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Sustainability and Economics of Aviation Industry

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Content

Introduction and Summary

Aviation draws people's attention, not only because it is a dream of human race to fly or the association to vacations, but its role in our modern economies. It is, first of all, an incredible investment, such as airports[1], aircrafts, lands, control systems…etc. There are great business opportunities as well as risks[2]. Moreover, the operation of airports[3], airlines or aircraft manufacturing[4] generate tremendous incomes and jobs, often vital to cities heavily relay on these business. Furthermore, politic issues, such as regulations, agreements, ownerships and business decisions in company level, are shaping the market. Last but not least, enhanced by aviation, the connectivity and attractiveness of city induce economic benefit in tourism, business and so on, are very seductive to governors hoping to exploit its economic potential. However, just like any aspect of economics, there are externalities, which is not always captured nor considered by decision makers.

Externality is always the first question I ask. To quantify and internalize them will enhance market efficiency and the fairness of society. Furthermore, the trend, abnormality or unobserved factors are crucial in this uncertain world if we want to estimate the future. Focusing on econometrics, i.e. applying statistical tools on economic data to spot estimators and to set models; reference points for discussion or decision could be provided while arousing the awareness of less-acknowledged matters by including them in the models.

Three papers are presented in this report. First of all, as the fastest growing transport mode, aviation sustainability and environmental costs are generally concerned. We tried to address the noise and emission of the global aircraft fleet and to argue the current technology progress is not vigorous enough, while examining the trade off of these externalities. We find a statistically significant impact of incremental technical progress on all environmental externalities. Substantial innovation is found to have positive effect on per-passenger externalities. These results point to the need for incentives in aviation technical progress.

Secondly, the blooming of passenger traffic, particularly contributed by low cost carrier (LCC) across Europe is changing the landscape of aviation market: revitalizing airports, exploiting regulations and inducing policies. By observing the carbon dioxide footprint of flights departing from four airports in Lombardy region, we reveal determinants having direct impact on CO_2 emissions in two dimensions: total emission and per available seat kilometer (emission efficiency). Also we show distinguished characteristics of LCC and try to capture the impact of air traffic policies of government and airlines.

Last but not least, we are interested in a less studied area of aviation industry – air cargo activities. In the era of new economy, characterized by just in time manufacturing and express e-commerce, GDP as the classic indicator of air cargo should be verified since GDP is weighting more on service industries nowadays but less on air-cargo-related manufacturing

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[1] Construction cost of an airport can be up to billions, and sometimes involve land formation. Some example from "Airport construction mid-year review", CAPA 2015.

[2] Delays of an airport opening can induce over-budget and harm business. The case of Berlin airport highlighted by "The farcical saga of Berlin's new airport", The Telegraph 2017.

[3] Memphis, whose economy is driven by trucking and transportation, is the "America's Distribution Hub" hosting FedEx headquarter.

[4] "Fears for 4,000 British jobs as Bombardier hit with 219pc US tariffs in subsidy dispute", The Telegraph 2017. The dispute of USA (Boeing) and Canadian Bombardier may affect jobs in Belfast, Northern Ireland, where part of the aircraft is produced.

industries. This is an attempt to estimate air cargo activities, which is an important component of the air transport industry and a strong driver of aviation development other than air passenger movement. We found that a country’s income level, online purchase activity and air cargo connectivity are all positive determinants of its air cargo level.

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The impact of technology progress on aviation noise and emissions

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ABSTRACT

This paper investigates the effects of incremental and substantial innovations on aviation emissions and noise levels among aircraft/engine combinations belonging to the Boeing B737 and the Airbus A320 families. We find a statistically significant impact of incremental technical progress on all environmental externalities both at the flight level and the passenger level. Although substantial innovation is found to have a limited impact at the flight level, a noteworthy positive effect exists on per-passenger externalities. These results point to the need for incentives in aviation technical progress in order to neutralize future negative environmental effects due to the expected traffic growth.

1. Introduction

Aviation continues to be a booming industry, with an annual growth rate that has often surpassed 4.6% in the past ten years,[1] which is 3.5% greater, on average, than advanced economies' GDP growth.[2] Such growth, boosted by the extension of deregulation as well as an increasing level of competition brought about by the entrance of low-cost carriers (LCC), is expected to continue for the next years. Although competition and development are beneficial since they have brought about lower fares and greater mobility to the air transportation industry, both the public and policymakers are increasingly concerned about the industry's overall impact on the environment.

At the global level, the aviation industry accounts for 3.5% of global greenhouse gases (Lee et al., 2009), with a predicted increase of 15% by 2050 (IPCC, 1999); however, at the local level, emissions and noise nuisance are the biggest concerns because such factors may harm areas outside the airport (the human population, animals, plants, water, soil, etc.). Heavy health impacts are related to both emissions (respiratory and brain diseases, as well as cancers) and noise nuisance (hearing impairment, hypertension, ischemic heart disease, annoyance, sleep disturbance, stress).

As the public agrees that environmental externalities should be internalized into the cost of the industry, several environmental standards and corresponding platforms have been introduced at global, regional, and local levels. On a global level, the Kyoto Protocol (signed in 1997) aims at fighting global warming by reducing greenhouse gas concentrations in the atmosphere. On a regional level, the European Union emission-trading scheme (started in 2005) was extended to airlines in 2012.

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[1] According to Statista, annual growth (2006–2014) in global air traffic passenger demand has always been greater than 4.6%, except in 2008 and 2009, resulting in an average growth rate of 4.8% (Statista, 2015).

[2] According to the IMF database, the GDP growth from 2006 to 2014 of advanced economies was +1.3% on average.

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On a local level, many European cities have applied curfew and emission and/or noise surcharges to incentivize operators to reduce pollution.

As indicated by Chèze et al. (2011a), emissions in air transportation could be reduced by energy efficiency gains in (1) air traffic management (ATM), (2) improvements in existing aircraft (incremental innovation), and (3) production of new aircraft (substantial innovation). Different from driver (1), factors (2), and (3) are both related to technical progress. Moreover, Leylekian et al. (2014) show that both incremental and substantive innovation can also contribute to noise reduction.

Despite the acknowledged importance of innovation in reducing aviation externalities, little is known about the ways that advances in new technology are shaping the air transportation industry.[3]

This paper is an attempt to fill this gap. To this end, we build a data set composed of 270 different aircraft/engine combinations that belong to the B737 and A320 families and investigate the influence of technical progress (innovation) on (i) noise, (ii) local pollutants, and (iii) global pollutants. Further, we look for the existence of a trade-off between noise and local pollutants, as suggested by previous studies (e.g., Phleps and Hornung, 2013). Last, we investigate the relationship between the size of newly designed aircraft and the per-passenger environmental impact. To the best of our knowledge, the current study is one of the first attempts to measure the influence of technical progress in air transportation through an econometric approach. We have not found many systematic statements in the literature on the effects of technological progress at both the flight and the passenger levels (a rare example is Swan, 2010).[4] Despite this lack of evidence, other than enhancing fuel efficiency, the tendency of building bigger aircraft is also magnifying the environmental impact of a single flight. We pose the questions: What is such an impact per single passenger transported? Would the marginal environmental cost of a single passenger decrease even if the increasing marginal cost of the single flight is taken into account?

The structure of the paper is as follows. Section 2 summarizes the literature contributions on the relationship between technological progress and the environmental impact of air transportation. Section 3 presents the aviation externalities considered in the analysis, the sources of technical progress, and the econometric model. Section 4 describes the data set used in this study and the corresponding data mining procedures. Section 5 presents the empirical results. Section 6 concludes the paper and highlights some possible policy implications.

2. Literature review

Previous literature on the environmental impact of air transportation has mainly focused on computing the amount of emissions and noise produced by airports or particular aircraft types and converting such amounts into a monetary damage.

Schipper (2004) studies the impact of aircraft operations on air pollution and noise in a small group of European airports. He focuses on some routes and calculates, by aggregating aircraft and routes factors, the annual monetary damages. A similar approach is followed by Lu and Morrell (2006), but applied only at Heathrow, Gatwick, Stansted, Schipol, and Maastricht airports. Several contributions carry out a quantification of monetary damages of emissions and noise. Morrell and Lu (2007) calculate the environmental costs of hub-to-hub versus hub-bypass networks applying the methodology presented in Lu and Morrell (2006) to a data set of eight large airports on different continents. Lu (2009) calculates the impact on air passenger demand of the introduction of emission charges in airfares. Givoni and Rietveld (2010) compare the environmental costs of using two different aircraft types (the narrow-body A320 and the wide-body B747) on two high-demand routes (London-Amsterdam and Tokyo-Sapporo). Lu (2011) calculates the environmental costs at the Taiwan Taoyuan International Airport following the approach of Lu and Morrell (2006). Miyoshi and Mason (2009) propose an aircraft-specific calculator for CO_2 emissions applied to U.K. domestic routes, intra-Europe routes serving the U.K., and North Atlantic routes.

To the best of our knowledge, only a few contributions have estimated the effect of innovation on environmental impacts. These studies mainly focus on fuel consumption and CO_2. Macintosh and Wallace (2009) provide an estimate of CO_2 aviation emissions from 2005 to 2025 using the following algorithm: $E_t = RTK_t \times EI_t$, in which E_t is the emission of CO_2 in year t, RTK_t is the projected revenue tonne kilometers, and EI_t is the emission intensity in aviation in year t. They assume a reduction in emissions equal to 1.9% per year, in line with the IATA target. After deriving calibrations and running different scenarios, the authors show that innovation is unlikely to offset the increase in CO_2 emissions. Chèze et al. (2011a) also measure innovation in terms of higher fuel efficiency, which leads to lower CO_2 emissions. They provide a historical trend of technical progress in aviation, both in terms of fuel consumption and CO_2 emissions, and show that the amount of energy burnt by an aircraft (measured in MJoule) per available seat kilometer (ASK) has improved by a factor of 3.5 between 1958 (when the Comet 4 aircraft model was issued) and 2011 (the introductory year of the A350-300). Moreover, using an algorithm similar to that of Macintosh and Wallace (2009), they compute that innovation has improved energy efficiency by 2.88% per year in the period 1983–2006. In order to obtain this result they assume an approximately 3% annual reduction in tonnes of jet fuel by available tonne kilometer, but consider in their evaluation both technical progress and improvements in ATM. Chèze et al. (2011b) extend this approach and analyze the impact of energy efficiency on aviation CO_2 emissions by showing that new aircraft are not necessarily more efficient than older ones. For instance, carbon intensity, measured as grams of CO_2 per revenue passenger kilometer (RPK), is higher for the new aircraft A380 (equal to 101.86 g CO_2/RPK), than for the B777-300

[3] Aircraft and engine manufacturers claim that newer aircraft burn less fuel, take off and land in shorter times, make less noise, and fly faster. Airport managing companies guarantee that noise levels are under control through introducing monetary incentives (i.e., noise surcharges), thus encouraging airlines to use younger aircraft.

[4] Swan (2010) reports that large airplanes make 2–3 times the noise per seat as small airplanes.

(launched in 1997, with 92.84 g CO_2/RPK). Furthermore, Chèze et al. (2013) suggest that, if current trends in technological progress in aviation continue, the projected annual increase in the amount of CO_2 generated is equal to +0.1% at the world level, and that the current innovation process (in fuel efficiency) is not outweighing the carbon emissions of the growing air traffic. Brugnoli et al. (2015) examine the various forces influencing the development of environmentally beneficial technical changes in commercial aircraft and find CO_2 reductions of about 1.34% a year due to endogenous technical progress.

All previous contributions estimate that innovation effects on fuel consumption and CO_2 emissions is approximately −1.3%/−3% yearly, however, this amount is based on algorithms (with the exception of Brugnoli et al. (2015)). This implies that *ad hoc* assumptions about future scenarios are required (e.g., future advances in technologies) and that any kind of statistical inference on the provided coefficients is not allowed. Moreover, the literature contributions do not include all of the aviation externalities, since they focus mainly on CO_2 and completely ignore the noise component.

We see the need for a study that investigates the effect of the aviation industry's incremental and substantial technology progress on both pollutant emissions and noise. Incremental innovation is given by the annual improvement in environmental performance—i.e., how much a younger technology improves—while substantial innovation refers to the introduction of new aircraft models.

Additionally, Phleps and Hornung (2013) highlight the possible trade-off between emissions and noise in air transportation. They analyze the impact on airline costs through two innovations: the geared turbofan and the rotating open rotor technologies. A comparison is made with the *status quo* technology, given by the latest models of the B737 and A320 families. They equate three possible scenarios: a "baseline" scenario that is similar to the current situation, a "green and growth" scenario that balances the production of externalities and the growth of aviation, and a "rapid aviation growth" scenario paying very little attention to environmental effects. They show that the open rotor aircraft may yield up to 9% higher fuel efficiency compared to a geared turbofan technology (and better than the *status quo*), but that these gains may be completely offset due to the implementation of higher noise standards (e.g., tighter ICAO future Annex chapters), pointing out that the technical progress limiting fuel consumption (and in turn emissions) is not complementary with noise annoyance reductions.

We will encompass these algorithms/scenario-based analyses by comparing the magnitude with indications of the effects of technical progress on emissions and noise levels from our estimated econometric model. Different indications would imply the presence of the Phleps and Hornung (2013) trade-off.

3. The empirical strategy

Our empirical investigation explores the following issues. First, we identify the different aviation externalities—that is, what externalities to investigate and how to quantify them. Second, we design an econometric model estimating the impact of technical progress on such externalities, after having controlled for different factors that may introduce, if omitted, some distortions in the estimates. Hence, in this section we first describe the types of externalities included in the analysis, and then present the specifications of our econometric model.

3.1. Emissions and noise in aviation

To evaluate the aviation externalities, we focus on the amount of local and global pollutants emitted, as well as the noise generated by different aircraft-engine combinations. This means that our reference point is purely a single flight and not an airport with its total volume of operations. In this way, we can identify the effect of technology progress on a particular flight, which could be regarded as a benchmark for regulation standards.

As shown extensively in Grampella et al. (2017), aviation emissions can be divided into landing and takeoff (LTO) emissions,[5] affecting mainly the local pollutant concentration, and global emissions, which affect climate change.

Dings et al. (2003) point out that LTO emissions are HC (hydrocarbon), CO (carbon monoxide), NO_x (nitrogen oxides), SO_2 (sulfur dioxide), and PM_{10} (particular matters), while global emissions are CO_2 (carbon dioxide), H_2O (moisture), contrails and NO_x. Dings et al. (2003) extensively discuss the relevance of these different emissions and highlight the following issues. First, global emissions are mostly produced during the aircraft cruise; hence, the total amount of emissions depends upon the stage length. This finding implies that some assumptions are needed to quantify the amount of global emissions. We consider seven stage lengths: 125 nautical miles (nm), 250 nm, 500 nm, 750 nm, 1,000 nm, 1,500 nm, and 2,000 nm. Second, as contrails only affect 10% of the cruise, we exclude them from the analysis. Third, while CO_2 and H_2O emissions are related to fuel consumption, NO_x global emissions are instead not related to fuel consumption, but depend upon combustion temperature, which increases with engine power settings. We follow Sutkus et al. (2001), who provide factors of 3.155 kg CO_2/kg fuel, 1.237 kg H_2O/kg fuel, as well as emission indices of NO_x depending on the aircraft/engine combination and the cruise altitude (we use a 9–13 km altitude). Fuel consumption for the seven different stage lengths is taken from the CORINAIR database.[6]

[5] Local emissions are mainly related to airport operations—i.e., aircrafts' different phases composing the LTO-cycle: taxing-in and taxing-out, take-off, climbing (up to 3000 ft) and final approach-landing.

[6] CORINAIR does not differentiate engines but only aircraft models. Hence the amount of CO_2 and H_2O produced during cruise is based on aircraft model only, independent of the engine installed. See the EMEP/CORINAIR Emission Inventory Guidebook for more information.

After first considering each pollutant alone, we then multiply the total amount of each substance by the monetary value of its cost of damage and obtain aggregate measures of both local pollution and global pollution. Such a cost quantifies, in monetary terms, the negative health effects of a pollutant. A comprehensive survey on the different approaches and evidence on pollutants' monetary damages is provided by Dings et al. (2003), a paper that represents a benchmark for many studies on aviation emissions (e.g., Givoni and Rietveld, 2010; Martini et al., 2013a, 2013b; Scotti et al., 2014; Grampella et al., 2017). The benchmarking costs of damage of pollutants considered in this contribution are as follows: € 4/kg HC, € 9/kg NO_x, € 6/kg SO_2, and € 150/kg PM_{10}[7] for local emissions, and €4/kg NO_x, € 0.03/kg CO_2, and € 0.0083/kg H_2O for global emissions.

The treatment of noise levels is more complex than that of emissions. On the one hand, noise can be measured linearly as a modification of the sound pressure. On the other hand, noise creates annoyance at the local level—the units of measure are respectively micro Pascal (μPa) and decibels (dB).[8] Human beings can perceive variations in sound pressure produced by a noise source if the sound occurs between 20 μPa (corresponding to a *status quo* level in which no noise is perceived) and 100 Pa (corresponding to the noise produced by an aircraft at maximum thrust power of its engines). The ratio of these two extreme is greater than 1 million. Although the human ear responds to stimulus produced by noise in a nonlinear way, it does follow a logarithmic scale. We consider both dimensions, as they are useful in different interpretations. According to ICAO certification data, noise is evaluated at three points: lateral, flyover, and take-off (climbing) during the LTO operations.

The literature regarding the cost of damage caused by noise is more limited than that regarding air pollution. Some contributions (e.g. Schipper, 2004; Lu and Morrell, 2006) have presented estimates based on specific case studies; however, these measures are airport-specific and cannot be easily generalized.[9] As a result, we choose to analyze separately the impact of innovation on noise from that on emissions. As previously mentioned, we would also like to determine if any trade-off exists between noise and air pollution.

Employing the ICAO certification system, we obtain emissions and noise for each aircraft-engine combination, as shown in Fig. 1, which also provides an overview of the externalities investigated in the analysis.

3.2. The econometric model

Our aim is to estimate the effect of technical progress on the amount of local air pollution, greenhouse gas (GHG) emissions, and noise produced by aviation. Moreover, we are also interested in untangling the effect of technical progress between per-flight externalities and per-passenger externalities. The former considers the amount of externalities generated by a single flight, while the latter considers the costs and benefits of individual mobility, as shown by Swan (2010). Hence, we have two measurement units of externalities as a dependent variable: (i) per-flight and (ii) per-seat.[10]

In the analysis of noise externalities, we consider the magnitude and the sign of technical progress in terms of the sound pressure variation, as well as the noise-level variation as perceived by human ears (see Brüel and Kjær, 2000; Passchier-Vermeer and Passchier, 2000). The former is linear, and thus the estimated coefficient describes the impact of technology progress on noise levels under the same (linear) unit, while the latter is logarithmic and hence the estimated coefficient displays the impact on decibels. Thus, an annual reduction of 1 dB obtained through technical progress would not imply a unit decrease in noise annoyance.[11]

Echoing to Chèze et al. (2011a, 2011b), we study both incremental and substantial innovation. Incremental technical progress is given by the annual variation in the aircraft/engine combinations' age, embedding general technical progress in aviation technology. Substantial innovation is given by the introduction of a new aircraft model.

As we are interested in estimating the annual percentage variation in aviation externalities in the presence of a unit increase in the incremental innovation index and the introduction of a new aircraft model, we estimate a log-linear model. The basic econometric model is therefore given by the following equation:

$$\log EXTER_i = \alpha + \beta_1 \times INCREM_i + \beta_2 \times SUBSTAN_i + \sum_{l=1}^{L} \gamma_l \times CONTR_{li} + \epsilon_i, \tag{1}$$

where $EXTER_i$ is the amount of externality produced by the aircraft/engine combination i (see Table 1 for the list of variables and corresponding measurement units), $INCREM_i$ is the index of incremental innovation in combination i, $SUBSTAN_i$ is the index of substantial innovation in i, $CONTR_{li}$ is a set of L control variables, while ϵ_i is the error term.

[7] The estimated health effects of CO produced during the LTO cycle are negligible and therefore not considered in the aggregate measure of local air pollution costs.

[8] Decibels (dB), a logarithmic scale is the universal measurement of perceived noise annoyance.

[9] An exception is Grampella et al. (2017), in which Schipper's (2004) two measures of monetary damages related to noise annoyance are adopted to quantify the social cost of the noise generated by aircraft during the LTO cycle.

[10] We consider the seats available on a typical aircraft/engine configuration. This means that we do not consider passenger load factors, which depend upon airlines' strategies (e.g., airfares, promotions, etc.). Hence, we do not focus on actual emissions in operating conditions (that will be a function of load factors, which in turn, influences thrust power), but on emissions in certified conditions, which are homogenous for all combinations (in terms of thrust power) and therefore feasible in comparing different models.

[11] For instance, two noise sources of 50 dB that reaches the same person give rise to a noise annoyance equal to 53 dB—that is, a 3-dB increase represents a double level of noise annoyance.

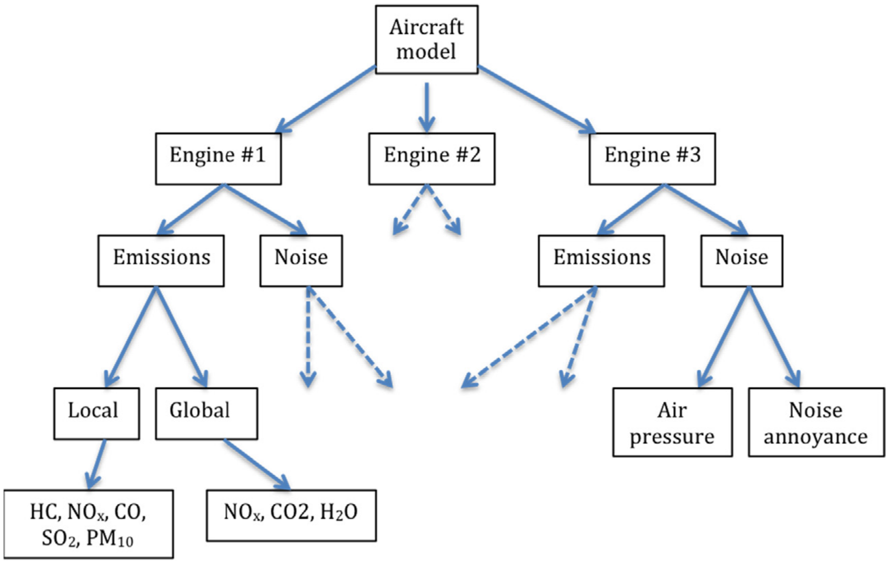

Fig. 1. Overview of aviation externalities.

Table 1
Dependent variables for the different specifications of Eq. (1).

Externality dependent variable	Description
HC	HC/grams generated by combination *i* during LTO-cycle
CO	CO/grams generated by combination *i* during LTO-cycle
NO_x	NO_x/grams generated by combination *i* during LTO-cycle
SO_2	SO_2/grams generated by combination *i* during LTO-cycle
PM_{10}	PM_{10}/grams generated by combination *i* during LTO-cycle
LAP	Total cost of local air pollution (LAP) generated by combination *i* during LTO-cycle in Euro (sum of HC + CO + NO_x + SO_2 + PM_{10})
CC125	Total cost of climate change pollution (CC) generated by combination *i* during cruise with stage length = 125 nm in Euro
CC250	Total cost of climate change pollution (CC) generated by combination *i* during cruise with stage length = 250 nm in Euro
CC500	Total cost of climate change pollution (CC) generated by combination *i* during cruise with stage length = 500 nm in Euro
CC750	Total cost of climate change pollution (CC) generated by combination *i* during cruise with stage length = 750 nm in Euro
CC1000	Total cost of climate change pollution (CC) generated by combination *i* during cruise with stage length = 1000 nm in Euro
CC1500	Total cost of climate change pollution (CC) generated by combination *i* during cruise with stage length = 1500 nm in Euro
CC2000	Total cost of climate change pollution (CC) generated by combination *i* during cruise with stage length = 2000 nm in Euro
NOISE_PRES	Variation of sound pressure generated by combination *i* during LTO-cycle in μPa (micro pascal)
NOISE_DB	Variation of noise annoyance generated by combination *i* during LTO-cycle in dB (decibel)

The index representing incremental innovation is based on the first operating year of aircraft/engine combination *i*. There is an issuing date on each ICAO certification, which has to be granted to every combination. Indeed, when a specific aircraft model has a new engine installed, it has to obtain a new ICAO certificate before flying. $YEAR_i$ indicates the age of the combination *i*, computed as the difference between 2014, and the abovementioned date. Hence $YEAR_i$ is our proxy for incremental technical progress—i.e., $INCREM_i = YEAR_i$. The birthday or vintage year of aircraft/engine combination *i* is obtained through the following multi-step procedure. First, various dates are collected: “Introduction year” (the first order by an airline company), “Maiden flight,” (the first flight of the aircraft—one of the last tests before certification) and “Entrance in service” (the first delivery of that aircraft) dates are taken from the ordering history and delivery files on aircraft manufacturers’ websites.[12] Second, Type Certificate application date (the date from which the regulations to be applied is frozen for a given amount of time to avoid the obligation to amend the design due to future introduction of new regulation) and issuance date (the date from which the aircraft can fly or the engine can be used) are collected both for aircraft and engines from the official documentation (the so-called “Type Certificate Data Sheets”) of the regulatory bodies—the Federal Aviation Administration (FAA) for the U.S. and the European Aviation Safety Agency (EASA) for Europe. Third, in order to determine the year from which a specific aircraft with a specific engine has entered into service ($YEAR_i$), we use the earlier between the two years between FAA and EASA certification dates. These dates represent, for both agencies, the older year between the issuance year of the engine and the issuance year of the aircraft model. Such a procedure appears reasonable given that (i) an aircraft cannot fly without receiving a

[12] These dates are used to check the coherence of the variable *YEAR*.

Table 2
Aircraft/engine combinations in the data set.

Aircraft model	Aircraft/engine combinations	Introductory years of different combinations
B737-200	10	1967, 1968
B737-200ADV	14	1968, 1969
B737-300	5	1984, 1986
B737-400	3	1988
B737-500	4	1990
B737-600	21	1998, 2000, 2004, 2006, 2010
B737-700	48	1997, 1998, 2000, 2003, 2006, 2010
B737-800	41	1998, 2000, 2006, 2010
B737-900	26	2001, 2006, 2010
B737-900ER	16	2007, 2010
A320	21	1989, 1990, 1993, 1995, 1996, 2006
A319	23	1996, 1999, 2006
A321	30	1993, 1994, 1996, 1997, 2001, 2006
A318	8	2003, 2005, 2006
Total	270	

certification for both the engine and model, and (ii) as soon as one of the two agencies issues the necessary certificates, the aircraft-engine combination is allowed to fly.[13] As confirmation, notice that (i) no aircraft in the data set exhibit an entry into service date antecedent to $YEAR_i$; and (ii) for each aircraft model, at least one observation has $YEAR_i$ corresponding to the first delivery date.

Substantial innovation is given by the introduction of a new aircraft model, which is represented by a dummy variable that is equal to 1 for combination i. Hence the substantial innovation variable is given by a set of $K - 1$ dummy variables (K is the total number aircraft models included in the analysis), and MOD_{ki} representing combination i—i.e., $\beta_2 \times SUBSTAN_i$ becomes $\sum_{k=1}^{K-1} \beta_{ki} \times MOD_{ki}$.

The set of control variables is given by combination i's size, expressed in maximum take-off weight, $MTOW_i$, and two dummy variables identifying two specific engine brands—i.e., CFM_i and IAE_i. The former is equal to 1 if the engine manufacturer is *CFM International*, while the latter is equal to 1 if the engine is produced by *IAE* (*International Aero Engines*). Hence, the engine manufacturer baseline case is *Pratt & Whitney*, given that B737s and A320s have installed engines designed only by CFM, IAE, or Pratt & Whitney. The resulting econometric model is as follows:

$$\log EXTER_i = \alpha + \beta_1 \times YEAR_i + \sum_{k=1}^{K-1} \beta_{ki} \times MOD_{ki} + \gamma_1 \times MTOW_i + \gamma_2 \times CFM_i + \gamma_3 \times IAE_i + \epsilon_i. \quad (2)$$

Eq. (2) is estimated by OLS. Notice that normal error distribution and constant error variance have been tested. In the majority of cases, errors are normally distributed, but with non-constant variance.[14] To avoid problems of biased standard errors, in the case of heteroskedasticity, we estimate robust regressions.[15]

Eq. (2) is estimated under different specifications given that different externalities act as the dependent variable. A list of such variables with their respective short descriptions is shown in Table 1.[16] Note that a single pollutant is identified by its chemical abbreviation (such as HC for hydrocarbon and CO for carbon monoxide), while local air pollution (LAP) represents the aggregate cost of damage produced by the joint effect of all the local pollutants generated by each aircraft/engine combination i during the LTO cycle. An added "s" as a final letter (see Section 5) indicates the per-seat amount (e.g., HCs and LAPs indicate respectively the per-seat amount of HC and LAP).[17]

4. Data

We build a data set that includes the most common aircraft models currently operating in short/medium-haul flights in the worldwide aviation network: the B737 and A320 families. Therefore, we consider ten B737 models (from the B737-200, with 1967 as the vintage year, to the B737-900ER, with 2007 as first operating year) and four A320 models (from the A320, with the 1989 as vintage year, to the A318, with 2003 as introductory year). Table 2 displays all combinations for the two

[13] In the few cases in which the two engines are different, the "younger" between them was considered.

[14] Normality has been tested through the Shapiro-Wilk W test (and also graphically), while homoscedasticity through (i) the White's test and (ii) the Breush-Pagan test.

[15] Notice that non-normality does not produce bias in the coefficient estimates, but problems related to standard errors. This is the reason we adopt robust standard errors, which do not change OLS coefficient estimates, but do provide more accurate p-values.

[16] Data for emissions and noise are taken from several databases: the EASA, the ICAO Emission Databank, and the FAA. The methodology is described in Grampella et al. (2017). The noise levels are taken from certification data and are expressed in dB. The conversion into air pressure metrics—i.e., in micro Pascal units—is implemented through the following formula: $\mu\text{Pa} = 20 \times 10^{\frac{\text{dB}}{20}}$, obtained by inverting the formula $\text{dB} = 10 \times log_{10}\left(\frac{x}{20\times\mu\text{Pa}}\right)$ where $20 \times \mu\text{Pa}$ is the static air pressure corresponding to no perception of noise.

[17] Per-seat emissions and noise levels are computed by dividing the amount of externality a combination produces (during LTO and cruise for emissions, and only during LTO for noise) by the number of seats according to a typical configuration of the aircraft model in combination i.

Table 3
Descriptive statistics of pollutant emissions and noise.

Variable	Obs	Mean	Std. Dev.	Min	Max	Unit
Local emissions during LTO-cycle						
HC_i	270	1,091.6	820.9	2	5,426	Grams
CO_i	270	10,884.7	3,457.8	3,312	22,468	Grams
NO_{xi}	270	9,373.3	2,384.0	5,458	17,292	Grams
SO_{2i}	270	670.9	65.1	532.8	827.2	Grams
PM_{10i}	270	167.7	16.3	133.2	206.8	Grams
Total costs of local emissions – LAP						
$LAPCOST_i$	270	117.9	22.8	77.5	191.9	Euro
Climate costs emissions						
$CC125_i$	270	247.13	20.4	206.6	311.1	Euro
$CC250_i$	270	356.6	30.3	304.8	446.3	Euro
$CC500_i$	270	552.7	61.1	441.1	689.8	Euro
$CC750_i$	270	737.8	41.3	649.8	812.1	Euro
$CC1000_i$	270	979.9	108.5	787.6	1,202.0	Euro
$CC1500_i$	270	1,407.0	156.1	1,134.2	1,714.2	Euro
$CC2000_i$	270	1,834.2	203.9	1,480.8	2,226.3	Euro
Noise levels during LTO-cycle						
$NOISE\_DB_i$	270	93.6	1.2	90.5	96.2	dB
$NOISE\_PRES_i$	270	961,165.7	128,324.5	671,098.4	1,292,313	μPa

families, which consists of 270 models out of 1460 in the current operating commercial fleet (i.e., about 20% of all aircraft/engine combinations flying today). However, the B737 and A320 families represent a much higher percentage of operating flights since the vast majority of airlines largely operate these aircraft models, especially low cost carriers (LCCs) (e.g., Ryanair only operates B737s and EasyJet A320s).[18]

Table 3 presents descriptive statistics of the emissions and noise regarding the 270 different combinations in the data set. The average amount of HC emitted during the LTO cycle is equal to 1092 g, while that of CO is much higher, equal to 10,885 g. The average amount of NO_x, SO_2, and PM_{10} are 9373 g, 671 g, and 168 g, respectively. The average total cost of local pollutants during LTO is about €118, with a minimum of €78 and a maximum of €207192. The average climate costs range from €247 for a cruise with a stage length of 125 nm to €1834 for a long-stage length equal to 2000 nm. Regarding noise, the average level of noise annoyance during the LTO cycle is 93.6 decibels, while the average sound pressure variation is 96,1166 μPa.

Concerning the distribution of the externality variables, PM_{10} and HC seem to be more concentrated, while HC, CO, and NO_x seem to resemble a normal distribution. Although the noise data also exhibit a certain degree of concentration (around 94 decibels), they are more dispersed.

Regarding incremental innovations, about 8% of the combinations are older than 40 years, while most of them are younger than 20 years; 30% of the combinations are 6 years old, and about 17% are younger than 4 years. Lastly, Table 4 presents the descriptive statistics of the control variables. The average maximum take-off weight is about 70,000 tonnes, while 87% of all combinations have CFM engines, and 3% have IAE engines.

5. Results

In this section we present the results of our econometric model. We divide the analysis into (i) local pollution, (ii) climate change, and (iii) noise, presenting first the evidence at the flight level and then at the per-seat level.

5.1. Results of the analysis at the flight level

5.1.1. Local air pollutants

Table 5 shows the OLS estimates of local emissions generated during the LTO cycle. Estimates of the amount of SO_2 are omitted since they are equal to those of PM_{10}. In fact, both substances are directly related to fuel consumption and are therefore perfectly correlated. In addition, both SO_2 and PM_{10} are incorporated into the LAP index weighted for their respective costs of damage.

The estimated coefficient of incremental innovation (*YEAR*) is positive and statistically significant for all pollutants (with the exception of CO) and for local total emissions (LAP). Hence, the older the aircraft/engine combination, the higher the amount of pollutants emitted will be, and thus, the higher the cost of aggregate total pollution. Since Eq. (2) is log-linear,[19] a one-year older combination will have the following effect on the amount of emissions: +3.5% of HC (col. LTO_HC),

[18] Due to space constraints, the list of all 270 aircraft/engine combinations (with the corresponding introductory year) is not reported in the paper, but it is available upon request.

[19] The expected percentage change in the dependent variable due to a one-unit change in the independent variable (continuous or dummy variable) is given by $100 * [\exp(b) - 1]$, where b is the coefficient of the variable.

Table 4
Descriptive statistics of control variables.

Variable	Obs	Mean	Std. Dev.	Min	Max	Unit
$MTOW_i$	270	70,438.6	9,349.8	48711.1	89,000	tonnes
CFM_i	270	87%				
IAE_i	270	3%				

Table 5
Incremental and substantial innovations in local emissions, OLS econometric estimates.

	LTO_HC	LTO_CO	LTO_NOx	LTO_PM10	LTO_LAP	LTO (RC)
YEARi	0.034***	−0.005	0.011***	0.004***	0.010***	0.009 ***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B200ADVi	0.126	−0.001	−0.010	−0.011	−0.000	–
	(0.27)	(0.17)	(0.06)	(0.03)	(0.05)	
B300i	−6.586***	0.281	0.182	0.059	0.074	–
	(0.28)	(0.16)	(0.15)	(0.04)	(0.11)	
B400i	−6.454***	0.287	0.166	0.049	0.066	–
	(0.29)	(0.17)	(0.16)	(0.05)	(0.12)	
B500i	−6.506***	0.206	0.346**	0.125**	0.209*	–
	(0.30)	(0.17)	(0.16)	(0.05)	(0.12)	
B600i	−5.348***	0.235	0.143	−0.031	0.086	–
	(0.36)	(0.21)	(0.15)	(0.05)	(0.11)	
B700i	−5.502***	0.246	0.246	0.024	0.169	–
	(0.37)	(0.21)	(0.15)	(0.05)	(0.11)	
B800i	−5.468***	0.308	0.168	−0.008	0.108	–
	(0.39)	(0.22)	(0.16)	(0.05)	(0.12)	
B900i	−5.704***	0.207	0.197	−0.008	0.119	–
	(0.38)	(0.22)	(0.17)	(0.05)	(0.13)	
B900ERi	−5.592***	0.216	0.176	−0.023	0.110	–
	(0.41)	(0.24)	(0.18)	(0.06)	(0.13)	
A318i	−5.144***	0.137	0.136	−0.072	0.077	–
	(0.34)	(0.20)	(0.14)	(0.04)	(0.10)	
A319i	−5.488***	0.054	0.100	−0.108*	0.027	–
	(0.35)	(0.20)	(0.15)	(0.05)	(0.11)	
A320i	−5.374***	0.169	0.067	−0.101*	0.011	–
	(0.38)	(0.22)	(0.16)	(0.05)	(0.12)	
A321i	−5.158***	0.297	0.234	−0.041	0.167	–
	(0.42)	(0.24)	(0.19)	(0.06)	(0.14)	
MTOWi	−0.00002	−0.00001	0.00002***	0.00001***	0.00002***	0.00002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CFMi	6.573***	0.172***	−0.080	−0.166***	−0.039	0.004
	(0.11)	(0.04)	(0.12)	(0.03)	(0.09)	(0.04)
IAEi	3.712***	−0.471***	0.112	−0.072*	0.085	0.090
	(0.15)	(0.09)	(0.13)	(0.03)	(0.10)	(0.05)
Constant	6.831***	9.744***	7.208***	4.506***	3.265***	3.273***
	(0.91)	(0.54)	(0.31)	(0.11)	(0.23)	(0.09)
R^2	0.763	0.352	0.661	0.711	0.673	

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

+1.1% of NO_x (col. LTO_NOx), +0.4% of PM_{10} (col. LTO_PM10); and will have +1% (col. LTP_LAP) in the total cost of local pollution (LAP). In short, we provide evidence that incremental innovation cuts the aviation emissions of local pollutants—that is, the annual amount of the total cost of local emissions will decrease by 1% when a one-year younger technology is employed.

Table 5 also shows the estimated coefficients of the substantial innovations—i.e., the aircraft model dummies. All of the aircraft model dummies make a reference to the B737-200 model—namely the oldest model in the data set, with 1967 as its vintage year. Some substantial innovations exhibit a statistically significant impact on local air pollution. Regarding the PM_{10} emission, the introduction of the A319 has reduced the amount by 10.2%, while the launch of the A320 has decreased it by 9.6% (compared with the amount of PM_{10} generated by the B737-200 combinations). Moreover, we prove that all new models (with the exception of the B737-200ADV) have generated a relevant reduction in the amount of HC emissions during the LTO cycle. Indeed, the average amount of HC produced by the B737-200 combinations is 1,862.4 kg (with a maximum value of 5,426 kg), while, for instance, the amount produced by the A321 is 1,098.5 kg (maximum 1,782 kg) and the one produced by the B737-900 is 623.1 kg (maximum 864 kg).

However, the introduction of new aircraft has also brought some negative impact. The B737-500 produces 41.3% more NO_x and 13.2% more PM_{10} (and SO_2, given the correlation between PM_{10} and SO_2). Note that the B737-500 is the only model

Table 6
Incremental and substantial innovations in climate change emissions, OLS econometric estimates.

	CC125	CC250	CC500	CC750	CC1000	CC1500	CC2000
YEARi	0.003***	0.002***	0.001**	0.001**	0.001*	0.001*	0.0005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B200ADVi	−0.004	−0.003	−0.001	−0.001	0.000	0.000	0.001
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
B300i	0.012	0.009	−0.038*	0.086***	−0.055***	−0.062***	−0.066***
	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
B400i	0.006	0.004	0.027	0.083***	0.020	0.017	0.015
	(0.04)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
B500i	0.060	0.042	−0.058**	0.103***	−0.091***	−0.104***	−0.111***
	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
B600i	−0.004	0.007	−0.108***	0.106***	−0.125***	−0.132***	−0.136***
	(0.04)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
B700i	0.037	0.042	−0.076***	0.130***	−0.099***	−0.108***	−0.113***
	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
B800i	0.019	0.032	0.033	0.130***	0.031	0.030*	0.029*
	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
B900i	0.023	0.035	0.076**	0.131***	0.078***	0.078***	0.079***
	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
B900ERi	0.015	0.029	0.070**	0.127***	0.074***	0.075***	0.075***
	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
A318i	0.006	0.087***	−0.167***	0.026	−0.188***	−0.196***	−0.201***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
A319i	−0.004	0.085**	−0.100***	0.036*	−0.108***	−0.111***	−0.113***
	(0.04)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
A320i	0.007	0.100***	−0.020	0.057**	−0.018	−0.017	−0.016
	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
A321i	0.068	0.146***	0.127***	0.093***	0.135***	0.139***	0.141***
	(0.05)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
MTOWi	0.000008***	0.000006***	0.000004***	0.000003***	0.000003***	0.000002***	0.000002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CFMi	−0.068**	−0.044**	−0.034**	−0.023**	−0.019**	−0.014**	−0.010**
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
IAEi	−0.004	−0.001	−0.004	0.001	−0.002	−0.001	−0.000
	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	4.961***	5.431***	6.035***	6.274***	6.699***	7.097***	7.381***
	(0.09)	(0.07)	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)
R^2	0.749	0.859	0.954	0.877	0.973	0.979	0.981

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

exhibiting the wrong direction, but has a statistically significant effect on the total cost of local pollution, which is increased by 23.2% in comparison with the older B737-200. In general, no statistical significant evidence exists that substantial innovations have, *ceteris paribus*, had an impact on the total cost of local emissions.

Regarding the control variables, aircraft size (*MTOW*) has a small but statistically significant effect on the emission of NO_x, PM_{10} (and SO_2), and total local emission costs. A larger aircraft size (i.e., an increase of 1 tonne in MTOW) induces a +0.002% increase in the amount of NO_x, a +0.001% increase in that of PM_{10} (and of SO_2), and a +0.002% in the total LAP cost. If the engine is provided by the manufacturers CFM and IAE, we obtain estimates of 15.3% and 6.9% lower levels of PM_{10} respectively, but higher HC levels, which leads to a non-significant aggregate effect at the LAP cost level. The goodness of fit (R^2) is rather high in all regressions.

The last column of Table 5 is included as a robustness check (RC) for the effect of incremental innovation. Both the significance and the sign of YEAR are also confirmed when the dummies representing substantial innovations are excluded from the model.[20]

To conclude, although the empirical analysis on local emissions provides robust evidence that an incremental innovation effect exists, which is quantified in a −1% annual reduction, there is no evidence of a substantial innovation effect at the flight level.

5.1.2. Global pollutants

Table 6 shows the estimates for climate change emissions. Again we find evidence of a positive effect of incremental innovation (*YEAR*), regardless if such an effect tends to lose both significance and relevance as the cruise length increases and

[20] We thank one of the referees for this suggestion. The same result is found for almost all the regressions with one of the single pollutants as a dependent variable. The only exception is represented by LTO_CO where the sign is confirmed, but YEAR becomes significant.

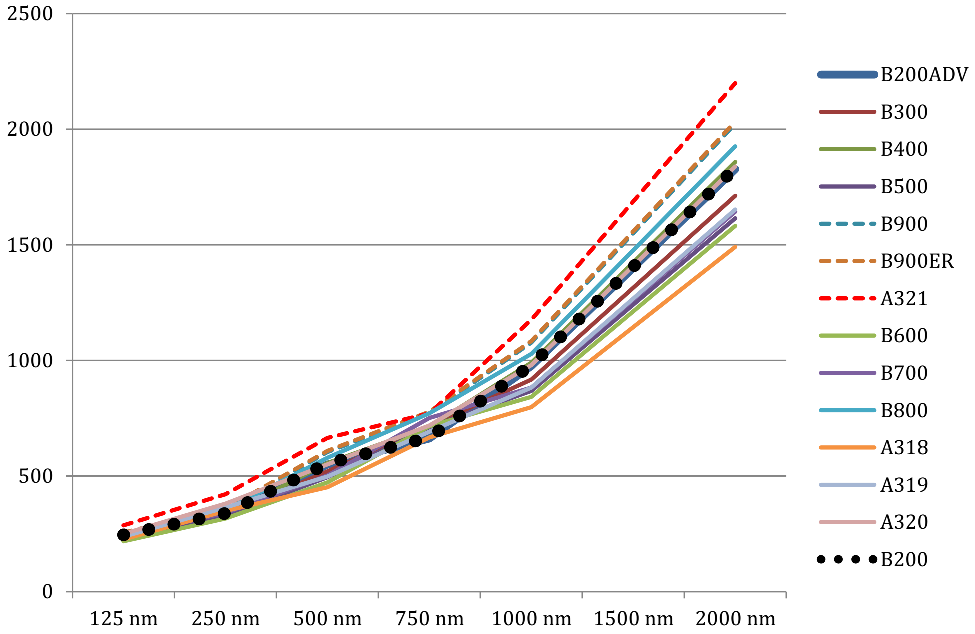

Fig. 2. Average climate change costs by aircraft model at different stage lengths.

becomes statistically insignificant at the longest length (2000 nm). Further, climate change cost reductions range between −0.3% for a 125-nm stage length and −0.1% for a 1500-nm stage length. This may be due to the fact that technical progress mainly affects emissions produced at the ascent—namely, the phase generating the highest amount of pollution—and reduces as the flight distance increases.

Unlike what is observed for local pollutants, substantial innovation significantly affects GHG emissions. Many models have generated a reduction in global emissions: the B737-300 from a stage length of 500 nm (−3.7%) to a stage length of 2,000 nm (−6.4%); the B737-500 has a −5.7% for 500 nm, and −8.7% for 1000 nm; −9.9% for 1,500 nm and −10.5% for 2,000 nm. Similar reductions are observed for the B737-600 and the B737-700. The A318 has a reduction of 15.4% for a 500-nm stage length, a 17.2% reduction for 1000 nm, a 17.8% reduction for 1,500 nm, and a 18.2% reduction for 2,000 nm. Similar (but lower) values are observed from the A319. However, we also find evidence of some positive signs regarding substantial innovation. That is, we notice that the positive signs seem to affect three models robustly (i.e., under different hypotheses of flight length)—namely the B900, the B900ER, and the A321—while the other few cases are mainly related to the specific flight distance of 750 nm, where the base case, i.e., the aircraft Boeing B200, exhibits a particularly good performance compared to the other models (as demonstrated in Fig. 2, which shows the average cost of climate change per aircraft model). Fig. 2 also clearly shows that the abovementioned B900, B900ER, and A321 are the models generating, on average, the highest climate change costs. This seems to suggest that, unlike the other models, controlling for size is not sufficient to eliminate such an effect—although it is important to keep in mind that part of the improvement is supposed to be captured by *YEAR* (even if the same aircraft models can obviously be with different ages in the data set).

Regarding control variables, size has an expected negative effect, ranging from +0.001 for a 125-nm stage length to a positive but negligible effect for longer stage lengths. Among the engine manufacturers, CFM distinguishes itself by a green performance as demonstrated by the effect ranging from −6.6% (125 nm) to −1% (2000 nm), despite a decreasing relevance with the stage length. Again, R^2 statistics are rather high in all regressions and the YEAR coefficient is found to be mostly robust to the exclusion of the aircraft model variables.

5.1.3. Noise

Table 7 shows the empirical evidence regarding noise. The first column represents the noise annoyance levels measured in decibels (*NOISE_DB*), and the third column represents the variation in sound pressure, measured in micro pascal (*NOISE_PRES*). Incremental innovation (*YEAR*) has an impact on both noise variables: +0.02% for noise annoyance and +0.2% for sound pressure. The magnitude for sound pressure can be taken as a benchmark since *NOISE_PRESS* is a linear variable. This means that incremental innovation generates an annual reduction of −0.2%, which is lower than the ones observed for both local emissions (−1%) and global emissions at short stage lengths (−0.3%), but higher than that registered for longer stage lengths (at most −0.1%). Hence, the improvements resulting from technical progress for noise do not seem to be higher than those observed for air pollution. This is despite the fact that noise is the aviation externality that has brought awareness more than any other environmental externality, as demonstrated by the many public complaints in towns surrounding airports. How-

Table 7
Incremental and substantial innovations in noise levels, OLS econometric estimates.

	NOISE_DB	NOISE_DB (RC)	NOISE_PRES	NOISE_PRES (RC)
YEARi	0.0002**	0.001***	0.002**	*0.007* ***
	(0.00)	(0.00)	(0.00)	(0.00)
B200ADVi	0.000	–	0.000	–
	(0.00)		(0.02)	
B300i	−0.005	–	−0.061	–
	(0.00)		(0.05)	
B400i	−0.008	–	−0.094*	–
	(0.00)		(0.05)	
B500i	−0.005	–	−0.054	–
	(0.01)		(0.06)	
B600i	−0.027***	–	−0.292***	–
	(0.00)		(0.05)	
B700i	−0.023***	–	−0.254***	–
	(0.00)		(0.05)	
B800i	−0.027***	–	−0.291***	–
	(0.00)		(0.05)	
B900i	−0.027***	–	−0.291***	–
	(0.00)		(0.05)	
B900ERi	−0.029***	–	−0.318***	–
	(0.01)		(0.06)	
A318i	−0.040***	–	−0.435***	–
	(0.00)		(0.05)	
A319i	−0.040***	–	−0.435***	–
	(0.00)		(0.05)	
A320i	−0.033***	–	−0.364***	–
	(0.00)		(0.05)	
A321i	−0.025***	–	−0.268***	–
	(0.01)		(0.06)	
MTOWi	0.000001***	0.000001*	** 0.00001***	*0.00001****
	(0.00)	(0.00)	(0.00)	(0.00)
CFMi	−0.007*	−0.017**	−0.073*	*−0.180***
	(0.00)	(0.01)	(0.04)	(0.06)
IAEi	−0.017***	−0.035***	−0.178***	*−0.380****
	(0.00)	(0.00)	(0.05)	(0.05)
Constant	4.497***	4.477***	13.317***	*13.103****
	(0.01)	(0.01)	(0.11)	(0.08)
R^2	0. 856	0.553	0. 856	0.556

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

ever, many substantial innovations significantly reduce noise: almost all of the new aircraft models generate a reduction in noise annoyance (from −0.8% of the B737-400 to almost −4% of the A318) and a high reduction in sound pressure (from −9% of the B737-400 to −35% of the A318). Hence, the effort to reduce noise in aviation seem to be concentrated on substantial innovation rather than on incremental ones.

Regarding control variables, size again exhibits a positive but very small negative effect, equal to +0.001% in the case of sound pressure (even smaller for decibels). Both engine manufacturers (CFM and IAE) perform better in terms of noise in comparison with other manufacturers in this aircraft market segment. R^2 are about 0.86 and robustness checks (columns 2 and 4 of Table 7), thus confirming the results regarding incremental innovation.

5.2. Results of the analysis at the passenger level

5.2.1. Local air pollutants

We now analyze the impact of technical progress at a per-seat level. This allows us to obtain an estimate that may be taken as a benchmark when comparing the costs and benefits of passenger mobility. Table 8 shows the results for Eq. (2) in relation to local emissions.

Incremental innovations have a positive effect on per-seat local emissions since the estimated coefficient for the variable *YEAR* is positive and statistically significant for all of the pollutants (again, with the exception of CO) and for the per-seat local air pollution cost. The magnitude of the estimated coefficient varies from an annual reduction of −3.5% for per-seat HC emissions, to −1.1% for per-seat NO_x, and −0.4% for per-seat PM_{10}. We derive an aggregate figure of −1% for the per-seat local air pollution cost. Note that coefficients are similar to those obtained for emissions at a flight level and that the effect is also found to be robust (see the last column of Table 8).

Table 8
Incremental and substantial innovations in per-seat local emissions, OLS econometric estimates.

	LTO_HCs	LTO_COs	LTO_NOxs	LTO_PM10 s	LTO_LAPs	LTO_LAPs (RC)
YEARi	0.034***	−0.005	0.011***	0.004***	0.010***	0.005***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B200ADVi	0.126	−0.001	−0.010	−0.011	−0.000	–
	(0.27)	(0.17)	(0.06)	(0.03)	(0.05)	
B300i	−6.678***	0.190	0.091	−0.032	−0.018	–
	(0.28)	(0.16)	(0.15)	(0.04)	(0.11)	
B400i	−6.778***	−0.036	−0.158	−0.275***	−0.257*	–
	(0.29)	(0.17)	(0.16)	(0.05)	(0.12)	
B500i	−6.535***	0.177	0.317*	0.096*	0.180	–
	(0.30)	(0.17)	(0.16)	(0.05)	(0.12)	
B600i	−5.439***	0.143	0.051	−0.122**	−0.005	–
	(0.36)	(0.21)	(0.15)	(0.05)	(0.11)	
B700i	−5.593***	0.155	0.155	−0.067	0.077	–
	(0.37)	(0.21)	(0.15)	(0.05)	(0.11)	
B800i	−5.798***	−0.021	−0.161	−0.338***	−0.221	–
	(0.39)	(0.22)	(0.16)	(0.05)	(0.12)	
B900i	−6.033***	−0.122	−0.132	−0.337***	−0.210	–
	(0.38)	(0.22)	(0.17)	(0.05)	(0.13)	
B900ERi	−6.073***	−0.265	−0.305	−0.504***	−0.371**	–
	(0.41)	(0.24)	(0.18)	(0.06)	(0.13)	
A318i	−5.144***	0.137	0.136	−0.072	0.077	–
	(0.34)	(0.20)	(0.14)	(0.04)	(0.10)	
A319i	−5.552***	−0.010	0.036	−0.172***	−0.037	–
	(0.35)	(0.20)	(0.15)	(0.05)	(0.11)	
A320i	−5.654***	−0.111	−0.213	−0.382***	−0.269*	–
	(0.38)	(0.22)	(0.16)	(0.05)	(0.12)	
A321i	−5.639***	−0.184	−0.247	−0.522***	−0.314*	–
	(0.42)	(0.24)	(0.19)	(0.06)	(0.14)	
MTOWi	−0.00002	−0.00001	0.00002***	0.00001***	0.00002***	0.000001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CFMi	6.573***	0.172***	−0.080	−0.166***	−0.039	−0.001
	(0.11)	(0.04)	(0.12)	(0.03)	(0.09)	(0.05)
IAEi	3.712***	−0.471***	0.112	−0.072*	0.085	0.155***
	(0.15)	(0.09)	(0.13)	(0.03)	(0.10)	(0.06)
Constant	1.918*	4.832***	2.295***	−0.406***	−1.648***	−0.483***
	(0.91)	(0.54)	(0.31)	(0.11)	(0.23)	(0.10)
R^2	0.782	0.484	0.395	0.877	0.505	0.181

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

There is evidence of a higher impact of substantial innovations on per-seat local emissions compared with that obtained for flight emissions, especially concerning PM_{10} and the total cost of LAP. The B737-400 has a −24% statistical significant impact on PM_{10} and a −23% on total cost of local emissions. B737-600 has a −11% reduction in the production of PM_{10}, the B737-800 a −29% in PM_{10}, and the B737-900 a reduction of −29% in PM_{10}. The B737-900ER has a statistically significant estimate of −40% reduction in PM_{10} and a −31% decrease in the total cost of local emissions. Regarding the A320 family, the A319 has a statistically significant estimated coefficient equal to −16% for the production of PM_{10}, the A320 a significant coefficient equal to −32% for PM_{10} and equal to −24% for total emissions, the A321 has an estimate of −41% in PM_{10}, and −27% in per-seat total cost of local emissions. Interestingly, almost all of the models (the only exception is the A320) with a significant reduction in terms of LAP cost—namely the B737-400, B737-900ER, and A321– exhibit an average seats/MTOW ratio higher than that of the B737-200, which suggests that they benefit from an increased capacity per unit of weight.

Control variables perform as in the flight case. R^2 statistics is rather high for all the regressions.

5.2.2. Global pollutants

Table 9 reports the evidence regarding per-seat global emissions that contribute to climate change. Incremental innovation (YEAR) has a positive statistically significant impact on per-seat global emissions for all stage lengths, with the exception of the longest one (2,000 nm), where it has no effect. The magnitude of the estimated coefficients is decreasing with the stage length: in the case of a flight with a stage length equal to 125 nm, incremental innovation has a −0.3% annual reduction on global emissions, while this coefficient monotonically decreases and becomes −0.06% of the annual reduction for a 1,500 stage length. The estimates are similar to those obtained at a flight level. Note that the effect is invariantly robust to the exclusion of the aircraft model dummies only for a stage length greater than 750 nm.[21]

[21] To detail, the signs and significance are simultaneously stable at 500, 1,000 and 1,500 nm. At 2,000 nm, the coefficient of YEARS (insignificant in the complete model) becomes significant, thus keeping the positive sign.

Table 9
Incremental and substantial innovations in per-seat climate change emissions, OLS econometric estimates.

	CC125s	CC250s	CC500s	CC750s	CC1000s	CC1500s	CC2000s
YEARi	0.003***	0.002***	0.001**	0.001**	0.001*	0.001*	0.0005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B200ADVi	−0.004	−0.003	−0.002	−0.001	−0.000	0.000	0.001
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
B300i	−0.079*	−0.083***	−0.129***	−0.006	−0.147***	−0.154***	−0.157***
	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
B400i	−0.318***	−0.320***	−0.296***	−0.241***	−0.305***	−0.307***	−0.309***
	(0.04)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
B500i	0.031	0.013	−0.086***	0.074***	−0.121***	−0.133***	−0.140***
	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
B600i	−0.096**	−0.085**	−0.199***	0.015	−0.217***	−0.223***	−0.228***
	(0.04)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
B700i	−0.054	−0.050	−0.167***	0.039*	−0.191***	−0.199***	−0.204***
	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
B800i	−0.310***	−0.297***	−0.296***	−0.199***	−0.299***	−0.299***	−0.300***
	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
B900i	−0.306***	−0.294***	−0.253***	−0.198***	−0.252***	−0.250***	−0.251***
	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
B900ERi	−0.466***	−0.452***	−0.411***	−0.354***	−0.408***	−0.405***	−0.406***
	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
A318i	0.006	0.087***	−0.167***	0.026	−0.189***	−0.196***	−0.201***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
A319i	−0.068	0.021	−0.164***	−0.028	−0.173***	−0.175***	−0.177***
	(0.04)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
A320i	−0.273***	−0.180***	−0.300***	−0.223***	−0.299***	−0.297***	−0.297***
	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
A321i	−0.413***	−0.335***	−0.355***	−0.388***	−0.347***	−0.342***	−0.341***
	(0.05)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
MTOWi	0.00001***	0.00001***	0.000004***	0.000003***	0.000003***	0.000002***	0.000002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CFMi	−0.068**	−0.044**	−0.036**	−0.023**	−0.019**	−0.013**	−0.010**
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
IAEi	−0.004	−0.001	−0.005	0.001	−0.001	−0.001	−0.000
	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.048	0.518***	1.121***	1.361***	1.786***	2.185***	2.468***
	(0.09)	(0.07)	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)
R^2	0.901	0.945	0.938	0.977	0.961	0.968	0.971

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

The higher impact at a per-seat level of substantial innovation is also confirmed for global emissions. All model dummy variables are statistically significant and negative, with the only exception of the B737-200ADV, which is found to be insignificant.[22] The mean (computed on the different stage-length estimates) coefficient for the different models is equal to −10% for the B737-300, −26% for the B737-400, −5% for the B737-500, −14% for the B737-600, −9% for the B737-700, −25% for the B737-800, −23% for the B737-900, and −34% for the B737-990ER. Regarding the A320 family, the mean estimated coefficients are −8% for the A318, −10% for the A319, −23% for the A320, and −30% for the A321. In general, the younger aircraft models have a higher impact, as expected. Control variables confirm the effects found at the flight level. Interestingly, the estimated coefficient of *MTOW* is positive and statistically significant, which suggests that larger aircraft tend to have higher per-seat total cost of total local emissions, and confirms Swan's (2010) findings. The R^2 is always higher than 0.9.

5.2.3. Noise

Table 10 shows the per-seat estimates regarding the impact of technical progress on noise. Incremental innovation affects both noise annoyance and sound pressure positively and significantly: according to our estimates, the annual reduction is −0.24% in terms of sound pressure and −0.02% in terms of decibels. There is also robust evidence of a strong impact of substantial innovations (since all model dummies have negative estimated coefficients) and high magnitude with the exception of the B737-200ADV (we remind readers that the B737-200 is the reference case model).

The estimated impact is higher for noise effect measured in per-seat sound pressure than for noise annoyance measured in decibels: the former has a mean coefficient (computed as the average of all models' statistically significant coefficients, as shown in the third column of Table 10) equal to −41.7%, while the latter has a mean coefficient equal to −20%. Hence the

[22] Some models have statistically significant estimated coefficients for some stage lengths: for instance, the B737-500 has a +8% increase for 750-nm stage length, the B737-700 a +4% increase for the same stage length, and the A318 a +9% increase for 250-nm stage length.

Table 10
Incremental and substantial innovations in per-seat noise levels, OLS econometric estimates.

	NOISE_PRESs	NOISE_PRESs (RC)	NOISE_DBs	NOISE_DBs (RC)
YEAR	0.002**	0.003*	0.000**	−0.003***
	(0.00)	(0.00)	(0.00)	*(0.00)*
B200ADV	0.000	–	0.000	–
	(0.02)		(0.00)	
B300	−0.153**	–	−0.097***	–
	(0.05)		(0.00)	
B400	−0.418***	–	−0.332***	–
	(0.05)		(0.00)	
B500	−0.083	–	−0.034***	–
	(0.06)		(0.01)	
B600	−0.383***	–	−0.118***	–
	(0.05)		(0.00)	
B700	−0.345***	–	−0.114***	–
	(0.05)		(0.00)	
B800	−0.620***	–	−0.356***	–
	(0.05)		(0.00)	
B900	−0.620***	–	−0.356***	–
	(0.05)		(0.00)	
B900ER	−0.799***	–	−0.510***	–
	(0.06)		(0.01)	
A318	−0.435***	–	−0.040***	–
	(0.05)		(0.00)	
A319	−0.499***	–	−0.104***	–
	(0.05)		(0.00)	
A320	−0.644***	–	−0.314***	–
	(0.05)		(0.00)	
A321	−0.749***	–	−0.505***	–
	(0.06)		(0.01)	
MTOW	0.00001***	−0.00001***	0.000001***	−0.00002***
	(0.00)	(0.00)	(0.00)	*(0.00)*
CFM	−0.073*	−0.185***	−0.007*	−0.022
	(0.04)	(0.05)	(0.00)	*(0.02)*
IAE	−0.178***	−0.314***	−0.017***	0.030
	(0.05)	(0.05)	(0.00)	*(0.03)*
Constant	8.404***	9.348***	−0.416***	0.721***
	(0.11)	(0.08)	(0.01)	(0.05)
R^2	0.922	0.713	0.999	0.822

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

average impact of a substantial innovation in the aviation industry is a reduction of about −42% in terms of per-seat sound pressure, almost double than that observed in terms of decibels. These figures show that, in terms of noise, technical progress has a stronger impact at a per-seat level rather than at a flight level, and the control variables behave the same as in the flight case. Again the MTOW has a positive and statistically significant coefficient, with the R^2 being close to 1. Interestingly, while the effect of YEAR is robust when the noise pressure is investigated (column 2 of Table 10), such robustness is not found for the noise measured in decibels (column 4 of Table 10).

5.3. Discussion

The flight and per-seat analyses have similarities and important differences. Similarities are observed mainly in incremental innovations and for all of the externalities dimensions considered in this contribution. The annual impact of incremental technical progress, which is −1% both for flight and per-seat local emission, is lower (between −0.3% and −0.1%) and decreases with the stage length for global emissions if we consider a flight or a per-seat perspective. It is also equal to −0.24% in the case of sound pressure generated by aircraft noise, and measured at −0.02% for decibels.

Relevant differences are observed for the substantial innovation case. The flight analysis has very few substantial effects for local emissions and concentrates on PM_{10}; more statistically significant positive impacts are observed for global emissions, but there are also a number of negative effects (i.e., regressive innovations). Instead, a widespread significant positive effect registers for noise reductions, which is equal on average, with all of the B737 and A320 models to a −2.8% reduction in decibels for the introduction of a new model and a −26% reduction in sound pressure. We find that the per-seat analysis presents a relevant effect of substantial innovation in terms of local emissions, as well as global emissions, and thus a much higher impact in terms of noise levels. Hence substantial innovations, namely the introduction of a new aircraft model, seem to be more effective in terms of passenger mobility rather than on a single flight. Such a result may be influenced by a general shift toward aircraft with a greater capacity. Note that in most of the cases, a new aircraft model is characterized by (1) a reduced environmental impact (e.g., due to increased fuel efficiency), and (2) an increased capacity in terms of available seats. Despite the correlation between capacity (seats) and size (MTOW), aircraft with the same MTOW provide different capacities. In other words, the per-seat pollution incorporates the ability to transport a higher number of passengers with a less-than-proportional increase in the weight (with respect to the previous technology). Our result suggests that this "efficiency" is often related to the introduction of a new aircraft model.

Last, we obtain very sparse evidence on the existence of a trade-off between emissions and noise. We find contrasting effects on global emissions and noise levels only for some substantial innovations: the B737-400, the B737-800, the B737-900, the B737-900ER and the A321 have all had a bad impact on global emissions in many stage lengths considered here, although they show a robust reduction in noise levels. However, excluding these cases (and only for some stage lengths), we do not observe a conflicting effect of both incremental and substantial technical progress between emissions and noise, which is a different finding than that of Phleps and Hornung (2013).

6. Conclusions

This paper investigates a data set composed of 270 different aircraft/engine combinations belonging to the B737 and A320 families, with a twofold goal: (1) to provide econometric evidence of the impact of both incremental and substantial technical progress on aviation externalities (i.e., both local and global emissions) and noise; and (2) to analyze whether innovation impacts in different ways flight externalities (i.e., the amount of pollution and noise generated by a flight operated by a specific aircraft/engine combination) and per-passenger externalities.

Incremental technical progress is embedded in the age of an aircraft/engine combination, while substantial innovation refers to the introduction of a new aircraft model (i.e., a new version of a B737; we consider 10 successive versions starting from year 1967 to year 2010. Regarding the A320, we consider 4 successive versions from year 1996 to 2006).

Our results show a general statistically significant impact of incremental technical progress. A one-year younger aircraft/engine combination leads to (i) −1% in terms of local pollution, (ii) a reduction ranging from −0.3% to −0.1% in terms of global pollution (that diminishes as stage length increases), and (iii) −0.24% and −0.022%, respectively, in sound pressure and decibels. Per-flight and per-passenger estimates are similar.

We also present some econometric evidence that although substantial innovation has a limited impact on local and global flight emissions, it has a significant positive impact on noise level, with an average reduction of −26% of noise when a new model is introduced. On the contrary, we find a widespread positive effect of substantial innovations on per-passenger externalities: many new models reduce local emissions (with an average estimated reduction equal to −24% on local totals), almost all new models reduce global emissions (an average effect of about −20% for all investigated stage lengths), while there is a strong significant effect of substantial innovations in terms of sound pressure reduction (the average effect is −42%, a smaller effect equal to −20% in terms of noise annoyance measured in decibels). Hence, the stronger effects of innovations are observed by looking at passenger mobility, while lower and less widespread effects are observed from the amount of externalities generated by a flight. Such a result may be due to the combined effect of technology improvement and increasing aircraft size/capacity over time. Indeed, a new model tends to have, on average, a greater size that may soften the possible effect of technological progress on the flight level.

When the per-seat impact is investigated, negative externalities are not only computed at the passenger level, but they also incorporate possible gains in terms of seat/weight (capacity/size) ratio. This seems to make the effect of substantial innovation emerge more clearly. In this sense, it is noteworthy that the per-passenger environmental impact can be reduced even when the per-flight impact is increased.

The above estimates are different from those found by previous contributions based on computational algorithms and ad hoc development scenarios. For instance, Macintosh and Wallace (2009) report a 1.9% per year improvement due to technical progress regarding only CO_2. Chèze et al. (2011a) present a −3% annual reduction in tonnes of jet fuel by available tonne kilometers. Although our estimate is moderate, it is based purely on data and econometric evidence, which is different from previous contributions that have focused on algorithms and simulations.

Our results underline the following policy implications. First, if we take into account the forecasts of an annual +4.5% increase in passenger traffic up to the year 2025, as well as a +6.1% increase in cargo traffic (Khandelwal et al., 2013), it is evident that a −1% yearly rate of reduction in emissions is not enough to outweigh the projected increased emissions and corresponding damage to the environment. For instance, Chèze et al. (2013) show that a 4.7% annual increase in aviation traffic yields a +1.9% per-year increase in CO_2 emissions. When we take this value as reference, a +4.5% annual passenger increase gives rise to a +1.8% increase in emissions that is not compensated by the −1% reduction in local emission due to incremental technical progress. Hence, it is essential to introduce policies that may encourage innovation in the aviation sector, so that technological progress happens at a faster pace compared to the current pace. A twice-faster pace of technical progress would be enough to suppress the emissions of today's trends. This confirms the argument by Chèze et al. (2013) that current innovation process in aviation does not guarantee future better performances in terms of emissions.

Second, our estimates may be adopted as benchmarks in aviation charges related to both emission and noise. For instance, emission surcharges may refer to a −1% reduction in local emissions, and, as such, tariffs may be created with penalties if airlines do not meet such benchmarks. Similarly, the benchmark for a noise surcharge would be a −0.2% annual reduction.

In the case of the more common decibels metric, the benchmark might be a −0.02% annual reduction. Regarding climate change, emission trading schemes such as the one adopted in the EU may include a dynamic incentive: a −0.1% reduction in global emissions.

This work may be scaled up by an analysis of the entire current commercial fleet, other types of substantial innovations (e.g., the introduction of successive ICAO Annex Chapters), or nonlinear incremental technical progress. Moreover, it may be interesting to develop a monetary value of noise damage cost that aggregates noise and emission externalities into a single index, and thus to study the aggregate impact of technical progress on the total social cost of aviation. These extensions are left for future research.

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The determinants of CO_2 emissions of air transport passenger traffic: An analysis of Lombardy (Italy)

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ABSTRACT

We study the determinants of aviation CO_2 emissions by designing an econometric model applied to a panel data set covering all flights departing from Lombardy, Italy over the 1997–2011 period. We consider two dimensions of CO_2 emissions: total and per available seat kilometer. The latter is a measure of emission efficiency. We focus on different categories of determinants: technical progress; aircraft and network carrier management; policy/business decisions that may not be oriented to limiting CO_2, but may indirectly affect it by offsetting projected outcomes of policies adopted to reduce emissions (e.g., the EU Emission Trading Scheme (ETS) or the ICAO Carbon Offsetting and Reduction Scheme for International Aviation); and others. We find that although aircraft size increases total emissions, it reduces emissions per available seat kilometers (ASK), while the route distance increases total emissions and decreases emissions per ASK, implying that CO_2 is less of a problem for long-haul connections. Technical progress decreases CO_2 emissions per ASK with an estimated elasticity equal to −0.06%. Last, liberalization in the EU market has generated the development of low-cost carriers, which in turn have lowered CO_2 emission per ASK, that is, liberalization in Europe has brought the collateral effect of reducing the CO_2 externality per passenger.

1. Introduction

With an average growth of 5% annually (Vespermann and Wald, 2011), global aviation activities play a key role not only in industry performance and economic development, but also in climate change. Among other pollutants (i.e., NO_x, SO_x, H_2O, soot, PM_{10}, contrails and cirrus), the amount of carbon dioxide (CO_2) produced by commercial aviation is substantial. In 2005, CO_2 was estimated to be 1.6% of total anthropogenic radiative forcing (Lee et al., 2009).

According to the Air Transportation Action Group (ATAG)[1] the global aviation industry, counting over 3 billion air passengers, produced 705 million tons of CO_2 in 2013, accounting for 2% of the human-induced CO_2 emissions and 13% of total transportation-related emissions. According to the 2016 European Aviation Environmental Report by European Aviation Safety Agency (EASA), there were 80% more European flights in 2014 compared with the number of flights in 1990. This environmental impact has increased regardless of possible technology improvements: in 2014, there was +5% more aviation-induced CO_2 with respect to the level in 2005, and +44–53% more CO_2 is estimated in 2035.

Politicians and regulators have agreed to limit CO_2 emissions in response to public pressure on the issue of climate change. For instance, the 2015 Paris agreement established a temperature increase limit to 1.5 °C above pre-industrial levels.[2] In 1997, the Kyoto Protocol was signed, and the International Civil Aviation Organization (ICAO) was assigned to lead the establishment of global aviation CO_2 regulation. Reaction to this regulation varied among countries. New Zealand and Australia initiated domestic aviation emission trading in 2010 and 2012 respectively, while the EU introduced the Aviation Directive in 2012 on both intra-EU and extra-EU flights as an extension of its already implemented Emission Trading Scheme (ETS) in other sectors in 2005. Extra-EU flights were then waived after legal action had been brought against the directive by some airlines and the International Air Transport Association (IATA)—the so-called “stop the clock” decision that should have stayed enforced until 2016. However, to the best of our knowledge, the directive is still in force today.

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[1] ATAG is an independent coalition of organizations and companies of the aviation industry, formed in 1990.
[2] Paris Agreement, an agreement within the United Nations Framework Convention on Climate Change, is adopted by consensus on 12 December 2015.

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After several meetings, during its 39th assembly, the ICAO approved a global market-based measurement (GMBM) scheme, the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA). This type of scheme will be enforced through different phases starting in 2020 (see Scheelhaase et al., 2018, for a detailed discussion). CORSIA, which is different from the EU-ETS, will be applied to all flights, not only flights in the European Economic Area.

Despite the ongoing, time-consuming negotiation process to limit CO_2 aviation emissions and reaching a path of environmentally sustainable growth, little is still known about factors that affect the amount of CO_2 generated by this sector. For instance, Chèze et al. (2011a, 2011b) point out that air traffic management (ATM), incremental innovation in existing aircraft, and substantial innovation (i.e., new aircraft) are the main drivers for reducing aviation emissions, including CO_2. Grampella et al. (2017a) show that a younger aircraft can generate -1% of local emissions per year and -0.3% of global pollution. However, to the best of our knowledge, research on econometric evidence of the determinants of CO_2 aviation emissions remains lacking. Specifically, a measure of the average flight distance impact on CO_2 emissions could provide the fundamentals for designing an ETS that is based on flight distances rather than a general overall reduction in annual airlines CO_2 emissions (equal to 95% of the average historical aviation emissions during the 2004–2006 period). This per-flight CO_2 emissions regulation could provide incentives to airlines for better aircraft management on different routes. For instance, such regulations could provide incentives to operate an aircraft fitting current demands on specific routes and thus avoid using aircraft flights with low load factors on some routes. Thus, providing an econometric estimate of the sign and magnitude of some factors regarding CO_2 aviation emissions is the first goal of this paper.

Moreover, it is necessary to take into account that CO_2 emissions comprise only one dimension in the air transportation sector, as emissions interact with such factors as economic performance, political motives, and regulations on market entry, among others. All of these other components influence the possible outcomes of decisions adopted to limit emissions. For instance, although liberalization may boost CO_2 emissions by stimulating demand through lower fares, a company restructuring its network to recover profitability may lead to lower emissions through more efficient ATM. In this paper we aim to consider the impact of such non-emission specific decisions on the amount of CO_2 generated by aviation. This will provide, if proven, that these factors should be included in a cost-benefit analysis that also covers the environmental effects (direct and indirect) of a political or management decision.

To accomplish this, we exploit three circumstances: (1) the impact of regulation identified by the liberalization of the EU industry; (2) the impact of political decisions, given by a traffic transfer Act that swaps flights between two airports; and (3) the role of managerial decisions such as de-hubbing to reshape the flight network and to recover profitability.

We analyze these issues by exploring data on aviation activities and aviation-related CO_2 emissions in Italy. Specifically, we focus on Lombardy in Northern Italy.[3] We design an econometric model to identify the impact of certain determinants of CO_2 aviation emissions and apply it to a new data set that spans from 1997 to 2011 and consists of all scheduled flights departing from Lombardy airports in January of each year. The per-flight CO_2 emissions are based on the aircraft model and the distance flown.

The effect of non-environment decisions is provided by the estimated effect on CO_2 emissions of the entry (deregulation) of low-cost carriers (LCCs) when the national government decided in 1998 to impose an aircraft-movement cap to one airport (Linate). The decision was made to transfer flights to Malpensa in order to have a hub in Lombardy (a political reason). In addition, in 2008, at the apex of one of its recurrent financial crisis, Alitalia decided to reshape its network and concentrate flights at Rome Fiumicino in an attempt to recover profitability (a managerial decision).

Each of these factors may have affected CO_2 emissions in different ways. For instance, some LCCs could have generated new flights (increasing CO_2), changing the pattern of air traffic by possibly focusing on shorter routes (decreasing CO_2 per passenger), divert passengers from other CO_2-intensive transportation modes (e.g. cars, buses, trucks for freight), use younger aircraft and generate higher load factors than traditional carriers, and hence lower CO_2 emissions per passenger.[4] Similar considerations could be developed for limiting Milan Malpensa (e.g., reshaping both the flight network and the aircraft management) and for Alitalia Malpensa's de-hubbing decision (LCCs may have replaced Alitalia flights with—if proven—connections using younger aircraft).

Our period of observation covers 15 years, starting in 1997 and ending in 2011. The beginning year allows us to consider the full impact of some exogenous decisions (e.g., the 1998 swap from Linate to Malpensa and the impact of liberalization that took place in the mid-2000s). The last year is limited to 2011 for data availability. Although we can look at the three-year period following the Malpensa de-hubbing to see the effects on CO_2 emissions, such a review does not allow us to consider both the impact of recent CO2 regulations such as the EU ETS (begun in 2013) and of ICAO CORSIA (approved in 2016).

The paper is organized as follows. Section 2 describes the literature review. Section 3 discusses our empirical strategy by computing the per-flight CO2 emissions and presents the econometric model. Section 4 describes the available data sets, the data mining process, and descriptive statistics in the econometric model variables. Section 5 presents our empirical results, while Section 6 concludes the paper and highlights some possible policy implications. The Appendix contains assumptions on aircraft models and a list of LCCs defined by the ICAO.

2. Literature review

Currently, two main streams of research on aviation externalities exist. The first stream focuses on the impact of aviation externalities (mainly emissions and noise) on airports' vicinity, while the second stream investigates the future impact of aviation emissions on climate change using *ad-hoc* algorithms.

Regarding the first stream, Schipper (2004) conducted a landing/take-off (LTO) cycle assessment and estimation on 1990 data. Vicinity environmental costs of European aviation were computed from noise, emissions, and accident risk, and then applied to a set of 36 European markets (routes) in a week in 1990. Lu and Morrell (2006) performed a similar study on four European airports and showed, after computing an aviation externality, that a large part of such externality (noise in this case) was omitted. Morrell and Lu (2007) compared hub-to-hub and hub-bypass networks and found that the latter generated fewer emissions than the former. Lu (2009) studied aviation emissions' charge effect on air transportation demand and provided some evidence that environmental surcharges could reduce passenger demand, especially in the case of LCCs, even if these carriers impose lower environmental costs to passengers. Givoni and Rietveld (2010) investigated narrow-body A320 and wide-body B747 in two routes (London-Amsterdam and Tokyo-Sapporo) and showed that higher aircraft size and lower frequency generates lower climate change costs but higher local pollution.

[3] Lombardy is one of Europe's wealthiest regions and exceeded 10 million habitants in 2016. Other than the exceptional tourism volume, Lombardy has important commerce, banking, fashion and design sectors in Milan, as well as strong industries and agriculture in Bergamo. Lombardy is one of the four motors for Europe (with Baden-Württemberg (Germany), Catalonia (Spain), and Auvergne-Rhone-Alpes (France) identified by the European Commission.

[4] We are grateful to Martin Dresner for raising this point.

However, the latter does not offset the benefit of the former—i.e., high aircraft size produces lower overall (local plus global) emissions. Lu (2011) calculated the environmental (social) costs and social benefits at Taoyuan International Airport in Taiwan, providing evidence that even considering the aviation externalities, the benefits of having an airport are greater than the costs.

The papers belonging to this stream of research aim at the total environmental cost or the best solution to limit externalities. They provide solutions such as an optimum fleet mix, giving importance to load factors, or to adopting newer, cleaner technologies. Moreover, these papers usually only consider the LTO cycle and not the whole flight journey. When vicinity environmental cost is studied, LTO is the best approach, as aviation activity lower than 1-km altitude most affects a neighborhood.[5] When studies explore the issue of different emissions and noise levels generated by various aircraft models and engine types, they adopt a simplifying assumption of using some categories rather than the specific aircraft/engine combination. An exception is Grampella et al. (2017b), who used certificate data for each aircraft-engine specification. They applied this approach to a data set on a national airport system (Italy) and found that aircraft size-total externality elasticity is +1.8%, aircraft movement elasticity is +1%, and aircraft age elasticity is +0.69%. Again, as they focused on airport vicinity effects, the LTO cycle emissions and noise were studied.

In this first stream of research, analyzing global emissions or CO_2 emissions in particular, was not emphasized. However, according to the IPCC[6] (2007), "about 50% of a CO_2 increase will be removed from the atmosphere within 30 years, and a further 30% will be removed within a few centuries. The remaining 20% may stay in the atmosphere for many thousands of years." Hence, this paper, by focusing on CO_2 emissions, is an attempt to fill this literature gap.

The second group of papers focuses on forecasting CO_2 emissions mainly through computing fuel efficiency improvement. Hence, the main difference in this second stream is not finding the determinants of emissions, but rather using some algorithms based on the current and projected technology status to compare future alternative scenarios. Macintosh and Wallace (2009) developed an emissions projection (algorithm) by projecting revenue tons kilometers (for aviation demand) and global aviation emission intensity. Four scenarios were created from 2005 to 2025 based on forecasts of traffic growth and projections of technical progress aimed at reducing emissions. The scenarios showed that the latter is unlikely to offset the increase in CO_2 due to traffic growth. Chèze et al. (2011a) forecasted the yearly growth of air traffic flows until 2025, then converted the information into quantities of jet fuel using a geographic zone-specific energy coefficient, which is the amount of jet fuel required to power a unit of transportation. They provided evidence of an annual reduction of 3% in CO_2 emissions through lower fuel consumption thanks to both technical progress and better ATM. Chèze et al. (2011b) extended these results in which forecasts of future CO_2 emissions between international and domestic flights were compared, with the latter generating more emissions than the former, mainly due to a different (less environmental friendly) fleet mix.

Clearly, the findings of the second stream of research papers strongly depended upon *ad-hoc* assumptions of future demand and performance. A certain year is studied and then different scenarios based on hypothetical numbers of annual growth and improvements are plugged in that predict the future. Although a base past year can be carefully investigated, and the trend can then be calibrated, radical improvements or temporal events discriminating the base year or violating the trend cannot be netted by this method. Our paper is closer to the first stream of research, as we focus on finding some determinants of CO_2 emissions.

In addition to the two main research streams, there have been many contributions closer to our approach. Miyoshi and Mason (2009) proposed a bottom-up calculator for CO_2 emissions by route, stage length, aircraft type, number of seats on each aircraft, and the distance flown on each route. They used 2006 data for domestic air traffic and 2004 data for North Atlantic air traffic and provided a methodological reference for a part of our empirical research—namely, the computation of a specific aircraft CO_2 emissions during a specific route length. Pejovic et al. (2008) provided the same methodological base using samples from a day in 2004 to simulate the total annual CO_2 emissions. We follow these approaches, but use richer data and include several airports in a region.

Some recent papers have published empirical evidence on some determinants of CO_2 growth rates in aviation. Scotti and Volta (2015) found that European airlines grew 18.4% and 26.7% in terms of available seat kilometers (ASK) and revenue passenger kilometers (RPK) respectively from 2000 to 2010—i.e., airlines are carrying more people for a longer distance and earning more than before. They computed airline productivity in emission generation and identified the factors affecting it, providing evidence that load factor and a combined increase in stage length and aircraft size are determinants of increasing emission productivity, while fuel efficiency is a determinant only in the presence of a specific measure aimed at increasing CO_2 productivity. Brugnoli et al. (2015) examined CO_2 emissions in Europe and found that per-seat emissions were decreasing and suggested that the main factors leading to this result are airlines' effort to save on fuel costs, as well as the endogenous technical progress of the manufacturing industry. Kharina and Rutherford (2015) pointed out that the average fuel burn of new aircraft fell 45% from 1968 to 2014, and consequently CO_2 emissions fell. They also identified industry technical progress as the main determinant of this outcome.

However, even the recent contributions that are more related to our paper have not evaluated the direct impact of policies and management decisions not taken to reduce aviation environmental effects on total CO_2 emissions. This is possible in our paper, as we focus on airports in one region experiencing forces from different angles. As such, we consider the potential effect of business decisions made by Europe, Italy, and the aviation industry on Lombardy's aviation CO_2 emissions. This would allow for the control of such factors that may even offset the benefits that could come from, for instance, technical progress. Hence our paper is the first attempt, to the best of our knowledge, to establish the impact of decisions not intended to reduce CO_2 emissions on the amount of this externality generated by aviation. Thus, controlling for these factors, we aim to obtain better estimates of the influence of some determinants of CO_2 emissions—e.g., technical progress.

3. Empirical strategy

As mentioned in the introduction, our main goal is to estimate the signs and magnitude of some CO_2 emission determinants generated by aviation, and to assess how they are affected (or even counterbalanced) by some non-environmental measures taken by regulators, politicians, and industry managers.

As a first step in defining our empirical strategy to achieve such goals, we establish our research questions. First, we consider some determinants investigated by previous contributions (e.g., Scotti and Volta, 2015) that are typical of the aviation sector—such as the price of fuel—that may provide an incentive to reduce fuel consumption to save costs and therefore lead to more environmentally friendly aircraft/engine combinations. Hence, our first research hypothesis is as follows.

RH1. The price of fuel may be a negative determinant of aviation CO_2

[5] The LTO cycle refers to aircraft activity in altitudes below 3000 feet (915 m). Emissions during LTOs are a concern when studying local air quality and health impacts.

[6] The IPCC, Intergovernmental Panel on Climate Change, is a scientific body focusing on human-induced climate change, formed in 1988 in the United Nations.

emissions.

Similarly, the amount of CO_2 generated by a flight is strongly related to the route distance—i.e., the longer the stage length, the higher the CO_2. This argument is the basis of our second research hypothesis.

RH2. The route distance may be a positive determinant of CO_2 total emissions. However, we cannot make *ex-ante* predictions regarding the effect of distance on per-seat CO_2 emissions.

Moreover, the aircraft size has an impact on the thrust power and, in turn, the amount of CO_2 emissions. Hence we can investigate the issue below.

RH3. The average aircraft size may be a positive determinant of CO_2 total emissions. However, we are not able to make ex-ante predictions regarding the effect of size on per-seat CO_2 emissions.

Another typical determinant often considered in the air transportation literature is general technical industry progress (Grampella et al., 2017b). This is given by the aggregation of incremental innovations introduced in aircraft/engine combinations and in industry operations (e.g., better ATMs) that may generate an annual reduction in the amount of CO_2 emissions. Hence, we specify a trend variable capturing the impact of general technical progress.

RH4. : The technical industry progress is a negative determinant of both aviation CO_2 total emissions and per-seat emissions.

In addition to the abovementioned factors, we focus on some other determinants that may indirectly affect CO_2 and may offset the general benefits provided, for instance, by technical progress. The first determinant is related to aviation general regulation and in particular to the EU liberalization of air transportation. The latter has two main effects: (1) the entrance of LCCs and (2) the increase of flights (and routes).[7] The distance flown is already captured by the increase in flights and routes. The entrance of LCCs may instead reduce CO_2 emissions because they use, for example, younger aircraft. Hence we have our further research hypothesis.

RH5. LCCs may be a negative determinant of both total and per-seat CO_2 aviation emissions.

The second exogenous indirect determinant is given by Alitalia's dehubbing from Malpensa that occurred in April 2008 with the full effects starting in 2009.[8] This decision left several empty slots at Malpensa that were used by other airlines in the following years. The situation then created an entry opportunity, as well as the eventual establishment of a network in Malpensa, with possibly new and different-sized aircraft. Hence, the de-hubbing may have had the effect of reducing CO_2 emissions for flight limitations in the short run, which may have counteracted the entry effect over time. Moreover, the new airline networks may have had a positive impact on per-seat CO_2 emissions, for operating younger aircrafts and better ATM. This leads to the research hypothesis below.

RH6. Alitalia's de-hubbing from Malpensa in 2008 may have an effect on total and per-seat CO_2 emissions.

Lastly, the Italian national government's decision to impose a cap on flights at Milan Linate to help develop Milan Malpensa, which took place in 1998 (with full effects during the following year), may have generated a restructuring of the airline networks at both airports.[9] If Alitalia concentrated flights in Malpensa in an attempt to build a second hub (Rome Fiumicino is Alitalia's first hub), as shown by Redondi (2013), this may have increased the flight frequency and, in turn, the CO_2 emissions.[10] Moreover, such a concentration may have increased the aircraft size per movement, which could have reduced per-seat CO_2 emissions. Regarding the other airlines, they may have restructured their networks in both airports, thus affecting total and per-seat CO_2 emissions. Hence, no *a priori* impact could be identified. Our last research hypothesis is therefore the following.

RH7. The flight cap imposed on Milan Linate 1998 is a determinant of both total and per-seat CO_2 emissions.

In order to investigate these research questions, we first measured the CO_2 emissions generated by the sample of airports affected by the abovementioned exogenous decisions. Second, we designed an econometric model to provide some statistical evidence of the estimated coefficients of the possible determinants.

The airports included in our analysis are the four located in Lombardy, the region affected by the Italian government's decision, as well as the de-hubbing by Alitalia's. The four airports in Lombardy include Milan Malpensa (MXP), Bergamo Orio al Serio (BGY), Milan Linate (LIN), and Brescia Montichiari (VBS). We consider a 15-year time period, from 1997 to 2011. At the beginning of this period, Malpensa was the second-largest Italian airport with about 20 million passengers annually and the first that carried freight. Linate was the third-largest Italian airport with about 9 million passengers. Bergamo ranked sixteenth with 1.2 million passengers annually, but was third in terms of freight. Brescia was in the twenty-seventh position, with about 150,000 passengers annually, and no freight. At the end of the period, Malpensa ranked second in Italy, with about 19 million passengers annually (a reduction compared with the beginning figure, even though the sector has expanded in Italy), and first in terms of freight, with strong growth (+50% compared to the beginning of the year). Bergamo has had exponential growth; in 2011, there were 8.5 million passengers annually. The airport was ranked fifth in Italy, and third in terms of cargo. In 2011, Linate had about 9 million passengers annually, as in the initial year (1997). Brescia had almost no passengers in 2011 but significantly in terms of freight, passing from zero movement in year 1997 to about 40 thousand annual tons in 2011, ranking sixth in Italy. Currently, although Malpensa is still ranked second, in 2017, the airport grew to 22 million passengers annually and by far the first in terms of freight. Bergamo is currently the third Italian airport with 12.3 million passengers and third in freight. Linate ranks fifth with 9.5 million passengers, and Brescia still has very few passengers but ranks sixth in freight.[11]

We measured the amount of CO_2 emissions generated by these four airports during the observed period and then estimated the impact of some determinants. We now show how we measure aviation CO_2 emissions and subsequently present our econometric model.

[7] This implies generally considering the effect of Ryanair entry into the Bergamo airport in 2003, of easyJet's entry into the Malpensa airport in 2004 and of other LCCs such as Wizz Air and Flybe making smaller entries into various airports (mainly Bergamo) in the observed period.

[8] Seventy-six percent of departing flights were canceled and 17 daily intercontinental flights shrank to 3 non-daily intercontinental flights.

[9] This was based on the blueprint of a second Alitalia national hub in Malpensa in the observed period. As such, a traffic distribution rule (TDR) was put on Linate when a new terminal in Malpensa was completed in 1998. The TDR, called Burlando Act (enacted by the Italian Minister of Transport and Navigation in 1998), fixed the Linate quota to 34% of its capacity, meaning that around 8.5 million of its 14.5 million passengers had to move from Linate to Malpensa. Moreover, in 2000, with the Bersani Act (enacted by the succeeding Minister), Linate was officially capped by a further TDR that limited the service to European markets (e.g., only three and two daily returns to London Heathrow and Frankfurt, respectively).

[10] Redondi (2013) has explained how airlines fought back the TDR by multiple carrier codes or slot leases. Linate missed chance of 10% of growth as a consequence of TDR.

[11] Data was collected from Assaeroporti, an Italian airport association of the 36 companies managing the 38 airports in Italy, which was founded in 1967 and is affiliated with the Airport Council International.

3.1. Measurement of aviation CO_2 emissions

We considered departing flights from Lombardy in order to avoid unnecessary definition challenges of other perspectives—that is, entering flights, residency of passengers, airlines' base, or kerosene sales. In addition, only direct flights were considered; in cases of connecting flight, only the first leg leaving Lombardy was included.

We analyzed two flight phases: (1) the LTO cycle; and (2) the climb, cruise and descent cycle (CCD). These are divided, as fuel is burned in different patterns and has different types of environmental impact. In particular, during the LTO cycle, fuel flow can change with an engine's rated output in power settings of corresponding activities such as taxing, take-off, and climb out.

We considered an aircraft's total emissions on a particular journey. With the aid of the small emitters tool (SET) by Eurocontrol,[12] we obtained the estimated total fuel consumption of a certain aircraft model given the flight distance. SET takes the actual fuel consumption data of each flight under the EU ETS initiative and then runs separate linear regressions of each aircraft model, defining two parameters: the intercept (at zero distance) and the slope (kg of fuel per nautical miles flown). The overall fuel consumption is then translated into CO_2 according to the aircraft's engine type. In this study, we used the SET version 5.05 dated 2015.12.26. When some aircraft models in the sample could not be found in the SET, assumptions were made (See Appendix I for conversion table.).

We computed two CO_2 emissions indices: (1) the total amount and (2) the emission efficiency given by the amount of CO_2 generated by the available seat kilometers (ASK). As the total CO_2 emissions of a route is principally proportional to distance and frequency, by employing the second index, long-distance or high-frequency routes were not discriminated. Utilizing available seats in the second index formation further screened out the effect of varying aircraft sizes.

3.2. The econometric model

Our aim is to identify the determinants of total and per-ASK CO_2 emissions generated by the four Lombardy airports during the 1997–2011 period. Hence, we developed an econometric model to estimate the elasticity of some determinants on CO_2 emissions and to provide empirical evidence of the possible effects of decisions that may indirectly affect such emissions. Therefore, we used a log-linear model in which some determinants were expressed in logarithms and others as dummy variables. Airport dummy variables were also created as control variables. In this log-linear model, the percentage impact on a dependent variable when a dummy variable switches from 0 to 1 could be computed by applying the following expression: $100(e^{\delta}-1)$, where δ is the coefficient for the dummy variable. In the presence of a continuous variable as a regressor, given that the dependent variable is logged, its elasticity is given by β —i.e., the estimated coefficient of the logarithmic independent variable.

Our observation is given by the origin-destination (OD), the route provided by an airline in year t. The triplet origin-destination-airline (or the pair route-airline) is our "id" variable, with the label i. Hence we have a panel data set composed by i = 1, 2, …., and I triplets origin-destination-airline during the period t = 1, 2, …, 15. Four hundred and thirty-five routes and 197 different airlines were observed in the period data set; however, since not all routes operated every year, we had only 1082 route-airline pairs. Hence we generated an unbalanced panel data set composed of 4164 observations.

We designed two econometric panel data models and then estimated the models with random effects (RE) that are presented below (respectively, the first equation estimates the determinants of total CO_2 emissions while the second concerns the factors affecting per-seat-kilometer CO_2 emissions):

$$\log CO2_{it} = \alpha + \beta_1 \times logFUEL_t + \beta_2 \times logKM_{it} + \beta_3 \times \log SIZE_{it} + \beta_4 \times TIME_t + \delta_1 \times DEHUB_t + \delta_2 \times 1998_t + \delta_3 \times LCC_i + \delta_4 \times EU_i + \sum_{j=1}^{3} \gamma_j \times D\_airport_{ij} + \epsilon_{it} \quad (1)$$

$$\log CO2ASK_{it} = \alpha + \beta_1 \times logFUEL_t + \beta_2 \times \log KM_{it} + \beta_3 \times \log SIZE_{it} + \beta_4 \times TIME_t + \delta_1 \times DEHUB_t + \delta_2 \times 1998_t + \delta_3 \times LCC_i + \delta_4 \times EU_i + \sum_{i=1}^{3} \gamma_i \times airport_i + \epsilon_{it} \quad (2)$$

where i is the pair route-airline, t is the year, and j is the index regarding the three departing airports in Lombardy (Malpensa is the base airport). The model is estimated to account for possible heteroskedasticity—i.e., the estimate coefficients have robust standard errors. The effect of technology progress on CO_2 emissions is captured by the variable $TIME$ given by each year in the dataset. Equation (2) has a dependent variable given by an index of emission efficiency—that is, the amount of CO_2 per-seat per kilometer of flight ($CO2ASK$). Furthermore, as our aim is also to study the determinants of one-year variations in total CO_2 emissions and per-seat-kilometer CO_2 emissions, we estimated a panel data model with a one-year difference in time-varying variables and random effects given by the two following equations:

$$\log\left(\frac{CO2_{it}}{CO2_{it-1}}\right) = \alpha + \beta_1 \times log\left(\frac{FUEL_t}{FUEL_{t-1}}\right) + \beta_2 \times log\left(\frac{KM_{it}}{KM_{it-1}}\right) + \beta_3 \times \log\left(\frac{SIZE_{it}}{SIZE_{it-1}}\right) + \delta_1 \times (DEBUG_t - DEBUG_{t-1}) + \delta_2 \times (1998_t - 1998_{t-1}) + \upsilon_{it} \quad (3)$$

where Eq. (3) is related to variations in total CO_2, while Eq. (4) is for per-seat-kilometer CO_2,

$$\log\left(\frac{CO2ASK_{it}}{CO2ASK_{it-1}}\right) = \alpha + \beta_1 \times log\left(\frac{FUEL_t}{FUEL_{t-1}}\right) + \beta_2 \times log\left(\frac{KM_{it}}{KM_{it-1}}\right) + \beta_3 \times \log\left(\frac{SIZE_{it}}{SIZE_{it-1}}\right) + \delta_1 \times (DEBUG_t - DEBUG_{t-1}) + \delta_2 \times ((1998_t - 1998_{t-1})) + \upsilon_{it} \quad (4)$$

Table 1 illustrates the variable names and description.

The model presented in Eqs. (1)–(4) is applied to a data set described in the section below.

4. Data

We built a data set that included all Lombardy passenger flights from 1997 to 2011, all scheduled flights in January of each year departing from Lombard airports: Malpensa (MXP), Linate (LIN), Bergamo (BGY), and Brescia (VBS). The source of these data is the Official Airline Guide (OAG) database. The airports have different destination (airports), distances, carriers, frequencies, aircraft models, and available seats. CO_2 emissions are then estimated by feeding the aircraft model and distance traveled into SET, the emission calculation tool. We collected 4197 observations and some descriptive statistics on the observed flights, and their CO_2 emissions are shown in Table 2. The average, annual amount of total CO_2 generated by a route-airline pair is about 800 thousand kilograms, while the per-seat-kilometers is only 97 g+

Table 3 presents descriptive statistics of the variables that may indirectly affect emissions and the share of flights departing from the four

[12] SET was approved by the European Commission via the Commission Regulation (EU) No.606/2010 and is used by small emitters in fulfillment of their obligations pursuant to Article 14(3) of the Directive 2003/87/EC (the EU ETS Directive) and Part 4 of Annex XIV to Decision 2007/589/EC (monitoring and reporting guidance).

Table 1
Description of variables.

Variable	Description
CO2	Total amount of CO_2 emissions in kg of a particular route-airline *i* pair in year *t*
CO2ASK	Grams of CO_2 produced by flying one available seat per 1 km in pair *i* and year *t*
FUEL	Fuel price in January of year each in US cents
KM	Distance of a route in km (variable since a route can involve flying to different airports at same destination)
SIZE	Average aircraft size in the route-airline pair *i* in year *t*
TIME	Year index starting from 0 and up to 15
DEHUB	De-hubbing effect, starting at 2009, i.e. 1997–2008 as 0; and 2009 onward as 1
1998	Traffic distribution from LIN to MXP, i.e. 1997-98 as 0; and 1999 onward as 1
LCC	A set of LCC airlines defined by ICAO definition (see Appendix II) as 1
EU	Dummy variable = 1 if destination is in Europe
AIRPORT	Dummy variable of departing airports

Table 2
Descriptive statistics of observed routes.

Variable	Mean	St. Dev.	Min	Max
CO2 (kg)	821,386.4	1,203,953	2236	9,607,554
CO2ASK (g)	97.3	32.4	54.9	443.5
FUEL ($)	1.4	0.7	0.3	2.6
KM	6146.9	8554.9	64	133,800
SEAT	2016.2	2470.7	97	11,195
SIZE	154.6	67.78	19	546
ASK	9,104,834	1.30E+07	17,296	9.58E+07

Table 3
Descriptive statistics of independent variables.

Variable	Mean	St. Dev.	Min	Max
DEHUB	0.34	0.47	0	1
1998	0.96	0.19	0	1
LCC	0.21	0.41	0	1
EU	0.77	0.42	0	1
Bergamo	0.14	0.34	0	1
Brescia	0.01	0.09	0	1
Milan Linate	0.24	0.43	0	1
Milan Malpensa	0.62	0.49	0	1

airports. It is interesting to note that the average share of LCC flights is 21% in our sample while the share of those with destinations in the EU is 77%. Observations regarding the Malpensa airport comprise the majority (62%), while those related to Brescia are only a small percentage (1%).

Concerning the destination composition, also seen in Fig. 1, the total

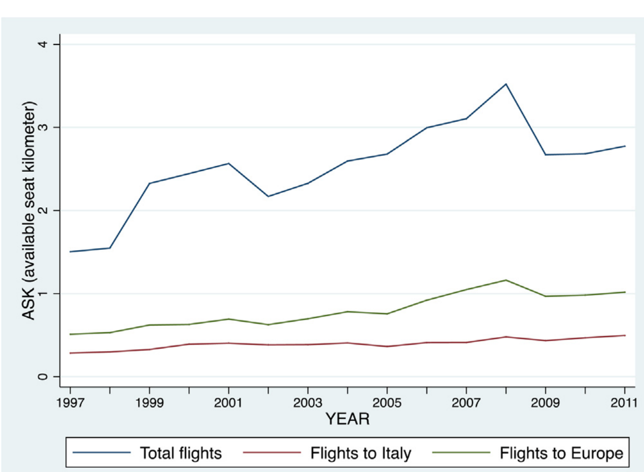

Fig. 1. Annual ASK (billion) departing in January from Lombardy by destination.

amount of EU ASK[13] varies from about 0.5 billion in 1997 to about 1 billion in 2011, while the total amount of ASK ranges from about 1.5 billion to about 2.8. Last total Italy ASK[14] increases from about 0.3 billion to about 0.5 billion. The ASK is growing in all levels with respect to the 1997 level.

Fig. 2 shows the effects of the traffic transfer Act and of Alitalia's de-hubbing on the level of ASK in Linate and Malpensa. The left-hand graph displays the impact of the Italian government's decision to transfer the traffic from Milan Linate to Milan Malpensa in 1998. It is evident that there is a big ASK reduction in Linate and a corresponding increase in Malpensa. The right-hand graph presents the impact of Alitalia de-hubbing from Malpensa, which involved a huge reduction in the ASK and no corresponding increased effect on Linate.

Fig. 3 reveals the share of aviation CO_2 emissions among the four airports in the data set. We show the total CO_2 emissions in regards to only departing flights in January of each year. The emission levels would be scaled up if every month in a year was considered, or if the incoming flight was also measured. The traffic distribution—that is, the steered traffic from Linate to Malpensa—is obvious since Linate has a sharp decrease of CO_2 emissions in 1999, while Malpensa has a sharp increase. Moreover, it is evident that the effect of Alitalia de-hubbing from Malpensa in 2009, with a strong reduction in total CO_2 emissions, is not counteracted by any increase in the other four Lombardy airports. Lastly, the development of LCCs in the Bergamo airport (mainly due to Ryanair) generates a continuous increase in total CO_2 emissions.

As we are interested in the technology progress reflected by the emission efficiency variations given by CO_2 per ASK (i.e., grams of CO_2 produced by one available seat per kilometer), the latter is computed for each flight. We can see the diverse LCC performances (red line in Fig. 4) compared with all airlines (blue lines) and the index number of flights departing from the four airports (Fig. 5). It is interesting to notice that LCCs have a lower CO_2 per ASK than traditional airlines. Moreover, Bergamo had a significant improvement in 2003 when LCCs began proliferating there. All airports or airlines have a decreasing trend of CO_2 per ASK, which could be a signal of environmentally friendly technical progress; however, the total CO_2, which we encountered before, has an increasing trend.

Finally, we present the indicator trends based on the 1997 value in Fig. 6. From this graph, we confirm the questionable relation of total CO_2 and CO_2 per ASK: the total CO_2 is unevenly increasing while CO_2 per ASK is steadily decreasing. ASK is confirmed to be correlated to CO_2 but we question if the fuel price is significantly impacting the CO_2 per ASK.

The 30 most important airlines in our data set are listed in Table 4. They are in ascending order of CO_2 per ASK. The share of the total of

[13] We refer to the EU ASK as the available seat kilometers to an EU destination; i.e., an intra-EU flight.

[14] IT ASK refers to the seat kilometers of a destination in Italy—i.e., a domestic flight.

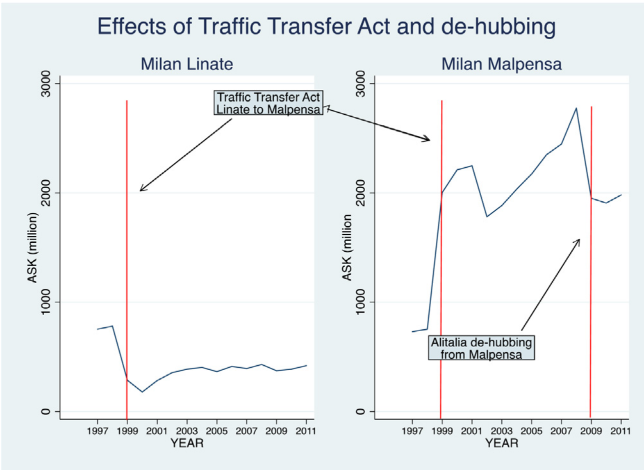

Fig. 2. Annual January departure ASK (million) from Lombardy by airport.

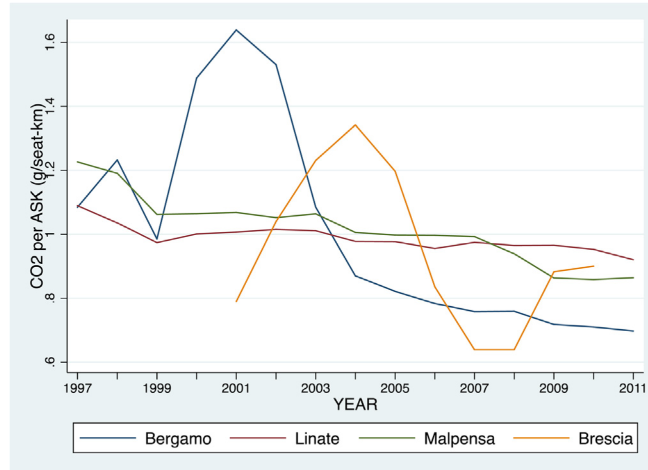

Fig. 5. Annual January departure CO_2 per ASK by airport.

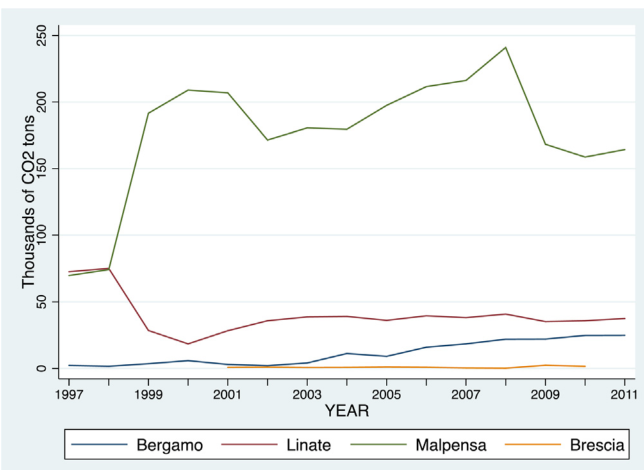

Fig. 3. Annual January departure CO_2 by airports in Lombardy.

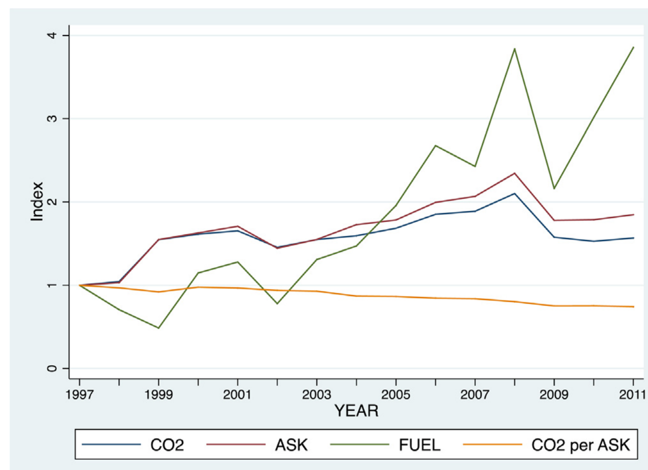

Fig. 6. Trend of annual January departure indicators based on the year 1997.

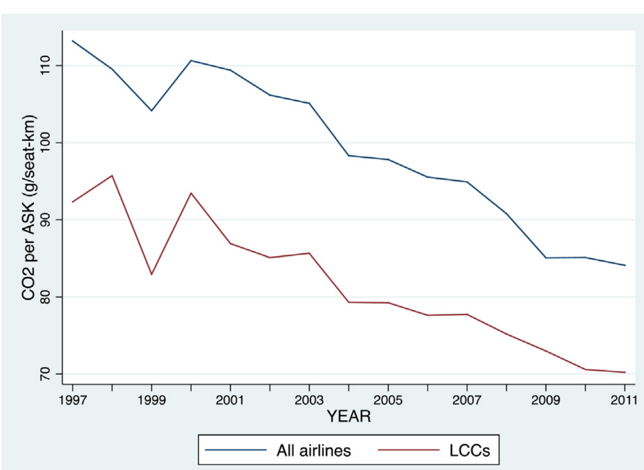

Fig. 4. Annual January departure CO_2 per ASK by LCCs.

these 30 airlines on the grand total of 197 airlines is reported, representing at least 80% of all dimensions including total CO_2, total frequency (movement), total km (distance) and total ASK. Total ASK is also a proxy of air transportation supply. The average seat and average km by movement could be interpreted as the median aircraft size and median route distance, respectively, of each airline.

5. Results

In this section we present empirical evidence regarding the seven previous research questions. We first show the estimated coefficients regarding the model for total CO_2 emissions (Eq. (1)), under two specifications: (1) with a dummy for all LCCs; and (2) with a dummy regarding only Ryanair and easyJet. The latter captures the impact on CO_2 emissions of the two most important LCCs in Europe with a strong presence in Lombardy; moreover, these two LCCs also tend to have younger aircraft.

The regressions outcome is shown in Table 5, with four models of different settings. The dependent variable of the first two models is the total amount of CO_2, while that of the latter two models is CO_2 per ASK. Regarding the independent variables, most of them are statistically significant, reflecting their impact on Lombardy aviation CO_2 emissions in an airline-specific route dimension by the corresponding coefficients' sign and magnitude. LCC is tested by two different definitions: (i) a list of LCCs by ICAO and (ii) only Ryanair and easyJet. In the (ii) case, the magnitude of impact is always strengthened.

When all LCCs are considered, as expected, distance (*KM*) and size (*SIZE*) have a positive impact on total CO_2 aviation emissions. The estimated elasticity is respectively +0.63% and +0.41%. Unexpectedly, the fuel price (*FUEL*) is also a positive determinant of total CO_2 emissions: the estimated elasticity is +0.11%. On the contrary, we do not find any evidence of technical progress effect on total CO_2. The exogenous policy and managerial variables also have no effects; however, if

Table 4
Listing of important airlines in Lombardy.

CODE	CARRIER NAME	Total CO_2 (kt)	Total Frequency	Total SEAT (thousand)	Total KM	Total ASK (million)	SEAT (mean)	KM (mean)	CO_2 per ASK (g/seat-km)
FR	Ryanair	103.86	9063	1709.27	8,441,413	1591.68	188.60	931.41	65.25
GJ	Eurofly	47.46	1078	215.34	2,711,191	643.06	199.76	2515.02	73.80
L4	Lauda Air	44.79	325	84.73	2,291,080	598.20	260.70	7049.48	74.88
U2	easyjet	72.95	6860	1069.81	6,185,361	964.38	155.95	901.66	75.64
LM	Livingston	59.73	462	119.66	2,915,541	763.14	259.00	6310.69	78.28
IB	Iberia	39.76	2924	489.92	2,935,138	499.86	167.55	1003.81	79.53
TP	TAP Portugal	20.74	1224	157.70	1,993,140	258.93	128.84	1628.38	80.10
PE	Air Europe	40.66	1749	266.70	2,447,032	500.77	152.48	1399.10	81.19
EK	Emirates	37.95	353	110.81	1,509,276	464.46	313.91	4275.57	81.71
BV	Blue Panorama Airlines	33.82	447	84.3	1,986,810	409.28	188.59	4444.77	82.64
VA	Volare Airlines	18.71	1207	201.99	1,213,669	219.82	167.35	1005.53	85.10
VE	CAI Second	30.75	1886	302.42	2,014,763	360.67	160.35	1068.27	85.27
DL	Delta Air Lines	79.55	620	131.57	4,259,775	904.45	212.20	6870.60	87.95
BA	British Airways	57.61	4794	657.95	4,815,786	650.72	137.24	1004.54	88.53
KL	KLM	20.53	2193	276.97	1,769,673	223.54	126.30	806.96	91.84
IG	Meridiana	58.78	4932	776.69	3,755,284	635.78	157.48	761.41	92.46
AZ	Alitalia	1483.26	76,657	10,053.92	87,571,292	15,786.57	131.15	1142.38	93.96
XM	CAI First	29.64	2549	368.86	2,139,463	311.15	144.71	839.33	95.25
AF	Air France	37.34	5370	654.29	2,952,033	384.38	121.84	549.73	97.14
CO	Continental Airlines	54.89	398	86.79	2,559,836	558.21	218.07	6431.75	98.33
SK	SAS Scandinavian Airlines	29.36	1809	233.46	2,350,695	298.15	129.05	1299.44	98.49
AP	Air One	105.28	13,205	1631.50	8,501,515	1060.45	123.55	643.81	99.28
SQ	Singapore Airlines	40.57	260	72.28	1,442,418	400.99	278.00	5547.76	101.18
JL	Japan Airlines International	90.47	325	117.77	2,453,119	884.92	362.36	7548.06	102.23
RG	Varig	67.90	382	96.623	2,628,354	662.19	252.94	6880.51	102.53
LH	Lufthansa Airlines	65.64	10,479	1053.77	5,977,403	596.71	100.56	570.42	110.01
OS	Austrian Airlines	12.40	1741	167.42	1,125,979	108.23	96.16	646.74	114.53
SN	Brussels Airlines	16.68	1981	201.39	1,338,995	136.38	101.66	675.92	122.34
G7	Gandalf Airlines	6.70	2124	75.71	1,204,055	43.51	35.64	566.88	153.92
LX	Swiss	6.10	1894	171.56	392,066	35.08	90.58	207.00	173.90
	Sum (30)	2813.88 (82.26%)	159,291 (83.68%)	21,641.14 (84.53%)	173,882,155 (80.38%)	30,955.68 (82%)	135.86	1091.60	90.90
	Total (197)	3420.92	190356	25600.396	216326034	37921.81	134.49	1136.43	90.21

Table 5
Regression results for total CO_2 aviation emissions.

Variables	Dependent variable: log of CO_2					
	Estimated coefficient	S.E.	*P*-value	Estimated coefficient	S.E.	*P*-value
log FUEL	0.109***	(0.036)	0.002	0.109***	(0.036)	0.002
log KM	0.628***	(0.063)	0.000	0.621***	(0.063)	0.000
log SIZE	0.406***	(0.066)	0.000	0.390***	(0.066)	0.000
TIME	−0.015	(0.010)	0.123	−0.016	(0.010)	0.108
DEHUB	−0.010	(0.043)	0.810	−0.013	(0.043)	0.762
1998	−0.007	(0.057)	0.900	−0.005	(0.057)	0.928
LCC	0.005	(0.070)	0.946			
EU	0.279**	(0.124)	0.024	0.233*	(0.123)	0.058
Linate	0.188***	(0.072)	0.009	0.206***	(0.072)	0.004
Bergamo	−0.436***	(0.083)	0.000	−0.505***	(0.077)	0.000
Brescia	−0.089	(0.229)	0.696	−0.153	(0.236)	0.517
LCC_R_E				0.317***	(0.081)	0.000
Constant	12.520***	(0.513)	0.000	12.672***	(0.509)	0.000
Observations	4164			4164		
R^2	0.34			0.34		

Robust standard errors in parentheses.
Legend: *** *P*-value < 0.01, ** *P*-value < 0.05, * *P*-value < 0.10.

the destination is in a EU member country, the total CO_2 is higher (the estimated elasticity is about +0.32%). Bergamo makes much less total CO_2 than Malpensa, which might be explained by the fact that almost all Bergamo flights are operated by LCCs, and this may explain why the variable LCC has no significance. Linate makes more CO_2 emissions than Malpensa, possibly due to older aircraft (Alitalia operated the Milan Linate-Rome Fiumicino routes that used a lot of old MD-80/81/82 for many years). Interestingly, when Ryanair and easyJet are included in the regression, the estimated effect is positive—i.e., they increase the total CO_2 emissions. In the case of Ryanair, the result may be explained by the negative coefficient for the Bergamo airport. Malpensa also makes less CO_2 than Linate, which may capture part of the possible negative effect from easyJet. This finding is confirmed by the results of a regression (not shown) that does not include the airport dummies; in this case, the LCC dummy is negative and significant.

Table 6 presents the results concerning emission efficiency—i.e., the CO_2 per ASK that is related to Eq. (2). The fuel price is not a determinant of CO_2 per ASK. Interestingly, the route distance and aircraft size are negative determinants of emissions (in)efficiency, as they both generate lower CO_2 per ASK. The estimated elasticities are, respectively, −0.14% and −0.28%. Moreover, there is a positive impact of technical progress on emission efficiency: the estimated coefficient for TIME is equal to −0.01, corresponding to a −0.06% annual improvement—a lower CO_2 emission per ASK. De-hubbing and the transfer traffic decision have no effect, while LCCs are producing less CO_2 per ASK than traditional carriers. These findings are confirmed and slightly higher in magnitude when we consider only Ryanair and easyJet. Flying to a EU destination yields a lower CO_2 per ASK, which may also be due to liberalization and airports charging pollution surcharges. Linate and Bergamo are more efficient than Malpensa.

We have also analyzed the impact of some possible determinants of the one-year changes in the amount of CO_2 generated per route-airline

Table 6
Regression results for total CO_2 per ASK aviation emissions.

Variables	Dependent variable: log of CO_2 per ASK					
	Estimated coefficient	S.E.	*P*-value	Estimated coefficient	S.E.	*P*-value
log FUEL	−0.001	(0.009)	0.918	−0.000	(0.009)	0.977
log KM	−0.140***	(0.016)	0.000	−0.142***	(0.016)	0.000
log SIZE	−0.282***	(0.020)	0.000	−0.283***	(0.020)	0.000
TIME	−0.006***	(0.002)	0.004	−0.007***	(0.002)	0.002
DEHUB	−0.010	(0.010)	0.318	−0.007	(0.010)	0.478
1998	0.007	(0.015)	0.656	0.007	(0.015)	0.643
LCC	−0.129***	(0.014)	0.000			
EU	−0.220***	(0.032)	0.000	−0.223***	(0.032)	0.000
Linate	−0.048***	(0.014)	0.001	−0.046***	(0.014)	0.001
Bergamo	−0.086***	(0.015)	0.000	−0.097***	(0.015)	0.000
Brescia	−0.018	(0.048)	0.703	−0.005	(0.047)	0.919
LCC_R_E				−0.168***	(0.014)	0.000
Constant	7.189***	(0.148)	0.000	7.201***	(0.149)	0.000
Observations	4164			4164		
R^2	0.53			0.53		

Robust standard errors in parentheses.
Legend: *** *P*-value < 0.01, ** *P*-value < 0.05, * *P*-value < 0.10.

Table 7
Regression Results for one-year variation in total and per-seat CO_2 emissions.

Variables	Dep. var.: log of CO_2			Dep. var.: log of CO_2 x ASK		
	Est. Coef.	S.E.	*P*-value	Est. Coef.	S.E.	*P*-value
log d.FUEL	0.080**	(0.032)	0.012	0.0004	(0.009)	0.965
log d.KM	5.326	(7.807)	0.495	−0.164	(1.533)	0.915
log d.SIZE	0.400***	(0.075)	0.000	−0.342***	(0.038)	0.000
d.DEHUB	−0.012	(0.046)	0.800	0.0001	(0.009)	0.992
d.1998	0.079	(0.050)	0.111	0.015	(0.015)	0.325
Constant	−0.024*	(0.012)	0.056	−0.006***	(0.002)	0.007
Observations	2930			2930		
R^2	0.03			0.20		

Robust standard errors in parentheses.
Legend: *** *P*-value < 0.01, ** *P*-value < 0.05, * *P*-value < 0.10.

pair and on the CO_2 per ASK using the model presented in Eqs. (3) and (4). The results are shown in Table 7. The first three columns have the logarithm of the total CO_2 generated as the dependent variable (i.e., the columns refer to Eq. (3)), while the last three columns give the results of regressing Eq. (4), with the logarithm of the CO_2 generated per ASK as the dependent variable. Both the dependent and the independent variables are the one-year difference, denoted as "d."

One identified determinant of one-year changes on total CO_2 is the one-year variation in aircraft size. If the latter increases we observe an increase in the variation of total CO_2 from one year to the following year. The estimated coefficient of the *d.SIZE* logarithm is equal to +0.40 and is statistically significant. The other determinant is given by the one-year variation in fuel price: the estimated coefficient is statistically significant and equal to +0.08. One-year variations in the route distance, the impact of Alitalia de-hubbing, as well as the 1998 Traffic Transfer Act from Linate to Malpensa have no effect on the total CO_2 one-year difference.

Table 7 shows that the only identified determinant of one-year changes in CO_2 per ASK is the one-year variation in aircraft size. The estimated coefficient is −0.34, which implies that a one-year increase in aircraft size yields a reduction in the one-year CO_2 generated for passengers (using seat kilometers as a proxy average). This is an interesting result since it demonstrates that a marginal (i.e., in the following two years) increase in aircraft size can produce a marginal decrease in the amount of CO_2 generated per passenger. This finding could signal a possible lower per-passenger impact of aviation on the environment if we could progressively augment the per-route aircraft size, keeping all other variables fixed (the sign and significance is the same if we also include a one-year variation in the total ASK operated on the route, after taking into account the total movements on that route).

Hence, to sum up our insights regarding the research questions, we can state the following. First, fuel price increases the total CO_2, differently from what we had expected. This suggests that airlines are not pushing efficiency in fuel consumption, which has the secondary effect of increasing emissions and might be explained by market power—that is, airlines may be transferring higher fuel costs to consumers. We did not find any effect on CO_2 per ASK and on one-year variations. Second, the route distance increases total emissions, and decreases emission per ASK, thus we have higher efficiency with a longer flight distance, implying that CO_2 is less of a problem for long-haul connections. There is no impact of distance on one-year variations. Third, although aircraft size increases total emissions, it reduces emissions per ASK, as well as one-year variations; therefore, it is a driver of emission efficiency. Fourth, technical progress does not impact total emissions, but it does decrease CO_2 emissions per ASK in that the estimated elasticity is −0.06%. Fifth, although LCCs have lower CO_2 emissions per ASK, as liberalization in Europe has brought a collateral effect of reducing CO_2 externality per passenger, LLCs also contribute to higher total emissions, probably due to their higher activity in the EU. Sixth, Alitalia dehubbing and the national government traffic transfer act from Linate to Malpensa did not have any effect any on the investigated dimensions of CO2 emissions, including one-year differences. This implies that managerial and government decisions made for reasons not connected with the environment did not generate an impact on CO_2, which is different from what was expected. In both cases, the airlines' network restructuring could generate an effect, but this has not been identified.

6. Conclusion

This study is an attempt to fill a gap in the existing literature regarding the possible determinants of CO_2 emissions generated by the commercial air transportation sector. Previous contributions (e.g., Chèze et al., 2011a; Grampella et al., 2017b) have identified that technical progress is a factor limiting emissions and we estimate an annual improvement in the range of −1% and −0.3%. However, other peculiar factors of the air transportation sector may influence CO_2 emissions—for instance, route distance and aircraft size. Furthermore, different institutions (ICAO, EU, and so forth) are involved in a lengthy process of establishing a policy limiting aviation emissions, with the EU ETS and the ICAO CORSIA framework as two examples. However, these efforts interact with other forces such as economic and business performance, political issues, and regulation on market entry. The latter factor may affect possible outcomes of decisions adopted to limit emissions. For instance, market liberalization may boost CO_2 emissions by stimulating demand through lower fares. Hence, in this contribution we analyzed the determinants of CO_2 aviation emissions that include different components: technical progress, traffic management airline decisions, and policies/business choices not oriented to the environment, but that can indirectly affect the level of emissions.

We studied emissions according to two dimensions: (1) the total CO_2 generated on a specific route by a specific airline, and (2) the CO_2 per ASK on the same unit of observation. While the first dimension provide insight into the determinants of global amounts of CO_2, the second may point out a relative measure of CO_2 per passenger—i.e., the environmental efficiency of air transportation.

In order to identify the determinants of CO_2 aviation emissions we designed an econometric model for panel data and applied it to a data set concerning all the flights departing from Lombardy, Italy, over the 1997–2011 period. The amount of CO_2 generated was computed by taking into account the aircraft model chosen by the airline operating on that route.

Our main results are as follows. First, the price of fuel is a positive determinant of total CO_2 emissions (RH1) but has no effect on per seat emissions. Airlines seem not to react to price variations in setting their schedule, maybe because the rebate the changes on higher ticket fares (Scotti and Volta, 2018). Second, as expected route distance increases total CO_2 emissions and decreases emissions per ASK (RH2). The latter outcome implies that there is higher emission efficiency for long-haul connections. Third, aircraft size increases total emissions, but reduces emissions per ASK (RH3); therefore, it is a second driver of emission efficiency. These two factors indicate that airline fleet management may be a sustainable growth path for commercial aviation. Fourth, there is a positive effect of general technical progress on per seat CO_2 emissions but not on total ones (RH4). Hence, differently from previous studies, once that we focus on the route-airline pairing we find that technical progress is not impacting total emissions, but it is decreasing CO_2 emissions per ASK. However, the estimated elasticity is lower than previous figures (-0.06%) and, above all, much lower than the estimated elasticities regarding aircraft management (the route elasticity is -0.14%, the aircraft size elasticity is -0.28%). Fifth, we provided mixed evidence regarding the indirect impact of policy/business decisions (not oriented toward CO_2) on emissions. On the one hand, the EU market liberalization has an impact on CO_2, and this may offset the outcome of other policies (e.g., the EU ETS or the ICAO CORSIA) adopted to limit pollution. In the observed period (1997–2011) liberalization has brought the entry and the development of LCCs into the EU, and we find that they have high total emissions, but lower CO_2 emission per ASK (RH5). The latter result implies that although liberalization has brought the collateral effect of reducing the CO_2 externality per passenger, it has also contributed to higher total emissions, probably due to higher LCC activity in the EU. On the other hand, we find that Alitalia de-hubbing from Malpensa in 2008 (RH6) and the national government Traffic Transfer Act from Linate to Malpensa in 1998 do not affect either total or per ASK CO_2 emissions (RH7). In both cases the airlines' network restructuring could have generated an effect, but this has not been identified.

From the abovementioned insights we can draw some interesting policy implications. First, aviation CO_2 emissions could be reduced, or emission efficiency could be increased through airline adoption of better aircraft and network management. Aircraft size can reduce CO_2, thus environmental policy should provide incentives for increasing aircraft size on different routes when demand allows for it, for instance, by reshaping the EU ETS according to this dimension. A higher tax may induce airlines to better aircraft management when possible, perhaps with less frequency and higher load factors. Second, it is necessary to provide an incentive to renovate aircraft fleets, since general technical progress is a determinant of aviation emission efficiency. Last, LLCs also increase emission efficiency, a further important consequence. This is because LCCs may generate new flights (increasing CO_2), divert passengers from other CO_2-intensive transportation modes (e.g., cars, buses, trucks for freights), use younger aircraft and generate higher load factors than traditional carriers, hence achieving a overall lower CO_2 emissions per passenger.

Restricted by the availability of data and resources, there are some limitations and drawbacks of this study. First and foremost is the underestimation of CO_2 emissions through the following examples: when an equivalent aircraft model (with a lower CO_2 emission value) is used for a badly defined aircraft model in our data set; when theoretical distance is used instead of actual distance flown (which is possible if each flight is monitored); when operation usage of fuel on the ground is neglected (although this might be responsible for only a tiny part of fuel consumption). A dedicated airport study should also take these factors into account. Second, in this paper CO_2 emissions are not an actual measurement of each flight in this, but a proxy. We compute CO_2 emissions based on a regression of certain aircraft model records, which is, by its nature, estimated. Third, no comparisons of different aircraft categories were made in this study. Engines and airframes characterize small/medium/large aircraft and thus fuel consumption. These topics are left for future research.

Appendix IAircraft Model Conversion

OAG name	OAG code	SET code	OAG name	OAG code	SET code
Airbus A300 Passenger	AB3	A30B	BAe 146–300 Passenger	143	B463
Airbus A300B2/B4/C4	AB4	A30B	BAe Jetstream 32	J32	JS32
Airbus A300B4/A300C4/A300F4	ABX	A30B	Beechcraft 1900D Airliner	BEH	B190
Airbus A310 Freighter	31F	A310	Boeing (douglas) DC10 (Freighter)	D1F	DC10
Airbus A310 Passenger	310	A310	Boeing (douglas) MD-11 (Freighter)	M1F	MD11
Airbus A310-300 Freighter	31Y	A310	Boeing (douglas) MD-11 Mixed Config	M1M	MD11
Airbus A310-300 Passenger	313	A310	Boeing (douglas) MD-11 Passenger	M11	MD11
Airbus A318	318	A318	Boeing (douglas) MD-80	M80	MD81
Airbus A318/319/320/321	32S	A318	Boeing (douglas) MD-81	M81	MD81
Airbus A319	319	A319	Boeing (douglas) MD-82	M82	MD82
Airbus A320	320	A320	Boeing (douglas) MD-83	M83	MD83
Airbus A321	321	A321	Boeing (douglas) MD-87	M87	MD87
Airbus A330	330	A330	Boeing (douglas) MD-88	M88	MD88
Airbus A330-200	332	A332	Boeing (douglas) MD-90	M90	MD90
Airbus A330-200 Freighter	33X	A332	Boeing 717-200	717	B712
Airbus A330-300	333	A333	Boeing 727 (Freighter)	72F	B721
Airbus A340	340	A340	Boeing 727 Advanced all Series (Pax)	72S	B721
Airbus A340-200	342	A342	Boeing 727-200	722	B722
Airbus A340-300	343	A343	Boeing 727-200 Advanced	72A	B722
Airbus A340-500	345	A345	Boeing 737 (Freighter)	73F	B732
Airbus A340-600	346	A346	Boeing 737 Advanced all Series	73S	B732
ATR 42-500	AT5	AT45	Boeing 737 Passenger	737	B732
ATR 72	AT7	AT72	Boeing 737-200 (Mixed Configuration)	73M	B732
ATR42/ATR72	ATR	AT43	Boeing 737-200/200C/200QC (Pax)	732	B732
Avro RJ100	AR1	RJ1H	Boeing 737-200/200C Advanced (Pax)	73A	B732
Avro RJ70	AR7	RJ70	Boeing 737-300 (Freighter)	73Y	B733
Avro RJ70/rj85/rj100	ARJ	RJ70	Boeing 737-300 (winglets) Passenger	73C	B733
Avro RJ85	AR8	RJ85	Boeing 737-300 Passenger	733	B733
BAe (BAC/ROMBAC) 1–11 500	B15	BA11	Boeing 737-400 Passenger	734	B734
BAe (BAC) 1-11	B11	BA11	Boeing 737-500 Passenger	735	B735
BAe 146 Passenger	146	B461	Boeing 737-600 Passenger	736	B736

BAe 146-100	141	B461
BAe 146–200 Passenger	142	B462
Boeing 737–800 (winglets) Passenger	73H	B738
Boeing 737–800 Passenger	738	B738
Boeing 747 (Freighter)	74F	B741
Boeing 747 all Series (Mixed Conf)	74M	B74D
Boeing 747 all Series (Passenger)	747	B74D
Boeing 747-200 (Freighter)	74X	B742
Boeing 747–200B/200C (Passenger)	742	B742
Boeing 747-300/747-100/200 Sud (Pax)	743	B741
Boeing 747-400 (Mixed Configuration)	74E	B744
Boeing 747-400 (Passenger)	744	B744
Boeing 747–400F (Freighter)	74Y	B744
Boeing 757 (Passenger)	757	B752
Boeing 757-200 (winglets) Passenger	75W	B752
Boeing 757–200 Passenger	752	B752
Boeing 757–200 PF (Freighter)	75F	B752
Boeing 767 Freighter	76F	B762
Boeing 767 Passenger	767	B762
Boeing 767–200 Passenger	762	B762
Boeing 767–300 Passenger	763	B763
Boeing 767–400 Passenger	764	B764
Boeing 777 Passenger	777	B772
Boeing 777–200 Passenger	772	B772
Boeing 777–300 Passenger	773	B773
Boeing 777–300 ER Passenger	77W	B773
Canadair Regional Jet	CRJ	CRJ1
Canadair Regional Jet 100	CR1	CRJ1
Canadair Regional Jet 200	CR2	CRJ2
Canadair Regional Jet 700	CR7	CRJ7
Canadair Regional Jet 900	CR9	CRJ9
De Havilland DHC-8 Dash 8	DH8	DH8A
De Havilland DHC-8 Dash 8–400 Dash 8q	DH4	DH8D
De Havilland DHC-8-300 Dash 8/8q	DH3	DH8C
Boeing 737-700 (winglets) Passenger	73W	B737
Boeing 737-700 Passenger	73G	B737
Embraer 120 Brasilia	EM2	E120
Embraer 170	E70	E170
Embraer 170/195	EMJ	E170
Embraer 175	E75	E170
Embraer 190	E90	E190
Embraer 195	E95	E190
Embraer RJ 135/140/145	ERJ	E135
Embraer RJ135	ER3	E135
Embraer RJ145	ER4	E145
Embraer RJ145	EM4	E145
Fairchild Dornier 328-100	D38	J328
Fairchild Dornier 328jet	FRJ	J328
Fairchild Metroliner	SWM	SW4
Fokker 100	100	F28
Fokker 50	F50	F50
Fokker 70	F70	F70
Fokker F27 Friendship/Fairchild F27	F27	F27
Fokker F28 Fellowship all Series	F28	F28
Ilyushin IL-86	ILW	IL86
Ilyushin IL-96-300	IL9	IL96
McD-Douglas DC10 all Series (Pax)	D10	DC10
McD-Douglas DC9 10/20 Series	DC9	DC91
McD-Douglas DC9 30/40/50	D9S	DC93
McD-Douglas DC9-20	D92	DC92
McD-Douglas DC9-30 (Passenger)	D93	DC93
McD-Douglas DC9-40	D94	DC93
McD-Douglas DC9-50	D95	DC95
Saab 2000	S20	SB20
Saab 340	SF3	SF34
Tupolev TU134	TU3	T134
Tupolev TU154	TU5	T154
Yakovlev Yak-40	YK4	YK40

Appendix II. List of LCC by ICAO Definition

This is an extraction of LCC present in Lombardy in the observation period from the original document published by ICAO on their web site http://www.icao.int/sustainability/Documents/LCC-List.pdf.

Name of LCC	IATA Code	Registered in Lombardy
Air Arabia Maroc	3O	2010
Air Europe	PE	1999
Atlas Blue	8A	2007
Belle Air Europe	L9	2011
Belle Air	LZ	2007
Blue Air	OB	2008
Blue Panorama	BV	2011
Blue1	KF	2008
BMIBaby	WW	2003
Buzz	UK1	2001
Centralwings	CO	2006
Clickair	XG	2008
Condor Flugdienst	DE	2000
easyJet	U2	2004
Flybe	BE	2008
Germanwings	4U	2003
GO	GO	1999
ItAli Airlines	9X	2007
Jet2.com	LS	2004
Jet4you	8J	2008
MyAir	8I	2006
Niki	HG	2009
Norwegian Air Shuttle	DY	2011
Ocean Air	VC	2006
Ocean Air	7VC	2006
Pegasus Airlines	H9	2011
Ryanair	FR	2001
Sky Europe Airlines	NE	2003
SkyEurope Hungary	5P	2004
Sterling	NB	2003
Transavia.com	HV	2002
TUIFly	X3	2008
Virgin Express	BQ	1997
Virgin Express	TV	1997
Vueling	VY	2005

Wind Jet	IV	2004
Wizz Air	W6	2005

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Econometric Approach to Reveal Determinants of Air Cargo Volume of European Countries

Abstract

GDP has long been used as an indicator of air cargo level as they both reflect international trading activity from different angles. This was true and proofed when international trading was mainly composed by manufacturing outcome. However, in the era of new economy, characterized by just in time manufacturing and express e-commerce, while GDP is weighting more on service industries, the indicator of air cargo should be verified. This paper explores alternative economic measurements of a country, which may be possibly related to its air cargo volume. Data of European countries from 2007 to 2015 are collected. After testing some hypothesis with a set of econometric model, we found that a country's income level, online purchase activity and air cargo connectivity are all positive determinants of its air cargo level. We also draw some policy implications in the conclusion according to the findings and our understanding of transport and economics.

1. Introduction

Transport, as a channel to move people and goods, is vital to an economy (Brugnoli et al. 2018). In 2016, air transport supported 12.2 million jobs and $823 billion in European economic activity, which are expected to grow at 3.4% per year (ATAG[1], 2018). In the era of e-commerce and just-in-time manufacturing, high value international trading and global manufacturing were possibly initiated and developed wherever markets can be easily connected frequently and quickly. The benefit for air transportation to tourist flow is well-studied, given the determinants of air passengers' movement and its effect on the local economies; little is still instead known about the factors affecting air cargo activities, i.e., the volume of goods that are shipped by air transport.

Air cargo revenue to an airport can be great enough to sustain a city. Memphis in the US is among the most extreme cases, having over 4 billion pounds of cargo enplaned in 2004 resulting in $10 billion of associated revenue[2]. The economic value of air cargo was not fully investigated despite of ICAO (2015) stressing that "air cargo services are a tremendous enabler for economic progress in developing countries…"[3]. Only 38% cost-benefit analysis

[1] Air Transport Action Group publish biennale report highlighting the industry outlook.
[2] Sparks Bureau of Business and Economic Research (2005) measured the benefits resulted from aviation related activities at Memphis International Airport.
[3] ICAO, International Civil Aviation Organization, highlighted the benefit to employment and economic growth by trading of electrical components, perishable products (food and flowers).

of airport, summarized by TRB[4] (2009), quantified cargo benefit, the rest regarded such benefit hard-to-quantify or side-product of passenger transport.

Comparing to measureable benefit generated by tourist, air cargo's contribution was not properly captured perhaps due to its complex nature and less obvious relationship with other activities in the aviation business. Firstly, the beneficiaries may not be restricted to airlines, airport or forwarder, but also manufacturers demanding reliable transport or consumers enjoying the express services. Evidence of economic benefit of air cargo was shown in CBA of Rock County Airport by Wisconsin DOT (2000)[5], where the potential losses of surrounding business during supply chain interruption is considered. Secondly, air freight has low volume share among all mode of freight transport. However, the value of goods transport by air is significantly important, especially to today's new economies. Button (2000) proofed the impact on new economy employment of international air service. These are values beyond the yield of airports, carriers or integrators. Feng et al. (2015) summarized the main differences between air cargo and air passenger business as uncertainty (changing in booking or reservation in cargo business is very common), complexity (capacity forecast consists of parameter such as pivot weight, pivot volume, and center of gravity) and flexibility (air cargo can be transshipped more than one stop as long as it meets the delivery time). These could explain the challenge in capturing the practical reality of air cargo business.

In 2014, as shown by Shepherd et al. (2016), 50 million tons of freight were carried by air accounting only for 1% by volume but 35% of values of world traded goods. There is a very wide range of goods favorable to air cargo, from fresh seafood and flowers to high value electronics and hazard chemicals. Therefore, there are specific handling requirement and thus specific players in the field. The boundaries between different category of service providers is blurring when integration and cooperation becoming more common, some extreme cases are express air cargo carrier providing extra door to door service in partnership or Amazon's prime air in turn providing air cargo service when there is extra capacity from their core business.

[4] Transportation Research Board, a division of the National Research Council of the United States.

[5] The airport analyse the constrained runway impact on cargo activity. The expansion was finally approved when economic efficiency of cargo was considered on top of transportation cost saving. It shows that potential economic efficiency of cargo accounts for 40 million USD of labour costs and revenue losses due to production slowdown. Potential job losses are also highlighted when production shutdown, shifting 23,000 workplaces to other regions or countries.

This paper is aiming at finding out some determinants of air cargo traffic at the country level, and at drawing some policy implications to airport or airline managers and governments, when a strategy will be needed to boost air cargo traffic, or where will be the right place to exploit air cargo traffic opportunities. We try to address these issues by building a data set regarding European countries (EU28 + Switzerland + Iceland) during the period of 2007-15 and by designing a set of econometric model where possible determinants of air cargo levels are investigated. We used different econometric methods to verify the robustness of the model. We focus on some determinants that may explain the cargo levels in European countries, e.g., the e-commerce activity, the country's air cargo connectivity and the country's income.

We show that, one percentage point growth in country wage leads to 0.5% or 0.8% growth in air cargo level, while one percentage point increase in online purchase activity of a country will impact positively 2% of air cargo level and lastly one additional route partner city may generate 1.3% increase in cargo level, such impact may vary depends on which continent this additional partner city is located. Hence, while the income effect confirms that air cargo is determined by economic levels, we provide some new evidences that e-commerce is one important driver of air cargo volumes. This has some interesting policy implications: for instance, e-commerce taxation may generate a decrease[6] in cargo air transportation services with secondary effects on local employment and growth. On the contrary, the diffusion of fast broadband connections though investments in the country infrastructure may boost aviation activities at the local level through a secondary effect of e-commerce.

The remainder of this paper is structured as follows: in Section 2 we summarize the outlook of air cargo industry in Europe, in Section 3 we discuss the literature review, in Section 4 we develop the econometric model, in Section 5 we present the data and some descriptive statistics, while in Section 6 we show our empirical evidence. Section 7 concludes the paper and draws some policy implications.

[6] Burcu Kuzucu Yapar et al. (2015) discussed the impact of taxation on e-commerce in the absent of physical appearance and cross border trading among different business, consumer and government.

2. Air Cargo Industry in Europe

In 2015, according to Boeing's World Air Cargo Forecast 2016-2017, markets' performance varies across regions. Below we highlight those numbers involving Europe. The three growing markets are intra-Europe market, Asia-Europe market and Middle East-Europe market, having traffic growth of, respectively, 3.9% since 2013, 6.4% since 1995 and 3,6% since 2006. Most importantly the Europe-Asia market comprises approximately 20.3% of the world's air cargo traffic in tonne-kilometres and 10.5% in tonnage while the intra-Europe air cargo market comprises approximately 3.1% of the world's air cargo tonnage, and 0.8% of the world's tonne-kilometre. Express traffic averaged 7.6% growth per year during the past 20 years in Intra-Europe market while documents and small packages averaged 6.2% annual growth in daily shipment count in both directions since 2000 in Asia-Europe market. Meanwhile trade with Europe represented 37.8% of the Middle East's international air cargo market.

From the same report of Boeing, weaker performance in other markets involving Europe was found. Concerning Europe-North America, although air trade expanded 7.9% in 2014 and 4.2% in 2015 in the Europe-to-US direction, at 2.95 million tonnes in 2015 (3.0% of the world's air cargo traffic in terms of tonne-kilometres and 1.8% in trade tonnage) the market was 10.6% smaller than its peak of 3.30 million tonnes in 2007. Market growth was not steady, for example 4.5% in 2014 and 1.8% in 2015. In the Latin America–Europe market, which represents approximately 3.0% of the world's air cargo traffic in terms of tonne-kilometres and 1.8% in trade tonnage, air cargo growth slowed from 2.8% in 2014 to 0.6% in 2015. While in the Africa-Europe market, with the global economic downturn in 2008, Africa air exports to Europe continuously declined until 2013 while finally rebounded, to more than 503,000 tonnes in both 2014 and 2015.

In the industry, there are several categories of carrier providing air cargo service, namely passenger airlines, combination carriers, integrators and all-cargo airlines. The first use belly space of passenger flights, the second may carry air freight, express packages, and mail in the belly space of passenger aircraft or operate dedicated freight aircraft (Li et al., 2012). Integrators use air freighters while setting up distribution centres and ground fleet to provide express door-to-door service while all-cargo airlines fly between airports, being responsive to the demand and collaborating with freight forwarders.

Belly space capacity is increasing as air passenger demand grows globally, especially middle-east hub carriers are expanding cargo capacity by using new aircraft with extra belly capacity, highlighted by Merkert & Ploix (2014). Pointed out by Kupfer et al. (2017), the relatively low price tag offered by belly operators resulted from its flexible cost allocation strategy make the air cargo business more competitive, leading to bankruptcies and capacity reductions in the all-cargo segment. Some combination carriers re-position their strategy. For example, Air France-KLM, Singapore Airlines and EVA Air reduce full freighter operations while switching to belly operations. According to IATA statistics, the share of all-cargo and combi traffic (in FTKs) is 50-50 from 2009 to 2014. Combi aircrafts, allowing changing set configuration and cargo compartment are also used by combination airlines to guarantee profitability of low or fluctuating passenger demand route. Integrators, such as UPS, FedEx (who acquired TNT in April 2015) and DHL are expanding by developing cargo hubs in European airports such as Paris Charles de Gaulle, Cologne Bonn and Leipzig Halle (Malighetti et al., 2018). Secondary hub of these integrators are spread across Europe, for example Milan Malpensa and London Stansted. They not only sell capacity to shippers but also sell excess capacity to freight forwarders (Feng et al., 2015). Cooperation between integrators and traditional airlines is not rare. At some airports, integrators are among the main customers of traditional airlines and vice versa (Kupfer et al., 2010). Beside the carriers, there are also other actors competing or enjoying the growing air cargo volume. They are forwarders, terminal operating companies, hinterland transport companies, custom brokers and cargo handlers who flourished around the area of cargo airports.

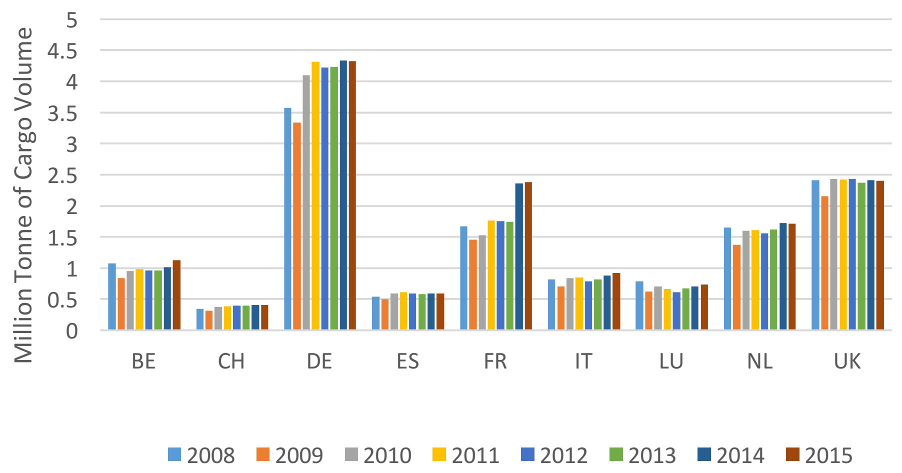

fig. 1 – air cargo volume of top 9 European countries
composed by author, Eurostat (database)

With data collected from Eurostat, we considered cargo level as freight and mail loaded and unloaded, representing the sum of cargo volume imported and exported by a country (instead of freight and mail on board which will double count transit volume). The following graph (figure 1) depicts cargo level of the top 9 countries, which account for 90% of total Europe cargo volume. All of these countries experienced a sudden drop in 2009 due to the global financial crisis hindering international trading. Then cargo volume picked up gradually afterward, highlighted by France's exceptional expansion in 2014.

A possible determinant of cargo activities is country income. Using data from Eurostat, it is possible to compare air cargo level with GDP. In figure 2, we show that cargo level's trend is generally increasing except the sudden drop in 2019 resulted by the global financial crisis. The air cargo's crest and trough seems to be driven by GDP. While in figure 3, this relationship is better illustrated in quarter on quarter growth from data until 2010. However, the magnitude of air cargo's growth is apparently more volatile than that of GDP. While the fact that we do not see growth of air cargo driven by growth of GPD in 2011 and the irregularity of 2014 suggest that there may be other determinants to be discovered. In fact, Kupfer et al. (2011) concluded that merchandise exports seem to be a better indicator to relate economic activity to air freight.

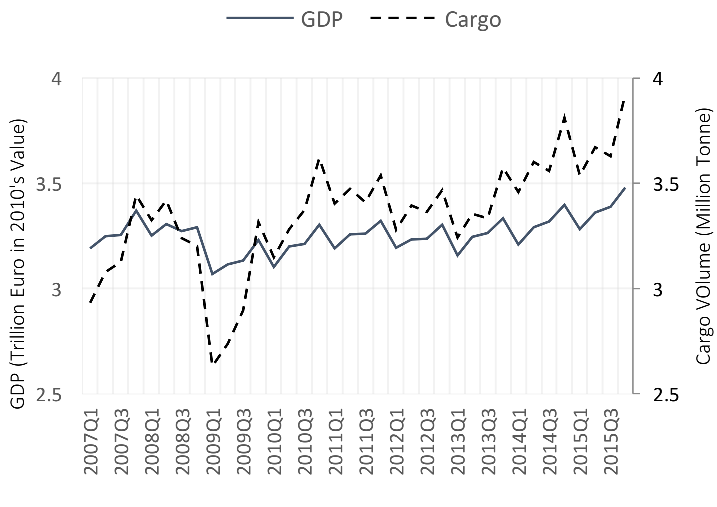

fig. 2 - Sampled European countries' GDP and Cargo Volume
composed by author, Eurostat (database)

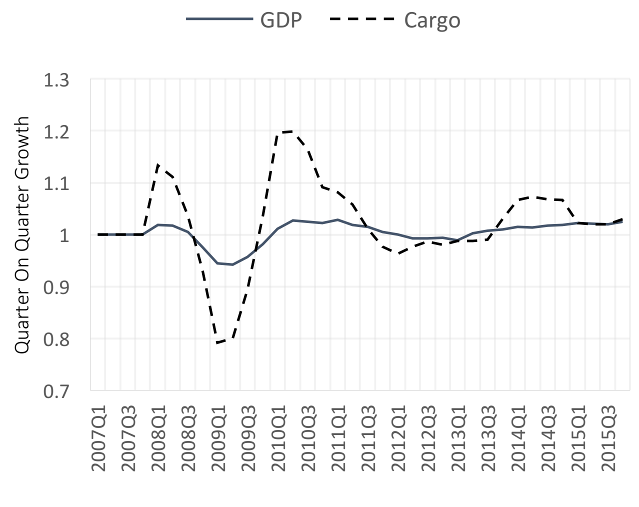

fig. 3 - EU28's GDP and cargo volume QOQ growth
i.e. comparing with the same quarter of previous year
composed by author, Eurostat (database)

3. Literature review

There are two streams of research papers of various scopes related to our contribution: firstly, econometric analysis and secondly, operation research. Economic analysis aims at find out relationship of economic indicators with air cargo attributes. The first empirical attempt was made by Kasarda & Green (2005) to investigate air cargo's relationship with other economic indicators. After indicating the predicting power (or correlation) of air cargo volume to GDP, they moved on the impact of liberalization, FDI, customs and corruption. Chang & Chang (2009) conduct a causality test of air cargo volume and GDP in Taiwan's data from 1974 to 2006, claiming that air cargo expansion plays a crucial role in promoting economic growth in Taiwan in a long run. Most recently, Button & Yuan (2012) found evidence of airfreight volume Granger causing growth in employment and income.

Other scholars tried to model the demand of air freight in global, country or airport level. By applying a model of global air cargo demand by merchandise trade, share of manufacturing in trade, air yield and oil price, Kupfer et al. (2017) attempted to to predict the future development of global air fright levels in the future base on 2010-13 growth. Lakew & Tok (2015) study socioeconomic determinants of air cargo traffic in California by a 7-year panel data (2003-2009) of quarterly employment, wage, population, and traffic data. They show that the concentrations of service and manufacturing employment as well as wages play a significant role in determining air cargo movement. Hwang & Shiao (2011) develop a gravity model of air cargo flows observing Taiwan Taoyuan International Airport. The model is developed based on the panel data of air cargo services on scheduled routes at during the years 2004–2007. The results indicate that population, air freight rate and three dummy variables, including the regional economic bloc of the ''Chinese Circle" (an informal partnership between Hong Kong, Macao, Taiwan and mainland China), the Open Sky Agreements and long established colonial links, are key determinants of international air cargo flows from/to Taiwan.

The other stream of operation research aim at the behaviour of players and the possible optimal solution. For example, fleet routing (e.g. Doan & Ukkusuri, 2015), flight scheduling (e.g. Yan & Chen, 2008). Some researches focus on airport, Kupfer et al. (2016) conducted interviews and set up discrete choice model to understand the airline mangers' choice on airport for cargo business while Nobert & Roy (1998), Ou et al. (2010) studies the impact of manpower and truck scheduling in terminal operation, specifically Merkert & Ploix (2014) investigated the importance of belly-hold freight. Boonekamp & Guillaume (2017) rank airports by capturing all possible air freight connections by connectivity model base on distance, time and frequency of operations while Mayer R. (2016) tried to categorize airports by cluster analysis using the share of air cargo activity in different dimensions. There are also literature investigating the revenue of carriers, for example Kasilingam (1997), Chao & Li (2017), Lin et al. (2017). Additionally, Yuen et al. (2017) discussed about gateway and hinterland airport. They suggest that there is potential competition and also cooperation among airports considering the Pearl River Delta region in China.

Contributions in both research streams have not explored yet the possible effect of some variables on cargo activity, such as the impact of e-commerce. Hence, our paper is a first attempt trying to fill this gap.

4. Empirical Strategy

As mentioned in the introduction, this paper is aiming at finding out the determinants of air cargo traffic at the country level, and aiming at drawing some policy implications. We define research questions to achieve such goal. Firstly, we consider determinants that may reflect consumption ability. Income level of a country may enhance the purchasing power and the total demand. Higher income of a country, which favor the fast but costly shipment reflected by air cargo level, may explain the relationship between white collar employment and demand of air cargo services. Hence, the following is our first research hypothesis.

RH1: The income of a country may be a positive determinant of air cargo level

Secondly, a strong growing element of air cargo industry is the express parcel carried as a result of booming e-commerce. Integrator will be more willing to invest in a country where local consumers are adapting such consumption mode quicker. Such purchasing pattern can be reflected by the percentage of population once purchased online in a country: for this reason, we investigate the following research hypothesis.

RH2: Online purchase activity may be a positive determinant of air cargo level.

Thirdly, we consider the aviation industry by air cargo transport connectivity of a country to the rest of the world. When a country is well connected by air, having more routes and reaching more cities in different continents, such country will be more attractive to carrier as it has higher strategic value to the penetration and responsiveness of the network. Consequently, we have our third research hypothesis, shown below.

RH3: The connectivity of a country may be a positive determinant of air cargo level

Such connectivity index is represented in two scenarios, firstly the aggregated index towards the rest of the world and secondly the disaggregated one by continents. We will investigate these research questions by developing a proper econometric model and by building a data set that allows us to consider variations in country cargo activities and characteristics, and, in turn, to draw some consistent estimates. Below, we show how the data set is generated.

4.1 Data mining

In the following paragraphs, we describe how the data is collected and how variables are constructed for 30 European countries (EU28 + Switzerland + Iceland) from 2007 to 2015 (36 quarters). Air cargo level is defined as air cargo volume (in tons) loaded and unloaded, representing the sum of cargo volume imported and exported by a country. This value is chosen instead of freight and mail on board because the later will double count transit volume. Quarterly data in country level is obtained from Eurostat. From the national account of same statistics body, we employed the quarterly income level of measured countries in 2010 Euro value. Furthermore, e-commerce statistics is available in Eurostat, where we can find percentage of internet users who bought or ordered goods or services for private use in the previous 12 months. Figure 7 shows the strong growth in online shopping activity across Euroepan countries.

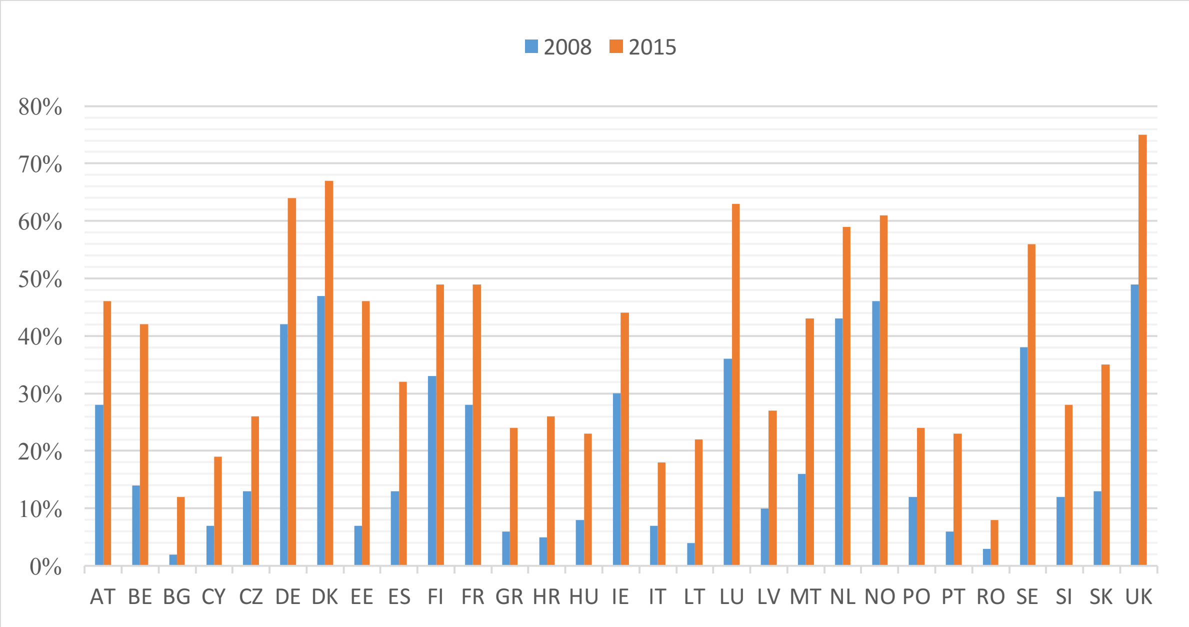

fig. 7 – Percentage of online shopper by country (percentage point in year 2008 and year 2015)

Connectivity is computed from database of OAG, which contain details of all routes in city-pairs level. We first screen all routes involving European countries with cargo volume recorded. Then aggregate the observed European country's partner cities by continents. So that we have the quarterly count of connected cities in a continent, which is having cargo flow with the observed country. Repeating the same for each observed European country, we then have a matrix of air cargo origin/destination in each continent for each quarter. We present below, by country, the average yearly cargo level (fig. 8) and the average quarterly connectivity (fig. 9).

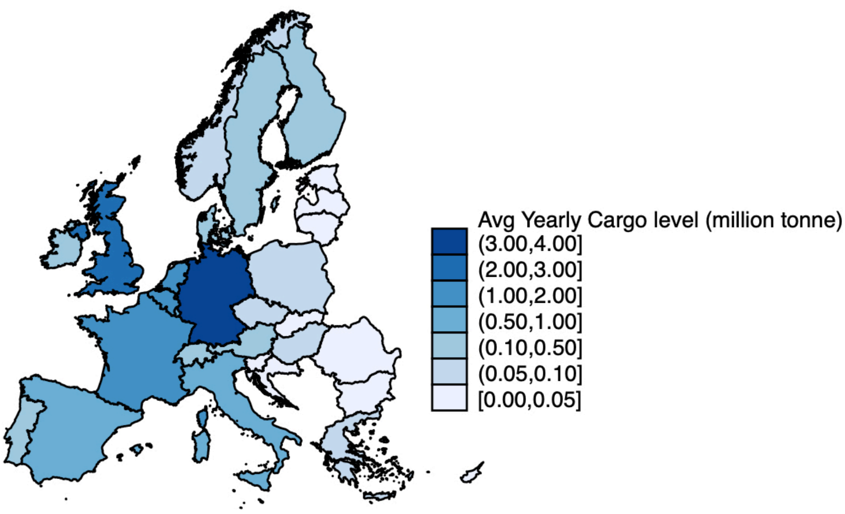

fig. 8 – Average yearly cargo level 2007 – 2015 (million ton)

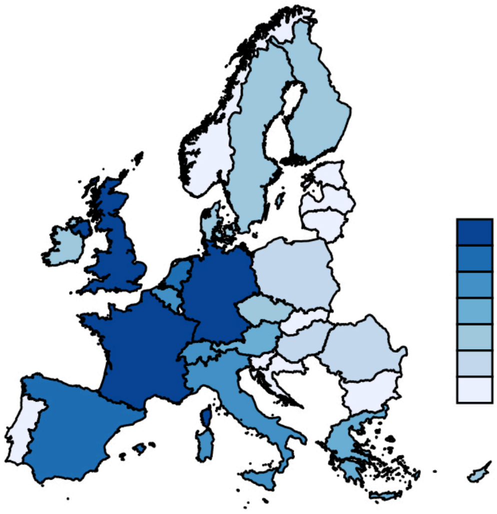

fig. 9 – Average quarterly connectivity 2007 - 2015 (O-D count)

4.2 Econometric model

Series of econometric models are constructed. These different econometric methods will be helpful to verify the robustness of the design. The first method employed is pooled OLS regression treating all data points, no matter of which country or of which year/quarter, in an unbiased manner. Meaning that there is no consideration of clustering any data point in the sample. The second method is panel data regression, deliberately taking into account the unobserved characteristics of a country and regard the data points in clusters according to the grouping, i.e. in our case the 30 European countries.

The econometric model is based on three equations and the two methods mentioned above, pooled OLS and panel data regression. In both cases, we use the robust estimator of variance-covariance matrix. Year and quarter are controlled in pooled OLS model while only year is controlled in panel data regression as the cluster is defined by country-quarter. We test RH1 and RH2 in the following the equation (1):

$$lnCARGO_{i,t} = \alpha + \beta_1 \times lnWage_{i,t} + \beta_2 \times perOnline_{i,t} + u_{i,t} \quad (1)$$

where *lnCARGO* is the logarithm of volume of air freight loaded and unloaded from country *i* at quarter *t*, *lnWAGE* is the logarithm value of total wage of country *i* at quarter *t*, and *perOnline* is the percentage of individual of country *i* making online purchase in the last 12 months, yearly data is duplicated in the quarterly format.

Then there is a second set of equations to test RH1, RH2 and RH3. Moreover, there are two specifications regarding connectivity. The first one includes a direct variable of general connectivity, that becomes equation (2). *CONN* is the count of partner cities among all routes of an observed country i in quarter *t*. Afterward, to further test the connectivity between observed countries and cities in different continents, namely Africa (*AF*), Asia (*AS*), Latin America (*LA*), Middle East (*ME*), North America (*NA*) and Europe (*EU*), we have the following extended equation (3).

$$lnCARGO_{i,t} = \alpha + \beta_1 \times lnWage_{i,t} + \beta_2 \times perOnline_{i,t} + \beta_3 \times CONN_{i,t} + u_{i,t} \quad (2)$$

$$lnCARGO_{i,t} = \alpha + \beta_1 \times lnWage_{i,t} + \beta_2 \times perOnline_{i,t}$$
$$+ \gamma_1 \times AF_{i,t} + \gamma_2 \times AS_{i,t} + \gamma_3 \times LA_{i,t} + \gamma_4 \times ME_{i,t} + \gamma_5 \times NA_{i,t} + \gamma_5 \times EU_{i,t} + u_{i,t} \quad (3)$$

For the second method of setting up a panel data, Hausman test confirms that fixed effect model is appropriated by rejecting the unique errors ($u_{i,t}$) are correlated with the regressors. The additional equations with variable in fixed effect panel date, α_i (n=1….30) the unknown intercept for each country, are not reported for the reason of simplicity. For the same reason the control variables of time are not shown in above equations.

Equations (1)-(3) present possible endogeneity problems, concentrated in the possible inverted causal relation between wage (the proxy for income) and cargo activity. In order to control for possible endogeneity we use a lagged variable for wage as instrument (presented as equation 2bis in the section 6). In this way we can check whether the previous year wage level in a specific country can determine the activity in air cargo in the current year. This should be enough to eliminate possible distortions arising from endogeneity.

5. Data

We observe 30 European countries (EU28 + Switzerland + Iceland) quarterly from 2007 to 2015 (36 quarters). Other than pool OLS model, unbalance panels are also set up. We have from all countries 1071 observation of air cargo level, per country ranges from 32 to 36 (mean 35.7). In total 9 data points are missing. 8 data points missing in 2007, when Croatia and Sweden were not reporting in that year. Another data point is missing from Norway 2008Q2. Furthermore, since e-commerce data of Switzerland is incomplete, leading to another 30 data point loss.

While log value is used in the model for some variables such as cargo level and wage, we report integer value in the following tables for cargo level and wage. Online purchase is percentage point in the following tables while multiplied by 100 to form integer from 0 to 100 in regression. For connectivity, both integer count is used in below table as well as regression.

The first table shows the descriptive statistics of the data set. Cargo levels range from 141 tons to 1,15 million tons with mean 0,124 million ton. Quarterly wages of observed countries vary from 497 million Euro to 385 billion Euro with mean 46 billion Euro. Online purchase user of European countries spread from 2% to 75% with mean 28.8%, of its population. Lastly, connectivity is lowest at 0 and highest at 180 per quarter per country, having a mean of 18.82 O-D (country-city) count.

Variable	Obs.	Mean	S.D.	Min	Max	Unit of measure
Cargo	1071	123992.5	221703.5	141	1145621	Tonne
Wage	1072	46449.83	72206.28	497.45	385140	Million Euro (in 2010 value)
PerOnline	1040	28.60	18.82	2	75	Percentage
Connectivity	1072	18.82	47.15	0	180	O-D count

Table 1 - Descriptive statistics of econometric model variables

The second table report the correlation of each variable in the data set. Cargo, wage and connectivity exhibit greater than 0.9 correlation, while Online purchase percentage has lesser than 0.5 correlation with all of the others.

Variable	Cargo	Wage	PerOnline	Connectivity
Cargo	1.0000			
Wage	0.9107	1.0000		
PerOnline	0.4895	0.4477	1.0000	
Connectivity	0.9085	0.9447	0.4211	1.0000

Table 2 – Correlation table

6. Results

In this following section, we present the result of the empirical strategy. First, we show results related to equation (1) with the first model, pooled OLS regression, on the left: and with the second model, panel data regression, on the right. In these models we use cargo level as explained variable while log value of wage and percentage point of online purchase user as explaining variables. Quarter and year are controlled in OLS while year is controlled in panel data as quarterly panel is established. Then it follows the result from equation (2) having the additional variable connectivity. And lastly the result from equation (3) is presented when connectivity is broken down in continent level.

Different from the above descriptive statistics presentation, log value is used in the model for some variables. They are cargo level and wage as their integer value is much greater than the other variables'. Thus log transformation will be considered, in any applicable case, when we discuss the results. From the pooled OLS regressions, we see strong significance in the variables that we are interested in. However, in panel data fixed effect regressions, those significance does not hold except wage. The strong fixed effect (or unobservable variable of each country) diminishes the explanatory power of the variables in such method. We tried running the estimation with only data from a quarter but the significance does not improve to a significant level. *P*-value is reported with * sigh according to its magnitude while *t*-ratio is reported in brackets under each coefficient.

	Dep. Variable: lnCargo Model 1 – pooled OLS regression				Dep. Variable: lnCargo Model 2 – panel data regression			
Variables	**Eq (1)**	**Eq (2)**	**Eq (2bis)**	**Eq (3)**	**Eq (1)**	**Eq (2)**	**Eq (2bis)**	**Eq (3)**
Constant	88.8 (2.64)	67.2 (2.18)	97.8 (3.82)	80.4 (2.39)	-89.6 (-1.58)	-87.5 (-1.55)	-63.7 (-3.56)	-89.4 (-1.721)
lnWage	0.858*** (37.4)	0.508*** (19.6)	0.530*** (17.6)	0.511*** (19.5)	0.688* (2.10)	0.675* (2.08)	0.678*** (7.36)	0.673* (2.11)
PerOnline	0.0212*** (7.96)	0.0193*** (7.86)	0.0213*** (12.1)	0.0217*** (6.56)	-0.00926 (-0.92)	-0.00910 (-0.91)	-0.00779 (-2.37)	-0.00924 (-1.00)
Conn		0.0129*** (17.6)	0.0118*** (14.1)			0.00234 (0.77)	0.00562 (3.07)	
AF				0.0339*** (8.81)				-0.00202 (-0.20)
AS				0.0125* (2.47)				-0.00589 (-0.27)
LA				0.0118* (2.25)				(omitted)
ME				0.0106* (2.47)				0.00967 (1.81)
NA				-0.0111 (-1.25)				-0.00451 (-0.49)
EU				(omitted)				0.0047 (0.42)
R^2	0.715	0.767	0.799	0.775	0.632	0.663	0.718	0.623
legend: * p<.05; ** p<.01; *** p<.001								

Table 3 – Econometric evidence

Wage is always significant in both methods of all equations, proofing the RH1, that the income of European countries is a positive determinant of air cargo level. The higher the income, or the more paid the workforce implying a higher percentage of white-collar, the more possible air cargo level will expand. 1 percentage point growth in wage leads to 0.86% or 0.69% growth in air cargo level according to pooled OLS model and panel data model respectively.

Then when we focus only on pooled OLS regressions, we can draw also the following results. Online purchase percentage is positively impacting air cargo level. So we proofed RH2, Online purchase may be a positive determinant of air cargo level. One percentage point increase in online purchase activity of a country will impact positively 2% of air cargo level, which is hold in all three equations.

There are two indexes about connectivity, the first one includes numbers of city connected in one variable while the second one disaggregates these cities with respect to their continents. In general, one additional partner city may generate 1.3% increase in cargo level (result from equation 2 in pooled OLS regression), in particular, additional destination in Africa will lead to above average marginal effect of cargo level (result from equation 3 in pooled OLS regression), while that of Asia, Latin America, Middle East will bring below average positive marginal impact. Lastly, North America partner city count is not significant in this model. We proofed RH3, the connectivity of a country may be a positive determinant of air cargo level while we also provide insight of such effect given by additional route partner may vary across different continents.

Since there is an inverted casual relationship between the level of cargo activities and the income (wage) at the country level, we control for this possible endogeneity by introducing a 1-year lag variable of wage as instrumental variable. The results are shown in Table 4, regarding equation (2). It is evident that using the instrument and controlling for possible endogeneity does not change the results. *P*-value is reported with * sigh according to its magnitude while *t*-ratio is reported in brackets under each coefficient.

	Model 1 – pooled OLS regression	**Model 2 – panel data regression**
Variables	**Eq (2bis)**	**Eq (2bis)**
Constant	97.8 (3.82)	-63.7 (-3.56)
$lnWage_{t-1}$	0.530*** (17.6)	0.678*** (7.36)
PerOnline	0.0213*** (12.1)	-0.00779 (-2.37)
Conn	0.0118*** (14.1)	0.00562 (3.07)
R^2	0.799	0.718
legend: * p<.05; ** p<.01; *** p<.001		

Table 4 – Result of introducing 1-year lag variable of wage as instrumental variable

We did also a check for multicollinearity by variance inflation factor of variables in the eq (2). Seen from table 5, we have the all VIF values of single variable and the mean VIF far lower than 10. None of them should be considered as a linear combination of other independent variables.

Variable	VIF	1/VIF
lnWAGE	3.01	0.332629
CONN	2.76	0.362468
perONLINE	1.31	0.760867
Mean VIF	2.36	

Table 5 - Variance inflation factor of variables in the eg (2)

To Sum up, the design of this model reveal some determinants of air cargo level among the European countries and during the period that we are observing. We also justify the hypotheses by applying the data set of European countries from 2007 to 2015 through this model. We show evidences that income, e-commerce activity and connectivity are positive determinants of air cargo level. Income estimated elasticity varies between +0.5% and +0.8%, while a +1% in the share of e-commerce gives rise to a +2% increase in cargo activity. Last a +1 route in country connectivity yields a +1.3% in cargo activity.

7. Conclusion

We would like to draw some policy implication and future research opportunity in below conclusion based on the above findings. First of all, the stimulation of online purchase, which principally relay on express shipment in the era of e-commerce, generates new demand of air cargo. This revolution mode of consumption reduces the commercial feasibility of traditional brick and mortar retail model which requires warehousing and extensive road transportation of goods. This may eventually reduce the demand and pollution from trucking. However, there may be trade off given by additional air freight traffic which will require a total analysis of possible scenarios.

Besides, we provide new evidence that e-commerce is one important driver of air cargo volumes. A possible e-commerce taxation will hinder e-commerce development and limit the growth of air cargo transportation services with secondary effects on local employment and growth. Meanwhile, the diffusion of fast broadband connections enabling online users in every aspect of their life, though investments in the country infrastructure may boost also aviation activities at the local level as a secondary effect of e-commerce.

Furthermore, liberalization in air transport enhance the flexibility of network, lowering the barrier of carriers to reach out new destinations. The connectivity improvement will again contribute to the supply of capacity and lowering the cost. Such relationship was seen in passenger flow. In this research we highlight the importance of connectivity to air cargo level while a deeper understand of such dynamic and a complete data base of more detailed O-D information will better define also the relationship of air cargo volume and liberalization.

Moreover, the result of this study can be useful to governors who may want to compete air cargo traffic share by facilitating e-commerce convenience and popularity, and to airline managers who may want to spot new cargo hub regarding the country's income level. Concerning connectivity, we also hinted the different degree of impact given by additional route partner city in different continents. It will be very interesting to investigate also the type of good which is transported between these countries to better illustrate the dynamic of air cargo transportation and the interdependence among economies. This may also eventually guide airline managers to build up a long term strategy for the air cargo network.

Last but not least, we would like to highlight the limitation and potential improvements of this paper. Income is the strongest indicator among the variables in the model while the rest of them are less significant in panel data. We agreed that there could be correlation or unobservable variable issues. A more elaborated data set may possible solve the issue when data about manufacturing goods movement by air, e-commerce trading path, air cargo movement by carrier category and route would be available. However, these are all privately ran business, therefore publication of such data is not strictly required by governments. To tackle unobserved variable in country level, future researches may move toward catchment area of air cargo airports, manufacturing activity, integrator presence or cooperation/competition with neighboring countries.

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