Anticipatory Pricing under Climate Transition Risk: Evidence from U.S. Airlines

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Abstract

We examine whether firms adjust product-market prices in anticipation of climate transition costs. We study this question in the U.S. airline industry, where high-frequency fare data and detailed fleet characteristics allow us to observe both pricing decisions and exposure to future regulation. Our empirical setting is the EPA's 2015 proposed Endangerment Finding for aircraft greenhouse gas emissions, a regulatory signal that increased the likelihood of future carbon standards but imposed no immediate compliance costs. Using carrier-route-quarter fare data and a difference-in-differences design, we compare airlines with greater pre-event exposure to future standards, measured by fleet age, to less-exposed airlines serving the same routes. We find that a one standard deviation increase in fleet age raises fares by 5–6 percent after the EPA signal. The effect is concentrated among carriers whose exposure is embedded in owned or capital-leased aircraft, consistent with transition risk affecting firms through residual-value risk in long-lived assets. The response is stronger among financially constrained carriers and is followed by liquidity drawdowns and accelerated fleet renewal. These findings suggest that firms use pricing not only to pass through realized regulatory costs, but also as a forward-looking risk-management tool before climate regulation binds.

Keywords: climate transition risk, risk management, product markets, pricing, carbon regulation, leasing

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1 Introduction

Climate transition risk arises when expectations about future carbon regulation alter the valuation of assets and the timing of expected cash flows. Once such expectations become credible, managers must incorporate anticipated compliance costs into budgets, investment plans, and financing decisions—even before regulation takes effect. Prior research shows that climate transition risk affects capital structure, disclosure, investment, and valuation (Bolton and Kackperczyk, 2023; Ilhan et al., 2021; Li et al., 2024; Sautner et al., 2023). Much less is known about whether firms adjust product-market prices in anticipation of future regulatory costs. This paper examines whether and how firms incorporate expected transition costs into prices following a legally consequential but non-implementing climate policy signal.

Our interpretation builds on corporate risk-management theory. When external finance is costly, internally generated cash helps firms preserve investment capacity (Froot et al., 1993). In settings where financial hedging instruments are limited, pricing can serve as an operational hedge: firms with sufficient pricing power can raise current prices after a credible regulatory signal to fund future adjustment. This response, however, is not automatic. Managers may delay price increases when implementation details remain uncertain, compliance costs are still distant, or political reversal remains possible. Even when firms want to raise prices, competitive pressure may limit their ability to do so: customers can switch to lower-priced rivals, and visible price increases may attract regulatory scrutiny. The key empirical implication is therefore that anticipatory pricing should be strongest where transition exposure is high, financing frictions are stronger, and pricing power is sufficient.

We study this question in the U.S. airline industry around the U.S. Environmental Protection Agency's (EPA) June 10, 2015 proposed Endangerment and Contribution Finding for aircraft greenhouse gas emissions. The proposal did not impose compliance costs or itself finalize binding standards. Instead, it converted an anticipated rulemaking into a formal public signal that aircraft greenhouse-gas emissions were likely to be regulated under Section 231; the EPA finalized the Endangerment and Contribution Finding in August 2016, establishing the binding legal foundation for subsequent aircraft carbon-dioxide standards.[1] The setting offers three features that map cleanly to the empirical question. First, aircraft are long-lived capital assets with multi-decade useful lives, making airlines exposed to regulation that affects assets already deployed or being planned today. Second, exposure varies cross-sectionally along the dimension future regulation will price: older, less fuel-efficient airframes

[1] The signal was partly anticipated: in September 2014, the EPA submitted an information paper to the International Civil Aviation Organization committing to propose the Finding by May 2015, and at least some airlines disclosed the expected proposal in their fiscal-year 2014 Form 10-Ks. We use the June 2015 proposal as the event because it converted this expectation into a formal regulatory signal.

face higher expected compliance costs and greater residual-value risk. Third, airfares are observable at high frequency at the carrier-route level, permitting within-market comparisons across carriers exposed to the same route-level demand and competitive conditions.

Our empirical design is a difference-in-differences that compares airfares before and after the EPA Finding across carriers operating on the same routes. Each carrier's pre-event fleet age serves as the exposure measure. We include market-by-carrier and market-by-date fixed effects. This allows us to control for carriers' pricing strategy in a given route, and route-level demand shocks and competitive conditions. Identification therefore comes from whether, within the same route and date, carriers with older pre-event fleets raise fares more after the Finding than carriers with younger fleets serving that same route. The identifying assumption is that, absent the EPA signal, high- and low-exposure carriers would have followed parallel trends within each market.

In the baseline specification, airlines with greater ex ante exposure raised fares significantly more after the EPA's regulatory signal. A one-standard-deviation increase in pre-event fleet age corresponds to a 5–6 percent increase in fares, or roughly \$12 per average ticket. Estimates are quantitatively similar across unweighted and seat-weighted exposure measures, robust to the inclusion of time-varying carrier and market controls. Event-study estimates show no visible pre-trend divergence and indicate that the divergence opens only after the EPA signal, with the cumulative effect building gradually, consistent with subsequent regulatory milestones reinforcing expectations of impending carbon regulation.

We next show that the pricing response is concentrated in assets for which the carrier bears greater residual-value risk. If transition risk affects asset values because future regulation reduces the residual value of carbon-intensive long-lived capital, then the pricing response should be strongest for assets whose residual-value risk remains with the carrier. Owned and capital-leased aircraft leave the carrier economically exposed to more of the asset's residual-value risk; operating leases leave substantially more of that risk with the lessor. Anticipatory pricing should therefore load on owned and capital-leased aircraft rather than on operating-leased aircraft.

To test this prediction, we partition each carrier's pre-event exposure into a residual-bearing component—owned plus capital-leased airframes—and an operating-lease component. We hold the partition fixed at its 2011–2014 average and re-estimate the baseline difference-in-differences with each component separately interacted with the post-Finding indicator. Our results align with the prediction. The post-event pricing response is substantially stronger for residual-bearing aircraft in both specifications. Operating-lease exposure is positive in the no-control specification, but attenuates to a small and statistically insignificant estimate once firm controls are included. This residual-value gradient is difficult to reconcile with explanations that operate only through aggregate carrier-level exposure, such as generic cost pass-through, capacity coordination, or legacy-versus-low-cost-carrier trends. Those explanations predict responses based on the carrier's overall fleet exposure, not on whether the carrier or the lessor bears the residual-value risk.

A risk-management interpretation of anticipatory pricing generates two further cross-sectional predictions. First, the response should be larger for firms with a greater shadow cost of external finance, because anticipatory pricing generates internal liquidity that substitutes for costly external borrowing. Second, the response should concentrate where carriers retain sufficient pricing power on the route. Even an industry-wide regulatory signal cannot support a price increase where competition is strong enough for rivals to undercut the carrier that moves first (Weyl and Fabinger, 2013). We test the first prediction by examining whether the post-announcement pricing response to pre-event exposure varies with carrier-level leverage, internal liquidity, and profitability. We test the second by asking whether the low-route-share differential in the exposure response is larger on less competitive routes than on more competitive routes. The logic is that carriers with weaker local route positions should have less incremental pricing room when competitive pressure is high, but may display a larger differential response when the route is less competitive.

Both predictions hold. The pricing response loads on high-leverage and low-liquidity carriers, consistent with anticipatory pricing as a source of internal funds for future fleet adjustment (Froot et al., 1993; Almeida et al., 2004). The route-competition split is sharper still: the incremental low-route-share differential is close to zero on high-competition routes but large and significant on low-competition routes. We interpret this as evidence that the low-share differential appears only where competition is weaker. Together, these heterogeneity results distinguish risk-management anticipation from explanations operating only through aggregate cost shocks. They identify the conditions under which the pricing lever is exercised: exposure to future transition costs, financing pressure, and sufficient pricing power.

Complementary real adjustments support this interpretation. If exposed carriers raise prices in anticipation of future transition costs, we should also observe changes in liquidity, investment, and fleet composition after the signal. We find that exposed carriers draw down internal liquidity and increase the capital-expenditure proxy after the EPA announcement. Their owned fleets become younger, with average owned-fleet age falling by about two to five years across specifications, and realized capital gains on aircraft disposals generally increasing. These adjustments point in the same direction as the pricing results: more exposed carriers raise fares more and subsequently adjust liquidity and fleet investment more strongly. We interpret this evidence cautiously. The firm-level tests complement the pricing design, but they do not identify a dollar-for-dollar financing flow from fare revenue to capital expenditure and cannot fully rule out unobserved shocks that simultaneously affect exposed carriers' pricing, liquidity, and investment.

Several tests help address alternative explanations. The result is unlikely to reflect fuel-cost pass-through: jet-fuel prices fell sharply around the event, and cheaper fuel should have reduced the operating disadvantage of older aircraft, biasing against our finding. The result also does not depend on fleet age as the exposure proxy; replacing age with carrier-level fuel-burn intensity per available seat mile yields a similar pattern, confirming that the response loads on the carbon dimension future regulation will price rather than on age per se. Nor is the pattern explained by the 2015 DOJ antitrust probe or generic legacy-versus-low-cost-carrier divergence. Market-by-date fixed effects absorb market-wide pricing shocks, and the estimates remain robust after allowing low-cost carriers to have their own post-announcement mean fare shift.

This paper contributes to three literatures. First, we extend research on how firms manage climate transition risk through capital reallocation, disclosure, valuation, and financial policy (Bolton and Kackperczyk, 2023; Ilhan et al., 2021; Li et al., 2024; Sautner et al., 2023; Dang et al., 2023; Ginglinger and Moreau, 2023). Existing evidence shows that transition risk is priced in equity, option, and credit markets, and that firms respond through investment, innovation, and financing choices. We identify a product-market margin through which firms proactively manage transition exposure: exposed firms adjust fares after a credible regulatory signal, and the same carriers subsequently display liquidity and investment patterns consistent with forward-looking adaptation when external finance is costly. This complements evidence that lenders reprice high-emission borrowers following cap-and-trade policy (Ivanov et al., 2023) and that anticipated carbon costs affect upstream energy prices (Acharya et al., 2025). We show that downstream firms also re-optimize on the revenue side. Consistent with this interpretation, Evdokimova and Millischer (2025) document that firms with greater cost pass-through capacity suffer smaller valuation losses when carbon prices rise, highlighting the importance of pricing power in transition-risk management.

Second, we contribute to the accounting literature on the real effects of recognition and classification rules for long-lived assets. A central question in this literature is whether accounting boundaries merely describe economic arrangements or also shape firms' real decisions (Leuz and Wysocki, 2016; Roychowdhury et al., 2019). In capital-intensive industries, accounting categories such as ownership, capital leases, and operating leases do more than classify assets for reporting purposes; they map closely onto the allocation of residual-value risk. We show that this allocation predicts firms' product-market response to forward-looking regulation. Around the same regulatory signal, carriers whose exposure is embedded in owned and capital-leased aircraft raise prices more strongly; operating-lease exposure is weaker and becomes statistically indistinguishable from zero once firm controls are included. Closest to our analysis, Li and Venkatachalam (2024) document that the 2019 adoption of ASC 842—which required U.S. airlines to recognize operating-lease assets on the balance sheet—shifted carriers away from leasing toward ownership, showing that lease recognition affects financing and investment choices. We document a complementary real effect operating through the product market: when forward-looking regulation threatens the residual value of long-lived assets, the ownership and lease structure of those assets predicts which firms incorporate anticipated costs into current prices. The result also complements work on contractual flexibility and secondary-market liquidity in capital-intensive industries (Gavazza, 2011; Pulvino, 1998).

Third, we contribute to the literature on the incidence and timing of sustainability costs. A growing body of work studies whether environmental and social costs are borne by firms, investors, workers, or consumers. In the airline industry, Hillmann et al. (2025) document that airlines raise fares after ESG-related operational incidents materialize, with larger responses among carriers with greater financial capacity. We document the reverse cross-section on the ex ante margin: financially constrained firms exhibit larger anticipatory price increases, consistent with a precautionary risk-management motive that substitutes pricing for costly external finance. The two results imply that the cross-section of cost pass-through depends on whether the cost is realized or anticipated. More broadly, our evidence shows that expected transition costs can appear in relative fares years before regulation binds, and that this ex ante pricing response depends on firms' asset exposure, financial condition, and ownership and lease structure.

The remainder of the paper proceeds as follows. Section 2 develops the conceptual framework. Section 3 provides institutional background on the EPA Finding and the U.S. airline industry. Section 4 describes the sample construction and empirical design. Section 5 presents the main pricing results, including the event-study evidence on parallel trends. Section 6 documents cross-sectional mechanism tests that sharpen the interpretation of the pricing response. Section 7 reports complementary real-adjustment evidence—firm-level financing and investment, fleet renewal, and aircraft disposals. Section 8 addresses robustness and potential confounders, and the final section concludes.

2 Conceptual Framework

Climate transition risk arrives before binding regulation. We expect a credible regulatory signal to change managers' expectations about future compliance costs, asset values, and investment needs even when no immediate cost is imposed. In capital-intensive industries this expectation channel is especially important, because firms make pricing, financing, and investment decisions around long-lived assets whose useful lives extend beyond the regulatory horizon.

While firms have tools for managing this risk (e.g. fuel derivatives), this set is limited. Traditional financial hedges are poorly suited for regulation that affects future asset values, replacement needs, and compliance investments. Raising external finance in advance can also be costly when external funds are more expensive than internal funds. Corporate risk-management theory therefore predicts that firms value internal liquidity because it preserves investment capacity when financing frictions bind (Froot et al., 1993). Product-market pricing, a readily available tool, can serve as operational hedge.

In differentiated product markets, firms with residual pricing power can incorporate anticipated future costs into current prices (Weyl and Fabinger, 2013). This pricing response serves two functions. First, it can move expected transition costs into current fares before regulation binds, to the extent carriers retain pricing power. Second, it can generate internal cash flow that helps preserve investment capacity for future real adjustment, such as fleet renewal. The response is not automatic: firms may delay adjustment if regulation remains uncertain, and competitive pressure may prevent price increases where rivals can undercut. The credible signal is therefore the *triggering* condition for anticipatory pricing; residual pricing power is the *necessary* condition. Together, these arguments imply that firms with greater exposure to the expected costs of transition should use pricing more aggressively once a credible regulatory signal arrives.

> **H1.** After a credible climate regulation signal, firms with greater exposure to transition risk increase product prices more.

Risk management behavior depends on the magnitude of the underlying risk (Froot et al., 1993). We expect the magnitude of the response to depend on who bears the residual-value risk of the affected assets. Owned aircraft expose the carrier to the asset's residual value over its useful life. Capital leases are economically similar because the lessee retains substantially all the risks and rewards of ownership. Operating leases, by contrast, provide a finite-term claim on aircraft services and leave residual-value risk with the lessor.

The accounting treatment makes this economic partition observable. Under SFAS 13, which governs our 2011–2018 sample period, owned and capital-leased aircraft are recognized on the lessee's balance sheet and are subject to impairment testing under SFAS 144 over the period in which the carrier bears the asset's economic risk. Operating leases, by contrast, remain off balance sheet under ASC 840. Even after ASC 842, which requires recognition of operating-lease right-of-use assets, the lessee's recognized exposure is tied to the remaining lease term rather than to the aircraft's full useful life. This distinction matters because residual-bearing carriers cannot avoid transition-related asset losses costlessly: selling or retiring older aircraft requires transacting in a secondary market that may itself be affected by the same regulation. Operating lessees, in contrast, have a contractual return margin at lease expiration that limits their exposure to the aircraft's terminal value. We therefore group owned and capital-leased airframes into a single *residual-bearing* category and compare this exposure with aircraft held under *operating leases*. If anticipatory pricing reflects exposure to future asset-value losses, the response should be strongest when transition risk is embedded in assets whose residual value remains with the carrier.

> **H2.** The anticipatory pricing response is stronger when transition exposure is concentrated in residual-bearing aircraft—owned and capital-leased aircraft—rather than operating-leased aircraft.

The pricing response should also depend on how valuable internally generated cash is to the firm. Corporate risk-management theory predicts that internal cash has a higher shadow value when external finance is costly, giving financially constrained firms stronger incentives to use available margins to build internal funds (Froot et al., 1993). This incentive is especially relevant in our setting because transition risk requires forward-looking real adjustment. Fleet renewal, capital expenditure, and the disposal of older airframes are costly actions, and constrained carriers expecting these adjustments should internalize the higher cost of financing them externally. Thus, financial constraints should amplify the use of pricing as an internal-liquidity margin.

> **H3.** Among exposed firms, the anticipatory pricing response is stronger when financial constraints are tighter.

3 Institutional Background and Setting

3.1 EPA Endangerment Finding and Regulatory Timeline

Section 231 of the U.S. Clean Air Act authorizes the Environmental Protection Agency (EPA) to regulate aircraft engine emissions that may reasonably be anticipated to endanger public health or welfare. In *Massachusetts v. EPA* (2007), the Supreme Court affirmed that greenhouse gases qualify as air pollutants under the Act. This decision established a legal basis for regulating aviation emissions once an endangerment finding is made.

By September 2014, the United States had publicly committed to initiating a domestic rulemaking for aircraft greenhouse gas emissions under Section 231. The EPA transmitted an information paper to the International Civil Aviation Organization (ICAO) that outlined a rulemaking timeline and announced its intent to issue a proposed endangerment finding by April 2015. This communication signaled clear movement toward regulation.

This regulatory trajectory was visible to airlines in real time. American Airlines' fiscal-year 2014 Form 10-K, filed in February 2015 (approximately four months before the proposed Finding was issued), disclosed under Item 1, Environmental Matters, that "the EPA announced in September 2014 that it is in the process of making a determination regarding aircraft GHG emissions and *anticipates proposing an endangerment finding by May 2015*. If the EPA makes a positive endangerment finding, the EPA is obligated under the CAA to set GHG emission standards for aircraft."[2] The identical language appears in the carrier's Risk Factors section, indicating that the impending Finding was treated as a material forward-looking regulatory exposure prior to its issuance.

On June 10, 2015, the EPA issued a proposed Endangerment Finding for six greenhouse gases emitted by aircraft, including carbon dioxide, methane, and nitrous oxide. The proposal concluded that aviation emissions contribute to climate change and endanger public welfare (U.S. Environmental Protection Agency, 2015a,b). At the time, aviation was the largest unregulated source of transportation greenhouse gases in the United States, accounting for roughly 11 percent of transportation emissions and 3 percent of total national emissions. U.S. carriers contributed nearly 29 percent of global aircraft greenhouse gas emissions (U.S. Environmental Protection Agency, 2015a).

The proposed finding represented the EPA's preliminary scientific determination that aircraft greenhouse-gas emissions contribute to harmful pollution. The 2015 proposal did not impose immediate limits and did not itself finalize the EPA's statutory obligation. It did, however, make the regulatory trajectory public and credible: if finalized, the finding would require EPA action under Section 231. For airlines, the proposal immediately altered expectations regarding fleet replacement and future compliance costs. The final Endangerment and Contribution Finding arrived in August 2016, and the standards eventually released in 2020 targeted new designs and new production rather than retroactive modifications on existing fleets.

Two developments reinforced the credibility of the 2015 signal. First, the EPA committed to align domestic standards with the ICAO framework, which was already in late-stage negotiation. This alignment reduced uncertainty and increased the perceived inevitability

[2] American Airlines Form 10-K for fiscal year ended December 31, 2014 (filed February 2015), Item 1: Environmental Matters. The same paragraph appears in Item 1A Risk Factors.

of carbon standards. Second, the proposal was issued in response to formal petitions from environmental organizations, which placed the EPA on a defined procedural timeline. This process culminated in the final Endangerment and Contribution Finding in August 2016 and the denial of reconsideration petitions later that year. These elements together made the June 2015 proposal a credible and broadly recognized signal of impending climate regulation.

In summary, the 2015 proposed finding represented a pivotal turning point in the policy environment for U.S. aviation. It did not finalize binding standards, but it made a previously anticipated regulatory process formal, public, and credible. The proposal clarified expectations about future regulatory costs, established a visible policy timeline, and provided firms with a forward-looking, non-implementing signal before direct compliance obligations arrived. Appendix Table A2 summarizes key regulatory milestones. The next subsection describes features of the airline industry that make it well suited for studying anticipatory responses to this regulatory development.

3.2 US Airline Industry

Airlines are particularly exposed to climate transition risk because their production technology is both carbon-intensive and relies on long-lived assets, with aircraft remaining in service for decades. Older fleets are less fuel efficient and more costly to retrofit, which increases vulnerability as carbon regulation tightens. The U.S. airline industry provides a natural setting in which to study anticipatory product-market responses to a forward-looking regulatory signal. Airfares are observable at high frequency at the carrier–route–quarter level, which allows fine-grained measurement of pricing. The market structure, consisting of many distinct origin–destination markets served by multiple carriers, permits within-route comparisons that absorb local demand and competitive conditions through fixed effects.

Airlines have long served as a standard setting for empirical research on price responses to cost, tax, and competitive shocks. Gerardi and Shapiro (2009) show that greater competition reduces price dispersion and lowers average fares. Azar et al. (2018) find that common ownership softens competition and raises prices. Hanlon et al. (2025) show that tax cuts enable financially stronger airlines to lower fares and expand market share. Hillmann et al. (2025) document that carriers raise fares following ESG-related incidents, which is consistent with reactive pricing in response to reputation shocks. Kim and Lu (2025) show that climate alliances neither raise prices nor improve environmental performance, which suggests that coordination alone does not shift pricing behavior. Our setting extends this literature by examining whether firms adjust prices before costs are realized in response to a credible climate policy signal rather than only after costs materialize.

Prospective carbon dioxide standards affect carriers differentially according to fleet composition. The EPA and ICAO frameworks emphasize fleet renewal as the primary channel for achieving emission reductions. This emphasis makes pre-event fleet age a predetermined proxy for regulatory exposure. The design does not require fleet age to be randomly assigned; it requires that, absent the regulatory signal, carriers with older and younger pre-event fleets serving the same market would have followed parallel fare trends after conditioning on the fixed effects and controls. Older aircraft are less fuel efficient and more likely to require accelerated replacement as standards tighten. In contrast, newer fleets already incorporate compliance technologies. EPA technical assessments indicate that emissions reductions are expected to occur primarily through the introduction of new, more efficient aircraft models rather than through retrofits of existing aircraft (U.S. Environmental Protection Agency, 2015a,b). Accordingly, we use fleet age to measure exposure to anticipated transition costs.

Fleet renewal is also emphasized by industry participants as a key lever for near-term decarbonization within a broader set of measures that also includes sustainable aviation fuels, new propulsion technologies, and operational efficiencies.[3] Firm disclosures reflect this perspective. For example, American Airlines reports in its 2022 Sustainability Report that ongoing fleet renewal has improved fuel efficiency by more than 10 percent since 2013 and identifies replacing older aircraft as one of the most significant ways the company can reduce its carbon footprint.

Financing structures further shape carriers' ability to manage transition exposure. Owned aircraft expose the carrier to the full distribution of the airframe's residual value over its useful life; leases, by contrast, are finite-term contracts with a return option at lease-end that converts residual-value risk away at zero cost to the lessee (Gavazza, 2010, 2011; Li and Venkatachalam, 2024). Transition risk is therefore magnified when older fleets are owned rather than leased, because owners bear the long tail of residual-value exposure and cannot shed the asset costlessly. Secondary-market redeployability—an asset-level characteristic that is independent of who holds title—compounds this exposure: thin secondary markets for specific airframe types raise the cost of orderly disposal when many owners attempt to exit simultaneously (Pulvino, 1998). Accounting adjustments reinforce this channel. Airlines recognize accelerated depreciation when planning retirements of older, less efficient aircraft. Examples include Southwest's 2016 acceleration of 737–300 retirements and Delta's 2017 increase in depreciation associated with planned retirements of the MD–88 and 767–300ER fleets.

[3] For example, modern aircraft typically deliver between 15 and 30 percent improvements in fuel burn relative to the models they replace. Wide-body aircraft such as the Boeing 787 provide approximately 25 percent improvement relative to the 767, and narrow-body aircraft such as the 737 MAX and Airbus A320neo provide improvements of roughly 20 percent (The Boeing Company, 2019; Airbus SE, 2025).

Airlines also operate with high fixed costs and constrained liquidity, which makes near-term cash flow management central to financial stability. Phillips and Sertsios (2013) show that financially distressed airlines often price more aggressively to boost short-term revenues and maintain market share. Busse (2002) find that weaker carriers are more likely to initiate price wars. These findings underscore the important role of liquidity in pricing and competition. In contrast, we examine whether firms facing higher transition exposure increase fares to generate the internal cash flow that finances forward-looking fleet adjustment, which highlights the dual role of pricing in financial management. Carriers themselves describe liquidity as a strategic asset for funding fleet investment. In its fiscal-year 2015 Form 10-K Risk Factors discussion (filed February 2016), American Airlines tied liquidity policy directly to forward-looking fleet renewal capital expenditures: "we believe it is important to retain liquidity levels above our network peers as we expect capital expenditures of approximately $4.5 billion in each of 2016 and 2017 as we continue our fleet renewal program."[4]

Airlines' pricing strategies combine cost-based, demand-based, and service-based elements depending on the route, customer segment, competitive conditions, and operational constraints. Cost considerations typically establish the minimum revenue requirements for sustainability, while demand conditions and service differentiation determine how fares can be optimized across passenger segments. Prior research in airline economics shows that ticket prices are strongly shaped by route-level competition, market concentration, and consumer demand elasticity. Classic studies document that airlines charge higher fares in concentrated markets and on routes with limited competitive pressure, while the presence of additional carriers—especially low-cost airlines—reduces prices (Borenstein, 1990; Kim and Singal, 1993; Evans and Kessides, 1994; Borenstein and Rose, 1994, 1995; Peters, 2006; Goolsbee and Syverson, 2008; Brueckner et al., 2013). The literature further emphasizes that airline pricing is highly dynamic and route-specific, reflecting differences in market structure, hub dominance, consumer substitution possibilities, and capacity constraints.

In the medium-term cost-based pricing ensures that airline revenues are sufficient to cover operating costs and maintain the financial viability of the carrier as a going concern. Because many airline costs — including aircraft ownership, labor, maintenance, airport fees, and fuel commitments — are substantial and relatively fixed in the short run, airlines must generate enough aggregate revenue across their network to recover these costs over time. Cost considerations thus act as important financial constraints within airline pricing strategy, establishing revenue thresholds necessary to support continued operations, fleet investment, and long-term solvency.

[4]American Airlines Form 10-K for fiscal year ended December 31, 2015 (filed February 2016), Item 1A: Risk Factors — Liquidity.

Taken together, the EPA's 2015 aircraft Endangerment Finding and the structure of the U.S. airline industry create a clean and theoretically relevant setting for examining anticipatory firm behavior. The EPA announcement provides a forward-looking and sector-wide regulatory signal that shifts expectations about future carbon costs without imposing contemporaneous operational changes. The industry provides high-frequency pricing data and well-defined heterogeneity in exposure through variation in fleet composition and financing structure. This combination allows a sharp test of whether firms incorporate anticipated transition costs into product-market prices and clarifies how credible policy signals translate into anticipatory corporate responses to climate regulation.

4 Data and Empirical Strategy

4.1 Sample Selection

We construct the sample by merging several public datasets from the U.S. Department of Transportation (DOT) and follow standard practices in airline pricing studies. The primary source is the DOT Origin and Destination Survey (DB1B), a 10% quarterly sample of all U.S. domestic airline tickets that reports fares paid, passenger counts, and the itinerary of the ticketing carrier. Consistent with Azar et al. (2018), we define a *market* as a non-directional origin–destination airport pair, pooling nonstop and connecting itineraries that share the same endpoints. Tickets are assigned to the ticketing carrier, which is the entity that sets and prints the fare. We draw on the replication code from Azar et al. (2018) for key steps in DB1B cleaning and market construction. These steps include defining valid itineraries and aggregating fares at the carrier $\times$ market $\times$ quarter level.

We restrict the sample to itineraries that are valid and unambiguous. We exclude open-jaw itineraries, itineraries containing surface segments, itineraries with more than six coupons or with break-point structure inconsistent with a single round trip. Standard round-trip tickets are split into two quasi-one-way segments with fare divided evenly across legs. Fares are deflated to 2008Q1 dollars using the BLS Consumer Price Index, and we drop observations with real one-way fares below \$25 or above \$2,500. Markets averaging fewer than 1,800 passengers per quarter ($\approx$ 20 per day, pooled across carriers) are excluded to ensure reliable price measurement.

The final dataset aggregates ticket-level observations to the carrier $\times$ market $\times$ quarter grain, which serves as the unit of analysis. The panel spans 2011Q1 through 2019Q4, providing approximately four years of data on either side of the June 2015 EPA aircraft endangerment finding. Because the finding was published on June 10, 2015, we code $\text{Post}_t = 0$

for 2015Q1 and 2015Q2 and $\text{Post}_t = 1$ from 2015Q3 onward. We require each carrier-market pair to have at least four pre-event and four post-event quarters of observations.

4.2 Variable Construction

The dependent variable, $Fare$, is the natural logarithm of the passenger-weighted average fare charged by a carrier in a given market and quarter, deflated to 2008Q1 dollars using the BLS Consumer Price Index:

$$Fare_{imt} = \log\left(\frac{\text{total real revenue}_{imt}}{\text{total passengers}_{imt}}\right).$$

The measure is aggregated over all tickets sold by carrier i in market m in quarter t.

Fleet characteristics are obtained from DOT Form 41 Schedule B-43, which reports aircraft-level information including age, seating capacity, and ownership type. Our primary measure of regulatory exposure is the logarithm of a carrier's pre-event airframe-weighted average fleet age, $AvgFleetAge$. This measure proxies for anticipated compliance costs because older aircraft are more fuel intensive, face greater replacement pressure under future carbon regulation, and expose carriers to residual-value risk. To keep exposure predetermined relative to the event, we compute each carrier's average fleet age over 2011–2014 and hold it fixed throughout the post-event regressions. We also construct a seat-weighted version, $AvgFleetAgeSW$, which adjusts for aircraft capacity. Finally, we define high and low exposure groups using an indicator for whether a carrier average fleet age is above or below the sample median.

Additionally, we partition fleet-age exposure by ownership status. The residual-bearing component is the log average age of owned and capital-leased aircraft. The operating-lease component is the log average age of aircraft held under operating leases, where the lessor retains the residual. This partition separates residual-value risk borne by the carrier from residual-value risk borne by an external lessor.

We include a broad set of control variables at both the carrier and market levels, following Azar et al. (2018) and Hillmann et al. (2025). Carrier-level financial and operational variables are obtained from DOT Form 41. Schedule B-1 provides total assets, noncurrent liabilities, cash, short-term investments, and capitalized lease property; Schedule P-1.2 provides operating income and salary expense; Schedule P-6 provides fuel and other operating-expense detail. Firm-level controls are size ($Size$, log assets), profitability (Roa, operating income over assets), leverage ($Debt$, noncurrent liabilities over assets), labor intensity ($StaffExp$, salaries over operating revenue), fuel cost intensity ($FuelExp$, fuel expense over operating revenue), and capital-leasing intensity ($Leasing$, capitalized lease property over assets).

The financial-constraints tests additionally use $CashAssets$, defined as cash plus short-term investments divided by total assets. All firm controls are lagged one quarter to reduce endogeneity concerns.

Route-level variables capture market structure and demand conditions. Using the T100 database, we construct the number of nonstop competitors, indicators for Southwest Airlines and other low-cost carriers, and passenger-connectivity shares at the market and carrier levels. We also compute the Herfindahl–Hirschman Index of passenger concentration. Socioeconomic variables, including population and income per capita, are drawn from the U.S. Bureau of Economic Analysis and measured as the geometric mean of endpoint metropolitan areas.

All control variables enter the regression in lagged form. This timing ensures that estimated effects capture forward-looking adjustments to anticipated regulatory exposure rather than responses to contemporaneous cost or demand shocks.

Table 1 reports summary statistics separately for the pricing-panel variables and the carrier-quarter variables used in the firm-level tests. In the pricing panel, the average fare is approximately \$220 and the mean log fleet age is about 2.5, corresponding to roughly 12 years in levels. The table also reports the residual-bearing and operating-lease exposure measures, fuel-burn exposure measures, route-competition variables, and the financial variables used in the heterogeneity tests. Table 2 reports pairwise correlations among the pricing-panel variables in Panel A of Table 1, shown in the same order as the descriptives. Aside from mechanically related exposure measures, the correlations do not indicate broad multicollinearity concerns for the specifications that follow.

4.3 Regression Specification

We estimate difference-in-differences regressions at the market, carrier, and quarter level to test whether carriers with greater pre-period exposure to climate transition risk increased fares after the EPA 2015 aircraft endangerment finding:

$$\text{Fare}_{imt} = \beta\,(\text{Post}_t \times \text{Exposure}_i) + \gamma_{im} + \delta_{mt} + \varepsilon_{imt}, \tag{1}$$

where Fare_{imt} is the log average fare charged by carrier i in market m in quarter t. The indicator Post_t equals one from the third quarter of 2015 onward, which is the first full quarter after the EPA proposed endangerment finding. The term γ_{im} represents market-carrier fixed effects, and δ_{mt} represents market-date fixed effects.

The key regressor is the interaction between Post_t and the predetermined measure of exposure, Exposure_i. Exposure is computed as the carrier's average over the pre-event period 2011–2014 and is held fixed over time. We construct four measures of exposure that vary in scale and weighting. These include a binary indicator for above-median average fleet age, a binary indicator for above-median seat-weighted fleet age, the logarithm of the unweighted average fleet age, and the logarithm of the seat-weighted average fleet age. For continuous measures, β represents the effect per log point of fleet age. For binary measures, β represents the difference in post-event pricing between high and low exposure carriers.

The coefficient β identifies whether, after the EPA announcement, carriers with older fleets charged higher fares relative to less exposed carriers that served the same market in the same quarter. Identification comes from within-market-date variation across carriers, scaled by carriers' pre-determined, time-invariant exposure ranking; the exposure main effect Exposure_i is absorbed by γ_{im}. The market-carrier fixed effects γ_{im} absorb all time-invariant carrier-market characteristics, such as hub status, brand premia, and persistent route specialization. The market-date fixed effects δ_{mt} absorb every market-quarter shock common to carriers serving the market, including local demand conditions, seasonal travel patterns, weather disruptions, congestion, and aggregate macroeconomic or fuel-price movements that propagate uniformly through a market-quarter. Standard errors are two-way clustered by market and by carrier-date, allowing for arbitrary within-market correlation (across carriers and over time, e.g., route-level demand and competitive shocks) and within-carrier-date correlation (across markets a carrier serves on the same date, e.g., system-wide pricing actions).[5] Baseline regressions include no additional controls. Later specifications add time-varying carrier characteristics to account for omitted variables.

The identifying assumption is that, absent the EPA 2015 regulatory signal, fares for carriers with different levels of pre-period exposure would have followed parallel trends within each market. This assumption implies that any post-event divergence between high and low exposure carriers reflects anticipatory pricing in response to the regulatory signal rather than pre-existing trends or concurrent shocks. Because fleet age is a choice variable accumulated before the event, the identifying assumption concerns differential trends conditional on fixed effects and controls, not random assignment of fleets. We evaluate this assumption using an event-study design.

5 Main Pricing Results

This section presents the main pricing results. We begin with the baseline difference-in-differences estimates (Section 5.1), report robustness to firm-level controls (Section 5.2), and

[5]This is similar to the approach of Hillmann et al. (2025). Results are robust to alternative clustering that follows Azar et al. (2018) or wild-cluster bootstrap inference.

conclude with event-study estimates that assess the parallel-trends assumption (Section 5.3). Appendix Table A3 reports an additional robustness check using a less saturated fixed-effects specification with explicit market controls. Inference uses conventional two-way clustered standard errors (market and carrier × date); the carrier-level wild-cluster bootstrap reported in Section 8 alleviates small-cluster concerns.

5.1 Baseline Effects

Table 3 reports the baseline difference-in-differences estimates that test whether airlines with greater pre-2015 exposure, measured by fleet age, raised fares after the EPA June 2015 aircraft endangerment finding.

Columns (1) and (2) use the log of average fleet age to capture exposure intensity, in both unweighted and seat-weighted form—the seat-weighted version accounts for differences in capacity composition within a carrier's fleet. Columns (3) and (4) report a corresponding binary above-median specification as a robustness check.

Across all specifications, the interaction between *Post* and exposure is positive and statistically significant. Using the continuous measure, the coefficient on $Post{\times}Exposure$ ranges from 0.202 to 0.203 in columns (1) and (2). Given a standard deviation of 0.29 in fleet age, this implies that a one-standard-deviation increase in pre-event exposure corresponds to approximately a 5–6 percent increase in fares, or roughly $12 per average ticket. Estimates are nearly identical when exposure is seat-weighted, which suggests that the effect is not driven by differences in aircraft mix. The binary specifications in columns (3) and (4) yield coefficients of 0.160 on $Post{\times}HighExposure$; we treat the binary specification as a robustness check rather than a headline because the continuous specification is more defensible economically and avoids implying an implausibly large discrete fare gap between above- and below-median carriers.

The fixed effects absorb rich sources of heterogeneity. Market-carrier fixed effects capture time-invariant differences across carrier and market pairs, including hub status, route specialization, and persistent differences in service quality. Market-date fixed effects capture all route-specific demand and cost shocks that are common to carriers in a given quarter. Identification therefore relies on cross-carrier differences in predetermined exposure within the same market and quarter.

Taken together, the results in Table 3 show that airlines with older and more exposed fleets raised fares relative to less exposed competitors after the EPA 2015 regulatory signal. The consistency of coefficients across exposure measures provides strong evidence for **H1**. Firms with higher transition exposure incorporate anticipated compliance costs into prices even before regulation is implemented.

5.2 Robustness with Firm Controls

Table 4 evaluates whether the baseline exposure effect in Table 3 is driven by time-varying carrier characteristics. The specification retains the same fixed effects structure, which includes market-carrier fixed effects and market-date fixed effects. It adds standard carrier-level controls that include size, return on assets, leverage, labor expense intensity, fuel expense intensity, and leasing intensity. Standard errors remain clustered by market and by carrier-date.

Across all specifications, the post-announcement exposure effect remains positive and highly statistically significant, although the magnitude is smaller once firm fundamentals are included. Using the continuous measure (the headline specification), the coefficient on $Post \times Exposure$ ranges from 0.150 to 0.155 in columns 1 and 2, relative to 0.202 to 0.203 in the baseline. Given the standard deviation of fleet age of 0.29, the continuous estimates imply that a one standard deviation increase in exposure corresponds to approximately a 0.044 log point increase in fares, or approximately 4 to 5 percent in levels. Seat weighting of exposure does not materially affect the results. The binary specifications in columns 3 and 4 yield a coefficient on $Post \times HighExposure$ of 0.109, compared with 0.160 in Table 3. The adjusted R^2 rises from the 0.747–0.748 range in Table 3 to the 0.770–0.771 range once firm controls are included, indicating that the controls explain additional variation without altering the core anticipatory-pricing effect.

Coefficients on the control variables are not the focus of this paper and we do not interpret them causally; they enter the specification to absorb time-varying carrier characteristics that could otherwise confound the post-event exposure differential. The $Post \times Exposure$ effect remains economically and statistically robust to their inclusion.

Overall, Table 4 confirms the robustness of **H1**. Carriers with greater transition exposure, measured by older fleets, increased fares more after the EPA regulatory signal. This relationship is not driven by contemporaneous changes in firm-level financial or cost conditions.

5.3 Event Study and Parallel Trends Assumptions

Figure 1 presents event-study estimates that test for pre-trends and examine the timing of the pricing response. The model interacts carrier exposure with leads and lags of the EPA June 2015 signal, using the same fixed effects structure of market-carrier fixed effects and market-date fixed effects as in Table 3. Coefficients are interpreted relative to the quarter one year before the proposed Endangerment Finding (2014Q3), which serves as the reference period. This reference quarter is selected to avoid potential contamination from the September 2014 ICAO information paper and the U.S. announcement that the EPA intended to begin domestic rulemaking.

Pre-event coefficients are close to zero and statistically indistinguishable from one another, indicating parallel trends in fares between high- and low-exposure carriers before the EPA announcement. After the June 2015 signal, coefficients turn positive and remain statistically significant through the end of the sample period. The cumulative effect rises gradually over time. By 2018–2019, the cumulative post-announcement estimates reach approximately 0.25 to 0.30 log points, consistent with the magnitude of the baseline difference-in-differences estimates in Table 3. The timing of the adjustment aligns with the regulatory developments that followed the 2015 proposal—the July 2015 advance notice of proposed rulemaking, the August 2016 final Endangerment and Contribution Finding, and the December 2016 denial of reconsideration petitions—each of which reinforced expectations of binding carbon-dioxide standards.

Overall, the event-study results support the identifying assumption by showing no visible pre-event divergence and a positive differential response only after the EPA regulatory signal became credible. This pattern is consistent with anticipatory pricing rather than with contemporaneous shocks unrelated to the policy environment. Combined with the baseline difference-in-differences estimates, the dynamic evidence supports **H1**: airlines with greater transition exposure raised fares relative to less-exposed competitors following the EPA 2015 regulatory signal.

6 Mechanism: Cross-Sectional Heterogeneity

The main pricing result establishes that exposed carriers raised fares after the EPA Finding. This section sharpens the interpretation by documenting heterogeneity along four cross-sectional dimensions that distinguish anticipatory risk management from alternative explanations of the pricing response. Section 6.1 tests the residual-value-exposure asymmetry developed in Section 2 by separating exposure into owned and leased fleet components. Section 6.2 examines whether financial constraints amplify the response. Section 6.3 identifies the boundary of the anticipatory response by interacting exposure with route-level competitive constraints. Section 6.4 validates the exposure proxy using carrier-level fuel-burn intensity, an emissions-direct measure of the dimension future regulation will price. A fifth dimension—operational complexity in multi-type fleets, captured by a Blau (1977) fleet-diversity index—is reported in Appendix Table A4 as supplementary evidence; we do not include it in the main text because the channel interpretation is conceptually ambiguous (fleet diversity can both amplify and cushion regulatory disruption depending on the type-by-type incidence of standards). All mechanism tests use the same pricing-panel inference as Section 5: two-way clustering by market and carrier $\times$ date. The carrier-level wild-cluster bootstrap appropriate for $G = 12$ identification is reserved for the firm-level tests in Section 7 and the small-cluster robustness check in Section 8.

6.1 Residual-Value Exposure by Lease Type

Table 5 tests **H2** by partitioning fleet exposure according to who bears residual-value risk. As developed in Section 2, residual-value exposure is the key economic distinction between residual-bearing and operating-leased aircraft. The partition is sharper than a simple owned-versus-leased split because capital leases (BTS Form 41 Schedule B-43 status code A) are economically equivalent to financed purchases: under SFAS 13 / ASC 840 lease classification rules used to define pre-event ownership status, capital-leased aircraft sit on the lessee's balance sheet and the lessee retains substantially all the risks and rewards of ownership, including residual-value risk. Operating leases (code B) are the institutional form in which the lessor retains the residual; the lessee holds a finite-term claim with a return option that converts residual-value risk away at lease-end. We therefore aggregate owned and capital-leased aircraft into a single *residual-bearing* fleet ($ExpCont_{ResBear}$) and contrast it with the operating-lease fleet ($ExpCont_{OpLease}$). This distinction has two empirical manifestations. The accounting manifestation is impairment recognition: residual-bearing aircraft are subject to SFAS 144 and ASC 360, while operating-lease right-of-use assets under ASC 842 carry impairment exposure bounded by the remaining lease term. The contractual manifestation is the exit option: the residual-bearing carrier cannot shed the asset costlessly (the alternatives are sale into a potentially stressed secondary market or accelerated retirement), while the operating-lease carrier walks at lease-end. Both manifestations imply that residual-bearing exposure should attract a stronger incentive to incorporate expected transition costs into current prices than operating-lease exposure.

The estimates support this prediction sharply. Without firm controls (Column 1), the Post $\times$ residual-bearing coefficient is 0.153 ($t = 10.22$), compared to 0.074 for operating-lease exposure ($t = 4.06$); the Wald test rejects equality at $p < 0.001$. With firm controls (Column 2), the residual-bearing coefficient is 0.148 ($t = 8.86$) and is unchanged in magnitude, while the operating-lease coefficient collapses to -0.024 and is statistically indistinguishable from zero ($p = 0.45$); the Wald test continues to reject equality at $p < 0.001$. The pricing response to transition risk is therefore much stronger in the part of the fleet whose residual value the carrier bears. The controlled specification is especially informative: residual-bearing exposure remains large and significant, while operating-lease exposure falls to a small, statistically insignificant estimate.

Together, the evidence supports a residual-value gradient in the pricing response. Carriers whose transition exposure is embedded in residual-bearing aircraft respond more strongly through prices, while the response associated with operating-lease exposure is weaker and disappears once firm controls are included. These findings support **H2** and are difficult to reconcile with explanations that do not invoke forward-looking expectations about future regulation.

6.2 Financial Constraints

This subsection tests **H3** by asking whether financial constraints amplify carriers' anticipatory pricing response to transition-risk exposure. Table 6 examines whether the anticipatory pricing response varies with carriers' financial capacity. The table interacts *Post* $\times$ *Exposure* with three proxies for financial flexibility: leverage (Debt), internal liquidity measured as Cash/Assets, and profitability (ROA). All three specifications include the same lagged firm controls used in Table 4, with standard errors two-way clustered by market and carrier-date as in the baseline.

The triple interaction with Cash/Assets is negative and significant at the 5% level (column 2: -0.295, $p = 0.032$): carriers with greater internal liquidity exhibit smaller post-event pricing responses. This is the most theoretically central financial-capacity result: carriers with lower balance-sheet liquidity respond more aggressively on the pricing margin, as the risk-management framework predicts. This pattern differs from Hillmann et al. (2025), who find that price increases following realized ESG incidents are larger for airlines with greater financial capacity. The contrast is informative: their setting captures ex post cost pass-through after ESG-related incidents materialize, where financially flexible carriers may have greater capacity to adjust supply and prices. Our setting captures ex ante pricing in anticipation of future transition costs, where limited internal liquidity increases the value of generating cash through current prices.

The triple interaction with leverage is positive and statistically significant at the 1% level (column 1: 0.290, $p = 0.005$): highly leveraged carriers exhibit larger post-event pricing responses. This finding is informative in light of the main effect of debt in Table 4, where leverage is negatively associated with fares on average, consistent with prior evidence that financially distressed carriers price more aggressively to maintain market share (Phillips and Sertsios, 2013; Busse, 2002). Once leverage is interacted with exposure after the EPA Finding, the sign reverses: highly leveraged *and* highly exposed carriers raise prices significantly more.

The triple with ROA points in the same direction as Cash/Assets (column 3: -3.07, $p = 0.001$): more profitable carriers exhibit weaker pricing responses, consistent with the risk-management interpretation that less-profitable firms substitute pricing for costly external finance. Across the three proxies, the interaction signs are consistent with stronger anticipatory pricing among carriers with less financial flexibility.

Taken together, these findings indicate that financial constraints amplify the differential fare response. Constrained firms have stronger incentives to preserve investment capacity through internally generated funds when external financing is costly; the firm-level tests in Section 7 provide corroborative evidence that liquidity and investment adjust after the signal. This interpretation is consistent with the broader literature linking financial frictions to corporate hedging behavior (Froot et al., 1993; Almeida et al., 2004) and with evidence that climate-exposed firms substitute toward lower financial leverage in advance of regulation (Ginglinger and Moreau, 2023; Dang et al., 2023).

6.3 Competitive Constraints

As developed in Section 2, anticipatory pricing requires both an industry-wide signal and residual pricing power. We test the latter at the route level: the EPA Finding supplies the triggering condition, and the boundary within which anticipatory pricing is feasible is the set of routes on which carriers retain pricing room. On routes where competition is tight, the threat of being undercut limits the firm's ability to raise prices in advance of cost increases even when rivals face symmetric exposure expectations. Table 7 reports a split-sample DiD that allows the exposure response to differ across high- and low-competition routes and estimates the incremental difference for carriers with below-median pre-period passenger share on the route.

The focal coefficient is the triple interaction $Post \times Exposure \times LowRouteShare$, where *LowRouteShare* equals one if the carrier's pre-period passenger share on the route is below the within-route median. This coefficient is an incremental differential relative to higher-share carriers within the same competition subsample. The incremental low-share differential is small and insignificant on high-competition routes (column 1: 0.013, n.s.) but large and statistically significant on low-competition routes (column 2: 0.130, $p < 0.001$). The difference across the two triple interactions is -0.126 ($p = 0.001$), indicating that the low-route-share differential emerges where local competition is weaker. We interpret the split-sample result as identifying the *boundary* of the anticipatory-pricing margin rather than as an independent climate-channel test.

6.4 Fuel-Burn Intensity

The fleet-age measure used as the baseline exposure is an indirect proxy for the regulatory exposure of interest—the carbon emissions intensity that future EPA rules will target. We confirm that the result is not an artifact of this proxy choice by re-estimating the baseline DiD with carrier-level fuel-burn intensity as an *alternative exposure proxy* in place of fleet age. Fuel-burn intensity is the carrier's pre-period (2011–2014) mean of total scheduled-service fuel gallons divided by either available seat miles (gal/ASM) or revenue passenger miles (gal/RPM), constructed at the carrier-month level from BTS Form 41 P-5.2 (fuel) and Form T-100 (segment traffic).[6]

We retain fleet age as the baseline exposure measure for two reasons. First, our theory is not only about emissions intensity per se, but about transition risk embedded in long-lived assets. Older fleets expose carriers to future compliance costs, accelerated replacement needs, and potential residual-value losses; these are the channels through which transition risk should affect pricing before regulation binds. Fleet age therefore maps more directly into the asset-side mechanism tested in Section 6.1, where the prediction depends on whether the carrier bears residual-value risk through owned and capital-leased aircraft. Second, fuel-burn intensity is a more direct emissions measure but also a more operational one: it can reflect aircraft utilization, stage length, seating density, load factors, and route mix, especially when normalized by RPM. Using pre-period averages mitigates this concern, but fleet age remains the cleaner baseline measure of predetermined exposure embedded in the carrier's capital stock. We therefore interpret the fuel-burn tests as validation that the fleet-age proxy captures the carbon dimension of transition risk, rather than as a replacement for the baseline measure.

Table 8 reports the result. Across all four specifications—two denominators (gal/ASM and gal/RPM) crossed with two functional forms (continuous and binary above-median)—the post-event pricing response loads positively and significantly on fuel-burn intensity. The continuous specifications (columns 1–2) yield $Post \times Exposure$ coefficients of 0.569 (gal/ASM) and 0.601 (gal/RPM), both significant at the 1 percent level. The binary specifications (columns 3–4) yield 0.024 ($p < 0.05$) and 0.092 ($p < 0.01$). The substantially larger continuous-coefficient magnitudes relative to the fleet-age baseline (0.150 in Table 4, col-

[6] Per-ASM normalization captures fuel use per unit of seat capacity offered and is closer to a pure measure of engine emissions intensity than per-RPM normalization, which mixes engine efficiency with load-factor variation. We report both as columns in the same table. The continuous measures yield similar coefficients; the binary above-median checks are both positive and significant but differ in magnitude.

umn 1) reflect both the different scaling of the exposure variable and the fact that fuel-burn intensity is a more direct measure of the regulatory dimension at issue. The two denominators yield similar inference in the continuous specifications, while the binary above-median specifications are both positive and significant but differ more in magnitude. Overall, the pricing response loads on a direct fuel-burn measure of the carbon dimension that future EPA rules would regulate, supporting the interpretation that the baseline fleet-age results capture climate-transition exposure rather than unrelated fleet characteristics.

7 Real Adjustments

The pricing response documented in Section 5 is consistent with anticipatory risk management. A skeptical interpretation, however, is that exposed carriers raised fares for reasons unrelated to forward-looking transition risk—for example, unobserved contemporaneous cost shocks or coordination unrelated to climate regulation. If firms are genuinely managing transition risk through pricing, we should observe complementary real adjustments at the firm level. We examine two such margins: firm-level financing and investment patterns (Section 7.1) and outright fleet renewal and disposals (Section 7.2). The unit of observation throughout is the carrier-quarter; the same balanced 2011–2019 window and the same predetermined exposure measure used in the pricing analysis are retained. Because identification reduces to twelve carriers at this level of aggregation, standard errors are clustered by carrier and stars reflect wild-cluster bootstrap p-values with Webb (2014) six-point weights.

7.1 Firm Financing and Investment

Table 9 reports firm-level DiD estimates for four financing- and investment-related outcomes. The coefficient of interest is Post $\times$ Exposure, where Exposure is the same predetermined log fleet age used in Section 5 (continuous in columns 1–3, binary above-median in columns 4–6). Carrier and year-quarter fixed effects absorb carrier averages and the industry common trend; columns 3 and 6 additionally include a Post $\times$ LCC interaction to allow low-cost-carrier-specific time variation.

Across the specifications, exposed carriers exhibit lower internal liquidity and higher capital investment following the EPA Finding. The natural logarithm of cash plus short-term investments falls by approximately 0.63 to 0.87 log points (Webb $p \leq 0.020$ in five of six specifications). Cash scaled by operating revenue falls by 0.48 to 0.54 (Webb $p \leq 0.029$ in all specifications). The change in debt scaled by assets is negative in four of six specifications and significant only in the no-controls specifications, so we treat the debt evidence as suggestive.

The change in the capital-expenditure proxy, defined as the sum of flight equipment and equipment-deposit advance payments scaled by assets, is positive in all six specifications and statistically significant at the 5–10% level once firm controls are included.

The combined pattern—internal liquidity drawn down and capital expenditure accelerated, with weaker evidence on debt growth—is consistent with exposed firms deploying internal liquidity alongside real investment, and is difficult to reconcile with a pure precautionary-cash-buffer interpretation, under which cash would have to *rise* in the post-event period. The pattern is the empirical analog of the corporate disclosure quoted in Section 3.2, in which American Airlines tied its policy of "retain[ing] liquidity levels above [its] network peers" directly to its forward-looking "$4.5 billion in each of 2016 and 2017 . . . fleet renewal program." Pricing, internal liquidity, and capital expenditure move together for exposed carriers in a way that is jointly consistent with the risk-management framework, though the carrier-quarter design does not identify a direct dollar-for-dollar financing flow from pricing to capex; we treat the joint pattern as corroborative rather than as a structural test.

7.2 Fleet Renewal and Old-Fleet Exit

If exposed carriers are using internal cash flow to renew their fleets, we should observe the average age of their owned aircraft falling, accelerated disposals of older airframes, and lower maintenance intensity as newer aircraft replace older ones. Table 10 tests these predictions on the same carrier-quarter panel using three level-based outcomes: the airframe-weighted average age of owned aircraft (from Schedule B-43), maintenance expense scaled by operating revenue, and realized capital gains on aircraft disposals scaled by operating revenue.

The average age of owned aircraft falls by approximately 2.2 to 4.7 years for exposed carriers in the post-2015 period, with all six specifications statistically significant at conventional Webb levels. This is the most direct evidence of real adjustment in Table 10: exposed carriers' owned fleets become younger in the years following the EPA Finding. Maintenance expense scaled by operating revenue declines by approximately 0.008 to 0.014, consistent with newer aircraft generating lower maintenance requirements. Realized capital gains on aircraft disposals rise by 0.002 to 0.005 of operating revenue across specifications, with five of six specifications statistically significant. We interpret the disposal-gain result as consistent with accelerated old-fleet exit, but the table does not separately identify sale timing, buyer type, or the book-value spread on each aircraft.

The three outcomes describe a coherent renewal response concentrated among *owned* aircraft, which is consistent with the residual-value-exposure asymmetry developed in Section 2. Owners bear the long-tail residual-value risk on capitalized aircraft and the institutional manifestations of that exposure—impairment recognition under SFAS 144/ASC 360 and the absence of a contractual exit option—make orderly disposal of older airframes a forward-looking risk-management response. Lessees, by contrast, return the plane at lease-end with no analogous incentive to actively dispose. The evidence in Table 10 is consistent with the residual-value risk mechanism: the strongest real-adjustment evidence appears for owned aircraft, where carriers bear the long-tail residual-value exposure.

Summary

Together, the two real-adjustment margins documented in this section—internal cash flow deployed alongside capital expenditure (Section 7.1) and accelerated fleet renewal and disposals concentrated in owned aircraft (Section 7.2)—are jointly consistent with anticipatory pricing operating as a forward-looking risk-management margin alongside real adaptation. We cannot rule out unobserved shocks that simultaneously affect exposed carriers' pricing and financing, so we treat the firm-level results as corroborative evidence that the post-signal adjustments operate on long-lived capital, the margin most directly implicated by aircraft carbon regulation.

8 Robustness and Potential Confounders

This section addresses four potential confounders to the headline pricing result and reports the inference cross-check that disciplines small-cluster significance throughout the paper.

Jet fuel prices and pass-through. Jet fuel is a major operating expense for airlines and a primary driver of short-run marginal costs, so large price swings can transmit to fares via cost pass-through. Market-date fixed effects absorb route-level fuel pass-through that is common to all carriers serving a market in a given quarter. Carrier-specific fuel-cost differences are further addressed in Table 4 through time-varying fuel-expense intensity controls. Appendix Figure 2 shows U.S. Gulf Coast jet-fuel spot prices from 2012 to 2019: prices were *higher* in the pre-period and fell sharply around 2015, remaining well below pre-2015 levels thereafter. If fuel costs were driving our results, we would expect high-exposure (older-fleet) carriers to diverge *before* 2015, when fuel was expensive, rather than only after June 2015. Moreover, cheaper post-period fuel reduces the operating disadvantage of older aircraft, biasing against finding larger post-period price increases for high-exposure carriers. The event study shows no pre-trend divergence and a break only after the EPA signal, which is inconsistent with a fuel-cost explanation.

DOJ collusion probe. In July 2015, the Department of Justice opened an investigation into potential capacity coordination among large U.S. airlines. Heightened antitrust scrutiny would be expected to discourage capacity discipline and overt price increases, putting downward pressure on fares rather than upward. Any market-wide effects are absorbed by *market-date* fixed effects; moreover, the probe targeted conduct, not environmental exposure, so it is unlikely to be correlated with our *pre-period* fleet-age measure. If anything, scrutiny fell most on the legacy carriers, which are more likely to operate older fleets, biasing against the positive $Post \times Exposure$ estimates we document. To the extent the probe affected airline pricing, it would bias our estimates toward zero rather than generate the positive differential we find.

Concurrent mergers. A potential concern is that concurrent consolidation in the airline industry affects the estimated pricing response. The most relevant transaction during our window is Alaska Airlines' acquisition of Virgin America, completed in December 2016. This merger could confound the analysis if post-event fare changes reflect changes in Alaska–Virgin's combined route network, fleet composition, or merger-integration pricing rather than exposure to transition risk. We address this concern in two ways. First, exposure is measured using each carrier's pre-event 2011–2014 fleet-age average and is held fixed throughout the analysis. The post-event change in corporate ownership therefore does not mechanically change carriers' exposure rankings. Second, the baseline result is robust to excluding the post-2000s low-cost carriers, including Virgin America, from the sample. This restriction removes the carriers most likely to be affected by the Alaska–Virgin transaction while preserving the positive and significant Post × Exposure coefficient; see Table 11.

Low-cost-carrier composition and legacy-vs-LCC trends. Another concern is that the estimated exposure effect reflects differential post-event pricing trends between legacy carriers and low-cost carriers (LCCs), rather than carriers' exposure to transition risk. This concern is relevant because LCCs generally operate younger fleets. As a result, any LCC-specific pricing shift around the EPA Finding could appear as a fleet-age effect. Table 11 addresses this concern by estimating the baseline specification under four alternative compositions: the baseline 12-carrier sample, a sample excluding the three legacy carriers (AA, DL, UA), a sample excluding the four post-2000s LCCs (NK, F9, B6, VX), and the full sample augmented with a Post × LCC interaction that absorbs any common LCC-specific post-event fare shift. The Post × FleetAge coefficient remains positive, statistically significant, and economically similar across all four specifications, ranging from 0.143 to 0.187. In the specification with the Post × LCC interaction, the coefficient is 0.1614 (SE = 0.0293), close to the baseline estimate. Thus, the pricing response is not driven by a broad legacy-versus-LCC post-event divergence; it is identified by residual variation in fleet age after accounting for carrier-type-specific post-event pricing shifts.

Cluster-robust inference. Our baseline pricing specifications use two-way clustering by market $\times$ date and carrier $\times$ date, matching the dimensions along which demand shocks and carrier-level pricing shocks are most likely to be correlated. Because the pricing panel contains more than 540,000 route-carrier-quarter observations and thousands of clusters along these dimensions, the asymptotic justification for this inference is strong. A separate concern, however, is that treatment variation ultimately comes from differences across twelve ticketing carriers. To address this small-G concern directly, Table 12 re-estimates the baseline DiD using a carrier-level wild-cluster bootstrap with Webb six-point weights, clustering on 12 `tkcarrier`. We implement this test for four alternative fleet-age exposure definitions. The baseline result remains statistically significant in all cases, with p_{webb} ranging from 0.0030 to 0.0097. For the firm-level real-adjustment tests in Section 7, where the unit of observation is carrier-quarter and the number of carrier clusters is necessarily small, we use the Webb six-point wild-cluster bootstrap as the primary inference mode.

9 Conclusion

This paper examines how firms respond to credible signals of climate transition risk through their product-market decisions. Exploiting the EPA's June 2015 proposed aircraft Endangerment and Contribution Finding as a formal, non-implementing policy signal, we show that airlines with greater ex ante exposure, proxied by pre-event fleet age, raised fares differentially following the announcement. In the no-control baseline, a one-standard-deviation increase in fleet age is associated with a 5–6% increase in fares (about $12 per average ticket); with lagged firm controls, the corresponding headline estimate is about 4–5%. The pricing response is stronger for exposure embedded in aircraft the carrier owns or holds under capital lease, which exposes the carrier to more of the asset's residual-value risk. Operating-lease exposure is weaker and becomes statistically insignificant once firm controls are included, consistent with the contractual return option shifting residual-value risk to the lessor. The response is also stronger for financially constrained carriers, consistent with anticipatory pricing serving as a source of internal cash flow for forward-looking adjustment when external finance is costly.

Complementary real-side adjustments support the risk-management interpretation. Exposed carriers draw down internal liquidity, increase the capital-expenditure proxy, reduce the average age of their owned fleet by about two to five years, lower maintenance expense intensity, and generally recognize higher realized gains on aircraft disposals. Pricing and real investment move together in a way that is jointly consistent with anticipatory risk management, although the firm-level evidence remains corroborative rather than a structural estimate of financing flows.

Ex ante versus ex post incidence. A direct contrast emerges with recent evidence on *ex post* carbon and ESG cost pass-through. Hillmann et al. (2025) document that airlines raise fares after ESG-related operational incidents materialize and that the largest responses come from *financially stronger* carriers. We document the reverse cross-section on the ex ante margin: *financially constrained* carriers exhibit larger anticipatory price increases, consistent with a precautionary risk-management motive that substitutes pricing for costly external finance. Taken together, the two findings imply that the cross-section of fare responses depends on whether the cost is realized or anticipated. Our setting shows that relative fares can adjust earlier in the regulatory pipeline than ex post pass-through evidence alone would suggest.

Measurement and accounting recognition. The asymmetric pricing response between residual-bearing aircraft (owned plus capital-leased) and operating-leased aircraft has implications for how transition-risk exposure is measured in financial statements. Under ASC 842, operating-lease right-of-use assets are capitalized but the recognized impairment exposure is bounded by the remaining lease term rather than the asset's useful life. Empirical measures of transition exposure that rely on balance-sheet aggregates may therefore understate the long-tail residual-value risk borne by residual-bearing carriers while overstating the short-tail exposure of operating lessees. Disentangling residual-bearing from operating-lease capital in transition-risk measurement is a productive direction for accounting research at the regulation–financial-reporting interface.

Scope. Our identification is built on twelve U.S. ticketing carriers and rests on cross-carrier variation in predetermined fleet age. The design does not identify a structural financing flow from pricing to capital expenditure dollar-for-dollar; we document that the two margins move together but treat the joint pattern as corroborative rather than as a structural test of internal-cash-flow financing. The carrier-quarter level of aggregation also limits power for some real-adjustment outcomes, which we address with wild-cluster bootstrap inference. Whether the patterns we document generalize to other capital-intensive sectors with heterogeneous asset flexibility, and whether anticipatory pricing welfare-dominates ex post pass-through, are natural questions for future work.

Policy. Credible regulatory signals can induce price and investment adjustments before rules take effect; recognizing these dynamics matters for how expected transition costs propagate through product markets. Future work could incorporate richer, aircraft-level measures of expected transition costs and study whether early pricing responses predict subsequent investment, retirements, or abatement. Extending the analysis to other capital-intensive sectors with heterogeneous asset flexibility would further clarify how anticipated regulation propagates through product markets and across stakeholders.

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Table 1: Summary Statistics

This table reports summary statistics for variables used in the pricing-panel and firm-level analyses. Panel A reports market–carrier–quarter variables used in the pricing and heterogeneity tests on the Table 3 baseline pricing sample. Panel B reports carrier–quarter variables used in the financing, investment, fleet-renewal, and disposal tests. The sample period is 2011Q1–2019Q4. Exposure variables are measured over 2011–2014 and then held fixed in the post-event regressions. Panel B reports available observations by variable because outcome availability differs across firm-level tests. All variables are defined in Appendix A1.

Variable	N	Mean	SD	Min	p25	p50	p75	Max
Panel A. Pricing-panel variables (market–carrier–quarter)								
Fare	555,047	5.385	0.348	3.220	5.206	5.408	5.588	7.724
AvgFleetAge	555,047	2.517	0.291	1.403	2.342	2.589	2.759	3.078
AvgFleetAgeSW	555,047	2.510	0.295	1.396	2.318	2.602	2.741	3.072
AvgFleetAgeResBear	555,047	2.540	0.304	1.689	2.281	2.762	2.762	3.077
AvgFleetAgeOpLease	555,047	2.526	0.289	1.403	2.296	2.624	2.756	3.091
HighExp	555,047	0.867	0.339	0	1	1	1	1
HighExpSW	555,047	0.867	0.339	0	1	1	1	1
FuelBurn gal/ASM	555,047	-4.203	0.063	-4.370	-4.240	-4.209	-4.187	-4.115
FuelBurn gal/RPM	555,047	-4.037	0.072	-4.226	-4.088	-4.051	-3.976	-3.944
LowRouteShare	555,047	0.343	0.475	0	0	0	1	1
HighComp	555,047	0.684	0.465	0	0	1	1	1
CarrierCount	555,047	1.839	2.268	0.000	0.000	1.000	3.000	20.000
Southwest	555,047	0.192	0.394	0	0	0	0	1
OtherLCC	555,047	0.189	0.392	0	0	0	0	1
PsgConnectMkt	555,047	0.639	0.394	0.000	0.218	0.928	1.000	1.000
PsgConnectCarr	555,047	0.823	0.356	0.000	0.976	1.000	1.000	1.000
Population	555,047	0.702	0.682	-3.863	0.238	0.652	1.152	2.794
IncomePC	555,047	3.802	0.135	3.241	3.713	3.791	3.878	4.751
HHI	555,047	0.490	0.202	0.151	0.337	0.438	0.588	1.000
Size	555,047	17.140	0.990	11.687	16.917	17.490	17.778	17.955
Roa	555,047	0.013	0.017	-0.132	0.005	0.012	0.020	0.127
Debt	555,047	0.406	0.187	0.000	0.206	0.455	0.554	1.670
StaffExp	555,047	0.029	0.011	0.014	0.022	0.025	0.029	0.103
FuelExp	555,047	0.032	0.023	0.012	0.017	0.025	0.039	0.277
Leasing	555,047	0.026	0.016	0.000	0.019	0.023	0.038	0.199
CashAssets	555,047	0.131	0.075	0.005	0.073	0.116	0.175	0.504
Panel B. Firm-level variables (carrier–quarter)								
ln(Cash + ST Inv.)	408	13.487	1.775	9.013	12.742	13.785	15.051	15.995
Cash / Op. Revenue	408	0.829	0.456	0.031	0.496	0.776	1.174	2.141
Δ Debt / Assets	412	-0.003	0.077	-0.759	-0.013	-0.004	0.007	0.451
Δ Capex Proxy	396	0.002	0.031	-0.206	-0.009	0.003	0.016	0.120
Average Age of Owned Aircraft	352	10.374	5.021	0.000	7.203	9.958	13.402	22.778
Maintenance Expense / Op. Revenue	424	0.085	0.027	0.041	0.062	0.082	0.101	0.211
Capital Gains on Disposals / Op. Revenue	397	-0.001	0.010	-0.139	-0.000	0.000	0.000	0.004
CashAssets	408	0.169	0.110	0.005	0.085	0.152	0.215	0.504
Size	424	15.452	1.746	11.687	14.062	15.480	17.006	17.955
Roa	424	0.018	0.028	-0.132	0.006	0.017	0.031	0.127
Debt	424	0.302	0.272	0.000	0.117	0.207	0.461	1.670
StaffExp	424	0.036	0.017	0.014	0.024	0.029	0.044	0.103
FuelExp	424	0.058	0.048	0.012	0.027	0.040	0.071	0.277
Leasing	408	0.025	0.029	0.000	0.000	0.021	0.042	0.199

Table 2: Correlation Matrix

This table presents pairwise correlations among the pricing-panel variables reported in Panel A of Table 1. Variables appear in the same order as in the descriptives table. All variables are defined in Appendix A1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
$Fare$ (1)	1.00																									
$AvgFleetAge$ (2)	0.28	1.00																								
$AvgFleetAgeSW$ (3)	0.29	1.00	1.00																							
$AvgFleetAgeResBear$ (4)	0.21	0.97	0.97	1.00																						
$AvgFleetAgeOpLease$ (5)	0.19	0.74	0.73	0.46	1.00																					
$HighExp$ (6)	0.18	0.84	0.85	0.79	0.69	1.00																				
$HighExpSW$ (7)	0.18	0.84	0.85	0.79	0.69	1.00	1.00																			
$FuelBurn_{ASM}$ (8)	0.08	0.46	0.47	0.53	-0.02	0.59	0.59	1.00																		
$FuelBurn_{RPM}$ (9)	0.07	0.37	0.37	0.42	0.00	0.60	0.60	0.95	1.00																	
$LowRouteShare$ (10)	-0.02	-0.13	-0.12	-0.12	-0.16	-0.18	-0.18	-0.11	-0.14	1.00																
$HighComp$ (11)	-0.02	-0.19	-0.19	-0.19	-0.12	-0.15	-0.15	-0.09	-0.06	0.00	1.00															
$CarrierCount$ (12)	-0.33	-0.09	-0.09	-0.04	-0.09	-0.07	-0.07	-0.04	-0.04	0.00	0.08	1.00														
$Southwest$ (13)	-0.28	-0.08	-0.08	-0.07	-0.03	-0.02	-0.02	0.01	0.04	0.02	0.11	0.35	1.00													
$OtherLCC$ (14)	-0.31	-0.15	-0.15	-0.08	-0.13	-0.14	-0.14	-0.08	-0.08	0.01	0.13	0.45	0.19	1.00												
$PsgConnectMkt$ (15)	0.37	0.10	0.10	0.05	0.10	0.10	0.10	0.06	0.06	-0.02	0.02	-0.71	-0.37	-0.47	1.00											
$PsgConnectCarr$ (16)	0.30	0.13	0.13	0.09	0.07	0.09	0.09	0.06	0.04	0.28	0.03	-0.46	-0.20	-0.28	0.54	1.00										
$Population$ (17)	-0.14	-0.15	-0.15	-0.09	-0.13	-0.10	-0.10	-0.04	-0.01	0.00	0.21	0.40	0.16	0.22	-0.39	-0.24	1.00									
$IncomePC$ (18)	0.00	-0.10	-0.10	-0.08	-0.08	-0.10	-0.10	-0.06	-0.04	-0.01	0.05	0.17	0.01	0.11	-0.18	-0.11	0.34	1.00								
HHI (19)	-0.10	0.11	0.11	0.10	0.08	0.09	0.09	0.06	0.05	0.01	-0.45	0.15	0.14	-0.03	-0.49	-0.19	0.04	0.03	1.00							
$Size$ (20)	0.29	0.80	0.81	0.74	0.63	0.75	0.75	0.43	0.38	-0.11	-0.18	-0.07	-0.05	-0.16	0.11	0.14	-0.10	0.02	0.10	1.00						
Roa (21)	-0.13	-0.24	-0.26	-0.26	0.00	-0.19	-0.19	-0.24	-0.17	-0.03	0.04	0.03	0.08	0.05	-0.03	-0.08	0.03	0.13	0.00	-0.18	1.00					
$Debt$ (22)	0.24	0.58	0.61	0.65	0.17	0.43	0.43	0.36	0.21	0.03	-0.14	-0.05	-0.12	-0.10	0.06	0.14	-0.09	-0.11	0.05	0.50	-0.48	1.00				
$StaffExp$ (23)	-0.25	-0.49	-0.50	-0.54	-0.15	-0.16	-0.16	-0.07	0.11	-0.07	0.14	0.04	0.13	0.06	-0.03	-0.11	0.09	0.06	-0.06	-0.52	0.34	-0.68	1.00			
$FuelExp$ (24)	-0.23	-0.56	-0.57	-0.53	-0.39	-0.37	-0.37	-0.14	-0.05	0.00	0.15	0.04	0.06	0.09	-0.06	-0.11	0.08	-0.12	-0.08	-0.79	0.01	-0.42	0.65	1.00		
$Leasing$ (25)	0.13	0.24	0.27	0.10	0.33	0.33	0.33	-0.01	0.01	0.01	-0.04	-0.03	-0.04	-0.06	0.04	0.04	-0.05	-0.07	0.01	0.18	-0.15	0.33	-0.15	-0.25	1.00	
$CashAssets$ (26)	-0.18	-0.48	-0.48	-0.34	-0.49	-0.29	-0.29	-0.04	-0.01	0.06	0.11	0.04	0.04	0.04	-0.03	-0.07	0.05	-0.12	-0.07	-0.57	0.03	-0.15	0.29	0.49	0.04	1.00

Table 3: Baseline Difference-in-Differences Estimates of Anticipatory Pricing

This table presents the results of estimating Equation (1). The analysis is conducted at the market–carrier–quarter level. The dependent variable is $Fare$, defined as the natural logarithm of the inflation-adjusted average ticket price. *Post* equals one for quarters from 2015Q3 onward; *Exposure* is the carrier's pre-event (2011–2014) average log fleet age. Columns 1–2 use the continuous measure (headline specification); Columns 3–4 use a binary above-median indicator (*HighExposure*) as a robustness check. Each pair appears in both unweighted and seat-weighted form. All regressions include market × carrier and market × date fixed effects. Standard errors are two-way clustered by market and by carrier × date; t-statistics in parentheses. All variables are defined in Appendix A1. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)
Dependent Variable	*Fare*	*Fare*	*Fare*	*Fare*
Exposure Weight	AvgFleetAge	AvgFleetAgeSW	AvgFleetAge	AvgFleetAgeSW
Exposure Form	Continuous	Continuous	Binary (Above-Median)	Binary (Above-Median)
$ExpCont \times Post$	0.203***	0.202***		
	(10.214)	(10.313)		
$HighExp \times Post$			0.160***	0.160***
			(9.104)	(9.104)
FE	Market × Carrier	Market × Carrier	Market × Carrier	Market × Carrier
	Market × Date	Market × Date	Market × Date	Market × Date
Std. Err.	Carrier × Date, Market	Carrier × Date, Market	Carrier × Date, Market	Carrier × Date, Market
adjR^2	0.748	0.748	0.747	0.747
N	555,047	555,047	555,047	555,047

Table 4: Robustness to Firm-Level Controls

This table presents the results of re-estimating Equation (1) with additional time-varying firm-level controls. The analysis is conducted at the market–carrier–quarter level. The dependent variable is $Fare$, defined as the natural logarithm of the inflation-adjusted average ticket price. *Post* equals one for quarters from 2015Q3 onward; *Exposure* is the carrier's pre-event (2011–2014) average log fleet age. Columns 1–2 use the continuous measure (headline specification); Columns 3–4 use a binary above-median indicator (*HighExposure*) as a robustness check. Each pair appears in both unweighted and seat-weighted form. Controls (size, ROA, leverage, labor-expense intensity, fuel-expense intensity, and leasing intensity) are lagged one period. All regressions include market × carrier and market × date fixed effects. Standard errors are two-way clustered by market and by carrier × date; t-statistics in parentheses. All variables are defined in Appendix A1. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)
Dependent Variable	*Fare*	*Fare*	*Fare*	*Fare*
Exposure Weight	AvgFleetAge	AvgFleetAgeSW	AvgFleetAge	AvgFleetAgeSW
Exposure Form	Continuous	Continuous	Binary (Above-Median)	Binary (Above-Median)
$ExpCont \times Post$	0.150***	0.155***		
	(7.033)	(7.155)		
$HighExp \times Post$			0.109***	0.109***
			(6.266)	(6.266)
$Size$	0.039**	0.038**	0.031*	0.031*
	(2.170)	(2.138)	(1.706)	(1.706)
RoA	0.245	0.221	0.129	0.129
	(1.046)	(0.953)	(0.539)	(0.539)
$Debt$	-0.183***	-0.183***	-0.192***	-0.192***
	(-5.692)	(-5.760)	(-6.052)	(-6.052)
$StaffExp$	0.628	0.619	-0.204	-0.204
	(0.470)	(0.468)	(-0.159)	(-0.159)
$FuelExp$	1.957***	1.871***	2.656***	2.656***
	(4.228)	(4.078)	(6.296)	(6.296)
$Leasing$	1.159***	1.215***	0.915***	0.915***
	(5.631)	(5.831)	(4.267)	(4.267)
FE	Market × Carrier	Market × Carrier	Market × Carrier	Market × Carrier
	Market × Date	Market × Date	Market × Date	Market × Date
Std. Err.	Carrier × Date, Market	Carrier × Date, Market	Carrier × Date, Market	Carrier × Date, Market
adjR^2	0.771	0.771	0.770	0.770
N	508,283	508,283	508,283	508,283

Figure 1: Pre-Trends and Dynamic Treatment Effects

This figure plots event study estimates of the relationship between fares and regulatory exposure around the EPA's June 2015 aircraft endangerment finding. The dependent variable is $Fare$, the natural logarithm of the inflation-adjusted average ticket price. Each point represents the coefficient on the interaction between the binary exposure indicator ($HighExposure$) and year indicators from an event-study specification corresponding to the baseline model with market × carrier and market × date fixed effects. The omitted category is the quarter one year before the EPA's proposed finding. Vertical bars show 95% confidence intervals based on standard errors two-way clustered by market and by carrier × date. All variables are defined in Appendix A1. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

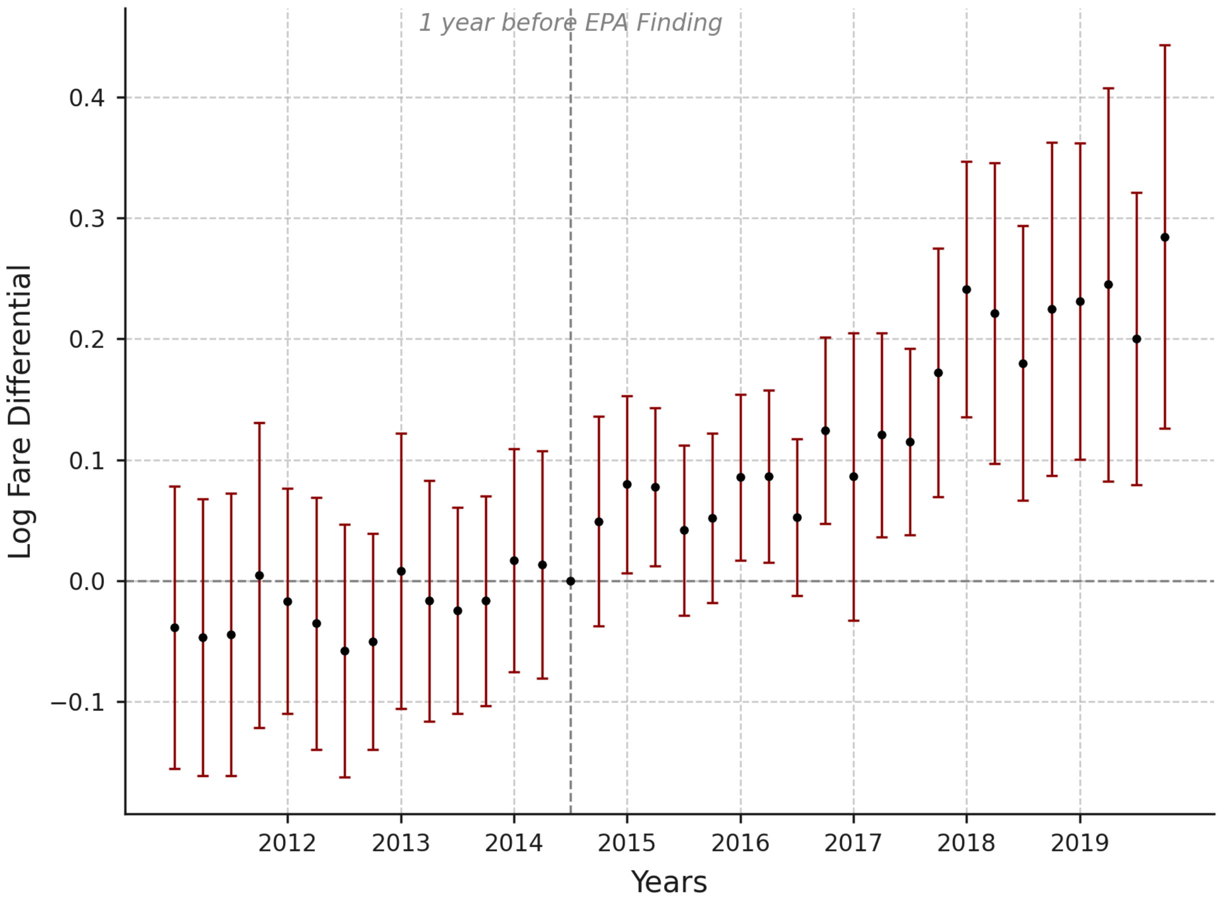


Table 5: Residual-Value Exposure: Residual-Bearing versus Operating-Lease Aircraft

This table presents the results of estimating Equation (1) with exposure partitioned by residual-value risk, as developed in Section 2. $ExpCont_{ResBear}$ is the log seat-weighted pre-event (2011–2014) fleet age of *residual-bearing* aircraft, defined as owned plus capital-leased airframes (BTS Form 41 Schedule B-43 status codes O and A); capital leases are aggregated with owned aircraft because, under SFAS 13/ASC 840 lease classification rules used to define pre-event ownership status, the lessee retains substantially all the risks and rewards of ownership, including residual-value risk. $ExpCont_{OpLease}$ is the log seat-weighted pre-event fleet age of operating-leased airframes (status code B), for which residual-value risk is borne by the lessor. The unit of observation is the market–carrier–quarter; the dependent variable is $Fare$, the natural logarithm of the inflation-adjusted average ticket price. *Post* equals one for quarters from 2015Q3 onward. Column (1) excludes firm-level controls; Column (2) includes time-varying controls for size, profitability, leverage, labor and fuel expense intensities, and leasing intensity. The Wald p-value tests equality of the residual-bearing and operating-lease coefficients. All regressions include market × carrier and market × date fixed effects. Standard errors are two-way clustered by market and by carrier × date; t-statistics in parentheses. All variables are defined in Appendix A1. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)
Residual-Bearing vs. Operating-Lease Fleet		
Dependent Variable	*Fare*	*Fare*
Firm-Level Controls	Excluded	Included
$Post \times ExpCont_{ResBear}$	**0.1533*** **	**0.1480*** **
	(10.220)	(8.862)
$Post \times ExpCont_{OpLease}$	**0.0736*** **	−0.0243
	(4.066)	(−0.750)
Wald p-value: $\beta_{ResBear} = \beta_{OpLease}$	<0.001	<0.001
FE	Market × Carrier, Market × Date	
Std. Err.	Carrier × Date, Market	
adj. R^2	0.730	0.736
N	546,095	532,188

Table 6: Financial Constraints and Anticipatory Pricing

This table presents the results of estimating Equation (1) with triple interactions that test whether the anticipatory pricing response varies with carriers' financial capacity. The unit of observation is the market–carrier–quarter; the dependent variable is $Fare$, the natural logarithm of the inflation-adjusted average ticket price. *Post* equals one for quarters from 2015Q3 onward; *Exposure* is the carrier's pre-event (2011–2014) average log fleet age. Financial capacity proxies are leverage (Debt), internal liquidity measured as Cash/Assets (cash plus short-term investments divided by total assets), and profitability (ROA). The main coefficients of interest are the triple interaction terms *Post*×*Exposure*×*FinancialCapacity*. All regressions include market × carrier and market × date fixed effects. Standard errors are two-way clustered by market and by carrier × date; t-statistics in parentheses. All variables are defined in Appendix A1. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)
Financial Capacity Proxy	Debt	Cash/Assets	ROA
Firm-Level Controls	Included	Included	Included
Post × *ExpCont*	**0.1520*** **	**0.0936*** **	**0.2034*** **
	(4.368)	(3.152)	(6.540)
Post × *FinancialCapacity*	**-0.8460*** **	**0.3626**	**6.8430*** **
	(−3.234)	(1.093)	(3.087)
ExpCont × *FinancialCapacity*	**0.2903*** **	**-0.3934*** **	**0.3382**
	(5.014)	(−2.940)	(0.759)
Post × *ExpCont* × *FinancialCapacity*	**0.2902*** **	**-0.2952** **	**-3.0725*** **
	(2.842)	(−2.153)	(−3.365)
FE	Market × Carrier, Market × Date		
Std. Err.	Carrier × Date, Market		
adj. R^2	0.756	0.757	0.754
N	541,007	541,007	541,007

Table 7: Anticipatory Pricing under Competitive Constraints (Split-Sample)

This table reports split-sample estimates of the anticipatory-pricing response on low-route-share carriers. The pricing-panel specification matches column (2) of Table 4. The unit of observation is the market–carrier–quarter; the dependent variable is $Fare$, the natural logarithm of the inflation-adjusted average ticket price. *Post* equals one for quarters from 2015Q3 onward; *Exposure* is the carrier's pre-event (2011–2014) average log fleet age. The route-level moderators are built from a 2012–2014 pre-window: *LowRouteShare* equals one if carrier i's 2012–2014 passenger share on route m is below the within-route median; *HighComp* equals one if the route's 2012–2014 mean number of carriers is at or above the within-sample median. Column (1) restricts to high-competition routes; column (2) restricts to low-competition routes. Time-invariant terms (route share and the high-competition indicator) are absorbed by the market × carrier fixed effect. The *Difference* row reports the gap ($\text{triple}_{\text{High}} - \text{triple}_{\text{Low}}$), recovered as the quadruple-interaction coefficient from the pooled regression; its p-value is the test of equality of the two split-sample triple coefficients. The reported triple interactions are incremental low-route-share differentials within each competition subsample, not total marginal effects for low-route-share carriers. All specifications include lagged firm controls (size, ROA, debt, staff intensity, fuel intensity, leasing intensity), market × carrier and market × date fixed effects. Standard errors are two-way clustered by market and by carrier × date; t-statistics in parentheses. All variables are defined in Appendix A1. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)
Dependent Variable	*Fare*	*Fare*
Subsample	*High Competition*	*Low Competition*
Cutoff	#Carriers ≥ median	#Carriers < median
Exposure × Post	0.134***	0.130***
	(6.410)	(5.878)
Exposure × Post × Low Route Share	**0.013**	**0.130*** **
	(0.825)	**(3.366)**
Diff. (High − Low)	**-0.1264*** **	[p = 0.0010]
Firm-Level Controls	Included	Included
FE	Market × Carrier, Market × Date	
Std. Err.	Carrier × Date, Market	
adj. R^2	0.767	0.715
N	380,714	160,337
Markets	2,613	2,604
Carriers	12	11

Table 8: Fuel-Burn Intensity as Exposure

This table re-estimates Equation (1) using carrier-level fuel-burn intensity in place of fleet age. The unit of observation is the market–carrier–quarter; the dependent variable is *Fare*; and *Post* equals one from 2015Q3 onward. Fuel-burn intensity is the carrier's pre-event (2011–2014) scheduled-service fuel gallons divided by available seat miles (gal/ASM, columns 1 and 3) or revenue passenger miles (gal/RPM, columns 2 and 4), using BTS Form 41 P-5.2 and Form T-100 segment traffic. Columns 1–2 use continuous log fuel burn; columns 3–4 use a binary above-median indicator. The continuous estimates are the main comparison across denominators; the binary estimates show sign robustness. All specifications include lagged firm controls and market × carrier and market × date fixed effects. Standard errors are two-way clustered by market and by carrier × date; t-statistics are in parentheses. Variables are defined in Appendix A1. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)
Dependent Variable	*Fare*	*Fare*	*Fare*	*Fare*
Exposure	FuelBurn (gal/ASM)	FuelBurn (gal/RPM)	FuelBurn (gal/ASM)	FuelBurn (gal/RPM)
Exposure Form	Continuous	Continuous	Binary (Above-Median)	Binary (Above-Median)
$ExpCont \times Post$	0.569***	0.601***		
	(8.821)	(9.351)		
$HighExp \times Post$			0.024**	0.092***
			(2.077)	(10.143)
$Size$	-0.015	-0.034	0.044**	-0.007
	(-0.695)	(-1.599)	(2.137)	(-0.366)
RoA	-0.023	-0.146	0.381	0.186
	(-0.088)	(-0.588)	(1.347)	(0.788)
$Debt$	-0.199***	-0.195***	-0.194***	-0.154***
	(-6.203)	(-6.326)	(-5.880)	(-5.041)
$StaffExp$	0.108	-0.552	0.799	-0.083
	(0.074)	(-0.407)	(0.521)	(-0.063)
$FuelExp$	2.737***	2.701***	3.435***	2.591***
	(5.451)	(5.986)	(6.621)	(5.943)
$Leasing$	0.597***	0.182	0.999***	-0.137
	(3.035)	(0.867)	(5.003)	(-0.635)
FE	Market × Carrier	Market × Carrier	Market × Carrier	Market × Carrier
	Market × Date	Market × Date	Market × Date	Market × Date
Std. Err.	Carrier × Date, Market	Carrier × Date, Market	Carrier × Date, Market	Carrier × Date, Market
adjR^2	0.753	0.754	0.750	0.754
N	541,077	541,077	541,077	541,077

Table 9: Firm-Level Financing and Investment Adjustment

This table reports firm-level DiD estimates around the EPA's June 2015 aircraft Endangerment Finding. The unit of observation is the carrier–quarter on a balanced 2011–2019 panel (±4 years around 2015). *Post* equals one for quarters from 2015Q3 onward; *Exposure* is the carrier's pre-event (2011–2014) average log fleet age, continuous in columns 1–3 and binary (above-median) in columns 4–6. Controls in columns 2–3 and 5–6 are lagged firm size (log assets), ROA, debt scaled by assets, staff expense intensity, fuel expense intensity, and leasing intensity. Columns 3 and 6 add a Post × LCC interaction, where LCC equals one for low-cost carriers (WN, B6, F9, NK, VX, G4, SY). All specifications include carrier and year-quarter fixed effects. Inference uses a wild-cluster bootstrap clustered by carrier with Webb 2014 6-point weights ($G = 12$, $B = 9{,}999$ replications, null imposed; `wildboottest`); Webb p-values are reported in brackets below each coefficient. Outcome definitions: ln(Cash + ST Inv.) is the natural log of dollar cash plus short-term investments; Cash/Op. Revenue is cash plus short-term investments scaled by quarterly operating revenues; Δ Debt/Assets is the quarter-to-quarter change in non-current liabilities scaled by total assets; Δ Capex Proxy is the quarter-to-quarter change in the capex proxy, defined as flight equipment plus equipment-deposit advance payments, scaled by total assets. All ratios are winsorized at the 1st and 99th percentiles. All variables are defined in Appendix A1. *, **, and *** denote significance at the 10%, 5%, and 1% levels (Webb).

	Continuous Exposure			*Binary High Exposure*		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Cash + ST Inv.)	**-0.873****	**-0.629*****	**-0.696****	**-0.686***	**-0.651*****	**-0.640*****
	[0.0111]	[0.0047]	[0.0197]	[0.0515]	[0.0033]	[0.0071]
	$N = 408$	$N = 396$	$N = 396$	$N = 408$	$N = 396$	$N = 396$
Cash / Operating Revenue	**-0.5441****	**-0.5018****	**-0.5417*****	**-0.4803****	**-0.4960*****	**-0.4813****
	[0.0124]	[0.0131]	[0.0079]	[0.0288]	[0.0028]	[0.0127]
	$N = 408$	$N = 396$	$N = 396$	$N = 408$	$N = 396$	$N = 396$
Δ Debt / Assets	**-0.0362****	**-0.0267**	**0.0170**	**-0.0239***	**-0.0059**	**0.0098**
	[0.0415]	[0.3611]	[0.5629]	[0.0958]	[0.8460]	[0.7166]
	$N = 412$	$N = 396$	$N = 396$	$N = 412$	$N = 396$	$N = 396$
Δ Capex Proxy	**0.0033**	**0.0156***	**0.0224****	**0.0061**	**0.0144***	**0.0155****
	[0.6057]	[0.0933]	[0.0104]	[0.2546]	[0.0664]	[0.0316]
	$N = 396$	$N = 396$	$N = 396$	$N = 396$	$N = 396$	$N = 396$
Lagged Controls	No	Yes	Yes	No	Yes	Yes
LCC × Post	No	No	Yes	No	No	Yes
Carrier FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Fleet Renewal and Old-Fleet Exit

This table reports firm-level DiD estimates of fleet renewal and old-fleet exit outcomes around the EPA's June 2015 aircraft Endangerment Finding. The unit of observation is the carrier–quarter on a balanced 2011–2019 panel. *Post* equals one for quarters from 2015Q3 onward; *Exposure* is the carrier's pre-event (2011–2014) average log fleet age (continuous in columns 1–3, binary above-median in columns 4–6). Columns and controls follow Table 9. The three outcomes are level-based: *Average Age of Owned Aircraft* is the airframe-weighted mean age (years) of aircraft owned by the carrier (F41 Schedule B-43, ownership status 'O'), aggregated to carrier-year and broadcast to each quarter; *Maintenance Expense / Operating Revenue* is total maintenance expense scaled by quarterly operating revenues; *Capital Gains on Disposals / Operating Revenue* is realized capital gains and losses on property disposals scaled by quarterly operating revenues. All ratios are winsorized at the 1st and 99th percentiles. All specifications include carrier and year-quarter fixed effects. Inference uses a wild-cluster bootstrap clustered by carrier with Webb 2014 6-point weights ($G = 12$, $B = 9{,}999$ replications, null imposed); Webb p-values are reported in brackets below each coefficient. All variables are defined in Appendix A1. *, **, and *** denote significance at the 10%, 5%, and 1% levels (Webb).

	Continuous Exposure			*Binary High Exposure*		
	(1)	(2)	(3)	(4)	(5)	(6)
Average Age of Owned Aircraft (years)	**-4.748****	**-3.695****	**-3.593*****	**-3.474***	**-2.403***	**-2.187****
	[0.0266]	[0.0217]	[0.0078]	[0.0713]	[0.0712]	[0.0386]
	$N = 352$	$N = 327$	$N = 327$	$N = 352$	$N = 327$	$N = 327$
Maintenance Expense / Operating Revenue	**-0.0109****	**-0.0136****	**-0.0102***	**-0.0085***	**-0.0098***	**-0.0079**
	[0.0157]	[0.0234]	[0.0581]	[0.0772]	[0.0819]	[0.1499]
	$N = 424$	$N = 396$	$N = 396$	$N = 424$	$N = 396$	$N = 396$
Capital Gains on Disposals / Operating Revenue	**0.0024**	**0.0042***	**0.0050***	**0.0032***	**0.0039****	**0.0039***
	[0.1602]	[0.0622]	[0.0655]	[0.0502]	[0.0428]	[0.0539]
	$N = 397$	$N = 379$	$N = 379$	$N = 397$	$N = 379$	$N = 379$
Lagged Controls	No	Yes	Yes	No	Yes	Yes
LCC × Post	No	No	Yes	No	No	Yes
Carrier FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Pricing-Panel Robustness: Carrier Subsamples and LCC Composition

This table reports robustness of the pricing-panel DiD estimate to alternative carrier subsamples and to a control for low-cost-carrier-specific time variation. The unit of observation is the market–carrier–quarter; the dependent variable is $Fare$, the natural logarithm of the inflation-adjusted average ticket price. *Post* equals one for quarters from 2015Q3 onward; *FleetAge* is the carrier's pre-event (2011–2014) average log fleet age. The baseline specification matches Table 4: lagged firm controls (size, ROA, debt, staff intensity, fuel intensity, leasing intensity), market × carrier and market × date fixed effects. Column (1) reports the baseline on the full 12-carrier sample; column (2) drops the three legacy major carriers (AA, DL, UA); column (3) drops the four post-2000s low-cost carriers (NK, F9, B6, VX); column (4) adds a Post × LCC interaction to the baseline regression, where LCC equals one for low-cost carriers (WN, B6, F9, NK, VX, G4, SY). Standard errors are two-way clustered by market and by carrier × date; t-statistics in parentheses. All variables are defined in Appendix A1. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1) *Baseline*	(2) *Drop legacies*	(3) *Drop LCCs*	(4) *+ LCC × Post*
Post × FleetAge	**0.1535*****	**0.1429*****	**0.1871*****	**0.1614*****
	(7.173)	(4.595)	(7.828)	(5.509)
Lagged Controls	Yes	Yes	Yes	Yes
LCC × Post	No	No	No	Yes
Carrier × Market FE	Yes	Yes	Yes	Yes
Market × Date FE	Yes	Yes	Yes	Yes
N	541,077	82,584	494,523	541,077
Carriers	12	9	8	12
Markets	5,217	3,601	5,178	5,217

Table 12: Main Baseline Pricing under a Carrier-Level Wild-Cluster Bootstrap (Webb at $G = 12$)

This table re-estimates the baseline pricing-panel DiD of Section 5 with the focal p-value computed via a carrier-level wild-cluster bootstrap. The unit of observation is the market–carrier–quarter; the dependent variable is $Fare$, the natural logarithm of the inflation-adjusted average ticket price. *Post* equals one for quarters from 2015Q3 onward; *FleetAge* is the carrier's pre-event (2011–2014) average log fleet age. Columns (1)–(2) use the continuous measure (headline specification); column (1) uses the simple airframe-count average and column (2) the seat-weighted average. Columns (3)–(4) replace the continuous measure with a binary indicator equal to one if the carrier's pre-event average fleet age is above the 12-carrier sample median (robustness check). All specifications include lagged firm controls and market × carrier and market × date fixed effects. Standard errors are two-way clustered by market and by carrier × date (asymptotic); t-statistics are reported in parentheses. The row below each coefficient is the wild-cluster bootstrap p-value with Webb (2014) 6-point weights, $B = 9{,}999$ replications and null imposed on the focal coefficient. Stars are driven by the Webb p-value. All variables are defined in Appendix A1. *, **, and *** denote significance at the 10%, 5%, and 1% levels (Webb).

	Continuous Exposure		*Binary High Exposure*	
	(1) *AvgFleetAge*	(2) *AvgFleetAgeSW*	(3) *AvgFleetAge*	(4) *AvgFleetAgeSW*
Post × FleetAge	**0.1535*** **	**0.1585*** **	**0.1146*** **	**0.1146*** **
	(7.173)	(7.304)	(6.663)	(6.663)
p (Webb)	[0.0033]	[0.0030]	[0.0097]	[0.0097]
Lagged Controls	Yes	Yes	Yes	Yes
Market × Carrier FE	Yes	Yes	Yes	Yes
Market × Date FE	Yes	Yes	Yes	Yes
N	541,077	541,077	541,077	541,077

Appendix: Table of Contents

Table A1: Variable Definitions

This table defines the variables used in the pricing-panel and firm-level analyses. Pricing-panel variables are measured at the market–carrier–quarter level unless otherwise stated; firm-level variables are measured at the carrier–quarter level. Exposure variables are computed over 2011–2014 and held fixed in post-event regressions.

Mnemonic	**Definition**	**Derived from**
Pricing-panel variables		
Fare	Natural logarithm of the quarterly CPI-deflated average fare for carrier i in market m and quarter t, computed as real ticket revenue divided by passengers.	DB1B, BLS
Post	Indicator equal to one for quarters from 2015Q3 onward, the first full quarter after the EPA's June 2015 proposed aircraft Endangerment and Contribution Finding.	EPA
Exposure variables		
AvgFleetAge	Natural logarithm of the carrier's airframe-weighted average fleet age, computed over 2011–2014 and held fixed in the regressions.	F41 B-43
AvgFleetAgeSW	Natural logarithm of the carrier's seat-weighted average fleet age, computed over 2011–2014 and held fixed in the regressions.	F41 B-43
HighExp	Indicator equal to one if *AvgFleetAge* is above the within-sample carrier median.	F41 B-43
HighExpSW	Indicator equal to one if *AvgFleetAgeSW* is above the within-sample carrier median.	F41 B-43
AvgFleetAgeResBear	Natural logarithm of the pre-event fleet age of residual-bearing aircraft, defined as owned plus capital-leased airframes (Form 41 Schedule B-43 status codes O and A).	F41 B-43
AvgFleetAgeOpLease	Natural logarithm of the pre-event fleet age of operating-leased aircraft (Form 41 Schedule B-43 status code B).	F41 B-43
$FuelBurn\ gal/ASM$	Natural logarithm of the carrier's pre-event scheduled-service fuel gallons divided by available seat miles, computed over 2011–2014 and held fixed in the regressions.	F41 P-5.2, T-100
$FuelBurn\ gal/RPM$	Natural logarithm of the carrier's pre-event scheduled-service fuel gallons divided by revenue passenger miles, computed over 2011–2014 and held fixed in the regressions.	F41 P-5.2, T-100
Carrier-level financial and operating variables		
Size	Natural logarithm of total assets; lagged one quarter when used as a control.	F41 B-1
Debt	Noncurrent liabilities divided by total assets; lagged one quarter when used as a control.	F41 B-1
Roa	Operating income divided by total assets; lagged one quarter when used as a control.	F41 P-1.2, B-1
StaffExp	Salary expense divided by operating revenue; lagged one quarter when used as a control.	F41 P-1.2
FuelExp	Aircraft fuel expense divided by operating revenue; lagged one quarter when used as a control.	F41 P-6
Leasing	Capitalized lease property divided by total assets; lagged one quarter when used as a control.	F41 B-1
CashAssets	Cash plus short-term investments divided by total assets; used as the internal-liquidity proxy in Table 6.	F41 B-1
CashOpRevenue	Cash plus short-term investments divided by quarterly operating revenue; used as the firm-level liquidity outcome in Table 9.	F41 B-1, P-1.2
Route-level variables		
CarrierCount	Number of nonstop competitors in the route-quarter.	T-100
Southwest	Indicator equal to one if Southwest serves the route-quarter.	T-100
OtherLCC	Indicator equal to one if a non-Southwest low-cost carrier serves the route-quarter.	T-100
PsgConnectMkt	Fraction of market-quarter passengers traveling on connecting itineraries.	DB1B
PsgConnectCarr	Fraction of carrier-market-quarter passengers traveling on connecting itineraries.	DB1B
Population	Natural logarithm of the geometric mean of endpoint metropolitan-area populations.	BEA
IncomePC	Natural logarithm of the geometric mean of endpoint metropolitan-area income per capita.	BEA
HHI	Herfindahl–Hirschman index of passenger shares in the route-quarter.	DB1B
LowRouteShare	Indicator equal to one if carrier i's 2012–2014 passenger share on route m is below the within-route median.	DB1B
HighComp	Indicator equal to one if the route's 2012–2014 mean number of carriers is at or above the within-sample median.	DB1B, T-100
Firm-level outcomes		
$\ln(Cash + ST\ Inv.)$	Natural logarithm of cash plus short-term investments at the carrier-quarter level.	F41 B-1
$Cash/Operating\ Revenue$	Cash plus short-term investments divided by quarterly operating revenue.	F41 B-1, P-1.2
$\Delta Debt/Assets$	Quarter-to-quarter change in noncurrent liabilities divided by total assets.	F41 B-1
$\Delta Capex\ Proxy$	Quarter-to-quarter change in flight equipment plus equipment-deposit advance payments, divided by total assets.	F41 B-1
Average Age of Owned Aircraft	Airframe-weighted average age, in years, of owned aircraft (Form 41 Schedule B-43 status code O), aggregated to the carrier-year level and assigned to carrier quarters.	F41 B-43
Maintenance Expense / Operating Revenue	Total maintenance expense divided by quarterly operating revenue.	F41 P-1.2
Capital Gains on Disposals / Operating Revenue	Realized capital gains and losses on property disposals divided by quarterly operating revenue.	F41 B-1, P-1.2

Table A2: Timeline of Key EPA Aircraft GHG Regulation

This table summarizes major milestones in the U.S. Environmental Protection Agency's (EPA) regulatory process for aircraft greenhouse gas (GHG) emissions under Section 231 of the Clean Air Act. The timeline traces key legal and procedural steps from early petitions through the finalization of U.S. aircraft CO_2 standards.

Date	Event	Description and Significance
2011–2013	Petitions and preparatory actions under the Clean Air Act	Environmental organizations petition the EPA to regulate aircraft GHG emissions under Section 231. The agency begins legal and technical groundwork following the Supreme Court's decision in *Massachusetts v. EPA* (2007).
Sep 2014	U.S. announces domestic rulemaking timeline under CAA Section 231	The United States submits an information paper to the International Civil Aviation Organization (ICAO) outlining its plan and schedule for domestic aircraft GHG regulation. In September 2014, the EPA publicly states its intent to issue a proposed endangerment finding by mid-2015.
Jun 2015	EPA issues Proposed Endangerment and Contribution Finding	The EPA proposes that six GHGs emitted by aircraft engines "may reasonably be anticipated to endanger public health and welfare." The proposal formalizes the regulatory trajectory but does not itself impose standards; the final August 2016 finding establishes the binding legal foundation under Section 231.
Jul 2015	Advance Notice of Proposed Rulemaking (ANPR)	The EPA releases the Advance Notice of Proposed Rulemaking, providing details on coordination with ICAO and outlining the potential structure of domestic CO_2 standards for aircraft.
Aug 2016	EPA finalizes Endangerment and Contribution Finding	The EPA publishes the final rule in the *Federal Register* (81 FR 54422), confirming that aircraft GHG emissions endanger public health and welfare under the Clean Air Act. This establishes the binding legal foundation for future aircraft CO_2 standards.
Dec 2016	EPA denies petitions for reconsideration	The EPA rejects petitions challenging the aircraft endangerment finding, reaffirming its determination and maintaining the regulatory trajectory toward domestic CO_2 standards.
Dec 2020	Final U.S. aircraft CO_2 emission standards	The EPA issues the first U.S. aircraft CO_2 standards, applying to new type designs and newly manufactured aircraft, aligned with the ICAO international standard.

Table A3: Robustness to Market Controls

This table re-estimates Equation (1) with common date fixed effects and time-varying market controls in place of market × date fixed effects. The unit of observation is the market–carrier–quarter; the dependent variable is *Fare*; and *Post* equals one from 2015Q3 onward. Exposure is the carrier's pre-event (2011–2014) average log fleet age. Columns 1–2 use the continuous measure; columns 3–4 use a binary above-median indicator. Market controls follow Azar et al. (2018): nonstop competitors, Southwest and other-LCC indicators, connecting shares, log population, log income per capita, and HHI. All regressions include market × carrier fixed effects. Standard errors are two-way clustered by market and by carrier × date; t-statistics are in parentheses. Variables are defined in Appendix A1. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)
Dependent Variable	*Fare*	*Fare*	*Fare*	*Fare*
Exposure Weight	AvgFleetAge	AvgFleetAge	AvgFleetAge	AvgFleetAge
Exposure Form	Continuous	Continuous	Binary (Above-Median)	Binary (Above-Median)
Post × Continuous Exposure	0.185***	0.142***		
	(8.491)	(5.895)		
Post × High Exposure			0.159***	0.105***
			(8.132)	(5.355)
Number of Nonstop Carriers	0.004*	0.004	0.003	0.003
	(1.742)	(1.597)	(1.484)	(1.378)
Southwest Indicator	-0.062***	-0.065***	-0.064***	-0.065***
	(-8.747)	(-9.000)	(-9.054)	(-9.116)
Other LCC Indicator	-0.042***	-0.041***	-0.044***	-0.042***
	(-6.562)	(-6.404)	(-6.939)	(-6.621)
Share Connect (Market)	0.032***	0.034***	0.031***	0.033***
	(3.116)	(3.260)	(3.039)	(3.140)
Share Connect	0.179***	0.171***	0.178***	0.169***
	(15.497)	(14.334)	(15.275)	(14.217)
Log(Population)	-0.181**	-0.063	-0.146*	-0.042
	(-2.010)	(-0.709)	(-1.685)	(-0.478)
Log(Income per Capita)	-0.029	-0.098**	0.009	-0.075
	(-0.629)	(-2.278)	(0.075)	(-1.588)
HHI	0.137***	0.134***	0.138***	0.134***
	(11.561)	(11.124)	(11.602)	(11.140)
Firm-Level Controls	Excluded	Included	Excluded	Included
FE			Carrier × Market, Date	
Std. Err.			Carrier × Date, Market	
adj. R^2	0.723	0.737	0.723	0.737
N	512,950	468,108	512,950	468,108

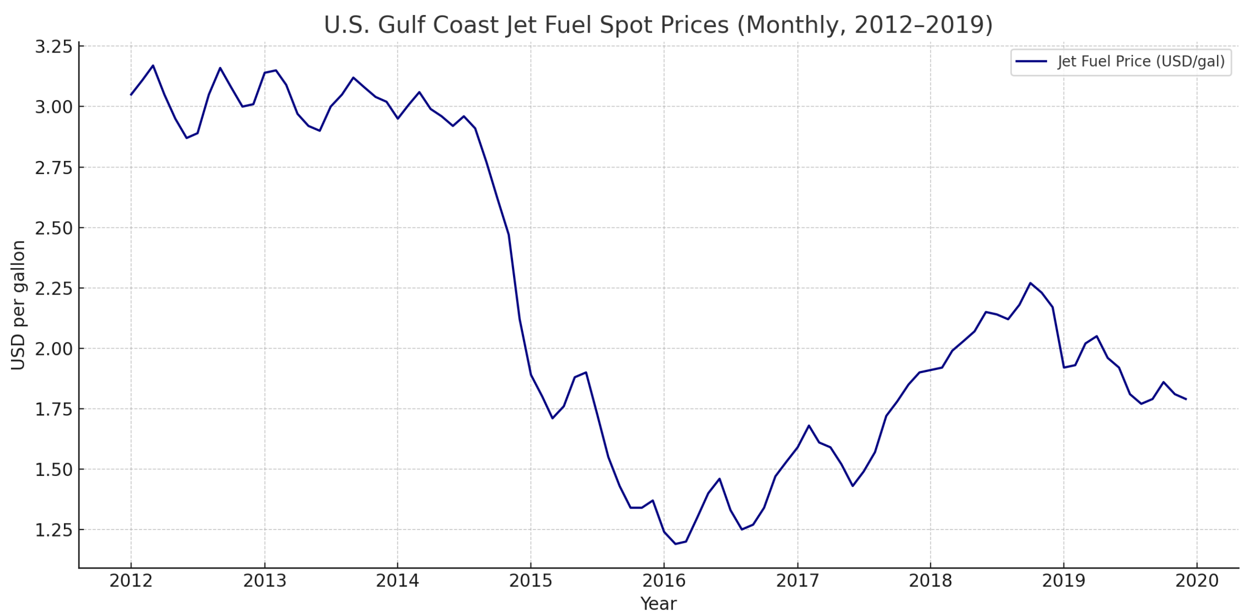
Table A4: Fleet Diversity (Blau Index) as a Moderator

This table reports a triple-interaction specification on the pricing panel that allows the post-event exposure effect to vary with the carrier's fleet diversity, measured by a Blau (1977) concentration index over aircraft types in the fleet (cleaned manufacturer-by-three-digit-model designators). The unit of observation is the market–carrier–quarter; the dependent variable is *Fare*, the natural logarithm of the inflation-adjusted average ticket price. *Post* equals one for quarters from 2015Q3 onward; *HighExp* equals one if the carrier's pre-event (2011–2014) average fleet age is above the within-sample median. Column (1) excludes firm controls; column (2) includes the same lagged firm controls used in Table 4. All specifications include market × carrier and market × date fixed effects. Standard errors are two-way clustered by market and by carrier × date; t-statistics in parentheses. All variables are defined in Appendix A1. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)
Dependent Variable	*Fare*	*Fare*
Firm-Level Controls	Excluded	Included
$HighExp \times Post$	**0.0541*** **	**0.0526** **
	(3.424)	(2.210)
$Post \times Blau$	**-0.2553*** **	**-0.1530** **
	(−3.571)	(−2.468)
$HighExp \times Post \times Blau$	**0.3027*** **	**0.1853*** **
	(4.152)	(2.803)
FE	Market × Carrier, Market × Date	
Std. Err.	Carrier × Date, Market	
adj. R^2	0.748	0.753
N	555,127	541,077

Figure 2: U.S. Gulf Coast Jet Fuel Spot Prices (Monthly), 2012–2019

This figure shows monthly spot prices for U.S. Gulf Coast kerosene-type jet fuel between 2012 and 2019.



Source: Federal Reserve Bank of St. Louis (FRED), Series ID: DJFUELUSGULF, U.S. Gulf Coast Kerosene-Type Jet Fuel Spot Price (Dollars per Gallon).