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Emission Pricing and Capital Replacement: Evidence from Aircraft Fleet Renewal

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Abstract

This paper empirically studies how emission pricing affects capital replacement and adoption of embodied environmental technology. A pricing policy encourages firms to accelerate retirement of old capital assets and replace them with newer more efficient assets, but this may crowd out replacements not regulated by the policy. Using asset-level data from the airline industry, I show that the inclusion of intra-European aviation in the European Union Emissions Trading Scheme decreased the retirement age of 'regulated' short-haul aircraft by 2.8 years (14 percent), while the retirement age of 'unregulated' long-haul aircraft increased by 2 years (11 percent). Accounting for the higher emissions of long-haul operations, the net environmental benefit of induced fleet renewal is virtually zero and may even be negative. This demonstrates that regulators must consider the impacts beyond regulated capital when environmental policies are incomplete.

JEL classifications: O33, L93, Q30, Q54, Q55, Q58

Keywords: environmental policy, emission pricing, carbon leakage, capital replacement, technology adoption, airline industry

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1 Introduction

To what extent do environmental policies, such as carbon pricing and tradable emission allowances, accelerate the replacement of capital assets and, hence, the adoption of more efficient production technologies? This paper examines the impact of the world's largest carbon market—the European Union's Emissions Trading Scheme (EU ETS)—on capital service life and the environmental efficiency of firms' capital stocks, with a focus on aircraft fleet renewal in the aviation sector.

The adoption of lower emission technologies is regarded as a critical means for meeting climate targets (IPCC, 2007, 2014, 2022). Many of the technologies used by firms are embodied in their capital assets, as noted by Solow (1960), and followers. The introduction of new technology then requires the replacement of entire capital goods. For example, in aviation, most technological change occurs at the aircraft-level, with limited options for retrofits and modifications of existing aircraft.[1] As such, the timely adoption of low-emission technologies crucially depends on the speed at which firms renew their capital stock.

Pricing plays a key role in determining the rate and direction of environmental technological change (Acemoglu et al., 2012; Aghion et al., 2016). Following John Hick's (1932) induced innovation hypothesis, raising the price of emissions spurs abatement efforts. With embodied technological progress, pricing should therefore result in old capital being retired and replaced by new, more environmentally efficient capital. Firms however express concerns that pricing impedes their ability to invest in new capital. For instance, the International Air Transport Association (IATA) argues that "punitive measures like taxes (...) siphon money from the industry that could support emissions' reducing investments in fleet renewal and clean technologies".[2] In similar vein, Eurocontrol, the EU's air navigation organisation, states that there is a need to "balance taxation" as "reducing emissions by the required amount is possible, but will require investment, and that needs a buoyant aviation sector".[3] Whether such claims are warranted has first-order implications for the rate of environmental technology adoption in aviation and numerous other industries that are or will be subject to emission pricing, such as electricity, manufacturing, road transport, etc.

The purpose of this paper is to shed light on these matters by empirically investigating the impact of the EU ETS on aircraft fleet renewal in the aviation industry. This case is of particular interest for a number of reasons. Aviation is an important and growing sector that is often in the

[1] Morrell and Dray (2009) estimate that the CO_2 emission savings of all historical re-enginings, one of the most significant changes to in-service aircraft in terms of environmental performance, account for only 0.1 percent of total emissions.

[2] IATA, "Tax is not the Answer to Aviation Sustainability": https://www.iata.org/en/pressroom/pr/2021-07-14-01/

[3] Eurocontrol, "Reducing Aviation Emission": https://www.eurocontrol.int/sites/default/files/2022-05/eurocontrol-think-paper-16-reducing-aviation-emissions-55-by-2030.pdf

spotlight of the environmental policy debate because of its high emission intensity and alleged difficulty to decarbonize. Asset-level data on the age and retirement of the main capital good—aircraft—utilized by airlines is also readily available, which permits an empirical analysis at a level of detail that is typically not possible using data from other industries. Further, the EU ETS is the largest carbon market in the world, making it a subject of ongoing interest to economists (see Martin et al., 2016, for a review), and a natural choice to study the effects of emission pricing on firm decisions. Finally, the specific way in which the EU ETS is implemented for aviation, namely only on intra-European routes, creates a clear separation between aircraft types that are subject to emission pricing and those that are not. This allows me to study the impact on the replacement of assets within and beyond a pricing policy's direct regulatory sphere.

The latter feature, that the scheme does not apply equally to all capital goods operated by firms, is shared by many environmental policies that are implemented in practice. A classic example are multinational, or interstate enterprises with plants and equipment across jurisdictions with different environmental stringencies (e.g., Fowlie, 2009). A related issue is the dissimilar treatment of different kinds of emissions that contribute to the same environmental problems. For instance, the EU ETS itself only applies to CO_2 emissions excluding other emissions that also have global warming consequences (Montzka et al., 2011). In this paper, I argue and empirically show that such cases of incomplete regulation enable firms to free up resources for the early replacement of regulated capital by delaying the replacement of unregulated capital. This crowding out effect can substantially offset the benefits of policy-induced capital replacement or, when unregulated assets are relatively more polluting, even cause overall emissions to increase.

To formalize this argument, I present an extended version of the replacement framework for a firm with a single capital good developed by Goolsbee (1998). Firms operate two types of capital goods only one of which is subject to emission pricing, representing a situation of incomplete pricing policy. This simple set-up shows that emission pricing leads to earlier replacement by increasing the value of the cost-savings associated with lower emission technology embodied in newer vintages, akin to the induced innovation hypothesis. It also illustrates that, under capital constraints, emission pricing increases the opportunity cost of capital goods that are not subject to pricing, leading to the deferral of their replacement.

These propositions are empirically evaluated using data on aircraft retirements from the fleets of all global airlines based in Europe and North America between 2004 - 2019, a period which covers the inclusion of aviation in the EU ETS in 2012. The EU ETS requires airlines to surrender emission allowances for all intra-European flights, while there exists a (temporary) derogation for intercontinental flights (see Section 4 for more details). This means that non-European airlines, even those that fly regularly in and out of Europe, are not covered by the EU ETS. For European airlines this creates a clear distinction between "short-haul" aircraft, mainly narrowbodies, which operate intra-European flights and hence require emission allowances for the majority of their operations, and "long-haul" aircraft, mainly widebodies, which are almost never deployed on intra-European flights and therefore are effectively exempt from the scheme.[4]

The empirical strategy combines a difference-in-differences design with a hazard-based duration model that takes into account the age dependency of aircraft retirements. Hence, I compare aircraft retirement ages in the European fleet before and after the implementation of the EU ETS, and relate those to their counterpart differences in the North American fleet. Following the propositions of the theoretical framework, one expects an increase in the retirement age of European short-haul aircraft and a decrease in the retirement age of European long-haul aircraft in response to the EU ETS implementation. Correspondingly, I find that the retirement age of the European short-haul fleet decreased by 2.8 years (or 14 percent), while the retirement age of European long-haul fleet increased by 2.1 years (or 11 percent) as compared to the counterfactual.

On balance, the EU ETS accelerates fleet renewal. The positive effect on short-haul aircraft is greater than the negative effect on long-haul aircraft, and the share of short-haul aircraft in the total fleet is relatively large. However, when differences in emission intensities are taken into account, the carbon leakage due to delayed replacement of the long-haul types negates virtually all emission savings from the induced replacement of short-haul types. Only in the initial period in which there was uncertainty with regards to the inclusion of long-haul operations from and to Europe in the EU ETS, the policy had positive induced replacement effects. Counterfactual simulations show that if the policy had been implemented as originally intended, the emission savings from induced fleet renewal would have been about fifty percent higher.

This paper identifies firms' capital replacement decisions as a novel channel for carbon leakage. More specifically, emission savings from early replacement of regulated capital leak through deferred replacement of unregulated capital if environmental policies do not apply equally to all capital assets that contribute to emissions. Moreover, this is the first study that quantifies the impact of emission pricing policies on capital replacement. While the absolute environmental impacts may be modest here, the relevance of the mechanisms uncovered in this paper will grow with rising carbon prices and when (more) evolutionary technologies enter the market.

[4]As shown in the Appendix, over 99 percent of the flights under the EU ETS are operated by "short-haul" aircraft types.

2 Related literature

This study connects to several strands of literature. Most directly, I contribute to papers that study the link between emission pricing and technological change. Like this paper much of the empirical work in this area has used the EU ETS as a policy shock. However, while ample of attention has been paid to induced technological innovation (Acemoglu et al., 2012; Aghion et al., 2016; Calel and Dechezleprêtre, 2016), the impact on technology adoption has not been researched much. Some studies have confirmed that emission pricing has lowered the emission-intensity of production (Petrick and Wagner, 2014; Colmer et al., 2022), but the empirical evidence not always points to induced adoption of lower emission technologies. For example, a number of studies, such as Borghesi et al. (2015), Jaraite and Maria (2016) and Calel (2020), find mixed or no statistically significant effects. The main contribution of this paper is to study (embodied) technology adoption by tracking the replacement of individual capital goods, which greatly helps in obtaining richer and more robust evidence on the extent to which pricing stimulates a shift to low emission technology.

In doing so, my work connects to a series of papers in economics and operational research that study capital replacement decisions by firms. Following the seminal work of Bellman (1955), the operational research society has developed numerous models to optimize the timing of replacement (e.g. Rust, 1987; Karabakal et al., 1994; Hartman, 2004). Most economic papers in this area document the macroeconomic implications of capital replacement the cyclical properties of replacements (Cooper and Haltiwanger, 1993; Goolsbee, 1998; Cooper and Haltiwanger, 1999), and capital adjustment costs (Cooper and Haltiwanger, 2006). Theoretical analyses like Xepapadeas and De Zeeuw (1999), Feichtinger et al. (2005), and Boucekkine et al. (2008), consider the relationship between environmental regulations and capital investments. None of these papers however empirically studies the response of capital replacement to an emission pricing policy, nor do they address the effect of the incompleteness that characterizes many pricing policies in reality.

This paper further contributes to an active academic debate on incomplete environmental policies and carbon leakage. Carbon leakage is typically understood as a shift of production to less regulated regions (see, e.g., Fowlie, 2009; Aichele and Felbermayr, 2015; Borghesi et al., 2020; Dechezleprêtre et al., 2022). Conversely, my results point toward a shift in investment prioritization from unregulated to regulated capital assets. To my knowledge, aus dem Moore et al. (2019) is the only paper that has looked into this type of investment leakage. They find that the EU ETS has increased asset investment in Europe, which is consistent with my findings. However, their more aggregate data—firms' fixed asset holdings—does not allow them to relate their findings to increased replacement investment in Europe at the expense of replacement investment outside of Europe. Several other related studies show that policy-induced environmental innovation tends to replace productive or dirty innovation (Gray and Shadbegian, 1998; Popp and Newell, 2012; Aghion et al., 2016). My focus however is on crowding-out among assets contributing to the same environmental issues, hence leading to the leakage effects just discussed.

Finally, this paper adds to a growing body of work on reducing the environmental impact of the aviation sector (Brueckner and Zhang, 2010; Adler et al., 2013; Czerny, 2015; Kahn and Nickelsburg, 2016; Brueckner and Abreu, 2017, 2020; Csereklyei and Stern, 2020; Fageda and Teixidó, 2022). My results confirm previous evidence that airline decisions can be positively affected by carbon pricing, but also demonstrate the unintended consequences of the current piecemeal policies, thus emphasizing the need for global action to address aviation emissions.

3 Theoretical Relationships and Econometric Model

3.1 Capital Replacement in Response to Emission Pricing

To motivate the empirical analysis, I use a basic framework that is closely related to previous models of the capital replacement problem (see Goolsbee, 1998), but allows for asset types with varying exposure to emission pricing. This key new element can reflect a situation of incomplete emission pricing, such as the EU ETS for aviation.

Consider a firm that operates two types of assets, say a short-haul and long-haul aircraft type. The two types operate in parallel but are economically dependent through a common budget constraint, creating a "parallel replacement problem" (Karabakal et al., 1994). The firm needs to decide *when* to replace existing assets for newer more fuel efficient models. All assets are assumed to generate the same amount of revenue, such that replacement decisions are purely cost-driven. An asset of type i incurs operating and maintenance expenses (excluding fuel costs) equal to m_i at the start of its lifetime, increasing at a rate δ_i in each subsequent period. Fuel costs are the product of per-period fuel usage E_i and the effective fuel price p_i, which captures both the base fuel price plus the costs due to emission pricing. For each asset type there is a new model available with per-period fuel usage E'_i, where $E'_i < E_i \; \forall i$, reflecting embodied technological progress. The cost of replacement is equal to q_i and the new asset is assumed to be immediately operational. Let θ be the discount factor.

As in Goolsbee (1998), the value of replacing an asset of type i and age a in the current period or waiting one more period, equals the difference between the net present values (NPV) of these two competing decisions:

$$\Delta_i(a) = \overbrace{\left[q_i + \sum_{t=0}^{\infty} \theta^t \left(p_i E_i' + m_i(1+\delta_i)^t\right)\right]}^{\text{NPV replacement current period}} - \underbrace{\left[p_i E_i + m_i(1+\delta_i)^a + \theta q_i + \sum_{t=1}^{\infty} \theta^t \left(p_i E_i' + m_i(1+\delta_i)^{t-1}\right)\right]}_{\text{NPV replacement next period}}, \tag{1}$$

which simplifies to:

$$\Delta_i(a) = p_i(E_i - E_i') - q_i(1-\theta) - m_i \left(\frac{1-\theta}{1-\theta(1+\delta_i)} - (1+\delta_i)^a\right). \tag{2}$$

The first term captures the benefit from operating a more fuel efficient asset in the current period, the second term the lost interest on the purchase price, and the third term the discounted difference in maintenance costs (which can be positive or negative, depending on the age of the existing asset, a). Emission pricing can be thought of as raising the effective fuel price, p_i. This raises the value of the fuel efficiency savings associated with the newer model and, in turn, the value of replacing asset i in the current period. On the margin, this brings capital replacement forward, leading to earlier retirement of capital goods that are subject to the pricing policy.

Due to the common budget constraint, a firm may find itself on the margin between replacing one type of asset over another type. The value of the immediate replacement of asset type j, can be regarded as the *opportunity costs* of replacing the asset type i (and vice versa). The value of replacing i in the current period given opportunity costs becomes $\Delta_i(a_i) - \Delta_j(a_j)$. It is straightforward to see that increasing the effective fuel price of the other asset type, p_j, raises the opportunity costs and, hence, decreases the value of replacing asset i in the current period. This pushes capital replacement backward, leading to delayed retirement of capital goods that are *not* subject to the pricing scheme. Note that this also provides the intuitive result that carbon leakage through replacements does not occur for firms without a binding budget constraint, as such firms are never on the margin between replacing one over another asset type, and therefore do not need to consider opportunity costs. In that case, one expects to see emission pricing increasing the speed of replacement of capital goods under the pricing scheme, without affecting the replacement timing of other capital goods.

In addition to the above presentation of the replacement problem for owned capital goods, the literature emphasizes the increasing importance of leased assets (Gavazza, 2010, 2011). However, as Belobaba et al. (2015) and other industry experts note, "the principal economic and financial trade-off faced by every airline considering the acquisition of new aircraft is between the promise of lower operating costs and higher ownership costs". Assuming that newer, more fuel-efficient assets command higher lease rates and that lessees generally remain responsible for fuel, operating and maintenance costs (Gavazza, 2011), this principle trade-off as captured in the model still holds. An increase in the effective fuel price raises the fuel savings of the newer assets, and hence encourages firms to lease newer models sooner leading to earlier 'retirement' ages.

3.2 Hazard Model for the Timing of Capital Replacement

One of the main implications of the theoretical framework is that emission pricing affects the timing of asset retirement; decreasing the retirement age of assets subject to emission pricing and, under capital constraints, increasing in the retirement age of assets that are exempt from pricing. To document these effects empirically, I examine how a policy shock that introduces emission pricing on a subset of assets impacts the asset retirement age.

My econometric strategy combines a semi-parametric proportional hazard model with a difference-in-differences design. Given discrete monthly duration data (described in the next section) and assuming proportional hazards, the retirement rate (i.e., hazard) at age j with covariates X_{it} for an asset i at time t, takes the complementary log-log form (see, e.g., Jenkins, 1995; 2005):

$$h(j, X_{it}) = 1 - \exp(-\exp[\lambda_j + \beta' X_{it}]). \tag{3}$$

The λ_j parameters summarize the baseline hazard, i.e. the pattern of duration dependence of retirements common to all assets. Sample size limitations prevent me from analysing how the baseline hazard varies between each monthly age. Hence I employ specifications with piecewise constant functions to estimate the baseline hazard across age intervals of, say, one year:

$$h(j, X_{it}) = 1 - \exp(-\exp[\delta_k I_k[12k \leq j \leq 12(k+1)] + \beta' X_{it}]). \tag{4}$$

This specification assumes a constant baseline hazard within each age interval, δ_k, which is allowed to vary freely between age intervals. In other words, the model does not impose a specific functional form on the baseline hazards, making it a type of semi-parametric analysis.

The β parameters scale the baseline hazards upward or downward according to the set of covariates, X_{it}. In my most basic specification these covariates include the typical treatment effects covariates in difference-in-differences designs. That is, a binary indicator variable $D_i = 1$ if asset i is operated by a firm in the regulatory environment where emission pricing is introduced, and zero otherwise; a binary indicator variable $d_t = 1$ for the time periods after the introduction of the emission pricing policy, and zero otherwise; and the interaction of these two variables:

$$h(j, X_{it}) = 1 - \exp(-\exp[\delta_k + \beta_1 D_i + \beta_2 d_t + \beta_3(D_i * d_t)]). \quad (5)$$

The coefficient of main interest, β_3, gives the causal impact of emission pricing on asset retirement rates, under the typical parallel trends assumption. The exponent of parameters in discrete time proportional hazard models give the multiplicative impact of the emission pricing policy on the asset retirement rate in each age interval (see p.42, Jenkins, 2005). Hence, a positive β_3 would indicate that the retirement rates shift upwards (leading to earlier retirement of assets), while a negative β_3 suggests that the retirement rates shift downwards (leading to later retirement of assets).

When estimating this model, I take account of a number of further issues. Some of these are specific to my context, while others apply more generally to hazard models of asset retirement. First, while the theoretical model considers replacements, the empirical strategy focusses on retirements. When firms contract their capital stock over time, not every retirement may represent a replacement. This is not necessarily a problem for the estimation strategy: if the difference in capital stock contraction is stable over time or regulatory environment, its effect on the retirement rate is picked up by the fixed effects, D_i or d_t, without distorting the effect of the emission pricing policy. If, on the other hand, capital downsizing is correlated with the introduction of the emission pricing policy—for example, because emission pricing leads to supply reductions—part of the emission price effect would be attributable to a need for less capital rather than an acceleration of its replacement. To rule out that this alternative mechanism, I perform a sensitivity analysis including only airlines whose fleets grew during the sample period, so that all retirements can be assumed replacements.

Second, as predicted by the theoretical framework an emission pricing scheme may also impact the retirement rates of assets that are not covered by the scheme. I test this proposition by separately estimating the model for short-haul and long-haul aircraft, next to an estimation of the aggregate effect over the total fleet. In the aggregate model, I allow the baseline hazards to differ in shape between the two types of aircraft to reflect their different retirement patterns.[5]

Third, two common features of duration data that needs to be accounted for, are *right-censoring* and *left-truncation*. For one, in my aircraft fleet data set, a non-negligible share of aircraft remain in the airline fleets after the observation window ends. For these observations I do not know their exact retirement age, only that they were still in service at a certain age, meaning that these observations are right-censored. There are also a number of aircraft that were already in the fleet before the observation window began. This creates a form of non-random sampling, called left-truncation, as aircraft that are retired later are more likely to be included in my sample causing observations with a high retirement age to be overrepresented.[6]

The presence of both right-censoring and left-truncation is addressed by using the 'easy estimation method' for discrete time duration models presented by Jenkins (1995). Essentially this method comes down to constructing an asset-age panel data set, where each asset is included in the panel from the age at which it enters the fleet or the start of the observation window (whichever comes first), and is removed from the panel after it retires or is right-censored. Let y_{ij} be the new binary dependent variable: $y_{ij} = 1$ if aircraft i retires from the fleet in age interval j, and zero otherwise. It is then possible to estimate the parameters of Eq. (5) using a standard binary dependent variable model with the complementary log-log link function.

Fourth, the effect of emission pricing through a trading scheme is likely to have dynamic effects. For one because the emission price is a market price which may vary over time. Besides there may be a temporary hike in retirement rates immediately following the policy introduction, as airlines adapt to the new policy situation. Assets that were still within their economic life in the absence of emission pricing, may suddenly be up for replacement due to the (discrete) increase in the benefit of operating more fuel efficient models. To test for such a dynamic response, I will add interval treatment effects to the model specification. Divide the time period (before and) after the introduction of the emission pricing policy into R periods and let d_r^* be a binary indicator variable $d_r^* = 1$ for the rth time period:

$$h(j, X_{it}) = 1 - \exp(-\exp[\delta_k + \beta_1 D_i + \beta_2 d_t + \sum_{r=1}^{R} \gamma_r (D_i * d_r^*)]). \tag{6}$$

[5]It is clearly visible in my data that narrowbodies are in general retired earlier than widebodies. This makes sense since the strongest wear-and-tear on aircraft are imposed during landing and take-off, which happen relatively more often for narrowbodies, due to their shorter flying cycles.

[6]This bias is long known from labour market models that look at the duration of unemployment (Salant, 1977; Chesher and Lancaster, 1983)

4 Empirical Setting and Data

4.1 Aviation Emissions and the EU ETS

My empirical context concerns the replacement of aircraft in civil aviation. Aviation is a major contributor to anthropogenic climate change, accounting for an estimated 3.5 percent of the economy's climate impact (Lee et al., 2021). Given strong projected demand growth, aviation is one of the sectors identified by the Intergovernmental Panel on Climate Change (IPCC) as needing to make ambitious efficiency improvements to contribute to the emission reduction pathways that are required to meet international climate goals (IPCC, 2018).

In this light, the European Commission decided to include aviation emissions in its greenhouse gas emissions trading scheme, the EU ETS. In the original directive as adopted in 2008, all airlines operating flights to and from Europe had to surrender emission allowances from the beginning of 2012 onwards (Directive 101/2008/EC). After facing fierce political opposition from third countries, and pending the implementation of global measures to control aviation emissions, the scope was reduced to flights within the European Economic Area (the 'stop-the-clock' regime, Decision 377/2013/EU). This scope derogation was originally envisioned for the period until 1 December 2016 (Regulation 421/2014), but was later prolonged to 31 December 2023 (Regulation 2017/2392). To date, the EU ETS has therefore only been applied to short-haul European traffic.

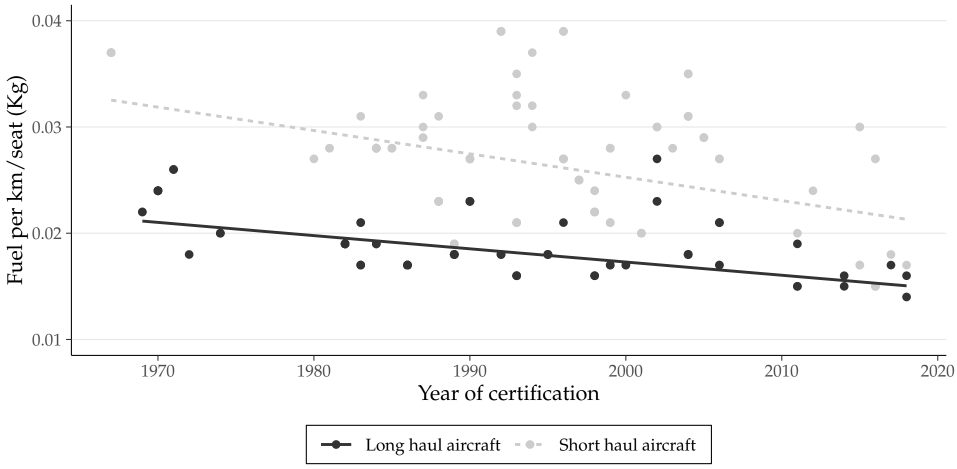
Like other emissions trading schemes, the EU Emissions Trading Scheme aims to reduce emissions at minimum costs by enabling trade of emission allowances between industries. Next to civil aviation, the scheme covers the electricity sector and energy-intensive industrial sectors (e.g., oil refineries, steel mills, cement production). During the first phase of the EU ETS for aviation, aviation's CO_2 emissions increased by 4.7 percent per year implying that the sector has been a net purchaser of emission allowances.(EASA, 2019). As noted by, among others, Fageda and Teixidó (2022), this does not imply absence of in-sector abatement, which would require a comparison with the increase in aviation emissions in the counterfactual situation without the EU ETS.

4.2 Emission Savings through Aircraft Fleet Renewal

One of the main ways airlines can reduce their emissions is by replacing old aircraft with newer models.[7] A necessary condition is that newer vintage aircraft are more fuel efficient, i.e. that there

[7] In the future, renewable aviation fuels (SAFs) may provide another way to reduce aviation emissions. At the time of writing, however, the uptake of SAFs is less than 0.1 percent of all fuel used by commercial aviation. Moreover, the relative

Figure 1: Aircraft fuel efficiency improvements (1970 - 2020)



Note.—This graph shows the fuel consumption per seat-kilometre (in kilograms) by year of certification, for all aircraft in my data. Fuel consumption is estimated with Eurocontrol's small emitter tool (SET) for typical 1,000 Km short-haul and 6,500 Km long-haul flights, divided by the certified maximum passenger seating capacities per aircraft.

is embodied technological progress on the aircraft level.[8] The existence of aircraft-level progress is demonstrated by Figure 1 which shows a decreasing trend in fuel consumption per seat-kilometre of about 0.8 percent per year for short-haul aircraft and 0.6 percent for long-haul aircraft. The fuel savings of the new generation of aircraft are most clearly illustrated for models that are explicit successors of older models. For example, the Airbus A320neo, introduced in 2015, consumes 0.016 kilograms of fuel per seat-kilometre, representing a 27 percent increase in fuel efficiency compared to its predecessor, the Airbus A320ceo, which consumes 0.022 kilograms per seat-kilometre.[9]

While there are multiple factors influencing aircraft replacement decisions (see, Belobaba et al., 2015), fuel and emissions savings are among the key considerations. For one, fuel costs make up around one-third of airline operating costs (Kahn and Nickelsburg, 2016). Aircraft manufacturers therefore frequently advertise with the fuel efficiency savings that can be obtained from replacing old aircraft with newer models. For instance, on the main web page of the A320neo, Airbus states that it "delivers 20 percent fuel savings and CO_2 reduction compared to previous-generation Airbus aircraft".[10] In line with this, airline reports often cite fuel savings as one of the core pillars of

price level of SAFs—about twice as expensive than kerosene-based fuels—prevents them from becoming a viable substitute until significant improvements in cost-efficiencies are realized.

[8]See Benmelech and Bergman (2011) for another paper that relies on this condition.

[9]The efficiency improvement is equal to 20 percent without the effect of increased passenger capacity.

[10]Airbus, "The most successful commercial aircraft family ever": https://aircraft.airbus.com/en/aircraft/a320/a320neo

their fleet planning programs. For example, Delta's 2021 ESG Report reads: "In 2021, Delta made capital expenditures of approximately $3.2 billion, the majority of which went toward new aircraft that are, on average, 25 percent more fuel efficient per seat mile than retired aircraft".[11] In addition to this motivational evidence, academic studies in this area consistently view reducing fuel costs as a major reason for using newer aircraft (e.g., Kahn and Nickelsburg, 2016; Csereklyei and Stern, 2020). At the same time, studies also show that the fleet fuel efficiency is lagging behind with technological progress (Adler et al., 2013; Csereklyei and Stern, 2020), which implies room for policy-induced improvement.

4.3 Historical Aircraft Fleet Data and Descriptives

My historical aircraft fleet data is obtained from Airfleets.net. It covers all airlines in the European Union (labelled as 'Europe') and the United States and Canada (labelled as 'North America') with both short-haul and long-haul aircraft in their fleet. This criterion amounts to all globally active carriers based in these regions.[12] My main sample comprises information on the aircraft active in the fleets of the sampled airlines during the observation window between January 1, 2004 and December 31, 2019. For each aircraft, I record an 'aircraft spell' which refers to the time between when the aircraft entered a sampled airline's fleets and when it exited that fleet. There are 7,607 aircraft spells in total. These aircraft spells are augmented with aircraft characteristics from a number of secondary sources and cast into an aircraft spell-month panel format, suitable for estimating the parameters of discrete proportional hazard models using binary dependent variable models. Full details on the data compilation process are in the Appendix.

Table 1 lists the sampled airlines and the size of their fleets at the start and end of the observation window. In December 2019, the fleets of these airlines represented around forty percent of the commercial aircraft fleets in Europe and North America (World Airliner Census, 2019). Most airlines had increasing fleet sizes over the sample period, while some experienced significant downsizing (most notably, Alitalia, Swiss and Iberia). While the North American fleet seems to have expanded at a higher rate than the European fleet, this is mainly because of greater industry consolidation in this region.

[11] Delta ESG Report 2021: https://www.delta.com/content/dam/delta-www/about-delta/corporate-responsibility/2021-esg-report.pdf

[12] There are two reasons for excluding non-global, often low cost, carriers. First, these carriers focus on operating short-haul routes using one standardized aircraft type. Therefore, the crowding out effect that is the focus of this paper does not apply to them. Second, many of the low cost carriers emerged in the (late) nineties and hence aircraft retirements before the implementation of the EU ETS for aviation in 2012 (i.e., control observations) are scarce for these carriers.

Table 1: Sampled airlines and their fleet size by the end 2019

Europe		North America	
Lufthansa	(267 → 314)	American Airlines	(801 → 953)
British Airways	(239 → 279)	Delta AirLines	(562 → 904)
Air France	(255 → 223)	United Airlines	(578 → 776)
SAS Scandinavian Airlines	(175 → 150)	Air Canada	(214 → 188)
KLM Royal Dutch Airlines	(99 → 122)		
Alitalia	(171 → 94)		
Swiss International AirLines	(124 → 90)		
LOT Polish Airlines	(38 → 88)		
TAP Air Portugal	(42 → 86)		
Iberia	(161 → 84)		
Austrian Airlines	(36 → 84)		
Finnair	(58 → 59)		
Aer Lingus	(37 → 58)		
Icelandair	(16 → 37)		

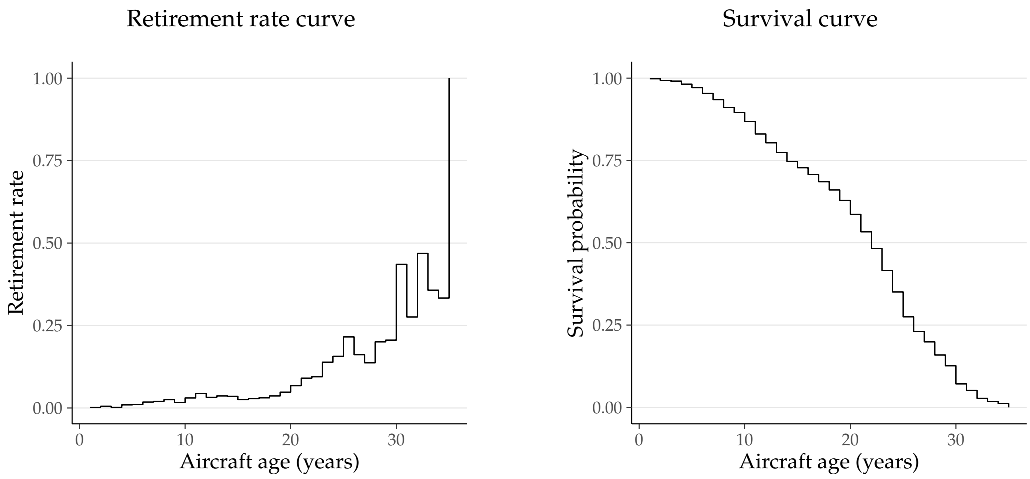
Note.—Fleet size at start/end of observation window—January 1, 2004 to December 31, 2019—in parentheses.

Figure 2 displays the retirement rate and the survival probability curves. The aircraft retirement rate shows the probability that an aircraft of age k (using yearly age intervals) is retired before it reaches age $k+1$. As expected, the retirement rate is increasing in aircraft age. This increase is more pronounced after an aircraft reaches twenty years of age, indicating that after this point the economic life of aircraft begins to exceed and airlines start finding it profitable to invest in replacements. The aircraft survival probability curve shows the percentage of aircraft 'surviving' past age k. This curve is directly related to the retirement rate curve and, by construction, decreases monotonically from one at age zero, to zero at the maximum retirement age which is 37 years in my sample. The median retirement age (i.e., the age at which 50 percent of the aircraft are retired) is approximately 22.5 years.

Table 2 depicts descriptive statistics on the aircraft in my sample, broken down by the European and North American fleet. The fleets of these regions are generally comparable in terms of aircraft characteristics. Most notably, Airbus has a greater market share in Europe and Boeing in the United States, indicating some "home bias" in aircraft manufacturing markets. In addition, the North American fleet is somewhat older and has almost no non-twinjet aircraft, while the fleet composition (short-haul versus long-haul aircraft) and average fuel consumption per seat/kilometre are very similar or exactly the same between Europe and North America.

Figure 3 provides the first graphical evidence of the impact of the EU ETS on aircraft fleet renewal. The upper panels plot the yearly retirement rates in Europe and North America, while the

Figure 2: Aircraft retirement rate and survival curve



Note.—These graphs show the retirement rate and survival probability curves. The retirement rate is calculated $h_k = \Pr(k - 1 < K \leq k)/\Pr(K > k - 1)$, while the survival probability can be derived from the retirement rate by $S_k = \prod_{l=1}^{k}(1 - h_l)$.

lower panels plot their difference. These yearly aircraft retirement rates are computed as the probability that an aircraft in the fleet of an airline in calendar year t is no longer in the fleet of that airline in year $t + 1$. It is important that the retirement rates shown here are not controlled for duration dependence—hence the figures should be regarded as providing suggestive evidence only.

The left side of the figure indicates that aircraft retirements in European short-haul fleet increased around the implementation of the EU ETS for aviation in 2012. Over the same period the retirements in the North American short-haul fleet show a persistent decline. On the right side of the figure the opposite pattern emerges: retirements within the European long-haul fleet decreases relative to retirements in the North American fleet, although admittedly the pattern is less clear. The trends in the figures are also indicative of anticipation effects starting from 2008 for both short-haul and long-haul aircraft, in line with the original directive targeting all routes, including long-haul operations to and from Europe. Overall, this rough evidence points in the direction of an impact of the EU ETS along the lines predicted by the theoretical framework.

Table 2: Descriptive statistics of European and North American aircraft fleets

	Europe		North America	
Aircraft history				
Year of assembly	2001.5	(9.4)	2000.4	(10.3)
Year of certification	1993.7	(9.2)	1992.1	(9.3)
Previous owner	0.67	(0.47)	0.75	(0.44)
Aircraft type				
Short-haul	0.65	(0.48)	0.67	(0.47)
Long-haul	0.35	(0.48)	0.33	(0.47)
Aircraft engines				
Twin engines	0.85	(0.36)	0.98	(0.15)
Jet engine	0.97	(0.18)	1.00	(0.00)
Fuel per km/seat (Kg.)	0.023	(0.005)	0.023	(0.005)
Aircraft manufacturer				
Airbus	0.49	(0.50)	0.25	(0.43)
Boeing	0.32	(0.47)	0.58	(0.49)
Other manufacturers	0.19	(0.39)	0.17	(0.37)

Note.—Table entries depict aircraft-level means, with standard deviation in parentheses.

5 Results

5.1 Effect of the EU ETS on Aircraft Replacement

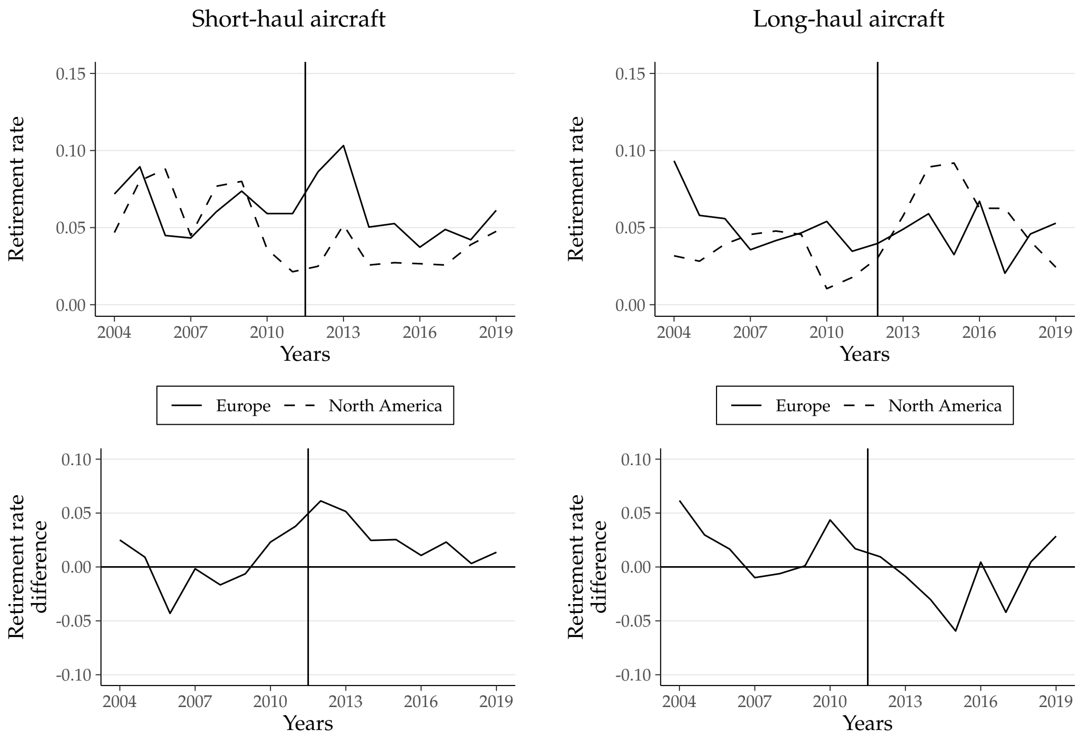
Table 3 reports the estimation results of the baseline proportional hazards model for the short-haul, long-haul and total fleet, respectively. All models include year and group fixed effects, with the grouping equal to the treatment/control regions, i.e., Europe versus North America.[13]

Column 1 focuses on the impact of the EU ETS on the short-haul fleet. The baseline hazard is allowed to change in yearly age intervals. The estimate of the EU ETS impact is 0.51 and is statistically significant at the 1 percent level. The implied hazard ratio of this estimate is equal to $\exp(0.51) = 1.66$, meaning that the probability of an European short-haul aircraft retiring in each age interval increases by 66 percent due to the EU ETS. This seems a particularly large effect, but one has to bear in mind that the baseline retirement rates are very low at younger aircraft ages and then increases sharply after about twenty years (as shown in Figure 2). As such this proportional increase in the retirement rate leads to a plausible decrease in the average aircraft retirement age as we will see later on.

In column 2, the model is estimated on the long-haul fleet. To prevent small sample issues due to fewer long-haul observations, the baseline hazard is allowed to change in two-yearly age intervals.

[13]In a later robustness check, I allow for airline-specific fixed effects, which leads to similar results.

Figure 3: Aircraft fleet retirement rates, Europe versus North America



The negative estimate of -0.38 is statistically significant at the 1 percent level and indicates that EU ETS caused a decrease in the retirement rates of the European long-haul fleet of about 32 percent. Column 3 shows the estimates of the impact on the total fleet. The baseline hazard is allowed to differ in shape between the two types of aircraft to reflect their different retirement patterns, with the baseline age intervals set to two-years corresponding to the smallest possible interval for the long-haul fleet. The estimated impact of EU ETS on the total fleet retirement rate is 0.19 and significant at the 5 percent level, implying a percentage increase of 21 percent in the total fleet aircraft retirement rate.

In sum, these findings are in line with the theoretical predictions that emission pricing (EU ETS) leads to earlier retirements of assets covered by it (short-haul aircraft), while it crowds out the retirement of exempted assets (long-haul aircraft). In the context of aircraft fleet renewal in response to the EU ETS, the first effect dominates the latter. Combined with the fact that regulated assets are more common (i.e., about two-thirds of the fleet is short-haul, see Table 2), this corresponds to accelerated overall retirement.

Table 3: Effects of EU ETS on Aircraft Retirement Rates

	Short-haul aircraft	Long-haul aircraft	Total fleet
	(1)	(2)	(3)
β_3 (ETS 2012 - 2019)	0.51*** (0.09)	−0.38*** (0.13)	0.19** (0.07)
Hazard ratio	1.66	0.68	1.21
N (observations)	463,319	284,894	748,213
N (aircraft spells)	5,055	2,609	7,664
Year FE	$N = 16$	$N = 16$	$N = 16$
Group FE	$A = 2$	$A = 2$	$A = 2$
δ_k (aircraft age intervals)	$K = 34$ (yearly)	$K = 17$ (two-yearly)	$K = 34$ (two-yearly * aircraft class)

Note.—This table presents the likelihood estimates and hazard ratios of the impact of the EU ETS on aircraft retirement rates, obtained from a discrete proportional hazard model estimated on an aircraft spell-month panel. Standard errors provided in parentheses.
* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

5.2 Dynamic Effects

Table 4 presents estimates from a more detailed analysis that complements the main results by accounting for dynamic effects. These models also test for an anticipation effect between the announcement of the EU ETS for aviation and the actual implementation.

The first row shows that retirement rates in the European short-haul fleet already increased in the years between policy announcement and implementation. Consistent with the original EU ETS for aviation including all flights to, from and within Europe, the anticipation effect extends to the long-haul fleet, although the estimate is not statistically significant at conventional levels. The remaining rows show that the largest impacts of the EU ETS, both the positive effect on the short-haul fleet and the negative effect on the long-haul fleet, occur in the years immediately following policy implementation. While this seems to contradict the fact that allowance prices quadrupled by the end of 2019, aircraft delivery times may not allow airlines to respond directly to rising emission prices.[14] Rather, these dynamic effects are in line with a "transition period", in which airlines reorganize their fleets to adapt to the new regulatory situation. This leads to an initial peak in the retirement rate followed by a decline over time as replacement cycle move into a new steady state.

Table B.1 presents the same dynamic analysis using two-year treatment intervals. The overall patterns of the results remain the same. In addition, this more granular breakdown shows that anticipation only occurred in the two years prior to policy implementation. This makes sense as early

[14] If allowance prices increase structurally, as seems to be the case with the current EU ETS allowances price still being significantly above the levels that were typical during most of my sample period, one expects to see increasing retirement rates. The pandemic prevents such an analysis for recent years, but future research could empirically test this expectation.

Table 4: Dynamic Effects of EU ETS on Aircraft Retirement Rates

	Short-haul aircraft	Long-haul aircraft	Total fleet
	(1)	(2)	(3)
γ_1 (ETS 2008 - 2011)	0.29** (0.13)	0.27 (0.19)	0.31*** (0.10)
Hazard ratio	1.34	1.31	1.37
γ_2 (ETS 2012 - 2015)	0.97*** (0.13)	-0.40** (0.17)	0.46*** (0.10)
Hazard ratio	2.65	0.67	1.58
γ_3 (ETS 2016 - 2019)	0.29** (0.13)	-0.10 (0.18)	0.18* (0.10)
Hazard ratio	1.34	0.90	1.20
N (observations)	463,319	284,894	748,213
N (aircraft spells)	5,055	2,609	7,664
Year FE	$N = 16$	$N = 16$	$N = 16$
Group FE	$A = 2$	$A = 2$	$A = 2$
δ_a (aircraft age dummies)	$J = 34$ (yearly)	$J = 17$ (two-yearly)	$J = 34$ (two-yearly * aircraft class)

Note.—This table presents the likelihood estimates and hazard ratios of the impact of the EU ETS on aircraft retirement rates, obtained from a dynamic discrete proportional hazard model estimated on an aircraft-month panel. Standard errors provided in parentheses.
* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

replacement long before actual policy implementation (i.e., replacing an aircraft in 2009 instead of 2011) would not change emissions under the EU ETS. Another interesting result is that the tipping point from a positive to a negative effect on long-haul aircraft retirement occurs in the 2012 - 2013 period, which is exactly the period in which the EU formally decided on the scope derogation.

5.3 Alternative Specifications and Subsamples

Table 5 presents a range of sensitivity analyses that test the robustness of my main results and rule out a number of alternative explanations. Column (1) shows that differences between European and North American aircraft fleets do not explain my findings—if anything, controlling for aircraft characteristics increases the effect sizes as compared to the main results.[15] This is expected given that the European and North American fleets are highly similar (see Table 2) and any stable difference is already captured by the fixed effects.

Column (2) shows the impact of using airline fixed effects, which allows for, among others, differences in replacement policies across airlines. The impact on the short-haul fleet remains the same, while the impact on the long-haul fleet is still negative but no longer statistically significant. However, the effect on the total fleet (37 percent) is substantially smaller than what one would

[15]The covariates included are dummies for aircraft engine characteristics (i.e., twin, jet), aircraft manufacturers and previous ownership.

Table 5: Effects of EU ETS on aircraft retirement rates: robustness checks

	(1) *aircraft covariates*	(2) *airline FE's*	(3) *heterogeneous hazards*	(4) *2000-2019*	(5) *linear trend*	(6) *growing airlines*
			A. Short-haul aircraft			
β_3 (ETS 2012 - 2019)	0.71*** (0.10)	0.64*** (0.10)	0.59*** (0.10)	0.40*** (0.09)	0.85*** (0.19)	0.55*** (0.14)
Hazard ratio	2.03	1.90	1.80	1.50	2.34	1.74
N (observations)	463,319	463,319	463,319	568,843	463,319	333,285
λ_a (aircraft age dummies)	$J = 34$ (yearly)	$J = 34$ (yearly)	$J = 14$ (four-yearly * region)	$J = 34$ (yearly)	$J = 34$ (yearly)	$J = 17$ (two-yearly)
			B. Long-haul aircraft			
β_3 (ETS 2012 - 2019)	−0.30** (0.13)	−0.16 (0.13)	−0.22 (0.14)	−0.33*** (0.11)	−0.80*** (0.27)	−0.26 (0.16)
Hazard ratio	0.74	0.85	0.80	0.72	0.45	0.77
N (observations)	284,894	284,894	284,894	357,234	284,894	219,532
λ_a (aircraft age dummies)	$J = 17$ (two-yearly)	$J = 17$ (two-yearly)	$J = 14$ (four-yearly * region)	$J = 17$ (two-yearly)	$J = 17$ (two-yearly)	$J = 5$ (six-yearly)
			C. Total fleet			
β_3 (ETS 2012 - 2019)	0.25*** (0.08)	0.31*** (0.08)	0.30*** (0.08)	0.12* (0.07)	0.26* (0.15)	0.29*** (0.10)
Hazard ratio	1.29	1.37	1.34	1.12	1.29	1.34
N (observations)	748,213	748,213	748,213	926,077	748,213	552,817
λ_a (aircraft age dummies)	$J = 34$ (two-yearly * aircraft class)	$J = 34$ (two-yearly * aircraft class)	$J = 32$ (four-yearly * aircraft class * region)	$J = 34$ (two-yearly * aircraft class)	$J = 34$ (two-yearly * aircraft class)	$J = 10$ (six-yearly * aircraft class)
Year FE	$N = 16$	$N = 16$	$N = 16$	$N = 20$	$N = 20$	$N = 16$
Group FE	$A = 2$	$A = 16$	$A = 2$	$A = 2$	$A = 2$	$A = 2$

Note.—These tables presents the likelihood estimates and hazard ratios of the impact of the EU ETS on aircraft retirement rates, obtained a discrete proportional hazard model estimated on an aircraft-month panel, using alternative specifications and various subsamples. Standard errors provided in parentheses.
* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

expect assuming a zero impact on the long-haul fleet, suggesting strong crowding out effects (i.e., the impact on short-haul aircraft multiplied by the percentage of short-haul aircraft in the fleet: $0.67 * 0.90 = 60$ percent).

Column (3) makes the duration dependence more flexible by allowing the shape of the baseline hazard to differ between Europe and North America, while the proportional effect of the treatment variables are still assumed constant. This essentially amounts to a stratified analysis in the spirit of Heckman & Singer (1982, 1984) and Ridder et al. (1998). The results of this specification mimic those obtained while using airline fixed effects.

Column (4) uses data from an extended observation window between 2000 to 2019. Although this increases the sample size, a reason for not using this wider window in the baseline estimation is a possibly different impact of the 9/11 terror attacks on aircraft retirement in Europe and North America. Notwithstanding this concern, estimates obtained here are in line with the results on the shorter window, both in direction, magnitude and statistical significance.

Column (5) estimates a model including a linear time trend difference between Europe and North America. Both the impact on short-haul and long-haul become substantially larger. As such, the main results still hold, but care should be taken in interpreting these results as the assumption of a linear trend difference might be too strict.[16]

Finally, column (6) focusses on the subset of airlines with growing fleets over the observation window. This rules out that differential fleet contraction in Europe vis-à-vis North America is driving my results. If fleet contraction is constant over time or regions it is already absorbed by the fixed effects, while a linear trend difference in contraction is something that the previous specification controls for. Reassuringly, I find very similar results in this more flexible sub sample analysis, indicating that my estimates capture an acceleration of capital replacement rather than a downsizing of the capital stock correlated with the EU ETS policy implementation.

The same sensitivity analysis are repeated for the dynamic model specification, with estimates reported in Table B.2 - B.4. The results are comparable to the baseline dynamic models shown in Table 4, although the precision and significance of (mostly) the long-haul estimates fall in some specifications which are quite demanding for the sample size.[17]

Overall, the positive impact of the EU ETS on the retirement of short-haul aircraft appears to be robust, while the negative impact on long-haul aircraft is somewhat more fragile. This is not

[16] In addition, there may be too few control years on which to calibrate the slope of the trend difference, which is a common problem with this type of specification (see, Wolfers, 2006).

[17] Using the longer time period to increase the sample size in these specifications, the usual pattern of results reappears. These estimates are available upon request.

surprising given that the sample of long-haul aircraft is much smaller and there was considerate uncertainty about the applicability of the EU ETS to long-haul routes in the first few years after the policy was announced. The impact on long-haul fleet renewal never changes direction. Moreover, the impact on the total fleet, which is estimated on the full sample of all aircraft and thus has a larger sample size, is always considerably smaller than the impact that might be expected assuming no crowding out, which is further evidence that the accelerated renewal of the short-haul fleet has partly come at the expense of the renewal of the long-haul fleet.

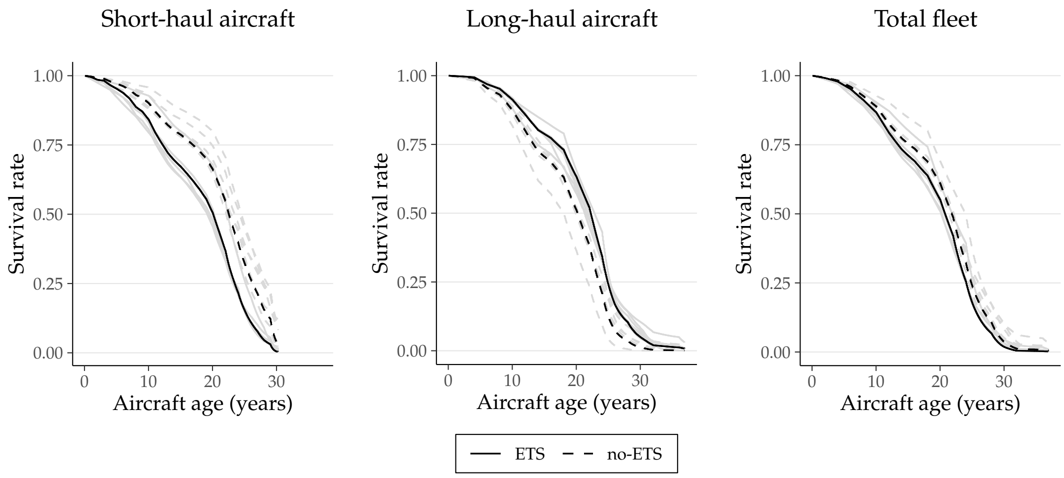
5.4 Aircraft Survival Probabilities and Average Retirement Age

To illustrate what my empirical results imply in terms of aircraft replacement, I use the model estimates to obtain predicted survival probabilities and average retirement ages for treated aircraft in the *actual* policy scenario and contrast them with a *counterfactual* scenario without the EU ETS.

As a first illustration, Figure 4 plots the actual and counterfactual aircraft survival curves. The actual survival curve is obtained by using the model estimates to predict the survival probability of all aircraft receiving the EU ETS treatment. The counterfactual survival curve is obtained by setting the effect of the EU ETS equal to zero and repeat the prediction. The left panel shows that the survival probabilities of short-haul aircraft in the situation with EU ETS are substantially below those without EU ETS. For example, at age twenty, the probability of a short-haul aircraft surviving under the EU ETS is 50 percent, whereas it would have been 66 percent in the counterfactual situation without the EU ETS. This picture is reversed in the middle panel, which shows higher survival probabilities for long-haul aircraft in the counterfactual situation without the EU ETS. The right panel shows that survival probabilities for the total fleet are again lower in the situation with the EU ETS, but the gap between the actual and counterfactual curves is much smaller than in the panel for the short-haul fleet. Considering again the differences at age twenty, the predicted survival probability of *all* aircraft is about 55 percent with and 61 percent without the EU ETS.

From the predicted survival curves, I derive the expected retirement age of aircraft in the actual and the counterfactual situation. The differences between these two expectations yields an average treatment effect on the treated. Table 6 gives both the mean and median retirement ages. The expected (truncated) mean retirement age is obtained by integrating the predicted survival curve to the month of the oldest observed retirement, assuming that all remaining planes retire immediately after, i.e. $sum_{j=1}^{J}[(S_{j-1} - S_j) * j] + S_J * (J + 1)$. It may be preferable to use the median retirement age, which is equal to the age interval in which the survival curve crosses the fifty percent survival

Figure 4: Factual and counterfactual aircraft survival curves



Note.—These plots present the survival curves of the treated observations (i.e., European aircraft after 2012) obtained from model estimates. The counterfactual survival curves (no-ETS) are obtained by imposing the treatment effect of the ETS to be zero. The black line is based on the baseline parameter estimates reported in Table 3, while grey lines are based on the robustness checks reported in Table 5.

probability line (i.e., the age at which half of aircraft retire). In practice, the average treatment effects on the treated computed from the mean and the median retirement ages do not differ much.

First consider the average treatment effect obtained from the baseline estimation results. The expected mean retirement age with and without the EU ETS for the sample of treated short-haul aircraft is equal to (rounded) 18.1 and 21.0 years, respectively. Thus, the introduction of the EU ETS for aviation reduced the average retirement age for short-haul aircraft by about 2.8 years, which represents a 13 percent decrease from the retirement age in the counterfactual scenario. In terms of the median retirement age, the decrease equals 2.5 years or about 11 percent. At the same time, both the mean and median retirement age for long-haul aircraft increased by 2.0 years, which equal an increase of 10 to 11 percent. Thus, both in absolute and percentage terms, the retirement age of short-haul aircraft is declining more strongly than the increase in the retirement age of long-haul aircraft. This is also reflected in the decreasing retirement age of the total fleet, which as shown in the lower panel, equals about 1.1 years for both the mean and median retirement age.

The remaining rows show the absolute lowest and highest average treatment effects, as obtained from the sensitivity analyses. Within each subsample, the treatment effects are always of the same sign, and in particular the results for the total fleet, appear to be very stable across specifications and subsamples. For example, with respect to the median retirement age for the total fleet, all sensitivity analysis yield treatment effects that are within the range of a 0.6 to 1.5 year reduction.

Table 6: Average Treatment Effect on the Treated: mean and median retirement ages

	Mean retirement age			Median retirement age		
Estimate:	(ETS)	(no-ETS)	Δ_{mean}	(ETS)	(no-ETS)	Δ_{median}
			A. Short-haul aircraft			
Baseline	18.1	21.0	-2.8	20.1	22.6	-2.5
Lowest	18.1	20.4	-2.3	20.2	22.2	-1.9
Highest	18.1	22.8	-4.6	20.1	24.2	-4.2
			B. Long-haul aircraft			
Baseline	20.7	18.7	2.0	22.2	20.2	2.0
Lowest	20.1	19.1	1.0	21.5	20.4	1.1
Highest	20.7	16.5	4.2	22.3	18.1	4.2
			C. Total fleet			
Baseline	19.0	20.1	-1.1	20.8	21.8	-1.1
Lowest	19.0	19.7	-0.7	20.8	21.3	-0.6
Highest	18.7	20.7	-2.0	20.2	21.8	-1.5

Note.—This table presents the average treatment effects on the treated in terms of mean and median retirement ages. The (truncated) mean retirement age is estimated $\sum_{a=1}^{A}[(S_{a-1} - S_a) * a] + S_A * (A+1)$, while the median retirement age is the point at which the survival curve crosses the 0.5 probability line (i.e., the age at which 50 percent of the aircraft are retired).

6 Simulations

To shed light on the net environmental benefit of aircraft fleet renewal induced by the EU ETS, I estimate the CO_2 emission savings of induced replacements under various policy scenarios. This exercise combines a simulation of aircraft retirement for the treated sample, with additional information on the fuel consumption and CO_2 emissions of aircraft.

The simulation applies the survival curves with and without the EU ETS to predict in which year and month each treated aircraft (i.e., European aircraft active after 2012) retires. The sum of the pairwise differences between the month of retirement with and without the EU ETS yields the total number of months of "early" retirement. E.g., if an aircraft retires in June 2016 under the EU ETS, and in March 2017 without the EU ETS, it contributes nine months to this sum. Delayed retirements contribute negatively to the sum. To verify the within-sample performance of the simulation, I first simulate aircraft retirements in the treated sample over the EU ETS period (2012 - 2019). The predicted number of retirements as well as the mean and median retirement ages resemble the actual values in the data, demonstrating that the simulation is able to predict actual retirement events quite well.[18]

[18]The predicted versus actual number of aircraft retirements are 496.1 versus 497 in the treated short-haul fleet, and 223.8 versus 228 in the treated long-haul fleet. Predicted versus actual mean (median) retirement age is 18.1 versus 17.1 (19.9

To calculate emission savings, I assume that all retirements are replacements. As such, each month of early retirement can be considered as a month in which a new instead of an old generation aircraft is operated (and vice versa for delayed retirements). Let r_i be the total number of months of early replacement for aircraft type i. The fuel consumption for old and new generation models E_i and E'_i are inferred from reference models. For short-haul, the fuel savings from a new generation model are approximately 20 percent (from 4 to 3.2 Kg/Km). For long-haul, I consider fuel savings of about 12.5 percent (from 8 to 7 Kg/Km) as well as fuel savings of about 20 percent (from 10 to 8 Kg/Km). The latter distinction illustrate the impact of different rates of technological progress between the regulated and unregulated types.[19] I further take into account differences in (monthly) aircraft utilization u_i between aircraft types, assuming four typical 1,000 Km daily flights for short-haul aircraft and one typical 6,500 Km daily flight for long-haul aircraft. Using the conventional CO_2 emission factor for jet fuel of 3.16 (Lee et al., 2021), the emission savings can be calculated as:

$$\widehat{SAV} = \sum_i 3.16 r_i u_i (E_i - E'_i) \tag{7}$$

With the above assumptions, it is also possible to calculate the total CO_2 emissions of the sampled airlines and compare them to the emissions reported under the EU ETS.[20] This calculation suggests that the short-haul operations of the sampled airlines are responsible for about 35 - 40 percent of the EU ETS's aviation emissions, which corresponds to their market share in Europe and hence provides confidence to the employed assumptions and input values.

Table 7 reports CO_2 emission savings for three different scenarios under greater technological progress for short-haul aircraft (Panel A) and equal technological advances (Panel B).[21] The first scenario is based on the constant EU ETS effect over the 2012 - 2019 period from Table 3, columns (1) and (2). Under unequal technological progress, the estimates imply CO_2 savings of 2.60 Mt (1.9 percent of total short-haul emissions) from induced replacement of short-haul types, and CO_2 leakage of 2.04 Mt (-0.8 percent of total long-haul emissions) from crowding out replacement of long-haul aircraft. The resulting total fleet impact is 0.56 Mt (0.1 percent of total emissions). Thus,

versus 19.4) and 19.5 versus 19.6 (20.0 versus 20.7), for short-haul and long-haul, respectively.

[19] One could argue that these emission savings can only be realized after the introduction of a new generation aircraft model (e.g., Boeing 787 in 2011, Airbus A320neo in 2016). Something to keep in mind here is that aircraft replacements typically occur after two decades of service, so there almost always is a more fuel-efficient substitute available. This is shown in Figure B.2, which plots the average fuel consumption per seat-kilometre of the retirement aircraft versus the newly acquired replacements: the average fuel efficiency of the replacements is always well below that of the retirements. The implied 'realized' average fuel savings in the period after the EU ETS are about 13.5 percent for short-haul aircraft and 10 percent for long-haul aircraft.

[20] EEA, "EU ETS Data Viewer": https://www.eea.europa.eu/data-and-maps/dashboards/emissions-trading-viewer-1

[21] The intermediate simulation results, averaged over a 1,000 simulation runs, are provided in Figure B.3

Table 7: Net Environmental Benefit of Induced Fleet Renewal

	CO_2 emission savings (%)		
	Short-haul fleet	Long-haul fleet	Total fleet
	A. Greater technological progress for short-haul		
EU ETS, 2012 - 2019, constant effect	2.60 (1.90%)	−2.04 (−0.80%)	0.56 (0.10%)
EU ETS, 2008 - 2019, dynamic effects	5.81 (2.80%)	−0.49 (−0.10%)	5.32 (0.90%)
EU ETS, 2008 - 2019, constant effect based on 2008 - 2011	2.96 (1.50%)	2.71 (0.70%)	5.68 (0.90%)
	B. Equal technological progress		
EU ETS, 2012 - 2019, constant effect	2.60 (1.90%)	−3.36 (−1.10%)	−0.76 (−0.20%)
EU ETS, 2008 - 2019, dynamic effects	5.81 (2.80%)	−0.80 (−0.20%)	5.00 (0.70%)
EU ETS, 2008 - 2019, constant effect based on 2008 - 2011	2.96 (1.50%)	4.47 (0.90%)	7.43 (1.10%)

Note.—Table entries show CO_2 emission savings in megatonne (Mt), with percentages in parentheses.

taking into account carbon leakage, the net environmental gain of induced aircraft replacement from the EU ETS is virtually zero. Under equal technological progress, the total fleet impact is even negative at 0.76 Mt (−0.2 percent). This reflects that crowding out becomes more environmentally harmful, the higher the fuel savings that can be obtained from replacing unregulated types.

The first scenario does not take into account dynamic responses to the EU ETS and ignores the anticipation effect in the 2008 - 2011 period. To amend this, the second scenario uses parameter estimates from the dynamic models presented in Table 4, columns (1) and (2). This increases the net CO_2 savings to 5.32 Mt (0.9 percent).[22] The main reason for the higher savings in this scenario is that initial policy uncertainty with respect to the inclusion of extra-European flights led to induced replacement of both short-haul and long-haul aircraft in the 2008 - 2011 period.

Building on this, the third scenario assumes a full scope EU ETS over the entire period. This is operationalized by extending the anticipation effects from Table 4, columns (1) and (2), into the subsequent periods. Instead of carbon leakage, emission savings now accrue from long-haul replacements in addition to the savings from short-haul replacements. While this only slightly raises the environmental benefits under the assumption of unequal technological progress, the emission savings under equal technological progress would have been nearly fifty percent higher than in the actual policy scenario with a reduced scope EU ETS. This demonstrates the benefits of having a complete policy that covers all assets operated by the regulated firms.[23]

[22]Note that these CO_2 emission savings are obtained over a longer period than in the first scenario, so the savings in percentage terms provide a better comparison than the savings in absolute terms.

[23]Using the 'realized' emission saving percentages obtained from comparing the average fuel efficiency of retirements

It can be concluded from the simulations that the current piecemeal application of the EU ETS does not substantially promote the environmental efficiency of aircraft fleets. This is in line with reports from the European Environment Agency (EEA) that the EU ETS for aviation has led to only marginal within-sector emission abatement so far.[24] Arguably, in this particular context, the channel for carbon leakage revealed in this paper is therefore of little economic consequence. However, once carbon prices rise structurally—as seems to be the case—or when more evolutionary technologies (e.g. hydrogen or electrically powered aircraft) become available, the environmental benefits of induced replacement and crowding out effects can play a major role as evidence by the relative effects.[25]

7 Conclusion

This paper documents the effect of emission pricing on the replacement cycle for capital goods and the net environmental benefits of policy-induced replacement. Empirically, I use detailed data on the retirement of aircraft, the most important capital asset in aviation, and a policy shock generated by the inclusion of aviation in the EU ETS in 2012. Since this policy only got implemented on intra-European routes, regulated and unregulated assets are clearly distinguishable, even within asset holdings of the same firm. Consistent with the predictions of a simple theoretical framework, I have two main results. First, firms accelerate the replacement of capital assets subject to emission pricing, in order to benefit from the lower emissions technology embodied in newer vintages of these assets. In the case of the EU ETS for aviation this creates carbon savings of up to three percent of the total CO_2 emissions produced by the assets covered by the policy.

Second, firms slow down the replacement of assets that are not subject to emission pricing, because the opportunity costs of such replacements increase. This leads to a kind of carbon leakage, as the abated emissions from the early introduction of newer, more environmentally efficient, regulated assets are offset by the extended operation of older, less efficient, unregulated assets. In the context studied here, the unregulated assets have a higher emission intensity, so that although the

and replacements (Figure B.2) leads to somewhat lower net environmental benefits, while the qualitative patterns remain the same (see Table B.5).

[24]This is not a criticism of the policy per se, as airlines may have paid for emissions reductions in other sectors that presumably have lower abatement costs, which is exactly what a tradable emissions allowance system is designed to do.

[25]In addition, one benefit of early replacement not taken into account in my simulation is that it also speeds up the next replacement. Given the short time horizon of my simulation and the fact that the retirement curve is almost flat in the first ten years, this is unlikely to have much impact on my results. In the longer run, however, this leads to the benefits of early replacement stacking up.

induced replacement of regulated types dominates the delayed replacement of unregulated types (i.e., the overall replacement speeds up), the net environmental impact of the induced replacement effects are close to zero or even negative.

These results emphasize the need for regulators to consider the effects of incomplete environmental policies beyond the impacts on assets that are covered by the policy. Leakage effects similar to the one shown here can also occur when a regulation does not cover all types of emissions, as is for instance the case with the EU ETS's focus on carbon. This incentivizes firms to replace capital that produces a relatively high amount of CO_2, while deferring the replacement of capital that produces more, say, NO_x or methane. The first-best solution remains to design and implement complete environmental policies. Indeed, my counterfactual simulations suggest that if the EU ETS would have been implemented for intra- and extra-European aviation, such that all assets of European airlines would have been covered, induced replacement would have led to positive and sizeable CO_2 emission savings.

My analysis raises several questions for future research. A first possibility is to examine what happens to assets that are retired—especially in light of assets that are sold to and further exploited in developing countries. Replicating my analysis on a global database may shed more light on the capital renewal effects of local environmental policies on global environmental outcomes. Second, how does taking lifecycle emissions change the story? Nearly all aircraft emissions occur during the use phase, but for capital assets with substantial production and/or recycling emissions, accelerating replacement might be less optimal. Incomplete environmental policies that regulate usage emissions but not production emissions may lead to further leakage. Third and finally, environmental policies affect equilibrium prices (see, e.g., Jacobsen and Van Benthem, 2015). While it may be unlikely that EU ETS has lead to changes in global aircraft list prices, European airlines might have experienced less leverage to negotiate discount on the newest short-haul aircraft models. This would offer an alternative explanation as to why the impact of emission pricing seems to diminish in the long(er) run of my dynamic model estimates. The exploration of such equilibrium effects and other extensions are left for further research.

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A Data Compilation

A.1 Aircraft Durations

The primary aircraft data are sourced from airfleets.net. The raw data set includes all aircraft historically operated by the airlines given in Table 1, but my main sample is restricted to aircraft that were part of these airlines' fleets between 1 January 2004 and 31 December 2019. This observation window roughly corresponds to the interim between the shocks caused by the 9/11 terror attacks and the COVID-19 pandemic. An additional advantage is that the implementation of the EU ETS for aviation happened exactly in the middle of this period.

The observations are on the aircraft spell-level, i.e. one observation per contiguous period that an aircraft was employed in the fleet of one of the sampled airlines. Aircraft with multiple spells within the *same* airline are collapsed to a single spell running from the first time an aircraft enters the airline's fleet until its ultimate exit—whereas aircraft with multiple spells with *different* airlines are regarded as independent observations.[26] There is no distinction between potentially different exit states, e.g. scrapped, sold, converted to freighter. Hence, 'aircraft retirement' should be taken to mean the moment an aircraft permanently exits an airline's fleet.

For each aircraft spell, I observe a manufacturing date, fleet entry date and retirement date. All dates are accurate to the year-month level (e.g., June 2009).[27] As explained in the main text, some aircraft remain in the fleet when the observation window ends and, hence, their retirement date is right-censored. For such spells I construct a censoring date which is set equal to December 2019. As also explained in the main text, some aircraft were already in the fleet at the start of the observations window, which leads to left-truncated non-random sampling since aircraft that retired too early to make it to the start of the observation window are systematically excluded from the sample. To cope with this I construct a truncation date which is set equal to January 2004, so that already active spells are considered at risk of retirement only from the start of the observation window.

The next step involves reorganizing the dataset into an aircraft-month panel. Per aircraft spell multiple records are created: one record for each year-month between the fleet entry/truncation

[26]Both cases are relatively rare. Aircraft with multiple spells within the same airline represent ∼7 percent of the final sample, with most of them not being genuine multiple spell observations, but rather tail number changes that show up as separate spells in the original source data. Aircraft with multiple spell at different airlines account for ∼3 of all observations.

[27]Manufacturing dates were only available on the year level (e.g., 1994). To get them to the year-month level, I assume that all aircraft with manufacturing year equal to the year of the entry date are newly purchased aircraft, and hence the manufacturing date can be set equal to the entry date. For the remaining aircraft it is assumed that manufacturing occurred in the middle of the year, i.e. in July.

Table A.1: Examples of aircraft spells in aircraft-month panel format

Aircraft spell #	Model	Airline	Year-month	Age (months)	Retirement indicator
431	737-823	AA	2014-11	1	0
431	737-823	AA	2014-12	2	0
⋮	⋮	⋮	⋮		
431	737-823	AA	2019-11	61	0
431	737-823	AA	2019-12	62	0
- - - -					
2772	320-111	AF	2004-01	179	0
2772	320-111	AF	2004-02	180	0
⋮	⋮	⋮	⋮		
2772	320-111	AF	2009-04	242	0
2772	320-111	AF	2009-05	243	1

date and the retirement/censoring date.[28] These records depict the period at which the aircraft was at risk of retirement from a given airline's fleet, the age of the aircraft in each year-month measured as the number of months since manufacturing, and a binary indicator variable equal to one if the aircraft retires in that month, and zero otherwise.

To make matters more concrete consider some examples in Table A.1. Aircraft spell #431 is a Boeing 737-800, that was manufactured and directly entered the fleet of American Airlines in November 2014, and remained in that fleet after the observation window ends in December 2019. Aircraft spell #2772 is an Airbus 320-100 which entered the fleet of Air France before the observation window started and hence starts being recorded from January 2004, at which point it was already 179 months old—it retired in May 2009, at an age of 243 months. The complete data includes 7,607 of such aircraft spells that cover 743,350 year-month records in total.[29] Together, they provide a complete picture of the fleet composition of the sampled airlines during the observation window.

A.2 Aircraft Characteristics

I use the aircraft model information to further augment the data with aircraft characteristics collected from three secondary sources. The first source is the International Civil Aviation Organization's (ICAO) Aircraft Type Designator database (ICAO Doc 8643). This document lists the aircraft manufacturers, type designators and engine information for all commonly used aircraft models. One important piece of information is each aircraft model's wake turbulence category,

[28] I.e., for left-truncated spells the truncation date is used as the starting month, otherwise the date of entry in the fleet. Similarly, for right-censored spells the censoring date is used as the final month, otherwise the date of retirement.

[29] After truncation of three clear outliers with survival ages of over forty years.

which ranges from Light (maximum take-off mass $<$ 7000 kilograms), to Medium (7000 kilograms $<$ maximum take-off mass $<$ 136,000 kilograms), Heavy (maximum take-off mass $>$136000 kilograms) and Super (specific category for Airbus A380). I use these to distinct between short-haul aircraft (Light and Medium categories) and long-haul aircraft (Heavy and Super categories). This roughly corresponds to a distinction between narrowbodies and widebodies, although there are exceptions such as the Boeing 757, which is a narrowbody that belongs to the Heavy category.

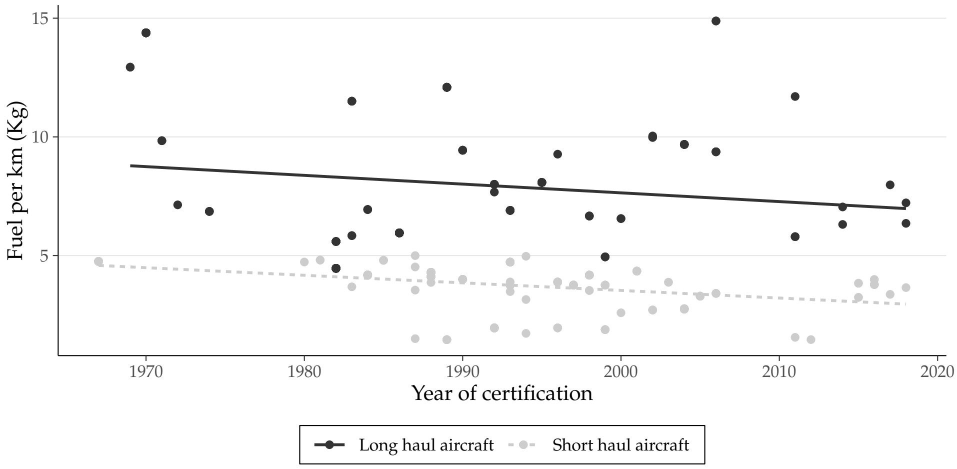
A key assumption underlying my empirical analysis is that almost all flights under the EU ETS are operated by short-haul aircraft (as defined above). As a sanity check, I analyse timetable data, including scheduled aircraft models, from the Official Airline Guide (OAG). In the third week of June 2019, more than 99 percent of all intra-European flights covered by the EU ETS were operated by aircraft belonging to the short-haul aircraft category. Moreover, of all the flights operated by the long-haul fleets of the European airlines in my sample, about 97 percent are non-EU ETS flights. Using a different week does not lead to a different conclusion. This provides strong support for the differential impact of the EU ETS on short-haul and long-haul aircraft.

The second source for aircraft characteristics is the small emitters tool (SET) from Eurocontrol, which enables estimation of each model's fuel burn per kilometre (and CO_2 emissions given the linear emissions factor of 3.16, Lee et al., 2021). The calculations underlying this tool are based on fuel burn samples of real life flight operations on the ICAO aircraft type designator's level. As the fuel burn per kilometre depends on the distance of the flight, one needs to assume a reference flight length to calculate an aircraft type's fuel burn. Based on the same OAG data as above, an average short-haul aircraft flight length of 800 km is assumed, while an average length of 6,500 km is assumed for long-haul aircraft flights.

The final source is each model's Type Certificate Data Sheet (TCDS). From these certification documents I derive the certification years and the certified maximum passenger seating capacities. To be consistent with the fuel burn data, these variables are collected on the ICAO aircraft type designator's level. When different models within the same ICAO type designation have different years of certification, I take the earliest certification year. In the case of differences regarding the maximum passenger seating capacity, the maximum across the different (sub)models is used.

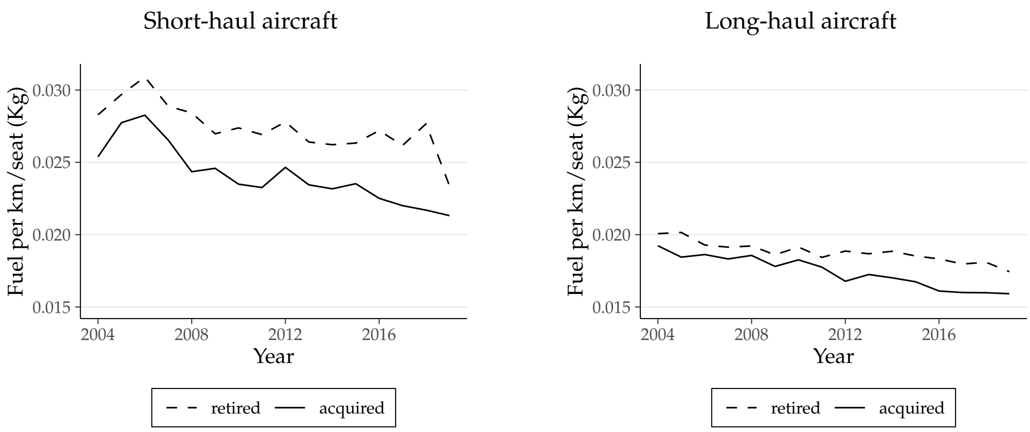
B Additional Figures and Tables

Figure B.1: Aircraft fuel efficiency improvements (1970 - 2020) - per kilometre



Note.—This graph shows the fuel consumption per kilometre (in kilograms) by year of certification, for all aircraft in my data. Fuel consumption is estimated with Eurocontrol's small emitter tool (SET) for typical 1,000 Km short-haul and 6,500 Km long-haul flights.

Figure B.2: Average fuel efficiency of retired versus acquired aircraft by year



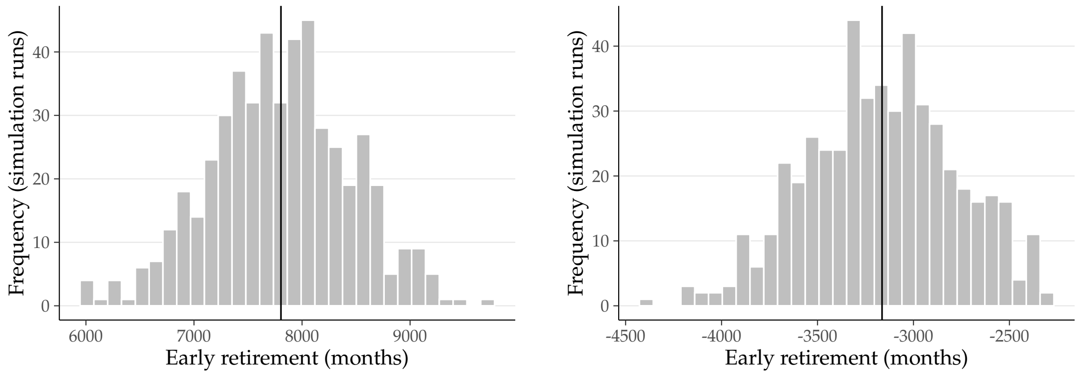
Note.—These graphs show the average fuel consumption per seat-kilometre (in kilograms) of the aircraft that were retired and acquired in each year.

Figure B.3: Aircraft retirement event simulation

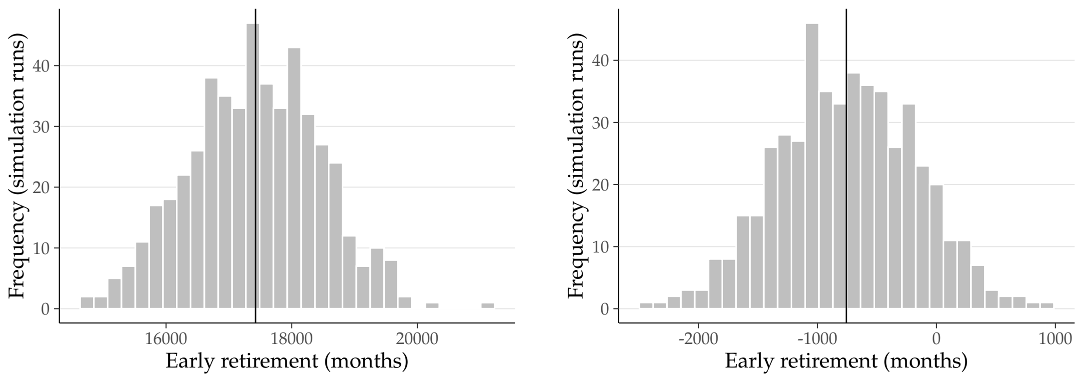
Scenario 1: EU ETS, 2012 - 2019, constant effect

Short-haul fleet

Long-haul fleet



Scenario 2: EU ETS, 2008 - 2019, dynamic effects



Scenario 3: EU ETS, 2008 - 2019, constant effect based on 2008 - 2011

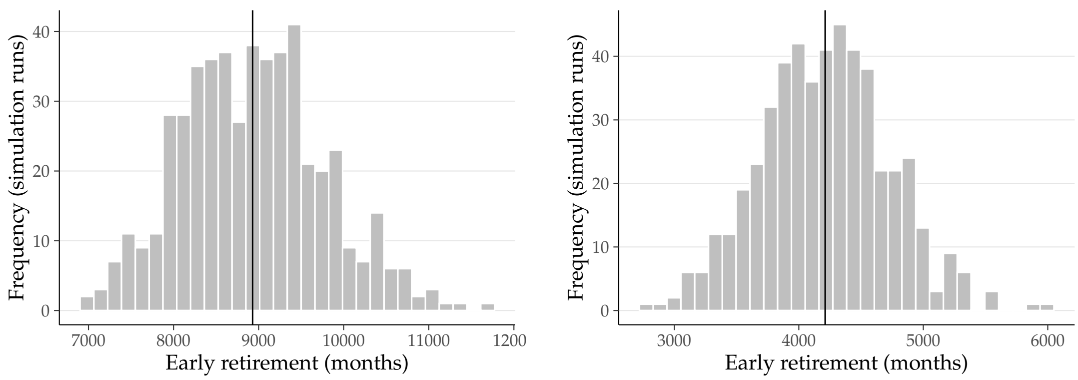


Table B.1: Dynamic Effects of EU ETS on Aircraft Retirement Rates

	Short-haul aircraft	Long-haul aircraft	Total fleet
	(1)	(2)	(3)
γ_1 (ETS 2008 - 2009)	-0.06 (0.15)	-0.24 (0.22)	-0.10 (0.12)
Hazard ratio	0.94	0.78	0.90
γ_2 (ETS 2010 - 2011)	0.88*** (0.18)	1.14*** (0.27)	1.01*** (0.15)
Hazard ratio	2.42	3.14	2.75
γ_3 (ETS 2012 - 2013)	1.03*** (0.15)	0.01 (0.22)	0.75*** (0.12)
Hazard ratio	2.80	1.01	2.12
γ_4 (ETS 2014 - 2015)	0.89*** (0.18)	-0.68*** (0.20)	0.14 (0.13)
Hazard ratio	2.43	0.50	1.15
γ_5 (ETS 2016 - 2017)	0.57*** (0.17)	-0.41** (0.21)	0.17 (0.13)
Hazard ratio	1.76	0.66	1.18
γ_6 (ETS 2018 - 2019)	0.10 (0.15)	0.30 (0.22)	0.19 (0.13)
Hazard ratio	1.11	1.35	1.21
N (observations)	463,319	284,894	748,213
N (aircraft spells)	5,055	2,609	7,664
Year FE	$N = 16$	$N = 16$	$N = 16$
Group FE	$A = 2$	$A = 2$	$A = 2$
δ_a (aircraft age dummies)	$J = 34$	$J = 17$ (two-yearly)	$J = 34$ (two-yearly * aircraft class)

Note.—This table presents the likelihood estimates and hazard ratios of the impact of the EU ETS on aircraft retirement rates, obtained from a dynamic discrete proportional hazard model estimated on an aircraft spell-month panel. Standard errors provided in parentheses.

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Table B.2: Effects of EU ETS on aircraft retirement rates: dynamic model robustness checks (short-haul)

	Short-haul aircraft					
	(1) *aircraft covariates*	(2) *airline FE's*	(3) *heterogeneous hazards*	(4) *2000-2019*	(5) *linear trend*	(6) *growing airlines*
γ_1 (ETS 2008 - 2011)	0.44*** (0.13)	0.37*** (0.13)	0.32** (0.13)	0.09 (0.12)	0.39* (0.21)	−0.17 (0.20)
Hazard ratio	1.55	1.45	1.38	1.09	1.48	0.84
γ_2 (ETS 2012 - 2015)	1.24*** (0.13)	1.14*** (0.13)	1.05*** (0.13)	0.77*** (0.12)	1.17*** (0.37)	0.94*** (0.19)
Hazard ratio	3.46	3.14	2.85	2.16	3.23	2.57
γ_3 (ETS 2016 - 2019)	0.58*** (0.13)	0.43*** (0.13)	0.37*** (0.14)	0.09 (0.12)	0.60 (0.55)	0.07 (0.18)
Hazard ratio	1.78	1.54	1.45	1.09	1.82	1.07
N (observations)	463,319	463,319	463,319	568,843	463,319	333,285
N (aircraft spells)	5,055	5,055	5,055	5,371	5,055	3,687
Year FE	$N = 16$		$N = 16$		$N = 16$	
Group FE	$A = 2$		$A = 2$		$A = 2$	
δ_a	$J = 34$		$J = 17$		$J = 34$	

Note.—These tables presents the likelihood estimates and hazard ratios of the impact of the EU ETS on aircraft retirement rates, obtained a discrete proportional hazard model estimated on an aircraft-month panel, using alternative specifications and various subsamples. Standard errors provided in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table B.3: Effects of EU ETS on aircraft retirement rates: dynamic model robustness checks (long-haul)

	Short-haul aircraft					
	(1) *aircraft covariates*	(2) *airline FE's*	(3) *heterogeneous hazards*	(4) *2000-2019*	(5) *linear trend*	(6) *growing airlines*
γ_1 (ETS 2008 - 2011)	0.28 (0.19)	0.38** (0.19)	0.19 (0.19)	0.31* (0.16)	0.35 (0.29)	0.59** (0.25)
Hazard ratio	1.32	1.46	1.21	1.36	1.42	1.80
γ_2 (ETS 2012 - 2015)	−0.35** (0.18)	−0.13 (0.18)	−0.31* (0.18)	−0.38*** (0.15)	−0.22 (0.50)	0.03 (0.23)
Hazard ratio	0.70	0.88	0.73	0.68	0.80	1.03
γ_3 (ETS 2016 - 2019)	0.03 (0.18)	0.20 (0.19)	0.10 (0.19)	−0.09 (0.15)	0.16 (0.70)	0.06 (0.24)
Hazard ratio	1.03	1.22	1.10	0.91	1.17	1.07
N (observations)	284,894	284,894	284,894	357,234	284,894	219,532
N (aircraft spells)	2,609	2,609	2,609	2,907	2,609	1,926
Year FE	$N = 16$		$N = 16$		$N = 16$	
Group FE	$A = 2$		$A = 2$		$A = 2$	
δ_a	$J = 34$		$J = 17$		$J = 34$	

Note.—These tables presents the likelihood estimates and hazard ratios of the impact of the EU ETS on aircraft retirement rates, obtained a discrete proportional hazard model estimated on an aircraft-month panel, using alternative specifications and various subsamples. Standard errors provided in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table B.4: Effects of EU ETS on aircraft retirement rates: dynamic model robustness checks (total fleet)

	Short-haul aircraft					
	(1) *aircraft covariates*	(2) *airline FE's*	(3) *heterogeneous hazards*	(4) *2000-2019*	(5) *linear trend*	(6) *growing airlines*
γ_1 (ETS 2008 - 2011)	0.40*** (0.11)	0.40*** (0.11)	0.31*** (0.11)	0.18* (0.09)	0.47*** (0.17)	0.01 (0.15)
Hazard ratio	1.49	1.50	1.36	1.20	1.60	1.01
γ_2 (ETS 2012 - 2015)	0.57*** (0.10)	0.65*** (0.10)	0.55*** (0.10)	0.31*** (0.09)	0.78*** (0.29)	0.49*** (0.14)
Hazard ratio	1.77	1.92	1.73	1.36	2.19	1.64
γ_3 (ETS 2016 - 2019)	0.28*** (0.11)	0.32*** (0.11)	0.30*** (0.11)	0.02 (0.09)	0.67 (0.42)	0.10 (0.14)
Hazard ratio	1.32	1.38	1.35	1.02	1.94	1.11
N (observations)	748,213	748,213	748,213	926,077	748,213	552,817
N (aircraft spells)	7,664	7,664	7,664	8,278	7,664	5,613
Year FE	N = 16		N = 16		N = 16	
Group FE	A = 2		A = 2		A = 2	
δ_a	J = 34		J = 17		J = 34	

Note.—These tables presents the likelihood estimates and hazard ratios of the impact of the EU ETS on aircraft retirement rates, obtained a discrete proportional hazard model estimated on an aircraft-month panel, using alternative specifications and various subsamples. Standard errors provided in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table B.5: Net Environmental Benefit of Induced Fleet Renewal

	CO_2 emission savings (%)		
	Short-haul fleet	Long-haul fleet	Total fleet
	C. Realized technological progress		
EU ETS, 2012 - 2019, constant effect	1.66 (1.20%)	−1.62 (−0.60%)	0.04 (0.00%)
EU ETS, 2008 - 2019, dynamic effects	3.65 (1.70%)	−0.31 (−0.10%)	3.34 (0.50%)
EU ETS, 2008 - 2019, constant effect based on 2008 - 2011	1.86 (0.90%)	1.72 (0.40%)	3.58 (0.60%)

Note.—Table entries show CO_2 emission savings in megatonne (Mt), with percentages in parentheses.