Airline Fleet Fuel Efficiency

Zsuzsanna Csereklyei*

David I. Stern

Crawford School of Public Policy, The Australian National University, 132 Lennox Crossing, Acton, ACT 2601, Australia.

* Corresponding author, e-mail: zsuzsanna.csereklyei@anu.edu.au

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Abstract

The airline industry is perhaps unique in the availability of global data on installed equipment at the individual machine and firm level, together with comprehensive information on model energy efficiency. In this paper, we estimate an econometric model using data on 1267 airlines to investigate the factors that affect airlines' choice of fleet fuel efficiency. Larger and newer planes are usually more fuel-efficient. Adjusting fleet fuel efficiency for the technical effect of aircraft size, we find that fleet fuel efficiency improves with the size of airlines and the price of fuel and deteriorates with higher capital costs. The elasticity of fuel efficiency with respect to the price of fuel is between -0.07 and -0.13. We find evidence for regional differences in fleet fuel efficiencies that are attributable to the adoption of distinct technologies, not related to age or size of aircraft or airline size.

JEL Classification: D22**,** L93, O14, Q40

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1. Introduction

The International Energy Agency (IEA) expects that up to 2040 reductions in energy intensity will contribute 42% of the reduction in greenhouse gas emissions relative to business as usual required to achieve the goal of limiting climate change to a 2°C increase in temperature (IEA, 2016). The IEA expects the majority of this improvement in energy intensity to come from improvements in the energy efficiency of energy services (IEA, 2014: 285-286). On the other hand, the mechanisms enabling the geographical spread of such energy saving technological improvements have not been sufficiently investigated (Barretto and Kemp 2008; Verdolini and Galeotti, 2011). The airline industry is perhaps unique in the availability of global data on installed equipment at the individual machine (and firm) level together with information on model energy efficiency. Though carbon emissions from air travel were less than 11% of transport emissions in 2010 (Sims *et al*., 2014), and a small share of global emissions, they will likely be of increasing importance (Nava *et al*., 2017). In this paper, we investigate the factors that affect the selection of fleet fuel efficiency by airlines across countries.

Aircraft fuel efficiency has been improving over time (EASA, 2016; GAO, 2014; IEA 2009; Peeters *et al*., 2005), even though the rate of efficiency improvement is currently slowing (IEA, 2009; Peeters *et al*., 2005), as airplane designs get closer to the technical optimum. At the same time natural diffusion processes might not “reliably spread the best innovations” in the market (Greve and Seidel, 2015). The IEA (2009) asserts that in the United States, technological and operational improvements led to a 60% improvement in the energy efficiency of aircraft between 1971 and 1998, even though the majority of improvements happened prior to the 1980s. On the other hand, there was an earlier decline in fuel economy due to the shift from piston engine to jet engine aircraft. (Peeters *et al*., 2005) The EASA (2016) reports that the mean age of European aircraft is increasing. This highlights the problem that the diffusion of newer, (more) efficient aircraft is generally slow, with the IEA (2009) noting that the average efficiency of fleet stock may lag 20 years behind new aircraft efficiency. However, there is no set of agreed international environmental and emissions standards for air transport, despite long-standing discussions by the ICAO (ICAO, 2016).

A number of studies deal with the historical and projected development of aircraft fuel efficiency (Babikian *et al*. 2002; Lee *et al*. 2001; Lee, 2010; Peeters *et al*., 2005, Zou *et al*., 2014), the impact of fuel prices on airline operations and finances (Adrangi *et al*. 2014;

GAO, 2014; Kahn and Nickelsburg, 2016; Murphy *et al*., 2013) and fleet scheduling and optimization (Naumann and Suhl, 2013; Rosskopf *et al*. 2014), and the impact of a carbon price on firm value (Vespermann and Wittmer, 2011; Scheelhaase *et al*., 2010, Murphy *et al*., 2013, Anger and Koehler, 2010). Also, a few studies estimate cost or production functions for relatively small numbers of airlines (e.g. Caves *et al*., 1984; Gillen *et al*., 1990; Oum and Yu, 1998; Coelli *et al*., 1999; Inglada *et al*., 2006). However, we are not aware of a study of similar scale to ours – which uses fleet data for 1267 airlines – that systematically examines the factors affecting airlines' choice of fuel efficiency.

We investigate the determinants of fleet fuel efficiency for 1267 unique airlines in 174 countries in 2015. The cross sectional units are individual airlines with commercial jets or turboprop airplanes in service as of 2015 (Flightglobal, 2015). Our model is based on a translog cost function where cost depends, *inter alia*, on the fuel efficiency of the planes owned or leased by each airline. We work with three different fuel efficiency variables. Simple fleet fuel efficiency is the seat weighted fleet fuel efficiency of the various aircraft models used by an airline. Larger (Babikian *et al*., 2002) and newer aircraft tend to be more fuel-efficient. Though airlines can improve fuel efficiency by using larger planes, the main reasons for using larger aircraft are route distance and traffic volume. Therefore, we also compute size adjusted fleet fuel efficiency, which removes the technological effect of aircraft size from aircraft fuel efficiency before computing fleet fuel efficiency. Though a major reason for using newer aircraft is to reduce fuel costs there will also be other motivations such as improving passenger comfort and reducing maintenance costs. Therefore, we also compute a size and age adjusted fleet fuel efficiency.

We find, irrespective of which measure of fuel efficiency we use, that higher domestic fuel prices and greater airline size are associated with better fleet fuel efficiency. The elasticity of fuel efficiency with respect to the price of fuel is between -0.07 and -0.13. Higher capital costs are associated with lower fleet fuel efficiency. The paper is structured as follows: Section 2 reviews the relevant literature, Section 3 introduces our model, Section 4 our data, Section 5 presents the results, and Section 6 concludes.

2. Airline Fuel Efficiency

Many factors affect airlines' decisions on the portfolio of planes they should hold and operate, including the average distance of the flights (long or short haul) usually flown, the fuel efficiency of the available aircraft, expected fuel prices (IEA, 2009), the price of new and used aircraft, financing requirements including owning vs. lease decisions (Gavazza, 2011), and the wages of staff.

For North American airlines the two largest expenditure items are fuel and labor (Neumann and Suhl, 2013). Kahn and Nickelsburg (2016) estimate that fuel prices make up about 25% of the operating expenses of US airlines, however, when kerosene and aviation fuel prices are higher the cost share of fuel can go up to 33% (Adrangi *et al*. 2014). Larger planes are usually more fuel efficient per seat-km for a given load factor (Naumann and Suhl, 2013), but they are also more difficult to fill, therefore, owning or leasing high-capacity airplanes in times of high fuel prices and low passenger numbers due to economic downturns can be financially very risky.[1]

The IEA (2009) claims that fuel-efficient aircraft can deliver net economic benefits already after a couple of years of service life. They estimate that given an oil price of USD 120/bbl that the benefit of upgrading and flying more efficient planes on long haul routes approximates to annually 6 to 8 million USD. Using a 10% discount rate and assuming 30 -years useful life, this amounts to about 10 years of undiscounted fuel savings or a net present value of 60 to 80 million. Assuming a purchase price of 40 million USD, the fuel savings easily pay for the additional price of newer aircraft.[2] These savings are larger the lower the discount rate is assumed to be. Since the price of oil has fallen to around USD 50/bbl since the IEA (2009) study was published, these savings have approximately halved resulting in much less incentive to improve fuel efficiency. However, the fleets in place in 2015 – the date of our study – will reflect the high oil prices in many recent years.

The relationship between fuel prices and fleet fuel efficiency has been the focus of longstanding academic interest. Two prominent examples from road transportation include Alcott and Wozny (2014), who find that consumers value discounted future gasoline costs only 76% of what they value purchase prices, and Li *et al*. (2009), who examine the channels

[1] As an example, it has been reported that Singapore airlines intends to terminate the lease on one of its A380, as it has problems filling it. (Leslie Joseph, Quartz, 15 September 2016).

[2] The United States Accountability Office (GAO) notes in its 2014 report that in response to fuel price increases airlines have taken a number of actions, including the “reconfiguration of fleets”, and increasing of operational efficiency. The GAO (2014) reports that many less fuel-efficient aircraft (e.g., Boeing 737-300/400/500 and McDonnell Douglas MD-80) were retired and replaced with technologically more advanced options such as Airbus A320 and Boeing 737-700/800/900. As a result, many manufacturers saw increased demand for more fuel-efficient aircraft in the second half of the 2000s.

through which gasoline prices affect fleet fuel economy such as the purchase of new efficient vehicles and the scrapping of older vintages. Their simulations indicate that a 10% increase in fuel prices results in 0.22% increase in fleet fuel economy in the short, and 2.04% in the long run. Burke and Nishitateno (2013) find that 1% increase in gasoline price leads to 0.15-0.2% improvement in new vehicle fleet fuel economy.

Zou *et al*. (2014) find by applying a stochastic frontier approach to studying 15 large jet operators in the US that the mean airline fuel efficiency in 2010 was 9–20% worse than that of the most efficient carrier, while the least efficient airlines were 25–42% behind industry leaders in terms of efficiency. Therefore, the hypothetical cost savings from enhanced efficiency for mainline airlines could be in the vicinity of a billion dollars in 2010. Airlines may improve their fleet fuel efficiency through technological innovation and the replacement of their stock, or through increasing operational efficiency. Adrangi *et al*. (2014) find a high effect of jet fuel price shocks on passenger revenue miles, and note that efficiency improvements are necessary for long-term survival. These improvements may arise from hedging, improved scheduling, optimal pricing, and the through the replacement of old vintage airplanes in the fleet with advanced technology aircraft. Similarly, Naumann and Suhl (2013) examine the importance of strategic flight planning in jet fuel consumption optimization. Kahn and Nickelsburg (2016) establish a binary choice model of airline fleet replacement and operation optimization based on US data. They find that in times of high fuel prices that airlines fly less fuel efficient planes more slowly, scrap older less efficient planes earlier, and use more fuel-efficient planes more.

Firms however might be constrained in their ability to quickly transition to a significantly more fuel-efficient fleet. This constraint might arise from the necessity to first sell their older planes to buy new aircraft, therefore, the associated transaction costs might be very high. Leasing planes makes it easier for airlines to replace their fleets. Accordingly, Gavazza (2011) finds that leased aircraft have 38% shorter holding durations on average, but fly 6.5% more hours than owned aircraft. As leasing reduces transaction costs, the number of new airplane leases have been constantly increasing in recent decades. Benmelech and Bergman (2011) claim that airlines are likelier to lease than to own aircraft in states with insufficient creditor rights, while Eisfeldt and Rampini (2009) assert that credit-constrained airlines are likely to lease more. The Economist (2012) estimated that about 40% of the world’s airline fleet is now rented. However, Kahn and Nickelsburg (2016) note that in times of higher jet fuel prices the lease price of efficient aircraft is also higher in the US.

A few authors have applied cost function or production frontier approaches to modeling airline decisions. Compared to these studies, our data set includes far more airlines and has much wider geographical scope. The tradeoff to reach this level of comprehensiveness is a lack of accurate firm level data on a number of variables of interest and as a result we use proxies for some explanatory variables.

Earlier studies (e.g. Caves *et al*., 1984; Gillen *et al*., 1990) focused mostly on the North American airline industry. Applying a translog total cost function and share equations to panel data, Caves *et al*. (1984) found no economies of scale that affected the relative costs of "trunk" and smaller regional airlines in the U.S. Instead, density of traffic within an airline's network rather than differences in the size of the network explained cost differences.

More recent studies (e.g. Oum and Yu, 1998; Coelli *et al*., 1999; Inglada *et al*., 2006) have investigated small numbers of international airlines. Oum and Yu (1998) apply a short-run translog unit cost function and cost share equations to 22 major international airlines over 1986-93. They construct a capital stock index for aircraft and ground equipment. Their other explanatory variables include *inter alia* aggregate output, labor, energy and materials prices, revenue shares of freight and mail, average stage length, a TFP index, and time fixed effects. They found that Non-Japanese Asian carriers were generally more cost competitive than the major U.S. carriers but Japanese carriers and major European carriers were less cost competitive. Coelli *et al*. (1999) apply a translog stochastic production frontier model to 32 international airlines in the period 1977-1990. The inputs include labor and capital and three "environmental variables" that explain "inefficiency": mean stage length, mean number of seats per aircraft, and load factor. However, they do not consider energy efficiency explicitly.

Inglada *et al*. (2006) estimate cost and production stochastic frontiers for 20 airlines for 1996-2000. The cost frontier has random efficiency terms but does not have biased technical change. Explanatory variables are KLEM prices and output measured in ton kilometers (using weight of passengers and freight), allowing for variable returns to scale. However, the study suffers from several endogeneity problems. In particular, capital prices are measured by capital expenditures divided by capacity and energy prices as energy cost divided by kilometers. However, all of these prices depend on the fuel economy and capital investment decisions made by airlines earlier, and so are not exogenous. Our paper addresses these issues by measuring the cost of capital by interest rates, and energy prices by exogenously determined gasoline prices and oil reserves.

3. Model

We assume that the total operating costs, *C*, of airline *i* at time *t*, is given by the cost function:

$$C_{it} = f(Q_{it}, p_t, d_{it}, r_{it}, w_{it}, E_{it}, \mathbf{z}_{it}, t) \qquad (1)$$

where Q is output, *p* is the international price of fuel, *d* is the domestic price of fuel, *r* is the cost of capital, *w* is the wage rate, *E* is fleet fuel efficiency, $\mathbf{z}$ is a vector of "environmental variables", and the final explanatory variable indicates that technology evolves over time. While fuel for international flights is effectively untaxed, fuel used for domestic aviation is taxed in many countries (Keen and Strand, 2007). We measure fleet fuel efficiency, *E,* as fuel consumed per seat-km assuming aircraft are used at full capacity. Therefore, it reflects the technical characteristics of the installed capital stock rather than actual operational fuel efficiency, which is influenced by load factors (and could be measured by fuel consumption per passenger-km). Environmental variables reflect the type of services provided by an airline – here we try to capture factors such as the typical flight segment length and plane size on costs. Details for all these variables are discussed in the Data Section below.

If larger aircraft are more fuel-efficient than smaller aircraft, *E* will depend on the size of aircraft employed. If newer aircraft are more efficient for a given seat size, *E* will depend on the age of the fleet as well. While airlines can choose larger and newer aircraft to improve fuel efficiency there are also other reasons why they would choose these over smaller and older aircraft. Therefore, we also investigate alternative measures of fuel efficiency, clean of size and age effects.

We assume that (1) can be represented by a translog cost function of the following general form:

$$lnC_{it} = \alpha_0 + lnA_t + \ln u_{it} + \boldsymbol{\beta}'\mathbf{x}_{it} + 0.5\mathbf{x}_{it}'\mathbf{B}\mathbf{x}_{it} + \mathbf{a}_t'\tilde{\mathbf{x}}_{it} + e_{it} \qquad (2)$$

where $\mathbf{x}_{it} = [\ln Q_{it}, \ln p_t, \ln d_{it}, \ln r_{it}, \ln w_{it}, \ln E_{it}, \ln \mathbf{z}_{it}]'$, $\tilde{\mathbf{x}}_{it} = [\ln p_t, \ln d_{it}, \ln r_{it}, \ln w_{it}, \ln E_{it}, \ln \mathbf{z}_{it}]'$, and primes indicate transposes. α_0 is a constant, $\ln A_t$ represents movement of the frontier due to technical change, $\ln u_{it}$ represents the technical inefficiency of airline *i* relative to the frontier, and e_{it} is a random error term. The vector $\mathbf{a}_t$ contains technical change biases. These are not restricted to interactions of a linear time trend and price. We explicitly assume that $\partial lnC_{it}/\partial lnE_{it}$ may change over time holding $\mathbf{x}_{it}$ constant. The cost function is homogenous of degree one in input prices.

We assume that conditional on output, prices, environmental variables, and technology that there is a cost minimizing fuel efficiency level, E_{it}^{*}. Partially differentiating (2) with respect to ln*E* we have:

$$\frac{\partial lnC_{it}}{\partial lnE_{it}} = \beta_E + \beta_{EQ} lnQ_{it} + \beta_{Ep} lnp_t + \beta_{Ed} lnd_{it} + \beta_{Er} lnr_{it} + \beta_{Ew} lnw_{it} + B_{EE} lnE_{it}^{*} + \sum_j B_{Ej} lnz_{it} + a_{Et} \quad (3)$$

Then setting (3) to zero, we can solve for E_{it}^{*}:

$$lnE_{it}^{*} = -\frac{\beta_E}{B_{EE}} - \frac{\beta_{EQ}}{B_{EE}} lnQ_{it} - \frac{\beta_{Ep}}{B_{EE}} lnp_t - \frac{\beta_{Ed}}{B_{EE}} lnd_{it} - \frac{\beta_{Er}}{B_{EE}} lnr_{it} - \frac{\beta_{Ew}}{B_{EE}} lnw_{it} - \sum_j \frac{B_{Ej}}{B_{EE}} lnz_{it} - \frac{1}{B_{EE}} a_{Et} \quad (4)$$

Our empirical analysis assumes that E_{it}^{*} is at a long-run equilibrium and we estimate the following regression for a cross section, where we add a random error term to account for optimization errors, measurement errors, omitted variables etc.

$$lnE_i^{*} = \gamma_E + \gamma_Q lnQ_i + \gamma_d lnd_i + \gamma_p lnr_i + \gamma_w lnw_i + \sum_j \gamma_i lnz_i + \varepsilon_i \quad (5)$$

Therefore, both the common international fuel price and the technical change bias term have fallen out.

The airlines in the sample vary tremendously in size from 15 to 183554 total seats. It is plausible that larger airlines will find it easier to adjust to the long-run equilibrium by maintaining a portfolio of different aircraft models and gradually introducing new models. By analogy with grouping heteroskedasticity, the variance of the residuals might be inversely proportional to the total number of seats. The Breusch-Pagan test statistic for heteroskedasticity related to the total number of seats in the first regression of Table 4 is 69.62, which is distributed as chi-squared with one degree of freedom (p=0.00). Therefore, we present weighted least squares (WLS) estimates as a robustness check, where the weights are the square root of the total number of seats available to each airline. We compute robust standard errors clustered by country for both OLS and WLS models. Using WLS together with heteroskedasticity consistent standard errors should result "in valid inference, even if the conditional variance model is misspecified" (Romano and Wolf, 2017, 2).

4. Data

Aircraft data

Our data on the aircraft operated by each airline is taken from the World Airliner Census (Flightglobal, 2015). The Census gives a snapshot as of 2015 of the type and number of different types of aircraft operated (owned and leased) by commercial airlines and air-freight companies throughout the world. After deleting 5 airlines for which we could not determine their country of registration, we have data on 1267 different airlines.

While the census data include "all commercial jet and turboprop-powered transport aircraft, built by Western, Chinese or Russian/CIS/Ukrainian manufacturers in service", as well as company orders, for the purpose of this study, we excluded not-yet delivered orders from the dataset. Flightglobal (2015) defines an aircraft "in service" when it is "active (in other words accumulating flying hours)."

The census data include all cargo, passenger and multi-purpose planes. We excluded aircraft types that are only used for cargo flights from the dataset,[3] as no seat number could be determined. If a plane is multi-purpose and can be operated both as a passenger plane and as cargo, we included it. Planes with fewer than 14 seats are excluded from the World Airliner Census data. We have allocated airlines to the countries where their company offices are registered. We determined the locations using information available on the Internet, such as ch-aviation.com, flightglobal.com, and other sources.

Technical Characteristics and Fuel Efficiency

We determine the maximum range, maximum fuel capacity, typical number of seats, and the year of first flight for each of the 143 aircraft types in our dataset. We use original company documentation from Airbus, Boeing, and other manufacturers, which are openly available on the Internet. For a small number of older aircraft, and for some specific models of a given type of aircraft we could not locate technical data. In this case, we took the data of the most

[3] Airbus A330-200F, Airbus C212, Antonov AN-12, Antonov AN-30, Antonov AN-124, Antonov AN-178, Antonov AN-225, Boeing 777F, GAF Nomad, Harbin Y-12, Ilyushin IL-76, Lockheed L-100 HERCULES, Lockheed L-188 ELECTRA, McDonnell-Douglas DC-3

similar model of the same type of aircraft, or the data for a different type of aircraft from the same manufacturer.[4] The exact list of aircraft used, their technical data, and the sources for the technical data are in the Appendix.

As explained above, we use three alternative measures of fleet fuel efficiency in our study. We calculate the simple fuel efficiency of aircraft model j, E_j, as follows:

$$E_j = \frac{F_j}{R_j S_j} * 100 \tag{6}$$

where F denotes maximum fuel capacity, R maximum range in kilometers, and S is the typical number of seats.[5] Fuel efficiency of each airline fleet is calculated by weighting aircraft model efficiencies by the total number of seats available for model j for that airline, S_{jit}, dividing by the total number of seats on all aircraft available to that airline, S_{it}, and summing over all models:

$$E_{it} = \sum_{j=1}^{J} \frac{S_{jit}}{S_{it}} E_j \tag{7}$$

Thus the metric we have is the average efficiency per seat in a fleet, calculated across the different aircraft types. Lower values indicate higher fleet fuel efficiency.

To account for the fact that larger aircraft tend to be more fuel-efficient, we also construct an alternative, "size-adjusted" fuel efficiency measure, clean of the effect of aircraft size. The reason we adjust the dependent variable rather than control for size in the regression analysis is that our intention is to remove only the technology effect of aircraft size on fuel efficiency. There may also be a behavioral effect of aircraft size on the choice fuel efficiency. This is done by regressing E_j on the average number of seats S_j for that model:

$$\ln E_j = \gamma_0 + \gamma_1 \left(\ln S_j - \overline{\ln S} \right) + \sum_{k=1}^{K} \gamma_{k+1} d_{kj} + \varepsilon_J \tag{8}$$

[4] These changes are documented in the Technical Appendix.
[5] We used typical number of seats in an aircraft. However, in some cases only maximum numbers were available. The exact sources and the seat number specifications are found in the Technical Appendix.

where $\overline{lnS}$ is the mean of lnS_j across all aircraft models. Because average aircraft size may have increased over time, we include K-1 decadal dummies, d_k, for each decade prior to the most recent decade. These control for the time of the first flight of each aircraft model.[6] We then predict size-adjusted fuel efficiency for each plane model:

$$E_j^A = exp\left(\ln E_j - \gamma_1\left(\ln S_j - \overline{\ln S}\right)\right) \tag{9}$$

We then aggregate these model efficiencies to airline efficiencies as before, giving us a size-adjusted fleet fuel efficiency:

$$E_{it}^A = \sum_{j=1}^{J} \frac{S_{jit}}{S_{it}} E_j^A. \tag{10}$$

Our third measure, size and age adjusted fleet fuel efficiency, also removes the effect of model age from the fleet efficiency variable:

$$E_j^B = exp\left(\ln E_j - \gamma_1\left(\ln S_j - \overline{\ln S}\right) - \sum_{k=1}^{K} \gamma_{k+1} d_{kj}\right), \tag{11}$$

We aggregate as before:

$$E_{it}^B = \sum_{j=1}^{J} \frac{S_{jit}}{S_{it}} E_j^B. \tag{12}$$

Wages:

We estimate wages *(w)* based on the available wage data in the ICAO (2015) database. A small number of airlines have wage data in nominal US dollars converted at market exchange rates for 2015 in the ICAO database. For these airlines we compute an average wage for all staff at the airline. We use mid-year data on staff numbers unless only year-end data were available. Some of this data is clearly anomalous and we deleted obviously incorrect values. This includes all average wages above \$200,000 and \$1,000.[7] For airlines without apparently reliable 2015 data but seemingly reliable wage for earlier years in the database, we used that earlier wage to project the wage in 2015 using the parameters from a within airline regression (i.e. using fixed effects for each airline) reported in Table 2. For Venezuela we used 2013 estimates. We could estimate wages for 491 airlines in this manner. The within regression

[6] Where data on the year of the first flight was not available, we allocated a decade based on our best guess. These assumptions are documented in the Appendix.
[7] We did use a value of \$834 in 2006 for Kyrgyzstan Airways to project the 2015 value.

regresses the logarithm of wages on GDP per capita data both in nominal US dollars converted at market exchange rates. Table 2 presents these results:

	Within Regression		Between Regression
Dependent Variable	ln wage		ln wage 2015USD
ln GDP per capita	0.8317***	ln GDP per capita 2015USD	0.5540***
	(0.0443)		(0.0234)
		Constant	4.9805***
			(0.2357)
N	2480		491
R-squared	0.309		0.598

Heteroskedasticity robust standard errors in parentheses. Standard errors for within regression are clustered by airline.

* p<0.10, ** p<0.05, *** p<0.01

Table 1: Wage Regressions

The regression shows that wages increase by 0.83% for a 1% increase in GDP per capita. This coefficient is significantly less than 1. We project the 2015 wage rate as follows:

$$\ln\widehat{W}_{i,2015} = \ln\widehat{W}_{i,b} + 0.8317\left(\ln G_{i,2015} - \ln G_{i,b}\right) \qquad (13)$$

where $\widehat{W}_{i,2015}$ is the projected wage, $W_{i,b}$ is the wage in the base year, and $G_{i,2015}$ and $G_{i,b}$ are GDP per capita in 2015 and the base year respectively in USD converted at market exchange rates.

Where no reliable wage data are available in the ICAO database we use the following regression procedure. First we converted all apparently reliable nominal wages to 2015 US Dollars using the US implicit GDP price deflator. We converted the GDP per capita for the relevant country and year in the same way. We then used the between estimator to estimate a regression of the log of wages on GDP per capita. The results are also in Table 1. A pooled OLS regression on the sample of 2480 original data points produces almost identical results. As we would expect, airline jobs are relatively well paying in poor countries and so the elasticity is substantially less than unity. We then used the between regression results to project wages to the remaining airlines using observations on GDP per capita in 2015 in US dollars converted at market exchange rates in the relevant country:

$$\ln\widehat{W}_{i,2015} = 4.9805 + 0.5540\ln G_{i,2015} \tag{14}$$

where $\widehat{W}_{i,2015}$ is the projected wage and $G_{i,2015}$ is 2015 GDP per capita in USD converted at market exchange rates. Where 2015 data were not available, we used the most recent year from the World Development Indicators. We used the Penn World Table to obtain values for 2014 for Syria and Taiwan. We used a variety of online sources for a number of small island countries such as the Cook Islands, Greenland, and Guam and for North Korea.

Interest Rates

Real interest rates *(r)*, which we use as proxy for the cost of capital, were sourced from the World Bank (2017) and the ECB (2017).[8] The World Bank uses the data from the International Monetary Fund, International Financial Statistics and its GDP deflator, to calculate real interest rates. As the World Bank data are missing interest rates for a large number of countries including all countries in the Euro Area, we calculated the real interest rates for a number of European countries, by using the ECB's (2017) composite cost of borrowing on new loans for non-financial corporations and deflating it with the World Bank's (2017) deflator.[9]

Output

We approximate output, which measures the effect of economies of scale, as the total seats available to an airline. This assumes that all airlines operate all plane types for the same fraction of available time with the same loading. Obviously, a more direct measure of traffic volume such as passenger-miles flown would be a better measure of output. While the IATA does offer monthly traffic data for some of its member carriers, the reported numbers are voluntary and only cover at most 130 airlines.

[8] "Real interest rate is the lending interest rate adjusted for inflation as measured by the GDP deflator. The terms and conditions attached to lending rates differ by country, however, limiting their comparability." (World Bank definition, series: FR.INR.RINR)
[9] "Inflation as measured by the annual growth rate of the GDP implicit deflator shows the rate of price change in the economy as a whole. The GDP implicit deflator is the ratio of GDP in current local currency to GDP in constant local currency." (World Bank definition, series: NY.GDP.DEFL.KD.ZG).

Aviation Fuel Price

Data on aviation fuel prices are not readily available for our dataset on a country level. While fuel on international flights is untaxed, countries within their jurisdiction may choose to tax domestic aviation fuel. Fuel prices for international flights at international trading hubs vary slightly. Also, airlines might not refuel in their country of origin, but might do so while flying different "legs" of their international routes and fuel prices for domestic and international airlines in some countries may differ. Platts offers jet fuel price comparison on a regional (continental) basis for one day of a year, while daily spot prices for several major trading hubs are only available on a subscription basis. Below is a snapshot of regional jet fuel prices as of 25 April 2017:

	Share in World Index	cts/gal	$/bbl	$/mt	Index value 2000=100%
Platts Global Index	100%	148.69	62.45	492.42	170.71%
Platts Regional Indices					
Asia & Oceania	22%	148.35	62.31	492.23	178.03%
Europe & CIS	28%	148.89	62.53	492.75	168.48%
Middle East & Africa	7%	144.33	60.62	478.28	181.02%
North America	39%	148.78	62.49	493.64	166.12%
Latin & Central America	4%	155.93	65.49	504.28	181.42%

Table 2: Platts Jet Fuel prices: snapshot from: http://www.platts.com/jetfuel, 26 April 2017.

The lowest average jet fuel prices are in the Middle East and Africa, and the highest prices in Latin and Central America. At the same time, the differences are not major, with only 8% difference between the lowest and highest price range. Given all this, we decided to assume that the international fuel price faced by each airline was the same and so in our cross-sectional estimation is absorbed into the constant.

We use different proxies for the domestic aviation fuel price, including the World Bank's (2017) information on road gasoline prices,[10] oil rents as a fraction of GDP,[11] and proven oil reserves per capita (Burke, 2013).

Environmental Factors

The environment, **z,** in which airlines operate has a significant impact on their cost function.

For our simple fleet fuel efficiency model, which does not remove the effects of aircraft size and model age from estimated fleet fuel efficiency, we alternatively control for the average seat size within a fleet, and for the estimated maximum age of the fleet. The vintage (V) of the fleet is calculated by deducting the year of the first (YF) flight for a specific model from 2015:

$$V_{i,t} = 2015 - YF_{i,t} \tag{15}$$

This gives us the maximum age of a specific aircraft flown in a fleet. We take the seat weighted average of the aircraft age, in a given fleet, giving us effectively the maximum age of a seat in a fleet.

$$V_{it} = \sum_{j=1}^{J} \frac{S_{jit}}{S_{it}} V_j \tag{16}$$

The average seat size within a fleet is calculated in a similar manner:

$$S_{it} = \sum_{j=1}^{J} \frac{S_{jit}}{S_{it}} S_j \tag{17}$$

All models also control for country area and population. These variables control for the fact that larger countries in both population and area might see a higher number of flights between cities and this might not simply be a function of either area or density. A higher average distance between cities would increase the share of domestic travel that takes place by air. While small countries usually would have more international air travel relative to domestic, a

[10] "Fuel prices refer to the pump prices of the most widely sold grade of gasoline. Prices have been converted from the local currency to U.S. dollars." (World Bank definition, series: EP.PMP.SGAS.CD).

[11] "Oil rents are the difference between the value of crude oil production at world prices and total costs of production."(World Bank definition, series: NY.GDP.PETR.RT.ZS.CD)

large small population country such as Australia might also have relatively more international travel than a large more densely populated country such as China. Country area controls for the increased likelihood of internal flights, which face the domestic fuel price. Both variables are sourced from the WDI (World Bank, 2017).

We control for the general air-traffic activity in a country by using data on the number of passengers carried per country (World Bank, 2017).[12] We also control for unobserved geographical and regional characteristics of the area airlines operate in, using dummy variables for the World Bank's regional classification including, East Asia and Pacific, Europe & Central Asia, Latin America & Caribbean, Middle East & North Africa, North America, South Asia, and Sub-Saharan Africa. East Asia and Pacific is the default region in our regressions.

5. Results

5.1. Characteristics of airline fleet fuel efficiency

Figure 1 presents the relationship between aircraft seat fuel efficiency, and the first year of flight. The Figure shows that on average the fuel efficiency of new aircraft models has been improving over the past 70 years, in line with our expectations.

[12] "Air passengers carried include both domestic and international aircraft passengers of air carriers registered in the country" (World Bank definition, series: EP.PMP.DESL.CD).

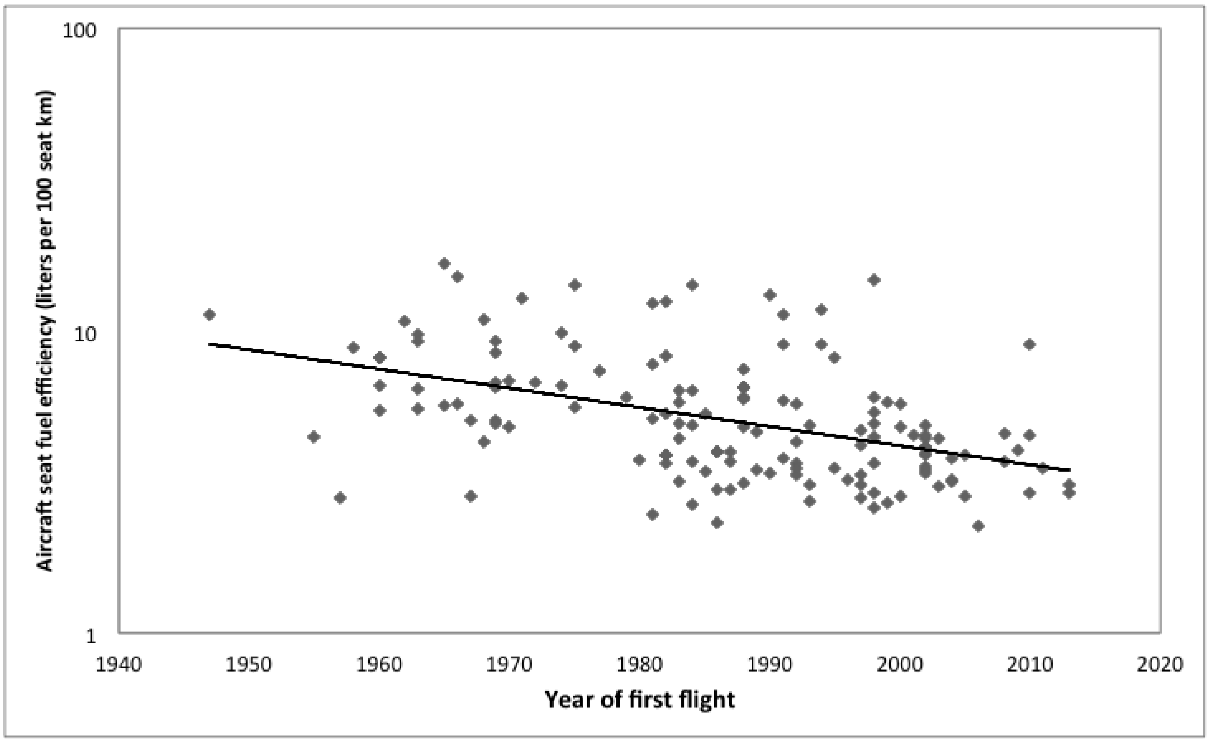

Figure 1: Aircraft fuel efficiency in the year of first flight for a sample of 143 aircraft models

Aircraft have also become larger over time, which is one of the main drivers of simple fuel efficiency. Figure 2 depicts the relationship between seat size and aircraft fuel efficiency. This relationship appears to be linear on a log scale meaning that while fuel efficiency improvements have progressed at a constant percentage rate, in absolute numbers there have been slowing incremental improvements, despite increases in aircraft size and other independent technical improvements. These findings are in line with the IEA's (2009) report on slowing efficiency gains as new aircraft models get closer to the technologically achievable fuel efficiency levels. However, older aircraft sometimes get retrofitted with newer engines and wingtips etc. Our data cannot capture such retrofitting.

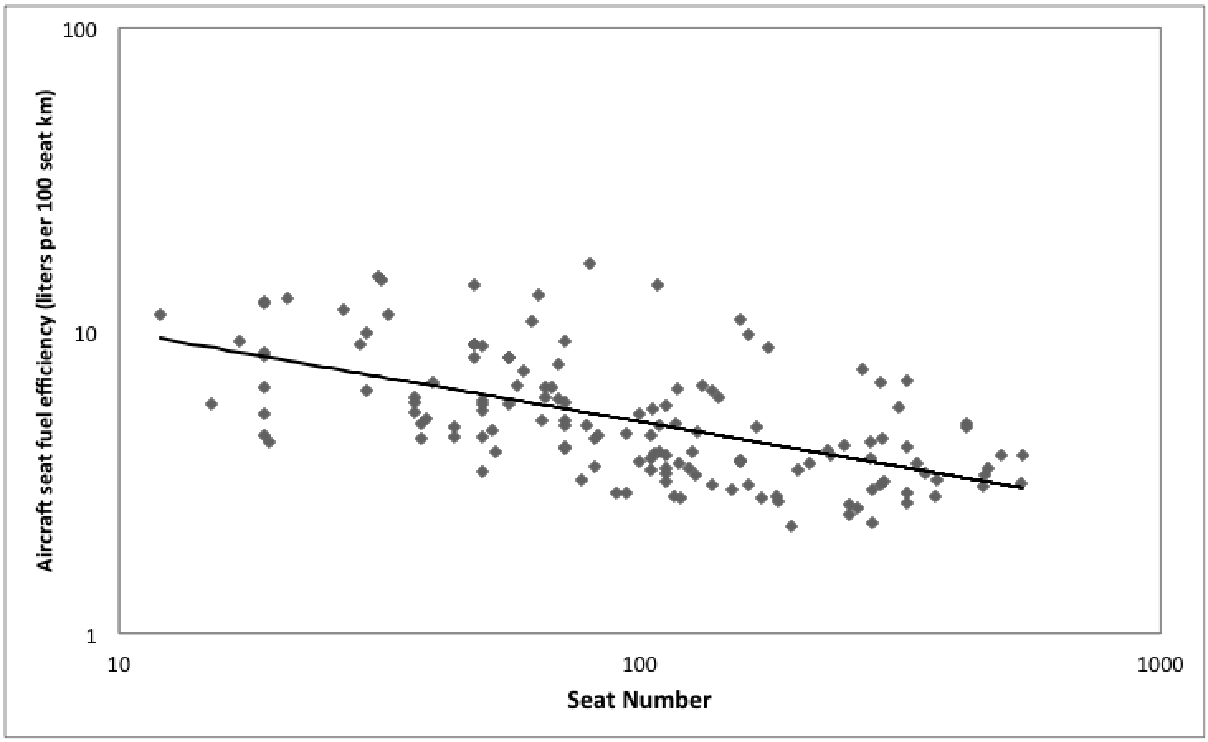

Figure 2: Aircraft fuel efficiency and seat numbers for a sample of 143 aircraft models.

	ln efficiency 1
Demeaned Log Seats	-0.274***
	(0.0333)
1940s	0.280***
	(0.0971)
1950s	-0.00663
	(0.335)
1960s	0.304**
	(0.138)
1970s	0.537***
	(0.0968)
1980s	-0.00112
	(0.0841)
1990s	0.0121
	(0.0903)
2000s	-0.168**
	(0.0755)
Constant	1.468***
	(0.0648)
N	143
adj. R-sq	0.468

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 3: The effect of seat size and the decade of first flight on aircraft fuel efficiency.

Table 3 shows the magnitude of the impact of aircraft size on efficiency, while controlling for the fact that technology has been changing over time. We find that planes with more seats are significantly more fuel-efficient independent of the time effect. The numbers indicate that aircraft introduced in the 1940s, 1960s, and 1970s were significantly less fuel-efficient than recent aircraft, *ceteris paribus*. Aircraft introduced in the first decade of the 21st Century were more fuel-efficient.

To account for the significant impact of plane size on efficiency, we created size-adjusted aircraft efficiencies as described in the Data Section. Figure 3 plots seat weighted airline fleet fuel efficiency against size-adjusted efficiency.

Less (more) fuel-efficient airlines tend to look relatively more (less) efficient using size adjusted fuel efficiency than simple fuel efficiency. Because larger airlines in terms of the total number of seats also tend to use larger aircraft, this correction also means that the relationship between fuel efficiency and airline size should be less pronounced using size adjusted fleet fuel efficiency than simple fuel efficiency. Figure 4 shows the relationship between simple fleet fuel efficiency and airline size. Larger airlines tend to fly longer legs with larger aircraft, therefore their seat weighted simple efficiency will be better due to the higher number of large aircraft.

In Figure 5 we show the impact of airline size on size adjusted fleet fuel efficiency. As expected, the relationship is less strong, but still suggests that there are economies of scale.

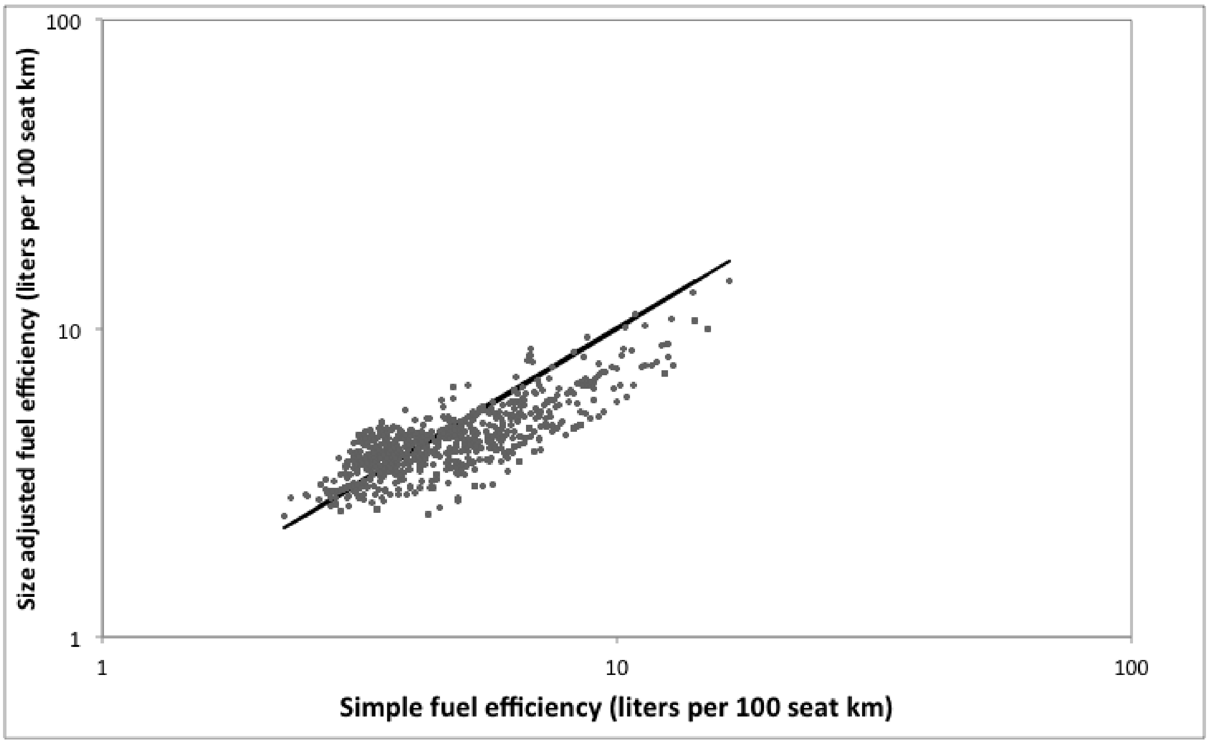

Figure 3: Airline simple fleet fuel efficiency vs. size-adjusted airline fleet fuel efficiency for 1267 airlines. The solid line represents a 45 degree line.

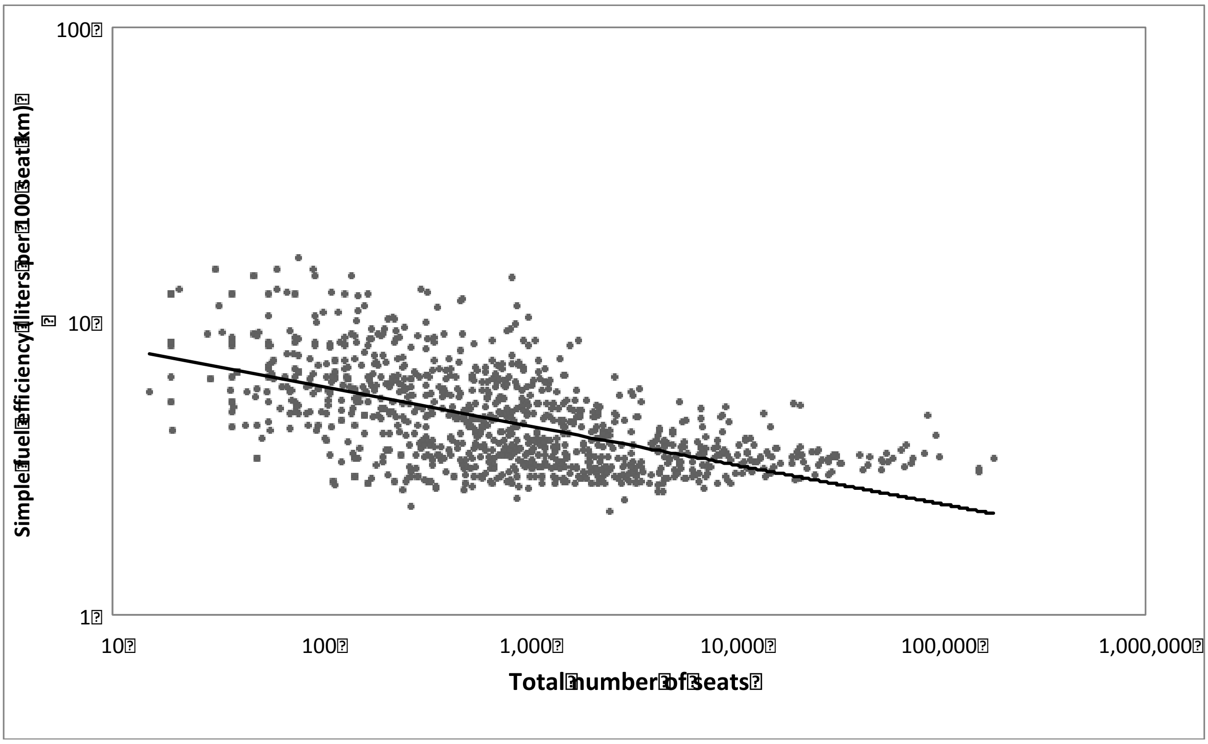

Figure 4: Airline simple fleet fuel efficiency and total number of seats

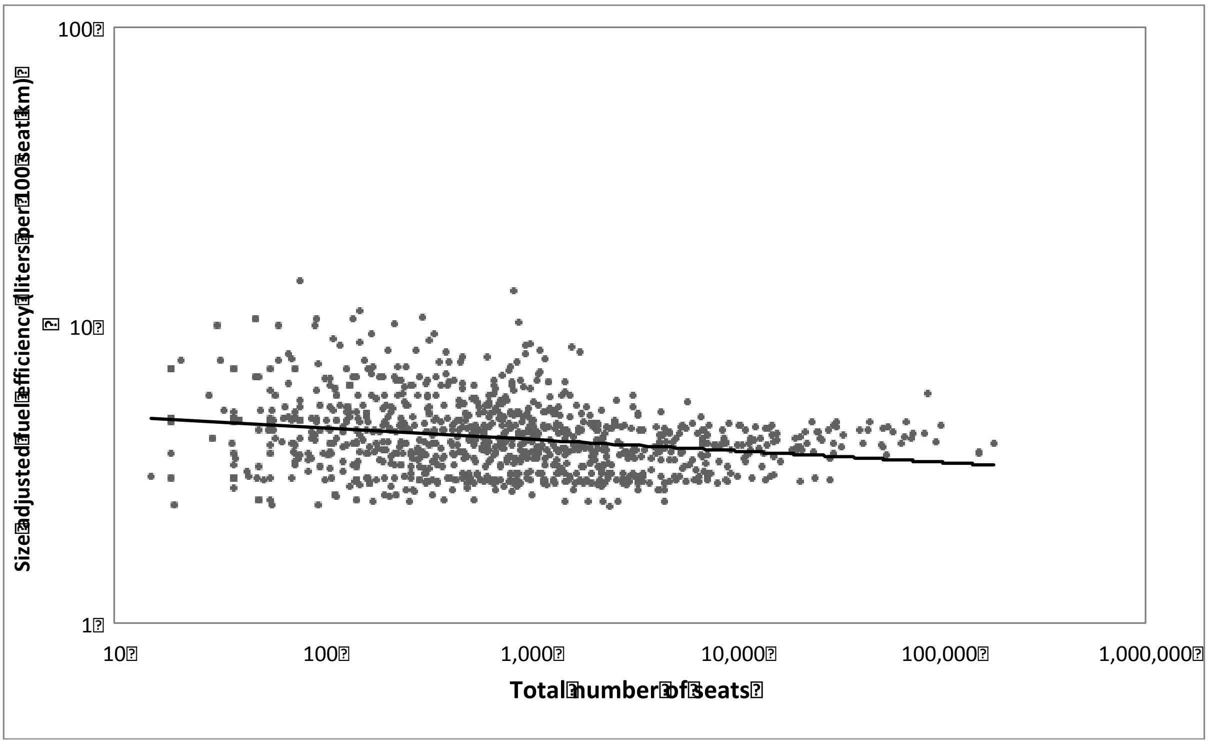

Figure 5: Airline size adjusted fleet fuel efficiency and total number of seats

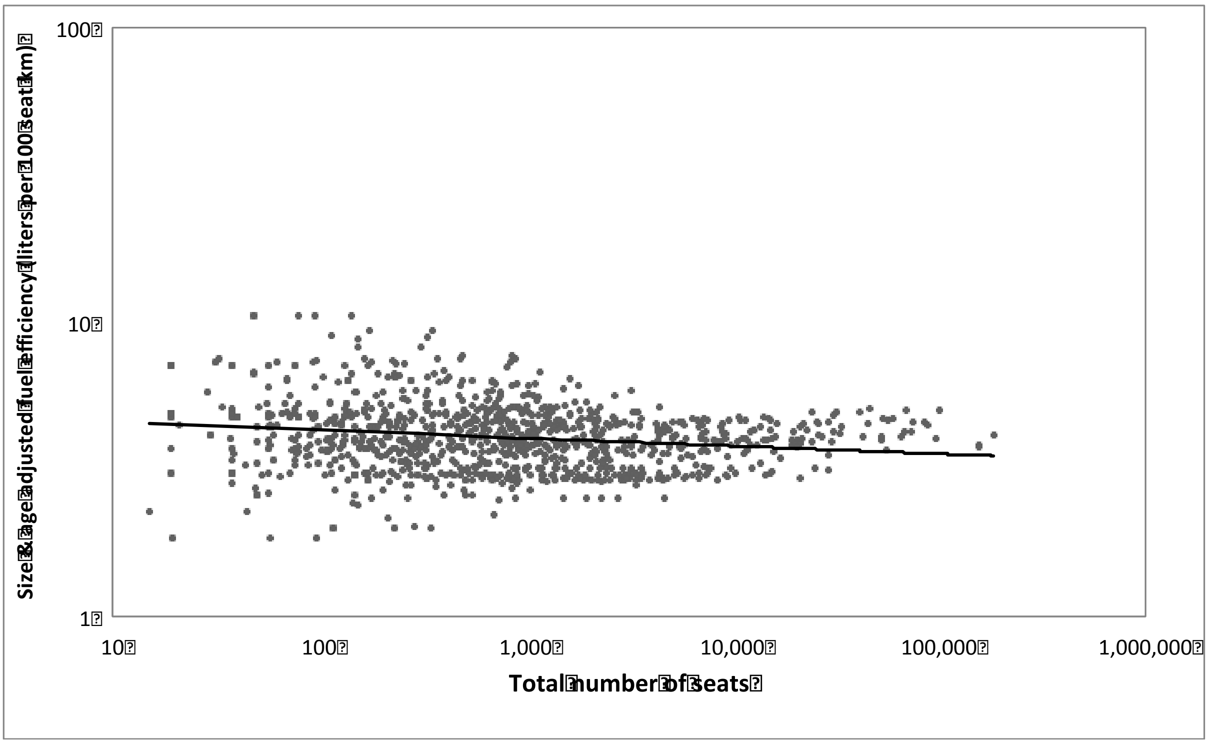

Figure 6: Airline size and age adjusted fleet fuel efficiency and total number of seats

Among the ten largest airlines in the world (over 70,000 total seats), five airlines (including the first three) are from the United States, two from China, and one from each of the UEA, the UK, and Germany. In our sample, 85 airlines have more than 10,000 total seats, while the majority (65%) of airlines have less than 1,000 total seats. When we clear the efficiency measure both of aircraft size and age, the relationship flattens again, indicating that larger airlines fly both larger and newer types of planes.

Average airline fuel efficiency of the 1267 airlines in our sample, has a mean value of 5.28 (liter/hundred seat-km), while the most efficient airline's efficiency is 2.25 (liter/hundred seat-km), and the least efficient airline's efficiency is at 16.56 liter/hundred seat-km. These are the real-world values. Accounting for differences in aircraft size, the modified efficiency measure shows a hypothetical average of 4.44 liter/hundred seat-km, with the most efficient airlines at 2.46, and the least efficient at 14.18 liter/hundred seat-km. Accenting for both size and age effects, the average is found at 4.27, the minimum at 1.83 and the maximum at 10.58 liter/seat-km. These statistics show that the differences in efficiency in a worldwide sample are far greater than the variation reported by Zhou *et al*. (2014) for the US.

5.2 Determinants of fleet fuel efficiency

Tables 4, 5, and 6 report the results of Eq. (5), for simple, size adjusted, and size and age adjusted fleet fuel efficiency. The explanatory variables in each table are the same except we control for the average number of seats and the average age of the fleet in Columns 3 and 4 in Table 4, where the dependent variable is simple fuel efficiency and for average age in Columns 3 and 4 in Table 5, where the dependent variable is size-adjusted fuel efficiency. These provide an alternative way of removing the effects of size and model age. However, they will remove both the possible effect of these variables on the behavior of airlines as well as the purely technical effect of size and model age on model fuel efficiency. Therefore, we prefer the estimates in Table Columns 1& 2 to those in Columns 3 and 4 in Tables 4 and 5.

The effect of economies of scale is measured by the natural logarithm of the total number of seats, given that the average number of seats in an airline are directly controlled for, or size-adjusted efficiencies are used. The coefficient on the log total number of seats is highly significant and negative in all regressions in Tables 4 to 6. In Table 4 Columns 1 and 2, where the dependent variable is simple fuel efficiency the coefficient of log total number of seats is largest (in absolute value) at -0.132. However, when we control for the average size and age of plane (Columns 3 and 4) the effect size is much smaller at -0.025 to -0.026. Here though the partial effect of a change in total seat number is equivalent to that of a change in the number of planes the airline operates. In Table 5 (Columns 1 and 2) the returns to scale effect is -0.038. Here the dependent variable adjusts for the technical effect of plane size on fuel efficiency. In Table 6, where the dependent variable is adjusted for model age, which reduces the variation in fuel efficiency further, the returns to scale effect is only -0.026, though still statistically significant. There may be various reasons why we find economies of scale. For example, larger firms may get better deals on new aircraft and have more flexible financing opportunities.

As international or domestic aviation fuel prices were not available, we use road gasoline prices, oil rents as a % of GDP, and oil reserves, as proxy variables. The results for gasoline prices are similar for the simple and size-adjusted efficiency measures, with elasticities ranging from -0.09 to -0.132 for simple fleet fuel efficiency, and -0.087 to -0.11 for size-adjusted fleet fuel efficiency, when we do not control for fleet model age and significant at the 1 or 5% level. In Table 6, where we adjust fuel efficiency for the model age of the fleet, the coefficient on the price of gasoline is smaller and not significant at the 5% level. This shows that the response to variations in fuel price is largely addressed by varying the model age of planes employed. Our reported elasticities are somewhat smaller than Li *et al*. 's (2009) and Burke and Nishitateno (2013)'s results on car fleet fuel economy, who respectively find that a 1% increase in fuel prices results in a 0.2% improvement in fleet fuel economy, and to a 0.15-0.2% improvement in new vehicle fleet fuel economy. Of course, cars have a much lower lifespan than aircraft and we only approximate jet fuel prices and, therefore, these estimates are likely subject to attenuation due to measurement error (Hausman, 2001). We also simultaneously control for oil rents as a percentage of GDP and for oil reserves in a country, both an indicator of fuel prices in general and of subsidies. We do not find the coefficient on either variable significant, after including gasoline prices.

Wages, which constitute one of the largest operating expenses of airlines were not found to be significant in any of the regressions in Tables 4 to 6, though the sign of the effect is as expected. As we estimated wages for many airlines based observations for other airlines and GDP per capita, this is likely the result of measurement error. We would expect that airlines operating in poor vs. rich countries would show differences in their airline fleet fuel efficiencies, although the generally higher interest rates in lower-income countries might be picking up this effect.

Dependent variable: ln simple airline fleet fuel efficiency				
	(1)	(2)	(3)	(4)
ln total seats	-0.132***	-0.132***	-0.0249***	-0.0257***
	(0.00921)	(0.00940)	(0.00725)	(0.00733)
ln wage	-0.0140	-0.0112	-0.0280	-0.0240
	(0.0237)	(0.0240)	(0.0186)	(0.0183)
ln gasoline price	-0.0904**	-0.132***	-0.0655**	-0.0864**
	(0.0432)	(0.0427)	(0.0321)	(0.0329)
ln oil reserves	-0.000831		0.0000740	
	(0.00119)		(0.000958)	
ln oil rents		-0.00703*		-0.000845
		(0.00412)		(0.00326)
ln real interest rate	0.0282***	0.0276**	0.0248***	0.0205**
	(0.0102)	(0.0105)	(0.00912)	(0.0101)
ln land area	0.0102	0.0165*	-0.0145*	-0.0137*
	(0.0101)	(0.00845)	(0.00772)	(0.00688)
ln population	-0.0168	-0.0150	0.0141	0.0152
	(0.0164)	(0.0186)	(0.0106)	(0.0119)
ln passengers	0.0315**	0.0289*	0.0136	0.0129
	(0.0141)	(0.0146)	(0.00901)	(0.00929)
ln average seats per airline			-0.276***	-0.273***
			(0.0130)	(0.0127)
ln average age of fleet			0.192***	0.206***
			(0.0543)	(0.0556)
Europe and Central Asia	0.130***	0.138***	0.119***	0.124***
	(0.0381)	(0.0363)	(0.0272)	(0.0255)
Latin America & Caribbean	0.0935**	0.0952**	0.0217	0.0272
	(0.0386)	(0.0397)	(0.0283)	(0.0279)
Middle East & North Africa	-0.130**	-0.128**	-0.0569	-0.0616
	(0.0561)	(0.0576)	(0.0428)	(0.0456)
North America	0.0862*	0.0803**	0.0380	0.0290
	(0.0440)	(0.0402)	(0.0364)	(0.0315)
South Asia	-0.0564	-0.0677	-0.0876**	-0.0927**
	(0.0525)	(0.0634)	(0.0423)	(0.0456)
Sub-Saharan Africa	0.0503	0.00115	-0.0110	-0.0376
	(0.0543)	(0.0557)	(0.0419)	(0.0441)
Constant	2.089***	1.964***	2.248***	2.138***
	(0.306)	(0.371)	(0.337)	(0.372)
N	890	852	890	852
adj. R-sq	0.375	0.378	0.560	0.564

Robust, country clustered standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 4: Determinants of simple fleet fuel efficiency. The regional dummy omitted was East Asia and the Pacific. Regressions 3 and 4 do not control for average seats or the average age of the fleet.

Dependent variable: Ln size adjusted airline fleet fuel efficiency

	(1)	(2)	(3)	(4)
ln total seats	-0.0375***	-0.0380***	-0.0180**	-0.0177**
	(0.00658)	(0.00672)	(0.00766)	(0.00781)
ln wage	-0.0262	-0.0243	-0.0251	-0.0219
	(0.0194)	(0.0198)	(0.0181)	(0.0181)
ln gasoline price	-0.0870**	-0.111***	-0.0660**	-0.0856**
	(0.0365)	(0.0376)	(0.0321)	(0.0331)
ln oil reserves	0.000144		0.000222	
	(0.000941)		(0.000936)	
ln oil rents		-0.00143		-0.000314
		(0.00333)		(0.00310)
ln real interest rate	0.0287***	0.0242**	0.0246***	0.0200**
	(0.00912)	(0.0100)	(0.00907)	(0.0100)
ln land area	-0.0105	-0.00727	-0.0132*	-0.0125*
	(0.00814)	(0.00711)	(0.00753)	(0.00655)
ln population	0.00783	0.00715	0.0137	0.0141
	(0.0119)	(0.0140)	(0.0107)	(0.0121)
ln passengers	0.0164*	0.0150	0.0117	0.0110
	(0.00900)	(0.00933)	(0.00906)	(0.00934)
ln average age of fleet			0.211***	0.224***
			(0.0547)	(0.0560)
Europe and Central Asia	0.129***	0.134***	0.108***	0.113***
	(0.0328)	(0.0314)	(0.0273)	(0.0256)
Latin America & Caribbean	0.0538*	0.0592*	0.0198	0.0244
	(0.0310)	(0.0312)	(0.0287)	(0.0283)
Middle East & North Africa	-0.0654	-0.0696	-0.0595	-0.0641
	(0.0465)	(0.0505)	(0.0433)	(0.0464)
North America	0.0545	0.0445	0.0401	0.0293
	(0.0407)	(0.0371)	(0.0364)	(0.0315)
South Asia	-0.0861**	-0.0844*	-0.0909**	-0.0915*
	(0.0420)	(0.0480)	(0.0434)	(0.0468)
Sub-Saharan Africa	0.00608	-0.0205	-0.00881	-0.0348
	(0.0420)	(0.0456)	(0.0398)	(0.0407)
Constant	1.589***	1.572***	0.782**	0.709*
	(0.261)	(0.325)	(0.327)	(0.363)
N	890	852	890	852
adj. R-sq	0.086	0.091	0.126	0.136

Robust, country clustered standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 5: Determinants of size adjusted fleet fuel efficiency. The regional dummy omitted was East Asia and the Pacific. Regressions 3 and 4 do not control for the average age of the fleet.

Dependent variable: ln size and age adjusted airline fleet fuel efficiency		
	(1)	(2)
ln total seats	-0.0248***	-0.0255***
	(0.00517)	(0.00520)
ln wage	-0.0107	-0.00849
	(0.0178)	(0.0177)
ln gasoline price	-0.0202	-0.0476*
	(0.0293)	(0.0284)
ln oil reserves	-0.000170	
	(0.000974)	
ln oil rents		-0.000133
		(0.00311)
ln real interest rate	0.0325***	0.0254***
	(0.00836)	(0.00872)
ln land area	-0.0153**	-0.0161**
	(0.00692)	(0.00618)
ln population	0.0195*	0.0181
	(0.0115)	(0.0125)
ln passengers	0.00690	0.00666
	(0.00950)	(0.00960)
Europe and Central Asia	0.103***	0.106***
	(0.0261)	(0.0244)
Latin America & Caribbean	0.0350	0.0409
	(0.0282)	(0.0272)
Middle East & North Africa	-0.0379	-0.0541
	(0.0388)	(0.0411)
North America	0.0410	0.0347
	(0.0336)	(0.0269)
South Asia	-0.0929*	-0.0882
	(0.0525)	(0.0566)
Sub-Saharan Africa	-0.0138	-0.0413
	(0.0413)	(0.0427)
Constant	1.345***	1.378***
	(0.248)	(0.291)
N	890	852
adj. R-sq	0.040	0.044

Robust, country clustered standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 6: Determinants of size and age adjusted fleet fuel efficiency. The regional dummy omitted was East Asia and the Pacific. Regressions 3 and 4 were carried out with country clustered standard errors.

Dependent Variable:	ln simple airline fleet fuel efficiency		ln size adjusted airline fleet fuel efficiency		ln size and age adjusted airline fleet fuel efficiency	
	(1)	(2)	(3)	(4)	(5)	(6)
ln total seats	-0.0856***	-0.0856***	-0.0141**	-0.0145**	-0.00103	-0.00143
	(0.0110)	(0.0111)	(0.00710)	(0.00719)	(0.00579)	(0.00582)
ln wage	-0.0239	-0.0236	-0.00432	-0.00594	0.0219	0.0219
	(0.0274)	(0.0284)	(0.0196)	(0.0202)	(0.0180)	(0.0186)
ln gasoline price	-0.0752***	-0.104***	-0.0809***	-0.0932***	-0.0559**	-0.0669***
	(0.0205)	(0.0241)	(0.0228)	(0.0250)	(0.0225)	(0.0237)
ln oil reserves	-0.00126*		-0.000444		-0.000394	
	(0.000750)		(0.000723)		(0.000761)	
ln oil rents		-0.00660*		-0.00167		-0.00127
		(0.00351)		(0.00310)		(0.00281)
ln real interest rate	0.0105*	0.0116**	0.0118	0.0107	0.0154**	0.0141*
	(0.00574)	(0.00564)	(0.00758)	(0.00774)	(0.00671)	(0.00717)
ln land area	0.00893	0.0133**	-0.00632	-0.00294	-0.00882	-0.00758
	(0.00640)	(0.00573)	(0.00585)	(0.00461)	(0.00537)	(0.00501)
ln population	-0.0231*	-0.0205	-0.000428	-0.000109	0.00892	0.00935
	(0.0134)	(0.0147)	(0.0102)	(0.0112)	(0.0100)	(0.0110)
ln passengers	0.0346***	0.0322**	0.00837	0.00654	-0.00240	-0.00274
	(0.0131)	(0.0135)	(0.00995)	(0.0100)	(0.00970)	(0.00990)
Europe and Central Asia	0.0692***	0.0769***	0.0584***	0.0666***	0.0401**	0.0444**
	(0.0210)	(0.0212)	(0.0211)	(0.0198)	(0.0201)	(0.0203)
Latin America & Caribbean	0.0563**	0.0605**	0.00121	0.00612	-0.00893	-0.00451
	(0.0282)	(0.0300)	(0.0234)	(0.0238)	(0.0222)	(0.0225)
Middle East & North Africa	-0.0785***	-0.0738**	-0.0611*	-0.0562	-0.0472	-0.0462
	(0.0285)	(0.0300)	(0.0324)	(0.0351)	(0.0306)	(0.0332)
North America	0.0504*	0.0603**	-0.00243	0.00357	-0.0274	-0.0246
	(0.0295)	(0.0288)	(0.0274)	(0.0255)	(0.0257)	(0.0239)
South Asia	-0.0615**	-0.0722**	-0.0893***	-0.0884**	-0.0894***	-0.0895**
	(0.0298)	(0.0335)	(0.0335)	(0.0361)	(0.0315)	(0.0342)
Sub-Saharan Africa	0.0874**	0.0607	0.0312	0.0217	0.0184	0.00616
	(0.0415)	(0.0437)	(0.0346)	(0.0384)	(0.0351)	(0.0385)
Constant	1.979***	1.876***	1.487***	1.473***	1.161***	1.137***
	(0.295)	(0.326)	(0.237)	(0.267)	(0.222)	(0.254)
N	890	852	890	852	890	852
adj. R-sq	0.305	0.303	0.026	0.029	0.009	0.008

Robust, country clustered standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 7: Determinants of fleet fuel efficiency: Weighted least squares estimates with the square root of total seats used as weights.

We find that real interest rates are significant at the 1% to 5% level in all specifications, and have a positive coefficient as expected. This means that a 1% increase in interest rates (for example from 1.0 to 1.01% in levels), will result in the worsening of long-run fleet fuel efficiency between 0.02 to 0.033 %. Higher interest rates not only mean a higher cost of capital for purchasing aircraft, but are also incorporated in lease-rates, effectively increasing the cost of renting an aircraft. Therefore, higher interest rates are likely to result in less investment into newer, efficient technologies.

Finally, we consider the environmental variables. We find that greater land area is associated with better fuel efficiency only when we adjust or control for model age. This indicates that even though we control for the size of the aircraft and the size of the airline, airlines based in larger countries fly more technically efficient aircraft. Population and passenger numbers were not found to be a significant driver of fleet fuel efficiency.

We find compared to the base region of East Asia and the Pacific that Europe and Central Asia has significantly worse fleet fuel efficiency. This result is remarkably robust in all three specifications, and is not only driven by airlines in Russia and the USSR successor states, but also by airlines in the European Union. The results are not attributable to the age of the fleets or to the size of the aircraft, but potentially to different technology used in planes of the same age and seat size. These planes are often manufactured by smaller companies. Compared to the base region, South-Asia also shows significantly higher efficiency in some specifications including our central estimates in Columns 3 and 4 in Table 5. In the simple fleet fuel efficiency regressions without the fleet age and average seat size controls, a number of regional dummies are significant. Most of these inferences disappear however, once we adjust or control for seat size and age.

We present weighted least squares estimates in Table 7 focusing on the size adjusted estimates in Columns 3 and 4. These are broadly similar to those in Table 5. The returns to scale effect is smaller here, the dummy for Europe and Central Asia has a smaller effect, and the coefficient of the South Asia dummy is much more significant.

6. Conclusions

We calculated efficiency levels for 1267 airlines in 2015 to estimate the drivers of fleet fuel efficiency. We collected technical data for 143 aircraft types including the typical number of seats, maximum range and fuel capacity. Based on these data we constructed three different types of fuel efficiency measures: simple (or actual) aircraft fuel efficiency, size adjusted fuel efficiency, where we clean the efficiency measure from the effect of aircraft seat size, and size and age adjusted fuel efficiency, where we clean the efficiency measure from the effects of aircraft seat size and age. Using this data, we constructed seat weighted fleet fuel efficiencies, using the World Airliner Census (Flightglobal, 2015) data, which lists the number and type of aircraft flown. We located the headquarters of 1267 airlines, and used various macroeconomic data to examine the drivers of the choices of fleet fuel efficiency.

Either adjusting the efficiency measure or controlling for the average size of aircraft flown , we find that, *ceteris paribus*, larger airlines – as measured by total number of seats – have higher fleet fuel efficiency. This suggests that there are economies of scale in fuel efficiency choice. Larger airlines not only fly larger, and thus more fuel-efficient planes, but they use more fuel-efficient aircraft independent of the size (and also model age) of aircraft. One of the explanations is that larger airlines potentially have better access to financing or lower capital costs and are willing to invest in more fuel-efficient aircraft. We also find that the elasticity of fleet fuel efficiency with respect to the price of fuel is between -0.07 to -0.13, depending on specification, where a negative sign indicates an improvement in fuel efficiency with higher fuel prices. This value is only a little lower than previous studies have reported for road vehicle fleet fuel economy. Higher interest rates are, on the other hand, associated with worse fleet fuel efficiency. Wages were not found to have a significant effect. We find that, despite a wide range of controls, some regional differences persist, which are independent of the age or the size of the aircraft or the other controls. These differences are best explained by the evolution of different technological designs for aircraft of the same size and age throughout the world.

Looking into the future, our findings confirm that airline fleet fuel efficiency is significantly though very inelastically responsive to changes in fuel prices as well as credit costs and availability. Both of these findings may be considered in designing policies to decrease aircraft emissions and improve the general level of fleet efficiencies.

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Appendices:

- List of aircraft types used and technical data
- Sources of technical information