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Abstract

The pursuit of fuel efficiency has become one of the most important policy goals for airline operations management. This paper 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-dimension sparse IV-LASSO methodology to account for airline dynamic fleet management (DFM). 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 three to four years earlier, possibly due to fleet rollover and fleet modernization. Furthermore, although competition may create incentives for improved fuel management to control costs, our results suggest that carriers do not improve their performance across all possible eco-efficiency dimensions.

Keywords: fuel efficiency; airlines; fleet management; LASSO; high-dimension sparse model.

JEL Classification: D22; L11; L93.

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1. Introduction

The growing concern with 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, concerning airlines, the pursuit of fuel efficiency has become one of the most important policy goals for operations management. Before the Covid-19 Pandemic crisis, the growth rates in demand for air travel surpassed the improvement rate in aircraft systems' energy efficiency (Lee, 2010). Consistently with this, Gudmundsson and Anger (2012) describe that the CO2 emissions from air transportation grow faster than the global economy–which justifies the increasing concerns about aviation's carbon footprint in society.

The literature has already raised the issue of fostering fuel savings in aviation through the introduction of technological advances–Morrison et al. (2010), McConnachie, Wollersheim & Hansman (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 airlines' resulting energy efficiency. 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 understanding of the factors that motivate the introduction of technological innovations in the sector that allows for enhancements in energy efficiency across time. The players who actually introduce technological innovation in the market are the original equipment manufacturers (OEM) such as Boeing and Airbus. It remains for the carriers to decide whether or not to adopt the OEMs' innovations at each decision-making time. The carriers, in general, have two instruments for adopting innovation: (1) *fleet rollover*–to control the aging of the fleet with the introduction of newer 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 paper aims at developing an econometric model to estimate airlines' fuel consumption main determinants. The objective is to empirically examine the association of fuel price changes and the long-term incentives of carrier 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 eco-efficient strategic fleet planning, aligning the incentives of airlines with the public interest. The analysis, therefore, contributes to the understanding of the long-term effectiveness of an environmental taxation on aviation fuel. We consider the case of Brazilian commercial aviation in the 2000s and 2010s. 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 2008 global oil price shock. We recognize, however, that our model has to deal with many unobservables, such as the en-route flight procedures and wind conditions, among others. We therefore propose a high-dimension sparse IV-LASSO methodology–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-dimension set of candidates to account for the endogeneity in the model. Finally, we propose a novel estimation approach that controls for the possible effects of carriers' practices of dynamic fleet management (DFM), also known as demand-driven dispatch (D^3)–Berge & Hopperstad (1993), Wang & Meng (2008), Fry and Belobaba (2016). 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 three to four years earlier are associated with increases in eco-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 pinpoint 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 fuel efficiency, energy price signals, and fleet management in the airline industry. Section 3 presents the research design, containing details of the empirical model development. Section 4 contains the estimation results, and Section 5 presents the conclusions.

2. Energy intensity, fuel price, and strategic fleet management

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 increase. Gudmundsson and Anger (2012) develop a meta-analysis of five studies in which they construct basic scenarios for the emission of gases and conclude 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) present 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.

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

Regarding the aerodynamics of large commercial aircraft, Abbas, De Vicente & Valero (2013) discuss using technologies to reduce laminar and turbulent drag and flow control devices. Lee (2010) highlights the improvements obtained over the years in wing design and integration between propulsion and airframe, based on computational and experimental design tools. McConnachie, Wollersheim & Hansman (2013) find 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) points out 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 the Airbus A350, aluminum has been replaced by composite materials–carbon fiber or fiberglass reinforced plastic, among other possibilities. Alemour, Badran & Hassan (2019) describe 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 easier than other materials. The authors say that the weight reduction allowed by the use of composite materials reached 20% in the case of the 787 Dreamliner. Additionally, they point out that each generation of Boeing's new aircraft had a higher incremental percentage composite material, the highest being the 787 Dreamliner's roughly 50%.

Regarding the technological innovations expected to be implemented on a larger scale in the future, we have alternative jet fuels. Analyzing hydrogen, Lee (2010) presents the new technology's pros and cons. The author argues 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 trails' formation of cirrus clouds. According to the US Department of Energy (2017), biofuels are essential to mitigate growth restrictions in the aviation industry, allowing an excellent opportunity to discontinue 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, plus the alkylation of light aromatics (FT-SPK/A); e isobutanol conversion (ATJ-SPK). The study pinpoints other seven pathways in line for certification. Each pathway has advantages and disadvantages, in addition to costs related to the Jet A-1 fuel. Many recent studies have analyzed the innovation potentials of these alternative jet fuels, such as Winchester et al. (2015), Kousoulidou and Lonza (2016), Wang & 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 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. Such a basic economic principle is of particular relevance in the vehicle and fuel sales markets. Klier, Linn & Zhou (2020) discuss 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 & Zhou (2019) develop 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 price increases. 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 & Zhou (2020) study 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 lessen the energy intensity of airlines–Schlumberger (2012), Wormslev et al. (2016), Murphy et al. (2018), among others. Such 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 hypothesis's underlying mechanism consists of airlines responding to increased fuel costs through adjustments in their operations over time to enhance their eco-efficiency. As a response to increased fuel costs, carriers may increase ticket prices and freight charges for the hold 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 pilot's use of landing flaps, thrust reverser, 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) observes that firms have relatively little flexibility in adapting to market conditions changes in the short term. In the medium term, carriers may perform flight frequency changes, route structure, and served markets–Morrison et al. (2010), Brueckner and Zhang (2010). For example, they may cut the short stage length traffic in their networks. However, some of these measures may generate the unintended outcome of forcing the airline to cancel or to postpone the receipt of new, possibly more eco-efficient aircraft–Winchester et al. (2013), McConnachie, Wollersheim & Hansman (2013).

One of the possibilities for carriers responding to fuel price increases would be to revise their long-term strategic fleet planning. Across 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 older aircraft's replacement with newer ones of a similar generation. Another option is to modernize its fleet through the acquisition of newer generation aircraft. For example, an airline may replace some old Airbus A320 airplanes with some more recently launched model A320neo. In this case, the carrier will be concomitantly performing *fleet rollover with fleet modernization*. McConnachie, Wollersheim & Hansman (2013) describe, 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 for acquiring younger airplanes of the same A320 type–namely, the A320ceo series–, we ponder that it will be performing *fleet rollover without fleet modernization*.

We aim at empirically testing the hypothesis of fuel prices sending signals for airlines to increase their energy efficiency–a topic still with scarce literature. The works that most closely match our approach are Wadud (2015), Brueckner and Abreu (2017), and Fukui & Miyoshi (2017), all reporting the US experience. Wadud (2015) performs a decomposition analysis of aviation fuel demand in the

US with a seemingly unrelated regression, in an approach that allows 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 mean load factors and fuel efficiency in the industry.

Brueckner and Abreu (2017) also investigate 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 considers the level of fuel efficiency–the current state of aircraft technology–as given. They recognize 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 & Miyoshi (2017) investigate 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 estimate a distributed lag model of US carrier's annual jet fuel consumption in gallons, using simultaneous quantile regression and year fixed effects.[1] They consider a lag length of three years. They estimate short-run and long-run price elasticities of jet fuel consumption but find many coefficients of the fuel cost per gallon variables statistically not significant. Their results suggest that fuel consumption and CO2 emissions reduction would be smaller in the longer term due to a rebound effect.

We build upon these studies by considering econometric models of fuel consumption and fuel efficiency. Our contribution to the previous literature relies on the explicit incorporation of fleet rollover and fleet modernization into the models' specification. 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 to public and corporate policies but so far relatively neglected by the empirical literature.

2.3. Dynamic fleet management and fuel efficiency

One of the relevant aspects of an airline's operations that may affect its fuel efficiency performance is dynamic fleet management (DFM)–"*the ability to swap aircraft with different capacities on or close to the day of operation*" (Holloway, 2008). Garrow, Kressner & Mumbower (2011) describe that in the late 1990s, airlines developed tools to allow swapping airplanes close to departure to better match supply with demand. Berge & Hopperstad (1993) describe that the DFM, also known as demand-driven dispatch (D^3), performs demand forecast updates as the flight departure approaches, in a way to assign the most suitable airplane according to the expected number of enplanements.

[1] See also Miyoshi & Fukui (2018)

Thus, one of DFM's great benefits 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 dynamic solutions to the well-known tail assignment problem, in possible integration with the company's yield management system. According to Grönkvist & 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) analyze 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, Atamtürk & Aktürk (2019) study 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 & Regan (2006), Wang & Meng (2008), García & Cadarso (2017), Busing, Kadatz & Cleophas (2019), Şafak, Atamtürk & Aktürk (2019).

In our case, the tail assignment decisions of airlines have direct implications on their fuel efficiency performance. We present an estimation strategy proposal to account for DFM's possible effects 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. Some other (few) small carriers operated regional routes. In Table 1, we present a set of economic and operational indicators of the industry. In 2018, 95.9 billion revenue-passenger kilometers (RPM) were produced, 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 – 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.

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 2000s, 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, 13.2% higher than in 2010. In parallel, Brazilian carriers' mean fleet age fell by 22.6%, from 9.8 (2000) to 7.6 years (2018), with a considerable part of this evolution observed from 2000 to 2010, with a 20.8% fall. There was also a drop 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 sum, the period under investigation is marked by extraordinary growth in demand, followed by increases in carriers' fuel efficiency. We suspect that a significant portion of these eco-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

[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.

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.

3.3. Empirical model

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

$$\begin{aligned} FUEL_{k,t} = {} & \delta_1 FLTIME_{k,t} + \delta_2 FREQ_{k,t} + \delta_3 ASIZE_{k,t} + \delta_4 MASS_{k,t} + \delta_5 TPR_{k,t} + \delta_6 \\ & SLOT_{k,t} + \delta_7 HUB_{k,t} + \delta_8 AGE_{k,t} + \delta_9 FLMOD_{k,t} + \delta_{10} HHI_{k,t} + \delta_{11} \\ & LCC_{k,t} + \delta_{12} TREND_t + v_{k,t}, \end{aligned} \tag{1}$$

where k denotes the domestic city-pair and t the periods (t = 1, …, 174 months). Below, we discuss the components of Equation (1).[5] Table 2 presents the descriptive statistics and the sources of each of the main variables.

- $FUEL_{k,t}$ is our metric of aircraft energy intensity. It is equal to the total fuel burn in liters by the city-pairs scheduled flights (in logarithm).
- $FLTIME_{k,t}$ is the mean actual flight time in minutes (in logarithm). In the flight management systems of modern airliners, it is the cost index parameter that typically governs the cruise Mach speed of a flight, and as a result, determines a significant portion of the flight time. The cost index is a ratio between time-dependent costs and fuel costs–Young (2018)–that recommends that the pilot sets a given cruise speed to optimize total fuel burn. 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.

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

[5] 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.

- $FREQ_{k,t}$ is the total number of nonstop flights on the city-pair (in logarithm). The greater the number of operations performed, the greater the energy intensity, with more significant total fuel burn.
- $ASIZE_{k,t}$ is the mean aircraft seat capacity on the city-pair (in logarithm). Given the cargo carried, 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–Lee et al. (2001), Givoni & Rietveld (2009), and Morrell (2009).
- $MASS_{k,t}$ 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 kilograms, plus the total cargo, mail, and baggage also in kilograms. Given the mean aircraft size and the flight frequency, the greater the mass, the greater the fuel burn.
- $TPR_{k,t}$ is the proportion of flights of turboprop airplanes on the city-pair. According to Babikian, Lukachko & Waitz (2002), regional aircraft such as those with a turboprop engine are 40–60% less fuel-efficient than their larger narrowbody and widebody counterparts. However, these comparative disadvantages can be explained mainly by differences in aircraft operations–such as lower load factors and a diminished number of flown miles to dilute fixed costs–and not by the equipment's technology. Ryerson & Hansen (2010) describe that, concerning short distance markets, turboprops are known in the industry for their low fuel consumption. Thus, given the aircraft's size, the ex-ante expectation is that a higher proportion of turboprop flights will be associated with lower total fuel consumption on the route.
- $SLOT_{k,t}$ is the percentage of flights operated at slot-constrained airports on the city-pair. It is the maximum proportion of flights operated at slot airports between the origin and destination cities. The airport slot system is mostly associated with runway congestion and possibly greater energy intensity. However, introducing slot constraints is a policy that aims to control flight delays through the imposition of "use-it-or-lose-it" penalties, which can contribute to mitigating fuel inefficiency at these airports. On the other hand, 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.
- $HUB_{k,t-h}$ 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 United States Federal Aviation Administration's definition of a "large hub." In principle, hub operations should be more energy-efficient, given that the hub

network structure represents a great effort in planning and management to reach optimal operational efficiency. However, large hubs are often very congested, which potentially increases fuel consumption due to flight delays.

- $AGE_{k,t}$ is a proxy for the mean age of the aircraft assigned to the route (in logarithm). It is our metric of airline fleet rollover. We consider the age of all operated airplanes on the date of each flight in the sample period. In calculating this variable, we use the plane's first flight date, according to the information available in the Brazilian Aeronautical Registry (RAB) of the National Civil Aviation Agency (ANAC).[6] 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 technological innovation adoption of carriers when introducing new generation aircraft in the market. Our indicator of airline fleet modernization is equal to the logarithm of the inverse of the mean aircraft model type age of the airplanes assigned to flights on the route, multiplied by 100, that is, ln ((1/mean model's age) ×100). The higher the model type's age, the lower the FLMOD indicator. We calculate the ages considering the date of the first flight of that model type's first aircraft. This information is available from queries on the websites planelogger.com, airfleets.net, jetphotos.com, and aviacaopaulista.com. We expect that the new generation airplanes 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.

- $HHI_{k,t}$ is the Herfindahl-Hirschman index of market concentration calculated from each carrier's share of revenue passengers on the city-pair. The more concentrated a market, the less pressure to reduce operating costs and fuel consumption. On the other hand, with lower quality-service competition among carriers, there is lower pressure to increase punctuality through cruise speed increases, allowing the carrier to free its pilots to set Mach speeds according to the cost index. The relationship between HHI and FUEL is, therefore, indeterminate. Following Greenfield's (2014) discussion, this variable is set as endogenous in our econometric framework.

- $LCC_{k,t}$ is a dummy of route presence of low-cost carriers (LCC) 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 across the years and if they

[6] 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.

have abandoned the concept of "low-cost operations" as soon as they increased their stake in the industry.[7] We then consider four years-period since the startup 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. These variables, therefore, aim to capture the materialization of investment plans in new aircraft and its effectiveness in producing actual fuel savings. We also develop an approach to pinpoint the possible dynamics of these adjustments over time. We then replace these covariates of Equation (1) with a set of lagged jet fuel price covariates, in line with Fukui & 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 (1) presents our modified version of the baseline model.

$$\begin{aligned} FUEL_{k,t} = {} & \gamma_1 FLTIME_{k,t} + \gamma_2 FREQ_{k,t} + \gamma_3 ASIZE_{k,t} + \gamma_4 MASS_{k,t} + \gamma_5 TPR_{k,t} + \gamma_6 \\ & SLOT_{k,t} + \gamma_7 HUB_{k,t} + \gamma_8 HHI_{k,t} + \gamma_9 LCC_{k,t} + \gamma_{10} FUELP_{k,t-24} + \\ & \gamma_{11} FUELP_{k,t-36} + \gamma_{12} FUELP_{k,t-48} + \gamma_{13} TREND_t + \omega_{k,t}, \end{aligned} \tag{2}$$

- $FUELP_{k,t-(h\times 12)}$, where h is the number of lags in years, $h = 2, 3, 4$. We then consider the relevant time window for lag length setting of four years.[10] FUELP is the inflation-adjusted after-tax price in the local currency of Jet A-1 fuel (in logarithm).[11] To build this metric, we use monthly fuel price data by region, plus 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 the period. In setting the variable, we use the minimum value of the mean jet fuel price observed

[7] However, in many international reviews, both companies continue to be classified as LCCs. See, for example, "*What Are The Largest Low-Cost Carriers In Latin America?*", September 18, 2020, available at simpleflying.com.

[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.

[10] The median delivery lead-time for Boeing and Airbus passenger aircraft has been 2.3 years since the 2010s. Source: Global Airline Industry/Commercial Aircraft Backlog: 2000 to 2016 – Airbus, Boeing, and Flightglobal, with own calculations. Fukui & Miyoshi (2017) use three-year lags.

[11] In Brazil, the aviation kerosene produced by the oil-producing company Petrobrás is called QAV-1.

on the route's endpoint cities. We use the lags of 2, 3, and 4 years to account for a fuel price increase's long-term effect. These variables allow us to test the hypothesis of fuel price signal effects in the 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 eco-efficiency in Brazil, in a complementary analysis to that allowed by Equation (1). We then replace the regressand ($FUEL_{k,t}$) with the following indicators:

- $RPKFUEL_{k,t}$, the total revenue-passenger kilometers produced in the city pair, divided by the total fuel consumption (in logarithm).
- $PAXFUEL_{k,t}$, the total revenue passengers carried in the city pair, divided by the total fuel consumption (in logarithm).
- $MASSFUEL_{k,t}$, the total transported mass–total aircraft load in kilograms–in the city pair, divided by the total fuel consumption (in logarithm).
- $ASKFUEL_{k,t}$, the total available-seat kilometers produced in the city pair, divided by the total fuel consumption (in logarithm).
- $FREQFUEL_{k,t}$, the total flight frequencies operated in the city pair, divided by the total fuel consumption (in logarithm).

Table 2 – Descriptive statistics of the model variables

Variable	Description	Metric	Mean	Std. Dev.	Min.	Max.	Sources
AGE	fleet age	years (ln)	1.94	0.60	-2.73	3.76	(i), (iii), (vii)
ASIZE	number of seats	count (ln)	4.73	0.50	2.20	5.33	(i)
ASKFUEL	available seat-kilometers per burnt fuel	unity per liter (ln)	3.32	0.30	1.37	4.47	(ii)
FLMOD	fleet modernization	index (ln)	1.76	0.43	0.78	5.29	(i), (ii), (iii), (vii)
FLTIME	flight time	minutes (ln)	4.48	0.47	2.70	5.64	(i)
FREQ	flight frequencies	count (ln)	4.33	1.15	0.00	8.32	(i)
FREQFUEL	flight frequencies per burnt fuel	100K per liter (ln)	3.59	0.87	1.77	6.33	(i), (ii)
FUEL	fuel burn	liters (ln)	12.25	1.60	6.64	15.99	(ii)
FUELP (2 years lag)	price per liter	deflated reais (ln)	0.93	0.22	0.16	1.43	(vi), (ix)
FUELP (3 years lag)	price per liter	deflated reais (ln)	0.94	0.23	0.16	1.43	(vi), (ix)
FUELP (4 years lag)	price per liter	deflated reais (ln)	0.92	0.27	0.06	1.43	(vi), (ix)
HHI	market concentration	index [0,1]	0.65	0.26	0.21	1.00	(ii)
HUB	proportion of hub passengers	fraction	0.17	0.10	0.00	0.47	(ii)
LCC	young LCC presence	dummy	0.08	0.27	0.00	1.00	(i)
MASS	aircraft uplifted mass	tons (ln)	13.18	1.51	9.02	17.46	(ii)
MASSFUEL	aircraft uplifted mass per burnt fuel	1000 per liter (ln)	7.83	0.55	5.17	10.52	(ii)
PAXFUEL	revenue passengers per burnt fuel	1000 per liter (ln)	3.33	0.57	0.70	5.85	(ii)
RPKFUEL	revenue passenger-kilometers per burnt fuel	1000 per liter (ln)	9.85	0.41	7.33	10.93	(ii)
SLOT	proportion of slot-related flights	fraction	0.18	0.31	0.00	1.00	(i), (x)
TPR	share of flights of turboprop aircraft	fraction	0.27	0.41	0.00	1.00	(i)

Sources: (i) Active Scheduled Flight Historical Data Series—VRA; (ii) Air Transport Statistical Database; (iii) Brazilian Aeronautical Registry—RAB; (iv) Brazilian Institute of Geography and Statistics—IBGE; (v) Central Bank of Brazil; (vi) National Agency for Petroleum, Natural Gas and Biofuels—ANP; (vii) websites planelogger.com, airfleets.net, jetphotos.com, and aviacaopaulista.com; (viii) Department of Air Traffic Control (DECEA) 's Aeronautical Information Circulars—AICs—and Aeronautical Information Service—AISWEB; (ix) state-specific legislation and online media news; (x) governmental regulations available online, website anac.gov.br; all figures computed with authors' calculations. See the supplemental material for a correlation table and other statistical analyses of the variables.

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 eco-efficiency equations' errors.

$$v_{k,t} = \Phi(ROUTE_k, TIME_t, AIRL^i_{k,t}, DIR^o_{k,s}, DIR^d_{k,s}, ATM^o_{k,t}, ATM^d_{k,t}, AIRC^j_{k,t}) + \varepsilon_{k,t}, \qquad (3)$$

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.

- $AIRL^i_{k,t}$ are dummy variables to account for the presence of airline *i* on route *k* at time *t*. To simplify, we denote these dummies of "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.

- $DIR^o_{k,s}$, and $DIR^d_{k,s}$ 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. 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)[12] 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*. Here we aim to account for the possible (unobserved) effects of aircraft mix changes on the route's fuel burn and eco-efficiency. We denote these dummies 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.

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

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. 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 & 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, & Hansen (2014a, b), and Chernozhukov, Hansen, & Spindler (2015). As discussed in Ahrens, Hansen & 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.[13] Our identification strategy involved the use of three categories of instrumental variables (IV): (1) exogenous demand shifters,[14] (2) characteristics of the service offered in the market (BLP Instruments), and (3) characteristics of the service offered in other markets (Hausman Instruments).[15] 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

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[13] See the supplemental material.

[14] 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.

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

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.[16]

3.5. Dynamic Fleet Management and deep operational controls

Airline dynamic fleet management (DFM) aims to assign the most suitable airplane according to demand in an optimal way. In our case, although the tail assignment decisions have a direct impact on the energy efficiency of carriers, the effects of dynamic fleet management 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 DFM's possible effects on companies' energy intensity in the market. As far as we know, this procedure has not yet been performed in the previous econometric literature applied to transport operations. Our approach aims to control the possible confounder effects of the airlines' DFM practices in our estimation that could cause bias in estimating our main results. To accomplish that, we incorporate into the model of Equation (1) 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, usually painted on the aircraft's tail. 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 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 of performing dynamic fleet management. In this way, the observed aircraft tail numbers' presence share variables make it possible to control these operating factors underlying the company's fuel burn phenomenon.

[16] See all results in the supplemental material.

4. Estimation results

In this section, we present the estimation results of the proposed econometric model. First, we present, in Table 3, the results of the estimates of the fuel consumption model. In sequence, in Table 4, we present the results of the energy efficiency models.[17] Table 3 contains 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) to (9), we present model specifications using the fuel price variables–FUELP lagged of 2, 3, and 4 years.

We first analyze the results of Columns (1) to (4). It is possible to note that most of the variables present estimated coefficients statistically significant and 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. On the other hand, 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 are unobservable to the econometrist.

The variable indicative of airline fleet rollover (AGE) has the expected positive and statistically significant effect in Column's most basic model (1). However, as we insert the variable FLMOD (Columns 2 to 4), this result is changed, and the variable becomes non-significant. Such behavior is probably indicative of the presence of multicollinearity between these variables, given that, in the period, airlines commonly accomplished the renovation of fleets through the introduction of new-generation aircraft. In fact, despite the VIF statistics for these variables being below 5, Pearson's correlation index of -0.6629 reveals a strong association of these variables. In any case, we have that 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 carriers' fleet modernization is associated with a reduction between 8% and 10% in fuel burn.

Finally, we have the results of the competition variables, HHI and LCC. The results of Columns (3) and (4) provide evidence of a fuel cost-cutting effect induced by competition. The results point to statistically significant estimated coefficients for HHI (positive sign) and LCC (negative sign). In both cases, it is possible to infer that an escalation in rivalry, either by a decreased market

[17] For simplicity of exposition, from now we omit subscriptions *k* and *t*.

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 at identifying 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 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 subject to penalization and shrinkage by LASSO. These specifications do not include the TREND variable, which is already controlled with 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 SLOT variables in these specifications become not significant. Regarding the lagged FUELP variables, we find evidence that ceteris paribus to the other market conditions, the energy intensity of carriers reduces after three years of an increase in fuel prices.[18] The estimated effect is relatively low, suggesting a fuel price elasticity between -0.01 and -0.11, with more significant effects associated with the 4-year lag. This result contrasts with the findings of Fukui & Miyoshi (2017)'s results of smaller effects in the longer term. We believe that with our sample period, which spans to 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 with an econometric model. Our results regarding the long-run impacts of fuel prices are robust to the specification changes across the columns of Table 3.

[18] The LASSO procedure also points to either statistically not significant or inactivated effect FUELP (2 years lag).

Table 3 – Estimation results: fuel consumption

	(1) FUEL	(2) FUEL	(3) FUEL	(4) FUEL	(5) FUEL	(6) FUEL	(7) FUEL	(8) FUEL	(9) FUEL
FLTIME	0.0975***	0.1094***	0.1186***	0.1097***	0.0836***	0.1038***	0.0529***	0.2353***	0.1752***
FREQ	0.9655***	0.9576***	0.9676***	0.9644***	0.9828***	0.9817***	0.9840***	0.9738***	0.9686***
ASIZE	0.2133***	0.2064***	0.1928***	0.1916***	0.1490***	0.1381***	0.1372***	0.2391***	0.1205***
MASS	0.0275***	0.0331***	0.0311***	0.0321***	0.0187***	0.0207***	0.0115**	0.0260***	0.0316***
TPR	-0.3219***	-0.3128***	-0.3192***	-0.3163***	-0.4169***	-0.4268***	-0.4000***	-0.2786***	-0.4154***
SLOT	0.0179***	0.0142***	0.0115***	0.0127***	0.0088***	0.0011	0.0034	0.0085***	0.0045*
HUB	0.0767***	0.0847***	0.0974***	0.0702***	-0.0187	0.0339*	-0.0299*	-0.0084	-0.0084
AGE	0.0466***	0.0041	0.0039	0.0020					
FLMOD		-0.0881***	-0.0940***	-0.0935***					
HHI (Endog)			0.1337***	0.1259***	0.1465***	0.1225***	0.0779**	0.1579***	0.1126***
LCC				-0.0446***	-0.0411***	-0.0424***	-0.0472***	-0.0547***	-0.0496***
FUELP (2 years lag)					-0.0066*	0.0075	–	–	–
FUELP (3 years lag)					-0.0159***	-0.0712**	-0.0174***	-0.0254***	-0.0148***
FUELP (4 years lag)					-0.0335***	-0.1091***	-0.0476***	-0.0503***	-0.0386***
TREND	-0.0072***	-0.0086***	-0.0084***	-0.0090***	-0.0017***				
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	37/37	37/37	26/37	26/37	28/37	25/37	12/37	12/37	12/37
Time controls	No	No	No	No	No	177/226	No	No	No
Dir-Qtr controls	No	No	No	No	No	No	614/3582	661/3582	635/3582
Airway-time controls	No	No	No	No	No	No	315/2260	331/2260	253/2260
Acft variant controls	No	No	No	No	No	No	No	55/134	No
Acft tail nr controls	No	No	No	No	No	No	No	No	427/1272
Adj R2 statistic	0.9500 [9]	0.9514 [6]	0.9508 [8]	0.9512 [7]	0.9597 [4]	0.9601 [3]	0.9572 [5]	0.9636 [1]	0.9632 [2]
AIC statistic	-146719 [4]	-149503 [1]	-148359 [3]	-149160 [2]	-124931 [8]	-125559 [7]	-121964 [9]	-132855 [5]	-131914 [6]
BIC statistic	-146283 [4]	-149057 [1]	-148008 [3]	-148800 [2]	-124559 [5]	-123613 [6]	-113340 [9]	-123155 [7]	-119780 [8]
RMSE statistic	0.1147 [9]	0.1130 [6]	0.1137 [8]	0.1133 [7]	0.0937 [4]	0.0930 [3]	0.0969 [5]	0.0892 [1]	0.0895 [2]
RMSE CV statistic	0.6581 [8]	0.6462 [6]	0.6444 [5]	0.6489 [7]	0.6404 [4]	0.6293 [3]	0.6643 [9]	0.5600 [1]	0.5866 [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.*

Table 4 – Estimation results: fuel efficiency

	(1) RPKFUEL	(2) PAXFUEL	(3) MASSFUEL	(4) ASKFUEL	(5) FREQFUEL
FLTIME	-0.2064***	-0.2576***	-0.2398***	-0.1777***	-0.2300***
FREQ	-0.9237***	-0.9245***	-0.9676***	0.0318***	0.0290***
ASIZE	-0.2310***	-0.2334***	-0.2006***	0.8331***	-0.2258***
MASS	0.9315***	0.9318***	0.9694***	-0.0295***	-0.0277***
TPR	0.2619***	0.2691***	0.3075***	0.3428***	0.2681***
SLOT	0.0004	-0.0014	-0.0049*	-0.0056**	-0.0053**
HUB	-0.0023	-0.0032	0.0209	0.0215	0.0162
HHI (Endog)	-0.0676**	-0.0755**	-0.1417***	-0.1280***	-0.1465***
LCC	0.0375***	0.0396***	0.0493***	0.0457***	0.0502***
FUELP (2 years lag)	-0.0025	-0.0022	0.0007	0.0019	0.0030
FUELP (3 years lag)	0.0081*	0.0090**	0.0199***	0.0191***	0.0205***
FUELP (4 years lag)	0.0488***	0.0496***	0.0474***	0.0407***	0.0468***
Estimator	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO
Airline controls	13/37	13/37	13/37	13/37	13/37
Dir-Qtr controls	662/3582	655/3582	648/3582	700/3582	661/3582
Airway-time controls	291/2260	294/2260	310/2260	246/2260	248/2260
Acft variant controls	49/134	49/134	50/134	55/134	51/134
Adj R2 statistic	0.8635	0.8647	0.8777	0.7443	0.5517
RMSE statistic	0.0923	0.0927	0.0861	0.0851	0.0864
RMSE CV statistic	0.2142	0.5615	0.5534	0.2104	0.5596
Nr observations	65,482	65,482	65,482	65,482	65,482

*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 4 presents the eco-efficiency models' estimation results, using indicators RPKFUEL, PAXFUEL, MASSFUEL, ASKFUEL and FREQFUEL as regressands. These specifications contain the same covariates as of Column (8) in Table 3. Important to note that, given that the regressands are now inversely proportional to FUEL, the sign of many coefficients in Table 4 may have the opposite sign from the one estimated in Table 3. The variables that have changed sign of estimated coefficients are FLTIME, TPR, HHI, LCC, and FUELP. In these cases, we interpret that the results in Table 4 confirm the findings of Table 3. However, FREQ, ASIZE, and MASS have estimated coefficients with changed sign in some of the columns in Table 4. For example, FREQ shows a positive and statistically significant coefficient in Columns (4) and (5), suggesting that the energy efficiency, as measured by ASKFUEL and FREQFUEL, tend to rise as flight frequency increases. On the other hand, the estimated effects of the MASS variable for these indicators are negative, although being positive for RPKFUEL, PAXFUEL and MASSFUEL–namely, Columns (1) to (3). In all cases, we believe that the estimation results are not inconsistent with the ex-ante expectation regarding these variables' effect. Again, concerning the lagged FUELP variables, we estimate long-term statistically significant effects and suggest an efficiency-enhancing effect.

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

4.1. Dynamic Fleet Management and deep operational controls

In this subsection, we discuss the models' estimation results, including our proposed dynamic fleet management controls. We re-estimate the model in Column (8) of Table 3 and all the models of Table 4, using 1,272 additional variables representing the shares of each aircraft tail number in the city-pair, all subject to the LASSO penalty procedure. These results are in Column (9) of Table 3 and Table 5, respectively. We interpret the controls not inactivated by LASSO as those that purge possible omitted variables biases, therefore being interpreted as nuisance parameters.

Concerning Column (9) of Table 3, most of the results remain statistically significant and with the same coefficients' sign as of Column (8). Note that the LASSO procedure does not inactivate 427 controls out of the 1,272 initially modeled. More specifically, the results regarding the lagged fuel price variables (FUELP) remain the same. Regarding the results in Table 5, most estimation results do not change, 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 most cases. The only exception is the FUELP (3 years lag) variable in Column (2)–the PAXFUEL model–, which proved to be statistically significant. Regarding FLTIME, FREQ, ASIZE, MASS, TPR, and HUB, the results obtained are robust to the insertion of deeper controls, with no change in interpretation.

The SLOT, HHI, and LCC variables' estimation results presented some instability that we must discuss, however. The most notable case is the LCC variable, which unlike the results of Table 3, is inactivated by LASSO in Columns (1) to (4) of Table 5. This variable is robust only with respect to the FREQFUEL specification–Column (5). In addition, the HHI variable is not significant in Columns (1) and (2) of Table 5. The results indicate 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 responses to higher competition and entry may depend on how flexible the dynamic fleet management of airlines is. Perhaps an effective DFM that allows quick decisions on which individual aircraft should operate which flight is one of the necessary conditions for carriers to fight the competition in the airline markets under consideration.

In sum, our results suggest that, although competition may create incentives for carriers to improve their fuel management to control costs, apparently, they do not improve their eco-efficiency across all possible dimensions. Table 5 shows no evidence of an association between HHI and the efficiency indicators related to passengers' number, RPKFUEL, and PAXFUEL–Columns (1) and (2). In contrast, the associations of that regressor with the performance metrics related to capacity, ASKFUEL, and, to a lesser extent, FREQFUEL, are statistically significant–Columns (4) and (5). The same result applies to MASSFUEL, a metric influenced by the transportation of cargo and baggage. These findings indicate that capacity and cargo may be adjustment variables preferred by airlines when performing their fuel management tactics during competitive episodes in the industry.

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

	(1) RPKFUEL	(2) PAXFUEL	(3) MASSFUEL	(4) ASKFUEL	(5) FREQFUEL
FLTIME	-0.1374***	-0.1920***	-0.1694***	-0.1387***	-0.1550***
FREQ	-0.9192***	-0.9203***	-0.9630***	0.0266***	0.0403***
ASIZE	-0.1267***	-0.1261***	-0.1199***	0.8667***	-0.1191***
MASS	0.9243***	0.9251***	0.9617***	-0.0296***	-0.0369***
TPR	0.3863***	0.3943***	0.3880***	0.3558***	0.3959***
SLOT	-0.0042	-0.0060**	-0.0079***	0.0000	-0.0082***
HUB	-0.0056	-0.0042	0.0128	-0.0001	0.0186
HHI (Endog)	-0.0260	-0.0309	-0.1079***	-0.1750***	-0.0558*
LCC	–	–	–	–	0.0522***
FUELP (2 years lag)	-0.0034	-0.0035	-0.0010	–	–
FUELP (3 years lag)	0.0069	0.0055	0.0186***	0.0138***	0.0213***
FUELP (4 years lag)	0.0478***	0.0456***	0.0472***	0.0425***	0.0438***
Estimator	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO
Airline controls	10/37	10/37	10/37	11/37	10/37
Dir-Qtr controls	615/3582	616/3582	614/3582	640/3582	619/3582
Airway-time controls	238/2260	237/2260	246/2260	207/2260	202/2260
Acft tail nr controls	370/1272	369/1272	371/1272	388/1272	345/1272
Adj R2 statistic	0.8593	0.8610	0.8714	0.7321	0.5274
RMSE statistic	0.0936	0.0938	0.0881	0.0906	0.0908
RMSE CV statistic	0.1909	0.5918	0.5858	0.1990	0.5994
Nr observations	65,482	65,482	65,482	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.*

5. Conclusion

The present paper estimates fuel consumption determinants and the market incentives for eco-efficiency in the airline industry using an econometric model. We develop an application for domestic air transport in Brazil over the 2000s and 2010s. Due to the complexity of the fuel consumption phenomena, we utilize high-dimension models with LASSO penalty, incorporating thousands of nuisance parameters in the model specifications to avoid the omitted variables bias. In particular, we propose an approach to account for carriers' dynamic fleet management strategies, using controls for the airlines' tail assignment problem.

Our results indicate the validity of the hypothesis that aviation Jet A-1 fuel has 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 the fleet rollover and the fleet modernization decisions of airlines. We also estimate the dynamic effects of shocks in fuel prices on the future fuel burn and fuel efficiency performance in the market. We find evidence of statistically significant fuel price signals with lags of three to four 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 into the topic.

Our work has important implications for public policies aiming to mitigate aviation fuel burn and emissions. In particular, we point to 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.

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