Transportation Research Part D 95 (2021) 102820

Contents lists available at ScienceDirect

Transportation Research Part D

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

Estimating fuel-efficiency while accounting for dynamic fleet management: Testing the effects of fuel price signals and fleet rollover

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A R T I C L E I N F O

JEL Classification:
D22
L11
L93

Keywords:
Fuel efficiency
Airlines
Fleet management
LASSO
High-dimension sparse model

A B S T R A C T

Fuel efficiency has become one of the most important policy goals for airline operations management. This study develops an econometric model to estimate airlines' fuel burn determinants, aiming to test the hypothesis of fuel price signals on carriers' incentives for energy-saving efforts. We propose a novel high-dimensional sparse IV-LASSO method to account for airline dynamic fleet management. Our model also provides controls for thousands of nuisance factors related to route direction, airway congestion, and aircraft model specificities, allowing for flexible time-varying unobserved effects of flight stages. The results show that energy intensity reduction induced by price increases was observed 3–4 years earlier, possibly due to fleet rollover and fleet modernization. Furthermore, although new competition may create incentives for improved fuel management to control costs, our results suggest that the overall effect of market deconcentration is unclear and may produce the unintended consequence of worse performance, as measured in some key fuel efficiency dimensions.

1. Introduction

Growing concern regarding environmental sustainability has motivated researchers to investigate the impacts of the use of carbon-intensive means of transport–and, in particular, commercial aviation–and alternatives to mitigate their emission of greenhouse gases. In parallel, the pursuit of fuel efficiency has become one of the most important policy goals for airlines operations management. Before the COVID-19 pandemic, the growth rates in demand for air travel surpassed the improvement rate in the energy efficiency of aircraft systems (Lee, 2010). Consistent with this, Gudmundsson and Anger (2012) describe that CO2 emissions from air transportation grow faster than the global economy, which justifies the increasing concerns about aviation's carbon footprint in society.

The existing literature has already raised the issue of fostering fuel savings in aviation through the introduction of technological advances (Morrison et al., 2010; McConnachie et al., 2013; Winchester et al., 2013; Zou et al., 2016; Brueckner and Abreu, 2017). However, few studies have focused on the determinants of fuel consumption and the resulting energy efficiency of airlines. Several operational, economic, and competition factors may determine the energy intensity in airline markets, making it necessary to assess each variable's relative strength inherent to the airline fuel burn phenomenon. In particular, we point to the need for a greater

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https://doi.org/10.1016/j.trd.2021.102820

understanding of the factors that motivate the introduction of technological innovations in the sector that allows for enhancements in energy efficiency across time. The companies who introduce technological innovations into the market are the original equipment manufacturers, such as Boeing and Airbus. It remains for the carriers to decide whether to adopt the original equipment manufacturers' innovations at each decision-making time. In general, carriers have two instruments for adopting innovation: (1) *fleet rollover*–to control the aging of the fleet with the introduction of new aircraft; and (2) *fleet modernization*–to acquire new-generation aircraft, that is, types of aircraft models and variants recently launched by manufacturers. In both cases, airlines may profit from fuel efficiency gains, with the benefits of reducing operating costs and reducing emissions.

This study aims to develop an econometric model to estimate airlines' main determinants of fuel consumption. The objective is to empirically examine the association between fuel price changes and the long-term incentives of carriers to foster fuel savings through investments in fleet rollover and fleet modernization. We formally test the existence of an effective signaling role for Jet A-1 prices that lead to more fuel-efficient strategic fleet planning, aligning the incentives of airlines with public interest. Therefore, the analysis contributes to the understanding of the long-term effectiveness of environmental taxation on aviation fuel.

We consider the case of Brazilian commercial aviation in the 2000 s and 2010 s. During this period, the industry experienced a set of shocks in fuel prices, caused by intense exchange rate volatility, as jet fuel is an input internally quoted in dollars, in addition to the 2008 global oil price shock. However, we recognize that our model has to deal with many unobservables, such as en-route flight procedures and wind conditions. Therefore, we propose a high-dimensional sparse IV-LASSO methodology by Belloni et al. (2012), designed to select among thousands of nuisance factors related to route direction, airway congestion, and aircraft model specificities, allowing for flexible time-varying unobserved effects of flight stages. The estimation also allows for the selection of instrumental variables within a high-dimensional set of candidates to account for endogeneity in the model.

Our first contribution relies on the development of proxies for fleet rollover and fleet modernization, which are incorporated into the econometric models of airline energy intensity. With these proxies, we aim to formally test the effects of airlines' technological innovation adoption on fuel burn. Our second contribution relies on the inclusion of controls for the dynamic fleet management (DFM) strategies of carriers, also known as demand-driven dispatch (Berge and Hopperstad, 1993; Wang and Meng, 2008; Fry and Belobaba, 2016). We propose a LASSO-based estimation approach to account for the possible effects of DFM practices. More specifically, our model controls the tail assignment tactics correlated with unobserved fuel management decisions–a possible source of omitted variable bias when estimating fuel efficiency determinants.

Our empirical results suggest that fuel price increases that occurred 3–4 years earlier are associated with increases in fuel efficiency. We find evidence that this outcome may be due to an intensification in fleet rollover and fleet modernization strategies by carriers. Our results also allow us to determine some of the market incentives for fuel-saving behavior created by competition in the airline industry.

This paper contains the following sections. Section 2 presents a literature review on aircraft fuel efficiency and technological innovation (2.1), the role of fuel price signals in airline fleet planning (2.2), and dynamic fleet management and fuel efficiency (2.3). Section 3 presents the research design, with details on the application (3.1), data (3.2), empirical model (3.3), estimation strategy (3.4), and accounting for dynamic fleet management (3.5). Section 4 contains the estimation results, with a detailed discussion of the effects of the dynamic fleet management controls (4.1). Section 5 presents the conclusions.

2. Literature review

2.1. Aircraft fuel efficiency and technological innovation

The literature on the environmental impacts of commercial aviation has become increasingly abundant as concerns about its carbon footprint in society have increased. Gudmundsson and Anger (2012) developed a *meta*-analysis of five studies in which they constructed basic scenarios for the emission of gases and concluded that technical progress plays a fundamental role in estimating future aviation CO2 scenarios. The adoption of technological innovation in this industry is a complex topic involving alternative fuels, air traffic control improvements, better management of airline flight operations, and new generations of aircraft. Lee et al. (2001) presented a breakdown of efficiency gains until the mid-1990s, describing that reductions in the energy intensity of aviation occurred mainly due to efficiency improvements of engines (57%), aerodynamics (22%), and enhanced use of the aircraft's capacity (17%), among other factors.

Regarding motorization, Snow (2011) described that the basic architecture of the original high-bypass engine of past generation aircraft in commercial aviation remains the same in current jets; however, there have been numerous improvements in engine design over the years. According to the author, the deviation bypass ratio was optimized to allow for outstanding performance. With higher internal operating temperatures, the combustion process is considerably more complete and leaner, and the entire operation is controlled electronically instead of hydromechanically. Lee (2010) showed that engines' cruise-specific fuel consumption improved by approximately 40% between 1959 to 2000. Pisarek (2017) described that some modern jets have already reached relatively low values of 3.5 L of fuel consumption values of 100 passenger-kilometers.

Regarding the aerodynamics of large commercial aircraft, Abbas et al. (2013) discussed the use of technologies to reduce laminar and turbulent drag and flow control devices. Lee (2010) highlighted the improvements obtained over the years in wing design and integration between propulsion and airframe, based on computational and experimental design tools. McConnachie et al. (2013) found evidence based on interviews with airline representatives that winglets effectively improve fuel efficiency–between 2% and 3% less burn depending on the flight stage's length.

Regarding airframe materials, Lee (2010) demonstrated that, for decades, large commercial aircraft were built almost exclusively of aluminum. In more recent generations, especially with the development of the Boeing 787 Dreamliner and Airbus A350, aluminum has been replaced by composite materials such as carbon fiber or fiberglass reinforced plastic, among other possibilities. Alemour, Badran, and Hassan (2019) described several advantages that the innovation allowed by the use of composite materials in the fuselage and wing structures brought to aircraft design. They can be manufactured to be light and have high resistance to damage, fatigue, and corrosion caused by weather and harsh chemicals, and can be molded into complex shapes more easily than other materials. The authors said that the weight reduction allowed by the use of composite materials reached 20% in the case of the 787 Dreamliner. Additionally, they indicated that each generation of Boeing's new aircraft had a higher incremental percentage of composite material, with the highest being approximately 50% by the 787 Dreamliner.

Regarding the technological innovations that are expected to be implemented on a larger scale in the future, we have alternative jet fuels. Analyzing hydrogen, Lee (2010) presented new pros and cons of technology. The author argued that although hydrogen-powered engines do not generate CO2 emissions at the point of use and can reduce NOx and particulate emissions, they may increase water vapor emissions threefold, contributing to the trail formation of cirrus clouds. According to the US Department of Energy (2017), biofuels are essential for mitigating growth restrictions in the aviation industry, allowing an excellent opportunity for the discontinuation of the use of fossil fuels. The study describes five aviation jet fuel production pathways certified by ASTM International, with maximum blending levels ranging between 10% and 50%, depending on the type: (1) Synthesis gas (syngas) FT synthetic paraffinic kerosene (FT-SPK); (2) Hydro-processed lipids (HEFA-SPK); (3) biochemical sugars– hydro-processed fermented sugars to synthetic isoparaffins (HFS-SIP); (4) syngas FT synthetic paraffinic kerosene, along with the alkylation of light aromatics (FT-SPK/A) and isobutanol conversion (ATJ-SPK). This study presents seven other pathways in line for certification. Each pathway has advantages and disadvantages in addition to the costs related to Jet A-1 fuel. Many recent studies have analyzed the innovation potential of these alternative jet fuels, such as Winchester et al. (2015), Kousoulidou and Lonza (2016), Wang and Tao (2016), Rondinelli et al. (2017), Grampella et al. (2017b), and Kieckhäfer et al. (2018).

2.2. *The role of fuel price signals in airline fleet planning*

The function of prices in a market economy is to provide buyers and sellers with the necessary information about the relative scarcity of a product or service. Regarding buyers, high prices can generate incentives for the substitution of the product in the short, medium, or long term when these alternatives exist. This basic economic principle is particularly relevant in the vehicle and fuel sales markets. Klier, Linn, and Zhou (2020) discussed the motivational factors on the demand side for adopting fuel-saving technologies. The authors argue that fuel costs increase with the price of fuel and decrease with fuel economy. Additionally, a rise in fuel prices would increase consumers' willingness to pay for a given fuel economy improvement.

Leard, McConnell, and Zhou (2019) developed a case study of new vehicle acquisitions by private companies and government agencies in the United States. They find evidence that purchases of low-fuel-economy vehicles fall relative to high-fuel-economy vehicles when gasoline prices increase. They estimate that a one-dollar increase in gasoline price is related to an increase in the fuel economy of new vehicles of 0.33 miles per gallon. Klier, Linn, and Zhou (2020) studied the effects of vehicle sales and fuel prices on fuel-saving technology adoption in passenger vehicles. They find evidence of a strong relationship between vehicle sales and energy efficiency, which allows them to conclude that manufacturers focus on technological improvements in the best-selling vehicles. They also find a positive relationship between the price of fuel and the adoption of technological innovations.

In the commercial aviation sector, many studies have suggested the role of fuel prices as a tool to create market incentives that reduce the energy intensity of airlines (Schlumberger, 2012; Wormslev et al., 2016; Murphy et al., 2018). This hypothesis of fuel price signals has motivated discussions about the application of levies on aircraft, fuel, or tickets, such as the air passenger duty (APD) in the United Kingdom and debates on the evolution of emissions trading schemes (ETS) in the European Union, as well as the agenda of the introduction of global sectoral market-based measures by the International Civil Aviation Organization (ICAO).

The fuel price signals that the underlying mechanism of the hypothesis consists of airlines responding to increased fuel costs through adjustments in their operations over time to enhance their fuel efficiency. As a response to increased fuel costs, carriers may increase ticket prices and freight charges for holding cargo. They may also introduce or raise existing checked baggage fees and fuel surcharges. Airlines may optimize cruise speeds in line with updated cost indexes on the flight management side, reduce the mandatory contingency fuel levels, control pilots' use of landing flaps, thrust reversers, and encourage delayed deceleration approaches–Dumont (2012), among others. Additionally, carriers may intensify some preventive maintenance measures such as jet engine washes and employ direct weight reduction measures, using zonal dryer units to remove moisture from the upper fuselage or the cargo area.

Clark (2017) observed that firms have relatively little flexibility in adapting to changes in market conditions in the short term. In the medium term, carriers may perform flight frequency changes, route structure, and served markets (Brueckner and Zhang, 2010; Morrison et al., 2010). For example, they may cut short-stage-length traffic in their networks. However, some of these measures may generate the unintended outcome of forcing the airline to cancel or postpone the receipt of new, possibly more fuel-efficient aircraft (Winchester et al., 2013; McConnachie et al., 2013).

One of the possibilities for carriers responding to fuel price increases would be to revise their long-term strategic fleet planning. In the years since deregulation, airlines have endeavored to make their fleet plans more flexible through periodic reassessments, increasingly aligning them with market conditions. With fleet rollover intensification, an airline can foster the replacement of older aircraft with newer ones of a similar generation. Another option is to modernize its fleet through the acquisition of a newer generation aircraft. For example, an airline may replace some old Airbus A320 airplanes with the more recently launched model A320neo. In this case, the carrier will concomitantly perform *fleet rollover with fleet modernization*. McConnachie, Wollersheim, and Hansman (2013) described, based on interviews with representatives of four major airlines in the United States, that carriers view fleet modernization as the best way to improve fuel efficiency. In our illustration, if the airline opts to acquire younger airplanes of the same A320 type, namely the A320ceo series, we infer that it will be performing *fleet rollover without fleet modernization*.

We aim to empirically test the hypothesis of fuel prices sending signals for airlines to increase their energy efficiency—a topic which remains underexplored. The works that most closely match our approach are Wadud (2015), Brueckner and Abreu (2017, 2020), and Fukui and Miyoshi (2017), all of which report the US experience. Wadud (2015) performed a decomposition analysis of aviation fuel demand in the US with a seemingly unrelated regression, in an approach that allows for testing the short-term impact of changes in jet fuel prices on airline fuel efficiency. The author's results suggest that fuel prices increase both the mean load factors and fuel efficiency in the industry.

Brueckner and Abreu (2017) also investigated the short-term impact of fuel prices on airline fuel consumption. The authors estimate that an increase of USD 0.25/gallon would reduce fuel burn by 1.3% and that a tax of USD 0.04/kg of CO2 emitted would produce a reduction of 2.2%. However, the authors' analysis considered the level of fuel efficiency—the current state of aircraft technology—as given. They recognized that the observed fuel-saving effect may underestimate the actual effect, as it does not consider the long-term efforts that would result from increased aircraft size and fuel management practices of the airlines subject to taxation. Fukui and Miyoshi (2017) investigated the impact of short- and long-term changes in aviation fuel tax on fuel burn and carbon emissions using data from the US airline industry. They estimated a distributed lag model of US carriers' annual jet fuel consumption in gallons, using simultaneous quantile regression and year fixed effects.[1] They considered a lag length of 3 years. They estimated the short-run and long-run price elasticities of jet fuel consumption but found many coefficients of the fuel cost per gallon variables that are not statistically significant. Their results suggested that fuel consumption and CO2 emissions reduction would be smaller in the longer term due to a rebound effect. In a related paper, Brueckner and Abreu (2020) investigated the effect of fuel prices on fuel burn in the US airline market. The authors employed controls for airline fleet characteristics, namely dummy variables for the aircraft model type. They confirmed the findings of Brueckner and Abreu (2017, 2020), in which the fuel conservation effect triggered by higher fuel prices is also present in a more disaggregated empirical model.

We build upon these studies by considering econometric models of fuel consumption and fuel efficiency. Our contribution to the literature relies on the explicit incorporation of fleet rollover and fleet modernization into model specifications. In this sense, our model allows us to directly inspect the effects of the airline's technological innovation adoption through fleet renewal investments–a crucial issue for public and corporate policies, but has so far been relatively neglected by the empirical literature.

2.3. DFM and fuel efficiency

One of the relevant aspects of an airline's operations that may affect its fuel efficiency performance is DFM:"*the ability to swap aircraft with different capacities on or close to the day of operation*" (Holloway, 2008). Garrow et al. (2011) showed that in the late 1990s, airlines developed tools to allow swapping airplanes close to departure to better match supply with demand. Berge and Hopperstad (1993) described that the DFM, also known as demand-driven dispatch and close-in re-fleeting, performs demand forecast updates as flight departure approaches, so as to assign the most suitable airplane according to the expected number of enplanements.

Thus, one of the benefits of DFM is to enhance flexibility in the airline's strategic planning process, seeking to take into account the stochastic nature of demand (Fry, 2015; Fry and Belobaba, 2016). In particular, DFM allows for dynamic solutions to the tail assignment problem in line with the airline's revenue management system. According to Grönkvist and Kjerrström (2005), the tail assignment is the problem of designating specific aircraft for flights to enable the development of a robust and fully operational schedule that, at the same time meets operational restrictions and minimizes costs. Fry (2015) and Fry and Belobaba (2016) analyzed how high-demand flights can be up-gauged or down-gauged according to the objective of generating more revenue or reducing fuel consumption and saving operating costs through DFM. Şafak et al. (2019) studied aircraft swapping as a tool to provide flexibility in reducing fuel costs and adjusting capacity to the airline. It is important to note that DFM implementation efforts and capabilities vary from airline to airline, and over time, making the problem of non-observability in our model more complex. The literature addresses several facets of DFM, as in Wang and Regan (2006), Wang and Meng (2008), García and Cadarso (2017), Busing, Kadatz and Cleophas (2019), and Şafak, Atamtürk, and Aktürk (2019).

According to Fry and Belobaba (2016), most approaches to DFM involve a fleet assignment optimization model in a time–space network. Shebalov (2009) described two major approaches to the problem: (1) to begin with an aircraft routing solution that already exists and then identify local opportunities for a swap of airplanes; and (2) using traditional leg-based or origin–destination-based fleet assignment approaches to resolve the entire fleet re-assignment problem. The author describes that most airlines use a leg-based approach for capacity allocation. Concerning origin–destination-based fleet assignment, the author recognizes that they are still not fully incorporating the complexity of current revenue management systems. Fry and Belobaba (2016) stated that fleet reassignment closer to departure time benefits from the additional information about demand and remaining capacity obtained from the status of actual bookings for the flight and the more accurate forecasts of expected bookings. A major drawback of these practices is their possible adverse effects on crew scheduling, maintenance, gate assignments, and catering due to unanticipated changes in operational plans. The authors emphasize that DFM implementation has a major challenge associated with re-assignment optimum implementation time, which must be close enough to departure to take advantage of more accurate demand forecasts but must not be so close as to impose excessive burdens on the remaining airline operations.

In our case, the tail-assignment decisions of airlines have direct implications on their fuel efficiency performance. We present an

[1] See also Miyoshi and Fukui (2018).

estimation strategy proposal to account for the possible effects of the DFM in our empirical model.

3. Research design

3.1. Application

Our econometric model uses data from the domestic Brazilian airline industry from 2000 to 2018. In 2018, the market had two major airlines, Latam and Gol, and two medium-sized carriers, Azul and Avianca. Gol and Azul have been positioned as low-cost carriers (LCC) since the beginning of their operations in 2001 and 2008, respectively. Other small carriers operated on regional routes. Table 1 presents a set of economic and operational indicators for the industry. 95.9 billion revenue-passenger kilometers (RPK) were produced in 2018, representing more than double the amount observed in 2000—an increase of 280.1%, from 25.2 billion. The increase in aviation fuel burning in the same period was 71.3%—from 2.1 in 2000 to 3.6 billion liters in 2018. This evolution resulted in a significant increase of 121.9% in fuel efficiency measured by RPK per liter of fuel, from 12.0 (2000) to 26.7% (2018).

Table 1 also shows the evolution of mean market concentration (HHI), jet fuel price, and fleet age. Due to the global oil price shock of the late 2000 s, there was a notable upsurge of 75.2% in fuel price from R$ 1.29 (2000) to R$ 2.25 (2010). In 2018, the mean fuel price was R$ 2.55, which was 13.2% higher than that in 2010. In parallel, the mean fleet age of Brazilian carriers fell by 22.6%, from 9.8 (2000) to 7.6% (2018), with a considerable part of this evolution observed from 2000 to 2010, with a 20.8% fall. There was also a decrease in market concentration by 12.0%, with the mean Herfindahl–Hirschman index (HHI) across routes dropping from 0.52 (2000 to 0.46 (2018, which is suggestive of an intensification of competition. In summary, the period under investigation is marked by extraordinary growth in demand, followed by an increase in carriers' fuel efficiency. We suspect that a significant portion of these fuel efficiency gains may have originated from the more significant rivalry between carriers, which fostered cost competitiveness in the market. We aim to examine whether these gains may also be associated with the more intense fleet renewal observed in the industry, possibly signaled by the period's higher price of aviation fuel.

3.2. Data

Our dataset consists of a panel of 997 domestic city-pairs in Brazil, with monthly observations between January 2000 and December 2018.[2] We group multiple airports belonging to the same city region.[3] We discard routes with less than one hundred passengers in a month and with less than six observations in the sample period. Air transport data are publicly available from the National Civil Aviation Agency (ANAC) on its website. ANAC supplies data on all the scheduled flights on the Active Scheduled Flight Historical Data Series (VRA). Another ANAC's online dataset is the Air Transport Statistical Database, air transport supply, and demand information at the aggregated (route) and disaggregated (flight) levels.[4] We also use jet fuel price information from the National Agency for Petroleum, Natural Gas, and Biofuels' (ANP) website. Our primary source of fleet characteristics of each airline is ANAC's Brazilian Aeronautical Registry (RAB). Additionally, we collect data on each aircraft registration's first flight and delivery dates from the websites planelogger.com, airfleets.net, jetphotos.com, and aviacaopaulista.com.[5] These websites are electronic databases for plane spotting which contain detailed information on each aircraft in the manufactures' historical construction lists, including the serial numbers, model and variant, recording plane registration/tail number, first flight and/or delivery dated, current and past operators, among others. In many cases the databases also display a photo of the aircraft. See the Appendix for a detailed presentation of each data source.

3.3. Empirical model

Equation (1) presents our baseline model of airline fuel consumption in Brazil.

$$\begin{aligned}\mathrm{FUEL}_{k,t} = {} & \delta_1\mathrm{FLTIME}_{k,t} + \delta_2\mathrm{FREQ}_{k,t} + \delta_3\mathrm{ASIZE}_{k,t} + \delta_4\mathrm{MASS}_{k,t} + \delta_5\mathrm{TPR}_{k,t} + \delta_6\mathrm{SLOT}_{k,t} + \delta_7\mathrm{HUB}_{k,t} + \delta_8\mathrm{AGE}_{k,t} + \delta_9\mathrm{FLMOD}_{k,t} \\ & + \delta_{10}\mathrm{HHI}_{k,t} + \delta_{11}\mathrm{LCC}_{k,t} + \delta_{12}\mathrm{TREND}_t + \mathrm{v}_{k,t}\end{aligned} \tag{1}$$

where k denotes the domestic city-pair and t the periods ($t = 1, \ldots, 174$ months). Below, we briefly discuss the components of Equation (1).[6] Table 2 presents a detailed description of the model variables and their interpretation. In the Appendix, we discuss each of the data sources and present the descriptive statistics of the main variables (Table 6).

[2] The number of sample periods is 226. Due to the 2014 World Cup's unique procedures, the regulator could not provide information about June and July.

[3] São Paulo, Rio de Janeiro, and Belo Horizonte metroplexes.

[4] See www.nectar.ita.br/avstats for a description of Brazilian air transport data and links to the original databases.

[5] To guarantee our results' reproducibility, we uploaded the complete survey dataset and the respective commands used on the Harvard Dataverse © platform. The dataverse is available at https://doi.org/10.7910/DVN/HNHJHU.

[6] To allow the interpretation of regression coefficients as elasticities, we use natural logarithms of all variables, except for fractions and indexes ranging between 0 and 1, and dummies.

Table 1
Airline market fundamentals, fuel efficiency, and fleet rollover dynamics in Brazil.

Years	RPK (Billion)	Fuel Burn (Billion Liters)	Fuel Efficiency (RPK/liter)	Market Concentration (HHI)	Jet Fuel Price (defl. reais)	Fleet Age (years)
2000	25.2	2.1	12.0	0.52	1.29	9.8
2010	69.9	3.3	21.1	0.47	2.25	7.8
2018	95.9	3.6	26.7	0.46	2.55	7.6
% Var						
2010/2000	*177.0%*	*57.8%*	*75.5%*	*−8.8%*	*75.2%*	*−20.8%*
2018/2010	*37.2%*	*8.5%*	*26.4%*	*−3.4%*	*13.2%*	*−2.3%*
2018/2000	***280.1%***	***71.3%***	***121.9%***	***−12.0%***	***98.3%***	***–22.6%***

Sources: Active Scheduled Flight Historical Data Series—VRA; Air Transport Statistical Database; Brazilian Aeronautical Registry—RAB; National Agency for Petroleum, Natural Gas and Biofuels—ANP; websites planelogger.com, airfleets.net, jetphotos.com, and aviacaopaulista.com; state-specific legislation and online media news; "RPK," "Fuel Burn" and "Fuel Efficiency" extracted at the national level for the domestic market; "Jet Fuel Price," "Aircraft Age," "Aircraft Model Age," and "Market Concentration" extracted at the city-pair level; figures computed with authors' calculations.

- $FUEL_{k,t}$ is our metric of aircraft fuel intensity. It is equal to the total fuel consumption in liters by the city-pairs scheduled flights (in logarithm).
- $FLTIME_{k,t}$ is the mean actual flight time in minutes (in logarithm).
- $FREQ_{k,t}$ is the total number of nonstop flights on the city-pair (in logarithm).
- $ASIZE_{k,t}$ is the mean aircraft seating capacity on the city-pair (in logarithm).
- $MASS_{k,t}$ is a proxy for the total aircraft load on the city-pair (in logarithm). It is equal to the number of passengers on the flight stage times 75 kg, plus the total cargo, mail, and baggage also in kilograms.
- $TPR_{k,t}$ is the proportion of flights of turboprop airplanes on the city-pair.
- $SLOT_{k,t}$ is the proportion of flights operated at slot-constrained airports on a city pair. It is the maximum proportion of flights operated at slot airports between the origin and destination cities.
- $HUB_{k,t}$ is a proxy for the hubbing activity of airlines. It is equal to the maximum proportion of passengers with fight connections at the origin and destination of a city pair. In calculating this variable, we consider only cities containing more than one percent of domestic traffic nationwide. This approach is consistent with the definition of a "large hub by the United States Federal Aviation Administration."
- $AGE_{k,t}$ is a proxy for the mean age of the aircraft assigned to the route (in logarithm). It is our metric for the airline fleet rollover. We considered the age of all operated airplanes on the date of each flight during the sample period. To calculate this variable, we use the plane's first flight date according to the information available in the Brazilian Aeronautical Registry of the National Civil Aviation Agency.[7] We supplement these data with each tail number collected from the websites planelogger.com, airfleets.net, jetphotos.com, and aviacaopaulista.com.
- $FLMOD_{k,t}$ is a proxy for the technological innovation adoption of carriers when introducing new-generation aircraft in the market. While $AGE_{k,t}$ is calculated considering the date when a given airplane first flew, FLMOD is calculated considering the date when the first airplane of its corresponding aircraft model first flew. In other words, it considers the date when the aircraft model–and not the particular aircraft–was first introduced. To develop this variable, we compute the mean age of the aircraft models for each route and period. Our indicator of airline fleet modernization is therefore equal to the logarithm of the inverse of the calculated mean age considering all the airplanes assigned to flights on the route, multiplied by 100, that is, ln ((1/mean model's age) $\times$ 100). The higher the aircraft model's age, the lower the FLMOD indicator. We calculate the ages considering the date of the first flight of the model's first aircraft. This information is available from queries on the websites of planelogger.com, airfleets.net, jetphotos.com, and aviacaopaulista.com. We expect that the new generation airplanes will contain technological improvements related to engines, aerodynamics, and composite materials that fuel airlines' fuel savings. The FLMOD proxy allows the assessment of how "modern" the airplanes are assigned to the markets concerning these possibly innovative attributes.

To illustrate the difference in ages computed in AGE and FLMOD, we use the following example. Consider the flight number GLO1520, operated on July 23, 2018, by Gol Airlines, between São Paulo (GRU) and Fortaleza (FOR). This flight was operated with the aircraft of tail number PR-GTP, which belongs to the Boeing 737–800 model. According to the website planelogger.com, the delivery date of that aircraft was August 9, 2007–see www.planelogger.com/Aircraft/Registration/PR-GTP. On the occasion of the Gol's GLO1520 flight, that airplane was almost 11 years old (captured by variable AGE). The model type 737–800 was launched by Boeing in 1994, with planelogger.com identifying its first flight on July 31, 1997–see www.planelogger.com/Aircraft/Registration/TC-SNY/516455. Thus, on the day of the GLO1520 flight, the assigned airplane's model age was 21 years (captured by variable FLMOD).

[7] In most cases, the first flight date is the reference for calculating the airplane's age. In the absence of this information, we use the date of aircraft delivery.

Table 2
Model variables description and interpretation.

Variable	Description	Interpretation	Metric	References
regressands				
FUEL	Fuel consumption.	Total fuel intensity.	Liters (ln).	Winchester et. al (2013), Chandra et al. (2014), Ryerson, Hansen and Bonn (2014), Zou et al. (2016), Brueckner and Abreu (2017, 2020).
FUELASK	Fuel consumption per available seat-kilometer (ASK).	Mean fuel intensity per capacity unit (ASK).	Liters per 100 units (ln).	
FUELFREQ	Fuel consumption per flight.	Mean fuel intensity per capacity unit (flights).	Liters per flight (ln).	
FUELMASS	Fuel consumption per the mass of flown passengers, cargo, mail and baggage (MASS).	Mean fuel intensity per output (uplifted ton).	Liters per ton (ln).	
FUELPAX	Fuel consumption per revenue passenger (PAX).	Mean fuel intensity per output (passenger).	Liters per passenger (ln).	
FUELRPK	Fuel consumption per revenue passenger-kilometer (RPK).	Mean fuel intensity per output (RPK).	Liters per 100 units (ln).	
FUELRTK	Fuel consumption per revenue ton-kilometer (RTK).	Mean fuel intensity per output (RTK).	Liters per 100 units (ln).	

Variable	Description	Interpretation	Metric	References
regressors				
AGE	Mean fleet age, with age defined as the flight date minus the first flight date of the assigned airplane.	Proxy for fleet rollover. The higher the mean fleet age, the less fuel-efficient the aircraft on the route due to higher weight and more frequent/more in-depth aircraft maintenance checks required. Expected sign: (+).	Years (ln).	Ryerson and Hansen (2013), Winchester et. al (2013), Brueckner and Abreu (2017).
ASIZE	Mean aircraft seating capacity.	Given the uplifted mass, larger aircraft have more seats and heavier structures, generating more significant drag and higher fuel intensity. On the other hand, larger aircraft generally have less fuel burn per seat kilometer flown. Expected sign: indeterminate.	Count (ln).	Lee et al. (2001), Givoni and Rietveld (2009), Morrell (2009), Ryerson and Hansen (2013), Ryerson and Kim (2014), Zou et al. (2016).
FLMOD	The inverse of the fleet's mean model age, with model age defined as the flight date minus the first flight date of the first constructed unit of the assigned airplane's model.	Proxy for technological innovation. The lower the mean model's age, the higher the degree of fleet modernization. If the technological advances in aircraft design and engines are effective, then higher fleet modernization should lower fuel intensity. Expected sign: (-).	Index (ln).	Ryerson and Hansen (2013).
FLTIME	Mean flight time.	Ceteris paribus to flight distance–which here is controlled through route fixed effects–a positive coefficient of FLTIME would be associated with flight delays that provoke extra en-route times and thus higher fuel burn. Expected sign: (+).	Minutes (ln).	Ryerson, Hansen and Bonn (2014), Khan et al. (2019).
FREQ	Total flight frequency.	The greater the number of flights, the higher the total fuel burn. However, the mean fuel intensity per flight may either decrease or increase if the performance of cruise speed optimization is somehow related to route density. Expected sign: indeterminate.	Count (ln).	Zou et al. (2016).
FUELP (2-, 3-, and 4-years lag)	Mean jet fuel price, lagged by two, three or four years.	The higher the fuel price, the higher is the incentive to engage in fuel savings, possibly from improved fuel management and fleet modernization (fuel price signal hypothesis). Expected sign: (-).	Deflated reais (ln).	Winchester et. al (2013), Zou et al. (2016), Fukui and Miyoshi (2017), Brueckner and Abreu (2017, 2020).
Variable	Description	Interpretation	Metric	References
regressors				
HHI	Herfindahl-Hirschman index of market concentration.	Higher concentration decreases price competition and soothes pressures for reductions in costs and fuel intensity. On the other hand, with lower competition, carriers may have a calm life to enjoy greater profits from optimizing cruising speeds and reducing fuel burn. Expected sign: indeterminate.	Index [0,1].	Ryerson and Kim (2014).
HUB		In principle, hub operations should be more energy-efficient, given that the hub network	Fraction.	Ryerson and Kim (2014).

(continued on next page)

Table 2 (*continued*)

Variable	Description	Interpretation	Metric	References
	Maximum proportion of passengers with flight connections at origin and destination airports.	structure represents a great effort in planning and management to achieve optimal operational efficiency. However, large hubs are often very congested, which potentially increases fuel consumption due to flight delays. Expected sign: indeterminate.		
LCC	Dummy of young LCC presence, in its first four years of operations.	The presence of new competition may force carriers to reduce prices, costs, and fuel intensity. On the other hand, carriers may engage in quality competition by reducing travel times through cruise speed increases and higher fuel burn. Expected sign: indeterminate.	Dummy.	Berghöfer and Lucey (2014).
MASS	Aircraft uplifted mass.	Given the mean aircraft size and the flight frequency, the greater the mass, the greater the fuel burn. However, the mean fuel intensity per ton may either decrease or increase if the performance of cruise speed optimization is somehow associated with route density. Expected sign: indeterminate.	Kg (ln).	Ryerson, Hansen and Bonn (2014), Khan et al. (2019).
SLOT	Maximum proportion of flights operated at slot-constrained airports between origin and destination.	Airport slot systems are mostly associated with runway congestion and possibly greater energy intensity. However, slot constraints is a policy which is implemented to control flight delays through the imposition of "use-it-or-lose-it" penalties, which can contribute to mitigating fuel inefficiency at these airports. Meanwhile, given the need to strictly meet schedule targets at slot airports, the cruising speed for the associated flights may be higher than that dictated by the cost index, which may provoke more significant fuel burn. Expected sign: indeterminate.	Fraction.	Miranda and Oliveira (2018).
TPR	Share of flights of turboprop aircraft.	Because turboprops are smaller and lighter, they are known in the industry for their low fuel consumption, particularly in short-distance markets. However, in many other route density situations, they are typically less fuel-efficient than their larger narrowbody and widebody counterparts. Expected sign: indeterminate.	Fraction.	Babikian, Lukachko and Waitz (2002), Ryerson and Hansen (2010), Marques Jr. et al. (2018).

- $HHI_{k,t}$ is the Herfindahl-Hirschman index (HHI) of market concentration calculated from each carrier's share of revenue passengers on the city pair. The more concentrated the market, the lower the pressure to reduce operating costs and fuel consumption. However, with lower quality-service competition among carriers, there is lower pressure to increase punctuality as cruise speed increases, allowing the carrier to free its pilots to set Mach speeds according to the cost index. Therefore, the relationship between HHI and FUEL was indeterminate. Following Greenfield (2014), this variable is set as endogenous in our econometric framework.
- $LCC_{k,t}$ is a dummy for the route presence of LCCs Gol and Azul airlines in their early years of operations. We consider only the "young" LCC period of these carriers because much is discussed in Brazil about their business model hybridization over the years and if they have abandoned the concept of "low-cost operations"' as soon as they increased their stake in the industry. We then consider a 4-year period since the start of each carrier.[8]
- $TREND_t$ is a time trend variable, equal to 1, 2, …, T, where T is the total number of sample periods (174).
- $v_{k,t}$ is the panel's composite error term consisting of city-pair fixed effects and a random term.[9] The δ's are the parameters to be estimated.

We interpret the role of covariates AGEk,t, and FLMODk,t as allowing formal tests of the effects of medium-to-long-term reassessments in carriers' fleet planning. Therefore, these variables aim to capture the materialization of investment plans in new aircraft

[8] For Gol, we set this dummy variable equal to 1 from January 2001 to May 2005, a period after which its major rivals ceased a codeshare agreement. For Azul, we assigned LCC with one from December 2008 to May 2012, when it announced a merger with regional carrier Trip airlines.

[9] We add high dimensional controls to that baseline specification. See the next subsection for a discussion.

and their effectiveness in producing actual fuel savings. We also develop an approach to determine the possible dynamics of these adjustments over time. We then replace these covariates in Equation (1) with a set of lagged jet fuel price covariates, in line with Fukui and Miyoshi (2017). With such a device, we aim to test the fuel price signals hypothesis of fuel price increases, creating incentives for airlines to revise their fleet rollover and fleet modernization plans over a couple of years.

Equation (2) presents our modified version of the baseline model.

$$\begin{aligned}\mathrm{FUEL}_{k,t} = {} & \gamma_1 \mathrm{FLTIME}_{k,t} + \gamma_2 \mathrm{FREQ}_{k,t} + \gamma_3 \mathrm{ASIZE}_{k,t} + \gamma_4 \mathrm{MASS}_{k,t} + \gamma_5 \mathrm{TPR}_{k,t} + \gamma_6 \mathrm{SLOT}_{k,t} + \gamma_7 \mathrm{HUB}_{k,t} + \gamma_8 \mathrm{HHI}_{k,t} + \gamma_9 \mathrm{LCC}_{k,t} \\ & + \gamma_{10} \mathrm{FUELP}_{k,t-24} + \gamma_{11} \mathrm{FUELP}_{k,t-36} + \gamma_{12} \mathrm{FUELP}_{k,t-48} + \gamma_{13} \mathrm{TREND}_t + \omega_{k,t},\end{aligned} \tag{2}$$

- $\mathrm{FUELP}_{k,t\text{-}(h\times 12)}$, where h is the number of lags in years, *and* $h = 2, 3, 4$. We then consider the relevant time window for a lag length setting of 4 years. FUELP is the inflation-adjusted after-tax price in the local currency of Jet A-1 fuel (in logarithm). To build this metric, we use monthly fuel price data by region and a proxy for the Brazilian state tax burden. The aviation fuel tax charges only domestic flights, with rates ranging from 3% to 25%, depending on the airport's state and period. In setting the variable, we use the minimum value of the mean jet fuel price observed in the route's endpoint cities. We use lags of 2, 3, and 4 years to account for the long-term effect of fuel price increases. These variables allow us to test the hypothesis of fuel price signal effects in airlines' strategic fleet planning efforts, our main research target.
- $\omega_{k,t}$ is the error term, and the δ's are the parameters to be estimated.

Finally, we develop a set of models to directly estimate the determinants of airline fuel efficiency in Brazil, in a complementary analysis to that allowed by Equation (2). We then replace the regressand ($\mathrm{FUEL}_{k,t}$) with the following indicators:

- $\mathrm{FUELRPK}_{k,t}$, the total fuel consumption divided by the total revenue-passenger kilometers produced in the city pair (in logarithm).
- $\mathrm{FUELPAX}_{k,t}$, the total fuel consumption divided by the total revenue passengers carried in the city pair (in logarithm).
- $\mathrm{FUELMASS}_{k,t}$, the total fuel consumption divided by the total transported mass–total aircraft load in kilograms–in the city pair (in logarithm).
- $\mathrm{FUELRTK}_{k,t}$, the total fuel consumption divided by the total revenue tons carried in the city pair (in logarithm).
- $\mathrm{FUELASK}_{k,t}$, the total fuel consumption divided by the total available-seat kilometers produced in the city pair (in logarithm).
- $\mathrm{FUELFREQ}_{k,t}$, the total fuel consumption divided by the total flight frequencies operated in the city pair (in logarithm).

3.4. Estimation strategy

Our estimation strategy recognizes that the problem of fuel burn by airlines is a complex and multifaceted phenomenon. There are technological, operational, and competitive issues inherent in the process that generates the data, and the econometrist does not fully observe that in our approach. To consider these unobserved effects to minimize possible model misspecification and inconsistent estimation, we use the following conception of the error term $v_{k,t}$ of Equation (1). This framework is also valid for the error term $\omega_{k,t}$ of Equation (3) and the fuel efficiency equations' errors.

$$v_{k,t} = \Phi(\mathrm{ROUTE}_k, \mathrm{TIME}_t, \mathrm{AIRL}^i_{k,t}, \mathrm{DIR}^o_{k,s}, \mathrm{DIR}^d_{k,s}, \mathrm{ATM}^o_{k,t}, \mathrm{ATM}^d_{k,t}, \mathrm{AIRC}^j_{k,t}) + \varepsilon_{k,t} \tag{3}$$

where:

- ROUTE_k is the fixed effect of route *k*, aiming to control the route-specific and endpoints-specific, time-invariant idiosyncrasies of the city-pair, such as the stage length, terminal control area, and airway geometry specificities, city locational factors, among others.
- TIME_t is the fixed effect of sample period *t*, aiming to control time-varying factors common across the routes. We drop these dummies in the specifications using the deeper time-related controls discussed below.
- $\mathrm{AIRL}^i_{k,t}$ are continuous variables of the share of flights of airline *i* on route *k* at time *t*. To simplify, we denote these variables as "airline controls" in the results tables. In all, we include 37 controls of this type, indicating several airlines' market presence at different times of the sample time.
- $\mathrm{DIR}^o_{k,s}$, and $\mathrm{DIR}^d_{k,s}$ are dummy variables that account for the route's direction's unobserved effects. These controls are city- and quarter-specific. Here we aim to control the impact of typical conditions of weather and prevailing winds on fuel burn, which are likely to vary across routes and seasons. First, we create dummies for each endpoint city in the database, equal to 1 if it is either origin or destination of a city-pair. We then interact these city dummies with other binary variables representing the route's direction from/to each city. To compute these variables, we utilize the 8-wind compass rose's cardinal and intercardinal directions according to the azimuth angle. This procedure associates each flight's orientation with the geographic locations of its origin and destination. Finally, we further interact these dummies with a set of quarters dummies to capture the seasonal effects (subscript *s*). In all, 3,852 high-dimension controls of this type were generated. We label these dummies as "dir-qtr controls" in the results tables.

- $ATM^{o}_{k,t}$ and $ATM^{d}_{k,t}$, are dummy variables of Flight Information Region (FIR)[10] to which endpoint airports belong, interacted with time dummies. These controls account for air traffic management's time-varying factors that influence the pilots' flight management decisions in all flight stages. We denote these dummies as "airway-time controls" in the results tables for simplification of the exposure. In all, we include 2,260 high-dimension controls of this type.
- $AIRC^{j}_{k,t}$ are continuous variables of the route share of flights of aircraft model variant *j* on route *k* at time *t*. In setting these variables, we treat each variant of each aircraft model as a separate type of aircraft. Here we aim to account for the possible (unobserved) effects of aircraft mix changes on the route's fuel burn and fuel efficiency. We denote these shares as "acft variant controls" in the results tables. Altogether, we consider 134 controls of this type.
- $\Phi(.)$ is an additive function, and $\varepsilon_{k,t}$ is the random error.

In one of our preferred specifications, we use all the deeper controls in (3). In simpler versions, we use only fixed effects, the presence of airlines ("airline controls"), and the time dummies ("time controls").

We perform the following diagnosis tests on our data set and models: correlation analysis, multicollinearity, heteroscedasticity, autocorrelation, normality, model misspecification, type of panel model, unit root and cointegration, and instrumental variables' quality. The results of these tests are available in the supplemental material. We confirm the presence of multicollinearity in the estimation, as we calculate mean and maximum VIF statistics of, respectively, 9.71 and 66.48 in our baseline model of fuel burn. With these results, we must be cautious when interpreting some non-significant results in our empirical models, as there is a false negative risk.[11] We confirm the presence of both heteroscedasticity and autocorrelation and employ the procedure of Newey-West to adjust the standard error estimates. We also employ cluster-robust penalty loads to tackle heteroscedasticity further–see Ahrens, Hansen and Schaffer (2020)–with city-pairs as clusters.

We perform the estimation of our empirical model using the econometric method of high dimensional sparse (HDS) regression of Belloni et al. (2012), Belloni, Chernozhukov, and Hansen (2014a, b), and Chernozhukov, Hansen, and Spindler (2015). As discussed in Ahrens, Hansen and Schaffer (2020), we use the IV-LASSO version, which is flexible in allowing a broad set of regressors, controls, and instrumental variables. The method uses the least absolute shrinkage and selection operator (LASSO) of Tibshirani (1996). In the final step, the procedure estimates the parameters with a traditional Two-Stages Least Squares (2SLS) using the controls and instruments selected in the LASSO estimation step. As we estimate fixed effects in all models, we label it as the "FE-IV-LASSO" estimator. Except for the FLTIME, FREQ, ASIZE, and MASS variables, we include all other covariates in the models in the set of variables penalized by the LASSO procedure.

We treat HHI as endogenous in our model. We performed a Durbin-Wu-Hauman test, rejecting the null hypothesis of exogeneity of this variable.[12] Our identification strategy involved the use of three categories of instrumental variables (IV): (1) exogenous demand shifters,[13] (2) characteristics of the service offered in the market (BLP Instruments), and (3) characteristics of the service offered in other markets (Hausman Instruments).[14] In all, we consider 360 candidates for being IV, which went through the penalization procedure of IV-LASSO. The final baseline model has only four IVs not inactivated in this process: two demand variables–the mean populations between origin and destination and the share of charter flights–and two BLP-type variables–the relative interquartile range and standard deviation of baggage weight per passenger. The IVs were systematically assessed for relevance and weak identification. Additionally, we analyze the stability of the estimated parameter and the orthogonality of selected IVs in a sequence of tests using tuples of the instrument set. In the vast majority of tests and analyzes, the instruments selected by LASSO perform satisfactorily.[15]

3.5. Accounting for DFM

Airline DFM aims to optimally assign the most suitable airplane according to demand. In our case, although the tail assignment decisions have a direct impact on the energy efficiency of carriers, the effects of DFM are among the unobservables of the model. More importantly, these latent factors are not necessarily captured by our fleet rollover and fleet modernization variables—AGE and FLMOD, respectively.

We present a proposal for an estimation strategy to control the possible effects of DFM on companies' energy intensity in the market. To the best of our knowledge, this procedure has not yet been performed in previous econometric studies applied to transport operations. Our approach aims to control the possible confounding effects of the airlines' DFM practices in our estimation, which could

[10] FIRs are divisions of airspace made by the Brazilian Department of Airspace Control, based on International Civil Aviation Organization (ICAO)'s recommendations.

[11] To check our results' robustness concerning multicollinearity, we developed alternative regressions in which each covariate was intentionally omitted from the main model. The results of these experiments confirmed the relevance of the multicollinearity issue. In most models, particularly in the model in which the calculated VIF was minimum–that is, after dropping variable MASS–the estimation results kept unchanged. We thank an anonymous reviewer for suggesting this experiment.

[12] See the supplemental material.

[13] For example, the gross domestic product (GDP), population size, GDP per capita, Gini index of income inequality, all extracted at the endpoint cities level. We utilize the maximum, minimum, simple, and geometric means between the origin and destination.

[14] See a discussion in Mumbower, Garrow and Higgins (2014) e Miranda and Oliveira (2018).

[15] See all results in the supplemental material.

Table 3
Estimation results: fuel consumption.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	FUEL	FUEL	FUEL	FUEL	FUEL	FUEL	FUEL	FUEL	FUEL
FLTIME	0.0723***	0.0851***	0.0928***	0.0893***	0.0677***	0.0957***	0.0648***	0.2319***	0.1299***
FREQ	0.9615***	0.9584***	0.9679***	0.9652***	0.9763***	0.9808***	0.9775***	0.9696***	0.9633***
ASIZE	0.2203***	0.2174***	0.2210***	0.2218***	0.1562***	0.1405***	0.1263***	0.2460***	0.1348***
MASS	0.0255***	0.0279***	0.0266***	0.0271***	0.0207***	0.0191***	0.0173***	0.0289***	0.0268***
TPR	−0.2827***	−0.2779***	−0.2806***	−0.2795***	−0.3723***	−0.3853***	−0.3742***	−0.2189***	−0.3643***
SLOT	0.0172***	0.0153***	0.0121***	0.0126***	0.0132***	0.0037	0.0164***	0.0094***	0.0092***
HUB	0.0480***	0.0488***	0.0585***	0.0473***	−0.0011	0.0657***	0.0048	0.0262*	−0.0232
AGE	0.0543***	0.0140***	0.0160***	0.0154***					
FLMOD		−0.0949***	−0.0956***	−0.0950***					
HHI (Endog)			0.0676***	0.0480***	0.0207	0.0101	−0.0005	0.0491***	−0.0242
LCC				−0.0181***	−0.0333***	−0.0279***	−0.0401***	−0.0380***	−0.0386***
FUELP (2 years lag)					0.0008	0.0604**	–	–	–
FUELP (3 years lag)					−0.0111***	−0.0688**	−0.0185***	−0.0229***	−0.0283***
FUELP (4 years lag)					−0.0413***	−0.1151***	−0.0652***	−0.0603***	−0.0733***
TREND	−0.0038***	−0.0065***	−0.0067***	−0.0070***	−0.0001				
Estimator	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO
Airline controls	23/32	23/32	23/32	23/32	21/32	22/32	8/32	7/32	6/32
Time controls	No	No	No	No	No	177/226	No	No	No
Dir-Qtr controls	No	No	No	No	No	No	662/3582	648/3582	635/3582
Airway-time controls	No	No	No	No	No	No	508/2260	419/2260	316/2260
Acft variant controls	No	No	No	No	No	No	No	50/134	No
Acft tail nr controls	No	No	No	No	No	No	No	No	405/1272
Adj R2 statistic	0.9502 [9]	0.9515 [6]	0.9512 [8]	0.9514 [7]	0.9612 [4]	0.9616 [3]	0.9586 [5]	0.9642 [1]	0.9621 [2]
AIC statistic	−147092 [4]	−149724 [1]	−149204 [3]	−149636 [2]	−127485 [8]	−128066 [7]	−124046 [9]	−133786 [5]	−129816 [6]
BIC statistic	−146789 [4]	−149411 [1]	−148882 [3]	−149304 [2]	−127176 [5]	−126149 [6]	−113261 [9]	−123485 [7]	−117364 [8]
RMSE statistic	0.1145 [9]	0.1129 [6]	0.1132 [8]	0.1130 [7]	0.0919 [4]	0.0912 [3]	0.0951 [5]	0.0885 [1]	0.0908 [2]
RMSE CV statistic	0.6753 [9]	0.6653 [6]	0.6655 [7]	0.6676 [8]	0.6494 [4]	0.6332 [3]	0.6595 [5]	0.5633 [1]	0.6185 [2]
Nr observations	97,628	97,628	97,628	97,628	65,482	65,482	67,255	67,255	67,255

Notes: Estimation results produced by the instrumental variables, post-double-selection LASSO-based methodology (IV-LASSO) of Belloni et al. (2012, 2014a,b). LASSO penalty loadings account for the clustering of city-pairs. Post-LASSO estimation is performed with a Two-Stage Least Squares, fixed-effects, procedure with standard errors robust to heteroskedasticity and autocorrelation. Control variables estimates omitted; "–" denotes that the LASSO procedure discarded the variable; blank cells indicate that the variable was not used; a number between square brackets denotes the rank of the statistic value according to each criterion–from the "best" to the "worse" across columns; FLTIME, FREQ, ASIZE, and MASS not penalized by LASSO; p-value representations: ***$p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

cause a bias in the estimation of our main results. To accomplish this, we incorporate into the model of Equation (2), a broader set of nuisance parameters, namely the shares of each aircraft tail number in the city pair. The tail number represents an aircraft's unique identity, which is usually painted on the tail of the aircraft. We consider that the assignment of an airplane to a given city pair at a given time is the outcome of the airline's specific operational management efforts. Each aircraft has an engine, aerodynamics, maintenance history, and other idiosyncrasies that make it unique. More generally, the mix of aircraft assigned to the route reveals the rationality of tail assignment and possibly the airline's capabilities to perform DFM. In this way, the observed aircraft tail numbers' presence share variables make it possible to control the operating factors underlying the company's fuel burn phenomenon. To account for DFM, we set $AIRC^{j}_{k,t}$ in Equation (3) as follows:

- $AIRC^{j}_{k,t}$ are continuous variables of the route share of flight of aircraft tail number *j* on route *k* at time *t*. We denote these shares as "acft tail nr controls" in the results tables. Altogether, we considered 1,272 controls for this type.

We hypothesize that the practice of DFM by airlines collaborates to reduce fuel consumption. Thus, when we insert the DFM controls in our specification, the new estimates of the effect of the fuel price on consumption could theoretically be impacted. However, the direction of this impact is not subject to ex-ante anticipation, which is a purely empirical issue. In principle, we expect these price effect estimates to shrink: with an increase in fuel price, carriers would intensify DFM's use to improve their energy efficiency and save fuel. Thus, when inserting the DFM controls, some of these efficiency gains would be absorbed by the new parameters inserted in the equation, selected by LASSO, which would shrink the price effect previously estimated. However, an increase in fuel prices can also cause airlines to increase fleet standardization (Narcizo et al., 2020). Similar to the DFM, airline fleet standardization is another latent factor in our analysis. As discussed in Garrow, Kressner, and Mumbower (2011), it can be argued that fleet standardization and DFM are negatively correlated, and when standardization increases, the possibilities of optimized management by DFM decrease. Even if airlines intensify DFM's use, given the less variability of their fleets, the benefits of applying these management techniques may be less expressive, or even null or negative, compared to the situation before the increase in prices. Therefore, in this case, when inserting the DFM controls, there could be an expansion–instead of shrinking–of the estimated price effect. Alternatively, there could be a null effect due to a combination of effects arising from an intensification of the use of DFM in parallel with a lower gain due to the greater standardization of the fleet.

4. Estimation results

In this section, we present the estimation results of the proposed econometric model. First, we present the results of the estimates of the fuel consumption model in Table 3. In sequence, in Table 4, we present the results of the energy-efficiency models.[16] Table 3 lists the nine columns. Columns (1)–(4) present specifications that allow testing for the impacts of our key variables of fleet rollover and fleet modernization, respectively, AGE and FLMOD. In Columns (5)–(9), we present model specifications using the fuel price variables, namely FUELP lagged by 2, 3, and 4 years. Note that we added several indicators of the estimation procedures at the bottom of Table 3. In particular, we include the number of variables selected by LASSO for each type of control: airline, time, direction-quarter ("Dir-Qtr"), airway-time, aircraft variant ("Acft variant"), and aircraft tail number ("Acft tail nr") controls.

First, we analyze the results of Columns (1)–(4). It is vital to note that most of the variables present statistically significant estimated coefficients with a sign consistent with the ex-ante expectation. For example, the operations-related variables FLTIME, FREQ, ASIZE, and MASS all have a positive estimated effect. Meanwhile, the TPR variable is negatively related to FUEL, suggesting a ceteris paribus effect of fuel burn lessening as turboprop aircraft's participation in the route increases. The SLOT and HUB variables showed a positive estimated coefficient, possibly indicating more significant congestion associated with airport operational constraints and flight connections. In all columns, the variable TREND points to evidence suggesting a drop in fuel consumption over the sample period, possibly related to flight operations management, and other improvements that are unobservable to the econometrician.

The variable indicative of airline fleet rollover (AGE) has the expected positive and statistically significant estimated effect. The FLMOD variable is statistically significant and negative in all specifications from (2) to (4), indicating that fleet modernization effectively reduces the airlines' energy intensity. Our results provide evidence that a 1% increase in carrier fleet modernization is associated with a reduction of between 9% and 10% in fuel burn. Finally, we present the results of the competition variables HHI and LCC. Columns (3) and (4) provide evidence of a fuel cost-cutting effect induced by competition. The results indicate statistically significant estimated coefficients for HHI (positive sign) and LCC (negative sign). In both cases, the results suggest that an escalation in rivalry, either by a decreased market concentration or by the entry of a young, low-cost operator, forces airlines to enhance their fuel management practices to control costs more effectively.

In the specifications of Columns (5)–(8) of Table 3, we insert the lagged fuel price variables (FUELP with 2-, 3-, and 4-year lags). In these specifications, we drop AGE and FLMOD, aiming to identify the possible dynamics that provoke the materialization of these variables as dictated by variations in FUELP. Column (5) presents the simplest version of the model, containing only the airline controls, in Column (6), we add time controls, in Column (7), we include direction-quarter and airway-time dummies; and Column (8) also comprises the aircraft model variant controls. The specifications in Columns (6) to (8) use at least 5,000 controls in total, all of which are subject to penalization and shrinkage by LASSO. These specifications do not include the TREND variable, which is already

[16] For simplicity of exposition, we omit subscriptions *k* and *t*.

Table 4
Estimation results: fuel efficiency.

	(1)	(2)	(3)	(4)	(5)	(6)
	FUELRPK	FUELPAX	FUELMASS	FUELRTK	FUELASK	FUELFREQ
FLTIME	0.1901***	0.2471***	0.2535***	0.2536***	0.1930***	0.2322***
FREQ	0.9271***	0.9283***	0.9711***	0.9709***	−0.0369***	−0.0300***
ASIZE	0.2048***	0.2055***	0.2150***	0.2147***	−0.7735***	0.2454***
MASS	−0.9351***	−0.9356***	−0.9704***	−0.9702***	0.0354***	0.0290***
TPR	−0.2154***	−0.2268***	−0.2642***	−0.2642***	−0.3004***	−0.2195***
SLOT	0.0037	0.0054**	0.0136***	0.0136***	0.0127***	0.0092***
HUB	0.0110	0.0103	0.0282*	0.0281*	0.0290**	0.0288*
HHI (Endog)	−0.0124	−0.0061	0.0545***	0.0546***	0.0318**	0.0513***
LCC	−0.0292***	−0.0300***	−0.0406***	−0.0406***	−0.0406***	−0.0377***
FUELP (2 years lag)	–	–	–	–	–	–
FUELP (3 years lag)	−0.0065	−0.0065	−0.0239***	−0.0239***	−0.0196***	−0.0244***
FUELP (4 years lag)	−0.0519***	−0.0552***	−0.0599***	−0.0599***	−0.0424***	−0.0585***
Estimator	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO
Airline controls	8/32	8/32	8/32	8/32	8/32	8/32
Dir-Qtr controls	657/3582	659/3582	646/3582	651/3582	676/3582	653/3582
Airway-time controls	496/2260	497/2260	483/2260	483/2260	420/2260	410/2260
Acft variant controls	55/134	55/134	51/134	51/134	55/134	49/134
Adj R2 statistic	0.8702	0.8713	0.8817	0.8817	0.7601	0.5511
RMSE statistic	0.0931	0.0933	0.0877	0.0877	0.0858	0.0886
RMSE CV statistic	0.2086	0.5714	0.5524	0.2532	0.2186	0.5621
Nr observations	67,255	67,255	67,255	67,255	67,255	67,255

Notes: Estimation results produced by the instrumental variables, post-double-selection LASSO-based methodology (IV-LASSO) of Belloni et al. (2012, 2014a,b). LASSO penalty loadings account for the clustering of city-pairs. Post-LASSO estimation is performed with a Two-Stage Least Squares, fixed-effects, procedure with standard errors robust to heteroskedasticity and autocorrelation. Control variables estimates omitted; "–" denotes that the LASSO procedure discarded the variable; FLTIME, FREQ, ASIZE, and MASS not penalized by LASSO; p-value representations: ***$p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

controlled by either aggregate or deep time effects, depending on the column.

The estimation results of Columns (5)–(8) of Table 3 confirm most of the evidence found in Columns (1)–(4). However, the HUB and HHI variables in these specifications are not significant in many cases, which leads us to infer that no evidence is found regarding the effect of hubbing activity and market concentration on fuel consumption. Regarding the lagged FUELP variables, we find evidence that ceteris paribus to the other market conditions, the energy intensity of carriers declines after 3 years of an increase in fuel prices.[17] The estimated effect is relatively low, suggesting a fuel price elasticity between −0.01, and −0.12, with more significant effects associated with the 4-year lag. This result contrasts with the findings of Fukui and Miyoshi's (2017) results of smaller effects in the longer term. We believe that with our sample period, which ends in 2018, we are in a better condition to estimate the long-run impacts of the 2008 global oil price shock than the authors, as the period of their data ends in 2013 and their calculation of impacts uses values from 2012. With an amplified period since the global shock, we may have had an easier task to estimate its long-run impacts using an econometric model. Our results regarding the long-run impacts of fuel prices are robust to specification changes across the columns of Table 3.

Table 4 presents the estimation results of the fuel efficiency models using indicators FUELRPK, FUELPAX, FUELMASS, FUELRTK, FUELASK, and FUELFREQ as regressands. These specifications contain the same covariates as in Column (8) in Table 3. The results in Table 4 confirm the key findings in Table 3. However, FREQ, ASIZE, and MASS have estimated coefficients with changed signs in some of the columns in Table 4. For example, FREQ shows a negative and statistically significant coefficient in Columns (5) and (6), suggesting that fuel consumption, as measured by FUELASK and FUELFREQ, tends to decline as flight frequency increases. Meanwhile, the estimated effects of the MASS variable for these indicators are positive, although they are negative for FUELRPK, FUELPAX, FUELMASS, and FUELRTK–namely, Columns (1) to (4). In all cases, we believe that the estimation results are not inconsistent with the ex-ante expectation regarding the effects of these variables. Again, concerning the lagged FUELP variables, we estimate the long-term statistically significant effects and suggest an efficiency-enhancing effect. However, the effect of FUELP (3-year lag) was not significant for FUELRPK and FUELPAX.

As a summary of our findings from the estimation results of Tables 3 and 4, we find that shocks in the price of aviation fuel apparently have a long-run impact on airlines' fuel efficiency in the sample period under investigation. This effect materializes 3–4 years after the shock, possibly associated with the airlines' strategic planning adjustments, aiming at the fleet's renewal and adopting new technologies launched by the aircraft manufacturers.

4.1. Effects of the DFM controls

In this subsection, we discuss the model estimation results when including our proposed DFM controls. We re-estimate the model in Column (8) of Table 3 and all the models in Table 4, using 1,272 additional variables representing the shares of each aircraft tail

[17] The LASSO procedure also indicates either statistically not significant or inactivated effect FUELP (2-year lag).

number in the city pair, all subject to the LASSO penalty procedure. These results are shown in Column (9) of Table 3 and in all columns of Table 5, respectively. We interpret the controls that are not inactivated by LASSO as those that purge possible omitted variable biases, therefore being interpreted as nuisance parameters.

Concerning Column (9) of Table 3, in our model of aircraft energy intensity (FUEL), most of the results remain statistically significant and have the same coefficients' sign as in Column (8). Note that the LASSO procedure does not inactivate 405 controls out of the 1,272 initially modeled. This represents 31.8% of the proposed variables employed to account for the airlines' unobserved DFM capabilities. For example, when experiencing a shock in demand, carriers may swap aircraft to adjust their capacity to market conditions, with possible implications for their fuel consumption performance on the route. In this case, the shares of each aircraft tail number in the city-pair–our proposed nuisance parameters–will change accordingly to control for that unobserved effect. Therefore, we have evidence that DFM plays a relevant role in almost one-third of the domestic markets under consideration.

The results of the lagged fuel price variables (FUELP) remain approximately the same. As discussed in Section 3.5, after inserting the DFM controls, the new estimates of the fuel price's effect on fuel consumption could be impacted in different ways. Given that the estimated coefficients of the fuel price effect in our specification in Table 3, Column (9) is not very different from the coefficients estimated in Columns (5)–(8), our results indicate a role for another latent factor: fleet standardization. The lack of change in coefficients suggests a combination of effects stemming from an intensification of DFM's use in parallel with a lower gain of the strategy due to higher fleet standardization. Additionally, we cannot rule out the possibility that the practice of close-in re-fleeting may be associated with unexpected events and disruptions that bring operational inefficiencies and additional fuel burns. Therefore, we recommend that the relationship between energy efficiency, fleet standardization, and disruptions should be further investigated in future studies.

Regarding the results of FUELP in Table 5, most estimation results do not change when compared with Table 4, either in terms of the sign, statistical significance, or inactivation by LASSO. The lagged fuel price variables (FUELP) present the same results as Table 4 in virtually all cases. Regarding FLTIME, FREQ, ASIZE, MASS, TPR, LCC, and, to a lesser extent, SLOT, the results obtained are robust to the insertion of deeper controls, with no change in interpretation.

However, the estimation results for HUB and HHI present some instability that must be discussed. Such instability makes us reiterate the conclusion that no evidence is found with respect to the overall relationship between these factors and fuel efficiency. However, we note that localized effects with respect to some fuel efficiency ratios may still exist. These estimated localized effects are ceteris paribus to the DFM controls, and in principle contradict the findings of Tables 3 and 4. First, HUB becomes statistically significant and negative in Columns (1) and (2) of Table 5, which may suggest that flight connections increase spoke densities and may enhance fuel-efficiency, at least when measured by FUELRPK and FUELPAX. In addition, HHI becomes always negative across columns, and statistically significant in Columns (1), (2), and (5), which indicates that market concentration may improve efficiency as measured by FUELRPK, FUELPAX, and FUELASK. These results emerge only when we introduce the DFM controls, and therefore suggest that the effect of these variables on the mean fuel efficiency in the market may be influenced by the airlines' tail assignment problem's restrictions. In other words, the fuel efficiency outcomes stemming from higher hubbing and market concentration may

Table 5
Estimation results: fuel efficiency – dynamic fleet management controls.

	(1)	(2)	(3)	(4)	(5)	(6)
	FUELRPK	FUELPAX	FUELMASS	FUELRTK	FUELASK	FUELFREQ
FLTIME	0.1038***	0.1667***	0.1687***	0.1689***	0.1097***	0.1269***
FREQ	0.9146***	0.9165***	0.9543***	0.9543***	−0.0468***	−0.0383***
ASIZE	0.1307***	0.1210***	0.1435***	0.1435***	−0.8268***	0.1385***
MASS	−0.9311***	−0.9318***	−0.9622***	−0.9622***	0.0369***	0.0287***
TPR	−0.3625***	−0.3745***	−0.3887***	−0.3887***	−0.3364***	−0.3472***
SLOT	0.0074**	0.0079***	0.0106***	0.0106***	0.0109***	0.0070***
HUB	−0.0330**	−0.0387**	−0.0135	−0.0136	−0.0016	−0.0252
HHI (Endog)	−0.0879***	−0.0774***	−0.0221	−0.0221	−0.0344**	−0.0264*
LCC	−0.0286***	−0.0295***	−0.0388***	−0.0388***	−0.0395***	−0.0352***
FUELP (2 years lag)						
FUELP (3 years lag)	0.0020	0.0006	−0.0190***	−0.0190***	−0.0134***	−0.0271***
FUELP (4 years lag)	−0.0544***	−0.0577***	−0.0604***	−0.0604***	−0.0497***	−0.0676***
Estimator	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO
Airline controls	7/32	7/32	6/32	6/32	6/32	7/32
Dir-Qtr controls	631/3582	626/3582	634/3582	632/3582	648/3582	629/3582
Airway-time controls	390/2260	398/2260	389/2260	389/2260	323/2260	310/2260
Acft tail nr controls	441/1272	441/1272	438/1272	438/1272	437/1272	399/1272
Adj R2 statistic	0.8640	0.8656	0.8794	0.8794	0.7484	0.5304
RMSE statistic	0.0950	0.0952	0.0883	0.0883	0.0877	0.0904
RMSE CV statistic	0.1808	0.6131	0.5906	0.2248	0.1893	0.6198
Nr observations	67,255	67,255	67,255	67,255	67,255	67,255

Notes: Estimation results produced by the instrumental variables, post-double-selection LASSO-based methodology (IV-LASSO) of Belloni et al. (2012, 2014a,b). LASSO penalty loadings account for the clustering of city-pairs. Post-LASSO estimation is performed with a two-stage least squares, fixed-effects, procedure with standard errors robust to heteroskedasticity and autocorrelation. Control variables estimates omitted; "–" denotes that the LASSO procedure discarded the variable; FLTIME, FREQ, ASIZE, and MASS not penalized by LASSO; p-value representations: ***p < 0.01, ** p < 0.05, * p < 0.10.

Table 6
Descriptive statistics of the model variables.

Variable	Mean	Std. Dev.	Min.	Max.
AGE	1.94	0.60	−2.73	3.76
ASIZE	4.73	0.50	2.20	5.33
FLMOD	1.76	0.43	0.78	5.29
FLTIME	4.48	0.47	2.70	5.64
FREQ	4.33	1.15	0.00	8.32
FUEL	12.25	1.60	6.64	15.99
FUELASK	1.29	0.30	0.14	3.23
FUELFREQ	7.93	0.87	5.18	9.74
FUELMASS	5.98	0.55	3.29	8.64
FUELP (2 years lag)	0.93	0.22	0.16	1.43
FUELP (3 years lag)	0.94	0.23	0.16	1.43
FUELP (4 years lag)	0.92	0.27	0.06	1.43
FUELPAX	3.58	0.57	1.06	6.20
FUELRPK	1.66	0.41	0.58	4.18
FUELRTK	4.06	0.43	2.46	6.64
HHI	0.65	0.26	0.21	1.00
HUB	0.17	0.10	0.00	0.47
LCC	0.08	0.27	0.00	1.00
MASS	13.18	1.51	9.02	17.46
SLOT	0.18	0.31	0.00	1.00
TPR	0.27	0.41	0.00	1.00

depend on the flexibility of the DFM of airlines. Perhaps an effective DFM that allows quick decisions on close-in re-fleeting is one of the necessary conditions for carriers to manage their hubs and fight competition in the airline markets under consideration.

In summary, our results suggest that, although new competition (LCC) may create incentives for carriers to improve their fuel management to control costs, the overall effect of declines in market concentration (HHI) is unclear. Our empirical findings indicate that ceteris paribus to LCC, a reduction in HHI may produce the unintended consequence of inducing worse fuel performance in the market, as measured by some key efficiency dimensions such as FUELRPK, FUELPAX, and FUELASK.

5. Conclusion

This study estimates fuel consumption determinants and market incentives for fuel efficiency in the airline industry using an econometric model. We develop an application for domestic air transport in Brazil during the 2000 s and the 2010 s. Owing to the complexity of the fuel consumption phenomena, we utilize high-dimensional models with LASSO penalty, incorporating thousands of nuisance parameters in the model specifications to avoid the omitted variable bias. In particular, we propose an approach to account for carriers' DFM strategies, using controls for the airlines' tail assignment problem.

Our results indicate the validity of the hypothesis that aviation Jet A-1 fuel plays the role of price signaling in carriers' market incentives to enhance their energy efficiency in the long run. We associate this effect with proxies for fleet rollover and fleet modernization decisions of airlines. We also estimate the dynamic effects of shocks in fuel prices on future fuel burn and fuel efficiency performance in the market. We find evidence of statistically significant fuel price signals with lags of 3–4 years. However, our model has the limitation of using aggregated data at the market level, with no specific conclusions on the relative performances of different airlines and aircraft model types. We recommend further investigation of this topic. Finally, our LASSO approach allows us to pinpoint evidence consistent with DFM playing a role in a relevant stake in the industry. However, it is essential to emphasize that as nuisance parameters, these controls may also capture other factors associated with airline aircraft mix changes on the routes. This limitation implies that we cannot detach the effects of DFM from the other possibly influencing, but unobserved, operational drivers of fuel consumption. We suggest that future studies address this issue by providing additional proxies for such drivers.

Our results also indicate that new competition may create incentives for carriers to enhance their fuel management to control costs. However, the overall effect of market deconcentration is unclear. We find evidence indicating that ceteris paribus to new carrier entry, a reduction in HHI may induce worse fuel performance in the market when measured by some key efficiency ratios of the industry.

Our work has important implications for public policies aimed at mitigating aviation fuel burns and emissions. In particular, we find a small, but statistically significant, long-term effect of fuel price, which suggests the effectiveness of environmental taxation initiatives through increases in fuel costs. Additionally, in terms of corporate strategies, the estimated models allow inspecting the more appropriate timing for airlines to intensify their fleet modernization efforts to enhance competitiveness and reduce their operations' environmental footprint.

Acknowledgments

The first author wishes to thank the São Paulo Research Foundation (FAPESP) – grants n. 2013/14914-4 and 2015/19444-1; National Council for Scientific and Technological Development (CNPq) – grants n. 301654/2013-1, n. 301344/2017-5; The second author thanks the Coordination for the Improvement of Higher Education Personnel (CAPES) – Finance Code 001. The authors wish to thank Paulo Ivo Queiroz, Cláudio Jorge P. Alves, José Guerreiro Fregnani, Cristian Vieira dos Reis, Luiz André Gordo, Vitor Caixeta Santos, Paula Guimarães, Rogéria Arantes. All remaining errors are ours.

Appendix A. .

Data sources
Route data

- Air Transport Statistical Database (aggregated level). This data set contains air transport supply and demand information aggregated at the route level (airport-pair/airline/month). Availability: since 2000. Data periodicity: monthly. These records contain the registration (tail number) of each operated flight in the scheduled domestic airline industry in Brazil. Links to the original database available on www.nectar.ita.br/avstats/anac_statdata.html. Source: National Civil Aviation Agency, ANAC. Variables developed with these data: FREQ, FUEL, FUELASK, FUELFREQ, FUELMASS, FUELPAX, FUELRPK, FUELRTK, HHI, HUB, MASS.

Flight data

- Air Transport Statistical Database (microdata). This data set contains air transport supply and demand information disaggregated at flight level (flight/airport-pair/airline/month). Availability: since 2000. Data periodicity: monthly. These records contain the registration (tail number) of each operated flight in the scheduled domestic airline industry in Brazil. Links to the original database available on www.nectar.ita.br/avstats/anac_statdata.html. Source: National Civil Aviation Agency, ANAC. Variables developed with these data: AGE, FLMOD, TPR (in combination with aircraft data - see below).
- Active Scheduled Flight Historical Data Series (VRA): flight numbers, departure and arrival times, delays and cancellations. Availability: since 2000. Data periodicity: monthly. Links to the original database available on www.nectar.ita.br/avstats/anac_vra.html. Source: National Civil Aviation Agency, ANAC. Variables developed with these data: ASIZE, FLTIME, LCC, SLOT.

Jet fuel price data

- Weekly weighted average prices practiced by producers (refineries, petrochemical plants and formulators) and importers of oil products, disaggregated by product - jet fuel prices included - and geographic coverage. Availability: since 2002. Data periodicity: weekly. Links to the original database available on www.nectar.ita.br/avstats/brazil_data.html. Source: National Agency for Petroleum, Natural Gas and Biofuels, ANP. Variables developed with these data: FUELP (2 years lag), FUELP (3 years lag), FUELP (4 years lag).

Aircraft data.

- Brazilian Aeronautical Registry (RAB): Registration and detailed information of Brazilian aircraft. Data periodicity: monthly. Links to the original database available on www.nectar.ita.br/avstats/anac_rab.html. Source: National Civil Aviation Agency, ANAC. Variables developed with these data: AGE, ASIZE, FLMOD, TPR.
- Aircraft spotting websites: detailed information on each aircraft in the manufactures' historical construction lists, including the serial numbers, model and variant, recording plane registration/tail number, first flight and/or delivery dates, current and past operators, among others. Planelogger: Brazilian fleet (www.planelogger.com/Airline/Search?Country = BR); aircraft manufacturers' construction list (www.planelogger.com/Aircraft). Airfleets: Brazilian fleet (www.airfleets.net/recherche/list-country-Brazil.htm); aircraft manufacturers' construction list (www.airfleets.net/listing/listing.htm). Aviação Paulista: Brazilian fleet (www.aviacaopaulista.com/frota/index.htm). Variables developed with these data: AGE, FLMOD.

Legislation information

- Airport slot regulations available online on www.gov.br/anac/pt-br/assuntos/regulados/empresas-aereas/slot. Variables developed with this information: SLOT.

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