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João B. T. Szenczuk
Alessandro V. M. Oliveira

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Abstract

Empirical studies of the determinants of flight delays typically take into consideration factors such as weather, airport and air traffic characteristics, competition, seasonality and secular effects. An unexplored factor in this literature is the effect of the Performance Based Navigation (PBN) concept. PBN is an advanced, satellite-enabled form of air navigation that creates precise and shorter 3-D flight paths. These new procedures can improve air traffic flow and increase airspace capacity, possibly reducing flight times and delays. This paper provides an econometric model to test the impacts of PBN on the average flight times of airlines in the domestic air transport industry of Brazil.

Keywords: air traffic management; flight delays; airborne delays; econometrics.

✈ Corresponding author. Email address: alessandro@ita.br.

▪ Affiliations: Center for Airline Economics, Aeronautics Institute of Technology, Brazil (both authors).

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1. Introduction

The present paper empirically investigates potential determinants of increased flight times with special attention to the effects of the Performance Based Navigation (PBN) concept implementation. On time performance is a key point for measuring the efficiency and level of service of airlines, air navigation service providers (ANSPs), and airports. Besides that, flight delays bring a set of undesired consequences to air transport, such as extra costs to airlines and passengers, and airspace and airport constraints. According to FAA (2018), the cost to an airline for one hour of delay ranges from about $1,400 to $4,500, with the value of passenger time ranging from $35 to $63 per hour. Ball et al. (2010) estimates the cost of delays in US domestic market, that hit $32.9 billion in 2007. According to Eurocontrol (2019), the European air space network generated a total of 19.1 million minutes of en route delay in 2018 (up 105% on 2017)[1]. Thus, the investigation of causes of flight delays along with means of mitigating them is essential to improve air transport quality.

Means of mitigating these costs include Air Traffic Management (ATM) improvements, with new technologies and operational concepts, like PBN. According to FAA, its NextGen program has already delivered $4.7 billion in benefits to passengers and airlines, being over $2 billion accounted to PBN procedures[2]. Such benefits were achieved with shorter and more precise flight paths, reducing travel times, delays and fuel consumption.

In Brazil, the Department of Air Traffic Control (DECEA), the Brazilian ANSP, started PBN implementations in 2009, and eight of the most demanded Terminal Maneuvering Areas (TMAs) are already equipped, besides routes in the south region and between Rio de Janeiro and São Paulo. According to DECEA straighter flight paths enable flight time reductions of eight minutes between São Paulo/Congonhas Airport (CGH) and Rio de Janeiro/Santos Dumont (SDU) and eleven minutes between CGH and Brasília (BSB)[3].

However, the real effects of PBN implementations are still undefined in literature. Thus, this paper develops an econometric model of flight times and their influencing factors, with special attention to the effects of the PBN concept implementation. For that, we analyze flights in the Brazilian domestic market pre and post implementations, with data from 2000 to 2018. Most factors

[1] “2018’s air traffic in a nutshell” – EUROCONTROL news, Jan, 10th, 2019.
[2] “NextGen by the Numbers” – FAA, May, 3td, 2018.
[3] Source: DECEA, Sirius | PBN: Fase RJ/SP.

considered in the model were identified in literature, such as airport characteristics, demand, market concentration, fuel price, slot coordination, and secular effects. Many studies have used econometric models to estimate the causes of flight delays, such as Mayer and Sinai (2003), Hansen & Hsiao (2005), Bendinelli, Bettini & Oliveira (2016) and Santos & Robin (2010), as presented in the following section. However, to the best of our knowledge, only Guzhva, Abdelghany and Lipps (2014) investigated the effects of improvements in Air Traffic Management (ATM) on flight times through an econometric model.

The remainder of the paper is divided as follows. Section 2 presents the discussion of the literature on determinants of flight delays and a brief explanation about PBN. Section 3 presents the empirical model. Section 4 presents the estimation results and discussions, which is followed by the conclusions.

2. Literature Review

Many studies have applied econometrics to investigate the causes of flight delays. Two main strands were identified on this literature, one focused on flight-related factors and another on market characteristics. Most papers employ proxies for possible flight disruption determinants such as weather conditions and airspace and airport congestion. Hansen & Hsiao (2005) estimate an econometric model of average daily arrival delay that incorporates the effects of arrival queuing, weather, seasonal effects, and secular effects. Their results suggest that there was a steady decline in delays from 2000 through early 2003 and a worsened scenario in late 2003 and early 2004, in the United States' National Airpace System (NAS). Some important factors like aircraft mix were not considered.

In Hansen & Hsiao (2006), queuing delays at different times of the day, general aviation, military traffic and volume of scheduled arrivals (as opposed to completed ones) were added to the model. Besides that, they suggest that weather impacts on delays may not be determined by weather itself, as was assumed in the first model, but by the interaction between the volume of scheduled arrivals and weather conditions. The results indicate that 31% of the total delay increase between early 2004 and early 2005 can be attributed to traffic growth and decreased queuing delay was the primary reason delays decreased between the first half of 2000 and the first half of 2005.

An innovative delay metric to cope with the distortions created by schedule padding[4] is presented in Hansen & Xiong (2007). Besides that, they analyze for the first time the impacts of weather forecast accuracy. Their results indicate that over-forecasting is the source of about 20% of total delay.

Lall (2018) uses a count regression model to study delays at the three New York city area airports, examining different causal factors of the hourly number of delayed flights. Results are reported separately for each airport and demonstrate significant difference among them. In general terms, the most important factors for explaining delay are weather conditions, specially thunderstorms, peak hours, delayed departures and share of heavy aircraft operations.

Borsky & Unterberger (2019) estimate the effects of sudden and slow onset weather events on flight departure delays. For sudden onset events, a difference-in-difference framework is used, allowing for inferences at the hourly level. For slow onset events a Prais Winstein estimator with panel-corrected standard errors is used. Results indicate that weather shocks like rainfall, snow and wind (sudden events) have a significant impact on departure delays within the U.S. aviation system. Regarding slow onset weather shocks, results suggest that cold conditions lead to additional departure delays.

Because of complex interactions among causal factors and their relationship and their nonlinear relationship with flight delays, Xu, Sherry, & Laskey (2008) develop multifactor models, using multivariate adaptive regression splines, for predicting airport delays in 15-min periods at 34 airports. Rodríguez et al. (2017) predict daily probabilities of arrival and departure delays. The main results indicate that the departure delay, the size of the airline, the size of the airport and the day of the flight (Tuesdays and weekends) are statistically significant factors to explain the probability of arrival delay.

Combining logistic and quantile regression methods, Wang & Vaze (2016) models the probability distributions of flight delays. The method enabled new inferences about delays. For instance, although the positive delay probability is found to be similar for low-cost and legacy carriers, longer delays are significantly less probable for the low-cost carriers. Besides that, while seasonality and time-of-day factors explain over half the variation in the positive delay probabilities, they explain very little of the variation in higher delay quantiles. Airport factors, however, explain probabilities of longer delays far better than they explain the positive delay probabilities. Differences were also

[4] Airlines' practice of scheduling extra time (buffer) than really needed for the trip.

evident when delays are caused by congestion in U.S National Airspace System (NAS) or by the airline.

On the other strand of literature, concerned with market characteristics, Rupp, Owens & Plumly (2001) analyze the relationship between route competition and on time performance with data from U.S. market in the period of 1997-2000. They find that more competitive routes experienced more flight delays. Seasonal effects, airport capacity constraints, demand and hubbing effects were also important factors. Mazzeo (2003), however, found that market concentration in positively correlated with worse on time performance, especially if only one airline operates on a route. Other important factors to explain flight delays were weather, congestion, and scheduling decisions.

Mayer & Sinai (2003) also investigated the US market, in the period of 1988–2000. Their results indicate that congestion externalities cause modest levels of air traffic delays and hubbing is the main economic contributor to air traffic congestion. Besides that, hub airlines themselves incur all the delay caused by hubbing. Santos & Robin (2010) follow a similar methodology for the European market. Factors analyzed were airport and airline fixed effects, airport concentration, slot coordination, demand and seasonal effects. Opposed to Mayer & Sinai (2003) their results indicate that while delays are higher at hub airports, hub airlines experience lower delays.

Bendinelli, Bettini & Oliveira (2016) investigate determinants of flight delays in Brazil, also with special attention to competition and dominance at both the route and airport levels. Results indicate self-internalization of congestion by hub airlines and a positive relationship between delays and route concentration. Aydemir et al. (2017) investigate flight delays in Turkey and their results are also consistent with the internalization hypothesis on domestic routes.

Prince & Simon (2009) explore the impact of multimarket contact on flight delays. Results show that multimarket contact increases delays and that this effect is greater for contacts on more concentrated routes, although the effect diminishes on highly concentrated routes. Deshpande & Arıkan (2012) examine causes of flight delays with special attention to the impact of scheduled block time.

Regarding the impacts of an air traffic optimization specifically, Guzhva, Abdelghany & Lipps (2014) evaluate the implementation of an Aircraft Arrival Management System (AAMS) with a regression model. The AAMS was implemented for only 6.5% of an airline’s arrivals at Charlotte-Douglas International Airport (CLT) and this relatively low percentage of flights was not enough to provide a noticeable change in the overall NAS on time performance. However, the participating flights indeed experienced lower dwell times by 43s in terminal area.

Despite the wide range of factors considered in the previous literature, to the best of our knowledge, the effects of Performance Based Navigation (PBN) remains unexplored in the econometric literature of flight delays. The PBN concept implementation is a number one priority of ICAO's Global Air Navigation Plan and one of its expected operational benefits is flight delay reductions. The PBN concept represents a change from flight trajectories based on ground navigation aids to trajectories based on the performance of a set of navigation systems that enable the creation of waypoints to mark out any desired route. PBN provides for more efficient design of airspace and procedures which collectively result in improved safety, capacity, predictability, operational efficiency, and environmental impacts. Specifically, improved access and flexibility help to enhance reliability and reduce delays by defining more precise terminal area procedures. The concept is divided into two specifications: Area Navigation (RNAV) and Required Navigation Performance (RNP). The difference is that RNP procedures require an onboard performance monitoring and alerting capability. Each RNAV or RNP procedure receives a numeral designation that represents its lateral navigation accuracy in nautical miles. RNP 1, for instance, indicates that the aircraft must maintain its path with one nautical mile of lateral accuracy for 95% of the time (ICAO, 2013; FAA, 2014; Nakamura & Royce 2008).

Therefore, the present paper develops an econometric model of flight times, based on the methodology of the presented literature, but adding new variables to capture the effects of PBN.

3. Research design

3.1 Application

The PBN concept has been implemented in Brazilian Terminal Maneuvering Areas (TMAs) since 2009, according to the Aeronautical Information Circulars (AICs) issued by the Department of Air Traffic Control (DECEA), the Brazilian ANSP. First implementations occurred in the Terminal Maneuvering Areas (TMAs) of Brasília, Recife, São Paulo and Rio de Janeiro (2009), followed by Belo Horizonte in (2015) and the south region in 2017. Figure 1 is a map showing where PBN was implemented. Circle sizes represent frequency of routes from a city. Table 1 shows the yearly number of city-pairs with PBN at both endpoint cities, only at origin, and only at destination.

Figure 1 - PBN terminals

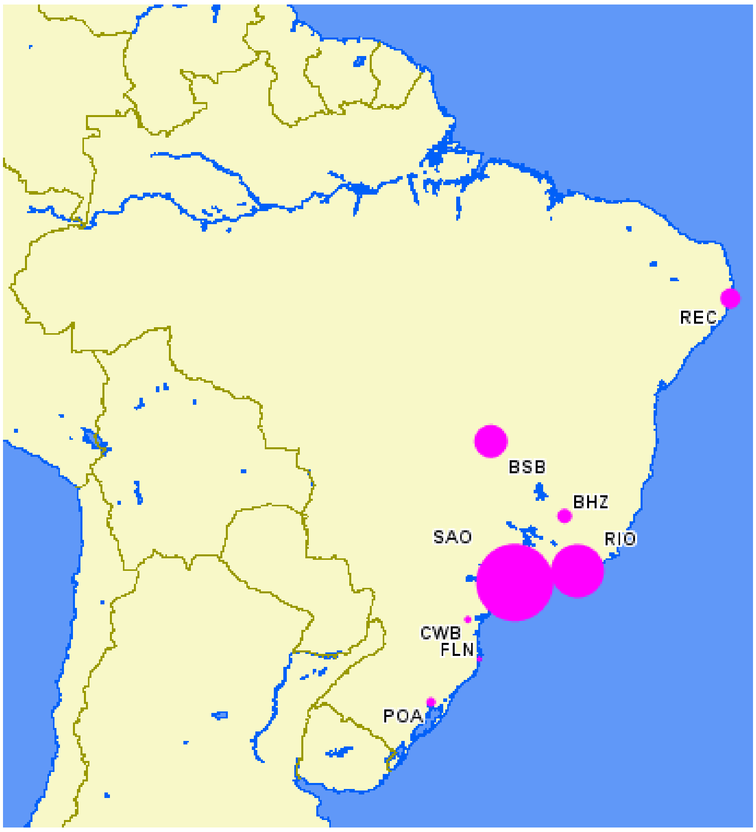
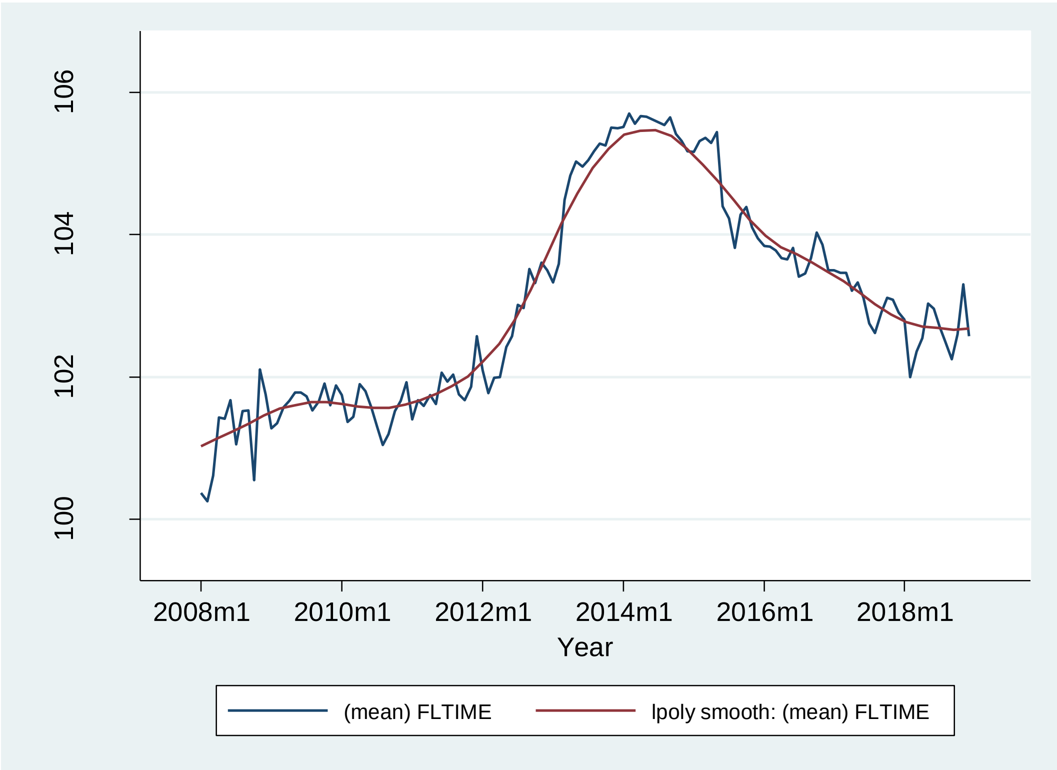


Table 1 – PBN distribution over the years

YEAR	PBN at orig. and dest. 0	1	Total	PBN at orig. 0	1	Total	PBN at dest. 0	1	Total
2000	6491	0	6491	6491	0	6491	6491	0	6491
2001	6106	0	6106	6106	0	6106	6106	0	6106
2002	5476	0	5476	5476	0	5476	5476	0	5476
2003	4889	0	4889	4889	0	4889	4889	0	4889
2004	5005	0	5005	5005	0	5005	5005	0	5005
2005	5587	0	5587	5587	0	5587	5587	0	5587
2006	5373	0	5373	5373	0	5373	5373	0	5373
2007	5782	0	5782	5782	0	5782	5782	0	5782
2008	6047	0	6047	6047	0	6047	6047	0	6047
2009	6317	0	6317	6317	0	6317	6317	0	6317
2010	6615	38	6653	6046	607	6653	6062	591	6653
2011	7396	144	7540	5986	1554	7540	6010	1530	7540
2012	7192	144	7336	5812	1524	7336	5811	1525	7336
2013	6575	144	6719	5173	1546	6719	5174	1545	6719
2014	5110	120	5230	3925	1305	5230	3927	1303	5230
2015	6515	160	6675	4918	1757	6675	4923	1752	6675
2016	6079	240	6319	4120	2199	6319	4131	2188	6319
2017	6017	328	6345	4080	2265	6345	4101	2244	6345
2018	6088	597	6685	4015	2670	6685	4034	2651	6685
Total	114660	1915	116575	101148	15427	116575	101246	15329	116575

PBN implementations are expected to reduce flight times through improved use of airspace, with more direct routes and airspace capacity (ICAO, 2013). Thus, we assume that the most appropriate metric to measure PBN real effects is flight time, or flight duration. Figure 2 shows the average flight times from 2008 to 2018 in minutes. For consistency, the data used in Figure 2 include only routes where we observe flights in each month of the entire period. The average flight time increased approximately five minutes from 2011 until mid-2014 when it started to decrease. This increase might be attributed to the adaptation period to the new procedures after PBN implementations and airspace restructuration in the TMAs of Brasília, Recife, São Paulo and Rio de Janeiro. However, this assumption requires further and more detailed analysis, since flight times depend on a wide range of factors. In this paper we consider that flight duration depends on six sets of variables: flight operations & costs, airports, competition, ANSP's measures, delays and routes fixed effects, that are discussed in the following sections.

Figure 2 - Average Flight Times



3.2 Data

Our data set consists of a panel data of domestic directional city-pairs in Brazil from January 2000 to December 2018. Multiple airports in a region are grouped. The main data source is publicly available from the National Civil Aviation Agency (ANAC), which provides information on all scheduled flights in the country in the Active Scheduled Flight Report (VRA). That dataset includes records of flight level data of carriers, airport-pairs, flight numbers, scheduled and actual departure and arrival times, and the justification code reported for each delayed and cancelled flight. The original VRA data is aggregated to form a city-pair/month data set. Only direct flights are considered. That leaves us with 116 575 observations of 1560 directional city-pairs, along 228 months. The PBN implementations are considered according to the Aeronautical Information Circulars (AICs) published by the Brazilian ANSP, DECEA.

3.3 Econometric model

The model employed in this paper (1) follows a similar specification of previous literature like Rupp, Owens & Plumly (2001), Mayer & Sinai (2003), Mazzeo (2003), Santos & Robin (2010). Our dependent variable is the natural logarithm of average flight times on city-pair *k* in month *t.* This variable is calculated with gate-to-gate time, including, therefore, taxi times. It is regressed against the six groups of variables, described in this section.

$$\begin{aligned} \ln FLTIME_{kt} = \; & \beta_1\, DENSITY_{kt} + \beta_2\, FREQ_{kt} + \beta_3\, LF_{kt} + \beta_4\, FUELP_{kt} + \\ & \beta_5\, TURBOPROP_{kt} + \beta_6\, NET\_15\_44_{kt} + \beta_7\, NET\_45\_69_{kt} + \\ & \beta_8\, NET\_70_{kt} + \beta_9\, CON\_10\_20_{kt} + \beta_{10}\, CON\_20\_30_{kt} + \\ & \beta_{11}\, CON\_30_{kt} + \beta_{12}\, SLOTPR_{kt} + \beta_{13}\, HHI_{kt} + \beta_{14}\, MAXHHI_{kt} + \\ & \beta_{15}\, MAXDEL_{kt} + \beta_{16}\, PBN_{kt} + \gamma_k + \gamma_t + u_{kt}, \end{aligned} \tag{1}$$

where *k* is the directional city-pair, (*k* = 1, …., 4161 routes), and *t* denotes the time period (*t* = 1, ..., 228 months).

Regressors: flight operations & costs

- $DENSITY_{kt}$ is the total number of revenue passengers on a city-pair *k* in month *t*, divided by 10000. With this variable we intend to capture the effects of airport demand, since flights in highly demanded airports generally require more time on the ground and terminal airspace.
- $FREQ_{kt}$ is the total number of direct scheduled flights in route *k* and time *t*, divided by 100. This variable captures the effects of airspace demand and service frequency. This variable can indicate if more frequently flown routes have any type of privilege in air traffic management.
- LF_{kt} is the division of Revenue Passengers Kilometer (RPK) by Available Seats Kilometer (ASK). It captures how loaded airplanes were in city-pair *k* and month *t.*

- $FUELP_{kt}$ is a proxy for fuel price. It is an approximation of the ICMS[5] in each state plus the average gravitational price of the fuel at the distributor in the states.
- $ASIZE_{kt}$ is a proxy for aircraft size. It is the total number of passengers divided by total take-offs. Since bigger airplanes, in general, fly faster, we expect the sign of this variable to be negative.
- $TURBOPROP_{kt}$ measures the proportion of turboprop aircrafts in route *k* and month *t.* As turboprops fly at slower airspeeds, we expect the sign of this variable to be positive.
- In model number 4 we exclude variable $TURBOPROP_{kt}$ and add the proportion of each aircraft type in route *k* and time *t.*
- $SLOTPR_{kt}$ is a dummy variable that indicates that an airport in city-pair *k* was slot-controlled in time *t.* Since airlines are more encouraged to keep on time performance in slot-controlled airports, we expect this variable to have some influence on flight time, with a negative sign.

Regressors: airports

Following Mayer & Sinai (2003) and Santos & Robin (2010) we divide cities by the number of destinations served from the airports of that city. We use the maximum value in the city-pair, from origin or destination.

- $NET\_15\_44_{kt}$ is a dummy variable that indicates that flights arrived at or departed from cities where airports serve from 15 to 44 destinations. $NET\_45\_69_{kt}$ is used for cities with 45 to 69 destinations and NET_70_{kt} for over 70 destinations. Our baseline case are cities that connect to up to 14 other cities.

Despite being a reasonable proxy for the size and complexity of an airport, the NET variables do not account for hubbing effects. We measure the level at which an airport operates as a hub by the number of passengers in connection. As with the NET variables, we use only the maximum value in the city-pair, from origin or destination.

- $CON\_10\_20_{kt}$ is a dummy variable that indicates that between 10 and 20% of passengers in a city's airports are in connection. We similarly have $CON\_20\_30_{kt}$, and CON_30_{kt} when over 30% of passengers are in connection.

[5] ICMS is a tax on movement of goods and services that varies among the Brazilian states.

Regressors: competition & dominance

- HHI_{kt} is the Herfindahl-Hirschman index of concentration of revenue passengers of city-pair *k* on time *t*. This variable captures the effect of airline market dominance at the route level.
- $MAXHHI_{kt}$ is the maximum Herfindahl-Hirschman index of concentration between the endpoint cities of city-pair *k* and time *t*. We intend to capture the effect of dominance at the airport level with this variable.

Regressors: delays

- $MAXDEL_{kt}$ is the maximum proportion of delayed flights between the endpoint cities of city-pair *k* and time *t*. Since delays can increase flight time, if they occur during flight operation, we expect this variable to positively influence flight time. This variable is also a proxy for congestion and adverse meteorological conditions, since they are the mains causes of delays reported in literature. This variable is used only in the baseline model. For the three following models we substitute it for delays at origin and destination, separately, using $DELO_{kt}$ and $DELD_{kt}$, respectively.

Regressors: PBN

- PBN_{kt} indicates that city-pair *k* in time *t* had PBN operations at both endpoints. $PBNO_{kt}$ indicates PBN operations only in the origin city and $PBND_{kt}$, similarly, in the destination city.

Fixed effects and disturbances

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

Table 2 presents descriptive statistics of the main variables of our empirical model. Henceforth indices *k* and *t* are omitted.

Table 2 – Descriptive statistics

Variable	Mean	SD	Min.	Max.
FLTIME	87.932	46.822	10.000	280.500
DENSITY	0.930	2.439	0.000	44.059
LF	0.635	0.173	0.122	0.953
FREQ	0.112	0.253	0.001	4.112
ASIZE	100.869	52.469	8.918	207.455
FUELP	2.428	0.628	1.060	4.187
TURBOPROP	0.403	0.466	0.000	1.000
NET_15_44	0.401	0.490	0.000	1.000
NET_45_69	0.236	0.424	0.000	1.000
NET_70	0.196	0.397	0.000	1.000
CON_10_20	0.332	0.471	0.000	1.000
CON_20_30	0.251	0.434	0.000	1.000
CON_30	0.246	0.431	0.000	1.000
SLOTPR	0.116	0.249	0.000	1.000
HHI	0.741	0.268	0.206	1.000
MAXHHI	0.593	0.273	0.223	1.000
MAXDEL	0.192	0.095	0.000	1.000
DELO	0.161	0.092	0.000	1.000
DELD	0.161	0.092	0.000	1.000
PBN	0.016	0.127	0.000	1.000
PBNO	0.132	0.339	0.000	1.000
PBND	0.131	0.338	0.000	1.000

3.4. Estimation strategy

We employed the Least Square Dummy Variables estimator with fixed effects for each month *t* and city-pair *k*. Standard errors are corrected for heteroscedasticity and autocorrelation with the Newey-West estimator. A Wald test was performed to the coefficients of the aircraft mix variables and the null hypothesis was rejected, indicating that these coefficients are not simultaneously equal to zero.

4. Results and discussion

Table 3 presents the main estimation results. Column (1) is our baseline model. In Column (2) we substitute MAXDEL for DELO and DELD. In Column (3) we substitute PBN for PBNO and PBND. Finally, in Column (4), we add controls for the proportion of flights by each aircraft type - the aircraft mix - and thus drop TURBOPROP.

Regarding flight operations and costs, all variables are statistically significant at the 1% level. Results indicate that routes with more passengers experience longer flight times, which may be associated with the complexity of flight operations due to increased traffic. The results for LF, SLOTPR and FREQ suggest that airlines make some effort to keep flights on schedule, adjusting flight speeds, when the direct cost of delay increases. The inherent capacity constraints of slot-controlled airports facilitate the propagation of delays to later flights. Besides that, a high proportion of delays may cause airlines to lose their slots. Moreover, delays in more loaded flights represent more passengers missing their connections.

Regarding aircraft characteristics, ASIZE and TURBOPROP are statistically significant with the expected signs. The estimate of ASIZE indicates that the average size of the aircraft mix of a route has a small negative effect on average flight times. This small effect of aircraft size is expected since the proportion of turboprop aircrafts, that are smaller and slower, is also in the model (Columns 1 to 3). In Column 4 the proportion of each aircraft type is used, controlling for performance differences among aircraft types.

The fuel price proxy is statistically significant and has a negative sign, which is a puzzling result, since airlines can manage their cost index. Cost index is the ratio of the time-related cost of an airplane operation, such as crew wages and maintenance hours, and the cost of fuel. Thus, if fuel price is higher, airlines can choose to fly at slower airspeeds to burn less fuel but spending more time. If fuel prices are lower, airlines can fly faster, burning more fuel, but reducing time-related costs (Roberson, 2007). A possible explanation for this result might be the occurrence of a practice known as "fuel tankering", which is a way to lower the fuel cost by refueling at departures where the fuel price is lower than at the destination of the flight.

The variable NET_15_44 has a negative sign, indicating that flights in medium airports are generally faster than those in small ones, with up to 14 destinations. A possible reason is that small airports usually do not provide Air Traffic Control (ATC) and operate under visual flight rules, which forces pilots to follow the entire visual circuit pattern in low speeds. In medium airports, where ATC is provided, but demand is much lower than capacity most of the time, flights may be vectorized more frequently. Cities with connection with 45 to 69 other cities do not show statistically significant difference against the baseline case. In big airports, with more than 70 destinations, as expected, flights take longer, probably because of traffic complexity and taxi times. Such estimates suggest that the relationship of the NET variables and flight times follow a quadratic function with concave up.

The proxies to capture hubbing effects all have positive signs, as expected, and show that flight times increase with the number of passengers in connection. Such results indicate that airlines cluster their flights in small time periods to serve as many connecting passengers as possible and reduce their total trip time. However, that practice may cause congestion or at least increase traffic complexity at the airports, which tends to increase flight times.

The coefficients of MAXHHI and HHI are negative and statistically significant, at least at the 10% level. The estimate of MAXHHI, that measures concentration at the airport level, corroborates the airport congestion internalization hypothesis, as in Mayer and Sinai (2003), Santos and Robin (2010) and Bendinelli et al. (2016). The estimate of HHI corroborates the results of Rupp et al. (2001), that find worse on time performance in more competitive routes. The delay variables are all statistically significant and have positive coefficients, as expected. If a high proportion of flights is delayed, flight times are expected to increase, on average.

Regarding the PBN variables, the estimation results suggest statistically significant relationships with respect to mean flight times. The negative sign shows that PBN operations apparently led to a reduction of 1% - 2% in flight times, as expected by aviation stakeholders. PBN operations at both endpoint cities implies in an estimated reduction in flight time by approximately 1,9% on average, according to this model. PBN only at origin airports suggests a 1,2% flight time reduction in Column (3). However, when the aircraft mix controls are included in the model (Column 4), such negative effect decreases to 0,8%, which suggests that variations among aircraft performances have a considerable effect on average flight times. PBN at arrivals reduce flight times at a higher value, on average by 2,3%. This difference between the estimates of PBNO and PBND was expected since the pool for improvement is bigger for descents than for climbs. PBN procedures facilitate the employment of Continuous Descent and Climb Operations (CDOs and CCOs, respectively), eliminating or at least diminishing holding patterns, that were present in conventional approach procedures.

Considering average flight times and the frequency of flights in each route and month we can obtain an estimate of the total number of flight hours in our sample period, that corresponds to approximately 19.9 million hours. From this total, about 2.5 million hours were flown on routes with PBN procedures at both endpoint cities, while 6.16 million hours were flown with PBN only at origin and other 6.15 million only at destination. The estimated number of saved flight hours based on the estimates of Columns 2 and 3 of Table 3 are displayed in Table 4.

Table 3 – Estimation Results

	(1) lnFLTIME	(2) lnFLTIME	(3) lnFLTIME	(4) lnFLTIME
DENSITY	0.0068***	0.0069***	0.0081***	0.0109***
LF	-0.0276***	-0.0289***	-0.0277***	-0.0134***
FREQ	-0.1107***	-0.1122***	-0.1105***	-0.1011***
ASIZE	-0.0002***	-0.0002***	-0.0002***	-0.0008***
FUELP	-0.0479***	-0.0477***	-0.0478***	-0.0519***
TURBOPROP	0.2218***	0.2223***	0.2228***	
NET_15_44	-0.0051*	-0.0052*	-0.0045*	-0.0074***
NET_45_69	0.0001	0.0001	0.0044	0.0006
NET_70	0.0120***	0.0123***	0.0203***	0.0176***
CON_10_20	0.0130***	0.0133***	0.0131***	0.0089***
CON_20_30	0.0176***	0.0178***	0.0167***	0.0156***
CON_30	0.0204***	0.0208***	0.0206***	0.0238***
SLOTPR	-0.0147***	-0.0146***	-0.0184***	-0.0077***
HHI	-0.0052*	-0.0053*	-0.0071**	-0.0067***
MAXHHI	-0.0095**	-0.0095**	-0.0108**	-0.0048**
MAXDEL	0.0895***			
DELO		0.0357***	0.0325***	0.0155***
DELD		0.0955***	0.0915***	0.0725***
PBN	-0.0196***	-0.0191***		
PBNO			-0.0125***	-0.0084***
PBND			-0.0232***	-0.0226***
Fixed effects	*two-way*	*two-way*	*two-way*	*two-way*
Aircraft mix control	*no*	*no*	*no*	*yes*
Adjusted R2	0.9818	0.9819	0.9819	0.9848
RMSE Statistic	0.0719	0.0717	0.0716	0.0657
Nr Observations	116,528	116,528	116,528	116,528

Results produced by the Least Square Dummy Variables Estimator (LSDV).
*P-value representations: ***p<0.01, ** p<0.05, * p<0.10.*

Table 4 – Estimated number of flight hours saved with PBN

	Flight Hours (millions)	Estimated Saved Hours (thousands)
PBN	2.5	48
PBND	6.15	139
PBNO	6.16	51
Total in Sample	19.9	238

5. Conclusions

This paper employed an econometric model to investigate determinants of flight times in Brazilian domestic market over the period of 2000 to 2018 with special focus on the effects of the Performance Based Navigation (PBN) implementations by the air traffic management authority. Our model uncovered key factors explaining the increased flight times, such as growth in delays, airport size and passenger traffic. Our results show that more concentrated routes and airports experience faster flights, which is consistent with the findings of the previous literature. Additionally, flights to or from cities with over 70 destinations and at hubs tend to be longer, an effect probably associated with increased complexity of air traffic management of major airports.

Our estimation results provide evidence that the PBN procedures reduced flight times by about 1,9% on average when both endpoint cities are equipped with PBN. When PBN is available only at the origin airport, results suggest 0,8% of time reduction if the effects of the aircraft mix are controlled for. On routes with PBN at destination, flight times were apparently reduced by 1,2% on average. The empirical evidence obtained in this paper therefore suggests that about 238,000 flight hours were saved during the sample period due to PBN procedures.

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