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Are on-time performance statistics worthless? An empirical study of the flight scheduling strategies of Brazilian airlines

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Abstract

Airlines may manage their on-time performance by lengthening schedules with engineered increases in planned flight times. We develop an econometric model of high dimensional sparse (HDS) regression to decompose the extra schedule block times into operational and strategic factors. We estimate the impact of extra times on flight delays, allowing for the moderation effects of runway congestion, slots, and propagated delay. We test the hypothesis of the existence and effectiveness of schedule padding practices. We find that a 2012 on-time disclosure rule may have induced carriers' padding behavior. In contrast, slot regulation may prevent the formation of extra block times.

Keywords: airlines; schedule padding; on-time performance; econometrics; LASSO regression.

JEL Classification: D22; L11; L93.

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1. Introduction

"Airlines are taking a little more conservative approach to ensure they're going to arrive on time." (...) "It's part of their marketing campaigns, part of their affinity programs to develop consumer loyalty." - Sean Cassidy (vice president of the US Air Line Pilots Association labor union and Alaska Airlines pilot).[1]

Flight scheduling is one of the most important tools of airline network management, as it is a key driver of operating costs. However, carriers may have strong incentives to plan scheduled flight times not only based on cost conditions but also on the status of service quality competition in the market. Setting longer flights confers airlines with more flexibility to deal with unexpected delays and still accomplish the scheduled arrival times, a strategy labeled "schedule padding" in the industry. By padding their schedules, airlines have often been accused of improving their on-time performance (OTP) in a spurious way.[2] This gaming behavior may damage the passengers' perception of service quality and eventually mask the entire air transportation system's inefficiencies.

However, scheduling longer travel times may be inevitable for an airline from a flight operations standpoint. Actually, the flight management systems on modern airliners optimally determine the cruise speed of a flight in line with the cost index parameter (CI), a ratio between time-dependent costs and fuel costs. Each flight cruise is typically assigned a speed that is between the "maximum range cruise speed"—a low speed consistent with a null CI level—and the "maximum permissible cruise speed"—a high speed consistent with the maximum CI level.[3] In the first case, the time-dependent cost is low relative to the unit fuel cost, allowing for longer flight duration and less fuel consumption; in the second case, the time-dependent cost strongly dominates the fuel cost, leading to flights with shorter duration and higher fuel consumption. In this sense, the task of scheduling flight times is strictly dictated by the relative operating costs of the airline, and as a result, not all extra times added to scheduled flight times constitute real strategic buffer times.

The objective of this paper is to empirically decompose the extra times incorporated by carriers into their schedules into strategic and operational determinants. We also aim to assess the efficiency of extra times in enhancing OTP by estimating their impacts on the odds of flight delays. We analyze the Brazilian airline industry from 2001 to 2018. In this period, the country witnessed relevant variations in its OTP records. In 2008, the São Paulo/Guarulhos (GRU) airport, a key international gateway in the country, was considered one of the most delayed airports in the world.[4] Ten years

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[1] "Airlines pad flight schedules to boost on-time records", USA Today, available at *www.usatoday.com*, Feb 14, 2013.
[2] See Yimga & Gorjidooz (2019).
[3] Young (2018), and Deo, Silvestre, & Morales (2020).
[4] *''The World's most-delayed airports",* Forbes, Jan, 14, 2008.

later, however, the situation had completely changed, with GRU now ranking number 10 among the top 20 major airports with respect to OTP.[5] While the occurrence of delays in the Brazilian market dropped from 27.5% in 2008 to 15.8% in 2018, the episodes of early arrivals increased from 0.4% to 44.3% in the same period.[6]

We inspect the market incentives of airlines to engage in strategic flight scheduling by means of an econometric of high dimensional sparse (HDS) regression that estimates the drivers of the extra scheduled block times in Brazil. We also investigate the impact of three regulatory reforms: the 2012 on-time disclosure resolution—which made it mandatory for airlines to publish their delay and cancellation statistics for each flight on their websites and other sales channels; the 2014 slot reform at major airports in the country; and finally, the introduction of a major Air Traffic Management (ATM) innovation—the implementation of performance-based navigation (PBN) procedures in Brazilian airports since the late 2000s.

This paper aims to contribute to the recent econometric literature on airline strategic scheduling, including works by Skaltsas (2011), Forbes, Lederman, &Yuan (2018), Fan (2019), Yimga & Gorjidooz (2019), Brueckner, Czerny, & Gaggero (2019). In particular, we study the decoupling of scheduled block times from the "unimpeded" block times, i.e., the gate-to-gate travel times accomplished under ideal flight circumstances.[7] We then test whether a lengthening in flight duration by carriers is motivated by a set of market-related drivers that are *ceteris paribus* to the cost index-related factors. To the best of our knowledge, this is the first study that empirically distinguishes the strategic buffer time from the operational extra time of airlines. We therefore examine whether carriers set longer scheduled block times purely as a schedule padding practice, by adding a strategic buffer to intentionally improve the reported OTP, or if such extra time is actually an unavoidable consequence of changes in operating conditions.

The literature has already emphasized the problems associated with the commonly utilized measures of flight delays - Forbes, Lederman, & Yuan (2018), Yimga & Gorjidooz (2019) are recent examples. El Alj (2003) discusses the limitations of using scheduled times as a reference when assessing OTP and airport and airspace system congestion, since airlines may anticipatedly plug expected delays into their schedules. Our study contributes to the literature by being the first to decompose airlines' extra block times into operational and strategic –i.e., competition-driven– factors. In this sense, we are the first to investigate the effects of market concentration and low-cost carriers' participation on the incentives that airlines have to engage in schedule padding to avoid

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[5] Source: Official Aviation Guide (OAG), Punctuality League 2019, Jan, 2019.
[6] Source: Active Scheduled Flight Report (VRA), National Civil Aviation Agency.
[7] Yimga & Gorjidooz (2019) and Fan (2019).

damages in their on-time performance. Additionally, we assess the extent of the impact of schedule padding on OTP indicators that are relevant to authorities, operators, and the consumer in general. Finally, we also contribute by estimating the effect of an on-time disclosure rule on schedule padding. This issue has been raised by the previous literature but has not been estimated in a *ceteris paribus* way, i.e., isolated from the operational causes of block time prolongation.

This paper is organized as follows. Section 2 provides a discussion of the literature on airline scheduling decisions and the determinants of flight on-time performance. Section 3 presents the empirical model. Section 4 presents the estimation results, which are followed by the conclusions.

2. Airline scheduling and the duration of flights

The schedule planning of an airline is a complex process, as it seeks to simultaneously optimize the exploitation of the resources to meet the demand across the carrier's multiple routes (Holloway, 2008) and to maximize revenues (Abdelghany, Abdelghany & Azadian, 2017). Scheduling becomes even more challenging due to the uncertainties of the system that affect demand, airlines' operations, and prices (Belobaba, Odoni & Barnhart, 2009). Most existing scheduling models ignore the uncertainties in actual operations by assuming that all flights will be operated as planned (Chiraphadhanakul & Barnhart, 2013).

Airlines' timetable setting has to consider aircraft utilization and flights convenience for passengers. It has to incorporate not only the necessary ground turnaround times, crew scheduling, routine maintenance requirements, but also set the most appropriate departure/arrival times for passengers and allow enough time for connections (Belobaba, Odoni & Barnhart, 2009). However, an "optimal" timetable cannot be completely determined, due to the vast combination of strategic decisions and operational constraints of an airline's network (Belobaba, Odoni & Barnhart, 2009; Holloway, 2008). Abdelghany, Abdelghany & Azadian (2017) state that a common practice is to conduct an iterative analysis, that sequentially solves parts of the scheduling process, to find a feasible (but not necessarily optimal) solution for the complete process. The authors describe that most major airlines develop the flight schedules of a given month based on the same period's historical schedules in previous years. Concerning flight duration, the historical block time distribution reflects the flight time reliability and has an key impact on the setting of scheduled block times (Hao & Hansen, 2014). Hao & Hansen (2014) find that while historical taxi-out and non-taxi-out times have an important effect on the scheduled block time, the historical gate delays are virtually not considered. They also analyze how different regions of the historical time distribution influence the scheduled block time and find evidence that these scheduled times are adjusted to mitigate historical earliness and lateness. Wang et al. (2019) investigate the differences between the scheduled block times setting in the United States and China, finding evidence that Chinese airlines mainly consider the left tail of the historical distribution of block times, while the left, middle, and inner right tails impact scheduled block times of US airlines.

Although aircraft technology is more advanced than ever, flight duration has actually increased for several routes over the years (Fan, 2019). For example, certain nonstop flights from London Gatwick to JFK and from Heathrow to Bangkok in 2018 were lengthened by 20 minutes when compared to their 2008 scheduled block times,[8] and flights from Heathrow to Newark were 35 minutes longer.[9] In parallel, and not coincidentally, airlines have reached notably high OTP records. In 2012, for the first time, there were more early arrivals than disrupted flights in the US, with 20% of the major airlines' domestic flights arriving at least 15 minutes early.[10] To date, a limited number of econometric studies have analyzed the determinants of variations in flight times. In what follows, we present details of the key findings of the previous literature.

2.1. Operational aspects of the setting of scheduled block times

Although airlines aim to build reliable schedules, some characteristics, such as weather and congestion, are not fully manageable. The predictability of flight times is key for the planning of schedules by airlines, as the more uncertain actual flight times are, the longer scheduled block times tend to be (Kang & Hansen, 2017). Adverse weather conditions are one of the main external factors that potentially affect delays and add a great deal of uncertainty to travel times. The scheduled block times can vary by season, on account of the prevailing winds, and even by time of day, because of possible congestion occurring during peak hours.[11] Fan (2019) shows that as airports and air traffic control become increasingly denser, there are more variabilities that can cause disruptions and cascade delays through other flights. Brueckner, Czerny, & Gaggero (2019) find that a higher variability of flight times, measured by the standard deviation of the actual flight times distribution, contributes to increasing the additional time of flight schedules.

A longer scheduled block time may be related to infrastructure constraints. Airport congestion and crowded airspace possibly contribute to airlines increasing their actual block times in an attempt to manage the risks associated with passengers' connections and flight disruptions (Fan, 2019). The OTP of a flight may be damaged by the propagation of a small flight delay that occurred much earlier (Kafle & Zou, 2016). Adding extra time to the minimum necessary time of the flight and ground

[8] The scheduled block time represents the difference between the gate arrival time at the destination airport and the gate departure time at the origin airport.
[9] *"Schedule padding: Is this why air travel is getting slower?"* Which, Aug, 27, 2018.
[10] "*Airlines pad flight schedules to boost on-time records"* USA Today, Feb, 14, 2013.
[11] See the relevant discussion in Holloway (2008).

turnaround operations can incorporate unexpected delays and absorb their propagation (Kafle & Zou, 2016; Brueckner, Czerny, & Gaggero, 2019). Kafle & Zou (2016) analyze how flight and ground extra times can be implemented to reduce newly formed and propagated delays. They find that flight extra times are usually smaller and vary less than ground extra times, with ground operations having greater heterogeneity than flight operations.

Mayer & Sinai (2003) and Forbes, Lederman, & Yuan (2018) note that setting longer scheduled block times implies a higher crew cost and less efficient use of aircraft due to the assigning of fewer missions to the existing fleet. In addition, travel duration also impacts aircraft fuel efficiency. Fuel expenses are one of the main cost components of carriers, and their importance increases with higher fuel price (Şafak, Atamtürk, & Aktürk, 2019). In situations of a rise in fuel prices, carriers may decide to fly at slower cruising speeds to reduce fuel consumption (Fan, 2019). Even though fuel consumption lowers with slower flights, time-dependent costs, such as crew costs and maintenance, increase with travel time (Edwards, Dixon-Hardy, & Wadud, 2016). There is an optimal cruise speed that corresponds to the lowest flight operating costs, when considering fuel, time-dependent and fixed costs, that is determined by the *cost index* of the flight. The cost index represents the ratio between the time-dependent costs and fuel cost per flight, being unique to each aircraft and airline (Young, 2018). The lower the cost index, the lower the cruise speed and the less that is fuel burnt. If a longer block time is a consequence of flying at slower speeds to reduce fuel consumption, the operating costs are not necessarily lower, as longer flights increase time-dependent costs. Higher fuel prices incentivize airlines to improve their fuel efficiency (Zou *et al.*, 2014) and may affect travel time. However, Fan (2019) notes an almost imperceptible impact of the fuel price on flight block time.

2.2. Scheduled block times and strategic buffer times

Regarding the passenger point of view, flights with shorter durations may be preferred (Kang & Hansen, 2017; Prince & Simon, 2009). In fact, shorter flights can be seen as a competitive advantage, especially along routes with intense competition (Skaltsas, 2011). However, adding extra scheduled time—a “buffer” to accommodate possible unexpected events—may have a positive impact on airline service quality, as it generates better on-time performance (OTP) statistics. Performance and reputation are important in improving passenger perception about airline service quality. Although such lengthening may attract more customers due to the guarantee of less delay (Kang & Hansen, 2017; Prince & Simon, 2009; Skaltsas, 2011), improving one dimension of airline service quality may cause other dimensions to deteriorate. Adding planned extra time will increase the reliability of arrival times but will also increase the total time of travel, and it is not straightforwardly evident that service quality will improve (Forbes, Lederman, & Yuan, 2018). Yimga & Gorjidooz (2019) associate schedule padding practices with negative effects on consumer welfare. They find that, although this practice generates a better OTP, its demand-increasing effect is offset by the aversion of passengers for longer scheduled flight times.

Kang & Hansen (2017) find that along highly competitive routes, airlines tend to increase their scheduled block times. Prince & Simon (2009) and Fan (2019) find evidence that carriers reduce their scheduled travel times in less competitive markets, where they are more vulnerable to delays. Forbes, Lederman, & Wither (2019) discuss how, as airlines engage in price and quality competition, if one carrier is encouraged to improve its reported OTP statistics, this can possibly induce its competitors to adopt the same strategy. Miranda & Oliveira (2018) find that schedule padding allows reducing the likelihood of flight disruptions without provoking cost-related price increases.

2.3. Impacts of changes in policies and regulations on flight scheduling

Changes in policies and regulation may provide incentives for airlines to adjust their scheduled block times. Quality disclosure programs set rules to make the OTP statistics publicly available. For example, the punctuality statistics of large US airlines have been published since 1995, following the On-Time Disclosure Rule (OTDR), set by the US Department of Transportation (DOT) in 1987. Shumsky (1993) observed that the scheduled block times of some domestic routes in the US market had lengthened during the years after the OTDR implementation, which is corroborated by Forbes, Lederman, & Wither (2019). The introduction of consumer protection legislation may have the unintended consequence of inducing carriers to adjust their scheduled times to improve their measured quality and avoid damages in quality-service reputation and the risk of losing slots at congested airports. As the DOT's regulation defines OTP based on a definition of flight delay being the difference between actual and scheduled arrival times, Forbes, Lederman, & Wither (2019) describe that, as the scheduled arrival times are set by the airline, carriers can, therefore, improve their reported OTP by merely scheduling more time for each flight.

Air traffic management (ATM) innovations and the resulting regulations constitute other sources of incentives for airline scheduling adjustments. The Single European Sky ATM Research (SESAR) in Europe and the Next Generation Air Transportation System (NextGen) in the US are examples of initiatives that aim at implementing a more efficient navigation system. They aim at implementing a paradigm shift from ground-based system to a fully satellite-based ATM system, with performance based navigation (PBN) being one of the tools for targeting more precise information about the position of airplanes in the air space. Diana (2017) finds evidence that the NextGen programs and airspace redesign in the US have possibly improved OTP since being implemented.

Airline on-time management is also influenced by the enforcement of airport slot regimes. Santos & Robin (2010) analyze the possible causes of delays in European airports, including an investigation of the impacts of slot coordination. They find evidence that delays are higher at fully coordinated airports, lower at schedule-facilitated airports, and the lowest at slot-constrained airports.

3. Research design

3.1. Application

We consider the domestic Brazilian airline industry from 2001 to 2018 to develop empirical models of extra scheduled block time and flight delays. Deregulation and low-cost carrier entry produced a notable intensification of price competition in this industry in the studied period. As a result, the market has expanded significantly, from 29.9 million domestic passengers transported in 2001 to 93.7 million in 2018.[12] The rapid growth has put pressure on the existing airport and air traffic management (ATM) infrastructure, with higher congestion and many episodes of cascading delays in the late 2000s. To address the problems associated with congestion, authorities have engaged in a sequence of important regulatory reforms to mitigate flight disruptions in the country. First, new management procedures and regulations of the air space, with the enforcement of performance based navigation (PBN), have been gradually introduced in some Brazilian airports since 2010.[13] PBN allows satellite-based air navigation with more accurate three-dimensional flight paths and, as a result, a more optimized airspace with more direct routes. Some of the expected operational gains of PBN are the reduction of flight times and flight delays.[14]

A second governmental measure to alleviate flight disruptions in the country was the launch of a new on-time disclosure rule in 2012.[15] The main objectives of that regulation are to allow the disclosure of the characteristics of the services provided by the airlines and to enhance transparency in consumer relations in the industry. The new regulation then enforced the obligation that airlines have to make their delay and cancellations statistics publicly available. More specifically, carriers must disclose the percentages of delays and cancellations of each flight not only on their airline website but also in all their ticket distribution channels, be they direct or third party. The disclosed figures must be the same calculated by the regulator, namely, the National Civil Aviation Agency

[12] Source: National Civil Aviation Agency and Department of Civil Aviation's Air Transport Yearbooks (2001, 2018)
[13] According to the aeronautical information circulars (AICs) released by the Department of Air Traffic Control from Brazil (DECEA).
[14] "Fact Sheet: NextGen and Performance-Based Navigation", Federal Aviation Administration, 2014. Available at: *www.faa.gov*
[15] ANAC Resolution nº 218, Feb 28, 2012.

(ANAC), for each airline-flight stage-period combination.[16] The information must be visible from the beginning of the sales process, i.e., as soon as the passenger inputs the desired flight itinerary and dates.

The third regulatory reform was implemented during the country's arrangements to host the 2014 FIFA World Cup and the 2016 Summer Olympics and was concerned with airport slots.[17] In Brazil, ANAC is the authority in charge of regulating the operation of slots at coordinated airports. The first airport declared to be coordinated in the country was São Paulo/Congonhas Airport (CGH) in 1996. The 2014 regulation incorporated the concept of seasons from IATA's Worldwide Slot Management Standards. A number of major airports in the country were declared to be coordinated besides CGH: São Paulo/Guarulhos (GRU), Rio de Janeiro/Santos Dumont (SDU) and Belo Horizonte/Pampulha (PLU), among others. The new rules stipulate fines to carriers that intentionally keep an allocated slot that they do not intend to operate, among other fines and penalties. The regulation utilizes the concept of airport "incumbent" and "entrant" airlines to define the target participation of each of these groups in the total amount of slots—at least 50% for entrants. Minimum slot usage percentages are enforced in a "use-it-or-lose-it" rule with targeted flight regularity and punctuality of at least 80% and 75%, respectively—90% and 80% at CGH—and 15 minutes of tolerated flight time deviation for the computation of flight delays. Alongside the rule, the agency stipulated that the concept of "entrant" could be flexibly redefined on occasions when the expected benefit from a more intense use of airport infrastructure could be technically proven. The new rule aimed to reduce the entry barriers to competition at slot-constrained airports.

Table 1 displays the recent evolution of early and delayed flight arrivals in the country. In the table, it is possible to see a significant increase in early flight arrivals concomitant to a decrease in delayed flights, especially since 2015, when the proportion of early arrivals exceeded the percentage of delayed flights for the first time. Additionally, note that in the more recent years, the proportion of delayed arrivals has become relatively stable, whereas the percentage of early arrivals has increased considerably, from 5.6% (2013) to 44.3% (2018). We believe that the figures of Table 1 thus provide some evidence of some flight time redundancy, with airlines possibly strategically increasing their flight times to sustain the lower flight delay rates, especially since the 2012 on-time disclosure rule. Therefore, we suspect that part of the explanation for the observed dynamics in the early and delayed flight arrivals may be a consequence of on-time performance improvement

[16] In face-to-face and telephone offers of the service, the information shall be presented to the consumer upon request.
[17] ANAC Resolution nº 338, Jul 22, 2014.

accomplished by strategic scheduling practices—a hypothesis that we will formally test with empirical modeling.

Table 1 - Proportion of early and delayed flight arrivals in Brazil[18]

Year	Early Arrivals	Delayed Arrivals
2007	0.3%	38.8%
2008	0.4%	27.5%
2009	0.4%	20.0%
2010	1.3%	24.0%
2011	2.6%	24.7%
2012	4.7%	21.7%
2013	5.6%	16.2%
2014	5.2%	16.4%
2015	13.9%	13.0%
2016	20.4%	12.9%
2017	19.4%	15.2%
2018	44.3%	15.8%

Notes: (i) Source: ANAC's VRA Report - domestic flights, with authors' own calculations; (ii) A flight is computed as delayed if it arrives 15 or more minutes later than the scheduled arrival time; (iii) An arrival is set as early if the flight's arrival time is earlier than the scheduled arrival time.

Figure 1 presents the evolution of the mean actual and scheduled flight times of on some of the densest routes in Brazil.[19] In line with Table 1, we observe that the actual flight times decreased in parallel with an increase in the scheduled flight times.

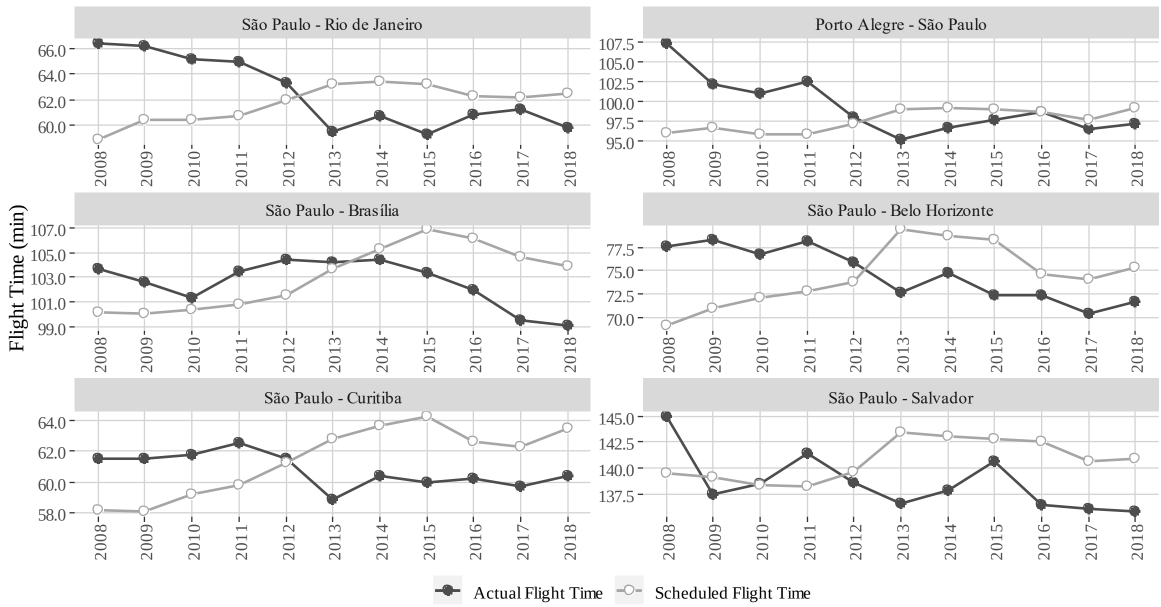

Figure 1 - Evolution of mean actual scheduled flight times of a selection of top-densest routes in Brazil

Source: National Civil Aviation Agency – VRA Report, with authors' own calculations

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[18] We consider a flight delayed if it arrives 15 or more minutes later than the scheduled time. Also, we consider an arrival early when the real arrival time is earlier than the scheduled time.
[19] The selected routes are 6 of the top 12 densest city-pairs in the Brazilian domestic market in 2018.

3.2. Data

Our dataset consists of a panel of 322 routes of the domestic airline industry in Brazil, with monthly observations between January 2001 and December 2018.[20] We consider only passenger flights and define a route as a directional city-pair, grouping multiple airports belonging to the same area.[21] We restrict our analysis to routes that involve two state capitals. These routes account for 84% or the passengers and 75% of the operated scheduled flights of the sample. Over the years, three low-cost carriers, six full-service airlines, and 25 regional carriers operated these markets in different periods. The same carriers are present on the out-of-sample (not included) routes, except for one regional carrier. Most data utilized are publicly available from the National Civil Aviation Agency (ANAC) in an online database. ANAC provides information on all the scheduled flights on the Active Scheduled Flight Report (VRA). We also utilize ANAC's Air Transportation Market Statistics Database, also available online, which contains flights operational data of each city-pair/airline aggregated by month. Jet fuel price information was obtained from the National Agency for Petroleum, Natural Gas and Biofuels' (ANP) website.

The original database contains information on 14.5 million domestic flights between 2000 and 2018. As we utilize lagged variables in the empirical models, observations from the year 2000 are discarded. Also excluded are observations related to flights between very small airports whose code is not included in the ANAC's statistical database of flown passengers, flights with abnormally early departure and arrival times, and flights delayed by more than six hours. Also, flights operated within the months of the 2014 FIFA World Cup–namely, June and July of that year–are missing in the data set. Finally, flights with either departure or arrival times close to midnight on the start and the end of the daylight saving time months underwent one-hour adjustments, as they presented erroneously declared information. After discarding canceled flights, we reached a database of 12.6 million domestic flights, which served as the basis for compiling the final sample for the present paper.

3.3. Empirical model

Equation (1) presents our empirical model of extra scheduled block time in our application to the Brazilian airline industry. Equation (2) presents our flight delay model.

[20] The number of sample periods is 212. Due to the special procedures for the 2014 World Cup, some months of that year were not available in the data sample.
[21] We define routes as city-pairs as in Brueckner, Lee, & Singer (2014) and Bendinelli, Bettini, & Oliveira (2016). In the case of multiple airport areas–namely São Paulo, Rio de Janeiro, and Belo Horizonte metroplexes–we consider all the city airports that belong to the same terminal control area. These areas have airports subject to the same congestion management procedures for the controlled airspace.

$$\begin{aligned} EXTBT_{k,t} = {} & \beta_1 FUELP_{k,t-h} + \beta_2 DENS_{k,t-h} + \beta_3 FREQ_{k,t-h} + \beta_4 ASIZE_{k,t-h} \\ & + \beta_5 RWYCONG_{k,t-h} + \beta_6 SLOTPR_{k,t-h} + \beta_7 HHI_{k,t-h} + \beta_8 LCCS_{k,t-h} + \beta_9 T_t \\ & + \beta_{10} T_t \times QUALREG_{k,t} + \beta_{11} T_t \times SLOTREG_{k,t} + \beta_{12} T_t \times ATMREG_{k,t} \\ & + \beta_{13} CASCDEL_{k,t-h} + u_{k,t}, \end{aligned} \tag{1}$$

$$\begin{aligned} ODDSDEL_{k,t} = {} & \varphi_1 DENS_{k,t} + \varphi_2 FREQ_{k,t} + \varphi_3 ASIZE_{k,t} + \varphi_4 RWYCONG_{k,t} \\ & + \varphi_5 SLOTPR_{k,t} + \varphi_6 HHI_{k,t} + \varphi_7 LCCS_{k,t} + \varphi_8 T_t + \varphi_9 T_t \times QUALREG_{k,t} \\ & + \varphi_{10} T_t \times SLOTREG_{k,t} + \varphi_{11} T_t \times ATMREG_{k,t} + \varphi_{12} CASCDEL_{k,t} \\ & + \varphi_{13} EXTBT_{k,t} + \varphi_{14} EXTBT_{k,t} \times RWYCONG_{k,t} \\ & + \varphi_{15} EXTBT_{k,t} \times SLOTPR_{k,t} + \varphi_{16} EXTBT_{k,t} \times CASCDEL_{k,t} + v_{k,t}, \end{aligned} \tag{2}$$

where k denotes the route (k = 1, …., 322 directional city-pairs), t the periods (t = 1, …, 212 months) and h is a time lag to denote the horizon for flight scheduling. Below, we discuss the components of (1) and (2). In the sequence, Table 2 presents the descriptive statistics and the sources of each of the main variables.

- $EXTBT_{k,t}$ is the route mean extra time added to flights in the sample period in minutes. We compute $EXTBT_{k,t} = SCHBT_{k,t} - UNIBT^*_{k,t}$—where $SCHBT_{k,t}$ is the scheduled block time, and $UNIBT^*_{k,t}$ is a proxy for the unimpeded block time evaluated on the occasion of the scheduling decision making, for each flight—and then extract the route mean for each time period. Concerning the configuration of $UNIBT^*_{k,t}$, we follow the approach of the literature—seen in Yimga & Gorjidooz (2019) and Fan (2019). For each combination of route, airline, month, and aircraft, we set the unimpeded block time as a low percentile of the actual flight times distribution. We utilize the 5th percentile but also experiment with the 10th percentile in a robustness check. The distribution of actual flight times–and the extracted percentile–is computed for each aircraft model and each time t. In the ODDSDEL equation, this variable is included as a regressor, aiming at allowing a formal test of the effectiveness of the extra times on the management of flight delays by carriers.
- $FUELP_{k,t}$ is a proxy for the jet A1 fuel price in deflated local currency. We add to that metric a proxy for the Brazilian state tax burden on the jet fuel burned on domestic flights, with rates ranging from 3% to 25% depending on the state and period in the sample. An increase in the price of jet fuel may induce airlines to adjust their cost index and consequently their scheduled flight time to achieve fuel consumption reductions targeting energy efficiency. $FUELP_{k,t}$ is computed as the minimum average jet fuel price observed at the endpoint cities of a route.

- $DENS_{k,t}$ is the total number of route passengers (in tens of thousands). This variable is intended to capture the adjustments made to the scheduled travel times according to the route density, as airlines are possibly more concerned with passenger satisfaction on the densest routes. The motivation for that behavior may be related to the reputational risk associated with poor OTP, which can be amplified in these markets and quickly spread to passengers in other markets. Beyond this strategic motivation, denser routes usually have more complex flight trajectories stemming from specific ATM procedures and have more connecting passengers, making airport terminal operations more complicated. These factors may lead airlines to schedule additional extra block time.

- $FREQ_{k,t}$ is the total number of nonstop flights (in hundreds). This variable aims to capture the fact that with city-pairs with high flight frequency, carriers possibly have to accomplish better operational efficiency with lower aircraft turnaround times. As a result, there is less opportunity to lengthen the flight time. In contrast, routes with higher flight frequency are more vulnerable to flight delays. On the other hand, asymmetries in the flight frequency portfolio of carriers may undermine the effect of $FREQ_{k,t}$ on operational efficiency–for example, a dominant airline may have a large proportion of flights while a market fringe of rivals may operate only a few flights. Therefore, the *ceteris paribus* effect of this variable is indeterminate ex-ante, and thus being an empirical matter.

- $ASIZE_{k,t}$ is the average number of seats in aircrafts on the route. *Ceteris paribus*, larger jet airliners may present higher cruise speeds than smaller regional airliners. Additionally, passenger and baggage handling associated with larger aircraft may be more complex and costly. Finally, although total flight costs are usually higher in large airplanes, economies of density may emerge in such a way as to decrease the unit costs of the nonfuel-related inputs; as a consequence, the cost index may be an indirect function of the seating capacity of the airliner. One key issue with this variable is that the utilization of the average value may be misleading. With varying types of aircraft in operation on a route, by solely relying on $ASIZE_{k,t}$ we would expose our models to an unobserved source of variation in cost index ranges and cruise speeds stemming from asymmetries in the fleet composition of carriers. As our target here is to control for the effects of those operational indicators, we combine the use of $ASIZE_{k,t}$ with a set of aircraft type dummies–see the discussion of the controlling of the unobserved effects in 3.4.

- $RWYCONG_{k,t}$ is the percentage of flights operating during congested hours along the route. An hour is considered "congested" when any of the endpoint airports operates more flights than its declared runway capacity when considering arrivals and departures. This variable is expected to control how airlines set their extra scheduled time according to past airport congestion.

- $SLOTPR_{k,t}$ is the percentage of flights operated at slot-constrained airports. It allows us to investigate the effect of a slot regime on flight scheduling, as airlines may set shorter flight times when operating at coordinated airports. It is calculated as the maximum percentage of airport slot flight –considering the total operated flights not only on the route but at the city level–between the origin and destination cities.
- $HHI_{k,t}$ is the Herfindahl-Hirschman index of city-pair concentration (multiplied by 100) based on revenue passengers. It is related to the variations in the intensity of airline rivalries and their effects on the incentives for scheduling aimed at strategically controlling on-time performance (OTP) levels by carriers. As it is clearly associated with the market conduct of airlines, we believe that formal hypothesis tests of the nullity of the coefficient of this variable may allow us to empirically assess the existence of schedule padding practices in the market.
- $LCCS_{k,t}$ is the share of flights of low-cost carriers (LCC) Gol, Webjet, and Azul airlines. By distinguishing routes with and without LCCs, we aim to test if the enhanced price competition with LCCs induce OTP to be of less relative importance. Prince and Simon (2015) find that OTP worsens in response to the LCC Southwest Airlines' actual and potential entry in the US market. In the schedule padding equation, this variable allows us to test whether airlines compensate such effect by padding their schedules to avoid these possible damages in their OTP reputation.
- T_t is a time trend variable, T = 1, 2, ..., TP, where TP is the total number of sample time periods.
- $T_t \times QUALREG_t$ is an interaction variable that captures a possible structural break in the trend from the launch of the airline on-time disclosure regulation in Brazil. $QUALREG_t$ is a dummy variable, assigned 1 after May 2012, the time when the new regulation came into force. As the regulation established that all carriers must report their flight delays and cancelation statistics to consumers at the time of sale, the rule may have strengthened the incentives for padding schedules to target a better OTP.
- $T_t \times SLOTREG_{k,t}$ is an interaction term to capture a possible break in the trend after the regulatory reform of airport slots of 2014 in which stricter “use-it-or-lose-it” slot rules were introduced at a broader set of major airports. $SLOTREG_{k,t}$ is a dummy variable set with 1 after July 2014.
- $T_t \times ATMREG_{k,t}$ is an interaction variable used to capture the effect of the introduction of new air navigation procedures and regulations of performance based navigation operations from the

air traffic management (ATM) authorities in a set of airports since 2010. $ATMREG_{k,t}$ is a dummy variable that indicates whether a given city-pair conducts PBN operations at the endpoint cities.

- $CASCDEL_{k,t}$ is a proxy for cascading delays that may affect all flights along a given route. As Mayer & Sinai (2003) discuss, a cascading delay is a sequence of flight disruptions caused by "*a late-arriving aircraft on the previous inbound flight*" (p. 1196). We aim at constructing a proxy that incorporates the outcome of cascading effects on the whole airport operations. We then define this variable as the maximum proportion of delayed flights between the origin and the destination airports of the route. A flight is computed as delayed if the difference between the actual and the scheduled arrival time is at least 15 minutes. This variable aims to capture the impact of overall delays–and overall damages to on-time performance–on the expectations of schedule planners, which may add extra time to routes that historically involve more delayed airports. In the ODDSDEL equation, this variable helps control the time-varying unobservables at the level of the terminal control area, e.g., propagation of flight delay following adverse weather conditions.
- $ODDSDEL_{k,t}$ is the log odds of flight delays, i.e., $ODDSDEL_{k,t} = \ln [DEL_{k,t}/(1-DEL_{k,t})]$, where the $DEL_{k,t}$ is the proportion of scheduled nonstop flights reported with arrival delays, divided by the total scheduled nonstop flights on the route.[22] Again, we utilize a period of 15 or more minutes to identify whether a flight is delayed.
- $EXTBT_{k,t} \times RWYCONG_{k,t}$ is an interaction variable that allows us to test the moderation effects of runway congestion on the possible relationship between EXTBT and ODDSDEL in Equation (2). We therefore aim to inspect whether the impact of the inclusion of extra scheduled block time on flight delays is stronger or weaker depending on the intensity of runway congestion on the route; this and the next two variables aim to extend the flight delays model of Miranda & Oliveira (2018), which does not allow for moderation effects of EXTBT.
- $EXTBT_{k,t} \times SLOTPR_{k,t}$ is an interaction variable used to inspect the existence of possible moderation effects of the slot regime on the relationship between ODDSDEL and EXTBT; here, we aim to investigate whether the effectiveness of the extra block times in affecting the odds of flight delays is altered on routes that include slot-constrained airports.
- $EXTBT_{k,t} \times CASCDEL_{k,t}$ is an interaction variable used to inspect the existence of moderation effects of cascading delays on the relationship between ODDSDEL and EXTBT; this variable

[22] To simplify the visualization of the scale of the estimated coefficients, we multiply this variable by 10.

aims to analyze whether the effect of the extra block times on flight delays is weaker or stronger with the occurrence of propagated delays at the airport level.

- $u_{k,t}$ and $v_{k,t}$ are the composite error terms of the panels, and the βs and φs are the parameters to be estimated.

Table 2 – Descriptive statistics of the model variables

Variable	Description	Metric	Mean	Std Dev	Min	Max
$EXTBT_{k,t}$	Extra scheduled block time (i)	minutes	14.255	14.989	0	220
$FUELP_{k,t}$	fuel price (v), (viii)	BRL deflated	2.482	0.573	1.168	4.187
$DENS_{k,t}$	passengers (ii)	count, 10,000s	2.090	3.676	0.001	44.059
$FREQ_{k,t}$	flight frequencies (i), (ii)	count, 100s	2.215	3.799	0.010	41.120
$ASIZE_{k,t}$	number of seats (i), (ii)	count	141.844	33.461	9.643	207.455
$RWYCONG_{k,t}$	runway congestion (iv)	%	12.679	19.709	0	100
$SLOTPR_{k,t}$	slot flights proportion (i), (iii)	%	14.008	27.053	0	100
$HHI_{k,t}$	market concentration (ii)	index x 100	54.800	22.431	20.817	100
$LCCS_{k,t}$	market share of flights of LCCs (i)	%	43.950	32.240	0	100
T_t	time trend	discrete sequence	115.669	60.320	1	212
$QUALREG_t$	quality regulatory reform (iii), (viii)	dummy	0.417	0.493	0	1
$SLOTREG_{k,t}$	slot regulatory reform (iii), (viii)	dummy	0.104	0.305	0	1
$ATMREG_{k,t}$	ATM regulatory reform (iii), (viii)	dummy	0.044	0.206	0	1
$CASCDEL_{k,t}$	propagated delays (i)	%	19.016	8.296	0	79.339
$DEL_{k,t}$	proportion of delayed flights (i)	fraction	0.183	0.139	0	1

Sources: National Civil Aviation Agency's (ANAC) Active Scheduled Flight Report—VRA (i) and Air Transportation Market Statistics Database (ii); governmental regulations available online (iii); "Study of the Air Transport Sector in Brazil"—Brazilian Development Bank, 2010 (iv); National Agency for Petroleum, Natural Gas and Biofuels—ANP (v); Brazilian Institute of Geography and Statistics—IBGE (vi); Central Bank of Brazil (vii); and digital media press websites (viii). All figures computed with authors' own calculations.

3.4. Estimation strategy

In our empirical framework we set the specification of the unobserved component related to the addition of the extra block time ($EXTBT_{k,t}$) by carriers–namely, the error term $u_{k,t}$ of Equation (1)–in the following way. We associate $u_{k,t}$ with the existing uncertainties when making scheduling decisions with respect to future flight operations and with respect to quality-service competition in the market. To account for such factors, our econometric approach treats $u_{k,t}$ as a component error term related to route-specific idiosyncrasies and a set of time-varying controls. Using indexes *k* (route) and *t* (time), we then define:

$$u_{k,t} = \Phi(ROUTE_k, UNC_{k,t}, RWYCONG_{k,t} \times UNC_{k,t}, DIR^o_{k,s}, DIR^d_{k,s}, AIRL^i_{k,t}, AIRC^j_{k,t}) + \varepsilon_{k,t}, \quad (3)$$

where:

- $ROUTE_k$ is the fixed effect of route *k* designed to control for the route-specific operating and time invariant market idiosyncrasies not observed by the econometrician.
- $UNC_{k,t}$ is a proxy for the level of uncertainty on the scheduling decision-making of carriers. It accounts for both operational and strategic uncertainty. It is calculated as the coefficient of variation—i.e., the ratio of the standard deviation to the mean—of the actual block time distribution of route *k* and time *t*. *Ceteris paribus*, airlines may need to add additional extra time to flights on routes associated with more uncertain times. Note that, as the other regressors utilized in Equation (1), this variable is inserted as lagged realizations to account for the fact that the scheduling decision-making is taken some months before the flight is operated.
- $RWYCONG_{k,t} \times UNC_{k,t}$ is an interaction variable used to capture the moderating effects of airport runway congestion (RWYCONG) on the relationship between uncertainty and the unobserved error. We utilize lagged realizations of this variable in Equation (1).
- $DIR^o_{k,s}$ and $DIR^d_{k,s}$ are a set of dummy variables that account for the unobserved effects associated with the direction (DIR), the region of the endpoint city (origin or destination, namely, *o* and *d*), and the season (*s*) on route *k*. With such terms, we aim to control the impact of weather and prevailing winds on flight times, which are likely to be region- and season-specific. Including a combination of route direction-endpoint airports and regions-seasons controls is essential when analyzing scheduled and actual flight times, especially when accounting for the potential effect of prevailing winds, because airlines can take advantage of the tailwinds to reduce their flight times (Irvine, Shine and Stringer, 2016). We believe that our proposed framework may also be utilized in different contexts, being especially useful in the case of strong jet streams—a phenomenon that is very important in some regions of the globe but typically neglected in econometric airline studies. In Brazil, jet streams typically occur in the southern region. The dummies are associated with the origin and destination regions of a city pair, considering the five Brazilian geographic regions (North, Northeast, Central-West, Southeast and South). We interact these endpoint regions dummies with other dummies that relate each directional route with the cardinal and intercardinal directions of the 8-point compass rose using the azimuth angle. We therefore associate the orientation of each flight with the geographic locations of its origin and destination. Finally, we interact these combinations with a set of dummy variables representing the seasons (summer, winter, fall and spring). As an illustration, a São Paulo–Rio de Janeiro flight has both endpoint cities located in the Southeast of Brazil and a predominant orientation to the east; we therefore have a dummy of Southeast (origin)/east (route direction) and a dummy of Southeast

(destination)/east (route direction), for each season, and thus totaling eight dummies for each directional route.[23]

- $AIRL^{i}_{k,t}$ is a set of dummy variables that control for the presence of airline *i* on route *k* at time *t*. With these dummy variables, we take into consideration the impacts of carrier/time-specific scheduling strategies on the overall flight operations on the route.
- $AIRC^{j}_{k,t}$ is a set of continuous variables that measure the route share of flights of aircraft model *j* on route *k* at time *t*. With these proportions, we aim to account for the possible (unobserved) effects of changes in the aircraft mix and technology evolution on the flight operations of the route.
- $\Phi(.)$ is an additive function, and $\varepsilon_{k,t}$ is the random error.

Also note that with the EXTBT model in Equation (1), we provide ways of isolating some of the fundamental market forces that produce incentives for airlines' strategic behavior when setting their schedules. In particular, we consider $HHI_{k,t}$ and $LCCS_{k,t}$ as the factors that are more related to the strategic sources of EXTBT. More specifically, we define "schedule padding" as the extra block time associated with these competition-driven variables. We also consider $T_t \times QUALREG_t$ as measuring the possible intensification in schedule padding after the introduction of the quality-disclosure rule of 2012. The other variables of Equation (1) are either more linked to operational justifications for scheduled flight time prolongation–such as $FUELP_{k,t}$ and $RWYCONG_{k,t}$–or constitute a combination of operational and strategic factors that in principle cannot be isolated–such as $DENS_{k,t}$ and $FREQ_{k,t}$. We are aware that every scheduling decision of a carrier is likely to be influenced by the dynamics of market events. For example, there may be market incentives to account for congestion in setting scheduled block times. However, in an econometric framework such as the one provided by Equations (1) and (2), the effect of more operational-related variables is estimated in a *ceteris paribus* way, being therefore isolated from the competition variables $HHI_{k,t}$ and $LCCS_{k,t}$, already included in the models. Additionally, we think that route distance plays a role in conditioning the operational-strategic motivations for increasing scheduled time–as flight time increases, the marginal importance of on-time delivery may decrease. We control for such a phenomenon with the route fixed effects and the other time-varying dummies. However, as a possible extension to the present analysis, we suggest further investigation into the eventual decomposition of the effects of flight distance on airlines' schedule padding behavior.

[23] As many routes share the same origin and destination regions, the total number of dummies inserted in the specification is much less than the number of routes multiplied by the eight compass points utilized. We actually computed 288 regions/directions/seasons dummies.

Another important setting of the EXTBT model in Equation (1) is related to the setup of the scheduling decision-making horizon. Considering that airline schedules are designed some months in advance of actual flight operations and thus utilize a three-month lag to examine the impact of past realizations of key variables on the scheduling decisions of carriers, we set $h = 3$. We also examine the robustness of the results to changes in this setting.[24]

We perform some diagnosis tests of the residuals, namely, the Pagan-Hall, White/Koenker and Breusch-Pagan/Godfrey/Cook-Weisberg heteroscedasticity tests and the Cumby-Huizinga test of autocorrelation. In the tests, we confirm the presence of both problems. We employ the procedure of Newey-West to adjust the standard error estimates. Additionally, we examine the problem of multicollinearity in the estimation. We calculate mean and maximum VIF statistics of 4.69 and 17.49 (EXTBT model), respectively, and of 5.27 and 17.53 (ODDSDEL model) in our preferred specifications.[25] These results reveal relevant multicollinearity issues, indicating that we should cautiously interpret the results of the nonsignificant variables in our empirical models.

With respect to the ODDSDEL model—Equation (2)—we utilize a similar specification of the error term of Equation (1) discussed above.[26] However, motivated by the previous literature—Greenfield (2014) and Bendinelli, Bettini, & Oliveira (2016)—we assume that the unobserved components of the flight delays on city-pair market k at time t are correlated with the status of competition in that market. As a result, we must treat the market concentration and LCC share of flights—namely, HHI and LCCS—as endogenous in the ODDSDEL equation. We then employ the two-step feasible efficient generalized method of moments (2SGMM) with standard errors robust to arbitrary heteroscedasticity and autocorrelation.

Our identification strategy employs demand shifters associated with the size of the air travel market as instrumental variables. In particular, we utilize key socioeconomic metrics such as the gross domestic product (GDP), population size, GDP per capita, Gini index of income inequality, and number of active bank agencies, all extracted at the endpoint cities level.[27] For all these demand shifters, we also utilize the maximum, minimum, simple and geometric means between the origin and destination of a route. The data sources are the Brazilian Institute of Geography and Statistics (IBGE) and the Brazilian Central Bank. Other instrumental variables utilized for identification of the ODDSDEL equation are a set of lagged regressors of the EXTBT equation—namely, RWYCONG,

[24] See a discussion in 4.2.
[25] To be more conservative, we do not include fixed effects and controls in the regressions for these VIF extractions.
[26] The only difference is that in the ODDSDEL model we do not include the terms related to scheduling uncertainty.
[27] Some of these metrics have yearly periodicity and therefore require interpolation to produce monthly series.

SLOTPR and FUELP. Finally, we utilize Hausman-type instrumental variables, considering concentration levels of other routes to instrument the concentration level of a given route.

Apart from the fixed effects related to the 322 routes, in principle, our approach has to deal with the estimation of 364 parameters of control variables (288 from $DIR^{o}_{k,s}$ and $DIR^{d}_{k,s}$, 37 from $AIRL^{i}_{k,t}$, and 39 from $AIRC^{j}_{k,t}$ controls), in addition to the set of 61 instrumental variables. We utilize the econometric method of high dimensional sparse (HDS) regression models of Belloni et al. (2012), Belloni, Chernozhukov, & Hansen (2014a,b), and Chernozhukov, Hansen, & Spindler (2015). The HDS approach is flexible in allowing a large set of regressors and/or instrumental variables under the assumption that the model is sparse—i.e., only a smaller subset of the initial regressors/instruments are important for capturing the main features of the regression in the data generation process. The approach utilizes the least absolute shrinkage and selection operator (LASSO) of Tibshirani (1996). We apply the instrumental variables post-double-selection (PDS) estimation, which has a final step that estimates a traditional (non-LASSO) regression utilizing the controls and instruments selected in the LASSO estimation step. In our case, the final step of the PDS estimation of EXTBT and ODDSDEL utilized the fixed effects implemented with the ordinary least squares (OLS) estimator and the 2SGMM estimator, respectively.

4. Estimation results

Tables 3 and 4 present the results of our empirical models of extra scheduled block time (EXTBT) and arrival flight delays (ODDSDEL) in Brazil. To simplify the exposition, we omit indexes *k* and *t*. In both tables, the respective Column (4) contains our preferred model; Columns (1) to (3) present a set of subspecified versions of the main model, in which we drop some key variables; and finally, Columns (5) to (8) display the results of some robustness checks. In both tables, it is possible to observe that most results are in line with our ex-ante expectations regarding signs and statistical significance of the estimated coefficients. Additionally, regarding the motivations airlines have when planning their flight schedules, the results of Table 3 suggest that block time lengthening is a result of a combination of both operational and strategic behaviors in the market. Furthermore, the results of Table 4 suggest that adding extra times to flights is effective in reducing the chances of delays.

Let us focus on the main results of Table 3 first—the EXTBT model. Considering the more operational side of the problem, we find evidence that carriers tend to add extra time to flights in response to jet fuel price increases: the coefficient of the FUELP variable is statistically significant and positively associated with EXTBT in all specifications. This result supports the proposition that jet fuel price hikes provoke drops in the expected cost indexes of future flights, leading airlines to set slower planned cruise speeds and consequently longer flight durations, targeting fuel consumption reductions as a response to the expected higher cost pressure. In contrast, on the strategic side, the results of Table 3 suggest that carriers schedule longer block times on routes with higher competition—i.e., with lower market concentration. The negative and statistically significant coefficient of HHI is in line with the findings of Prince & Simon (2009), which found that in more competitive routes, a more intense service-quality competition is observed.[28] We therefore find evidence of actual schedule padding by carriers—a strategic behavior that is *ceteris paribus* to operational, cost-index-related factors that may also provoke block time lengthening. We also find that the higher the extent of LCC presence (LCCS) the more carriers increase their extra block times, which is consistent with the findings of Prince and Simon (2015).

The positive and statistically significant coefficient of the DENS variable in Table 3 provides evidence that carriers have dual motivations to strengthen their EXTBT, stemming from operational and market incentives. As discussed, denser routes are usually associated with increased operational complexity stemming from flight connections but are also the markets in which carriers are more concerned with the satisfaction of passengers, so as to minimize damage to their overall institutional reputation. The reputational risk contagion, i.e., the quick spread of negative consumer assessments, from online reviews and/or through word-of-mouth, from one route to the entire system may be higher on those routes due to the higher size of the travelling public.

Let us now turn to Table 4. Our key research interest here is to investigate the impact of the extra block time addition (EXTBT) on the odds of flight delays (ODDSDEL). In line with Miranda & Oliveira (2018), our preferred model (Column 4) provides evidence that one additional minute of extra block time is associated with a reduction of approximately thirteen percent in the odds of flight delays,[29] as shown by the estimated coefficient of -0.1260 of the variable EXTBT. However, given the positive and statistically significant coefficients of the interaction variables EXTBT × SLOTPR, this effect is moderated by the operating conditions at the endpoint airports. More specifically, the reduction in the odds of flight delays allowed by extra block times is less effective on routes operated at airports under an airport slot regime. In contrast, in this model we find no evidence that the intensities of propagated delays (CASCDEL) and of runway utilization (RWYCONG) moderate the relationship between ODDSDEL and EXTBT.

[28] Kang & Hansen (2017) find that airlines that set longer SCHBT in highly competitive markets. Here, we further explore the issue by examining the relationship between competition and EXTBT, and between EXTBT and flight delays.
[29] With a 95% confidence interval of [-15.41, -11.35].

Table 3 - Estimation results: extra scheduled block time (EXTBT)

	(1) EXTBT	(2) EXTBT	(3) EXTBT	(4) EXTBT	(5) EXTBT	(6) EXTBT	(7) EXTBT	(8) EXTBT
FUELP (*lagged*)	0.7772***	0.7023***	0.6895***	0.7096***	0.6888***	0.6575***	0.4563**	0.4383**
DENS (*lagged*)	0.1976**	0.1771**	0.2126**	0.2187**	0.2051**	0.2293***	0.3594***	0.3996***
FREQ (*lagged*)	-0.2232**	-0.2130*	-0.2666**	-0.3118***	-0.3013***	-0.3038***	-0.5412***	-0.6139***
ASIZE (*lagged*)	-0.0553***	-0.0555***	-0.0542***	-0.0537***	-0.0536***	-0.0508***	-0.0534***	-0.0527***
RWYCONG (*lagged*)	0.0139*	0.0137*	0.0128	-0.0042	-0.0040	-0.0022	0.0152	-0.0142
SLOTPR (*lagged*)	-0.0435***	-0.0441***	-0.0441***	-0.0438***	-0.0456***	-0.0404***	-0.0486***	-0.0257**
HHI (*lagged*)	-0.0260***	-0.0267***	-0.0230***	-0.0242***	-0.0246***	-0.0216***	-0.0281***	-0.0201***
LCCS (*lagged*)	0.0374***	0.0370***	0.0364***	0.0368***	0.0362***	0.0410***	0.0390***	-0.0060
T	-0.0447***	-0.0432***	-0.0433***	-0.0435***	-0.0438***	-0.0425***	-0.0377***	-0.0416***
T × QUALREG	0.0307***	0.0320***	0.0318***	0.0316***	0.0316***	0.0285***	0.0256***	0.0295***
T × SLOTREG	-0.0114***	-0.0114***	-0.0110***	-0.0109***	-0.0105***	-0.0095***	-0.0137***	-0.0166***
T × ATMREG	0.0043*	0.0042*	0.0044*	0.0045*	0.0045*	0.0037	0.0036	0.0024
CASCDEL (*lagged*)		0.0370***	0.0299**	0.0289**	0.0267**	0.0271**	0.0144	-0.0141
UNC (*lagged*)			0.1198***	0.0995***	0.0992***	0.1131***	0.0646**	-0.0104
RWYCONG × UNC (*lagged*)				0.0025**	0.0026**	0.0019*	0.0020*	0.0037***
UNIBT*	5th pctl route-airc-time	5th pctl route-airc-time	5th pctl route-airc-time	5th pctl route-airc-time	5th pctl route-airc-time	10th pctl route-airc-time	5th pctl route-airc	5th pctl route-airc-time
Route fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Nr lags (regressors)	3	3	3	3	3	3	3	12
High-dim controls								
Dir-Reg-Seas controls	18/288	42/288	43/288	40/288	no	40/288	40/288	37/288
Airline controls	28/37	28/37	28/37	29/37	29/37	29/37	29/37	27/37
Aircraft controls	38/39	38/39	38/39	36/39	36/39	36/39	36/39	37/39
R^2 Adj Statistic	0.2880	0.2888	0.2892	0.2895	0.2885	0.2762	0.2895	0.2891
RMSE Statistic	12.7984	12.7910	12.7869	12.7847	12.7936	12.5257	12.7847	12.7883
Nr Observations	39,499	39,499	39,499	39,499	39,499	39,499	39,499	37,404

*Notes: results produced by the post-double-selection (PDS) LASSO-based methodology of Belloni et al. (2012, 2014a,b). Post-LASSO estimation is implemented with a fixed effects procedure with standard errors robust to heteroskedasticity and autocorrelation. Selected control estimates are omitted; R^2 adjusted and RMSE statistics are extracted from an equivalent least-squares dummy variables estimator (LSDV); p-value representations: ***p<0.01, ** p<0.05, * p<0.10.*

Table 4 - Estimation results: odds of flight delays (ODDSDEL)

	(1) ODDSDEL	(2) ODDSDEL	(3) ODDSDEL	(4) ODDSDEL	(5) ODDSDEL	(6) ODDSDEL	(7) ODDSDEL	(8) ODDSDEL
DENS	0.6565***	0.2234***	0.2626***	0.2697***	0.2700***	0.2643***	0.2958***	0.2463***
FREQ	0.0243	0.1725**	-0.0179	-0.0174	-0.0235	0.0096	-0.1048	-0.0015
ASIZE	0.0422**	0.0376**	0.0175	0.0144	0.0157	0.0166	0.0111	0.0512***
RWYCONG	0.0388***	0.0244***	0.0218***	0.0247***	0.0247***	0.0237***	0.0230***	0.0239***
SLOTPR	0.0404***	0.0168***	0.0080*	0.0015	0.0022	0.0039	-0.0009	0.0061
HHI (*endogenous*)	0.2859***	0.0660**	0.0329	0.0453	0.0391	0.0521*	0.0210	0.0035
LCCS (*endogenous*)	-0.1321***	-0.1633***	-0.0777**	-0.0744**	-0.0758**	-0.0827**	-0.0557	-0.1484***
T	-0.0052	0.0212***	0.0131***	0.0140***	0.0135***	0.0153***	0.0116**	0.0129**
T × QUALREG	-0.0291***	-0.0084***	-0.0077***	-0.0080***	-0.0077***	-0.0085***	-0.0089***	-0.0046**
T × SLOTREG	-0.0025	-0.0037**	-0.0037**	-0.0038**	-0.0038**	-0.0037**	-0.0046***	-0.0037**
T × ATMREG	-0.0005	-0.0021	-0.0015	-0.0015	-0.0015	-0.0016	-0.0013	-0.0014
CASCDEL		0.6946***	0.6871***	0.6752***	0.6743***	0.6738***	0.6476***	0.6928***
EXTBT			-0.1072***	-0.1260***	-0.1284***	-0.1220***	-0.1648***	-0.1260***
EXTBT × RWYCONG				-0.0001	-0.0001	0.0000	0.0000	-0.0001
EXTBT × SLOTPR				0.0004**	0.0004**	0.0003*	0.0005***	0.0003
EXTBT × CASCDEL				0.0007	0.0008*	0.0010**	0.0016***	0.0011**
UNIBT*	-	-	5^{th} pctl route-airc-time	5^{th} pctl route-airc-time	5^{th} pctl route-airc-time	10^{th} pctl route-airc-time	5^{th} pctl route-airc	5^{th} pctl route-airc-time
Route fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Nr lags (regressors)	3	3	3	3	3	3	3	12
High-dim controls								
Dir-Reg-Seas controls	35/288	64/288	64/288	51/288	no	52/288	52/288	42/288
Airline controls	30/37	30/37	30/37	30/37	30/37	30/37	30/37	30/37
Aircraft controls	37/39	37/39	37/39	35/39	35/39	35/39	35/39	35/39
High-dim instruments	10/68	10/68	10/68	10/68	10/68	10/68	10/68	10/68
R^2 Adj Statistic	0.3372	0.5258	0.5437	0.5430	0.5406	0.5401	0.5433	0.5429
RMSE Statistic	7.6431	6.4644	6.3412	6.3466	6.3627	6.3666	6.3443	6.3473
Nr Observations	38,036	38,036	38,036	38,036	38,036	38,036	38,036	36,181

*Notes: results produced by the post-double-selection (PDS) LASSO-based methodology of Belloni et al (2012, 2014a,b). Post-LASSO estimation is implemented with a 2-step generalized method of moments (2SGMM) estimator with a fixed effects procedure and standard errors robust to heteroskedasticity and autocorrelation. Selected control estimates are omitted; R^2 adjusted and RMSE statistics are extracted from an equivalent least-squares dummy variables (LSDV) estimator; p-value representations: ***p<0.01, ** p<0.05, * p<0.10.*

Most other results in Tables 3 and 4 are in line with our ex-ante expectations regarding signs and statistical significance of the estimated coefficients. For example, in Table 3, we find negative and significant coefficients of the FREQ variable, suggesting that carriers have higher operational efficiency—i.e., lower time-related costs with respect to fuel costs in their cost indexes—on routes with higher frequency flights;[30] we also find that both the levels of propagated delays (CASCDEL) and uncertainty (UNC) perceived by planners at the scheduling decision-making period increase EXTBT. In Table 4, all models show evidence that denser routes (DENS) and routes operated to/from airports with more congested runways (RWYCONG) are more likely to have delayed flights. The former set of routes, but not the latter, are associated with longer extra scheduled block times, as presented in Table 3. Therefore, even with block time lengthening, flights on denser routes still seem to be the ones that are delayed the most. Importantly, we only find evidence of a direct effect of airline competition on the odds of flight delays in Columns (1) and (2) of Table 4, concerning a statistically significant coefficient of HHI. Such an effect is fully dissipated when the EXTBT variable is inserted in the model (Column 3) and persists as statistically insignificant at 5% in the other columns.[31] Interestingly, LCCS is statistically significant in almost all specifications of Table 4. This result suggests that the prolonged block time strategy put into practice during stiffer competition with LCCs–with cost-cutting behavior, as reported by Prince and Simon (2015)–may not only fully compensate for the possible damages on OTP, but may also enhance punctuality during these periods.

4.1. Estimated impacts of the regulatory reform events

A key topic in our empirical analysis of the extra block time—and schedule padding—formation by carriers in Brazil is related to the events of regulatory reform observed in the sample period. We find the following results in Tables 3 and 4. Before the introduction of the on-time disclosure rules of 2012, carriers had an estimated trend of reducing their extra block time additions, apparently tolerating a concurrent trend of increase in the odds of delays in their flights. Indeed, the estimated coefficients of variable T in most columns of Tables 3 and 4 are statistically significant and negative and positive, respectively. After the regulatory reform, however, both trends are somewhat reverted: the coefficient of the interaction variable T × QUALREG is always positive in Table 3, and negative in Table 4, with estimated effects in most cases accounting for more than half of the original trend. This result suggests that the new regulation has provoked an intensification in the schedule padding behavior by airlines. We argue that such movement can be classified as "schedule padding," as it is

[30] This result may be a consequence of the lower turnaround times of carriers with higher flight frequency.

[31] This is in contrast with Bendinelli, Bettini, & Oliveira (2016), which obtain statistically significant results for both variables. We recommend that this issue be further investigated.

ceteris paribus to the other factors related to operations and may have been motivated by the need to be strategically positioned in the market with the new on-time disclosure requirements. A similar phenomenon was reported in the US market after the implementation of same regulation, as observed by Shumsky (1993), Forbes, Lederman, & Wither (2019) and Yimga & Gorjidooz (2019).

To allow for better visualization of our results regarding not only the isolated effects of the new disclosure rule but also the other strategic-related time additions of that period, we develop the following counterfactual analysis. We first create a ranking of routes based on each sample route's actual proportions of on-time flights. The resulting route ranking is similar to the "Punctuality League" kept by the Official Aviation Guide (OAG).[32] We then investigate the impact on mean route on-time performance that would be incurred if carriers did not engage in strategic extra time additions, i.e., a situation of absence of schedule padding motivated by purely market-driven factors. To accomplish that calculation, we utilized the estimated parameters of HHI (lagged) LCCS (lagged) and T × QUALREG of Column (4) in Table 3. We then compute an "Adjusted EXTBT" measure– i.e., EXTBT net of the estimated effect of those regressors–and plug it into the ODDSDEL equation in replacement of EXTBT. For this purpose, we utilize the specification of ODDSDEL of Column (4) in Table 4. With such an "Adjusted ODDSDEL" figure, we can recalculate the mean on-time performances and, as a consequence, to entirely rerank the routes. We display the results of such computations for a set of sample periods in Table 5.

Table 5 – Counterfactual analysis of mean route punctuality: adjustment for strategic EXTBT

Period	Flight Delays (Proportion)			Delayed Flights (Thousands)				Route Rank Changes (After adjustment)				
	(1) Actual Rate	(2) Adjusted Rate	Diff.	(3) Delayed	(4) Delayed Adjusted	Diff.	Diff. %	Nr Routes	Kept Position (Nr and %)		Changed Position (Nr and %)	
2009-2011	22.3%	22.5%	*0.1%*	128.4	129.1	*0.7*	*0.6%*	117	71	*60.8%*	46	*39.2%*
2012-2014	17.0%	17.8%	*0.8%*	100.1	104.9	*4.8*	*4.8%*	123	55	*44.6%*	68	*55.4%*
2015-2017	11.8%	12.6%	*0.8%*	69.9	74.6	*4.7*	*6.8%*	127	61	*48.3%*	66	*51.7%*
2018	15.3%	16.2%	*0.9%*	88.6	93.9	*5.3*	*6.0%*	131	45	*34.4%*	86	*65.6%*

Source: available data set with authors' calculations. Note: "route rank" is a constructed yearly ranking of actual mean punctuality rates comprising all sample routes. The figures represent the extracted mean over each considered period.

[32] See *OAG Punctuality League 2018. On-time performance for airlines and airports and Top 20 busiest routes. Based on full year data 2017*. Available at oag.com. In our route ranking, we consider all sample routes instead of restricting attention to the Top 20 busiest ones. OAG discontinued the classification of routes on its 2019 edition, keeping only the airline and airport rankings.

Table 5 shows the proportion of flight delays–actual and adjusted rates, and their difference–and the total flights delayed in thousands–again, actual and adjusted, together with the absolute and percentual difference among them. Finally, the table displays the changes in the ranking of routes after the removal of market-driven EXTBT, indicating the amount that kept position with the adjustment, and how many suffered changes. We perform the counterfactual analysis for five sample periods: 2009-2011, 2012-2014, and 2015-207 (annual averages) and the most recent year, 2018.

We can see in Table 5 that the removal of market-driven EXTBT implies an increase of 0.9% in the proportion of flights delayed in 2018, i.e., from 15.3% to 16.2%. This effect is small, especially considering the significant drop in the actual rate of 7%, falling from 22.3% in 2009-2011 to 15.3% in 2018. However, if we analyze these results in absolute numbers, the counterfactual analysis suggests that more than five thousand flights in 2018 were classified as "punctual," apparently only due to the addition of strategic time by the airlines. If the carriers did not practice schedule padding, the number of delayed flights in the country would increase from 88.6 to 93.9 thousand–a difference of 6%, which grew mainly from 2012-2014, with the introduction of the quality-disclosure rule in 2012.

Concerning changes in positions in the OTP ranking after the adjustment, Table 5 shows that almost two-thirds of the routes would undergo a place change in the 2018 list. In contrast, these changes would impact a minority of routes immediately preceding the new rule–the 2009-2011 period.[33] Therefore, Table 5 allows us to address the question of the title of the paper "Are on-time performance statistics worthless?" at least concerning aggregate performance in the market. There is some evidence that key route-level OTP punctuality indicators can be altered by practices associated with schedule padding. In this sense, implications for airport and air traffic infrastructure policy-making can be impacted. However, we note that the distortions observed are small in terms of the mean flight delay proportions, and therefore these considerations must be put into perspective. Nevertheless, we believe our results are conservative in that the EXTBT adjustments may be more impactful if we consider a more disaggregated ranking. We recommend further investigation into this issue, and in particular, with data disaggregated at the airline-route level.

[33] In the composition of the punctuality ranking of the routes, we observe that the changes due to the performed adjustment generally occur only in exchanges of a few positions. For example, with the adjustment applied over the year 2018, the route connecting the cities of Maceió and Salvador (MCZ-SSA), in the Northeast of the country, would raise three positions, from the 25th to the 23rd place. The Brasília-Rio Branco route (BSB-RBR), connecting the Center-West to the North of the country, would fall two positions, from the 21st place to the 23rd place. There are no changes on the top-10 most regular routes that year, however. Among the fifty most punctual routes, there are a few cases of shifts higher than three positions. For example, the Curitiba-Porto Alegre (CWB-POA) route in the south fell nine places after the adjustment, dropping from the 37th to the 46th place. These findings suggest that the adjustment made is not neutral in terms of affecting the positions of the routes in the punctuality ranking, even though the changes caused are notably small.

The second regulatory reform observed in the sample period was the new 2014 airport slot regulation. Again, analyzing Tables 3 and 4 jointly, we first note that routes associated with slot-constrained airports present lower mean extra scheduled time additions and a higher propensity for delay—as indicated by the estimated coefficients of SLOTPR in those tables. However, the analysis of the results regarding variable T × SLOTREG shows that the new regulation has provoked a drop in both EXTBT and ODDSDEL. Indeed, most estimates of those coefficients in both tables are negative and statistically significant. These results indicate that the introduction of a stricter and more comprehensive regulation of airport slots since 2014 may have been effective in reducing flight delays and thus reducing the need for block time lengthening by carriers—a result that is in line that of with Fan (2019).

Regarding the implementation of the PBN operations in some Brazilian airports since the early 2010s, the estimated coefficient of the interaction term T × ATMREG suggests no statistically significant effect, as displayed in Tables 3 and 4. Although our results indicate that the new ATM regulatory framework has not produced effects on the extra scheduled block times (EXTBT) of carriers, it may have produced an effect on the unimpeded block times (UNIBT). Nevertheless, PBN apparently did not produce any effect on the likelihood of flight delays (ODDSDEL).

4.2. Robustness checks

We developed a set of robustness checks aiming at studying the sensitivity of our main estimation results displayed in the fourth columns of Tables 3 and 4. We present the results of these experiments in Columns (5), (6), (7), and (8) of those tables. First, in Column (5) of Tables 3 and 4, we experiment with an estimation procedure that does not include any region-direction-seasonal dummies, namely, the $DIR^{o}_{k,s}$ and $DIR^{d}_{k,s}$ controls discussed in Section 3.4. Second, in Column (6) of both tables, we experiment with the 10^{th} percentile of the actual block time distributions as an alternative measure of UNIBT* when computing EXTBT. Third, in Column (7) in both tables, we utilize another alternative measure of UNIBT*, this time extracting its values at the route-aircraft level, instead of the route-aircraft-time levels utilized in all other columns. As a final robustness check, in Column (8) of Tables 3 and 4, we change the number of lags employed to compute the lagged regressors of the EXTBT model and the lagged instrumental variables of the ODDSDEL model. We consider a scheduling decision-making window equal to 12 months and therefore set the number of lags h = 12. As can be found in the estimates of Columns (5)-(8) in Tables 3 and 4, in none of the robustness checks did we observe significant changes in the main results.

5. Conclusion

This paper investigates the main drivers of the extra times incorporated into the flight schedules of Brazilian airlines. We utilize an econometric method of high dimensional sparse (HDS) regression that employs the least absolute shrinkage and selection operator (LASSO) of Tibshirani (1996) to select adequate controls from among a vast set of available variables. Our estimation has the methodological contribution of decomposing the extra schedule block times into operational and strategic factors after controlling for the uncertainty in the scheduling process. We also estimate the effect of additional times on flight delays, allowing for the moderation effects of runway congestion, slots, and propagated delay. Finally, our empirical framework accounts for a set of critical unobserved regional and seasonal effects formed at the route level. In particular, we include deeper route direction-specific controls to account for the potential impact of prevailing winds—a procedure that may be even more relevant in other realities characterized by strong jet streams that affect the en-route performance of flights.

Our results show evidence that the extra time inserted by carriers in their flights can be decomposed into the adjustments following changes in flight operating conditions and the strategic buffer time. We find evidence confirming the hypothesis of the existence and effectiveness of schedule padding practices, i.e., extra time additions correlated with the status of the competition in the market. Furthermore, the empirical results of on-time performance suggest that one additional minute of extra time is associated with a reduction of roughly thirteen percent in the odds of flight delays, which is apparently an effective strategy to enhance on-time performance.

Concerning the policy implications of our study, the estimation results suggest that on-time disclosure regulation, implemented since 2012, has possibly encouraged airlines to lengthen their flight times strategically. We estimate a decreasing trend in the odds of flight delays after the introduction of the new regulation. In contrast, the implementation of slot controls at major airports since 2014 has apparently inhibited the addition of extra block time by carriers.

In this study, on account of the configuration of the data set, we focus on the impacts that the strategic and tactical management of punctuality by airlines may have on OTP indicators at the level of routes. However, other performance inspections are possible with OTP analyzes of airlines and airports, as well as the air traffic control subsystems. We suggest future studies in this regard.

After all this, are on-time performance statistics worthless? Our empirical results show suggestive, but conservative and statistically significant evidence that on-time disclosure regulations may create incentives for airlines to engage in schedule padding behavior. Therefore, the current official punctuality statistics may not always allow for the reliable analyses of on-time performance in the Brazilian airline industry—and possibly in other countries. The problem associated with the strategic buffer times is that they misalign carriers' incentives in their pursuit of maximum operational efficiency and optimized cruise speeds dictated by cost indexes. The padding behavior induces suboptimal exploitation of flight resources. It may mask the infrastructure inefficiencies that provoke airport congestion and propagated delays, especially in periods when the air transport industry is growing fast.

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