

The Analysis of Impact of Larger Aircraft A-380 on Frequency of Flights

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Abstract—An innovations in airline industry has significant impact on the behavior of its participants: airline companies, airports and passengers. In this paper the innovation that is studied is an introduction of double-deck plane – A-380, which is currently the largest aircraft. Due to its size, it is able to carry at once approximately twice as many passenger as the other medium-sized aircraft, thus, allowing to reduce the frequency, and, as a consequence, induce lower environmental impact. However, in reality, flight frequency depends on many other factors such as airport fees, demand and strategic decision of companies to maximize their profits under competition. Using the monthly panel observations of airline companies over 10 years on 121 routes, we test if the utilization of A-380 leads to the decrease in airline company's flight frequency. Moreover, we analyze the response of the use of A-380 on the competitors' frequency. We find that increase in usage of A-380 leads to the decrease of company's own frequency, whereas the competitors have incentive to increase its frequency by differentiating their flights by departure time in order to attract passengers who value the availability of flight at a particular hour.

Index Terms—A-380, frequency of flight, airline innovation, airline competition

I. INTRODUCTION

Air transport market is characterized by numerous interactions between airlines, passengers, service providers, official regulators as well as countries. Given this complex system, growing traffic flow and the global appeal for sustainable development, the airline market is challenged to adapt strategies in order to achieve operational efficiency and preserve high profits under the vigorous competition. In return, aircraft manufacturers have to address these issues by providing innovative solutions for the future aircraft generation. Their solutions will impact airlines companies as well as the other participants of the air transport system. One of such examples is the launch of the biggest passenger double-deck aircraft A-380. We aim to contribute and deepen theoretical understanding of air stakeholders' behavior given the introduction of this innovation, which allows to accommodate growing air traffic with lower impact on environment. The main objective of this paper is to identify if after the introduction of A-380 there is a decrease in flight frequency for airline companies on the route due to higher capacity of airplane, allowing for better operational efficiency and lower level of carbon footprint. The flight frequency is defined in this study as the total number

of flights between departure and destination points supplied by one airline company in a month. To answer this question we will summarize a review of existing studies, describe the available data and define initial econometric model that impacts the frequency of flights.

II. LITERATURE REVIEW

In 2013 the air transport activities contributed 12% to transport and 2% to total world CO_2 emission [18]. With rising global environmental concern and volatile oil prices, aircraft manufacturers aim to bring innovative technologies and adjust operation efficiency of new generation of aircraft. A-380 is the biggest passenger aircraft that due to economies of size provides efficiency in terms of fuel burn, taking into account the classic seat configuration provided by the manufacturer [8]. King (2007) in his analysis of A-380 highlights that the aircraft suits long-haul and high-density markets, allowing to absorb high-frequency operations. The author notes that if flying intelligently the aircraft can sustain markets in the periods of high fuel price by reducing the fuel cost per passenger kilometer. The reduction of frequency is directly linked to the reduction of fuel burn and correspondingly lower level of carbon emission.

The selection of scientific literature aims to answer the earlier research question:

- If the air carriers introduce A-380 in their fleet does it lead to the reduction of frequency of flights on the routes?

We analyzed the existing studies that address the behavior of aviation sector under environmental constraints and innovation. The studies introduced one of the following ideas:

- 1) The influence of aircraft type and size on fuel consumption and CO_2 emission
- 2) Current fuel and operational efficiency of airline companies

While studying the fuel emission some authors take a company-specific approach or industry as a whole and others consider the effect on passenger demand. Wei, Cui, and Gil [18] identify that pressure from competitors and strict governmental regulations are the driving forces for innovation in airline industry. They study how environmental innovations affect the companies financial and operational performance.

The other scholars (Scotti and Volta [16], Park and O’Kelly [15], Morrell [11], Miyoshi and Mason [9]) focused on the relationship between aircraft size and environmental productivity, arriving to the conclusion that larger aircraft provides improvement in efficiency and that there is an overall trend in change to larger aircraft types for short and medium haul flights. These articles provided a ground for a base assumption on the efficiency of larger aircraft. Pagovi and Psaraki-Kalouptsidi [13] come up with creative instruments to tackle endogeneity between market share (measure of concentration of the market) and frequency. These are market related instruments (number of airlines on the market, number of offered connections), route-level instrument (if the airport is hub for the operating airline) and rival related instruments (percentage of non-stop rival routes[13]). In our specification, we will test if number of airlines characterizes the market concentration, since other indexes such as Herfindahl-Hirschman Index (HHI), calculated by adding the squared market shares [7], does not vary sufficiently over time.

Babic, Kuljanin, and Kalic [1] notes that airline companies by increasing market share have higher probability of profit maximization and there are two strategies that airlines can follow, which are either to increase frequency or to increase seating capacity with larger airplanes. They also note that efficiency is a likewise important factor that impact market share.

Pai [14], Wang et al. [17] and Bilotkach [2] examine the frequency strategies and aircraft sizes. Wang et al. [17] found that in emerging markets airlines adjust the growing traffic by increasing frequency. They also concluded that more concentrated¹ market structures resulted from merges lead to the reduction of frequencies. Even though collective research approached the topic from different angles, the collected findings demonstrate that airline companies have to adopt efficient strategies to sustain their competitiveness under the conditions of volatile and dynamic market.

III. DATA

The database is the OAG schedule analyzer - database of Official Airline Guide, which is a UK company that provides airline data services [12]. It is a powerful tool, which contains the past, current and future information on supplied scheduled flights. Being first published in 1929, today OAG holds information for 1000 airlines and 4000 airports. The advantage of Schedule analyzer is that it allows to view activities of competitors on different routes and obtain information on the relative share of supply. It contains different variables such as airports, carriers, flight frequencies, aircraft types, alliance etc. This is one of the most comprehensive and widely used data on traffic flow.

The other database is ENAC database on Air Transport. The ENAC database contains information for 500 airline companies and consist of three separate databases on Airlines

¹More concentrated refers to the concentration in terms of HHI (HHI close to 1), when there are less number of carriers

companies, Airports and Traffic flows. It contains data on different indicators from various sources (IATA [5], ICAO [6], Airline Monitor [10], etc). ENAC database was used to extract the actual recorded traffic flow on the routes, which represent the demand proxy in the model. Data structure is panel data. Besides having cross sectional and time series dimension, our panel data has more complex hierarchical form [4]: the dependent variables y measures the frequency of flights for the airline i on Origin-Destination route j at time t . The panel structure was chosen due to the following advantages[4]:

- It allows to conduct more precise inference due to higher variability: presence of greater number of observations allows for more degrees of freedom [4].

Moreover, by capturing inter- and intra- individual characteristics with panel data, it is possible to model more complex behavior. In our case it is an important aspect, since the change of aircraft is not an immediate process, it takes several months or years for companies to adopt new fleet. Thus, the timing allows to capture the response dynamics to see the impact of innovation.

- Panel data allows to control the omitted variables [4]

By capturing effect between individuals and their behavior over time we are able to legitimately ignore the impact of omitted variables that are constant over time. These could be company or route-specific characteristics that are not observable in our case. Time-series dimension of panel data captures the dynamics of development, since market entrance merge and exit are common practices in airline industry. Thus, we are able to control highly dynamic and rapidly changing competition structure of the market.

However, along with all the benefits of panel structure, there are potential issues that could lead to biased estimation of coefficients of regression models. Often time-series data exhibits seasonal behavior [4], which is the case for airline market. Depending on the route, there are particular periods when passenger traffic increases substantially due to vacation, business seasons etc. The graph 1 shows that seasonality is a common feature for airline market.

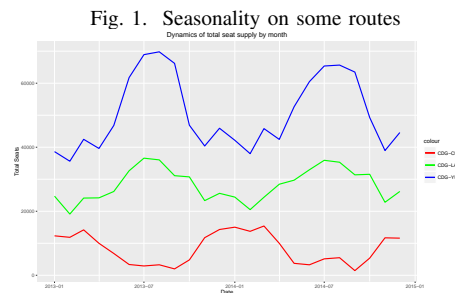


Fig. 1. Seasonality on some routes

As it could be seen from the figure 1 there is a clear seasonal trend, however, the pattern is not the same². For CDG-LAX (Charles de Gaulle – Los Angeles Airports), CDG-YUL (Charles de Gaulle – Montréal Airports) routes we see

²Blue line corresponds to the airport pair of Paris-Montréal, green - Paris-Los Angeles, red - Paris-Cancun.

that seats surge dramatically for summer periods with peaks in July-August, whereas for CDG-CUN (Charles de Gaulle – Cancun Airports) the highest points fall in a December-January period. This is not a surprising fact, people travel from Paris to Los Angeles and Montréal in summer period, whereas destination Paris-Mexico is the more favorable for tourism during winter. In our sample routes have the same seasonality pattern. Seasonality will be controlled in this study by introducing monthly dummy variables[4].

Overall, there is an annual increase in passenger traffic, as shown in figure 2:

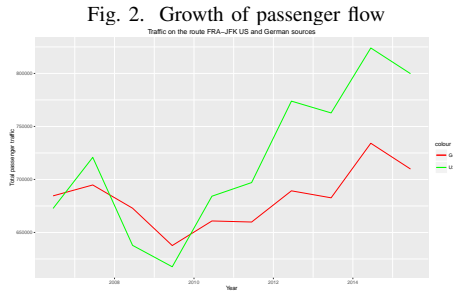


Fig. 2. Growth of passenger flow

Despite the shock in 2007 to 2009 on figure 2 due to global financial crisis, there is an upward trend, which is consistent with predictions of scholars that in future passenger flow will continue to increase. Therefore, in our model we will control for special events and shocks using dummy variables for years 2008, 2009 and 2010.

In total there are 151 airport-to-airport routes on which A-380 aircraft operates. Due to its size, A-380 is designed for long-haul routes with high demand. A long-haul route [15] is considered to be a non-stop fly with distance greater than 2000 km. Therefore, after conducting the qualitative analysis of the routes, we decided to include only routes that correspond to the definition of long-haul routes. Therefore, 30 routes with distance less than 2000 km were removed from our data set. The airlines on these 30 routes did not use A380 on the regular basis, these were rather exceptional cases, which could potentially be for airlines’ experimental purposes. We observe the data on monthly bases for the last 10 years on 121 routes. In total it constitutes N=35,371 observations. The descriptive statistics of the data set is presented in table I.

TABLE I
DESCRIPTIVE STATISTICS OF VARIABLES

Statistic	Mean	St. Dev.	Min	Max
Distance in km	6,147.7	3,090.9	1,985	13,802
Flight frequency	54.7	51.9	1	548
Log of population	15.3	1.1	12.9	17.5
Number of companies	4.3	2.9	1	17
Ratio of weight A380	0.086	0.242	0.000	0.983
Competitors’ ratio of weight A380	0.084	0.197	0.000	0.975
Log of annual traffic*	13.5	0.8	1.1	15.231

Notes: N=35,371, N*=33,983

As it could be seen from table I, the mean distance of the route - 6147 km. The average frequency per airline serving

the route is 54 flights per month. On average there are 4 competitors on the route, however, there are routes that are entirely supplied by a single carrier.

In this specification we are interested to test the two proxy for demand - logarithm of population and annual route traffic, which was collected from the ENAC autonomous database. However, out of 121 long-haul routes, traffic data is available only for 118. The elimination of three routes decreased the number of observations to N=33,983.

The figure 3 represents the plot of the mean value of frequency per period from 2010 to 2015 with blue range indicating – 95% confidence interval. From this graph we can deduct that there is a slight upward trend and the mean value of frequency changes over time. Even though this graph depicts only mean values, it provides the rough intuition which show the clear seasonality in the data as well as slightly upward trend.

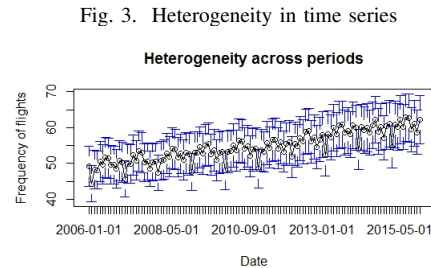


Fig. 3. Heterogeneity in time series

The figure 4 is a density plot of frequency of flights. We see that the most common frequency is between 0 and 50. The diagram is skewed to the right with the highest frequency of 300 per month.

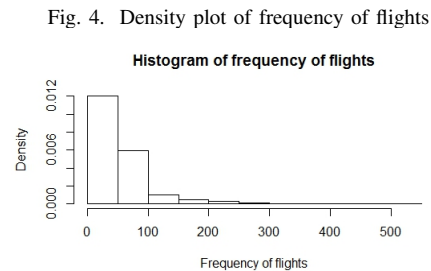


Fig. 4. Density plot of frequency of flights

Therefore, the visual inspection of the data suggests the presence of heterogeneity in the data. Thus, in order to account for individual-specific effects, it is a common practice in econometrics to use Fixed Effect model, where the individual-specific effects, which cannot be explained by the independent variables, are subtracted.

IV. TEST AND SELECTION OF THE MODEL

From the visual inspection of the data, it could be seen that airline data contains time-invariant latent effect that might be specific to route or airline company.

General model with individual effect has the following specification [19]:

$$y_{it} = \mathbf{x}_{it}\boldsymbol{\beta} + \alpha_i + \epsilon_{it} \quad (1)$$

where α_i is an individual unobserved heterogeneity and u_{it} is an idiosyncratic error. Depending on the model specification α_i is interpreted as random or fixed effect [19]. These types of models provide consistent estimation under the strict exogeneity condition, which restricts the effect of independent variables on y_{it} conditional on the unobserved effect α_i :

$$E(y_{it} | \mathbf{x}_{it}, \alpha_i) = \mathbf{x}_{it}\boldsymbol{\beta} + \alpha_i \quad (2)$$

In terms of idiosyncratic errors this condition is equivalent to the following assumption:

$$E(u_{it} | \mathbf{x}_{it}) = \mathbf{0} \quad (3)$$

If this assumption does not hold, the common treatment of panel data cannot be applied. The fixed/random effect model due to unobserved heterogeneity will be a starting point in statistical inference. It is one of the most popular approach for estimation of non-dynamic panel regressions. The

Below is the description of initial model, which has its limitation and potential endogeneity due to the fact that airline companies act strategically and the frequency of the competitor has impact on airline behavior. It will be later modeled with IV variable or as simultaneous equations.

$$\begin{aligned} \text{FREQ}_{ijt} = & \beta_0 + \beta_1 \text{NUMBCOMP}_{it} \\ & + \beta_2 \text{LOGPOP}_{it} \text{ (or } \beta_2 \text{LOGTRAF}_{it}) + \beta_3 \text{RATIO380}_{ijt} \\ & + \beta_4 \text{COMPRATIO380}_{ijt} + \beta_5 \text{DUMMY2008}_{ijt} \\ & + \beta_6 \text{DUMMY2009}_{ijt} + \beta_7 \text{DUMMY2010}_{ijt} \\ & + \beta_8 \text{FEB}_{ijt} + \beta_9 \text{MAR}_{ijt} + \beta_{10} \text{APR}_{ijt} + \beta_{11} \text{MAY}_{ijt} \\ & + \beta_{12} \text{JUN}_{ijt} + \beta_{13} \text{JUL}_{ijt} + \beta_{14} \text{AUG}_{ijt} + \beta_{15} \text{SEP}_{ijt} \\ & + \beta_{16} \text{OCT}_{ijt} + \beta_{17} \text{NOV}_{ijt} + \beta_{18} \text{DEC}_{ijt} + \alpha_i + \epsilon_{ijt} \end{aligned} \quad (4)$$

where

FREQ is the frequency of flights supplied by airline j on the route i per month t .

NUMBCOMP is the number of companies that operate on the route i in the period t . This variable is used to account for the structure of competition on the market. The other competition measurements, such as HHI, do not exhibit sufficient variation and thus were excluded.

LOGPOP is the logarithm of population in the departure airport of the route i per year, proxy for demand for airline services.

LOGTRAF is the logarithm of two-way annual traffic on the route, another proxy for demand for airline services. These two demand proxies will be tested separately to test the robustness of the model.

RATIO380 is the ratio of maximum total weight (seats and cargo converted to kg) transported by aircraft A380. It reflects the intensity of utilization of A380 on the route with respect

to other aircraft types to total weight transported by all type of aircraft.

COMPRATIO380 is the competitors' ratio of total weight (seats and cargo converted to kg) transported by aircraft A380 on the route to total weight transported by all type of aircraft. It reflects the intensity of utilization of A380 by competitors on the route with respect to other aircraft types.

DUMMY2008 is the dummy variable indicating year 2008 period of financial crisis

DUMMY2009 is the dummy variable indicating year 2009 period of financial crisis

DUMMY2010 is the dummy variable indicating year 2010 period of financial crisis

FEB - DEC are the dummy variables indicating the month of the year

A. Testing the validity of model

Test	Results
1 Lagrange Multiplier Test - (Breusch-Pagan):	t(1) = 5229133.7, p < .001
2 Lagrange Multiplier Test - time effects :	t(1) = 1366.60, p < .001
3 Hausman Test for FE or RE models:	t(18) = 843.41, p < .001
4 Augmented Dickey-Fuller Test:	t(1) = -14.66, p = .010
5 Breusch-Godfrey test for serial correlation:	t(1) = 26224.48, p < .001,
6 Breusch-Pagan test for heteroskedasticity:	t(124) = 109891.60, p < .001

The table IV-A presents a list of tests that were performed to evaluate the validity and justify the final specification of the model.

The first Breusch-Pagan Lagrange-Multiplier for random effects test helps to decide whether or not there is a panel effect. The null hypothesis is that there is no variance across individuals [19]: $H_0 : \sigma_0 = \sigma_1 = \dots = \sigma_n = 0$. However, as we can see, the corresponding p-value is lower than 0.001, thus, we reject null hypothesis in favor of alternative, indicating significant heterogeneity across entities.

The next test is also Lagrange Multiplier test for time effects. As we can see from p-value, which is lower than 0.001, there is a strong evidence for using time fixed effects. These two tests allowed to reject the simple OLS model in favor of fixed or random effect and establish the significant influence of time series dimension of panel structure.

The next test is the Hausman test for fixed effect vs random effect estimation. In this specification we have the following generalization of the model:

$$y_{it} = \beta_0 + \beta_1 x_{it} + \alpha_i + u_{it} \quad (5)$$

where y is the independent variable, x is the dependent variable, both varying for individuals across time and some unobserved factor α_i . The random effect model along with strict exogeneity (3) assumes that there is no covariance between unobserved effect α_i and independent variables: $Cov(\alpha_i, x_{it}) = 0$. If this condition holds, then both random effect and fixed effect estimators are consistent, with random effect estimator being the most efficient one [19]. If this condition does not hold, then random effect is no longer consistent. The null hypothesis of the Hausman test is $H_0 : Cov(\alpha_i, x_{it}) = 0$. From the p-value of the test, we

reject null hypothesis and conclude that random effect model is not appropriate, since unique errors are correlated with the independent variables.

Fixed effect approach removes the unobserved effect by preserving time-demeaned data [19], however; the explanatory variables that are constant over time are removed from equation, therefore the variable such as route distance, which may play significant role on airline policy does not enter the equation. The general equation of fixed effect is below, where \bar{y} is the individual mean value:

$$y_{it} - \bar{y}_i = \beta_1(x_{it} - \bar{x}_i) + u_{it} - \bar{u}_i \quad (6)$$

Under the earlier mentioned strict exogeneity assumption 3, where each error term is uncorrelated with explanatory variables across all time periods, the fixed effect regression provides an unbiased estimation.

The next is Augmented Dickey-Fuller test to verify that the independent variables are coming from the same data generating process in all time periods, which means that the independent variable x in period t follows the same process as in period $t+1$ and other periods. There are three conditions of the stationary process [19]:

- $E(x_t) = \mu$
- $Var(x_t) = \sigma^2$
- $Cov(x_t, x_{t+h}) = f(h) \neq g(t)$

The first is that the expected value of x_t is equal to constant μ . The second conditions is that variance of x_t is constant. The last is that covariance between x_t and x_{t+h} is a function, independent of time. Therefore, if we want to establish the linear relationship between y_t and x_t , the stationary of time series is a necessary condition. Moreover, the presence of stationary data allows to ensure the application of Law of Large Numbers and Central Limit Theorem. The idea in Augmented Dickey-Fuller test is to run the following regression [19]:

$$\Delta y_t = \alpha + \delta y_{t-1} + \epsilon_t \quad (7)$$

where the null hypothesis is that there is a unit-root: $H_0 : \delta = 0$. In the table the value of p-statistics is less than 0.01, therefore, we reject null hypothesis in favor of alternative hypothesis for stationarity of time series.

The following test is the Breusch-Godfrey test for serial correlation or in equivalent terms autocorrelation. The definition of serial correlation is that the covariance between the two error terms is not equal to zero[19]: $Cov(u_{it}, u_{st'}) \neq 0$, $\forall i, s, t, t'$. The presence of serial correlation leads the estimators to be no longer best linear unbiased estimators, there are other estimators that are more efficient with lower variance. In the table the p-value for Breusch-Godfrey is lower than 0.001, therefore, there is a strong evidence against $H_0 : Cov(u_{it}, u_{st'}) = 0$, in favor of alternative hypothesis, justifying the presence of serial correlation. Therefore, our next approach is to construct a model with serial correlation robust inference.

The last test is Breusch-Pagan test for heteroskedasticity. In the presence of homoskedastic errors, the following condition

holds: $H_0 : Var(u_{it} | x_{it}) = \sigma^2$, the variance of the error terms given the independent variables is constant, whereas under heteroskedasticity it is a function of the regressors: $Var(u_{it} | x_{it}) = \sigma^2 f(x_{it})$. In the test table p-value is less .001, indicating the presence of heteroskedasticity. Therefore, the robust errors will be provided accounting for non-constant variance.

B. Correcting for serial correlation: AR(1) process

The presence of serial correlation indicates that the usual test statistics is no longer valid[19]. If we consider that errors follow the AR(1) process:

$$u_{it} = \rho u_{it-1}, \text{ for all } t \quad (8)$$

then the variance of error term is:

$$Var(u_{it}) = \frac{\sigma_e^2}{1 - \rho^2} \quad (9)$$

One of the measures to tackle autocorrelation is to change model by quasi-differencing:

$$y_{it} - \rho y_{it-1} = (1 - \rho)\beta_0 + \beta_1(x_{it} - \rho x_{it-1}) + (u_{it} - \rho u_{it-1}) \quad (10)$$

The error terms of the above equation are not serially correlated. The estimator ρ is the sample autocorrelation estimate of residuals, obtained by regression and iteration. The quasi-differenced coefficients of the above equation are the special case of Feasible GLS estimator. In this paper, we will use Prais-Winsten method instead of Cochrane-Orcutt, since the last uses the notion of lag and loses the first observation. Moreover, we will apply heteroskedasticity robust errors.

V. RESULTS

In the table II we present the results of the following models:

- 1) The equation 4 using Fixed Effect estimation with robust errors on 121 routes with logarithm of population as a demand proxy, number of observations is 35,371
- 2) The equation 4 using iterated Prais-Winsten estimation with heteroskedasticity and autocorrelation robust errors on 121 routes with logarithm of population as a demand proxy, number of observations is 35,371
- 3) The equation 4 using iterated Prais-Winsten estimation with heteroskedasticity and autocorrelation robust errors on 118 routes with logarithm of population as a demand proxy, number of observations is 33,983
- 4) The equation 4 using iterated Prais-Winsten estimation with heteroskedasticity and autocorrelation robust errors on 118 routes with logarithm of annual traffic on the route as a demand proxy. The number of observations is 33,983

As it was mentioned above the total number of routes that are defined as long-haul routes (distance more than 2000 km) is 121 routes. However, only for 118 routes out of 121 there was available data on the annual traffic. Annual traffic and logarithm of population are proxies for airline demand. These two proxies were tested to verify the robustness of the model.

For comparison we provided the results of heteroskedasticity-robust Fixed Effect coefficients with serial correlation in column 1 of table 2. The three following columns are calculated with Prais-Winsten iteration on 121 and 118 routes with different proxies of demand to prove the robustness of our model.

TABLE II
MODEL REGRESSION

	Dependent variable: frequency of flights			
	(1)	(2)	(3)	(4)
	Robust FE estimator 121 routes	Prais-Win. estimator 121 routes	Prais-Win. estimator 118 routes	Prais-Win. estimator 118 routes
Constant	-	-85.177*** (30.24)	-341.605*** (87.85)	-191.755*** (52.52)
Number of companies	2.048*** (0.578)	0.279** (0.12)	0.269** (0.12)	0.268** (0.12)
Log of population	66.895*** (7.878)	7.758*** (2.00)	3.287 (3.82)	-
Log of annual traffic	-	-	-	0.287** (0.14)
Share of A380 tonnes	-7.540*** (1.637)	-4.926*** (0.69)	-4.960*** (0.70)	-4.958*** (0.70)
Competitors Share A380	-7.053*** (1.909)	1.468** (0.475)	1.207* (0.476)	1.214* (0.476)
fixed effect 2008	-0.790 (0.548)	0.065 (0.24)	0.068 (0.24)	0.090 (0.24)
fixed effect 2009	-1.621*** (0.615)	-0.570** (0.26)	-0.580** (0.27)	-0.571*** (0.27)
fixed effect 2010	-1.941*** (0.579)	-0.293 (0.20)	-0.296 (0.20)	-0.293 (0.20)
Feb	-5.097*** (0.271)	-5.343*** (0.12)	-5.195*** (0.11)	-5.200*** (0.11)
Mar	-0.128 (0.143)	0.438** (0.15)	-0.456** (0.15)	-0.466** (0.15)
Apr	-0.577** (0.261)	-1.234*** (0.18)	-1.211** (0.18)	-1.226** (0.18)
May	1.099*** (0.345)	0.273 (0.19)	0.237 (0.19)	0.216 (0.19)
Jun	-0.128 (0.394)	-1.087*** (0.19)	-1.061*** (0.19)	-1.088*** (0.19)
Jul	2.401*** (0.422)	1.398*** (0.19)	1.333*** (0.19)	1.301*** (0.19)
Aug	2.591*** (0.420)	1.406*** (0.19)	1.339*** (0.19)	1.302*** (0.18)
Sep	0.043 (0.389)	-1.153*** (0.18)	-1.142*** (0.18)	-1.185*** (0.18)
Oct	1.420*** (0.314)	0.226 (0.17)	0.192 (0.18)	0.144 (0.17)
Nov	-0.808*** (0.201)	-2.129*** (0.14)	-2.139*** (0.14)	-2.193*** (0.13)
Dec	1.588*** (0.219)	0.121 (0.09)	0.043 (0.11)	-0.016 (0.09)
Observations	35,371	35,371	33,983	33,983
Adjusted R ²	0.182	0.161	0.165	0.165
DW statistics	1.001	2.264	2.264	2.264

Note:

*p<0.1; **p<0.05; ***p<0.01

As we can see from the table there is a significant difference in the value of the coefficients from Fixed Effect and Prais-Winsten method. Nonetheless, in most of the cases the variables that are statistically significant under Fixed Effect are also significant under Prais-Winsten estimation. Important to notice that the robust errors of Prais-Winsten estimations are consistently higher relative to the value of coefficient than the robust errors of Fixed Effect, which corresponds with the idea of Feasible GLS estimation accounting for serial correlation. The Fixed Effect robust errors generally underestimate the truly existing variation of estimators and, thus should be taken with caution if there is a presence of significant serial correlation as it was in our case.

In the last row of the table II we can see the value of Durbin-

Watson test. The value of DW statistic is asymptotically equal to $DW = 2(1 - \rho)$ with ρ being the sample autocorrelation of residuals. Thus, $DW=2$ indicates no autocorrelation, significantly less than 2 - positive autocorrelation, greater than 2 - negative autocorrelation. As we can see from the results Fixed Effect model exhibits significantly positive serial correlation with p-value less than 0.001. The value of DW statistics for Prais-Winsten estimations is close to 2 indicating that we corrected serial correlation, and thus, we can reject the initial Fixed Effect model.

The coefficients of three Prais-Winsten models have same values, except for the variable logarithm of population, which loses its significance if the sample is decreased by three routes. In this model specification, we will not explain the value of the coefficient, the interpretation of which is not straight forward, since ρ represents the ratio, but rather will focus on the value of the sign, indicating direction of the change in the behavior, in order to identify if there is an anticipated response after the introduction of innovation. The signs of coefficients in this model correspond to the theoretical expected results. The increase in the number of companies increases the competition, leading to increase in frequency of flights. If there is an increase in the population, then it has positive impact on frequency of flights: the higher is the demand, the more often airlines will schedule flights. However, in the third column, which provides Prais-Winsten estimation for 118 routes, in comparison to 121 routes in second column, lacking more than 1000 observations this demand proxy has no longer significant impact. Therefore, with the 118 routes for which we had data on annual traffic, we used it as a proxy of demand, instead of logarithm of population. As it could be seen, the increase in the annual traffic leads to an increase in frequency of flights. The next variable is the ratio of the usage of A-380 on the route, the innovation, the variable of interest in our model. It has negative sign, indicating that the increase in the ratio of use of A380, decreases the airline own frequency. This is an interesting result, which corresponds with the hypothesis that the increase in the size of aircraft leads to decrease in frequency of flights. Thus, indeed, we see that the companies optimize the passenger demand by increasing the number of seats and decreasing the frequency, and possibly lower level of CO_2 emission. The next variable is the ratio of use of A380 by the competitors on the route also provides interesting insights. From the Fixed Effect model we might falsely conclude, that if the competitors increase their ratio of usage of A380, the airline own response is to reduce frequency as well, whereas in fact the Prais-Winsten estimation shows the opposite reaction on the competitors' behavior. The spacial competition in airline industry - scheduled hours for the flight departures could provide some insights for the positive sign of the coefficient of the competitors ratio of A380. The schedule of flights could be analyzed in Hotelling framework with airline location on the 24-hour clock [3]. Consumers are distributed not in distance terms but are located over time. The interpretation of the coefficient is that increase in the competitors' ratio of total tonnes carried by A380 increases

airline's own frequency of flight. The availability of additional hour on the flight schedule represents product differentiation in airline market: there is a consumer, who values the availability of flight in a particular hour of day [3]. Thus, firms in order to capture this marginal consumer may have incentive to locate closer to competitors' time in order to capture demand. If the airline company introduced A380 on a route, it leads to the decrease of its own frequency as the coefficient on the ratio of use of A380 suggests. This in turn provides additional free slot on the time-schedule, which provides an incentives to competitors on the route to move closer to the airline company in order to 'steal' customers.

The other variables are dummies for month and year indicating that, in fact, the financial crisis led to the decrease in frequency of flights. The sign of coefficients on monthly dummies indicate that there is seasonal effect on the frequency depending on summer or winter periods.

VI. CONCLUSION

The study analyzes if use of A-380 on the route leads to the decrease in flight frequency. The model presented is a starting point in the analysis of behavior of airline companies and environmental benefits that operation of A-380 might potentially generate. The results suggest that larger size of aircraft A-380 leads to the reduction in frequency of flights, however, positively affects the frequency of the competitor. The next steps in this study are to enhance model by incorporating the fuel cost for all planes as well as to test instrumental variable and simultaneous equations approaches to tackle endogeneity caused by interdependence of strategic decisions of airline companies, which will allow to further understand to what extent A-380 can contribute to the evolution of more sustainable air transportation system.

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