NBER WORKING PAPER SERIES

DECARBONIZING AVIATION:
CASH-FOR-CLUNKERS IN THE AIRLINE INDUSTRY

Jan K. Brueckner
Matthew E. Kahn
Jerry Nickelsburg

Working Paper 32205
http://www.nber.org/papers/w32205

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
March 2024

Kahn thanks the USC Wrigley Insitute for Environment and Sustainability for generous funding. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Decarbonizing Aviation: Cash-for-Clunkers in the Airline Industry
Jan K. Brueckner, Matthew E. Kahn, and Jerry Nickelsburg
NBER Working Paper No. 32205
March 2024
JEL No. Q54,R49

ABSTRACT

The durability of the transportation capital stock slows down the pace of decarbonization since newer vintages feature cutting-edge technology. If older vintages were to be retired sooner, the social cost of travel would decline. This paper analyzes and explores the viability of a potential cash-for-clunkers program for the airline industry, which would help to hasten decarbonization of US aviation. Our estimation and calculations show that airlines can be induced to scrap rather than sell older planes upon retirement with a payment that is less than the forgone carbon damage, yielding net social benefits.

Jan K. Brueckner
Department of Economics
UCI
3151 Social Science Plaza
Irvine, CA 92697
jkbrueck@uci.edu

Matthew E. Kahn
Department of Economics
University of Southern California
3620 South Vermont Ave.
Kaprielian (KAP) Hall, 300
Los Angeles, CA 90089-0253
and NBER
kahnme@usc.edu

Jerry Nickelsburg
University of California, Los Angeles
Anderson School of Management
Los Angeles, CA 90095
jerry.nickelsburg@anderson.ucla.edu

Decarbonizing Aviation: Cash-for-Clunkers in the Airline Industry

by

Jan K. Brueckner, Matthew E. Kahn, and Jerry Nickelsburg[†]

1. Introduction

With the transportation sector contributing 29% of total US carbon emissions in 2021, decarbonization of the sector is a major policy goal. Since a first-best carbon tax is politically infeasible, automobile CAFE standards constitute the most important current US policy tool serving this goal.[1] Commercial aviation, a smaller but rapidly growing part of the transportation sector, accounts for 8% of its emissions and 2-3% of overall US emissions.[2] But unlike in the case of automobiles, US government intervention designed to reduce aviation emissions is mostly absent, although small efforts to spur production of sustainable (nonpolluting) aviation fuels, which are currently unaffordable, have begun.[3]

A different and faster-acting policy for addressing aviation emissions could mirror the automobile "cash-for-clunkers" program, which operated briefly in 2009. The program provided a voucher for purchase of a new fuel-efficient vehicle in return for scrappage of an old vehicle. Its intention was both to boost automobile production during the downturn of the Great Recession and to eliminate the carbon emissions from old fuel-inefficient vehicles. The program was very popular, exhausting its $3 billion budget in less than 60 days and leading to scrappage of almost 700,000 vehicles.[4]

In this paper, inspired by the automobile program, we analyze and explore the viability of a potential cash-for-clunkers program for the airline industry, whose goal would be to induce

[†] We thank Calvin Ryan for excellent research assistance and thank (without implicating) Bill Branch, Alberto Gaggero, Kangoh Lee and Cliff Winston for comments.

[1] See Knittel (2005) for an overall analysis of transport decarbonization. The 29% transportation emission share is from `https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions`.

[2] See `https://www3.epa.gov/otaq/documents/aviation/420f15023.pdf`

[3] See `https://www.energy.gov/eere/bioenergy/sustainable-aviation-fuels`.

[4] See Li, Linn and Spiller (2013), Davis and Kahn (2011), and Davis, Fuchs and Gertler (2014). CAFE standards, by raising new-car prices, may keep older cars in use, as analyzed by Gruenspecht (1982) and Stavins (2006).

an airline to scrap rather than sell older planes retiring from its fleet. Even though the target of an airline program is not an individual car owner but a carrier solving a complex fleet optimization problem, the incentives created are very similar, and the outcome would mirror the achievements of the automobile program. Currently, older aircraft being retired by major US airlines are often sold to carriers in developing countries or to domestic start-ups, continuing to generate emissions long after these retirements.[5] Under a cash-for-clunkers program, the government would pay US airlines to scrap rather than sell these older planes, thus terminating the emissions that would otherwise be ongoing. Such a "clunkers" payment is worthwhile, however, only if the forgone carbon damage from scrappage of the plane exceeds the payment's magnitude.[6] We establish this relationship, showing the viability of the program.[7]

Like the automobile program, an airline cash-for-clunkers program addresses the environmental downside of the durability of capital stocks, which slows the decarbonization of the economy. By paying their owners not to pollute, both programs would prevent ongoing emissions from aging durable capital goods that are in use for too long from an environmental viewpoint, given the availability of new cutting-edge technology. A similar program could be implemented for other durable, polluting capital goods, such as ships and railroad locomotives.

To see the logic of an airline program, suppose that an older plane has a market value of $2.5 million and a scrap value of $1.2 million, the amount that a scrapping company would pay.[8] Then, in the absence of any intervention, the plane would be sold rather than scrapped, and to reverse the airline's decision, the government would need to pay it $1.3 million, the difference between the market and scrap values. If forgone carbon damage from the plane's scrappage exceeds this clunkers payment, then the payment improves social welfare. Otherwise, the forgone carbon damage is too small to justify the payment, and it should not be made. Note that the forgone damage is the difference in carbon damage between the sold aircraft and

[5] This pattern mirrors the sale of US used cars to buyers elsewhere, as studied by Davis and Kahn (2011) and Newman et al. (2024). That phenomenon, along with sale of old planes, resembles filtering in the market for housing (another durable capital good), as analyzed by Sweeney (1974) and others.

[6] Paying airlines to scrap planes is analogous to buying coal mines to prevent use of coal, as in Harstad (2012).

[7] Note that the payment does not affect an aircraft's retirement date but only its disposition after retirement.

[8] See Hahn (2005) for an analysis of scrappage.

a newer one the buyer would instead purchase in the event of scrappage.

Our analysis operationalizes this idea, relying on several sources of data. We collect the market values of aircraft from proprietary airline bluebooks, estimate forgone carbon damage using data from the US Bureau of Transportation Statistics, and estimate unobservable aircraft scrap values through a logit analysis of airline scrap vs. sell decisions for retiring planes. Individual aircraft histories are needed in the exercise, and they come from the Planespotters.net website. The details of the methodology are explained in section 3.

The cash-for-clunkers calculations are carried out for the 585 aircraft retired by the six largest US carriers over the 2015-2019 period (for which we have market-value data), from among over 5,000 observed aircraft histories. We focus on the 65 planes in this group with logit scrappage probabilities less than 0.5, which were unlikely to be scrapped and thus were candidates for a clunkers payment.[9] For each of these 65 aircraft, the clunkers payment is equal to the negative of the fitted value from the logit regression, or the difference between the market and estimated scrap values. In each case, this clunkers payment is smaller than a conservative estimate of the forgone carbon damage,[10] indicating social gains from a cash-for-clunkers program. The aggregate outlay on clunkers payments for the 65 planes equals \$146 million, while the aggregate forgone carbon damage equals \$821 million, yielding a large aggregate benefit/cost ratio of 5.61. The general-equilibrium and other second-order effects of a cash-for-clunkers program are discussed in the conclusion.[11]

The literature on automobile decarbonization is large and includes contributions by Li, Timmins and Von Haefen (2009), Knittel (2011), Klier and Linn (2010), Anderson and Auffhammer (2014), and Holland, Mansur and Yates (2021), along with those cited in previous footnotes.[12] The literature on decarbonization of the airline industry is, by contrast, small but growing. Brueckner and Abreu (2017, 2020) and Fukui and Miyoshi (2017) study how airline

[9] The relatively small share of these low-probability planes reflects the high US scrappage rates.

[10] Our calculations are based on carbon damage of \$40 per metric ton.

[11] Moral hazard is not an issue in a cash-for-clunkers program because buying a plane solely to attract a clunkers payment yields less than the purchase price.

[12] Knittel (2011) argues that, even though car producers (like aircraft manufacturers) can achieve higher fuel efficiencies than before, consumer demand for large vehicles (which Anderson and Auffhammer (2014) argue serves a self-protection motive) offsets this effect.

fuel usage responds to fuel prices and thus can predict the reductions in carbon emissions from potential fuel taxes. Fageda and Teixido (2022) study the impact of actual taxes by studying the operational responses of European carriers to their inclusion in EU's Emissions Trading System, which taxes airlines by requiring the purchase of emission permits. de Almeida and Oliveira (2023) and Brueckner, Kahn and Nickelsburg (2024) quantify other airline operational responses to higher fuel prices, which include slower flying, lower aircraft utilization, and faster retirements of old planes.

The plan of the paper is as follows. Section 2 presents a theoretical model that illustrates slower-than-optimal decarbonization of aviation, while section 3 discusses data and empirical strategies. The empirical results, which also include estimation of an hedonic aircraft price function, are presented in Section 4. Section 5 offers conclusions.

2. Theoretical model

This section develops a model to show that airline decarbonization is too slow. To start, consider an airline that, over time, operates a sequence of aircraft types with progressively lower fuel consumption, reflecting technological progress in attaining better fuel efficiencies. While fuel consumption is constant over an aircraft type's life, maintenance cost rises as the type ages according to the common function $m(a)$, where a is age and $m'(a) > 0$. Let F_i denote annual fuel consumption for the ith aircraft in the sequence, and suppose that the fuel price and carbon damage per gallon are constant over time, equal to f and c, respectively. With little loss of generality, we focus on a simple setting with just two aircraft types and a fixed retirement time H for the second type. The social planner's problem is then to choose the year T at which the first type ceases and the second type begins to operate, so as to minimize social costs.

Letting r denote the discount rate, the present value of these costs is given by

$$\int_0^T [(f+c)F_1 + m(t)]e^{-rt}dt \;+\; \int_T^H [(f+c)F_2 + m(t-T)]e^{-rt}dt. \tag{1}$$

Using Leibniz's rule, the planner's first-order condition for choice of T is

$$G(T) \;=\; (f+c)F_1 \;+\; m(T) \;-\; [(f+c)F_2 \;+\; m(0)] \;-\; \int_0^{H-T} m'(t)e^{-rt}dt \;=\; 0, \quad (2)$$

where $G(T)$ is the derivative of (1) with e^{-rT} factored out. The (positive) difference between the first two terms is the current cost increase from postponing T (recall $F_1 > F_2$ and $m(T) > m(0)$), while the second term is the present value of reductions in maintenance-cost from having a younger type-2 aircraft at each future operating time. Since $G'(T) > 0$, an interior solution T^* to (2) represents a global cost minimum (the G function thus slopes up).

The objective function of a cost-minimizing airline, which ignores carbon damage, differs from (1) by absence of c. Its first-order condition for T thus involves an (upward-sloping) function $\widehat{G}(T)$ that is lower than G by the amount $c(F_1 - F_2)$ and thus intersects the horizontal axis to the right of G's intersection, at $T^{**} > T^*$, as shown in Figure 1. By not internalizing the reduction in carbon damage from switching to the type-2 aircraft, the cost-minimizing airline then operates the type-1 plane longer than the planner. Ignoring the maintenance elements of cost, the welfare cost of this delayed switch can be approximated by $c(F_1 - F_2)(T^{**} - T^*)$. This expression is also the forgone carbon damage from the cash-for-clunkers program, which incentivizes an airline to retire an older plane.

It is important to note that the foregoing analysis concerns operation, not ownership, of the aircraft, with changes in ownership having no effect on the conclusions. If the type-1 aircraft changes hands during its life, it is easily seen that the second owner will choose the same $T = T^{**}$ as before, thus also operating the aircraft too long.

3. Data and empirical strategies

3.1. Data sources and variables

The empirical analysis in this paper relies on three data sources. The first is the *AVITAS BlueBook of Jet Aircraft Values*, an annual proprietary source from which we could obtain data only for the years 2015, 2017, and 2019. For each aircraft type in a given year, the bluebook shows the market value (denoted *mkt_val*) according to the aircraft's vintage, or year of manufacture. For example, for the Boeing 737-300, the 2015 bluebook shows the market value in 2015 for aircraft of this type for different years of manufacture, which range between 1984 and 1999. The blue book also gives the aircraft type's characteristics, including seat capacity (denoted *capacity*), range in miles (*range*), number of engines (*engines*), and a widebody dummy (*widebody*), all of which are independent of year of manufacture. Aircraft age in years (denoted *age*) is generated by subtracting the year of manufacture from the current year (2015, 2017, or 2019).

The second data source, which was also used in Brueckner et al. (2024), is the T2 data set of the U.S. Bureau of Transportation Statistics (BTS).[13] This source provides annual fuel usage (denoted *gallons*) by aircraft type, airline, and year, along with annual seat-miles by aircraft type, airline and year. Using both variables, an inverse measure of fuel efficiency, gallons per seat-mile (*gallons_seat_mile*), can be computed by aircraft type, airline and year.

Using the blue-book and T2 data, the first part of the analysis estimates an hedonic aircraft price function, which gives the log of market value (*lmkt_val*) as a function of aircraft characteristics: *capacity*, *range*, *age*, *gallons_seat_mile*, *engines*, *widebody* and an Airbus dummy (*airbus*). This regression also includes dummy variables for the years 2017 and 2019, with 2015 being the omitted year. The year dummies capture demand forces, which may partly depend on fuel prices, although these prices are almost constant over the 2015-2019 period. While the hedonic regression is not needed for the cash-for-clunkers analysis, it is natural to exploit our unique data by estimating it. For the frequencies of aircraft types appearing in the hedonic data set, see Table A1 in the appendix.

The third data source, which is used in the cash-for-clunkers analysis, is the Planespotters.net website, whose information was supplemented and cross checked with Planelist.net and Airfleets.net. The Planespotters website tracks of usage of each aircraft, identified by the manufacturer's serial number, over all the years since its manufacture. We collected the Planespotters data for a long period, the years 1991-2019, in order to generate an adequate picture of aircraft lifespans. Planespotters yields 5,108 US aircraft histories, and in each year, the website indicates the passenger airline or other air carrier operating the aircraft or whether

[13] `https://www.transtats.bts.gov/Fields.asp?gnoyr_VQ=FIH`

it has been scrapped or written off (as would occur in the case of a crash). Scrappage means that the aircraft is sold for scrap, held as a source of spare parts, or possibly stored.

The coding of carriers uses a focal set of passenger airlines, which are individually identified, with carriers outside this set not being identified but coded as other OECD passenger carriers, non-OECD passenger carriers, cargo carriers of any country, or other carriers (private service, air taxi, medevac or military transport). The focal US carriers are the largest ones in 2019: American, Delta, United, Southwest, JetBlue and Alaska.

To predict the scrappage vs. sale decisions of airlines upon retirement of aircraft, the cash-for-clunkers analysis relies on a logit scrappage regression for planes that are retired over the years 2015-2019, as explained further below. These are the years for which we have (or can interpolate, as explained below) market values. Retirement in one of these years (say t) means that, in year $t-1$, an aircraft is operated by a focal carrier, while in year t, it is either operated by a non-focal carrier (indicating a sale) or scrapped, with $t = 2015$, 2016, 2017, 2018, or 2019. The retirement year of an aircraft within this period, equal to one of these years, is denoted ret_yr. Focusing on aircraft that retired over this period greatly reduces the number of relevant aircraft histories.

An additional requirement for a focal-carrier retirement is that the aircraft is operated by a focal carrier in each consecutive year of the 2014-2018 period prior to its retirement. Aircraft occasionally cycle between focal and non-focal carriers, with a plane starting out operated by a focal carrier, then shifting to a non-focal carrier, and then shifting back to the same (or a different) focal carrier, and we exclude these patterns near retirement.

Airlines operating a large number of aircraft of a given type may face a stronger incentive to scrap rather than sell a retired plane, which then can be used as a source of spare parts for the remaining aircraft. Accordingly, we create a variable denoted $type\_count$, which gives the annual count for an aircraft of a particular type in an airline's fleet. The count is created by looking across an airline's aircraft histories in a given year and summing by type, with only counts for 2015-2019 needed.

As explained further below, the market value of a plane is an important factor in the scrap vs. sell decision. We have market values for the years 2015, 2017, and 2019, but using all the retirements over the 2015-2019 period in the logit regression requires imputing the missing market values for 2016 and 2018. We do so by setting, for planes of a given type and age, the 2016 market value equal to the average of the 2015 and 2017 values, and setting the 2018 value equal to the average of the 2017 and 2019 values. In the few cases where the data structure rules out this interpolation, we set the missing 2016 or 2018 value equal to the value in the previous year.

The full set of aircraft histories starting at 1991 is used to estimate the average lifespan of aircraft types. In doing so, note that the few rare histories where an aircraft is scrapped and later returns to service (having been stored) are not present in the data set, having been removed. Then, the interval between the year of manufacture (which may predate 1991, the earliest history year) and the year of scrappage (if it is observed) is computed. The resulting lifespan is averaged within aircraft types, yielding a type-specific average lifespan (denoted avg_life). The expected remaining life for an aircraft not scrapped upon retirement (denoted $remain\_lf$) is then equal to the average lifespan minus the retirement year ($avg\_life - ret\_yr$). The $remain\_lf$ variable is used to compute carbon damage from continued operation of a retired aircraft, required in the cash-for-clunkers analysis, as explained below.

3.2. The logit scrappage regression

An airline's scrappage decision depends on the difference between an aircraft's market value and its scrap value. The scrap value captures the proceeds from selling the plane for scrap or else the aircraft's value as a source of spare parts. Scrap value thus depends on a subset of the aircraft's characteristics and on $type\_count$, which captures the benefits of using the plane for spare parts. Crucially, while the market value is observed, the scrap value is unobserved and must be estimated. Let the scrap value be written as $X\beta$, where X is vector containing the relevant set of determining variables, and let P denote market value. Then, a retired plane will be scrapped rather than sold when

$$P \;<\; X\beta \;+\; \epsilon, \tag{3}$$

where ϵ is an error term that captures the unobserved determinants of scrap value. The probability of scrappage is then

$$Prob\,(\epsilon > P - X\beta) \;=\; 1 \;-\; Prob\,(\epsilon < P - X\beta) \;=\; 1 \;-\; F(P - X\beta), \tag{4}$$

where F is the cumulative distribution function of ϵ. If ϵ has the logistic distribution, then $F(z) = exp(z)/(1 + exp(z))$, and

$$\begin{aligned} Prob\,(\epsilon > P - X\beta) \;&=\; 1 \;-\; \frac{exp(P - X\beta)}{1 + exp(P - X\beta)} \\ &=\; \frac{1}{1 + exp(P - X\beta)} \;=\; \frac{exp(-P + X\beta)}{1 + exp(-P + X\beta)}. \end{aligned} \tag{5}$$

Based on the final expression in (5), β can be estimated using a logit regression with $-P + X\beta$ on the right-hand side.[14] Note that the coefficient of P must be constrained to equal -1 when running the regression.

The logit regression is run using two different specifications, with the scrappage dummy *scrap* being the dependent variable. In the first specification, X includes the variables *capacity*, *age* and *type_count*, along with year dummy variables. Aircraft with large seat capacities are likely to have high scrap values, as are planes where *type_count* is large, making their spare-parts value high. Older planes may have lower scrap values, although such a vintage effect could be absent. Holding capacity and age constant, it appears that scrap value would not further depend on aircraft characteristics such as range and fuel-efficiency (inversely measured by *gallons_seat_mile*), so that these characteristics are omitted from the logit regression.

Under a second specification, *capacity* is dropped as a covariate, while aircraft-type dummy variables are added to the logit regression. These variables capture capacity as well as any other unobserved aircraft features that influence scrap value. The *age* variable and *type_count*, which vary independently of the aircraft dummies, continue to appear as covariates.

From the logit post-estimation sample, the fitted value $-P + X\widehat{\beta}$ (denoted fit_val) and the fitted probability of scrappage (denoted *prob_scrap* and equal to (5) evaluated at fit_val) are recovered. They are used in the cash-for-clunkers calculation, which is explained next.

[14] We experienced probit convergence problems in some cases, thus using logit instead.

3.3. The cash-for-clunkers calculation

Under a cash-for-clunkers program, the government would pay an airline to scrap an old plane rather than sell it for ongoing usage, thus avoiding the carbon damage from continued operation. Aircraft that would be targeted are those likely to be sold rather than scrapped, having $prob\_scrap < 0.5$. The remaining aircraft in the logit post-estimation sample are thus dropped, with calculations proceeding on those planes likely to be sold rather than scrapped. With $prob\_scrap < 0.5$ holding for these aircraft, $fit\_value < 0$ also holds, impying $-P + X\widehat{\beta} < 0$ or $P > X\widehat{\beta}$. To induce scrappage of these aircraft, the government would need to pay the airline the difference between P and the estimated scrap value $X\widehat{\beta}$, or an amount equal to $-fit\_value$. Let this payment be denoted $clunkers\_pmt$.[15]

To decide whether the payment is socially desirable, the benefit from the foregone carbon damage must be calculated. Let D denote the annual carbon damage from continued operation of the retiring aircraft and let T denote its remaining life after being sold. Then, scrappage of retiring aircraft eliminates own carbon damage equal to

$$own\_damage \quad = \quad \int_0^T De^{-rt}dt \quad = \quad D(1 - e^{-rT})/r. \tag{7}$$

But as seen in the model of section 2, the proper damage measure is the forgone damage, which is the difference between the damage from the old retiring plane and the carbon damage from a younger plane the buyer would operate instead if the older one were scrapped and unavailable. This damage difference would equal $\Delta D \equiv D - \widetilde{D}$, where $\widetilde{D}$ is annual damage from the younger plane. Letting $\widetilde{D} = \delta D$, for some $\delta < 1$, it follows that $\Delta D = (1 - \delta)D$, with δ's magnitude discussed below. Forgone damage, denoted fgn_damage, is then equal to (7) with D replace by $(1 - \delta)D$.

The next step is to produce an estimate of D. We note from Brueckner and Abreu (2017) that each gallon of jet fuel burned generates 9.75 kg of CO_2, and we use a conservative damage value of \$40 per metric ton (*mton*) of carbon. Then, using the annual *gallons* value for the

[15] When retirement means return of an old leased plane, the clunkers payment goes to the lessor, who compares it to the present value of ongoing lease revenue (= market value) minus the scrap value.

retiring aircraft type, the estimate of D equals

$$\widehat{D} \;=\; gallons \;\times\; 9.75\; kg/gallon \;\times\; 10^{-3}\; mton/kg \;\times\; \$40/mton. \tag{8}$$

Setting $r = 0.5$, replacing T by $remain\_lf$, and replacing D in (7) with $\widehat{D}$ then yields

$$own\_damage \;=\; \widehat{D}\,[1 - exp(-0.05 \times remain\_lf)]/0.05. \tag{9}$$

The estimate of fgn_damage is given by (9) multiplied by $1 - \delta$. Since the forgone damage is the benefit from the scrappage induced by the clunkers payment, the associated benefit/cost ratio is

$$benefit/cost \;=\; \frac{fgn\_damage}{clunkers\_pmt} \;=\; (1-\delta)\,\frac{own\_damage}{clunkers\_pmt}. \tag{10}$$

In our calculations based on (10), the own_damage ratio in the last expression is computed for each aircraft with $prob\_scrap < 0.5$, and its magnitude after multiplying by $1 - \delta$ is evaluated for realistic δ values. A clunkers payment is worthwhile when the resulting benefit/cost expression exceeds 1.

Aircraft that are sold to a non-OECD passenger airline or a cargo carrier may end up being utilized less intensively over a longer lifespan than by a US passenger airline. In this case, the damage must be adjusted, but our verdict on the desirability of cash-for-clunkers payments is mostly robust to any such adjustment, or to a change in discount rate.

4. Empirical results

4.1. The hedonic aircraft price function

Table 1 shows the estimated hedonic aircraft price function, along with mean values of the covariates. Recall that the estimation is based on the blue-book market values of aircraft. Given the likely influence of unobservables that are common within an aircraft type, the logit standard errors are clustered by type. From the estimated coefficients, we see that larger, newer, longer-range, and more fuel-efficient aircraft have higher market values. Other things equal, widebody aircraft and those with more engines have lower values, although the larger capacity and range of such planes raises value. Recalling that the dependent variable is in logs, a 1-year increase in age reduces value by 9%, a 10-seat increase in capacity raises value by 4%, and a 100-mile increase in range raises value by 2%. Holding capacity fixed, a 4-engine aircraft is worth 56% less than a 2-engine plane, with a widebody aircraft worth 41% less than a narrow-body plane, other things equal.[16]

Market values do not vary significantly across the three sample years, and the values of Airbus planes are no different from those of other manufacturers (mainly Boeing), holding characteristics constant. The regression has 1,394 observations, which are divided across aircraft types as shown in Table A1 in the appendix, and the R^2 value is high, at 0.946. Although the results in Table 1 match expectations, we are not aware of any other estimated hedonic aircraft price functions in the literature.

4.2. The logit scrappage regression

Table 2 gives the summary statistics for the US logit data set, showing the aircraft types represented in them, their frequencies, and the mean values of a number of variables. For the US case, 757-200 aircraft are the type experiencing the most retirements over the 2015-2019 period, with 737-300s and MD-82s being the next most-retired planes. The 1.0 mean value of *scrap* shows that the single retired 737-700 was scrapped, as were all of the more numerous 767-200ERs and 767-300s. In addition, 737-500s, 747-400s and MD-82s were almost always scrapped rather than sold upon retirement. Average market values range from a high of \$11.8 million for the lone 737-700 to a low of \$1.0 million for MD82s. Average ages at retirement are all over 20 years, except for the 737-700, for which *ret_age* equals 18 years. The data show that this plane (operated by Southwest) suffered nose-wheel damage and was used for parts for the carrier's large fleet of this type (410 planes). The number of individual aircraft observations in the data set equals 585, the sum of the frequencies. Of the 126 aircraft out this total that were not scrapped (21.6%), 37 were sold to an OECD (possibly US) passenger airline, 26 went to a non-OECD passenger carrier, and 63 went to a cargo airline.

[16] Since the coefficient is large, the *widebody* effect is not given by the coefficient α but instead equals $exp(\alpha) - 1$, and similarly for the *engines* effect.

In addition to collecting scrappage data for the US, we also collected a smaller European data set (with 203 observations) for a focal-carrier group consisting of Air France, KLM, Iberia, Lufthansa, SAS, TAP, Ryanair, and EasyJet. Our initial intention was to pool the data sets for the logit regression, but we chose not to do so because the US and Europe exhibit very different aircraft scrappage environments. The scrappage rate over the 2015-2019 period is much lower for the European case than for the US case, 17.2% vs. 78.4%, possibly reflecting an EU policy environment (including airline coverage by the EU's ETS) that encouraged carriers to unload their older planes before they were ready to scrap. Intensity of aircraft usage may also be higher in the US than in Europe, making scrappage upon retirement more likely (hard evidence is lacking, though). We do not report the European logit results (which are available on request), nor do we carry out European cash-for-clunkers calculations.[17]

Table 3 shows the US logit results, with the first regression relying only on aircraft characteristics, while column 2 includes type dummies. In both regressions, the standard errors are clustered by type. Recall that the estimated coefficients should be viewed as reflecting the contribution of a variable to an aircraft's scrap value. As can be seen in the first regression, a larger *capacity* and a higher *type_count* both raise scrap value, as expected. The *age* coefficient is negative but statistically insignificant, although it gains significance when clustering is dropped (an action that may be preferred anyway given the small number of clusters). The insignificant year dummy coefficients show no variation in scrap value across the period. Despite the parsimonious specification, the percent of correct logit predictions is a high 84.44%, as seen at the bottom of the table.

In the second regression, where *capacity* is dropped and the aircraft type dummies added, the *type_count* coefficient loses significance, while the *age* coefficient is again insignificant (both conditions persist without clustering). The year dummy coefficients are again insignificant. As for the type dummies, coefficients for the aircraft types that are always scrapped (see above) cannot be estimated, so these type dummies are omitted and viewed as the reference group. Relative to this group, the negative dummy coefficients for the remaining types naturally show

[17] Of 203 aircraft in the European data, 168 (82.8%) were not scrapped, with 156 being sold to an OECD (possibly European) passenger airline, 11 going to a non-OECD passenger carrier, and 1 to a cargo airline.

that they all have lower scrap values. This second logit regression has a somewhat higher rate of correct predictions than the first one, at 87.01%, which makes it the preferred specification.

4.3. Cash-for-clunkers calculations

As explained above, the cash-for-clunkers calculations are done only for the US case. Based on the second logit regression in Table 3, the set of aircraft retiring in the 2015-2019 period that have $prob\_scrap < 0.5$ (thus being candidates for clunkers payments) consists of 65 planes out of the 585 in the US logit sample. This relatively small number reflects the low rate at which US planes were sold upon retirement.[18]

The first panel of Table 4 shows the elements of the clunkers calculations for this group. For these 65 planes, the values of the key variables in the calculations are averaged within aircraft types, with the results shown in the table. The type-average of mkt_val is shown along with the type-average logit fitted value, which is negative given $prob\_scrap < 0.5$. These numbers are in units of millions of dollars. The table then shows the type-average annual $gallons$ and the type-average $remain\_lf$. The type-average of own carbon damage (own_damage, based on (7) and (8)) from continued operation is also shown, as is the type-average cash-for-clunkers payment ($-fit\_val \times 10^6$ to yield actual dollars). Then δ is shown along with the benefit/cost ratio for $\delta = 0$, equal to the ratio of the type-averages of own_damage and $clunkers\_pmt$. The adjusted ratio, equal to $(1 - \delta)$ times this unadjusted ratio, is shown in the last column of the table.

The first thing to note from Table 4 is that the cash-for-clunkers payments are large, ranging from just below $1 million per aircraft for 757-200s to over $7 million per plane for A320-200s. Nevertheless, assuming for the moment that $\delta = 0$, all of type-average benefit/cost ratios associated with these payments are greater than 1, ranging from a low of 8.17 for 737-400s to 99.47 for 757-200s.[19] The ratios must be adjusted downward, however, since the $1 - \delta$ factor is missing, but after doing so, the cash-for-clunkers benefits remain larger than costs.

To see the details, consider the case of the 737-400, which has $gallons\_seat\_mile$ equal to

[18] Since $prob\_scrap$ only indicates the likelihood of scrappage, it need not exactly predict actual scrappage. In fact, 21% of the 65 aircraft with $prob\_scrap < 0.5$ were actually scrapped.

[19] Two 737-400 aircraft with unadjusted benefit/cost ratios below 1 but negligible remaining lifespans were dropped as unrepresentative in creating the first panel of Table 4.

0.0167 (see Table 2 of Brueckner et al., 2024). A likely newer alternative to this aircraft for the buyer in the event of scrappage would be a 737-800, which has *gallons_seat_mile* of 0.0130. The value of δ (the ratio of alternative to own *gallons_seat_mile*) for the 737-400 would then be $0.0130/0.0167 = 0.78$, so that $1-\delta = 0.22$. In this case, the adjusted benefit/cost ratio equals 1.80, remaining larger than 1. The same conclusion applies for the other aircraft types in the first panel of Table 4, assuming that likely alternatives are the 777-300 (*gallons_seat_mile* of 0.0159 vs. 0.0173) for the Boeing 747-400, the A321-200neo (0.0107 vs. 0.0143) for the 757-200, the 787-8 (0.0146 vs. 0.0154) for the 767-300ER, and the A320-200neo (0.0111 vs. 0.0136) for the A320-200. Since the $1-\delta$ values in these cases are of a similar order of magnitude to that in the 737-400 case (ranging from 0.05 to 0.25, as seen in the table) while the unadjusted benefit/cost ratios are much larger than 1, the adjusted ratios remain larger than 1, as can be seen in the last column.

The benefit/cost verdict can be affected by which newer alternate aircraft is chosen. If the alternate plane for the 737-400 were the somewhat older 737-700 instead of the 737-800, with *gallons_seat_mile* of 0.0147 instead of 0.0130, then the $1-\delta$ value would be 0.12 instead of 0.22. The adjusted benefit/cost ratio for the 737-400 would then equal 0.98 instead of 1.79, indicating that sale rather than scrappage of these planes is slightly preferred. Similarly, if the alternate aircraft for the 767-300ER were the 767-400ER (with *gallons_seat_mile* of 0.0150) instead of the 787-8, $1-\delta$ would equal 0.03 instead of 0.05, and the adjusted cost-benefit ratio would equal 0.77. Since the alternate aircraft that would be sought by a buyer to replace the unavailable scrapped plane may not be fully predictable, some uncertainty may then enter the cash-for-clunkers calculations. However, a less conservative approach that replaces our \$40/*mton* carbon damage value with, say \$100 or \$190, would again make these ratios larger than 1.

To summarize, the ratios shown in the last column of Table 4 show that, using the chosen alternate aircraft, the payments required to induce airlines to scrap rather than sell retiring planes are less than the forgone carbon damage from scrappage, making the program viable. To get a sense of aggregate magnitudes, we can multiply the type averages of *clunkers_pmt* and $(1-\delta)$*own_damage* by the corresponding number of aircraft for the type: 24 757-200s, 19 767-

300ERs 12 737-400s, 8 A320-200s and 2 747-400s. Summing to produce totals, the aggregate forgone carbon damage is \$821 million and the aggregate outlay on clunkers payments is \$146 million, yielding an aggregate benefit/cost ratio of 5.61 and net social benefits of \$675 million.

The numbers in Table 4 can also be used to produce a McKinsey (2009) abatement-cost curve, which shows the marginal cost of carbon emissions forgone (abated) at different levels of total emissions. To generate the curve, the inverse of the adjusted benefit/cost ratio in the last column of Table 4 is computed and then multiplied by 40 to give the cost per metric ton of forgone emissions for the given aircraft type. These costs, in ascending order, are graphed against the total tons of forgone emissions (in millions) from scrapping the different plane types (own damage divided by 40 times $1-\delta$), taking account of the number of each type and its forgone emissions, with the results shown in Figure 2. The initial long flat segment is at height \$1.60, the cost per ton of forgone emissions for 757-200s, and the length of the segment equals the forgone emissions per aircraft times the number of planes (24 for this type). The next short segment is at height \$6.80, the cost per ton for 747-400s, and the length of the segment is the forgone emissions per aircraft times the number of planes (2 in this case). The remaining segments of the curve are for A320-200s, 737-400s, and 767-300ERs, respectively, as shown. The fact that the curve lies below a horizontal line at height \$40 indicates that the marginal abatement costs are all below the assumed carbon damage of \$40/$mton$ and are therefore worth incurring.

Since the fitted values and scrappage probabilities differ somewhat under the first logit regression in Table 3, which does not include type dummies, the cash-for-clunkers numbers that emerge are somewhat different, as seen in the second panel of Table 4. Moreover, an additional plane type (767-300s) emerges as a cash-for-clunkers candidate, although the number of eligible aircraft falls to 54. However, the main implications of the second panel of Table 4 are the same as before. Although cash-for-clunkers payments per aircraft are large, the adjusted benefit/cost ratios are all larger than 1, indicating net social benefits from the policy.

5. Conclusion

This paper has analyzed a potential cash-for-clunkers program for the airline industry, which would help to hasten decarbonization of US aviation. Our estimation and calculations show that airlines can be induced to scrap rather than sell older planes upon retirement with a payment that is less that the forgone carbon damage, yielding net social benefits. To actually operate an airline cash-for-clunkers program, the government could gain access to market-value data for additional years, allowing estimation of the logit scrappage regression on a larger data set. Next, the government would ask airlines to list the aircraft they plan to retire in the following year, without revealing their scrap/sell intentions. Using the results of the updated logit regression, the government would then identify which retiring aircraft are likely to be sold rather than scrapped. It would offer the airline clunkers payments in return for scrappage of these planes, doing so only if the payment is less than the forgone carbon damage.

The discussion so far has not touched on the general-equilibrium and other second-order effects of a cash-for-clunkers program. One effect is that the buyers of the now-scrapped planes would have to purchase a newer aircraft at a higher cost, possibly foregoing a purchase entirely.[20] The required outlay may further escalate due to the program-induced supply reduction for used aircraft and consequent worldwide price increase, whose size depends on the price elasticity of demand. While these effects, which may retard growth of aviation in the developing world, are environmentally efficient, LDC governments may wish to partly mitigate them by subsidizing aircraft acquisition for their carriers.

[20] In this case, forgone damage would simply equal own damage, since the aircraft is removed without being replaced by an alternate.

Table 1: Hedonic aircraft price function

VARIABLES	coefficient	var. mean
capacity	0.00455**	208.78
	(0.000849)	
age	-0.0939**	16.75
	(0.00611)	
range	0.000203**	4347.43
	(4.32e-05)	
gallons_seat_mile	-108.2**	0.016
	(34.83)	
engines	-0.357**	2.08
	(0.0697)	
airbus	0.0700	0.25
	(0.0828)	
widebody	-0.484**	0.44
	(0.125)	
d2017	-0.0228	0.33
	(0.0280)	
d2019	0.0504	0.34
	(0.0438)	
Constant	4.742**	–
	(0.365)	
Observations	1,394	
R^2	0.929	

Dependent variable is log *mkt_val*

Standard errors clustered by *type* in parentheses

** p<0.01, * p<0.05

Table 2: Summary statistics for US logit data set

type	*frequency*	*scrap*	*ret_yr*	*mkt_val*	*capacity*	*ret_age*	*type_count*
737-300	112	0.85	2017.4	2.56	126	24.3	75.5
737-400	36	0.17	2016.9	3.69	147	22.7	17.2
737-500	15	0.93	2016.3	1.61	110	24.7	9.2
737-700	1	1.00	2018.0	11.80	126	18.0	410.0
747-400	40	0.95	2017.2	10.36	416	22.8	14.4
757-200	141	0.74	2016.2	6.42	200	25.1	89.1
767-200ER	3	1.00	2015.0	3.23	181	27.7	3.0
767-300	15	1.00	2017.2	4.07	218	27.1	10.2
767-300ER	35	0.37	2017.2	6.82	218	26.7	43.2
A320-200	25	0.68	2016.2	7.46	150	22.5	61.6
MD-82	83	0.98	2016.3	1.00	143	27.0	53.5
MD-83	36	0.78	2016.9	1.20	143	25.0	50.0
MD-88	43	1.00	2018.6	1.20	143	29.4	106.2

The table gives mean values by *type* of variables other than *frequency*. Units for *mkt_val* are $ millions.

Table 3: US logit results

VARIABLES	scrap	scrap
mkt_value	-1	-1
capacity	0.0427**	–
	(0.00530)	
ret_age	-0.127	-0.0589
	(0.0881)	(0.102)
type_count	0.0274**	0.00318
	(0.00639)	(0.0228)
d2015	-0.331	1.682
	(0.480)	(2.271)
d2016	0.663	2.206
	(0.852)	(1.804)
d2017	-0.597	0.945
	(0.506)	(1.355)
d2018	-0.890	0.0811
	(0.489)	(1.191)
d737_300	–	-19.81**
		(6.739)
d737_400	–	-22.86**
		(8.638)
d737_500	–	-20.64*
		(8.624)
d747_400	–	-5.197
		(8.644)
d757_200	–	-17.33*
		(7.039)
d767_300ER	–	-18.85*
		(7.647)
dA320_200	–	-17.44*
		(7.464)
dMD_82	–	-19.85**
		(7.694)
dMD_83	–	-21.91**
		(7.350)
Constant	0.317	24.94**
	(2.702)	(7.467)
Observations	591	591
% correct	84.44%	87.01%

Standard errors clustered by *type* in parentheses
** $p<0.01$, * $p<0.05$

Table 4: Cash-for-clunkers calculations

Using US logit results with *type* FEs (yielding 65 aircraft)

type	*mkt_val*	*fit_val*	*gallons*	*remain_lf*	*own_damage*	*clunkers_pmt*	$1-\delta$	*benefit/cost* $\delta = 0$	$\delta > 0$
737-400	3.78	-1.28	0.96e+07	3.6	1.04e+07	$1,279,819	0.22	8.16	1.79
747-400	24.00	-3.06	3.70e+07	9.6	1.11e+08	$3,060,717	0.16	36.22	5.80
757-200	8.66	-0.93	4.78e+07	5.5	9.24e+07	$928,602	0.25	99.47	24.87
767-300ER	8.06	-2.32	4.25e+07	3.61	5.93e+07	$2,317,174	0.05	25.59	1.28
A320-200	15.73	-7.32	3.49e+07	10.0	1.03e+08	$7,319,435	0.18	14.02	2.52

Using US logit results without *type* FEs (yielding 54 aircraft)

type	*mkt_val*	*fit_val*	*gallons*	*remain_lf*	*own_damage*	*clunkers_pmt*	$1-\delta$	*benefit/cost* $\delta = 0$	$\delta > 0$
737-400	4.56	-0.32	0.44e+07	6.0	9.00e+06	$318,101	0.22	28.28	6.22
747-400	20.65	-3.90	3.70e+07	8.1	9.65e+07	$3,899,903	0.16	24.74	3.96
757-200	8.56	-1.07	4.75e+07	5.2	8.18e+07	$1,067,951	0.25	76.61	19.15
767-300	8.60	-2.17	4.51e+07	8.07	1.17e+08	$2,173,909	0.05	53.71	2.68
767-300ER	8.32	-1.22	4.25e+07	3.8	6.06e+07	$1,218,870	0.05	49.73	2.49
A320-200	14.89	-8.67	3.49e+07	9.3	9.57e+07	$8,668,231	0.18	11.04	1.99

To generate the numbers in the tables, retiring aircraft with a scrap probability greater than 0.5 are excluded from the logit post-estimation samples, leaving planes where scrappage is unlikely. In addition, a few aircraft with negative remaining lives are excluded. Then, calculations are undertaken using the formulas below for individual aircraft (2 aircraft in the US group with benefit/cost ratios less than 1 were excluded). Finally, the results for each variable are averaged within aircraft types. Being based post-calculation averages, the numbers in the table themselves do not fit the formulas.

$$\textit{units of mkt\_val} \text{ are \$ millions; } fit\_val = -mkt\_val + X\widehat{\beta};$$

$$gallons \text{ is annual gallons of fuel consumed by the type}$$

$$remain\_lf = avg\_life - ret\_age \text{ (retirement age)}$$

$$own\_damage = gallons \times (9.75\ kg\ CO_2/gallon) \times (10^{-3}\ metric\ tons/kg) \times$$

$$(\$40\ CO_2\ damage/metric\ ton) \times [1 - exp(-.05 * remain\_lf)]/.05;$$

$$clunkers\_pmt = -fit\_val \times 10^6;\ benft/cst|_{\delta=0} = own\_damage/clunkers\_pmt$$

$$benft/cst|_{\delta>0} = (1-\delta)own\_damage/clunkers\_pmt$$

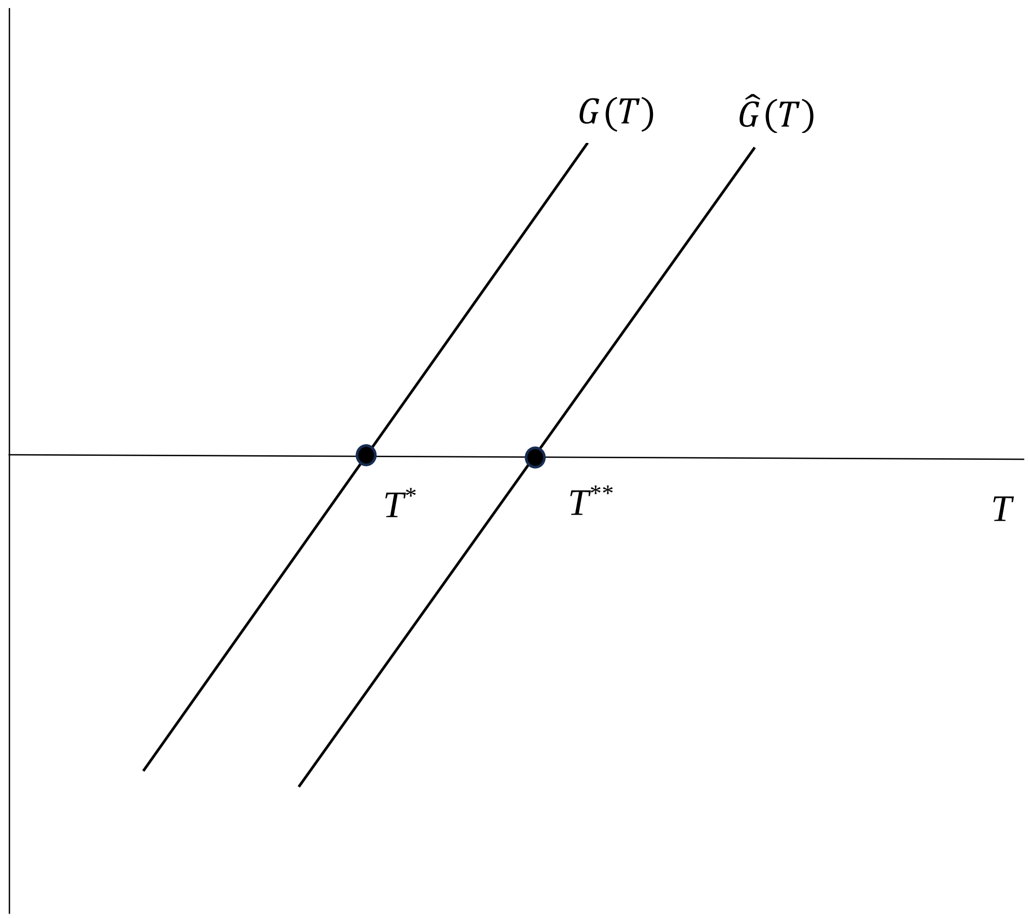

Figure 1: Aircraft Retirement Dates

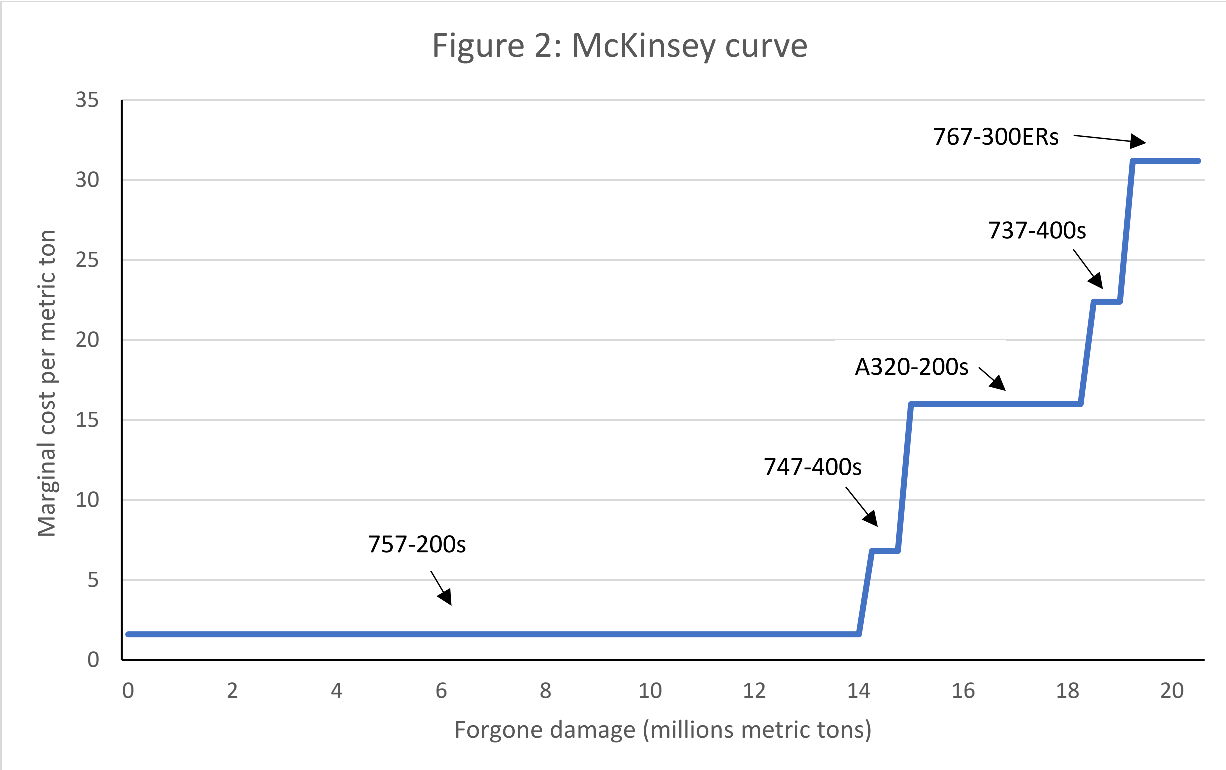

Figure 2: McKinsey curve
35
30
25
20
15
10
5
0
Marginal cost per metric ton
767-300ERs
737-400s
A320-200s
747-400s
757-200s
0
2
4
6
8
10
12
14
16
18
20
Forgone damage (millions metric tons)

Appendix

Table A1: Aircraft type frequencies in hedonic data set

type	frequency
717-200	27
737-300	48
737-400	36
737-500	33
737-800	63
737-900	18
737 Max 8	6
737 Max 9	3
747-200B	2
747-300	2
747-400	54
757-200	69
757-200ETPS	68
757-300	21
767-200ER	34
767-300	44
767-300ER	82
767-400ER	12
777-200	42
777-200ER	54
777-300ER	45
787-8	18
787-9	16
A300-600	9
A300-600R	36
A310-300	27
A318-100	21
A319-100	69
A320-200	90
A320-200neo	9
A321-200neo	6
A330-200	63
A330-300	57
A350-900	15
MD-82	51
MD-83	45
MD-88	36
Total	1,394

Repeated aircraft observations are generated by different ages and years.

References

de Almeida, E.E., Oliveira, A.V.M., 2023. An econometric analysis for the determinants of flight speed in the air transport of passengers. *Scientific Reports* 13, article 4573.

Anderson, M.L., Auffhammer, M., 2014. Pounds that kill: The external costs of vehicle weight. *Review of Economic Studies* 81, 535-571.

Brueckner, J.K., Abreu, C., 2017. Airline fuel usage and carbon emissions: Determining factors. *Journal of Air Transport Management* 62, 10-17.

Brueckner, J.K., Abreu, C., 2020. Does the fuel-conservation effect of higher fuel prices appear at both the aircraft-model and aggregate airline levels? *Economics Letters* 197, article 109647.

Brueckner, J.K., Kahn, M.E., Nickelsburg, J., 2024. How do airlines cut fuel usage, reducing their carbon emissions? CESifo Working Paper.

Davis, L.W., Kahn, M.E., 2010. International trade in used vehicles: The environmental consequences of NAFTA. *American Economic Journal: Economic Policy* 2, 58-82.

Davis, L.W., Kahn, M.E., 2011. Cash for clunkers? The environmental impact of mexico's demands for used vehicles." *Access Magazine* 1, no. 38, 15-21.

Davis, L.W., Fuchs, A., Gertler, P., 2014. Cash for coolers: evaluating a large-scale appliance replacement program in Mexico. *American Economic Journal: Economic Policy* 6, 207-238.

Fukui, H., Miyoshi, C., 2017. The impact of aviation fuel tax on consumption and carbon emissions: The case of the US airline industry. *Transportation Research Part D* 50, 234-253.

Fageda, X., Teixido, J.J., 2022. Pricing carbon in the aviation sector: Evidence from the European emissions trading system. *Journal of Environmental Economics and Management* 111, article 102591.

Gruenspecht, H.K., 1982. Differentiated regulation: The case of auto emissions standards. *American Economic Review* 72, 328-331.

Hahn, R.W., 1995. An economic analysis of scrappage. *RAND Journal of Economics* 26, 93-112.

Harstad, B, 2012. Buy coal! A case for supply-side environmental policy. *Journal of Political*

Economy 120, 77-115.

Holland, S.P., Mansur, E.T, Yates, A.J., 2021. The electric vehicle transition and the economics of banning gasoline vehicles. *American Economic Journal: Economic Policy* 13, 316-344.

Jacobsen, M.R., Sallee, J.M., Shapiro, J.S., Van Benthem, A.A., 2023. Regulating untaxable externalities: Are vehicle air pollution standards effective and efficient? *Quarterly Journal of Economics* 138, 1907-1976.

Klier, T., Linn, J., 2010. The price of gasoline and new vehicle fuel economy: Evidence from monthly sales data. *American Economic Journal: Economic Policy* 2, 134-153.

Knittel, C.R., 2011. Automobiles on steroids: Product attribute trade-offs and technological progress in the automobile sector. *American Economic Review* 101, 3368-3399.

Knittel, C.R., 2012. Reducing petroleum consumption from transportation. *Journal of Economic Perspectives* 26, 93-118.

Li, S., Timmins, C., Von Haefen, R.H., 2009. How do gasoline prices affect fleet fuel economy? *American Economic Journal: Economic Policy* 1, 113-137.

Li, S., Linn, J., Spiller, E., 2013. Evaluating "cash-for-clunkers": Program effects on auto sales and the environment. *Journal of Environmental Economics and Management* 65, 175-193.

McKinsey & Company, 2009. Pathways to a low-carbon economy: Version 2 of the global greenhouse gas abatement cost curve. `http://www.mckinsey.com/clientservice/ccsi/pathways_low_carbon_economy.asp`.

Newman, S.J., Schulte, K., Morellini, M.M., Rahal, C., Leasure, D.R., 2024. Offshoring emissions through used vehicle exports, emissions through used vehicle exports. *Nature Climate Change,* `https://doi.org/10.1038/s41558-024-01943-1`.

Stavins, R.N., 2006. Vintage-differentiated environmental regulation. *Stanford Environmental Law Journal* 25, 29-63.

Sweeney, J.L., 1974. A commodity hierarchy model of the rental housing market. *Journal of Urban Economics* 1, 288-323.