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An econometric study of the effects of airport privatization on airfares in Brazil

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Abstract

This paper develops empirical models to test the impact of airport privatization on airline fares. We employ a difference-in-difference approach combined with an endogenous switching regression model to account for the selection of airports to be privatized. The results suggest that prices for tickets on routes with at least one privatized airport at an endpoint are about 3~3.5% higher than on routes between two publicly managed airports. By testing moderating effects, we find evidence that market dominance enforces the privatization impact on airfares. The main conclusions are consistent using various control group classifications.

Keywords: air transport; privatization; airports; airlines; econometrics.

JEL Classification: D22; L11; L93.

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1. Introduction

Twenty-four years after the British Airports Authority's (BAA's) initial public offering (IPO), the event that marked the beginning of airport privatizations worldwide, Brazil inaugurated its airport privatization program. In 2011, São Gonçalo do Amarante International Airport, in the state capital of Rio Grande do Norte, Natal, became the first privatized airport in the country. The National Civil Aviation Agency (ANAC) was responsible for the sale. The change of the airport to private management fueled a debate in Brazil over the benefits of privatizing public infrastructure. Over the decades, segments in Brazil have shown concern over privatizing state assets, presuming that privatization is associated with poorer service quality and possibly higher prices.

From a political perspective, airport privatization is generally sold to the public with a plausible social justification, including how passengers will be positively affected by this action. Based on social welfare, the assumption is that gains in management efficiency from a newly profit-oriented administration will be advantageous to air transport operations, reflecting positively on passenger outcomes (i.e., lower prices, better service).

Several major airports, such as Zurich, Copenhagen, Sydney, and Buenos Aires, have been privatized and others may follow. In France, the privatization of Groupe ADP, a national enterprise that manages Paris airports, including Charles de Gaulle, one of Europe's busiest, is under discussion. India, the third-largest aeronautical market in the world, has recently undergone a privatization process involving its main airports.[1] In the United States, terminal privatization has been used to obtain funding for redevelopment efforts.[2]

The method of privatization used by the Brazilian government has been a public-private partnership (PPP) concession approach. A private company purchases the right to exploit the airport facilities commercially for a predetermined period. The government has imposed strict quality service and price cap regulation on fees at privatized airports.

This study investigates whether Brazilian airport privatization has led to the unintended consequence of higher prices for domestic passengers. To perform this investigation, we develop an econometric model of airfare pricing with privatized airports as the focus of the analysis. We consider data from the Brazilian domestic passenger air transportation industry between 2010 and 2018. During this period, the government held auctions for ten airports. The justification offered was the possibility of attracting investments to the industry to promote physical expansion of the airports and to improve the quality of the country's airport infrastructure.

[1] "*Billionaire Gautam Adani Adds Airports To His Already Vast Empire*" - Forbes, Feb, 26, 2019

[2] "*US airports launch major renovation projects*" – Born2Invest, Apr, 4, 2019

The first auctions occurred before two significant events in the country, the 2014 World Cup and the Rio Olympics 2016. Therefore, there was a great concern with the airport infrastructure and its capability to meet the demand that these international competitions would attract. The perceived need for large investments in airport infrastructure encouraged public authorities to consider privatization. Moreover, a combination of Brazilian economic growth and decreasing airfares (with the growth of low-cost carriers) had spurred domestic demand for Brazilian air transportation. Authorities were concerned that inadequate airport infrastructure would soon constrain the sector's growth.

This study adds to the literature on empirical studies of determinants of airfares. Previous papers have addressed a vast array of variables that may contribute to airfares. Pertinent to this study, Adler & Liebert (2014) find that airfares are higher at majority-private airports compared to public airports. The literature also suggests that privatization causes a change in airline-airport relationships and that airport privatization may strengthen a dominant carriers' market power, potentially allowing for greater pricing power (Basso & Zhang, 2008; D'Alfonso & Nastasi, 2014). Therefore, we account for how airport privatization and market power may interact in influencing airline fares at privatized airports.

We divide this paper into six parts, this introduction being the first. Section 2 provides an overview of the existing literature, emphasizing three subjects: pricing, relations between airports and airlines, and privatization. Section 3 presents and discusses the estimation strategy. Section 4 is devoted to a discussion of the results. The fifth section presents a set of robustness checks and, finally, the last section is dedicated to the conclusions.

2. Literature review

2.1. Airline and airport pricing

Research on airline pricing determinants has indicated that fares can be affected by an airline's direct costs and by market characteristics. From classic studies (e.g., Borenstein 1989) to more recent publications (e.g., Wang, Zhang & Zhang, 2018), characteristics such as oil prices, general airline expenses, and city-pair demographics have been frequently considered as airfare determinants. However, it is well-established in the literature that market structure, potential, and actual entry, and airport dominance are generally the most notable drivers of airline pricing. Several papers examine the impact of route market concentration (e.g., as measured by passenger HHI on a route), route dominance (e.g., as measured by passenger market share on a route), airport concentration (e.g., as measured by HHI based on flights or departures at an airport) and airport dominance (e.g., as measured by passenger market share at an airport) on airfares - Evans and Kessides (1993), Hofer, Windle & Dresner (2008), Brueckner, Lee & Singer (2013), and Bilotkach & Lakew (2014), Wang, Zhang & Zhang (2018), among many others.

Concerning airport pricing, Zhang & Zhang (2003) study the effects of concessions and privatization on airport charges and capacity expansion. They employ a theoretical approach to compare the price decisions of privatized, unregulated airports with the price decisions of public airports that maximize social welfare. They find that private airports would charge a higher price than the socially optimal level.

Bel & Fageda (2010) develop an econometric model of the determinants of the prices charged by airports to the airlines in major European airports. They find evidence that that private airports not regulated tend to charge higher prices than public or regulated airports. Additionally, the specific airport regulation mechanism - rate of return or price-cap regulation - does not play an influential role on charges. Bilotkach et al. (2012) also investigate airports in Europe. Contrary to Bel & Fageda (2010), they find that aeronautical charges are lower when airports are privatized, a phenomenon that they associate with efficiency gains of airport privatization. They also suggest that privatized airports may be more innovative in attracting new customers using lower aeronautical charges. They also find that hub airports set higher charges. In contrast, price-cap regulation and the presence of nearby airports are not significant drivers of airport fees.

Choo (2014) investigates the factors affecting aircraft landing and passenger fees at major US airports. The author finds evidence of cross-subsidization from non-aeronautical revenue to aeronautical charges, and that hub airports and airports with higher international traffic have higher charges. Finally, the study reveals a possible substitution effect in the price setting of landing charges and terminal charges, with higher landing charges associated with lower terminal charges and vice versa. Conti, Ferrara & Ferraresi (2019) study the role of the EU Airport Charges Directive in reducing aeronautical charges. Utilizing a differences-in-differences approach (Diff-in-Diff), they estimate a statistically significant decrease in airport charges, but with a time lags of a few years.

2.2. Privatization: motivations and outcomes

In a privatization process, we consider the main stakeholders to be the government (pre-privatization owner), the investors (airport concessionaires), and the clients, including airlines and air passengers (Tang, 2016; Xu, Hanaoka & Onishi, 2019). According to Mantin (2012), airports have become more attractive to private sector investors as the industry has matured. Over time, this sector has demonstrated the capability to be economically self-sufficient with the ability to generate revenue from commercial activities, as well as from aeronautical-related business. This maturity suggests that the economic potential of airports is a major factor influencing privatization.

Bettini & Oliveira (2016) and Gillen (2011) point out that the concept of two-sided platforms describes an airport's role in the aviation industry. There is a clear demand-side interdependency between airlines and passengers. The platform's two sides are revenue sources from the aeronautical side (landing, boarding, and aircraft parking charges) and the non-aeronautical side (food, retail, car rental, car parking services). With this configuration, an airport can benefit from the internalization of the network effects between the two platforms. Along the same lines, Kim & Shin (2001) indicate that airports will seek to maximize concession revenues (non-aeronautical revenues) as they become commercially-oriented.

From the governmental perspective, airport privatization may provide benefits, relieving them of the obligations to fund capital and operating improvements at airports. But the privatization decision may also impose political risks if the privatization results are not as positive as expected. Graham (2011) carries out a comprehensive review of the literature on motivations for airport privatization. She ranks the general objectives for airport privatization from most to least common as follows: (1) improve efficiency, (2) provide investment, (3) improve or diversify management, (4) improve quality, (5) obtain state financial gains, and (6) reduce state influence on management.

Several papers, such as Oum, Yan & Yu (2008) and lo Storto (2008), investigate the relationship between privatization and economic efficiency improvement at airports. The underlying assumption is that commercially oriented management will pursue profit maximization and adopt cost-effective policies. However, relevant papers (i.e., Adler & Liebert, 2014 and Oum, Adler & Yu, 2006) do not always find evidence of better productivity at privately managed airports compared to their publicly operated counterparts. After analyzing several papers, Graham (2020) claims it was impossible to establish a reliable, statistical link between privatization and efficiency. Three reasons are provided: First, the methodology and data used are not consistent among the studies. Second, gains in efficiency depend on an airport's situation prior to privatization. And, finally, there may be selection bias; that is, the airports picked for privatization are likely among the best performing prior to privatization. Consequently, it is difficult to develop a causal link between privatization and efficiency.

Graham (2020), states that the need for investment capital or additional revenues may be a bigger motivation for privatization than the need for efficiency gains. This motivation for privatization, has also been addressed by Cruz & Sarmento (2017) and Oum, Adler & Yu (2006). As the demand for air transportation increases, there is a need to expand airport infrastructure and to develop funding sources for this expansion.

Some countries have relied on the private sector for funds to compensate for deficits in public finances. Papers such as Cruz & Sarmento (2017) and Lin & Mantin (2012) find that that the leading motivation for airport privatization may be to rapidly raise funds. In their detailed review of the literature, Cruz & Sarmento (2017) note that the sale of monopolistic entities, such as airports, may become more attractive as the facilities increase in value.

2.3. Airport-airline relationships

Airport privatization shifts the goals of airport managers (e.g., from welfare maximization to profit maximization) potentially changing the airport-airline relationship. Non-aeronautical revenues may become more important to privatized airports, as managers seek new revenues. The two-sided platform concept may, thus, be emphasized in privately administered airports (Bettini & Oliveira, 2016; Gillen, 2011). The broad range of profit opportunities may motivate a strengthening of commercial relationships between airports and airlines, with the primary purpose to find better ways to explore joint revenue generation potential. As a result, airport concession arrangement effects may arise, with implications to the associated revenue (Zhang & Zhang, 1997; Czerny, 2013; D'Alfonso, Jiang & Wan, 2013; Gillen & Mantin, 2014). However, the airport-airline relationship may be impacted by the model used to regulate airport prices. Thus, pricing regulations may, in part, dictate the commercial relations between airports and airlines.

The literature describes how airport privatization may impact the commercial relationship between airports and airlines. Basso & Zhang (2007) and D'Alfonso & Nastasi (2012) discuss the transformation of this relationship, from a traditional (horizontal) approach to a vertical relationship (supplier-buyer), with the stakeholders' commercial interests better aligned. Bettini & Oliveira (2016) state that an airport's privatization should strengthen its role as a facilitator, allowing a better development of direct and indirect network effects between airlines and passengers. According to the authors, a privatized airport may be attractive to airlines because of its flexible management structure, facilitating vertical relations. Moreover, there may be less administrative bureaucracy under a private administration, making it easier to negotiate services and infrastructure usage with carriers.

While publicly managed airports may be more likely to treat all airlines equally, private commercial-oriented airports could apply distinct policies and differentiate across its clients according to its economic interests. Thus, a privatized airport may favor certain airlines when it proves to be financially advantageous. For example, airlines that use an airport as a hub may generate more non-aeronautical revenues than non-hub airlines, and thus may be favored by airport management in terms of slot and gate access, or through the airport's fee structure.

Governments often regulate airport prices given the assumption that airports possess locational market power. Privatized airports may be more subject to price regulation than public airports since they may exploit monopoly power by raising prices while profit maximizing. However, Gillen (2011) addresses the necessity for regulation by questioning whether airports have significant market power. He argues that airports compete with other airports in the same catchment area, as well as with distant airports as potential hubs. On the other hand, Bel & Fageda (2010) and Adler & Liebert (2014) provide empirical evidence supporting the need for regulating privatized airports. For example, the results obtained by Bel & Fageda (2010) indicate a positive and statistically significant influence of unregulated, private airports on airport charges. This evidence suggests potential market power that can be exercised by privatized airports.

In this paper, we examine the relationship between airport privatization and airline prices. Following prior literature, we note that this relationship may not be straightforward, since the competitive structure at airports may change with privatization. Therefore, we incorporate factors related to this competitive structure into our modeling framework.

3. Research Design

3.1. Application

We add to the literature by assessing the impact of airport privatization on passenger fares. The database considered for this study covers the first ten privatizations in the Brazilian commercial aviation market, with observations from 2010 to 2018.[3] Figure 1 illustrates the ten airports considered in this research. Table 1 summarizes the auction information.

3.2. Data

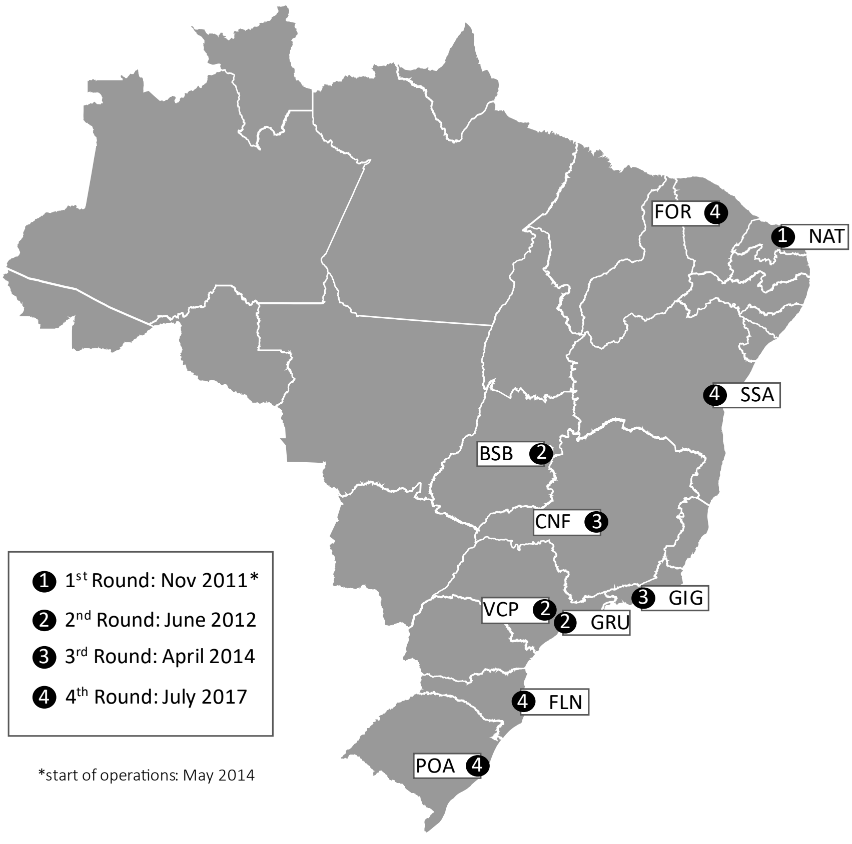
To investigate the impact of airport privatization on airfares, we propose an econometric analysis of ticket prices, relying on historical passenger flight information in the Brazilian air transportation network. The data are organized onto a panel for the period July 2010 to December 2018, with monthly observations for all domestic origin and destination (O&D) routes. We define a route as a directional city pair, grouping multiple airports in the same catchment area. City pairs with fewer than 100 monthly passengers and with fewer than 6 monthly observations are dropped.

[3] There have been two additional rounds of privatization since 2018.

Table 1 - Public airport auctions in the sample period

Round (year)	Airport (IATA)	Winning Consortium	Value [BRL billion] (premium)
1st (2011)	Natal (NAT)	Inframerica	0.17 (228%)
2nd (2012)	Guarulhos (GRU)	Invepar/ACSA	24.00 (347%)
	Brasilia (BSB)	Inframerica	
	Viracopos (VCP)	Triunfo/UTC/Egis Avia	
3rd (2014)	Galeão (GIG)	Changi/Odebrecht	21.00 (253%)
	Confins (CNF)	CCR/München GmbH/Zürich AG	
4th (2017)	Porto Alegre (POA)	Fraport	3.70 (94%)
	Salvador (SSA)	Vinci	
	Fortaleza (FOR)	Fraport	
	Florianópolis (FLN)	Flughafen Zürich AG	

Source: National Civil Aviation Agency (ANAC)'s website at www.gov.br/anac/pt-br/assuntos/concessoes.



Source: National Civil Aviation Agency (ANAC)'s website at www.gov.br/anac/pt-br/assuntos/concessoes

Figure 1 - Airports privatized in the first four concession rounds according to the concession contract signature dates

The National Civil Aviation Agency (ANAC) is the primary source of air transportation-related information in this dataset. This information is publicly available and is retrieved from the agency's website. We utilize ANAC's Active Scheduled Flight Historical Data Series, Airfares Microdata, Air Transport Statistical Database, Brazilian Aeronautical Registry (RAB), and airport regulations.[4] We also extract airport capacity data from a 2010 study of the air transport sector by the Brazilian Development Bank. We collect socioeconomic data from the Brazilian Institute of Geography and Statistics (IBGE) and the Brazilian Central Bank. We acquire jet fuel price data from the National Agency for Petroleum, Natural Gas and Biofuels' (ANP) website, and jet fuel tax data from ANAC's reports and digital media press websites.

3.3. Econometric model

Equation (1) presents our empirical model, with ticket prices as the dependent variable. The regressors are a set of control variables, and two dummy variables, one accounting for a private airport's presence on a route and the other representing a comparison control group with routes between two publicly operated airports:

$$\begin{aligned}\ln \mathrm{P}_{k,t} = {} & \beta_1 \mathrm{FUELP}_{k,t} + \beta_2 \mathrm{PAXPF}_{k,t} + \beta_3 \mathrm{FEE}_{k,t} + \beta_4 \mathrm{CONGEST}_{k,t} + \\ & \beta_5 \mathrm{FREQ}_{k,t} + \beta_6 \mathrm{FLTIME}_{k,t} + \beta_7 \mathrm{AGE}_{k,t} + \beta_8 \mathrm{TOUR}_{k,t} + \\ & \beta_9 \mathrm{ENTRY}_{k,t} + \beta_{10} \mathrm{HUB}_{k,t} + \beta_{11} \mathrm{HHIroute}_{k,t} + \beta_{12} \mathrm{HHIcity}_{k,t} + \\ & \beta_{13} \mathrm{PRV}_{k,t} + \beta_{14} \mathrm{PLA}_{k,t} + \beta_{15} \mathrm{MILLS}_{k,t} + \gamma_k + \gamma_t + \varepsilon_{k,t},\end{aligned} \quad (1)$$

where k denotes city pairs (representing routes), and t denotes the time period. The components of Equation (1) are the following:

- $\mathrm{P}_{k,t}$ is the mean airline price on the city-pair (inflation-adjusted local currency values);
- $\mathrm{FUELP}_{k,t}$ is the fuel price of aviation kerosene (jet A1) in inflation-adjusted local currency. We add the specific value of each state's fuel taxation;
- $\mathrm{PAXPF}_{k,t}$ is the mean number of revenue passengers per flight;[5]
- $\mathrm{FEE}_{k,t}$ is the mean value of the landing fees rates on the city pair (inflation-adjusted local currency values). The government has imposed strict quality service and price cap regulation on airport charges since privatization. As airports are regulated through price caps, we utilize the price cap

[4] Available at www.gov.br/anac.

[5] To compute this variable, we consider all flights and passengers on the flight segment constituted by the origin and destination endpoints of a route.

value as a proxy for the aeronautical charges imposed on every flight's landing.[6] In the period, the price cap value for the landing fee rates extracted at the sample mean has increased from 7.46 (2011) to 8.73 (2018) BRL/MTOW.[7] As our dataset is directional, we utilize the landing fee rates at the destination airport of the route. We also employ the geometric mean between the origin and destination airports in an alternative experiment;

- $\mathrm{CONGEST}_{k,t}$ is the proportion of daily scheduled flights operated during congested periods, in which the number of aircraft movements are greater than the airport's declared capacity;
- $\mathrm{FREQ}_{k,t}$ is the total number of nonstop flights (in hundreds) on the route;
- $\mathrm{FLTIME}_{k,t}$ is the mean actual flight time on the route (in minutes);
- $\mathrm{AGE}_{k,t}$ is the mean age of the airplanes operating on a city pair. It is calculated as the difference between the date of the flight and the date the manufacturer delivered the airplane;
- $\mathrm{TOUR}_{k,t}$ is a proxy for the leisure-traveling passengers on the route. It is equal to the share of charter flights on the route;
- $\mathrm{ENTRY}_{k,t}$ is a binary variable that indicates the presence on a route of airlines that are newcomers to the industry. In particular, Azul Airlines may have contributed to increased price competition on the routes it entered. This dummy variable is set equal to 1 on routes in which Azul is observed, from the beginning of the sample period until May 2012, when Azul merged with the regional carrier Trip Airlines;[8]
- $\mathrm{HUB}_{k,t}$ is a variable that indicates the maximum share of connecting passengers between the origin and destination endpoints on a route that contains at least one airport considered as a hub, according to Federal Aviation Administration (FAA) criteria;
- $\mathrm{HHIroute}_{k,t}$ is the Herfindahl-Hirschman Index of market concentration on the route. It is calculated using the share of each airline's revenue passengers;

[6] ANAC's regulations are available at www.gov.br/anac.

[7] BRL means Brazilian Real, the local currency in constant values of January 2019; MTOW means aircraft maximum take-off weight in tons. The reported airport fees are related to domestic operations. The major source of airport charges differences across Brazil comes from airport size and ownership type. Airports managed by the public company Infraero are classified into four categories for charging purposes. In contrast, price caps for airport concessions are dictated by the respective concession contracts and their regulations for annual adjustment.

[8] An alternative would be to use a dummy for low-cost carrier (LCC) presence. However, the business models of Brazilian LCCs have changed across the year. Therefore, we believe that a new entrant dummy is more appropriate to account for changes in market rivalry on a route.

- $HHIcity_{k,t}$ is the Herfindahl-Hirschman Index extracted at the city level. It is equal to the maximum concentration (based on passengers) at a route endpoint on a city pair. This variable provides a proxy for airport/city dominance by airlines at route endpoints;
- $PRV_{k,t}$ is a dummy variable that indicates the presence of at least one privatized airport in the city pair market (treatment group). This variable takes the value of 1 from the start of the airport's management by the concessionaire. We group airports in the same catchment area and consider the city pair as being influenced by privatization if one of the airports in a city is managed by a concessionaire;
- $PLA_{k,t}$ is a dummy variable that indicates routes between two public airports in the control group. We discuss this variable in detail in the next section;
- $MILLS_{k,t}$ is the inverse Mills ratio, calculated considering the two-step Heckman model;
- δ_k and δ_t are the route and time-specific fixed effects. They control for unobservable market characteristics related to city pairs and time periods;
- $\varepsilon_{k,t}$ is the disturbances term.

Table 2 presents descriptive statistics and correlation coefficients for the main variables in our models. We also present a breakdown of statistics for the whole, treated, and non-treated samples.

Table 2 - Descriptive statistics and correlations of the main model variables

	Variable	Description	Person coefficient of correlation														
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	P	airfare (BRL)	1.00														
(2)	FUELP	fuel price (BRL/liter including tax)	0.09	1.00													
(3)	PAXPF	pax per flight (mean passengers/flight/10)	0.08	-0.14	1.00												
(4)	FEE	destination landing fee price cap (BRL)	-0.03	0.02	0.34	1.00											
(5)	CONGEST	proportion of flights in congested hours (%)	0.02	0.01	0.15	0.04	1.00										
(6)	FREQ	flight frequency (flights/100)	-0.13	0.02	0.22	0.13	0.31	1.00									
(7)	FLTIME	flight time (hours)	0.57	-0.06	0.46	0.16	0.13	-0.06	1.00								
(8)	AGE	mean aircraft age (years)	-0.03	-0.07	-0.39	-0.14	-0.02	-0.12	-0.22	1.00							
(9)	TOUR	share of charter flights (%)	0.05	-0.09	-0.02	-0.03	-0.02	-0.08	0.01	-0.01	1.00						
(10)	ENTRY	presence of a newcomer on the route (boolean)	-0.01	0.08	0.07	-0.03	0.07	0.16	0.09	-0.19	-0.02	1.00					
(11)	MAXHUB	share of connecting passengers in a hub (%)	0.12	-0.09	0.26	0.29	0.13	0.10	0.20	-0.10	-0.01	-0.03	1.00				
(12)	HHIroute	route level market concentration	0.11	-0.04	-0.58	-0.21	-0.29	-0.44	-0.19	0.26	0.10	-0.21	-0.19	1.00			
(13)	HHIcity	city level market concentration	0.05	0.11	-0.60	-0.34	-0.05	-0.23	-0.29	0.40	0.07	-0.13	-0.19	0.56	1.00		
(14)	PRV	treatment group - privatization (boolean)	0.07	-0.24	0.34	0.23	0.43	0.17	0.26	0.07	0.03	-0.20	0.25	-0.21	-0.15	1.00	
(15)	PLA	control group (placebo)	-0.06	-0.11	-0.06	0.04	-0.17	-0.09	-0.07	-0.06	-0.01	-0.09	0.11	0.17	-0.03	-0.32	1.00

Whole Sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Mean	422	2.5	8.8	8.0	15.1	1.3	1.7	16.0	0.0	0.1	0.2	0.7	0.5	0.4	0.1
SD	182	0.5	3.9	2.0	19.3	2.9	0.8	4.5	0.1	0.2	0.1	0.3	0.2	0.5	0.3
Min	34	1.5	0.2	0.5	0.0	0.0	0.3	1.6	0.0	0.0	0.0	0.2	0.2	0.0	0.0
Max	2347	3.5	18.3	11.2	100.0	41.1	7.0	42.9	1.0	1.0	0.5	1.0	1.0	1.0	1.0

Treated	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Mean	434	2.4	9.7	8.2	20.3	1.7	1.9	15.9	0.0	0.1	0.2	0.7	0.5	0.6	0.0
SD	176	0.5	3.8	1.9	20.5	3.4	0.8	4.2	0.1	0.3	0.1	0.3	0.2	0.5	0.0
Min	46	1.5	0.2	0.5	0.0	0.0	0.5	2.4	0.0	0.0	0.0	0.2	0.2	0.0	0.0
Max	1727	3.4	18.3	11.2	100.0	41.1	7.0	42.9	1.0	1.0	0.5	1.0	1.0	1.0	0.0
Non-treated	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**
Mean	399	2.4	7.4	7.6	5.9	0.5	1.5	15.3	0.0	0.0	0.2	0.8	0.5	0.0	0.7
SD	161	0.5	2.9	2.0	10.3	0.4	0.7	4.5	0.1	0.1	0.1	0.2	0.3	0.0	0.5
Min	84	1.5	0.6	0.5	0.0	0.0	0.3	1.6	0.0	0.0	0.0	0.3	0.2	0.0	0.0
Max	1934	3.4	16.7	11.0	59.4	2.4	4.9	35.3	1.0	1.0	0.5	1.0	1.0	0.0	1.0

3.4. Estimation strategy

As stated by Equation (1), we consider a log-linear specification for pricing, so that the unit variation of an independent variable produces an approximate percentage change in the response variable. In the equation, the regressand is the natural logarithm of the mean ticket price of a city pair route. The explanatory variables aim to control for airline operations and costs, the competitive dynamics at the route, city level characteristics, route characteristics, and airport-related features. The dataset is structured as a panel, and we control for route and time idiosyncrasies with two-way fixed effects.

We employ a difference-in-differences (DiD) approach to assess the impact of airport privatization on airline prices. We consider a quasi-natural experiment where a particular group of observations receives a specific treatment. We compare this group's outcomes with a similar group without the treatment - i.e., the control, or "placebo" group. Our study compares airfares on flights on routes involving privatized airports with prices on flights on routes between two publicly owned airports with similar characteristics. We also experiment with treatment groups in which both origin and destination airports are privatized.

The success of the DiD framework is conditioned by the proper selection of observations to comprise the placebo group. We utilize three different group assignment approaches: 1. Ad-hoc classification, based on geographic and economic proximity; 2. Propensity Score Matching (PSM); and, 3. Synthetic Control Method (SCM).[9] We consider the ad-hoc assignment as our baseline model, and employ the other methods to inspect the robustness of our main results.

We assign airports to the placebo group based on two main features: regional economic relevance and the geographic distance to a privatized airport. Since all privatized airports in the sample period are located within the catchment area of state capitals, we consider only airports serving state capitals as placebos to satisfy the regional relevance criterion. For each privatized airport, the placebo group includes the three public airports at state capitals, closest to the privatized airport. Routes between the placebo airports and other publicly owned airports are considered as the control group.

Another relevant econometric issue concerns sample selectivity. Graham (2020) points that it is unlikely that governments choose airports to be privatized at random. Usually, large, busy, and efficient airports can attract private sector attention, and therefore are more likely to be selected in a privatization program. As the selection for treatment is a crucial problem in our analysis, we utilize an endogenous switching regression model to address potential selection bias in our estimation.[10] To implement the required Heckman correction for this approach, we build upon Rolim, Bettini &

[9] Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010, 2014)

[10] See a discussion in Maddala (1983).

Oliveira (2016) and Alderighi, Gaggero & Piga (2015). We use a two-step process, in which the first step consists of modeling a selection decision equation estimated with a probit model, as expressed by Equations (2) and (3). We utilize socioeconomic, political and airport operating features in our selection model. In the second step, we use the estimated selection probabilities to calculate the Inverse Mills Ratio ($MILLS_{k,t}$) and input this feature into the primary model (Equation 1).

$$\text{Prob}(PRV_{k,t} = 1 \mid Z_{k,t}) = \Phi(\gamma Z_{k,t}) \tag{2}$$

$$Z_{k,t} = Z\left(\ln PAX_{k,t}, \ln INC_{k,t}, \ln POP_{k,t}, HUB_{k,t}, CONGEST_{k,t}, POLINFL_{k,t}\right), \tag{3}$$

where $PRV_{k,t}$, $HUB_{k,t}$, and $CONGEST_{k,t}$ are as defined before. The other variables are as follows:

- $PAX_{k,t}$ is the total number of passengers carried by all airlines on the city-pair;
- $INC_{k,t}$ is a proxy for mean income. It is equal to the per capita gross domestic product's geometric mean between the origin and destination cities (inflation-adjusted local currency values);
- $POP_{k,t}$ is the geometric mean of the population of the origin and destination cities;
- $POLINFL_{k,t}$ is a proxy for the political influence of the endpoint states on a route. It is equal to the geometric mean of the share of votes of the incumbent party in the 2010 presidential election;[11]
- $\text{Prob}(.)$, $\Phi(.)$, and Z, are, respectively, the probability operator, the Normal cumulative distribution function, and a vector of regressors;
- γ is the vector of unknown parameters to be estimated.

Our study treats demand-related and market-related features PAXPF, HHIroute, HHIcity, and FEE as potentially endogenous, as we suspect they might have a simultaneity relationship with the response variable. To inspect the sensitivity of this approach, we experiment with models considering HHIcity and FEE as exogenous, as well. We consider a set of exogenous demand shifters in our identification strategy. As instruments, we use metrics for gross domestic product (GDP), population size, GDP per capita, Gini index of income inequality, the amount of available credit for loans and debts, and the number of bank agencies and cell phones, all extracted at the endpoint city level.[12] Finally, we experiment with the market concentration of other routes

[11] www.tse.jus.br/hotsites/pesquisas-eleitorais/resultados_anos/2010.html.

[12] We utilize the maximum, minimum, simple, and geometric means between the origin and destination. When appropriate, we also compute the respective per capita figures.

(Hausman Instruments).[13] From the 172 instrumental variable set initially proposed, only 35 are activated by LASSO in our preferred specification (a shrinkage rate of 79.7 %), with none Hausman IVs among the ultimately selected.

As we have many candidates for instrumental variables, we utilize the post-double selection with least absolute shrinkage and selection operator (PDS-LASSO) approach of Belloni et al. (2012), Belloni, Chernozhukov, & Hansen (2014a,b) and Chernozhukov, Hansen & Spindler (2015). This approach assumes that the model is sparse. Therefore, due to the regularization procedure, only a reduced subset of the initial regressors and instruments remain active. After this initial step, we make use of fixed effects implemented with a Two Stage Least Squares (2SLS) estimator with heteroskedasticity- and autocorrelation-robust standard errors. We also allow the treatment and placebo group dummies, and the time fixed effects, to be penalized by the LASSO procedure. We label the full estimation approach as "FE/IV/LASSO."[14]

To inspect the quality of our instrumentation approach, we report the results of underidentification tests (Kleibergen-Paap rk LM statistic) and weak identification tests (Kleibergen-Paap rk Wald F statistic) of the instruments ultimately selected by LASSO at the bottom of the results tables. We also examine the results with just-identified estimates,[15] and perform overidentification tests (Hansen J statistic) of our preferred model with only a few instruments (number of overidentifying restrictions equal to 1).[16] All these tests confirm the relevance and orthogonality of the LASSO-selected instruments and the robustness of results under alternative identification strategies.

4. Estimation results

We begin the presentation of our estimation results with a graphical analysis allowed by the Synthetic Control Method (SCM). With SCM, we estimate the effect of privatization by comparing the evolution of the mean price of the privatized airports after privatization with the evolution of the mean prices of a synthetic control group, formed by a weighted combination of control units - the "donors." We set as donors all state capitals that did not have privatized airports during the sample period.[17] We present the mean airline prices of the treatment group and the control group over the lags and leads in years, prior and post to privatization. Figure 2 presents the results for the four largest cities. In all cases, the correlation coefficient between treatment and control group prices in

[13] See Mumbower, Garrow & Higgins (2014) and Miranda & Oliveira (2018).

[14] See also Oliveira et al (2021).

[15] Just-identified estimates are less likely to be subject to weak instruments problems (Angrist & Pischke, 2008, p. 157).

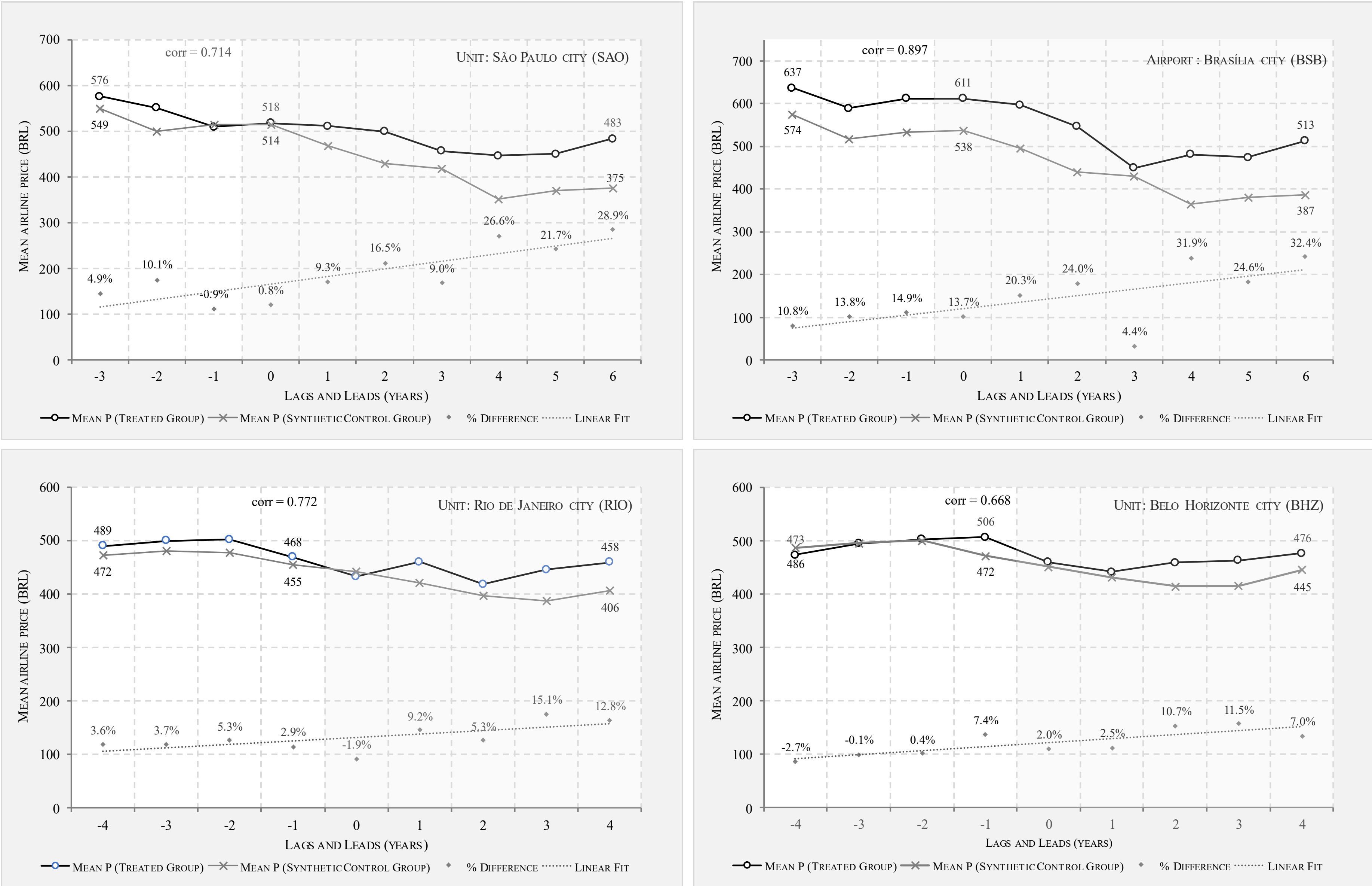
[16] In this estimation, the reported Hansen J statistic is equal to 0.5001, with a p-value of 0.4795.

[17] We do not include cities in the distant Northern region of Brazil, since they are far from the privatized airports.

the pre-treatment period is above 0.66, indicating a good association between the series and providing evidence of parallel trends. In all cases, it is possible to observe that the percentage differences in prices between the treated group and the control group increase after the start of the treatment. The price differences estimated by the synthetic control method are between 7% (BHZ city) and 32.4% (BSB city) in the years after privatization. These results provide initial evidence that privatization may have contributed to an increase in the price of airline tickets.

Table 3 presents the estimation results from the first step of the endogenous switching regression model, namely the determinants of selection for privatization (PRV), as stated by Equations (2) and (3). Table 3 contains six columns, ranging from the most under-specified model in Column (1) to our preferred and complete model in Column (5). We estimate these specifications using a probit model. To check for the robustness of the results, Column (6) presents the results from a logit model. Overall, the proposed variables have intuitive results that are consistent with our ex-ante expectations. We find evidence that the government selected airports for privatization based on passenger movements (PAX), given that larger airports are generally more attractive to private investors due to revenue potential. In addition, INC and POP have positive and statistically significant effects. POLINFL reveals the statistically significant influence of political factors on the privatization decision. Finally, the estimation results show evidence that airports with a higher intensity of flight connections (HUB), proportion of international passenger traffic (INTNL) and congestion issues (CONGEST), may drive the government's decision making when selecting airports for concession. The estimates in Column (6) are consistent with our main results, thus confirming the robustness of the results.

Table 4 presents the main empirical results for Equation (1). We first discuss the control variables. As expected, fuel price (FUEL) has a positive influence on airfares, similar to the result found by Wadud (2015). The estimated coefficient for the number of passengers per flight (PAXPF) is negative and statistically significant in most models, suggesting the effects of economies of traffic density. The estimated parameter for airport landing fees (FEE) is generally positive and statistically significant. This result suggests that airlines may pass these charges through to airfares.



Notes: Estimation results produced by synthetic control method for causal inference in comparative case studies of Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010, 2014). The specification is the same of Equation (1).

Figure 2 - Privatization effects estimated by synthetic control method - SAO, BSB, RIO, and BHZ

Table 3 - Estimation Results - first step of the Heckman model (determinants of PRV)

	(1)	(2)	(3)	(4)	(5)	(6)
ln PAX	0.0510***	0.0149***	0.0062***	0.0071***	0.0066***	0.0102***
ln INC		1.1098***	1.1336***	0.9442***	1.0641***	1.8505***
ln POP		0.7150***	0.8085***	0.6042***	0.5887***	1.0033***
HUB			0.0280***	0.0280***	0.0278***	0.0486***
INTERNL			0.0378***	0.0461***	0.0451***	0.0952***
CONGEST				0.0160***	0.0166***	0.0273***
POLINFL					0.0069***	0.0113***
Estimator	PROBIT	PROBIT	PROBIT	PROBIT	PROBIT	LOGIT
AIC Statistic	78,654	70,638	68,901	66,676	66,604	66,745
BIC Statistic	78,672	70,675	68,956	66,740	66,677	66,818
Nr Observations	68,970	68,970	68,970	68,970	68,970	68,970

*Notes: Dependent variable: PRV. Estimation results in Columns (1)-(5) produced by a probit model; results in Column (6) produced by a logit model. Blank cells indicate that the variable was not used. P-value representations: ***p<0.01, ** p<0.05, * p<0.10.*

The share of flights during congested hours (CONGEST) has a positive influence on airfares in Columns (3)-(6).[18] The positive effect of CONGEST is intuitive and may be due to the emergence of price premiums charged during periods of high demand (Hofer, Windle & Dresner, 2008). Moreover, during congested periods, the occurrence of delays is common, representing higher operating expenses for airlines. Finally, airport congestion internalization pricing behavior by carriers may arise (Brueckner, 2002; Wan, Jiang & Zhang, 2015; Bendinelli et al., 2016; Guo, Jiang & Wan, 2018; Miranda & Oliveira, 2018).

An increase in flight frequencies on a route (FREQ) has a decreasing effect on fares, perhaps due to lower costs stemming from higher asset utilization by the airlines on busier routes (Schmidt, 2017). The mean flight time duration (FLTIME) has a positive influence on airfares. This result is expected since longer flights are more costly to operate, in general, than shorter flights (Zuidberg, 2014). The mean age of aircraft on a route (AGE) has a positive effect on prices, consistent with higher operating costs for older aircraft (Oliveira et al, 2021).

Regarding the profile of passengers served on a route, the tourism variable (TOUR) has a negative coefficient in most specifications. Morlotti et al. (2017) present evidence that the price elasticity of demand for business passengers is lower than for passengers traveling for leisure, which could contribute to the lower fares charged by airlines on tourist-oriented routes.

[18] In these specifications, the concentration variables are accounted for, suggesting that CONGEST is correlated with unobserved factors that engender market and airport concentration.

Table 4 - Estimation results: airline price (ln P)

	(1)	(2)	(3)	(4)	(5)	(6)
FUELP	0.2344***	0.2015***	0.2443***	0.2403***	0.2404***	0.2516***
PAXPF	-0.0100***	-0.0419***	-0.0094	-0.0169**	-0.0173**	-0.0085
FEE	0.0053*	0.0926***	0.0260**	0.0221**	0.0222**	0.0171
CONGEST	-0.0001	-0.0000	0.0015***	0.0014***	0.0015***	0.0024***
FREQ	-0.0936***	-0.1065***	-0.0235***	-0.0244***	-0.0238***	-0.0247***
FLTIME	0.0417***	-0.0136	0.0414**	0.0307*	0.0297*	0.0448***
AGE	0.0044***	0.0025***	0.0075***	0.0071***	0.0071***	0.0075***
TOUR	-0.0096	-0.0519***	-0.0965***	-0.1071***	-0.1084***	-0.0967***
ENTRY	-0.1390***	-0.1276***	-0.0783***	-0.0699***	-0.0693***	-0.0694***
HUB	0.2384***	0.2063***	0.1924***	0.1839***	0.1835***	0.3741***
HHIroute			1.0063***	1.0237***	1.0393***	1.0178***
HHIcity			0.5554***	0.5538***	0.5379***	0.4588***
PRV				0.0335***	0.0345***	0.0287***
PLA					0.0025	0.0051
MILLS						0.0984**
Estimator	FE/IV/LASSO	FE/IV/LASSO	FE/IV/LASSO	FE/IV/LASSO	FE/IV/LASSO	FE/IV/LASSO
Panel Time Controls	101/101	101/101	101/101	101/101	101/101	101/101
IV Count	-	33/160	36/160	35/160	35/160	35/160
AIC Statistic	-4,031	-165	857	1,107	1,289	205
BIC Statistic	-3,043	823	1,862	2,121	2,312	1,237
UnderId Statistic	-	596	405	421	417	426
WeakId Statistic	-	19	12	13	13	13
RMSE Statistic	0.2348	0.2434	0.2457	0.2463	0.2467	0.2442
Nr Observations	54,071	54,071	54,071	54,071	54,071	54,071

*Notes: Dependent variable: ln P. Estimation results in Columns (2)-(6) produced by the instrumental variables, post-double-selection LASSO-based methodology of Belloni et al. (2012), Belloni, Chernozhukov & Hansen (2014a,b), with fixed effects (IV-LASSO). Post-LASSO estimation is performed with a Two-Stage Least Squares, fixed-effects, procedure with standard errors robust to heteroskedasticity and autocorrelation. Column (1) implemented with OLS and post-double-selection LASSO. Time effects estimates omitted. Blank cells indicate that the variable was not used. PRV, PLA, MILLS, and time effects penalized by LASSO. Endogenous variables: PAXPF, FEE, HHIroute, and HHIcity. UnderId and WeakId mean the statistics associated with, respectively, the Kleibergen-Paap rk LM test of underidentification and the Kleibergen-Paap rk Wald F test of weak identification. P-value representations: ***p<0.01, ** p<0.05, * p<0.10.*

The estimated parameters for the competition- and hub-related variables are consistent across the columns of Table (4). Market concentration on a city pair (HHIroute) has a positive impact on fares. The concentration level at an airport (HHIcity) positively impacts fares, similar to market concentration at the route level. The estimated effect of ENTRY is negative and statistically significant. An increase in the number of connecting passengers at an airport (HUB) also contributes to higher fares, in a process that may be related to market dominance stemming from hubbing. These results are in line with the conclusions of previous empirical work, such as Evans and Kessides (1993), Hofer, Windle & Dresner (2008), and Zou & Hansen (2014), among others.

Finally, we turn attention to our variable of interest. The estimated coefficient for the privatization dummy (PRV) is positive and statistically significant. In contrast, the estimated coefficient for the control/placebo group (PLA) is not statistically significant, suggesting that fares at the control airports are not different from the overall fare level in Brazil. This result indicates that, *ceteris paribus*, fares on routes to/from privatized airports are higher than on routes between two publicly operated airports. This result remains the same when we run the endogenous switching model by introducing the inverse mills ratio (MILLS) variable in Column (6).[19] The results of the models in Columns (4) to (6) of Table 4 point to prices between 3% and 3.5% higher on routes with privatized airports compared to routes in the control group.

Once we observe an estimated positive and statistically significant difference between the mean prices of routes involving privatized and non-privatized airports, a crucial issue concerns the reasoning behind these results. To investigate the higher airline prices on routes with privatized airports we introduce interaction variables. We suspect two reasons for the higher prices on routes with privatized airports are the following: 1. Different costs at privatized airports due to operating efficiencies leading to the establishment of airline fees below the regulated price cap; and/or 2. Greater market dominance at privatized airports stemming from airline-airport vertical relations. In the first case, the FEE variable alone may not capture the effects of the regulatory regime on airline prices. In the second case, concentration at the airport level, as measured by HHIcity, may be influenced by privatization. In short, the FEE and HHIcity variables may moderate the impact of airport privatization on airfares.[20] To make the analysis more accurate, we use fees and concentration variables computed specifically for the privatized airports - and not for the city mean, denoting these regressors with indicator "p": FEEp and HHIcityp. Table 5 presents the estimation results with the moderating variables.

[19] The result in Column (6) is not altered when we apply a stratified bootstrap estimation procedure to the endogenous switching model.

[20] We thank one of the anonymous reviewers for suggesting this analysis.

Table 5 - Estimation results: airline price (ln P) - interaction variables

	(1)	(2)	(3)	(4)	(5)	(6)
FUELP	0.2398***	0.2473***	0.2479***	0.2506***	0.2372***	0.2477***
PAXPF	-0.0106	-0.0045	-0.0046	-0.0031	-0.0102	-0.0078
FEE	0.0256**	0.0219**	0.0221**	0.0009	0.0100	0.0082
CONGEST	0.0014***	0.0020***	0.0020***	0.0019***		0.0008**
FREQ	-0.0195***	-0.0201***	-0.0194***	-0.0171***	-0.0165***	-0.0155***
FLTIME	0.0441***	0.0545***	0.0542***	0.0567***	0.0444**	0.0487***
AGE	0.0076***	0.0079***	0.0079***	0.0082***	0.0080***	0.0080***
TOUR	-0.1037***	-0.0957***	-0.0967***	-0.0977***	-0.1042***	-0.1039***
ENTRY	-0.0625***	-0.0624***	-0.0619***	-0.0579***	-0.0616***	-0.0589***
HUB	0.1863***	0.3267***	0.3236***	0.3103***	0.0476	
HHIroute	1.1540***	1.1387***	1.1560***	1.1149***	1.0322***	1.1137***
HHIcity	0.2380	0.1867	0.1622	0.4095**	0.7227***	0.5315***
PRV	-0.0544***	-0.0582***	-0.0583***	-0.0492***	-0.0392**	-0.0452***
PRV × FEEp	-0.0001	-0.0002	-0.0002	0.0002	0.0002	0.0005
PRV × HHIcityp	0.2313***	0.2308***	0.2332***	0.2130***	0.2083***	0.2146***
PLA			0.0025	-0.0028	0.0902	0.0516
PLA × FEE				0.0096	0.0044	0.0057
PLA × HHIcity				-0.1649**	-0.2785***	-0.2157***
MILLS		0.0721*	0.0707*	0.0628	-0.0717***	-0.0522**
Estimator	FE/IVLASSO	FE/IVLASSO	FE/IVLASSO	FE/IVLASSO	FE/IVLASSO	FE/IVLASSO
Panel Time Controls	101/101	101/101	101/101	101/101	101/101	101/101
IV Count	35/160	35/160	35/160	34/160	34/160	34/160
AIC Statistic	1,418	859	1,092	1,524	2,301	2,330
BIC Statistic	2,450	1,900	2,142	2,592	3,360	3,389
UnderId Statistic	419	420	416	336	340	333
WeakId Statistic	13	13	13	11	11	10
RMSE Statistic	0.2470	0.2457	0.2462	0.2472	0.2490	0.2490
Nr Observations	54,071	54,071	54,071	54,071	54,071	54,071

*Notes: Dependent variable: ln P. Estimation results in Columns (1)-(4) produced by the instrumental variables, post-double-selection LASSO-based methodology of Belloni et al. (2012), Belloni, Chernozhukov & Hansen (2014a,b), with fixed effects (IV-LASSO). Post-LASSO estimation is performed with a Two-Stage Least Squares, fixed-effects, procedure with standard errors robust to heteroskedasticity and autocorrelation. Time effects estimates omitted. Blank cells indicate that the variable was not used. PRV, PLA, MILLS, and time effects penalized by LASSO. Endogenous variables: PAXPF, FEE, HHIroute, and HHIcity. UnderId and WeakId mean the statistics associated with, respectively, the Kleibergen-Paap rk LM test of underidentification and the Kleibergen-Paap rk Wald F test of weak identification. P-value representations: ***p<0.01, ** p<0.05, * p<0.10.*

It is possible to observe in Table 5, that in all specifications the coefficients for the interaction term, PRV × FEEp, are not statistically significant, while the coefficients for the interaction term, PRV × HHIcityp, are statistically significant and positive. Therefore, we find strong evidence pointing to higher airline prices in privatized airports related to airport concentration.

It is important to note that once the interaction variables are plugged into the models, the coefficient for the PRV variable becomes negative. However, this flipped sign does not imply a price reduction effect, given that the relevant impact in this case is the estimated full effect of privatization, taking into account the coefficients and values of PRV × FEEp and PRV × HHIcityp. At the sample means for these variables, the estimated full effect of PRV remains positive. These results are consistent after introducing MILLS, in Column (2), and the placebo variables and their interactions, PLA, PLA × FEE, and PLA × HHIcity, in Columns (3) to (4). Finally, Columns (5) and (6) present the estimation results when dropping CONGEST and HUB, respectively, with consistent results.

5. Robustness analysis

Table 6 and Table 7 present a series of robustness checks to assess the sensitivity of our main results. First, in Table 6, Column (1), we run the model using an alternative metric for FEE, in this case calculated as the geometric mean of landing fees at the origin and destination airports. In Column (2), we consider a simpler specification of the baseline model, in which we discard the operation variables FREQ, FLTIME, and AGE. In Column (3), we drop CONGEST, HUB, and HHIcity, which are airport-related factors. In Column (4), we discard FEE from the list of endogenous variables to be instrumented and include it as an exogenous variable. In Column (5), we do the same procedure for HHIcity. In Column (6), we disaggregate the PRV and PLA variables to consider breakdowns for privatized airports at the origin, destination, and both origin and destination. In all cases, major results are consistent with our main model.

Table 7 presents the results obtained by the specifications employing Propensity Score Matching (PSM) to select the placebo group of airports. We use probit regression to estimate the probability of an airport being selected for privatization employing data from the pre-treatment period. Based on estimated coefficients, we calculate propensity scores for all airports in the dataset. We employ the Nearest Neighbor and the Caliper algorithms to match a privatized airport to the closest airports with respect to the estimated propensity scores. Next Neighbor algorithm results are presented in Columns (1) and (3) and the Caliper algorithm results in Columns (2) and (4). Again, results are consistent with our main conclusions, thus confirming the statistical significance for the variables PRV and PRV × HHIcityp, and the absence of statistical significance for the variables PLA and PRV × FEEp.

Table 6 - Robustness checks (1): airline price (ln P)

	(1)	(2)	(3)	(4)	(5)	(6)
FUELP	0.2490***	0.2233***	0.2559***	0.2599***	0.2621***	0.2505***
PAXPF	-0.0125*	-0.0449***	-0.0128*	-0.0064	-0.0137*	-0.0107
FEE	0.0053	0.0304***	0.0419***	-0.0020	0.0215**	0.0186*
CONGEST	0.0025***	0.0006		0.0027***	0.0031***	0.0023***
FREQ	-0.0227***		-0.0249***	-0.0159***	-0.0281***	-0.0257***
FLTIME	0.0376**		0.0369**	0.0483***	0.0348**	0.0413**
AGE	0.0072***		0.0067***	0.0076***	0.0064***	0.0074***
TOUR	-0.1035***	-0.0981***	-0.0955***	-0.1019***	-0.1011***	-0.0987***
ENTRY	-0.0679***	-0.0905***	-0.0849***	-0.0661***	-0.0730***	-0.0682***
HUB	0.3740***	0.2350***		0.3928***	0.4269***	0.3624***
HHIroute	1.0641***	0.7136***	1.0665***	1.1786***	1.1709***	1.0042***
HHIcity	0.4447***	0.3488**		0.2855*	-0.2934***	0.4887***
PRV	0.0302***	0.0361***	0.0339***	0.0284***	0.0252***	
PLA	0.0041	0.0142	0.0028	0.0021	0.0050	
PRVo						0.0310***
PRVd						0.0284***
PRVo & PRVd						0.0306***
PLAo						0.0076
PLADd						0.0255
MILLS	0.0955**	0.0340	-0.0949***	0.1023***	0.1145***	0.0912**
Estimator	FE/IVLASSO	FE/IVLASSO	FE/IVLASSO	FE/IVLASSO	FE/IVLASSO	FE/IVLASSO
Panel Time Controls	101/101	101/101	101/101	101/101	101/101	101/101
IV Count	32/160	35/160	34/160	21/160	34/160	34/160
AIC Statistic	905	-2,084	-611	2,210	483	170
BIC Statistic	1,938	-1,079	394	3,243	1,515	1,229
UnderId Statistic	406	505	562	412	493	429
WeakId Statistic	14	14	18	21	15	14
RMSE Statistic	0.2458	0.2391	0.2424	0.2488	0.2448	0.2441
Nr Observations	54,071	54,071	54,071	54,071	54,071	54,071

*Notes: Dependent variable: ln P. Estimation results in Columns (1)-(6) produced by the instrumental variables, post-double-selection LASSO-based methodology of Belloni et al. (2012), Belloni, Chernozhukov & Hansen (2014a,b), with fixed effects (IV-LASSO). Post-LASSO estimation is performed with a Two-Stage Least Squares, fixed-effects, procedure with standard errors robust to heteroskedasticity and autocorrelation. Time effects estimates omitted. Blank cells indicate that the variable was not used. PRV, PLA, MILLS, and time effects penalized by LASSO. Endogenous variables: PAXPF, FEE, HHIroute, and HHIcity. UnderId and WeakId mean the statistics associated with, respectivelly, the Kleibergen-Paap rk LM test of underidentification and the Kleibergen-Paap rk Wald F test of weak identification. P-value representations: ***p<0.01, ** p<0.05, * p<0.10.*

Table 7 - Robustness checks (2): airline price (ln P)

	(1)	(2)	(3)	(4)
FUELP	0.2508***	0.2486***	0.2454***	0.2444***
PAXPF	-0.0084	-0.0096	-0.0049	-0.0060
FEE	0.0172	0.0207*	0.0224**	0.0262**
CONGEST	0.0024***	0.0023***	0.0020***	0.0019***
FREQ	-0.0247***	-0.0260***	-0.0196***	-0.0210***
FLTIME	0.0456***	0.0438**	0.0544***	0.0525***
AGE	0.0075***	0.0075***	0.0079***	0.0079***
TOUR	-0.0964***	-0.0974***	-0.0967***	-0.0975***
ENTRY	-0.0695***	-0.0694***	-0.0621***	-0.0621***
HUB	0.3770***	0.3703***	0.3282***	0.3212***
HHIroute	1.0154***	0.9916***	1.1542***	1.1244***
HHIcity	0.4646***	0.5171***	0.1660	0.2306
PRV	0.0261***	0.0237***	-0.0614***	-0.0619***
PLA	-0.0060	-0.0089	-0.0152	-0.0114
PRV × FEEp			-0.0002	-0.0002
PRV × HHIcityp			0.2330***	0.2298***
MILLS	0.0992**	0.0958**	0.0721*	0.0686*
Estimator	FE/IVLASSO	FE/IVLASSO	FE/IVLASSO	FE/IVLASSO
PSM algorithm	NxtNeighb	Caliper	NxtNeighb	Caliper
Panel Time Controls	101/101	101/101	101/101	101/101
IV Count	35/160	36/160	35/160	36/160
AIC Statistic	204	171	1,066	820
BIC Statistic	1,236	1,204	2,116	1,870
UnderId Statistic	415	437	409	430
WeakId Statistic	13	13	13	13
RMSE Statistic	0.2442	0.2441	0.2461	0.2456
Nr Observations	54,071	54,071	54,071	54,071

*Notes: Dependent variable: ln P. Estimation results in Columns (1)-(4) produced by the instrumental variables, post-double-selection LASSO-based methodology of Belloni et al. (2012), Belloni, Chernozhukov & Hansen (2014a,b), with fixed effects (IV-LASSO). Post-LASSO estimation is performed with a Two-Stage Least Squares, fixed-effects, procedure with standard errors robust to heteroskedasticity and autocorrelation. Time effects estimates omitted. Blank cells indicate that the variable was not used. PRV, PLA, MILLS, and time effects penalized by LASSO. Endogenous variables: PAXPF, FEE, HHIroute, and HHIcity. UnderId and WeakId mean the statistics associated with, respectively, the Kleibergen-Paap rk LM test of underidentification and the Kleibergen-Paap rk Wald F test of weak identification. P-value representations: ***p<0.01, ** p<0.05, * p<0.10.*

6. Conclusions

This study develops econometric models to investigate whether the privatization of airports in Brazil affect airline prices in the domestic market. We employ a difference-in-difference approach that accounts for differences between the treatment group (consisting of routes with at least one privatized airport) and the placebo group (with publicly owned airports at both endpoints). We combine this model with an endogenous switching regression framework, equivalent to a Heckman model to account for the selection of airports for privatization by the government. Our framework employs post-double selection IV-LASSO estimation with two-way fixed effects.

The literature suggests that government motivations for airport privatization include the opportunity to attract investments for expansion projects, the possibility of rapidly raising funds, and the improvement in operational efficiency. With the imposition of price caps, the Brazilian regulator inhibits privatized airports from exerting monopoly power to increase charges to airlines. However, our results provide evidence of a positive fare effect from privatization. Moreover, our results point to a statistically significant intensification effect of privatization on airfares associated with city-level concentration. We suggest that the results may be driven by vertical relationships between airlines and the privatized airports that can confer local competitive advantages to the airlines. However, the estimated fare effect is relatively small, around 3~3.5% of mean airline ticket prices. The main conclusions do not alter when we employ either propensity score matching or synthetic control methods instead of an ad hoc procedure to define our placebo group.

We highlight two limitations to our analysis. First, as the airport privatization rounds took place on different occasions during the sample period, we observe panel imbalances related to the number of lags and leads of the treatment event. Expanding the sample period to incorporate more recent airport privatization events that occurred in Brazil could improve the robustness of our analysis. Additionally, the quality of the passenger experience at airports is an unobserved effect in our setting. Given that privatized airports may engage in terminal expansions and renovations, and are subject to service quality regulation, the higher airfares estimated by our models may be associated with a higher willingness-to-pay for traveling on flights at these airports. We recommend further investigation to address these possibly relevant issues.

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