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Keywords: air transport demand, emerging markets, COVID-19, LASSO regression

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The economic downturn and the air travel crisis triggered by the recent Coronavirus pandemic pose a substantial threat to many emerging economies' new consuming class. In Brazil, considerable improvements in social inclusion have fostered the emergence of hundreds of thousands of first-time fliers in the past decades. We propose a methodology for identifying air transport markets characterized by greater social inclusion, using indicators of the local economy's income distribution, credit availability, and access to the internet. We perform an empirical analysis of the air travel demand's plunge since the pandemics, differentiating markets by their social inclusion intensity. Controlling for the potential endogeneity stemming from the spread of the COVID-19 through air travel, our results suggest that regional routes–but not routes feeding larger airports–are among the most impacted markets. Besides, we estimate that a market segment with one percent higher social inclusion is associated with a 0.9 percent more pronounced decline in demand during the pandemic. Therefore, markets that have benefited from greater social inclusion in the country are the most vulnerable to the current crisis.

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1. Introduction

The COVID-19 outbreak triggered a dramatic worldwide shock to air transport demand. The health issue, intensified by the pandemic fear associated with the risk of contracting and spreading the Coronavirus,[‡] provoked the closure of several international borders and forced an unprecedented wave of flight cancellations. So far, it has strongly impacted the commercial aviation and the related-tourism sectors and brought the risk of a severe economic crisis that may endure for many years. In many emerging economies, the short, medium, and long-term consequences of the pandemic pose a substantial threat to the segment of middle-income consumers that has expanded considerably over the past few decades.[§]

In Brazil, considerable advances in social inclusion since the 1990s have allowed the emergence of hundreds of thousands of middle-class travelers–Neri (2015), Klein, Mitchell, & Junge (2018). Macroeconomic stabilization policies, economic growth, and improvements in living conditions, combined with the industry's economic deregulation, decisively contributed to the greater participation of new consumers. Additionally, in 2019, income inequality indicators at work had ceased worsening, after four years since the beginning of the recession in 2015.[**] However, with the advent of the Coronavirus crisis, income inequality has been deteriorating across the country, only partially mitigated by the temporary emergency aid grant from the government to more than 60 million people.[††] As a result of the slump in economic activity and the Coronavirus's health crisis, air travel dropped by 81% —from 45.7 million revenue passengers in the second and third quarters of 2019 to only 8,7 million in the same period in 2020.

This paper investigates the impact of the Coronavirus crisis on air transportation, with a particular focus on the future dynamics of airlines' market positioning. In Brazil, the low-cost carrier (LCC) business model has been losing strength over the years, with only Gol airline operating in this segment but without large differentials in ticket prices and mean yield as compared with its primary rival Latam.[‡‡] Since its merger with the regional Trip Airlines, Azul Airlines, another incumbent,

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[‡] Ornell et al. (2020).

[§] See "An emerging middle class" (Mario Pezzini), 2012, available at www.oecdobserver.org; "The emergence of the middle class: an emerging-country phenomenon" (Clàudia Canals), September 16, 2019, available at www.caixabankresearch.com; "What China's Middle Class Says About Trump, Trade and Tomorrow," February 27, 2019, available at www.bloomberg.com; "The 'Bird of Gold': The Rise of India's Consumer Market," May 2007, available at www.mckinsey.com.

[**] "After four years, income inequality at work stops worsening" ("Após quatro anos, desigualdade de renda do trabalho para de piorar"), November 20, 2019, available at www.https://valor.globo.com/.

[††] "With the Coronavirus crisis, inequality worsens in metropolitan regions" ("Com crise provocada pelo coronavírus, desigualdade piora nas regiões metropolitanas"), October 22, 2020, available at g1.globo.com; "Brazil faces hard spending choices in 2021," December 19, 2020, available at www.economist.com.

[‡‡] See Wang, Zhang, & Zhang (2018) for the impacts of the presence of LCC on the demand of other emerging airline markets.

has been positioning itself more strongly toward the high-yield passengers and the monopolistic, regional markets. The Coronavirus crisis has brought relevant challenges to each of these firms as the traditional passenger segment has changed its purchasing behavior, with business travelers swapping trips for videoconferencing. In this context, in which markets has the current crisis most impacted on non-business passengers' demand? The markets wherein this type of passengers has a strong participation usually are those related to tourist destinations as well as the regions marked by more social inclusion over the past decades.

Our econometric methodology for identifying markets characterized by greater social inclusion in the Brazilian air transportation industry allows us to quantify the drivers of the pandemic's short-term demand shrinkage throughout 2020 and to conjecture about the demand evolution for the coming years as well as the airlines' attendant business model needs for adjustment. This methodological framework employs indicators that capture income distribution, credit availability, and internet access at the local level to build proxies for social, financial, and digital inclusion phenomena in the industry and thus to estimate their impacts on air travel. We contribute to the literature by carrying out an empirical analysis of the determinants of the sharp drop in demand for air travel since the pandemic by differentiating the markets according to their estimated intensity of social inclusion. Furthermore, this approach addresses endogeneity issues that arise due to the possible spread of COVID-19 through air travel, a factor that may cause inconsistent estimation and bias in air transport demand coefficients when considering 2020 data. Our results suggest that, ceteris paribus to the intensity of contagion by the Coronavirus, social inclusion factors are relevant in explaining the fall in traffic on domestic routes in the period.

This paper comprises five sections. After this introduction, Section 2 reviews the relevant literature on the impacts of the COVID-19 pandemic on air travel markets; Section 3 describes the Brazilian air transport industry and discusses the improvement in the social inclusion indicators and the emergence of air transport's new consumers, the data sample, the empirical model, and the estimation strategy; Section 4 presents and interprets the estimation results; and Section 5 concludes.

2. The impacts of the COVID-19 pandemic on air travel markets

The literature on the impacts of the COVID-19 pandemic on air transport markets worldwide is flourishing. To date, these studies have focused on the crises' impacts on airlines, the air transport-related sectors, and the local economy and seek to discuss government actions to mitigate the associated effects.

Taking the passenger perspective, Monmousseau et al. (2020) investigate the impact of the travel restriction measures implemented during the COVID-19 pandemic on the U.S. airline industry. They compute indicators extracted from social media to measure how the travel restrictions impacted on the relationship between passengers and airlines in close to real-time. Iacus et al. (2020) develop a forecasting model to project air passenger traffic during the Coronavirus outbreak. They estimate that in the first quarter of 2020, the impact of aviation losses may be associated with a world GDP decline by 0.02% to 0.12%. Maneenop & Kotcharin (2020) estimate the short-term impact of COVID-19 on the stock returns of 52 listed airline companies worldwide by using event study methodology. Estimating the effects of historical uncertainty shocks on airline employment, Sobieralski (2020) finds that job loss is nearly 7% of the airline workforce, with an upper bound of over 13%, and that the recovery following the shocks takes between 4 and 6 years. Brown & Kline (2020) study the U.S. airlines' managerial preparedness in the COVID-19 pandemic and conclude that airline management teams failed to learn from previous outbreaks. Czerny et al. (2020) focus on the Chinese aviation market's post-pandemic recovery.

Macilree & Duval (2020) discuss ICAO's role in coordinating safety provisions during the pandemic and nationwide state aid in airline bailouts, recapitalization, and ownership. Abate, Christidis & Purwanto (2020) study the government support to airlines in the aftermath of the COVID-19 pandemic, indicating that governments prioritize sustaining air transport connectivity to protect economic activity and jobs in both the aviation and tourism sectors.

Naboush & Alnimer (2020) investigate the circumstances under which an air carrier is liable for the transmission of COVID-19 and the scope of the safety measures required by ICAO to prevent its spread. Prince & Simon (2020) focus on the geographic heterogeneity of the impact of international travel on the spread of COVID-19 in the U.S. In the same line, Nakamura & Managi (2020) calculate the overall relative risk of the importation and exportation of COVID-19 from every airport in local municipalities worldwide.

By contrast, Lamb et al. (2020) consider the travelers' perspective and investigate the factors associated with their willingness to fly during the COVID-19 pandemic. They survey six hundred and thirty-two participants in the U.S., extracting characteristics of demographics, personality, emotional state, and travel purposes, and develop regression models for both business and pleasure travel. They find that the perceived threat from COVID-19, agreeableness, affect, and fear are statistically significant regressors for both business and pleasure type of fliers. The absolute value of their estimated standardized coefficients associated with "the perceived threat from COVID-19" and "fear" variables are higher for pleasure travelers when compared to business travelers: -0.172 against -0.159 for "perceived threat from COVID-19" and -0.063 against -0.050 for "fear". Their approach allows us to better understand passenger behavior in the years following the crisis. With the authors' breakdown of passenger types–business and pleasure segments–it is possible to project adjustments to market positioning and even restructuring of the airline business models in the crisis aftermath.

In line with Lamb et al. (2020), we perform a type of market segmentation for analysis. Unlike them, however, we focus on an emerging market country's air transport industry wherein social inclusion is a key factor to determine the consumer segments' relative participation: the higher the social inclusion, the lower the participation of the mainstream segment of business-related travelers. In contrast with theirs, our econometric approach uses panel data from city pairs across the country to identify the routes that most rely on middle-class consumers and to investigate the vulnerability of these markets to the impacts of the economic crisis brought about by the pandemic. Based on Prince & Simon (2020), who suggest that geographic heterogeneity of the spread of COVID-19 in the U.S. may be related to population density, cultural differences, public response, and potential virus carriers' inflow, we use a geographic heterogeneity lens to understand the effects of the pandemic on air transport demand.

3. Research design

Our methodology for identifying air transport markets related to greater social inclusion relies on data for the period when social inclusion significantly advanced in Brazil. Since the macroeconomic stabilization in the 1990s, Brazil has experienced spurts of optimism regarding economic growth and welfare improvement for the less favored classes. At the same time, income transfer programs have helped fighting extreme poverty in the country, while a declining income inequality gave rise to the emergence of a "new middle class" (Neri, 2015), which started consuming new goods as well as basic health, education, financial, and technology services. Combined with the airline industry's deregulation in the early 2000s, this social development hugely contributed to the emergence of hundreds of thousands of new air transport consumers in the 1990s and 20000s. Air transport has become a less associated with a consumer elite to become a more frequent item in the consumption basket for many households. Nonetheless, the mid-2010s economic downturn along with the Coronavirus outbreak of 2020 have posed significant challenges in such evolution.

3.1. The Coronavirus outbreak in Brazil

On March 11, 2020, the World Health Organization (WHO) characterized the disease caused by the new Coronavirus, COVID-19, as a pandemic.[§§] Officially, the first cases of the disease appeared in China in December 2019, but soon new cases were diagnosed in Europe and other parts of Asia, spreading then to the rest of the world. In Brazil, the first official record of the disease was on

[§§]"WHO characterizes COVID-19 as a pandemic", March, 11 2020, available on www.who.int.

February 26, 2020.[***] On March 17, 2021, COVID-19 had already caused more than 284 thousand deaths in the country.[†††]

Commercial aviation's total revenue passenger-kilometers (RPK) azilian c grew in Brazil by 0.6% in 2019.[‡‡‡] The record passenger movement in January 2020 (more than 9.8 billion RPKs) as compared to January in the previous years,[§§§] raised then optimistic performance expectations for the sector. However, the alarming diffusion of the new Coronavirus in Brazil in the early 2020 led the Ministry of Health to launch precautionary measures to deter its spread over the country, which soon proved insufficient. This sequence of events forced the government to announce a mandatory quarantine in mid-March.[****]

The severity and high rate of contagion of the disease and the government's attendant sanitary measures to contain it dramatically affected most sectors of the economy and cast uncertainty over the near future. The tourism-related sectors have been among the most hit by the pandemic, notably air travel, due to the perception that they could be a conduit to the virus's spread. As in other countries, Brazilian airlines had to deal with an unprecedented adverse demand shock. Passenger traffic fell sharply with the nationwide spread of the disease. According to ANAC,[††††] Brazilian airlines suffered a record 94.5% plunge in passenger movement in April 2020 as compared to the same period in 2019. Aircraft occupancy rate also registered a sharp drop in the same period, from 81.9% to 65.4%.[‡‡‡‡] Moreover, losses of the leading airlines exceeded R$ 15 billion in the first six months of 2020.[§§§§]

In March and April 2020, the government and airlines tried to tackle the crisis by relaxing slots rules at controlled airports (slots waiver), postponing the airport concessionaires' contractual payments for the concession, and implementing an "essential airline network", among other measures.[*****] In search of solutions to accelerate the recovery and avoid further losses, Azul and

[***] "Coronavirus timeline in Brazil" ("Linha do tempo do coronavírus no Brasil"), February 26, 2020, available on Coronavirus.saude.gov.br.

[†††] "Coronavirus panel" ("Painel Coronavírus"), accessed on January 7, 2021, available on COVID.saude.gov.br.

[‡‡‡] "Air transport demand and supply - ASK, RPK and Utilization – Reference: last 12 months of December 2019."

[§§§] "Air transport demand and supply - ASK, RPK and Utilization – Reference: January 2020."

[****] Diário Oficial da União, Portaria Nº 356, 11 de março de 2020, available on www.in.gov.br.

[††††] "iNFRADebate: Impacts of the pandemic on civil aviation - What are the horizons for the resumption of the sector" ("iNFRADebate: Impactos da pandemia na aviação civil – Quais os horizontes para a retomada do setor?"), by Fabiana Todesco e Mauro Césa Santiago Chaves, September 3, 2020, available on www.agenciainfra.com.

[‡‡‡‡] "Air transport demand and supply - ASK, RPK and Utilization – Reference: April 2019 and 2020", with own calculations.

[§§§§] "2nd quarter data reveal impact of more than 6 billion on Brazilian airlines" ("Dados do 2º tri revelam impacto de mais de 6 bilhões nas aéreas brasileiras"), October 23, 2020, available on www.anac.gov.br.

[*****] "Main measures in the airline industry after the beginning of the COVID-19 pandemic–Timeline" ("Principais medidas do setor aéreo após início da pandemia de COVID-19–Linha do Tempo"), June 2, 2020, available on www.anac.gov.br.

Latam signed in August a codeshare agreement.[†††††] Combining Latam's presence in the country's leading hubs and Azul's capillarity on flights to destinations with less demand and infrastructure support, the agreement expanded their network and the frequency of flights offered to passengers.

3.2. Data

We rely on two separate datasets. One is a panel of directional city-pairs of the domestic passenger flights with monthly observations between July 2010 and December 2018. To compute a city-pair, we group multiple airports on the same catchment area. We only consider routes with at least six observations and a hundred passengers in each period. The full sample has 65,452 observations, but in some specifications that include social inclusion variables the sample has only 48,957 observations. The second dataset comprises only data for 2020. More specifically, it includes 544 of the original city-pairs that still had scheduled flights in 2019. To thoroughly examine the drivers of the remarkable plunge in air travel demand in 2020, we consider only the first full quarters after the pandemic outbreak period (the second and third quarters of 2020), develop a cross-section of routes, and then compare the figures for 2020Q2-Q3 with those for 2019 Q2-Q3 to analyze the pandemics' short-run effects on the air travel markets.

Most data for both datasets are available at National Civil Aviation Agency (ANAC) public online databases.[‡‡‡‡‡] This agency provides information on all domestic and international scheduled flights on its Air Transportation Market Statistics Database and Active Scheduled Flight Report (VRA). For the social inclusion proxies, we utilize the following sources: the Firjan Municipal Development Index (IFDM), a standard of living, health, and education data set organized by Firjan (Industry Federation of the State of Rio de Janeiro);[§§§§§] the ESTBAN database, provided by Brazil's Central Bank, from which we drew data for our financial inclusion proxies, such as the number of branches and balance sheet data for each local bank at the city-month level; the National Telecommunication Agency (ANATEL), for the digital inclusion proxies at the city-month level; and datasets from the Brazilian Institute of Geography and Statistics (IBGE), the National Agency for Petroleum, Natural Gas and Biofuels (ANP), the National Land Transport Agency (ANTT), the Ministry of Health (Coronavirus cases), and the Brazilian government's Transparency Portal (www.portaltransparencia.gov.br) for emergency aid benefits).

3.3. Empirical model

[†††††] "Azul and Latam start codeshare: understand how it works" ("Azul e Latam iniciam codeshare: entenda como funciona"), G1, August 12, 2020, available on g1.globo.com.

[‡‡‡‡‡] See www.nectar.ita.br/avstats for a description and access to all air transport datasets in Brazil.

[§§§§§] See Avelino, Bressan, & Cunha (2013) for a description of the Firjan index.

Equation (1) represents our model for air travel demand in Brazil:

$$\begin{aligned}\mathrm{PAX}_{k,t} = {} & \beta_1\mathrm{INC}_{k,t} + \beta_2\mathrm{P}_{k,t} + \beta_3\mathrm{PBUS}_{k,t} + \beta_4\mathrm{TOUR}_{k,t} + \beta_5\mathrm{NET}_{k,t} + \\ & \beta_6\mathrm{P}_{k,t}\times\mathrm{LEIS}_k + \beta_7\mathrm{TREND}_t + \beta_8\mathrm{TREND}_t\times\mathrm{REC}_t + \beta_9\mathrm{HDI(DSL)}_{k,t} + \\ & \beta_{10}\mathrm{LOAN}_{k,t} + \beta_{11}\mathrm{DEBT}_{k,t} + \beta_{12}\mathrm{CELL}_{k,t} + u_{k,t},\end{aligned} \tag{1}$$

Equation (2) presents a framework to pinpoint the effects of the COVID-19 pandemic on air travel demand:

$$\begin{aligned}\mathrm{PAXVAR}_k = {} & \delta_1\mathrm{PVAR}_k + \delta_2\mathrm{INFECTED}_k + \delta_3\mathrm{DIST}_k + \delta_4\mathrm{DENSBEF}_k + \\ & \delta_5\mathrm{INCBEF}_k + \delta_6\mathrm{SOCINCL}_{kt} + \delta_7\mathrm{FEEDER}_k + \delta_8\mathrm{REGIONAL}_k + \\ & \delta_9\mathrm{EMERG\ AID}_k + \delta_{10}\mathrm{HISTGRW}_k + \varepsilon_{kt},\end{aligned} \tag{2}$$

where *k* denotes the city-pair, *t*, the periods, $u_{k,t}$ is the composite error term in Equation (1), ε_k is the error term consisting of city-pair fixed effects and a random term in Equation (2), β_s and δ_s are the parameters to be estimated in Equations (1) and (2) respectively, and the remaining variables are presented below:[******]

- $\mathrm{PAX}_{k,t}$ is the logarithm of the number of total air tickets sold by airlines for the city-pair (Source: ANAC's Airfares Microdata).
- $\mathrm{INC}_{k,t}$ is a proxy for income equal to the logarithm of the geometric mean of the per capita inflation-adjusted gross domestic products of the origin and destination cities in the Brazilian currency;[††††††]
- $\mathrm{P}_{k,t}$ is the logarithm of the mean inflation-adjusted market fare on the city-pair flight in the Brazilian currency (Source: ANAC's Airfares Microdata);
- $\mathrm{PBUS}_{k,t}$ is the logarithm of the mean inflation-adjusted bus price per kilometer on the city-pair in the Brazilian currency. The variable is calculated by using a reference of bus yield from the regulator legislation on July 2015 (equal to 0.1524 BRL per kilometer), with variations across time dictated by the bus price inflation computed in Brazil's consumer price index per major city. For the medium and small cities, we utilize the countrywide bus price inflation metric (Sources: ANTT and IBGE);

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

[††††††] When defining a "city" to calculate socioeconomic indicators, we consider the full mesoregion to approach its airports' catchment area. Over the sample period, IBGE employed the concept of "mesoregion" as a grouping of cities in the same region for statistical purposes. Since 2017, the concept has been revised and named "intermediary geographic regions." For all our local economies' metrics, we use the concept of mesoregion as a grouping of cities that belong to the endpoint airports routes' catchment areas.

- $TOUR_{k,t}$ is a proxy for the size of the tourist market for the route, measured as the number of total charter flights per ten million of the population of origin and destination cities' geometric mean (Sources: ANAC’s Air Transport Statistical Database and IBGE);
- $NET_{k,t}$ is a metric for the air transport network's size and quality, measured as the geometric mean of the number of network points (cities) serving the origin and destination cities (Source: ANAC’s Air Transport Statistical Database);
- $P_{k,t} \times LEIS_k$ is an interaction variable of $P_{k,t}$ with $LEIS_k$, which is a proxy for the proportion of leisure passengers traveling on the city-pair (Source: FIPE’s survey of air travelers, 2009);[‡‡‡‡‡‡]
- $TREND_t$ is a time trend variable to control for the national level demand evolution;
- $TREND_t \times REC_t$ is an interaction variable designed to control for a possible structural break in the national trend in demand due to Brazil’s mid-2010s recession, where REC_t is a dummy variable valuing one for the technical recession period (from April 2014 to December 2016);[§§§§§§]
- $HDI_{k,t}$ is the logarithm of the geometric mean of the Human Development Index (HDI) for the origin and destination cities. According to the United Nations Development Programme (2020, p. 244), the HDI is “(…) *a composite index measuring average achievement in three basic dimensions of human development—a long and healthy life, knowledge and a decent standard of living*.” To compute this variable, we extract a monthly interpolation of the yearly available, city-specific, Firjan Municipal Development Index (IFDM). The IFDM is a simple mean of indexes covering these three dimensions of the human development (Avelino, Bressan, & Cunha, 2013): “Employment and Income” (decent standard of living), “Education” (knowledge), and “Health” (long and healthy life)–hereafter, HDI (DSL), HDI (KNOW), and HDI (LHL), respectively. All indexes have a theoretical range from 0 to 1–the closer to 1, the higher the city’s development levels. In practice, no index reaches neither extreme values. To compute our HDI measure, we aggregate the Firjan’s IFDM by endpoint mesoregions using population sizes as weights. If social inclusion is a driver of the air transport demand in Brazil during the sample period (2010-2018), HDI should be positively correlated with PAX;

[‡‡‡‡‡‡] The Institute of Economic Research Foundation (FIPE), “Characterization and Dimensioning of the Matrix Origin- Destination of Air Transport in Brazil,” 2009.

[§§§§§§] See “Brazil’s economy slips into recession”, August, 29, 2014, available at www.ft.com.

- HDI $(DSL)_{k,t}$ is the geometric mean between the origin and destination cities of the HDI dimension for "decent standard of living" (DSL). If social inclusion is a driver of air transport, then, ceteris paribus, HDI (DSL) should be positively correlated with PAX;

- $LOAN_{k,t}$ is a proxy for financial inclusion capturing households' access to credit measured as the geometric mean of the origin and destination cities' logarithm of per capita inflation-adjusted value in BRL of new loans net of the loans paid off in the last twelve months.[*******] [†††††††] To account for the effect of new bank credit grants, we only consider the variable's positive values, setting it to zero when negative (Source: Central Bank of Brazil);

- $DEBT_{k,t}$ is another proxy for financial inclusion capturing household indebtedness measured as the geometric mean of the origin and destination endpoint cities' logarithm of the inflation-adjusted household bank debt per capita in BRL. This metric is a stock variable and includes current bank financing and loans (Source: Central Bank of Brazil);

- $CELL_{k,t}$ is a proxy for digital inclusion measured as the geometric mean of the number of cell phones per 100 inhabitants of the endpoint cities of a route (Source: ANATEL).[‡‡‡‡‡‡‡]

For Equation (2), the variables are the following:

- PAXVAR is a proxy for the revenue losses during the COVID-19 pandemic, measured as the difference between the logarithm of the total air tickets sold by airlines in the second and third quarters of 2020 (2020 Q2, Q3) and that for the same period in 2019 (2019 Q2, Q3) on the city-pair (Source: ANAC's Airfares Microdata);

- $PVAR_k$ is a proxy for the decline in the mean price during the COVID-19 pandemic, measured as the difference between the mean price logarithm in the second and third quarters of 2020 (2020 Q2, Q3) and that for the same period in 2019 (2019 Q2, Q3) on the city-pair (Source: ANAC's Airfares Microdata);

[*******] According to the World Bank, financial inclusion means "*that individuals and businesses have access to useful and affordable financial products and services that meet their needs–transactions, payments, savings, credit and insurance–delivered in a responsible and sustainable way*", therefore being a relevant booster of prosperity. See "Financial Inclusion," available at www.worldbank.org/en/topic/financialinclusion. García-Escribano (2013) shows that total credit to GDP in Brazil rose from 25 to about 49 percent of GDP during the 2000s, with the consumer credit categories experiencing strong growth rates.

[†††††††] To compute the logarithm of this variable, we added one to it.

[‡‡‡‡‡‡‡] According to the United Kingdom's NHS, the definition of "digital inclusion" includes: being able to use digital devices, such as computers and smart-phones; access to the internet; and digital services designed to meet the users' needs ("Definition of digital inclusion," last edited April 21, 2020, available on digital.nhs.uk).

- $INFECTED_k$ is the geometric mean of confirmed Coronavirus disease cases per capita in the endpoint cities from February 25 to November 30, 2020 (Source: Brazil's Ministry of Health COVID-19 Portal, available at COVID.saude.gov.br);
- $DIST_k$ is the geodesic distance between origin and destination cities using the Vincenty formula and the respective latitude/longitude points;
- $DENSBEF_k$ is a proxy for route density observed before the pandemic, set equal to the logarithm of the lagged number of total air tickets on the city-pair. To be consistent with the computation of $PAXVAR_k$, we consider the second and third quarters of 2019 for computing this variable (Source: ANAC's Airfares Microdata);
- $INCBEF_k$ is a proxy for per capita income before the pandemic, measured as the geometric mean of the origin and destination cities' logarithm of the per capita inflation-adjusted gross domestic product in BRL in the second and third quarters of 2019 (Source: IBGE);
- $FEEDER_k$ is a dummy variable to account for the routes embracing one state capital and one country town–defined as non-state capital–as endpoints. These routes are typically more likely to be operated by airlines with feeder flights to fill the mainline flights on the capitals' denser routes;
- $REGIONAL_k$ is a dummy variable to account for the routes linking two country towns (non-state capitals) as endpoints. These routes are typically thin flows operated by regional airlines;
- $SOCINCL_k$ is one of our proxies for capturing the influence of the long-term social inclusion trend on changes in the passenger profile on the route. It is estimated from Equation (1), being equal to $\frac{1}{T}\sum_t \widehat{\mathrm{SI}}_{k,t}/\widehat{\mathrm{PAX}}_{k,t}$, where $\widehat{\mathrm{SI}}_{k,t} = \hat{\beta}_9\mathrm{HDI(DSL)}_{k,t} + \hat{\beta}_{10}\mathrm{LOAN}_{k,t} + \hat{\beta}_{11}\mathrm{DEBT}_{k,t} + \hat{\beta}_{12}\mathrm{CELL}_{k,t}$, with the hat operator indicating predicted values and T equal to the number of periods. To avoid contaminating this variable's effect with the recession period of 2014-2016, we consider only predicted values until 2013. This variable is designed to estimate the differentiated impact of the COVID-19 pandemic according to social inclusion on Brazil's domestic routes;
- SOCINCL (HIGH) and SOCINCL $(INTERM)_k$ are dummy variables to account for city-pairs estimated as "high" and "intermediate" levels of social inclusion–namely, the $SOCINCL_k$ indicator. SOCINCL $(INTERM)_k$ is set equal to 1 for values of $SOCINCL_k$ between the interquartile range and SOCINCL $(HIGH)_k$ is equal to 1 for values of $SOCINCL_k$ above the third quartile. These dummies' baseline is the set of routes with a low level of social inclusion, i.e. for values of $SOCINCL_k$ below the first quartile;

- $EMERG\ AID_k$ is a proxy for the effects of the emergency aid benefit on the local economies during the COVID-19 pandemic. measured as the geometric mean of the origin and destination cities' logarithm of the total amount of emergency aid grants over the city's 2020 inflation-adjusted gross domestic product of 2018. The emergency aid was a financial benefit granted by the federal government from April to December 2020 to individual workers, individual micro-entrepreneurs, self-employed and unemployed. It reached over 65 million people in up to nine monthly payments ranging from approximately 30% to 60% of the minimum wage. We hypothesize that the aid may have helped the local economies keep at least partial economic activity during the crisis, preventing a steeper air travel drop;
- $HISTGRW_k$ is a proxy for the route's historical demand growth trend, being equal to the difference of the logarithm of the total air tickets sold by airlines on the second and third quarters of 2019 (2019 Q2, Q3) and total air tickets sold on the same period in 2018 (2018 Q2, Q3) on the city-pair. It is therefore a lagged version of PAXVAR (Source: ANAC's Airfares Microdata).

3.4. Estimation strategy

Our empirical approach faces two specification challenges. First, we need to account for the unobserved factors that drive air travel demand across a big country like Brazil. Unequivocally, Equations (1) and (2) cannot deal with the cornucopia of regional idiosyncrasies that may either foster or hinder air transport demand. For example, psychological effects related to the fear of the Coronavirus contagion, which Equation (2) does not take into account, may drive consumers' risk assessment and purchase behavior–Lamb et al. (2020), Kim et al. (2020), and, for a theoretical framework, Kahneman & Tversky (1979). Moreover, although we control for the government's emergence aid granted since the first months of the pandemic, the local economies' actual evolution is a critical unobserved factor. Therefore, we consider an enhanced set of control variables to account for such unobservables. In Equation (1), we employ 300 season-specific route dummies and 228 time dummies to control for local seasonality and global time effects. In Equation (2), we use 100 city and 27 state dummies to account for specificity to the endpoint airports' regions of the routes.

The second challenge is endogeneity. Equations (1) and (2) bear a typical problem of demand-side endogeneity of the right-hand side price variables P, P × LEIS, and PVAR. Therefore, we rely on instrumental variables (IV) for these variables to provide consistent estimations: cost shifters, Hausman-type, Stern-type, and BLP-type instrumental variables.[§§§§§§§] We also employ these variables interacted with $LEIS_k$ as additional instruments. As further instruments, we use the origin

[§§§§§§§] See Mumbower, Garrow & Higgins (2014) for a detailed discussion of these classes of IVs.

and destination's minimum, mean, median, and maximum local temperatures as instruments.[********] All IVs are computed in logarithm.

A subtler endogeneity issue is related to the pandemic effect on air travel decline intensity. Equation (2) includes INFECTED, which is potentially correlated with the unobserved factors that drive PAXVAR. The endogeneity of INFECTED owes to the possible spread of the COVID-19 through air travel–Adiga et al. (2020), Barnett & Fleming (2020), Prince & Simon (2020), and Nakamura & Managi (2020). As the Coronavirus contagion is possibly positively correlated with the unobserved dynamics of the local economies, INFECTED may be correlated with the error term ε_{kt} of Equation (2), bringing the risk of inconsistent estimation due to a positive bias that may underestimate the downward effect of this variable. To address this issue, we utilize other factors that may be correlated with the spread of the COVID-19, such as the endpoint cities' population densities, areas, and public health and educations conditions, all of which we calculate with data drawn from IBGE and Firjan.

We estimate Equations (1) and (2) by using the high dimensional sparse (HDS) regression approach of Belloni et al. (2012), Belloni, Chernozhukov, & Hansen (2014a, b), and Chernozhukov, Hansen, & Spindler (2015). We employ both the PDS-LASSO and IV-LASSO implementations of the models, as discussed in Ahrens, Hansen & Schaffer (2020). The PDS-LASSO is the Post-Double Selection methodology that uses the least absolute shrinkage and selection operator (LASSO) of Tibshirani (1996) in the first step to select regressors from a possibly large set of variables and thus avoid model overfitting, and, in the second step, a post-estimation OLS that considers the regressors selected in the first-step estimator. LASSO's model selection is performed through model parameter penalization and shrinkage.

Our preferred specifications rely on IV-LASSO, which is the instrumental variable version of PD-LASSO. IV-LASSO allows in addition to select the instrumental variables (IVs) from a possibly large set of candidates and run a Two-Step Least Squares model in the second step, considering only the selected IVs. Following Ahrens, Hansen & Schaffer (2020), we employ cluster-robust penalty loads to tackle heteroscedasticity–, with 1,013 city-pairs as clusters in Equation (1) and 85 city-or-origin as clusters in Equation (2). For Equation (1), we utilize a fixed-effects version of IV-LASSO, which we call FE-IV-LASSO, and compute heteroskedastic and autocorrelation consistent (HAC) standard errors in the final step of the PDS/IV-LASSO procedures.

We use a two-step procedure to estimate the effect of social inclusion on the demand contraction caused by the pandemic. In the first step we estimate the social inclusion parameters of demand in

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[********] We also created gravity versions of these variables, namely the minimum, maximum, and geometric mean between the origin and destination of each route at each period. Our source is the Meteorological Database for Education and Research of the Brazilian National Institute of Meteorology (BDMEP/INMET).

Equation (1), and in the second step we estimated the social inclusion metrics $SOCINCL_k$, $SOCINCL(HIGH)_k$, and $SOCINCL(INTERM)_k$ and insert them into Equation (2). The estimation problem here is that the second-stage parameters' standard errors must be adjusted, as the social inclusion variables were previously estimated. Thus, we use a stratified bootstrapping procedure to compute adjusted standard errors, with the cities of origin as the strata and 2,000 bootstrap replications.

4. Estimation results

Table 1 presents the estimation results of our empirical model for air travel demand in Brazil (PAX) using data between 2010 and 2018.[††††††††] The estimations reported in the five columns rely on the FE-IV-LASSO procedure. Column (1) shows the baseline model, which has no social inclusion proxy. The estimated income (INC) and price (P) elasticities of demand (1.9094 and -1.3686, respectively, indicate a relatively high sensitivity of demand to these variables. The PBUS, TOUR, and NET variables have positive, statistically significant coefficients (0.5388, 0.0110, and 0.1713, respectively), implying that demand increases with them. The trend variable (TREND) points to a decline in the demand over time, which is intensified during the mid-2010s recession, as the negative coefficient of the TREND x REC variable suggests. All of these results remain relatively the same in the other specifications in columns (2) to (5), the only exceptions being INC and PBUS, whose coefficients fall significantly when time controls are included, as Columns (4) and (5) show, indicating a correlation of these variables with factors with variability at the national level.

[††††††††] To simplify the exposition of results, we omit indexes *k* and *t* of the model variables.

Table 1–Estimation results: air travel demand (PAX)

	(1) PAX	(2) PAX	(3) PAX	(4) PAX	(5) PAX
INC	1.9094***	1.8777***	1.4636***	0.4862***	0.4880***
P	-1.3686***	-1.3521***	-1.3367***	-1.5909***	-1.5417***
PBUS	0.5388***	0.3285***	0.5058***	0.0938	0.1026
TOUR	0.0110***	0.0126***	0.0130***	0.0107***	0.0107***
NET	0.1713***	0.1545***	0.0958***	0.1014***	0.1010***
P × LEIS					-0.0527***
TREND	-0.0046***	-0.0024***	-0.0039***		
TREND × REC	-0.0002***	-0.0006***	-0.0002***		
HDI		0.3500*			
HDI (DSL)			0.4327***	0.3134***	0.3224***
LOAN			-0.0023*	-0.0015	-0.0015
DEBT			-0.0366***	-0.0736***	-0.0727***
CELL			0.5592***	0.7387***	0.7323***
Estimator	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO	FE-IV-LASSO
City-Pair Clusters	1,041	1,013	1,013	1,013	1,013
Route/Seas Controls	No	No	No	193/300	199/300
Time Controls	No	No	No	72/228	72/228
AIC Statistic	20,605	7,229	5,933	5,075	3,839
BIC Statistic	20,669	7,299	6,029	7,486	6,303
Adj R2 Statistic	0.4718	0.4626	0.4767	0.4884	0.5012
RMSE Statistic	0.2855	0.2632	0.2597	0.2561	0.2528
RMSE CV Statistic	1.2760	1.2585	1.3682	1.3678	3.2103
Nr Observations	65,452	48,957	48,957	48,957	48,957

*Notes: Estimation results produced by the instrumental variables, post-double-selection LASSO-based methodology of Belloni et al. (2012, 2014a,b), with fixed effects (IV-LASSO). Post-LASSO estimation is performed with a Two-Stage Least Squares, fixed-effects, procedure with standard errors robust to heteroskedasticity and autocorrelation. LASSO penalty loadings account for the clustering of city-pairs. Control variables estimates omitted. INC, P, PBUS, TOUR, and NET are not penalized by LASSO. Cross-validation was performed with a 4-fold procedure. P-value representations: ***p<0.01, ** p<0.05, * p<0.10.*

Column (2) in Table 1 shows that the coefficient for the Human Development Index regressor is positive but statistically significant only at 10%. Column (3) breaks down the social inclusion indicators to capture geographical and temporal improvements in metrics of life conditions, as HDI (DSL), financial inclusion (DEBT and LOAN variables), and digital inclusion (CELL). Columns (3) to (5) provide evidence that some of these factors are statistically related to air travel demand. The variables HDI (DSL), CELL, and DEBT have statistically significant estimated coefficients, those for the first two variables being positive and that for the latter, negative. These results do not change when we add deeper route/station and time controls (Column 4), nor when we include variable P × LEIS, which may capture the effect of the possibly more price-elastic demand in a relevant subset of markets that could be a confounding factor. Thus, demand seems to be positively driven by socioeconomic factors, such as income distribution, HDI (DSL), and access to the internet (CELL). The negative coefficient for household indebtedness (DEBT) reveals that financial inclusion may have the downside of increasing household indebtedness, which can discourage air travel. The LOAN variable, a proxy for financial inclusion through access to bank credit, is not statistically significant in most specifications, yielding some evidence that families did not count on bank credit for purchasing airline ticket during the period under investigation. Table 2 presents the estimation results of Equation (2), whose regressand is the air travel demand drop (PAXVAR) in the first quarters of the COVID-19 outbreak (2020 Q2 and Q3) .. In all of the five specifications, we employ the IV-LASSO estimator. As discussed before, we apply stratified bootstrapping to adjust the standard errors of the estimates in the specifications with social inclusion variables (SOCINCL). Regarding endogeneity, our baseline model in Column (1) has PVAR as the only instrumented variable, while in the other specifications both PVAR and COVID are instrumented.

Table 2–Estimation results: air travel demand change due to the COVID-19 pandemic (PAXVAR)

	(1) PAXVAR	(2) PAXVAR	(3) PAXVAR	(4) PAXVAR	(5) PAXVAR
PVAR	-1.4595*	-1.4405**	-1.2710***	-1.3537***	-1.0511**
INFECTED	-0.0483	-0.2728**	-0.2961**	-0.4352***	-0.4209***
DIST	0.2141***	0.2120***	0.2683***	0.2533***	0.2514***
DENSBEF	-0.0033	-0.0033	-0.0046	-0.0055	-0.0022
INCBEF	0.2810**	0.2615**	-0.0624	-0.0763	-0.0004
FEEDER	-0.0271	-0.0249	-0.0127	-0.0326	-0.0891
REGIONAL	-0.4183***	-0.4104***	-0.2367**	-0.2529**	-0.2454**
SOCINCL (HIGH)			-0.2673***		
SOCINCL (INTERM)			-0.0622**		
SOCINCL				-0.9686***	-0.9231***
EMERG AID					0.0448
HISTGRW					0.0725
Estimator	IV-LASSO	IV-LASSO	IV-LASSO	IV-LASSO	IV-LASSO
City Clusters	85	85	85	85	85
State controls	10/27	10/27	11/27	10/27	7/27
City controls	60/100	60/100	28/100	28/100	25/100
AIC Statistic	106	106	186	230	201
BIC Statistic	137	136	224	265	244
Adj R2 Statistic	0.2380	0.2390	0.3363	0.2872	0.3982
RMSE Statistic	0.2634	0.2632	0.2823	0.2946	0.2859
RMSE CV Statistic	0.2988	0.3289	0.3112	0.3418	0.3074
Nr Observations	544	544	544	544	544

*Notes: Estimation results of Columns (1)-(5) produced by the instrumental variables, post-double-selection LASSO-based methodology (IV-LASSO) of Belloni et al. (2012, 2014a,b). Standard errors are computed using stratified bootstrapping, given the SOCINCL variables' estimation in an earlier step (strata: the city of origin; 2000 replications). LASSO penalty loadings account for the clustering of cities of origin. Control variables estimates omitted. Cross-validation was performed with a 4-fold procedure. PVAR, INFECTED, DIST, DENS, INC, FEEDER, and REGIONAL not penalized by LASSO. P-value representations: ***p<0.01, ** p<0.05, * p<0.10.*

C comparing the results of Columns (1) and (2) in Table 2, we observe that only the estimated coefficient for the variable accounting for the COVID-19 cases (INFECTED) had a very large change. Controlling for endogeneity with our instrumentation approach in Column (2), that variable becomes statistically significant and with an estimated absolute value more than four times higher than that in Column (1). This result points to a positive correlation of INFECTED with the error term of PAXVAR, indicating non-observed effects of variations in the local economic activity throughout 2020. Thus, these results support the hypothesis of endogeneity underlying the relationship between air travel demand variation and the number of COVID-19 cases over that period. Concerning the remaining variables, the results from Columns (1) and (2) provide evidence that routes with higher-than-average stage length are less impacted by the pandemic outbreak, probably due to consumers' difficulty in substituting road trips for air travel.[‡‡‡‡‡‡‡‡]

Additionally, *ceteris paribus*, regional routes in the specifications in those two columns are more impacted than other domestic routes, as the estimated coefficient for the REGIONAL variable is statistically significant and negative (-0.4). However, the value of that variable coefficient falls to almost half in the remaining columns (3–5), although keeping statistical significance. By contrast, the coefficient of INC is positive and statistically significant in Columns (1) and (2) but loses significance in the other specifications. The DENS and FEEDER variables are consistently nonsignificant in all specifications.

The specification in Column (3) adds the dummy variables of high and intermediate social inclusion — SOCINCL (HIGH) and SOCINCL (INTERM), respectively. The estimated coefficients of both these variables are negative and statistically significant, indicating that demand for the routes with greater social inclusion suffered more during the first quarters of the COVID-19 pandemic crisis. As Columns (4) shows, this conclusion is robust to the replacement of these discrete variables for the continuous social inclusion indicator (SOCINCL). Focusing on that variable, a 1% increase in social inclusion on a route is associated with an almost 1% additional drop in demand due to the COVID-19 crisis. Results do not change adding either the proxy for local economy's possible stimulus coming from the government's emergency aid as of April 2020 (AID), or the proxy for the recent demand growth in the route (HISTGRW). Therefore, the results from Table 2 allow us to conclude that the most benefited markets from the higher social inclusion, identified by our demand model in Equation (1), were more severely hit by the crisis brought about by the 2020 Coronavirus pandemic. This conclusion may shed light on airlines' possible policies and strategies related their market repositioning and business model adjustments the next challenging years. With fewer emergent-class passengers, demand is bound to shrink and become less price-elastic. Moreover, the pandemic-induced partial replacement of air travel with virtual meetings for corporate passengers is likely to have permanent shrinking effects on the demand from the business segment. Consequently, carriers should find ways to conquer non-business passenger air travel demand. Expanding the low-cost business model to recover at least part of the profitability lost in 2020 from the exploitation of leisure travel segments may turn out to be a rewarding path.

5. Conclusion

[‡‡‡‡‡‡‡‡] This result is consistent with "Air travel takes back seat to road trips in the summer of Coronavirus: Fuel for Thought," S&P Global, May 20, 2020, available on www.spglobal.com.

This paper developed an empirical framework to pinpoint some of the drivers of the sharp decline in the air transport domestic demand in Brazil since the Coronavirus outbreak. More specifically, we focused on the pandemic's impacts on the routes linking cities marked by higher social inclusion. New consumers from the emergent classes have entered the air travel market with more intensity since the mid-nineties. The proposed methodology aimed to identify air transport markets possibly characterized by greater social inclusion and inspect their behavior during the first quarters of the pandemic period. Our contribution lies in assessing the possible impacts on the air travel demand of social inclusion indicators at the local economy level, such as income distribution, credit availability, and access to the internet. Another contribution is the approach to address endogeneity regarding the possible COVID-19 contagion through air travel, avoiding therefore inconsistent estimation of demand during the virus outbreak.

We produce evidence of air travel markets' differentiated reactions to the pandemic shock according to their social inclusion intensity. We find that the demand plunge in regional routes was the most dramatic, whereas routes feeding larger airports did not show any differentiated behavior in the period. We estimate that a market with one percent higher social inclusion is associated with roughly a 0.9 percent more pronounced decline in demand during the pandemic. Our results show that the most benefited markets from greater social inclusion in Brazil are the most vulnerable to the COVID-19 persistence. Finally, finding a positive correlation of COVID-19 cases with the error term of demand variation during the first quarters of the pandemic, we tackle this endogeneity by employing a LASSO-based instrumental variable approach.

Our findings provide some groundwork for taking stock of the adjustments in business models airlines need to undertake to hasten the return to the pre-pandemic traffic levels. In particular, the evidence we raise underpins the view that markets more reliant on social inclusion should be targeted with deeper discounts to bring back price-sensitive consumers to the market. Carriers that react more quickly to these new market conditions are likely to get a head start in the post-pandemic environment.

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