concerned, this is the first empirical dynamic pricing study to account for strategic interaction among players when performing their yield management strategies.[19]

4.2. Limitations

Our study has notable limitations. First, it deals with nonstop one-way flights only. Although Brueckner et al. (2013) conclude that LCC competition has lower price effects in connecting markets than in nonstop markets, we believe that taking into consideration the price responses related to flights with stops and round-trip passengers would be beneficial to the better understanding of the strategic behavior of airline incumbents. Second, our analysis is limited to the incumbents' reaction based on pricing. There are certainly many other strategic and tactical dimensions of competitive responses to entry in the airline industry that do not necessarily hinge on pricing, such as adding flights and increasing aircraft size on the routes where the LCC has entered, strengthening entry barriers at major airports, establishing a low cost carrier subsidiary, among many other possibilities. And finally, our database is restricted to a sample collected from a single OTA, on a few data collection points, and under absence of direct information of the pricing dynamics from the carriers' own websites. We certainly

[18] We thank an anonymous reviewer for raising this issue.
[19] This procedure is in line with the simulation model of Oliveira (2003).

believe that future studies should consider more amplified datasets, with a broader portfolio of airline offerings under different market conditions and a more dense sequence of booking days, and thus to allow for a better analysis of the behavior of carriers when engaging in the strategic use of their distribution channels.

5. Conclusion

This paper presents the first effort in the airline dynamic pricing literature to investigate how incumbent airlines adjust their temporal profiles when exposed to competition from low cost carriers (LCCs). We propose and empirically test two hypotheses regarding the market activity of incumbents when faced with LCC competition: dynamic pricing responses to entry and strategic distribution management responses to entry. We utilize an original database of airfares collected by a web robot on the website of an online travel agent (OTA). The resulting sample comprises the domestic airport-pairs of the largest aviation market in Brazil. Our empirical approach is a Heckit procedure that is structurally motivated by the unobserved interaction of airlines' distribution management and yield management systems, which may be a source of sample selection bias in the estimation. We therefore first estimate a probit model of airfare search results on the OTA website and then estimate a model of temporal price profiles conditional on the estimated selection probabilities obtained in the first stage.

Our empirical evidence is consistent with both hypotheses, thus lending support to the notion that incumbents intensively adjust their dynamic pricing and distribution management in a strategic reaction to entry. In particular, we find that incumbents enhance their airfare availability on the OTA website by 11% and reduce fares by between 3.4% and 9.0% for advanced purchases made two months before departure.

Our results suggest that when responding to a new LCC player, major airlines compete for the early-booking price-sensitive passengers who constitute the target market of the newcomer. In this sense, the entry of the LCC partially spoils the existing market segmentation schemes of incumbent airlines, forcing them to reshape their airfare temporal profiles and revise their channel management strategies. The competitive outcome is a simplification of available fare structures, with a migration from a non-monotonic, U-shaped price curve to a weakly monotonic, S-shaped price curve. The main result is therefore that in response to entry, the incumbents lower their fares on advance purchases in a more intensive way than they do with fares on late purchases. As the willingness to pay of the average consumer is typically higher the closer the departure date, this finding is suggestive of important welfare implications stemming from new entry in the airline industry, with not only an overall enhanced competitive environment, but also a transfer of surplus from late bookers to early bookers.

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Appendix A.

See Table 6 and Figs. 4–8.

Table 6
Route entries by LCC Azul Airlines in the sample period.

Destination from São Paulo/Campinas (VCP)	Region in Brazil	Start date - bookings	Start date - flights
Porto Alegre (POA)	South	Dec 4, 2008	Dec 15, 2008
Salvador (SSV)	Northeast	Dec 4, 2008	Dec 15, 2008
Curitiba (CWB)	South	Dec 4, 2008	Feb 1, 2009
Vitória (VIX)	Southeast	Dec 4, 2008	Feb 1, 2009
Recife (REC)	Northeast	Feb 5, 2009	Feb 15, 2009
Fortaleza (FOR)	Northeast	Mar 4, 2009	Mar 16, 2009
Rio de Janeiro/Santos Dumont (SDU)	Southeast	Mar 19, 2009	Mar 20, 2009
Navegantes (NVT)	South	Mar 11, 2009	Apr 1, 2009
Manaus (MAO)	North	Mar 18, 2009	Apr 6, 2009
Campo Grande (CGR)	Center-West	May 8, 2009	May 28, 2009
Maceió (MCZ)	Northeast	May 19, 2009	Jun 2, 2009
Maringá (MGF)	South	May 14, 2009	Jun 5, 2009
Belo Horizonte/Confins (CNF)	Southeast	Jul 1, 2009	Aug 10, 2009
Natal (NAT)	Northeast	Oct 17, 2009	Dec 1, 2009
Florianópolis (FLN)	South	Nov 5, 2009	Dec 15, 2009
Goiânia (GYN)	Center-West	Jan 26, 2010	Mar 3, 2010
Porto Seguro (BPS)	Northeast	Apr 13, 2010	May 1, 2010
Cuiabá (CGB)	Center-West	Apr 29, 2010	Jun 7, 2010

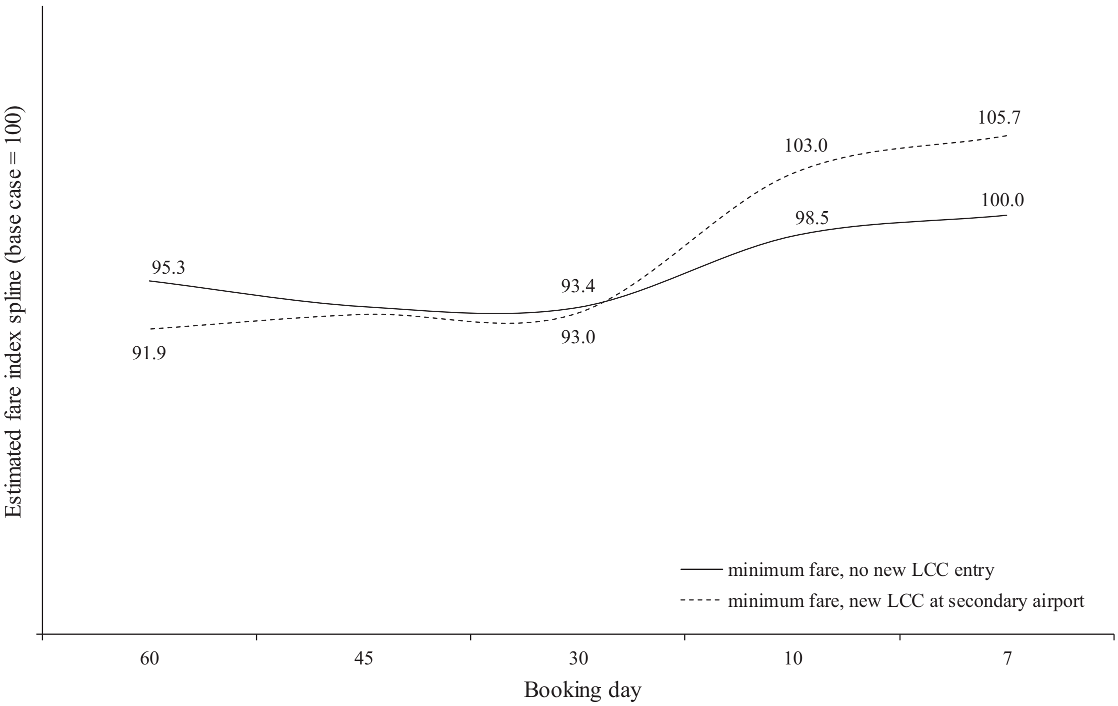

Fig. 4. Estimated dynamic pricing of incumbent airlines - minimum fare.

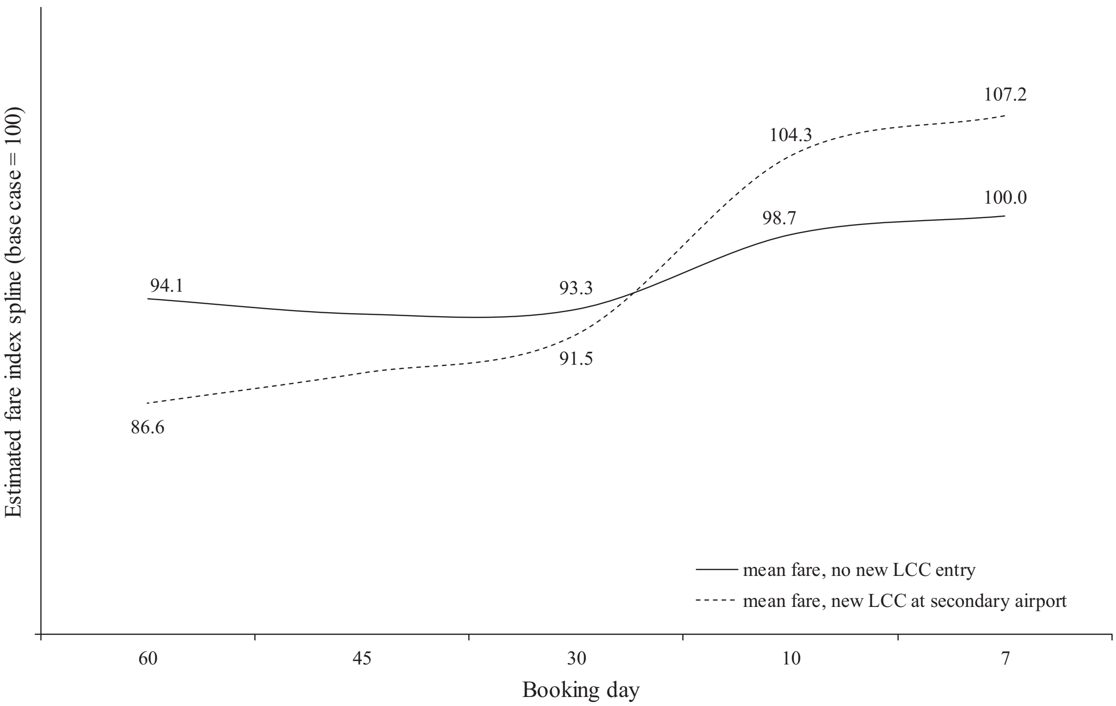

Fig. 5. Estimated dynamic pricing of incumbent airlines - mean fare.

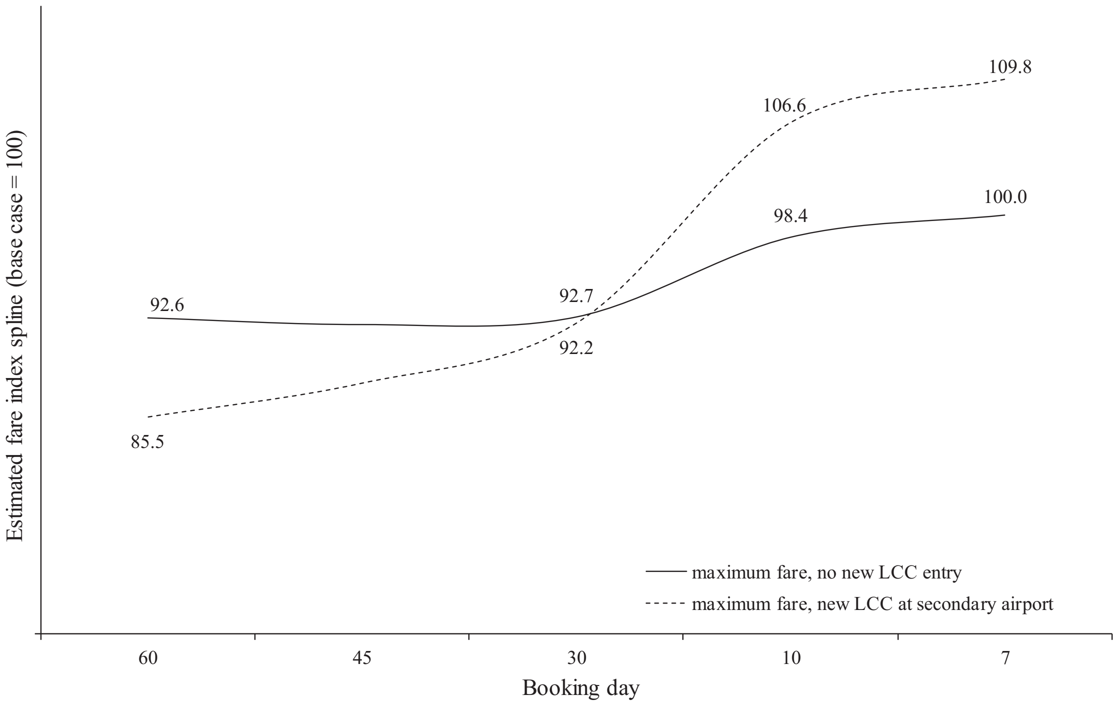

Fig. 6. Estimated dynamic pricing of incumbent airlines - maximum fare.

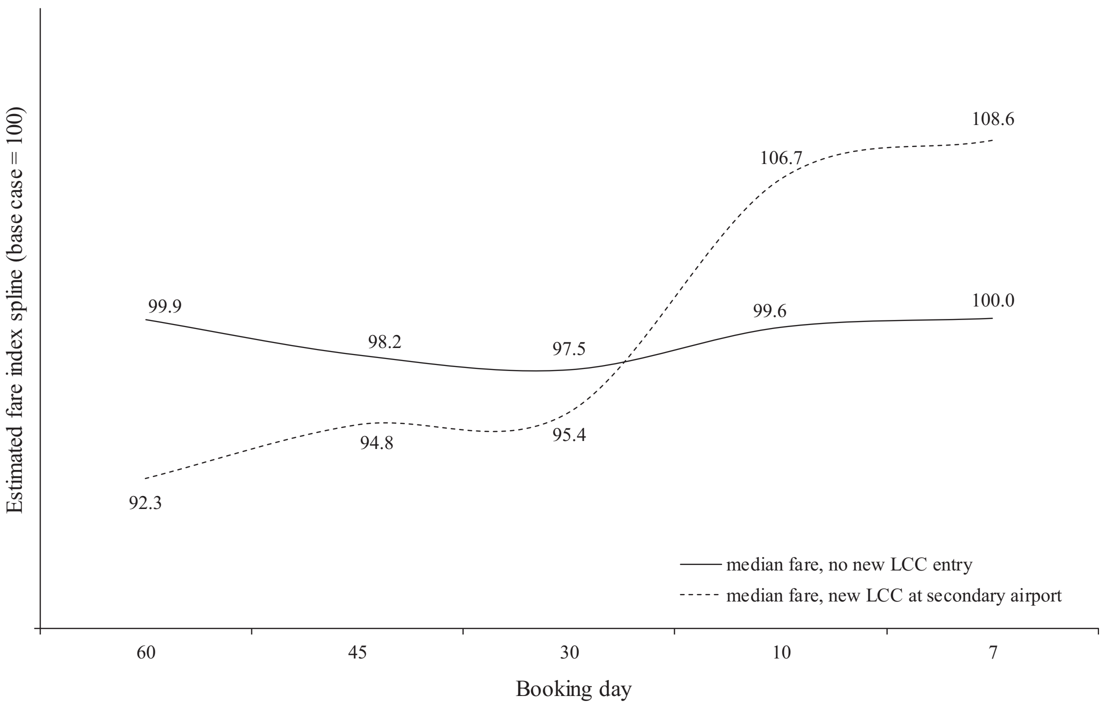

Fig. 7. Estimated dynamic pricing of incumbent airlines - median fare - incumbent Tam.

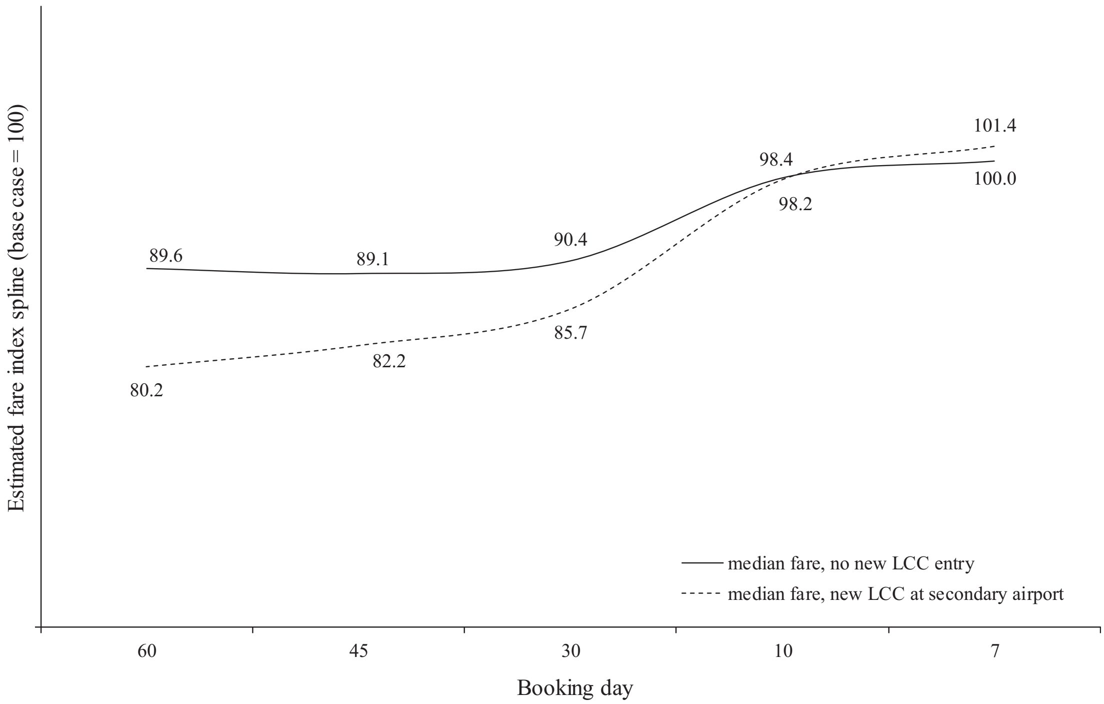

Fig. 8. Estimated dynamic pricing of incumbent airlines - median fare - incumbent Gol.

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