Flights of the Living Dead: Zombie Credit and Product Market Competition

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Abstract

We use granular US airline data to study price and non-price competition between "zombies"—non-viable firms sustained by subsidized lending—and their healthy, bankrupt, and non-subsidized-distressed rivals in well-defined product markets. While we confirm that markets with zombies exhibit fare disinflation, we show that this result is mostly driven by the non-zombie carriers, especially the non-subsidized distressed. A Bartik-style shift-share instrument supports a causal interpretation. Consistent with strategic responses to zombie pressure, the non-subsidized distressed carriers also cut fares preemptively in markets threatened by zombie entry, and they improve their service quality in markets in which they directly compete with zombies. Yet, the aggressive competition does not pay off: The non-zombie carriers lose market share and are more likely to exit relative to their less efficient zombies rivals. Zombie lending thus distorts both competitive behavior and market selection.

KEYWORDS: Zombie firms; product market competition; airline industry.
JEL CLASSIFICATION: G31, G32, D22, D25

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1 Introduction

The rise of zombie firms—nonviable firms kept alive by their creditors' subsidized lending—has become a growing concern in academia and policy. Caballero et al. (2008) show that zombie firms congested Japanese markets in the 1990s, flooding them with output, delaying restructuring, and imposing negative externalities on their rivals. Similarly, Acharya et al. (2022, 2024) report that zombie firms in Europe and the US caused disinflation and depressed the markups, investment, and productivity of their rivals during the new millennium. Yet existing studies largely treat non-zombie firms as responding only passively to zombie rivals (see, e.g., Caballero et al. (2008); Acharya et al. (2025); Aretz et al. (2026)), leaving open questions regarding whether and how zombie lending reshapes strategic product-market interactions and market selection. Do non-zombie rivals accommodate zombie competitors, or do they compete aggressively against them? If they compete aggressively, can they prevail against rivals sustained by subsidized credit? And if non-zombie rivals ultimately exit zombie-inhabited markets, does their exit reflect efficient market selection or distorted survival?

In this paper, we address these questions using novel, granular data from the US airline industry, where zombie and non-zombie carriers compete in well-defined product markets: airport-to-airport routes. Our main conclusion is that zombie credit reshapes product-market competition in economically meaningful ways. We confirm that markets with zombie presence exhibit fare disinflation, but unpack this market-level result to reveal that it is driven largely by non-subsidized distressed carriers, whose fare inflation falls even more than that of their zombie rivals. A Bartik (1991)-style shift-share instrument supports a causal interpretation of this finding. We then show that non-subsidized distressed carriers respond strategically to zombie pressure along two margins: in markets threatened by zombie entry, they significantly lower fare inflation, consistent with anticipatory entry-deterrence behavior; and in markets where they compete directly with zombies, they complement their aggressive pricing with improved service quality, reducing arrival delays and cancellations and operating more modern aircraft. Despite these efforts, non-subsidized distressed carriers lose market share to their zombie rivals and ultimately exit, ceding markets to less efficient competitors. Overall, our evidence indicates that zombie credit distorts competition along two dimensions: first, by changing carriers' competitive behavior and, second, by altering which carriers survive.

The US airline industry provides an unusually rich setting for studying how zombie credit maps into product-market outcomes. First, unlike studies that rely on industry- or country-level aggregates, we observe outcomes at the level of the individual carrier. While aggregate data can clarify whether markets with zombies experience lower overall inflation, they cannot disentangle the price behavior of zombies and non-zombie rivals competing in the same product market, making it impossible to study competitive price dynamics between these two types of firms. In contrast, our data allow us to compare the pricing policies of zombies and non-zombies operating in the same market and at the same time. Second, we can precisely defined product markets—airport-to-airport routes—so that

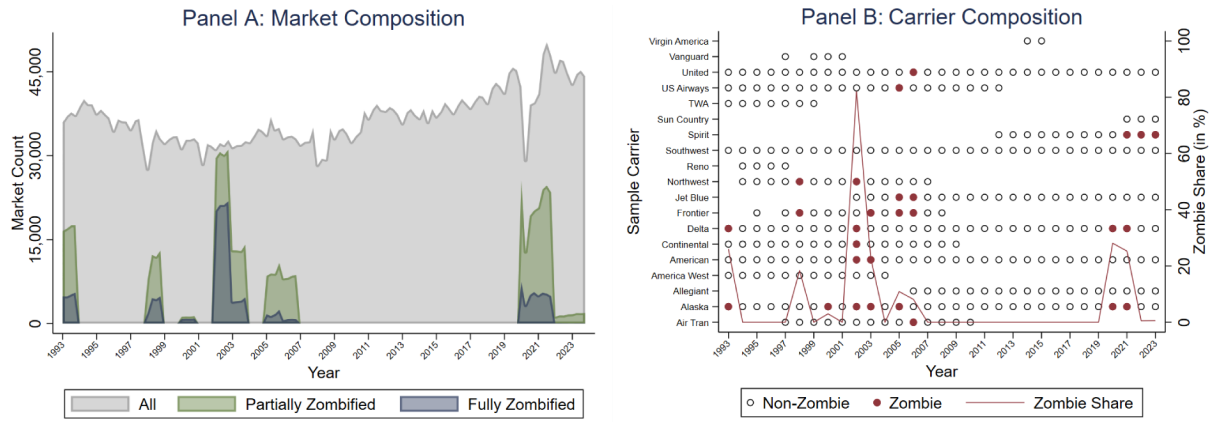

Figure 1. In this figure, we show the market and carrier composition of our sample data. In Panel A, we plot the total number of markets (grey area), the number of markets with both zombies and non-zombies ("partially zombified markets;" green area), and those with only zombies ("fully-zombified markets;" blue area) over our sample period. In Panel B, we plot our non-zombie (hollow dots) and zombie (filled dots) sample carriers and the passenger-weighted zombie share (solid line) over the same period.

rivalry is measured across product market competitors rather than across firms within an industry-country. The narrow market definition yields an average of about 35,000 markets per year-quarter (Panel A of Figure 1), permitting the demanding market-time fixed effects on which our identification relies. Third, our data extend beyond prices, enabling us to construct precise measures of service quality, operational efficiency, and real outcomes. Finally, the US airline industry has experienced meaningful episodes of zombification. Panel B of Figure 1 shows that several sample carriers meet our zombie definition, and that zombification is concentrated in a few distinct periods, suggesting it occurs in waves. These waves broadly align with those in Altman et al. (2024), who document that overall zombification is most severe in the early 1990s, again in 1998–2002, and during the pandemic.[1]

We begin by studying how non-zombie carriers adjust their fare inflation in response to zombie presence in a market. In accordance with the literature, we define a zombie carrier as one that (i) has an interest coverage ratio below one; (ii) has an Altman (1968) z-score below 1.80; (iii) pays an interest rate (i.e., the interest expense to total debt ratio) below that of the most creditworthy carriers in the US airline industry; and (iv) is not operating under Chapter 11 bankruptcy protection. Consistent with Acharya et al.'s (2024) evidence, we find that partially zombified markets exhibit *lower* fare inflation, and sometimes outright fare disinflation. However, fully zombified markets—markets served exclusively by zombie carriers—exhibit *higher* fare inflation. This contrast offers a first indication that competition between zombies and non-zombies, rather than zombie status alone, shapes fare dynamics. Focusing on non-zombie carriers, we find that they lower their fare inflation when the zombie share in one of their markets rises ("time-series contrasts") and that they exhibit lower fare inflation in partially zombified markets than in non-zombified markets at the same

[1] See Altman et al. (2024), specifically Figure 2 in their main paper as well as their Internet Appendix.

point in time ("cross-sectional contrasts"). Both contrasts indicate that non-zombie carriers are active drivers of disinflation in partially zombified markets.

We next zoom in on partially zombified markets and directly compare zombie and non-zombie carriers in the same market-quarter, showing that non-zombie carriers reduce their fare inflation more than their zombie rivals. The non-zombie category, however, is heterogeneous: it includes healthy carriers, non-subsidized distressed carriers, and bankrupt carriers operating under Chapter 11 protection. Separating carriers into these subgroups, we find that the effect is driven primarily by the non-subsidized distressed and, to a lesser extent, the bankrupt carriers. The differences are economically meaningful: in our most comprehensive specification, which includes market-time and carrier fixed effects, non-subsidized distressed carriers reduce fare inflation by an additional 1.5 percentage points (t-statistic: –12.43) relative to their zombie rivals in partially zombified markets. Repeating the analysis separately for high- and low-growth markets, we show that these differences are stronger in low-growth markets but remain present in high-growth ones. This evidence suggests that the pricing differences are not driven solely by weak demand or market distress.

To further address endogeneity concerns, we use a Bartik-style shift-share instrumental-variable (IV) strategy similar to Acharya et al.'s (2024). Our instrument isolates variation in carrier zombie status that is unlikely to reflect carrier fundamentals or market demand conditions, exploiting instead carriers' pre-existing exposure to weak banks affected by adverse shocks, as such banks have strong incentives to zombify bad loans. In implementing this strategy, we focus on the 2019–2023 sample period: the US airline industry contained no zombies over the prior eleven years, plausibly implying that 2018 banking relations were unrelated to zombie concerns, yet the number of zombies rose sharply during the period (recall Figure 1). For each carrier, we compute the average, taken over all creditors funding the carrier in 2018, of a creditor's 2018 tier 1 capital ratio times the concurrent drop in the aggregate loan-loss reserves in the creditor's home state. The IV tests corroborate that non-subsidized distressed carriers reduce their fare inflation more than their zombie rivals: in our most comprehensive specification, the instrumented estimate implies a 4.4 percentage-point differential (t-statistic: –10.44). The fare inflation differential between zombie and non-subsidized distressed carriers could arise because the latter actively undercut their zombie rivals in a strategic attempt to push them out of the market. Alternatively, it could arise if market conditions deteriorate and non-subsidized distressed carriers adjust their fares accordingly while zombies—possibly because subsidized credit dulls their incentives to respond—adjust only sluggishly or not at all.

To distinguish between these explanations, we exploit a setting in which non-zombie carriers' response to zombie pressure can be observed in isolation: markets in which non-zombie incumbents face a heightened threat of entry by zombie carriers. Because the zombie has not yet entered these markets, any fare response by the incumbent reflects its own strategic conduct, unconfounded by

zombie pricing.[2,3] Following Goolsbee and Syverson (2008) to identify zombie-threatened markets, we show that when a non-subsidized distressed carrier's market becomes threatened, the carrier lowers its fares by about 1.5 percentage points (t-statistic: –9.82) after controlling for aggregate time effects. In more demanding specifications, we compare the same carrier's threatened and non-threatened markets within the same quarter to absorb carrier-quarter shocks. Those specifications reveal that non-subsidized distressed carriers lower their fares by about 0.8 percentage point (t-statistic: –5.03) more in threatened-versus-non-threatened markets. Overall, this evidence shows that non-subsidized distressed carriers respond strategically to zombie pressure, supporting the undercutting explanation over pure zombie inertia.

We next explore whether non-zombie carriers also compete more aggressively against their zombie rivals along non-price dimensions. Relative to their zombie rivals, all non-zombie carriers cancel fewer flights, only the non-subsidized distressed carriers improve on-time performance, and only the healthy and non-subsidized distressed carriers operate more jet-engine aircraft. The non-subsidized distressed carriers, for example, exhibit non-negative arrival delays about five percent shorter than those of their zombie rivals. The one exception to this pattern is flight frequency: all non-zombie carriers except the healthy reduce their daily flight offerings, limiting customer choice.

Finally, we examine the performance and survival outcomes associated with non-zombie carriers' competitive responses. We find that the non-subsidized distressed and bankrupt carriers produce lower price-cost ratios and Lerner markups than their zombie rivals, consistent with their aggressive pricing behavior in partially zombified markets. Still, all non-zombie carriers, including the healthy, experience lower passenger growth and market-share growth than those rivals. They are also more likely to exit markets. The non-subsidized distressed carriers, for example, lose a significant three percentage points of market share to their zombie rivals over the one-year period surrounding the focal quarter and have a seven-percentage- point higher exit rate than those rivals over the next three years, which is large relative to the average three-year exit rate of 11%. The main takeaway is that aggressive competition against subsidized rivals seems unlikely to ensure survival.

We add to the literature on zombie firms. One strand of this literature studies the origins of zombie lending: Peek and Rosengren (2005) and Acharya et al. (2021) show that undercapitalized banks are prone to extend zombie loans to distressed firms, especially when their capital ratios are close to regulatory minimums; and Becker and Ivashina (2022) report that zombie lending is more prevalent in countries with weaker insolvency and restructuring laws. A second strand documents its consequences for markets and rivals: Zombies cause disinflation (Acharya et al., 2024); induce non-zombie rivals

[2]A carrier's behavior toward a potential entrant need not reveal how it competes with that carrier in markets where both are incumbents. However, if non-zombie incumbents strategically adjust prices when a zombie carrier credibly threatens entry, this provides evidence of anticipatory strategic behavior in response to zombie pressure.

[3]Aretz et al. (2026) show that non-zombies adapt their capacity and hiring choices to zombie threats; we examine anticipatory pricing responses.

to curb investments in capital and labor and depress their markups, productivity, and profitability (Caballero et al., 2008; McGowan et al., 2018; Acharya et al., 2022); render rivals less innovative (Schmidt et al., 2024); and induce rivals to adjust corporate policies not only to realized zombification but already to its threat (Aretz et al., 2026). Altman et al. (2024) document that these patterns are global, with zombie firms emerging in nearly all industries around the world. We contribute by studying strategic product-market interactions between zombie firms and their rivals. Rather than focusing on aggregate outcomes or corporate policies, we show that some non-zombie rivals—especially non-subsidized distressed firms—respond aggressively along both price and non-price dimensions, yet ultimately lose market share and exit at higher rates, leaving markets to less efficient survivors.

We also contribute to the literature on product-market competition and financial distress (see, e.g., Maksimovic (1988); Phillips (1995); Campello (2006); Ciliberto and Schenone (2012a); Ciliberto and Schenone (2012b)). Our work relates particularly closely to the "deep purse" theories of Bolton and Scharfstein (1990) and Rotemberg and Scharfstein (1990), which we discuss in detail in the next section. Our results show that zombie lending affects not only rivals' prices and policies but also their survival: because subsidized credit sustains the apparent prey, predation fails, skewing market selection toward less efficient firms.

We proceed as follows. Section 2 summarizes theoretical models of predation related to our empirical work. Section 3 discusses our data sources and variable definitions. In Section 4, we investigate price and non-price competition between zombie and non-zombie carriers in markets in which both are present. In Section 5, we explore the real outcomes arising from the non-zombie carriers' competitive strategies. Section 6 concludes. We offer a variable definition table in Appendix A.1.

2 Zombie Credit and Predation under Financial Constraints

Models of predation under financial constraints support the prediction that zombie lending can generate product-market effects between rival firms. In particular, Bolton and Scharfstein (1990) and Rotemberg and Scharfstein (1990) show that increased debt invites predation in a competitive environment: stronger firms have an incentive to compete aggressively in the product market to worsen their rival's performance, increasing the likelihood that investors sever funding and ultimately force the rival to exit the market.[4] Consistent with such predatory behavior, Opler and Titman (1994) show that financially distressed firms lose substantial market share to healthier competitors ("competitor-driven losses"), and Chevalier (1995) reports that financially strong rivals cut prices more aggressively when competing against a firm whose leverage recently rose substantially in a leveraged buyout (LBO). The evidence of predation is stronger when healthy firms compete with

[4] See also, for example, Benoit (1984), Fudenberg and Tirole (1986), and Maksimovic (1988).

distressed ones.[5] The key mechanism in these models is thus that predation weakens the product-market performance of a financially constrained firm, reducing its ability to secure funding and raising the likelihood that it must exit the market.

Two features of zombie lending alter how this mechanism plays out in our setting. First, in the classic models, the predator is the financially strong, deep-purse firm and the prey the financially constrained one. Zombie lending inverts this configuration in a subtle way: the zombie appears financially weak on observable fundamentals, yet its subsidized credit endows it with what is effectively the deepest purse in the market. Second, zombie lending is plausibly opaque—creditors have little incentive to advertise that they support nonviable borrowers—so rivals are unlikely to observe the subsidy. Rivals may consequently misperceive the zombie as vulnerable prey and attack it, expecting the standard predation mechanism to run its course. Because subsidized credit severs the link between product-market performance and access to funding, however, that mechanism stalls: the prey is not starved of finance, regardless of its performance.

This reasoning yields three predictions that organize our empirical analysis. First, non-zombie rivals—particularly those that view themselves as relatively stronger than the seemingly failing zombie—should compete aggressively against zombie carriers on price and, potentially, non-price margins, and should do so even preemptively when zombie entry merely threatens their markets. Second, this aggression should nonetheless fail. Subsidized credit not only shields the zombie from exit, but also funds its competitive resistance: unlike a financially constrained prey, the zombie need not retrench, cede capacity, or concede customers to conserve cash. Aggressive rivals should therefore fail to convert their price cuts into market-share gains. Third, market selection should be distorted: the unsuccessful aggressors are more likely to exit than their subsidized rivals, leaving markets to less efficient zombie survivors. Testing these predictions requires observing rivals' behavior within well-defined product markets; we now describe data that permit this.

3 Data and Definitions

In this section, we outline our data sources and describe the calculation of our variables. We also offer descriptive statistics and present some preliminary univariate comparisons.

[5] More specifically, Phillips (1995) and Chevalier (1995) find that product-market competition *softens* rather than strengthens when the competing firms are all highly levered. Phillips (1995) studies four industries in which the leading firm undertook an LBO: only in the industry in which rivals were not highly levered did prices fall following the LBO. Similarly, Chevalier (1995) shows that, in the supermarket industry, prices in a local market drop following an incumbent's LBO only when the other incumbents are not highly leveraged.

3.1 Data Sources

3.1.1 Airline Flight Data

We create our sample data from a number of Bureau of Transportation Statistics (BTS) databases, particularly, the Airline Origin and Destination Survey (DB1B), the T100 Domestic Segment, and the Airline On-time Performance databases. We obtain price (i.e., airfare) data from the DB1B database, a ten-percent random sample of all itineraries issued by US certified airlines flying within the US borders and its territories. There are three components in that database. The *coupon* component includes data for each coupon (i.e., flight segment) in an itinerary, such as the origin and destination of each segment, and the identity of the segment's operating and ticketing carrier.[6] The *market* component identifies the (ultimate) origin and destination airports, and the *ticket* one includes ticket fare data. We combine all these data to create a dataset at the market-ticketing carrier-year-quarter level. We restrict the sample to itineraries with at most four coupons — two coupons in either direction in a round trip ticket, and drop itineraries with multiple ticketing carriers ("interline tickets") as we cannot attribute their pricing to a specific carrier. Following Borenstein (1989), we allocate tickets sold under code-sharing agreements (e.g., a ticket operated by one airline but ticketed by another) to the ticketing carrier, in line with the ticketing carrier having access to the seats ("metal") of the operating carrier. We further apply standard itinerary restrictions.[7]

We define a market as a directional trip between airports, rather than cities, as in Borenstein (1989) and subsequent studies. Thus, a flight from Washington Dulles (IAD) to Chicago O'Hare (ORD) is one market, while a flight from IAD to Chicago Midway (MDW) is another. This airport-level definition allows different airports within the same metropolitan area to face different demand conditions. A market is defined irrespective of intermediate transfers ("layovers"). Hence, a non-stop flight from IAD to San Francisco (SFO), for example, belongs to the same market as a flight from IAD to SFO that connects through ORD. Finally, following Armantier and Richard (2008), Gerardi and Shapiro (2009), Berry and Jia (2010b), and Luttmann (2019), our market definition is directional, allowing demand conditions and fares to differ by trip origin. Thus, IAD–SFO and SFO–IAD are distinct markets. For

[6] A coupon identifies a segment of travel. For example, a one-way flight from Atlanta (ATL) to San Francisco (SFO) stopping in Los Angeles (LAX) would have two coupons, namely ATL–LAX and LAX–SFO.

[7] We drop interline tickets which involve agreements between competing airlines to handle passengers on an itinerary, resulting in different operating carriers serving different segments of the itinerary and thus uncertainty regarding which carrier is actually setting the ticket fare. We also drop code-sharing tickets involving flights operated by one airline but which are jointly marketed and/or ticketed as a flight for other airlines as well. We exclude "open jaw" tickets, which correspond to itineraries where a passenger flies from one airport to another but returns either to the original airport from a different airport ("destination open jaw") or from the same airport but to an airport different than the origin ("origin open jaw"). Finally, we also drop itineraries with more than one directional break (i.e., tickets with a stop for reasons other than a connecting flight) as well as tickets involving flights outside the contiguous United States (Alaska, Hawaii, and territories since these are subsidized by U.S. mail services), tickets whose fare credibility is questioned by the Department of Transportation, and itineraries involving surface segments. For details, see also Berry (1990a), Berry (1990b), Borenstein and Rose (1994), Goolsbee and Syverson (2008), Gerardi and Shapiro (2009), Berry and Jia (2010a), Ciliberto and Schenone (2012a), Ciliberto and Schenone (2012b), Snider and Williams (2015), and Dennis et al. (2022).

one-way tickets, the market is the observed origin-destination airport pair. For round-trip tickets, we decompose the itinerary into outbound and return directional trips, assign one-half of the round-trip fare to each direction, and retain only the outbound direction to avoid double-counting the itinerary. We include only itineraries for which all coupons correspond to economy-class travel and deflate all fares using the CPI, expressed in 2008 dollars. We then aggregate to the market-carrier-year-quarter level by averaging fares across all itineraries operated by each carrier in each market and year-quarter.

We obtain capacity data from the T100 Domestic Segment of Form 41-Traffic dataset. This dataset is not a sample of flights but a census of all monthly flight segments between an origin and destination airport within the U.S. boundaries or its territories. Since these data contain only non-stop segments, it is much smaller than the aggregated DB1B data. The T100 data include passengers enplaned, seats available, number of scheduled and performed departures, and load factors at the monthly carrier-aircraft level. To collapse the data, we sum the number of seats, enplaned passengers, and scheduled and performed departures and average the load factor by carrier-market-year-quarter.

We collect data from the Airline On-Time Performance database to study carriers' ontime performance. This database covers only non-stop flights by U.S. certified air carriers accounting for at least one percent of domestic scheduled passenger revenues and includes daily flight information for each market served by a carrier, such as scheduled and actual departures, departure and arrival times, and scheduled and actual flight times. For each flight, we calculate arrival delays as actual minus scheduled arrival times (in minutes). We then aggregate the data to the carrier-market-year-quarter level.[8]

We supplement the BTS DB1B data with population data from the Bureau of Economic Analysis (BEA) at the MSA-level to construct the geometric means of endpoint populations.

Finally, we compile aircraft characteristics by first extracting the set of aircraft types used by each carrier in each market during a year-quarter from the T100 database and then matching each type to externally sourced technical information.[9] The data include information on first ("maiden") flight, maximum takeoff weight (MTOW), and published speed (where available).[10]

3.1.2 Airline Accounting and Event Data

We obtain the annual accounting data necessary to identify zombie carriers from Compustat. We start with retrieving data for all public US airlines (SIC code: 4512). We next manually match these data with the BTS data based on airline names. We collect data on airline mergers and acquisitions (M&As) as well as bankruptcy filings from Capital IQ, again using airline names to merge.

[8] See Ciliberto and Schenone (2012b) and Aggarwal and Schenone (2019) for more details on the on-time data.

[9] The primary sources were official manufacturer materials, including current product pages, technical brochures, historical archive documents, and, where relevant, documents from current type-certificate holders.

[10] Because source materials report specifications in heterogeneous formats, all quantitative variables were harmonized into common units including kilograms for weight, kilometers for range, and kilometers per hour for speed. Conversions from nautical miles and knots used standard conversion factors, while Mach-based speed measures were translated into approximate kilometers per hour using a standard cruise-altitude speed-of-sound assumption.

3.1.3 Bank Accounting Data

In the spirit of Acharya et al. (2024), we use an instrument for variations in zombie status based on bank-carrier relations and bank characteristics. We rely on Dealscan data on term loans and revolvers to link banks and carriers over the maturity times of those instruments, using Michael Robert's mapping file to identify our sample carriers in those data. We employ Call Report data to calculate bank characteristics, using Michael Schwert's mapping file to link with Dealscan.

3.2 Variable Definitions

3.2.1 Dependent Variables

Our main outcome variable in our price analysis is the annual fare inflation of a carrier in a market (*AnnualInflation*), calculated as the log ratio of its average fare over the current quarter to that over the same quarter in the prior calendar year. We sometimes also directly consider the average fare (*TicketFare*). We also look into annual inflation at the market level (*AnnualMarketInflation*), calculated as the log ratio of the average fare over all carriers in the market over the current quarter to that over the same quarter in the prior year. In our service analysis, we measure a carrier's service quality in a market using its log mean non-negative arrival delay in minutes (*LogDelay*), its log mean number of daily flights (*LogNumberDailyFlights*), the difference between its scheduled and actual departures scaled by its scheduled departures (*CancellationRatio*), and the quarterly log change in the share of jet-engine (rather turboprop) aircrafts used in its flights (*JetEngineChange*). We use *JetEngineChange* as a service quality measure since customers strongly prefer flying jet engine aircrafts.

Conversely, we estimate the efficiency with which a carrier operates in a market using its total passengers-to-total seats ratio (*CapacityUtilization*),[11] the quarterly log change in its fleet's average vintage age (*PlaneVintageChange*),[12] the difference between its log average speed (i.e., the natural log of total distance flown to total elapsed time) and its log average cost per passenger (i.e., its operating cost per seat mile multiplied by the route distance scaled by capacity utilization; *SpeedCostEfficiency*), and the product of its average maximum take-off weight (MTOW) and its capacity utilization (*MTOW*

[11] *CapacityUtilization* equals revenue-miles to seat miles at the route level, the industry's definition for the load factor.

[12] We obtain the aircraft make and model operated by each carrier in a market over a sample quarter from the T-100 Domestic Segment data. A carrier may use multiple aircraft types on the same route in a quarter, reflecting variations in demand across departure times or aircraft availability or the need to match capacity and service configurations to market conditions. For each aircraft type, we collect technical characteristics from manufacturer sources and airline fleet descriptions, including its first-flight date. To measure an aircraft's vintage, we calculate the difference between the year-quarter during which an aircraft is operated and the year-quarter of its maiden flight. We then aggregate this statistic using weighted averages, where the weights are the frequency with which each aircraft type is used. We note that our vintage measure does not capture the physical age of a carrier's aircraft or the length of time the aircraft has been in the carrier's fleet but rather the technological vintage of the aircraft type, reflecting variations in aerodynamics, engine generation, fuel efficiency, range, speed, and structural capacity rather than in depreciation or maintenance.

x Load).[13] We stress that a higher *SpeedCostEfficiency* indicates that a carrier provides faster realized service at lower estimated passenger cost, whereas a higher *MTOW x Load* suggests that a carrier can spread flight-level fixed costs over more passengers and is thus more operationally efficient.

We also look into several real outcome variables for a carrier in a market. To be more specific, we study the ratio of a carrier's average fare to the product of its operating cost per seat mile and the route distance (*PriceCostRatio*) and the difference between those two variables scaled by the average fare (*LernerMarkUp*) for a market. Moreover, we also examine the difference in a carrier's log total passengers in a market (*AnnualPassengerGrowth*) and its percent-point change in its passenger-weighted market share (*MarketShareGrowth*) over the one-year period surrounding the focal quarter. An advantage of using the percent-point change for the market share growth variable is that it sums to zero within a market. We finally also consider a carrier's future exit rates from a market. To that end, we assume that a carrier exits a market when it serves that market over each of the prior four quarters but over none of the subsequent four. We then compute dummy variables equal to one if an exit occurs over the next four, eight, and twelve quarters and else zero (*OneYearAheadExit*, *TwoYearAheadExit*, and *ThreeYearAheadExit*, respectively). We stress that these dummies are designed to capture more permanent exits from a market which a carrier was previously strongly committed to.[14]

3.2.2 Main Independent Variables

Our main independent variables measure zombie presence at two levels: the market share of zombies and the status of single carriers. To create these variables, we follow Caballero et al. (2008), Becker and Ivashina (2022), and Aretz et al. (2026) in identifying a zombie carrier as a carrier with (i) an interest coverage (i.e., EBIT-to-interest expense) ratio below one; (ii) an Altman (1968) z-score below 1.80; (iii) an interest rate (i.e., interest-to-debt ratio) below the average paid by investment-grade carriers ("subsidized-credit condition"),[15] and (iv) not in Chapter 11. Based on those criteria, we calculate a market's passenger-weighted zombie share (*ZombieShare*) and a dummy variable equal to one if all carriers in a market are zombies and else zero (*DummyZombieMarket*). We also construct a dummy variable equal to one if a carrier is *not* a zombie and else zero (*NonZombie*). We finally decompose the non-zombie carriers into healthy, non-subsidized distressed, and bankrupt carriers. First, we identify a non-subsidized distressed carrier as a carrier satisfying zombie criteria (i), (ii), and (iv) (i.e., the interest coverage, z-score, and Chapter 11 ones) but not (iii) (i.e., the subsidized credit one). Next, we identify bankrupt carriers as those in Chapter 11. We classify all remaining non-zombie carriers as healthy. We

[13] We also manually collect the MTOW data and prepare it analogously to the vintage age data (see footnote 12).

[14] Setting the exit dummies to missing for carriers which do not serve a market over each of the prior four quarters (as, e.g., seasonal carriers) and can thus never exit based on our assumptions, has virtually no effect on our conclusions. The reason is that such carriers contribute an only tiny number of observations to our sample data.

[15] We benchmark against investment-grade rather than AAA-rated carriers since no single carrier has a rating above BBB+ over certain periods within our sample period.

then construct three dummy variables equal to one if a carrier is healthy (*Healthy*), non-subsidized distressed (*NonSubDistressed*), or bankrupt (*Bankrupt*) and else zero.

We also consider the strategic response of non-zombie incumbents to the threat that zombies enter their markets. To do so, we use the methodology of Goolsbee and Syverson (2008) to define zombie-threatened markets, defining the dummy variable *ZombieThreat* to be equal to one if at least one zombie threatens market m in quarter t and else zero (see Section 4.4 for more details).

3.2.3 Control, Conditioning, and Instrumental Variables

We use carrier and market-specific control variables. The carrier-market specific controls include the log mean number of miles flown (*LogMilesFlown*); the fraction of round-trip itineraries (*RoundTrip*); the ratio of routes starting from the origin endpoint airport served by the focal carrier over all routes starting from that airport (*NetworkSize*); and the average taken over all of a carrier's rivals in a market of the ratio of the number of all markets served by both focal carrier and rival to the number of all markets served by the focal carrier (*MultiMarketContact*). A higher *NetworkSize* likely implies that a carrier offers more attractive frequent flyer programs and other services (e.g., number of ticket counters, service desks, lounges, etc.) at an airport, perhaps rendering its fares less elastic. Conversely, a higher *MultiMarketContact* suggests that a carrier has more repeated interactions with its rivals, possibly inducing it to be less aggressive to avoid retaliations across its wider network.

The market-specific controls include the number of carriers (*NumberCarriers*), the log geometric mean of the population at the origin and destination (*LogRegionalPopulation*), and a dummy variable equal to one if Southwest operates in the market and else zero (*SWNonStop*). In some tests, we control for dummy variables indicating whether each of the 19 unique carriers is present in a market ("In-Market Variables").[16] In the market-level tests in which we cannot include *LogMilesFlown* and *RoundTrip*, we rather include the log mean number of miles flown (*LogMeanMilesFlown*) and the mean fraction of round-trip itineraries (*MarketRoundTrip*) over all carriers in the market. We stress that our choice of controls is completely standard in the airline industry literature.

In our subsample tests conditional on market health, we measure market health through the log percent change in the number of passengers flying the market over the prior two years.

Finally, we calculate an instrument for a carrier's status (e.g., zombie-vs.-non-zombie) using a bank's tier 1 ratio, defined as its Basel III tier 1 capital scaled by its Basel III risk-weighted assets, and the log percent drop in the aggregate loan loss reserve in a bank's home state.

Table A.1 in our appendix concisely summarizes the definitions of all our analysis variables.

[16]The presence of a specific carrier in a market could influence competition if, for example, the carrier uses a more modern fleet or operates during more business-related times of day.

3.3 Descriptive Statistics and Univariate Comparisons

In Table 1, we give descriptive statistics for our analysis variables. While Panel A focuses on variables derived from the DB1B dataset, Panel B concentrates on those derived from the T100 dataset. Panel A suggests that the average fare is about $256 (*TicketFare*). Interestingly, annual carrier and market inflation are both, on average, slightly negative (*AnnualInflation* and *AnnualMarketInflation*). Zombie carriers make up about 7% of our sample data (1–*NonZombie*) and transport an average of 7% of all passengers (*ZombieShare*). Looking into the non-zombie carriers, the vast majority of them are healthy, a meaningful number is non-subsidized distressed, and a small number is in Chapter 11 (contrast *Healthy*, *NonSubDistressed*, and *Bankrupt*). The average market is composed of around three carriers (*NumberCarriers*). The average flight is over close to 2,000 miles (*MilesFlown*, the non-logged version of *LogMilesFlown*) and connects areas with a mean population of about 1.7 million (*RegionalPopulation*, the non-logged version of *LogRegionalPopulation*). The discount airline Southwest offers non-stop flights in about 5% of markets (*SWNonstop*). Finally, the average carrier serves a large fraction (about 57%) of all routes out of the origin airport (*NetworkSize*) and competes with the same rivals in a large fraction (about 46%) of its markets (*MultiMarketContact*).

TABLE 1 ABOUT HERE.

Turning to the T100 variables, Panel B suggests that the average non-negative flight delay is about twelve minutes (*Delay*, the non-logged version of *LogDelay*), the average number of daily flights is close to four (*NumberDailyFlights*, the non-logged version of *LogNumberDailyFlights*), about 1% of flights are cancelled (*CancellationRatio*), and about 0.07% of flights are switched to jet engine aircrafts per quarter (*JetEngineChange*). The mean capacity utilization ("load factor") is around 73% (*CapacityUtilization*), and the mean carrier switches to more modern aircrafts over time (*PlaneVintageChange*). The average carrier is profitable in its market (i.e., its mean *PriceCostRatio* is 1.85 and its mean *LernerMarkUp* 0.12) and grows its annual number of passengers by around 4% (*AnnualPassengerGrowth*). Finally, the average market exit rates are about 5%, 9%, and 11% over the subsequent one, two, and three years (*OneYearAheadExit*, *TwoYearAheadExit*, and *ThreeYearAheadExit*), all respectively.

In Table 2, we offer a first comparison of the price and non-price competition variables across carrier types (zombie, non-subsidized distressed, healthy, and bankrupt in Panels A to D, respectively) and market types (healthy, partially zombified, and fully zombified). Column (1) shows that while the healthy carriers are dominant across all markets (observation share: 61%), it is their non-healthy counterparts, specifically, the zombies and the non-subsidized distressed, which dominate partially zombified markets (share: 81%). Thus, zombies signal market distress. Interestingly, while, consistent with existing evidence that zombie markets produce lower inflation, the majority of carriers charge low fares and lower their fares in partially zombified markets, we find striking differences in those tendencies across carrier types (see columns (2) and (3)). First, only the zombie and non-subsidized

distressed carriers lower their fares in those markets: The healthy and bankrupt raise them. Second, the non-subsidized distressed carriers lower their fares markedly more than the zombies in those markets, –5.9% vs. –3.1%. They also charge lower average fares, $222.06 vs. $233.29. Switching to the non-price competition variables in columns (4) to (7), we also find differences in them in partially zombified markets. For instance, the non-subsidized distressed carriers are more on-time than the other carries in those markets. Overall, this evidence shows that the non-zombie carriers in partially zombified markets do not behave homogeneously, hinting at competition effects.

TABLE 2 ABOUT HERE.

4 Price and Non-Price Competition in Zombie Markets

In this section, we study price and non-price competitive dynamics among carriers in markets with zombies. We first show that Acharya et al.'s (2024) evidence that zombie exposure is associated with lower inflation also holds in our airline setting. We then use the granularity of our data and show that non-zombie carriers contribute to the lower fare inflation in partially zombified markets. Next, we zoom into partially zombified markets and compare the fare inflation of the zombie, non-subsidized distressed, bankrupt, and healthy carriers in them. We then address endogeneity concerns by, first, comparing high and low-demand markets and, second, using a shift-share instrument for zombie status. After that, we examine whether non-zombie carriers respond strategically to zombie pressure by analyzing non-zombie incumbents' responses to the threat that zombies enter their markets. We finally turn to non-price competition dynamics between the different carrier types.

4.1 The Inflationary Effects of Zombies in Airline Markets

We begin by studying the effect of zombie credit on fare inflation at the market level. Figure 2 looks into industry-wide annual inflation, plotting the annual passenger-weighted mean percent fare change in our sample data (Panel A) and the annual airline industry inflation rate reported by the Bureau of Labor Statistics, BLS, (Panel B) against the industry-wide passenger-weighted share of zombie carriers over our sample period. The figure shows that the inflation measures in the two panels are highly similar, suggesting that the DB1B data are representative of the entire industry (correlation: 0.663). More importantly, the figure reveals that overall inflation tends to be lower — and can, in fact, be negative — during high zombie-share periods, in agreement with the literature. Studying the BLS measure in Panel B, we, for example, observe disinflation at the start of each single meaningful zombie period, specifically, in 1998, from 2002 to 2003, in 2005, and from 2019 to 2021.

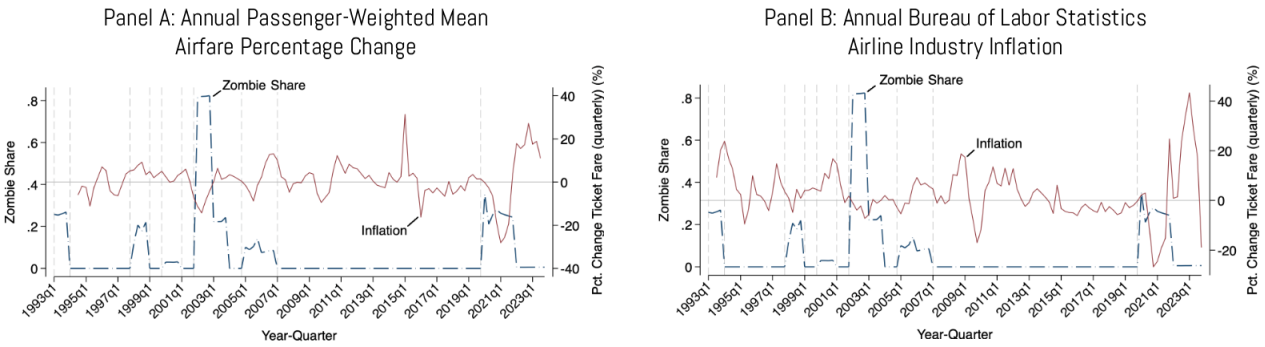

Figure 2. In this figure, we plot annual airline industry inflation (solid line; left y-axis) and the proportion of passengers served by zombies (broken line; right y-axis) over our sample period (1993-2023). While we calculate inflation in Panel A as the annual passenger-weighted percentage change in average airfares in our DB1B sample data, we rely on the Bureau of Labor Statistic's annual airline industry inflation rate in Panel B. The broken vertical lines separate periods with and without zombies.

To investigate the relation between zombie credit and fare inflation at a more granular level, we estimate the following market level regression:

$$\begin{aligned} AnnualMarketInflation_{m,t} &= \beta\, ZombieShare_{m,t} + \gamma\, DummyZombieMarket_{m,t} \\ &+ \delta\, MarketControls_{m,t} + \alpha_m + \alpha_t + \epsilon_{m,t}, \end{aligned} \tag{1}$$

where *AnnualMarketInflation* is the annual log average fare change of market m until the end of quarter t, *ZombieShare* is the passenger-weighted share of zombies, *DummyZombieMarket* is a dummy variable equal to one if the market is fully zombified (*ZombieShare* is equal to 100%) and else zero, *MarketControls* is vector of the market-level controls, β, γ, and δ are parameters or parameter vectors, and α_m and α_t are static market and time fixed effects, respectively. We cluster standard errors at the market level. In some cases, we impose: (i) $\gamma = 0$ and $\delta = 0$ or (ii) $\delta = 0$ (no controls).

To study how non-zombie-carriers contribute to the overall inflation in markets with zombies, we estimate the following market-carrier-time level regression on only non-zombie carriers:

$$\begin{aligned} AnnualInflation_{c,m,t} &= \beta\, ZombieShare_{m,t} + \gamma\, CarrierControls_{c,m,t} \\ &+ \delta\, MarketControls_{m,t} + FE + \epsilon_{m,t}, \end{aligned} \tag{2}$$

where *AnnualInflation* is the annual log average fare change of non-zombie carrier c in market m measured until the end of quarter t, and *CarrierControls* is a vector of the carrier-level controls. We use either (i) dynamic market-carrier and static time ("time-series contrasts") or (ii) dynamic carrier-time and static market ("cross-sectional contrasts") fixed effects (*FE*). We double cluster standard errors at the market-carrier and market time levels. In some cases, we impose $\gamma = \delta = 0$.

Table 3 offers regression results, with columns (1) to (3) focusing on the market (Eq. (1)) and (4) to (7) on the non-zombie-carrier (Eq. (2)) estimations. Plain numbers are estimates and those in round brackets t-statistics. Column (1) shows that, in conflict with the literature, a higher zombie share raises — and not lowers — fare inflation. Yet, columns (2) and (3) reveal that, once we control for fully zombified markets (i.e., markets with only zombies), the effect of the zombie share becomes negative and significant, pointing to competitive dynamics determining fare inflation. Our most comprehensive model in column (3), for example, suggests that a one-percent rise in a market's zombie share lowers its annual inflation by close to one basis point (t-statistic: –4.18).

TABLE 3 ABOUT HERE.

Switching to market carrier level regressions, columns (4) to (7) suggests that non-zombie carriers contribute to the disinflationary market fare effects. Concentrating on our most comprehensive model with market-carrier and time fixed effects, column (5) shows that a one-percent rise in the zombie share in one market leads the non-zombie carriers in that market to lower their fare inflation by about 59 basis point (t-statistic: –2.58). Turning to the equivalent model with dynamic carrier-time and market fixed effects, column (7) demonstrates that the non-zombie carriers reduce their fares by an additional about 1.17 basis points (t-statistic: –5.26) in a market with a one-percent higher zombie share relative to another market at some point in time.

4.2 Price Competition in Zombified Airline Markets

Having shown that fare inflation decreases with the share of zombie firms in partially zombified markets and that non-zombie carriers add to that effect, we now zoom into those markets, contrasting the fare inflation of the different carrier types within them. To do so, we run the following carrier-level regression using only observations from partially zombified markets:

$$AnnualInflation_{c,m,t} = \beta\, CarrierType_{c,m,t} + \gamma\, CarrierControls_{c,m,t} + \alpha_{m,t} + \alpha_c + \epsilon_{m,t}, \quad (3)$$

where *AnnualInflation* is the annual log average fare change of non-zombie carrier c in market m until the end of quarter t, *CarrierType* is either *NonZombie* or [*Healthy*, *NonSubDistressed*, *Bankrupt*]′, β and γ are parameters or parameter vectors, and $\alpha_{m,t}$ and α_c are dynamic market-time and static carrier fixed effects, respectively. We double-cluster standard errors at the market-carrier and market-time level. In some specifications, we impose the restriction $\gamma = 0$ (no controls).

Table 4 presents the regression results. Plain numbers are estimates, while those in round brackets are t-statistics. The estimates suggests that the non-zombie carriers in partially zombified markets produce a significantly lower fare inflation than the zombie carriers. Looking into the model with controls, column (3), for example, reveals that the non-zombies reduce their fares by an additional 1.09

percentage points (t-statistic: –10.39) in comparison to the zombies. Decomposing the non-zombies into healthy, non-subsidized distressed, and bankrupt carriers reveals that the overall difference is attributable to the non-subsidized distressed and bankrupt carriers. Concentrating on the model with controls again, column (4) demonstrates that while the bankrupt carriers reduce their fare inflation by an additional –0.89 percent point (t-statistic: –4.82) relative to the zombies, the corresponding effect for the non-subsidized distressed carriers is a starker –1.49 points (t-statistic: –12.43). In contrast, the healthy carriers either raise (in the absence of controls; see column (2)) or do not change (in their presence; column (4)) their fare inflation in comparison to their zombie rivals.

TABLE 4 ABOUT HERE.

4.3 Price Competition in Zombified Airline Markets: Causal Inferences

A standard concern in the zombie literature is that the negative correlation between zombies and price growth could be driven by demand effects. Specifically, weak demand may simultaneously depress fare inflation and push firms into financial distress, increasing the likelihood that they receive subsidized loans.[17] This endogeneity concern is mitigated in our setting because our specifications include market-time fixed effects, absorbing shocks common to all carriers in the same market and quarter. Thus, identification in our empirical tests originates from differences across carriers within the same market-quarter rather than comparisons across markets experiencing different demand conditions. Notwithstanding, we next estimate the regression in Eq. (2) separately for high and low-growth markets, first, to assess whether our results are stronger in weak-growth markets, but, more importantly, because all carriers in high-growth markets plausibly benefit from stronger demand, making it less likely that unobserved demand variation across carriers drives our results.

Table 5 gives the results from the high and low-growth market subsample regressions, with columns (1) and (2) focusing on high-growth and columns (3) and (4) on low-growth markets. We define a high (low) growth market as a market with past two-year total passenger growth above (below) the second (first) full-sample tercile. Consistent with the demand-based interpretation, the table shows that the fare-inflation differences between zombie and non-zombie carriers are stronger in low-growth markets. In particular, columns (1) and (3) show that while the non-zombie carriers reduce their fares by an additional 1.30 percentage points (t-statistic: –5.08) relative to zombies in high-growth markets, the corresponding estimate for low-growth markets is 2.03 percentage points (t-statistic: —11.78). Columns (2) and (4) show that the difference across the two market types is mostly due to the non-subsidized distressed carriers. Importantly, however, all non-zombie carrier types reduce their

[17] For example, markets involving recession-sensitive destinations such as Las Vegas during the Great Recession may have experienced declining passenger demand and lower fare growth, as passenger traffic through McCarran fell sharply in 2008–2009. At the same time, carriers heavily exposed to such routes may have been more likely to become financially distressed and to receive subsidized support from lenders.

fares markedly more than their zombie rivals even in high-growth markets, offering first evidence that demand variation alone is unlikely to explain the inflation differences across carrier types.

TABLE 5 ABOUT HERE.

Despite our subsample evidence, there could still be the identification concern that unobservable carrier characteristics may simultaneously affect the carrier's pricing strategy and zombie status. A distressed carrier may, for instance, receive low interest rates because its creditors have favorable private information about its fundamentals—rather than because they are subsidizing a nonviable borrower. If these unobserved fundamentals also affect the carrier's fare inflation, then carrier zombie status and pricing would be jointly determined, causing zombie status to be correlated with the error term and biasing our estimates. To address this concern, we use an IV strategy exploiting variations in zombie status generated by pre-existing exposure to weak banks hit by adverse shocks rather than contemporaneous carrier fundamentals and/or route-level demand conditions.

We use a Bartik (1991)-style shift-share IV strategy in the spirit of Acharya et al. (2024) to isolate plausibly exogenous variation in carrier status. Our strategy hinges on the insight that undercapitalized banks (i.e., banks with tier-1 capital ratios close to their regulatory minimums) have incentives to zombify bad loans to avoid violating capital requirements. To implement the strategy, we focus on the 2019–2023 subsample period for two reasons. First, Figure 1 shows that the US airline industry contained no zombies over the eleven years prior to 2019, likely implying that bank lending relations were largely independent of zombification concerns in that year. Second, the 2019–2023 period saw a sharp rise in the number of zombies, with about half of all markets becoming fully or partially zombified from 2020–2022 due to effects of the Covid-19 pandemic (see Panel A of Figure 1).

We construct our instrument, *BSIV*, at the carrier-time level as:

$$BSIV_{c\,t} = \frac{1}{B}\sum_{b=1}^{B}\left[Tier1Ratio_{b,2018} \times AggLLRDrop_{b\,t}\right], \tag{4}$$

where the sum is over all banks b with outstanding term or revolver loans to carrier c in 2018, B is the number of such banks, *Tier1Ratio* is bank b's tier 1 capital ratio in 2018, and *AggLLRDrop* is the gross percent drop in the aggregate loan loss reserves of the state in which bank b is headquartered at time t (i.e., $LLR_{b,t-1}/LLR_{b,t}$, where LLR is the aggregate loan loss reserve, so that a number above (below) one signals a drop (rise)).[18] Intuitively, a low *BSIV* identifies carriers whose pre-existing creditors were more weakly capitalized (low Tier 1 ratio) and exposed to adverse loan-loss reserve shocks (low aggregate loan loss reserves drop), so that these creditors had strong incentives to zombify bad loans

[18]Loan-loss reserves reflect expected future loan losses. If a bank expects loan performance to considerably improve, it can significantly reduce loan loss reserves. However, if it does not expect loan performance to improve significantly, it cannot reduce reserves much. Therefore, a *low drop* in loan-loss reserves indicates less favorable lending news.

to not violate capital requirements. We note that the cross-sectional variations in the instrument come from banks' 2018 tier 1 ratios, while its time-series variations come from contemporaneous aggregate loan-loss-reserve shocks. As a result, *BSIV* varies across both carriers and time and is not absorbed by the market-time and carrier fixed effects in Eq. (2). In fact, the static carrier fixed effects ensure that our empirical evidence is robust to unobserved differences across carriers.[19]

Table 6 offers the results from the IV counterparts of our main regression in Eq. (2). Panel A shows the second-stage IV regression results and Panel B the first-stage ones. In the models with *NonZombie* as main independent variable in columns (1) and (3), we naturally instrument that variable with *BSIV*. Conversely, in the models in which decompose the non-zombie category in columns (2) and (4), we focus the IV analysis on the economically relevant at-risk margin: Distressed carriers receiving subsidized credit and thus being classified as zombies versus those not receiving subsidized credit and being classified as non-subsidized distressed. This margin is the one for which bank incentives to zombify weak borrowers are relevant. Since there are no bankrupt carriers over the 2019 to 2023 period, the decomposed IV specification compares zombie carriers with non-subsidized distressed carriers, instrumenting *NonSubDistressed* with *BSIV*. As a result, we interpret the decomposed IV estimates as causal evidence for the pricing difference between zombie and non-subsidized distressed carriers. We include healthy carriers as a separate category, but the IV strategy is not designed to identify the healthy-versus-zombie margin. Accordingly, the causal interpretation of the decomposed IV specification centers on the instrumented *NonSubDistressed* coefficient.

TABLE 6 ABOUT HERE.

The second-stage IV regression results in Panel A suggest that our evidence that the non-zombie carriers, specifically, the non-subsidized distressed, reduce their fare more than their zombies rivals in partially zombified markets is likely causal. Strikingly, however, the IV effects are about 4-5 times stronger than the corresponding ordinary least-squares (OLS) ones. Looking into the model with controls, column (3), for example, shows that the non-zombies lower their fares by an additional 5.21 percentage points (t-statistic: –11.50) relative to the zombies, which is much lower than the 1.09 point drop in the corresponding OLS model (see column (3) in Table 4). Decomposing the non-zombies into healthy and non-subsidized distressed carriers in that same model, column (4) reveal that while the healthy actually raise their fares by an additional 3.67 percentage points (t-statistic: 9.80) in comparison to the zombies, the non-subsidized distressed lower them by an

[19] Our instrument is essentially a firm-specific version of Acharya et al.'s (2024) instrument. While Eq. (4) averages over all 2018 banking relationships of carrier c, their corresponding measure, Eq. (4) in their paper, aggregates over the banking relationships of all firms in a market, which explains the additional weight factor $m_{bhj,2009}$ in their equation. A further difference is that Acharya et al. (2024) use aggregate loan growth in their main tests to capture systematic lending news, assuming that higher loan growth reflects better news. We do not use loan growth because aggregate loan growth rose sharply at the start of the Covid-19 pandemic as many firms drew down revolving credit lines. Instead, we use changes in aggregate loan loss reserves, which more directly capture banks' expectations about future loan losses.

additional 4.36 points (t-statistic: –10.44). Just like before, these two effects are also much more pronounced than their OLS counterparts of –0.04 and 1.49, respectively (see column (4) of Table 4).

Switching to the first-stage regression estimates and diagnostics, Panel B shows that *BSIV* significantly explains *NonZombie* and *NonSubDistressed*. In particular, in accordance with well-capitalized banks exposed to positive systematic lending news having few incentives to extend zombie loans, the instrument is positively related to both *NonZombie* and *NonSubDistressed*, with the relation, however, being stronger for *NonSubDistressed*. Considering the models with (carrier-level) controls, columns (3) and (4), for instance, show that while *BSIV* attracts a coefficient of 0.98 (t-statistic: 9.48) and a within R-squared of about 66% in the *NonZombie* estimation, the corresponding numbers for the *NonSubDistressed* estimation are 1.03 (t-statistic: 24.89) and about 95%, respectively. That *BSIV* performs better on *NonSubDistressed* is not too surprising since the regressions involving it control for healthy carriers which, at least theoretically, cannot become zombies. The bottom of the table demonstrates that the instrument passes standard IV-diagnostic tests with flying colors. To be more specific, the Kleibergen–Paap rk LM statistics suggest that *BSIV* is highly correlated with the endogenous variables and thus identified. Conversley, the Cragg-Donald F and the Kleibergen–Paap rk Wald F statistics easily refute concerns that our instrument may be statistically weak.

We interpret the IV results as identifying a relative pricing effect on the at-risk margin. Specifically, among distressed carriers whose zombie status varies with pre-existing exposure to weak banks hit by adverse shocks, the estimates indicate that non-subsidized distressed carriers exhibit lower fare inflation than otherwise equivalent zombie carriers in the same partially zombified markets. Thus, the IV results support a causal interpretation of the fare-inflation difference between zombie and non-subsidized distressed carriers. They do not, however, by themselves identify the strategic mechanism generating this difference. The difference could arise because (i) zombie carriers adjust fares sluggishly to market conditions, (ii) non-subsidized distressed carriers cut fares more aggressively when facing zombie rivals, or (iii) both. The next section offers additional evidence on the strategic interpretation ((ii)) by studying how non-zombie incumbents respond to threats of zombie entry.

4.4 Zombie Threat of Entry

In this section, we examine whether non-zombie incumbent carriers respond strategically to zombie pressure in a specific setting: prospective entry by a zombie carrier. If incumbents expect zombie entry, they may try to deter that by lowering fares, making the market less attractive to the potential entrant. We follow Goolsbee and Syverson (2008) in defining a threatened market as a market (an airport-to-airport route) in which a zombie establishes service at one endpoint airport after previously serving the other, but never served the market connecting the two airports. Thus, our zombie threat measure captures prospective entry rather than re-entry after temporary or seasonal exit.

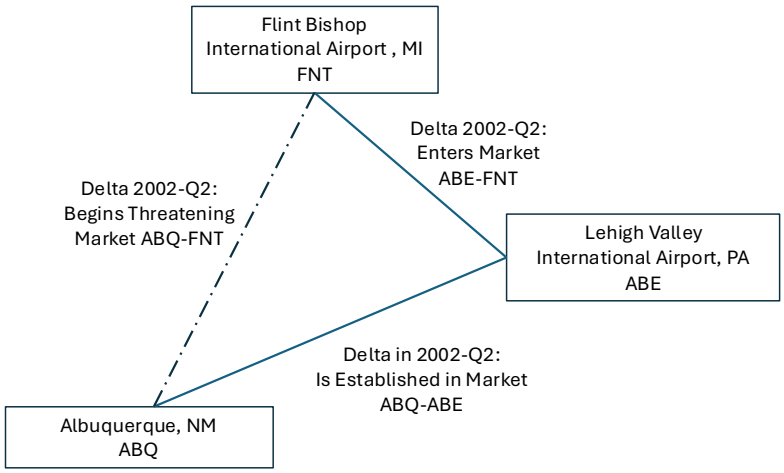

Figure 3. This figure illustrates how we identify markets threatened by zombie entry, focusing on a zombified Delta in 2002. Before 2002, Delta already served the Albuquerque (ABQ) to Lehigh Valley International Airport (ABE) market. In 2002, it established service in the ABE-to-Flint Bishop International Airport (FNT) market. Given that this entry established Delta service at both endpoint airports of the ABQ-to-FNT market, a market which Delta did not serve prior to 2002, the likelihood of Delta entering the ABQ-to-FNT market rises, rendering this a threatened market.

Figure 3 illustrates our definition of a threatened market using Delta in 2002—a year in which Delta was classified as zombie. In the second quarter of 2002, Delta already serviced the Albuquerque (ABQ)–Lehigh Valley International Airport (ABE) market for some period. In the same quarter, it, however, also began serving the ABE–Flint Bishop International Airport (FNT) market. Delta's entry into the ABE–FNT market gave it service at both endpoints of the ABQ–FNT market, a market it had not served at any time during our sample period and rendering it a threatened market. We apply this procedure to each zombie carrier in our sample, identifying all markets threatened by zombie carriers during our sample period. We define the dummy variable *ZombieThreat* to be equal to one if at least one zombie carrier threatens market m in quarter t and else zero. We also record whether, and when, the zombie carrier subsequently enters threatened markets.

To estimate the pooled effect of zombie-entry threats, we restrict the sample to non-zombie incumbent carriers and estimate the following regression:

$$\begin{aligned} AnnualInflation_{c,m,t} &= \boldsymbol{\beta}'\left(CarrierType_{c,t} \cdot ZombieThreat_{m,t}\right) + \boldsymbol{\gamma}' CarrierControls_{c,m,t} \\ &\quad + \boldsymbol{\delta}' MarketControls_{m,t} + \theta_{o(m)t} + \psi_{d(m)t} + \nu_{c,m} + \varphi_t + \epsilon_{c,m,t}, \end{aligned} \tag{5}$$

where *CarrierType* is either one or $[Healthy, NonSubDistressed, Bankrupt]'$, *ZombieThreat* is defined above, β, γ, and δ are parameters or parameter vectors, and φ_t and $\nu_{c,m}$ denote static time and dynamic carrier-market fixed effects, respectively. In alternative specifications, we replace φ_t with dynamic carrier-time fixed effects, $\varphi_{c,t}$. Some specifications also include origin-by-quarter and

destination-by-quarter fixed effects ($\theta_{o(m)t}$ and $\psi_{d(m)t}$, respectively). These fixed effects absorb origin or destination-specific shocks potentially coinciding with a zombie carrier's expansion into an endpoint airport and affecting incumbent pricing independently of the zombie-entry threat. Thus, they help isolate incumbents' market-specific responses to zombie-entry threats from contemporaneous airport-level changes. As *ZombieThreat* varies at the market-time level, we cannot include market-quarter fixed effects. Some specifications exclude controls, setting γ and/or δ to zero.

Table 7 offers the results from estimating the regression in Eq. (5). Columns (1) and (2) report estimates for the pooled response of non-zombie incumbents to zombie-entry threats. As these models include market-carrier and time fixed effects, they compare an incumbent carrier's fare inflation in one specific market across quarters with and without the threat of zombie entry. In both specifications, the coefficient on *ZombieThreat* is negative and significant. In column (1), zombie-entry threats are, for example, associated with a 0.26 percent-point (t-statistic: –3.28) drop in fares. The pooled response remains negative and significant in columns (5) and (6), which replace year-quarter fixed effects with carrier-by-quarter fixed effects and therefore contrast threatened and non-threatened markets served by the same incumbent carrier in the same quarter. The lesson to take away is that non-zombie incumbents lower their fares in response to credible threats of zombie entry.

TABLE 7 ABOUT HERE.

Columns (3), (4), (7), and (8) decompose the aggregate non-zombie response by non-zombie type. The economically largest and most robust response comes from non-subsidized distressed carriers. Columns (3) and (4) show that these carriers reduce their fares by 1.30 and 1.48 percentage points (t-statistics: –12.65 and –9.82) when facing a zombie-entry threat, respectively. These effects remain negative and significant in the more demanding carrier-by-quarter specifications: Columns (7) and (8) imply far reductions of 0.91 and 0.84 percentage points (t-statistics: –8.25 and –5.03) in those, respectively. In contrast, the responses of healthy and bankrupt incumbents are not robust across specifications. Healthy carriers exhibit positive coefficients in Columns (3) and (4), but these become insignificant once we compare threatened and non-threatened markets served by the same carrier in the same quarter. The bankrupt-carrier coefficients also vary in sign and significance. All in all, our evidence suggests that the anticipatory pricing responses to zombie-entry threats are concentrated among the non-subsidized distressed and not bankrupt or healthy incumbents.

Taken together, our evidence in this subsection indicates that non-subsidized distressed carriers respond strategically to zombie pressure, reducing their fares in zombie-threatened markets. This response is consistent with an entry-deterrence motive: the carriers appear to make threatened markets less attractive to zombie entrants by lowering fare increases before entry occurs. In contrast, the responses of healthy and bankrupt carriers are more mixed and nuanced.

4.5 Service-Quality Competition in Partially Zombified Markets

We have thus far established that non-zombie carriers, in particular, the non-subsidized distressed, respond to zombie pressure by lowering their fares more than their zombie rivals and strategically lowering fares in markets where they are incumbents and face credible threats of zombie entry, consistent with entry deterrence. We now turn to those carriers' non-price strategic responses to zombie presence, focusing on service-quality competition. The airline industry provides a useful setting for this analysis because several dimensions of service quality are directly observable and have a natural ordering: better on-time performance and shorter arrival delays, fewer cancellations, higher flight frequency within a market (leading to a better alignment between offered flights and passengers' preferred travel times), and greater use of jet-engine aircrafts rather than turboprops.

Table 8 gives the results from estimating Eq. (3) using *LogDelay*, *LogNumberDailyFlights*, *CancellationRatio*, or *JetEngineChange* rather than *AnnualInflation* on only observations from partially zombified markets. The table demonstrates that the non-zombie carriers, especially the non-subsidized distressed, offer a higher service quality than their zombie rivals on several margins: They have shorter delays, cancel fewer flights, and switch to more jet-engine aircrafts than those rivals. Columns (1) and (2) show that the non-zombie carriers have about two percent (t-statistic: –2.73) lower non-negative arrival delays than their zombie rivals, with the corresponding number for the non-subsidized distressed even being five percent (t-statistic: –5.46).[20] The non-zombie carriers also have cancellation ratios three percentage points (t-statistic: –8.05) lower than their zombie rivals, with that difference being driven by all three non-zombie carrier types (see columns (5) and (6)). We also find statistically significant albeit economically small differences in jet-engine aircraft use: Column (8) reveals that the non-subsidized distressed and healthy carriers switch to 0.16 and 0.11 percent point (t-statistics: 2.12 and 2.29) more jet-aircraft aircrafts than their zombie rivals, respectively. The only margin on which the non-zombies perform worse is the daily flight frequency. Non-zombie carriers operate about four percent (t-statistic: –2.95) fewer daily flights than their zombie rivals, with that difference coming from the non-subsidized distressed and bankrupt carriers (see columns (3) and (4)).

TABLE 8 ABOUT HERE.

Overall, the service-quality results indicate that non-zombie carriers, especially the non-subsidized distressed, respond to zombie presence not only through fare inflation, but also non-price competition. In particular, they improve several observable dimensions of service quality relative to zombie carriers, including arrival delays, cancellations, and jet-engine aircraft use. The only exception is that they reduce their flight frequency. These results suggest that non-subsidized distressed carriers

[20] We note that the coefficients can be interpreted approximately as percentage differences in non-negative arrival delays relative to zombie carriers. *LogDelay* is the log of one plus non-negative arrival delays. We set early arrivals, corresponding to negative delays, equal to zero.

attempt to make their products more attractive despite pricing aggressively against their zombie rivals. Whether these efforts translate into better market outcomes is an open question. We turn to this question next by examining markups, passenger growth, and market-share growth.

5 Real Outcomes and Exit Rates

While our evidence suggests that the non-zombie carriers, specifically, the non-subsidized distressed, behave aggressively toward their zombie rivals along both the price and non-price dimension, we now investigate the consequences of those policies. We first look into the immediate effects on carriers' mark-ups and passenger and market share growth. We then contrast market exit rates across zombie and non-zombie carriers over the next one to three years. We finally gauge the efficiency of the carriers most likely to survive in markets with competition between zombies and non-zombies.

5.1 Mark-Ups, Passenger Growth, and Market Share Growth

In Section 2, we discuss theories in which a predatory firm competes aggressively in the product market, lowering its output prices even at the cost of its short-term profitability to attract customers away from a rival and to drive the rival out of the market (see, e.g., Bolton and Scharfstein (1990)). To examine whether the aggressive price cuts of the non-zombie carriers, especially, the non-subsidized distressed, are associated with higher passenger and market-share growth relative to their zombie rivals at the expense of their current profitability, we estimate the following carrier-market-quarter-level regression using only observations from partially zombified markets:

$$ShortTermResult_{c,m,t} = \beta\, CarrierType_{c,m,t} + \gamma\, CarrierControls_{c,m,t} + \alpha_{m,t} + \alpha_c + \epsilon_{m,t}, \quad (6)$$

where *ShortTermResult* is the *PriceCostRatio*, *LernerMarkUp*, *PassengerGrowth*, or *MarketShare-Growth* of carrier c in market m over quarter t, *CarrierType* is either *NonZombie* or [*Healthy*, *NonSub-Distressed*, *Bankrupt*]′, *CarrierControls* is a vector of the carrier-level controls, β and γ are parameter vectors, and $\alpha_{m,t}$ and α_c are dynamic market-time and static carrier fixed effects, respectively. We double-cluster standard errors at the market-carrier as well as market-time level.

Table 9 gives the results from estimating the regression in Eq. (6). Consistent with the non-zombie carriers' greater fare reductions relative to zombies in partially zombified markets in Tables 4 to 6 and their alleged willingness to forego short-term profits, the table shows that the non-zombie carriers are less profitable than their zombie rivals in those markets. For example, column (3) reports that they have a 0.08 (t-statistic: –58.51) lower Lerner mark-up than their zombie rivals. Decomposing the non-zombies into non-subsidized distressed, bankrupt, and healthy carriers, we find that the lower overall profitability comes entirely from the non-subsidized distressed and bankrupt: The healthy

carriers are more profitable than their zombie rivals, in line with them less aggressively undercutting their zombie rivals relative to the other two non-zombie carrier types. Despite the non-subsidized distressed and bankrupt carriers' profitability sacrifices, all non-zombie carriers grow their passengers less strongly and lose market share to their zombie rivals. Directly zooming into the non-subsidized distressed, column (6), for example, demonstrates that their passenger growth over the four quarters surrounding the focal quarter is 40 basis points (t-statistic: –53.93) lower than that of their zombie rivals. Conversely, column (8) reveals that they lose about five percentage points (t-statistic: –51.19) of their market share over that period to those same rivals. The surprising conclusion is that the non-zombie carriers' aggressive strategies do not work, not even in the short-term.

TABLE 9 ABOUT HERE.

5.2 Future Market Exit Rates

Having shown that the non-subsidized distressed and bankrupt carriers' fare cuts do not allow them to steal market share from their zombie rivals in partially zombified markets, we next explore the exit rates of the different carrier types in those markets. To do so, we rerun the regression in Eq. (6) replacing *ShortTermResult* with *OneYearAheadExit*, *TwoYearAheadExit*, or *ThreeYearAheadExit*.

Table 10 offers the results from those regressions. In line with our passenger and market-share growth results, the table suggests that the non-zombie carriers do not succeed in driving their zombie rivals out of their markets—and ultimately decide to leave themselves. Looking over the next year, column (1) shows that the non-zombies have a three percent point (t-statistic: 37.76) higher exit rate than their zombie rivals, an economically huge difference in comparison to the unconditional mean of *OneYearAheadExit* of 0.05 (see Table 1). Column (2) reveals that the higher exit rate over that horizon comes mostly from the non-subsidized distressed and healthy carriers, and only to a lesser extent from the bankrupt. Investigating longer future horizons, column (5) indicates that the exit rate differential between zombies and non-zombies grows, with it becoming six percentage points (t-statistic: 54.10) over the next three years, also an economically huge difference compared the unconditional mean of *ThreeYearAheadExit* of 0.11 (see again Table 1). Interestingly, however, column (6) indicates that the higher three-year exit rate comes almost exclusively from the non-subsidized distressed and bankrupt carriers, not the healthy. Thus, while the distressed, in particular, the bankrupt, carriers are initially more reluctant to exit than the healthy, the situation reverses over longer horizons. Still, it is the zombies which are ultimately most likely to survive in partially zombified markets.

TABLE 10 ABOUT HERE.

5.3 Long-Run Characteristics of Partially Zombified Markets

We finally evaluate the broader implications for consumers and society of the zombies being more likely to survive in partially zombified markets than the non-zombies, looking into the long-run characteristics of those markets. To that end, we rerun the regression in Eq. (6) replacing *ShortTermResult* with *CapacityUtilization*, *PlaneVintage*, *SpeedCostEfficiency*, and *MTOW x Load*.

Table 11 gives the results from these regressions. The table suggests that, in comparison to their non-zombie rivals, the zombie carriers have a lower capacity utilization (columns (1) and (2)) and deploy larger aircraft at lower passenger utilization ((7) and (8)). While column (1), for example, shows that the zombies have a 1.2 percentage points (t-statistic: 7.19) lower capacity utilization than the non-zombies, column (2) reveals that all non-zombie carrier contribute to that difference. We reach similar conclusions in case of the scaled MTOW variable. Looking into technological traits, the table further demonstrates that the zombies refresh their aircraft types less quickly (columns (3) and (4)) and offer a lower realized speed per estimated passenger cost dollar ((5) and (6)) than their non-zombie rivals. While column (3), for example, indicates that the zombies lower the vintage age of their fleet by 0.38 (t-statistic: –1.65) less over the prior quarter than their non-zombie rivals, column (4) reveals that the healthy carriers, but not the non-subsidized distressed and bankrupt, are responsible for that difference. We reach similar conclusions in case of the speed-cost efficiency variable.[21]

TABLE 11 ABOUT HERE.

Overall, this section offers evidence that the non-zombies ultimately lose their wars against their zombie rivals, with negative consequences for consumers and society. While the non-zombies' aggressive pricing policies plausibly make them less profitable than their zombie rivals in partially zombified markets, they still lose passengers and market share to those same rivals. As a result, they are far more likely to exit markets over the next one to three days relative to the zombies. Upon their exit, the markets are left with operationally and technologically less efficient carriers.

6 Concluding Remarks

We examine product market interactions between zombie and non-zombie carriers in the airline industry. While we confirm existing evidence that markets inhabited by both carrier types produce a lower inflation, we show that the non-zombie carriers, particularly, the non-subsidized distressed, lower their fares more in those markets than their zombie rivals. Supporting a causal interpretation, this result emerges in both high and low passenger-growth markets as well as in IV regressions in

[21] We note that our results in this section may also have environmental implications. Because aircraft emissions are largely generated at the flight level, lower load factors and less efficient aircraft deployment can increase emissions per passenger-mile. Moreover, slower renewal of aircraft types may delay the adoption of more fuel-efficient technology.

which we instrument a carrier's zombie status with the sum of the product of a creditor's pre-existing tier 1 capital ratio and the aggregate loan loss reserve drop in its home state taken over all creditors funding the carrier. Corroborating the view that our evidence indicates that the non-subsidized distressed carriers behave aggressively toward their zombie rivals, the same carriers further reduce their fares in response to zombie entry threats and improve their service quality relative to those same rivals. Notwithstanding, the aggressive strategies do not seem to work: The non-subsidized distressed carriers are not only less profitable than their zombie rivals but also lose market share to them in partially zombified markets, likely explaining why they are more likely to exit those markets and cede them to their less efficient competitors over the next one to three years.

Taken together, our evidence suggests that competition on its own is not a cure for zombification problems. Instead, zombie firms distort competitive outcomes in the markets in which they operate, inducing non-zombie firms plausibly unaware of the subsidized credit made available to zombie firms to erroneously view the zombies as weak and attack them. Yet, since the non-zombie firms' aggressive strategies are often unsuccessful, they are far more likely than their zombie rivals to exit co-inhabited markets, leaving customers in those markets to the less efficient zombies.

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Table 1. Descriptive Statistics

In this table, we report descriptive statistics, including the number of observations (# Obs.), the mean, the median, and the standard deviation. Panel A focuses on the DB1B variables and Panel B on the T100 variables. See Table A.1 in the appendix for variable definitions. The sample period is 1993 to 2023.

	# Obs	Mean	Median	Standard Deviation
	(1)	(2)	(3)	(4)
Panel A: Full-Sample Market-Carrier Characteristics (Panel Statistics)				
TicketFare	9,257,241	256	234	114
AnnualInflation	7,368,692	–0.74	–0.23	38.37
AnnualMarketInflation	3,796,405	6.45	–0.36	46.72
ZombieShare	9,257,241	0.07	0.00	0.21
DummyZombieMarket	9,256,643	0.02	0.00	0.15
NonZombie	9,256,643	0.93	1.00	0.26
NonSubDistressed	9,256,643	0.27	0.00	0.45
Bankrupt	9,256,643	0.05	0.00	0.21
Healthy	9,256,643	0.61	1.00	0.49
ZombieThreat	9,257,241	0.11	0.00	0 .31
NumberCarriers	9,257,241	3.08	3.00	1.93
RegionalPopulation	8,224,934	1.72	1.13	1.78
LogRegionalPopulation	8,224,934	0.17	0.12	0.85
MilesFlown	9,257,241	2,090	1,869	1,113
LogMilesFlown	9,257,241	7.49	7.53	0.60
LogMeanMilesFlown	4,561,303	7.41	7.46	0.61
RoundTrip	9,257,241	0.66	0.73	0.32
MeanRoundTrip	9,257,241	0.66	0.69	0.26
SWNonStop	9,257,241	0.05	0.00	0.21
NetworkSize	9,257,241	0.57	0.57	0.23
MultiMarketContact	6,901,817	0.46	0.45	0.15
Panel B: Non-Stop-Flight Sample Market-Carrier Characteristics (Panel Statistics)				
Delays	443,355	11.78	10.42	7.11
LogDelay	443,355	2.39	2.44	0.61
NumberDailyFlights	389,484	3.76	2.81	5.03
LogNumberDailyFlights	389,484	0.98	1.03	0.78
CancellationRatio	589,035	0.01	0.01	0.17
JetEngineChange	534,652	0.07	0.00	4.58
CapcityUtilization	589,035	0.73	0.76	0.15
PlaneVintageChange	547,512	0.37	1.17	14.56
SpeedCostEfficiency	428,601	1.88	1.92	0.59
MTOWxLoad	556,093	51.11	52.35	21.32
PriceCostRatio	9,256,643	1.85	1.37	1.60
LernerMarkUp	9,256,643	0.12	0.27	0.65
PassengerGrowth	7,907,601	0.04	0.00	1.38
MarketShareGrowth	7,907,601	0.00	0.00	0.18
OneYearAheadExit	9,257,241	0.05	0.00	0.23
TwoYearAheadExit	9,257,241	0.09	0.00	0.28
ThreeYearAheadExit	9,257,241	0.11	0.00	0.32

Table 2. Univariate Comparisons

In this table, we offer univariate comparisons of price and service quality variables across zombie (Panel A), non-subsidized distressed (Panel B), bankrupt (Panel C), and healthy (Panel D) carriers in different markets. The variables are the ticket fare (*TicketFare*; in $); the log annual carrier-level inflation (*AnnualInflation*; in %); the average non-negative arrival delay in minutes (*Delay*); the average number of daily flights (*NumberDailyFlights*); the average number of non-operated (i.e., canceled or rescheduled) flights (*CancellationRatio*); and the quarterly log change in the share of jet engine aircrafts (*JetEngineChange*). The markets are all markets, markets with healthy and zombie carriers (Partially Zombified Markets), and markets with only zombie carriers (Fully Zombified Markets). The plain numbers are averages (Panels A to D) or the differences in averages (Panel E) and those in square brackets are robust White (1980) t-statistics. The sample period is 1993 to 2023.

		Price Competition		Non-Price Competition			
	# Obs. (1,000s)	Ticket Fare ($)	Annual Inflation (%)	Arrival Delay (Mins)	Daily Number Flights	Cance-lled Ratio	Jet Engine Change
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Zombie Carriers							
All	672	244.79	–3.13	11.29	3.40	–0.35	0.25
Partially Zombified	447	233.29	–3.07	11.45	3.41	0.00	0.10
Fully Zombified	225	267.58	–3.27	9.23	3.33	–2.22	1.36
Panel B: Non–Subsidized Distressed Carriers							
All	2,537	247.72	–3.58	11.30	3.62	0.76	0.12
Partially Zombified	523	222.06	–5.85	9.96	3.46	1.00	0.10
Panel C: Bankrupt Carriers							
All	445	263.00	2.80	11.73	3.76	–0.47	–0.02
Partially Zombified	106	244.45	3.15	11.20	3.66	–2.16	0.01
Panel D: Healthy Carriers							
All	5,603	260.41	0.40	11.99	3.85	1.07	0.05
Partially Zombified	261	232.21	4.38	12.54	3.17	0.93	0.01
Panel E: Differences in Partially Zombified Markets							
Zombie-vs.-NonSubDis.		11.23	2.79	1.50	–0.06	–1.00	0.13
		(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.04)
Zombie-vs.-Bankrupt		–11.16	–6.22	0.26	–0.26	2.16	0.27
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)
Zombie-vs.-Healthy		1.08	–7.45	–1.09	0.23	–0.93	0.21
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)

Table 3. The Effect of Zombies on Market and Non-Zombie Ticket-Fare Inflation

In this table, we report the results from market (columns (1) to (3)) and non-zombie-carrier ((4) to (7)) level regressions of annual ticket-fare inflation on the passenger-weighted share of zombies in a market (*ZombieShare*), control variables (in some columns), and fixed effects. We calculate a carrier's annual ticket fare inflation in a market as the log difference between its average fare in the market over the current quarter and the corresponding fare over the same quarter one year ago, and we aggregate up that estimate to the market level using passenger numbers as weight. In columns (1) to (3), we use static market and time fixed effects and cluster standard errors at the market level. In columns (4) and (7), we exclude zombie carriers from the regressions. While we use dynamic market-carrier and static time fixed effects in columns (4) and (5) ("time-series contrasts"), we use dynamic carrier-time and static market fixed effects in columns (6) and (7) ("cross-sectional contrasts"). We cluster standard errors at the market-carrier and market-time level. Columns (3) and (6) further add dummy variables indicating the presence of each carrier in a market ("In-Market Variables"). See Table A.1 in the appendix for control variable definitions. The plain numbers are estimates and those in round brackets *t*-statistics. The bottom rows also report the adjusted R-squared and number of observations (in 1,000s). The sample period is 1993 to 2023.

Market and Carrier-Level Annual Inflation Regressions							
	Market Inflation			Non-Zombie-Carrier Inflation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ZombieShare	1.20***	–1.80***	–0.94***	–0.42**	–0.59***	–0.59***	–1.17***
	(6.75)	(–8.32)	(–4.18)	(–1.97)	(–2.58)	(–2.91)	(–5.26)
DummyZombieMarket		4.13***	2.80***				
		(17.52)	(11.10)				
NumberCarriers			–1.98***		–1.24***		–1.40***
			(–67.07)		(–6.30)		(–7.77)
LogRegionalPopulation			3.05***		–0.56***		–0.44***
			(6.12)		(–4.47)		(–4.27)
LogMeanMilesFlown			16.85***				
			(38.73)				
LogMilesFlown					15.81***		1.53***
					(–54.61)		(10.58)
MeanRoundTrip			–73.40***				
			(–138.02)				
RoundTrip					–39.76***		–29.20***
					(–179.17)		(–211.91)
SWNonStop			–1.80***		0.07		0.03
			(–10.00)		(–0.57)		(0.32)
NetworkSize					2.08***		6.68***
					(9.79)		(46.00)
MultiMarketContact					3.66***		3.05***
					(15.34)		(12.77)
Market FE	✓	✓	✓			✓	✓
Time FE	✓	✓	✓	✓	✓		
Mkt-Carrier FE				✓	✓		
Carrier-Time FE						✓	✓
In Market Variables					✓		✓
Cluster Market	✓	✓	✓				
Cluster Mkt Carrier				✓	✓	✓	✓
Cluster Mkt Time				✓	✓	✓	✓
Adj. R^2	0.07	0.07	0.10	0.05	0.09	0.06	0.11
Obs. (in 1,000s)	3,791	3,791	3,261	6,885	6,257	6,885	4,769

Table 4. The Ticket Fare Inflation of Different Carriers in Zombie Markets

In this table, we report the results from carrier-level regressions of annual ticket-fare inflation on either a dummy variable equal to one if a carrier is not a zombie and else zero (*NonZombie*) or a dummy variable equal to one if a carrier is distressed but not a zombie and else zero (*NonSubDistressed*), a dummy variable equal to one if a carrier is in Chapter 11 and else zero (*Bankrupt*), and a dummy variable equal to one if a carrier is healthy and else zero (*Healthy*), control variables (in columns (3) and (4)), and fixed effects. We calculate a carrier's annual ticket fare inflation in a market as the log difference between its average fare in the market over the current quarter and the corresponding fare over the same quarter one year ago. See Table A.1 in the appendix for control variable definitions. We use dynamic market-time and static carrier fixed effects and cluster at the market-carrier and market-time level. The plain numbers are estimates and those in round brackets *t*-statistics. The bottom rows also report the adjusted R-squared and number of observations (in 1,000s). The sample period is 1993 to 2023.

Carrier-Level Annual Inflation Regressions				
	(1)	(2)	(3)	(4)
NonZombie	–1.03***		–1.09***	
	(–10.30)		(–10.39)	
NonSubDistressed		–1.49***		–1.49***
		(–13.14)		(–12.43)
Bankrupt		–1.23***		–0.89***
		(–6.45)		(–4.82)
Healthy		0.58***		–0.04
		(3.57)		(–0.28)
LogMilesFlown			–3.63***	–3.59***
			(–11.11)	(–11.01)
RoundTrip			–32.31***	–32.31***
			(–94.64)	(–94.62)
NetworkSize			0.84**	1.11***
			(2.05)	(2.69)
MultiMarketContact			14.95***	14.91***
			(22.47)	(22.33)
Market-Time FE	✓	✓	✓	✓
Carrier FE	✓	✓	✓	✓
Cluster Mkt Carrier	✓	✓	✓	✓
Cluster Mkt Time	✓	✓	✓	✓
Adj. R^2	0.21	0.21	0.25	0.25
Observations (in 1,000s)	1,009	1,009	941	941

Table 5. The Ticket Fare Inflation of Different Carriers in High and Low-Demand Zombie Markets

In this table, we report the results from carrier-level regressions of annual ticket-fare inflation on either a dummy variable equal to one if a carrier is not a zombie and else zero (*NonZombie*) or a dummy variable equal to one if a carrier is distressed but not a zombie and else zero (*NonSubDistressed*), a dummy variable equal to one if a carrier is in Chapter 11 and else zero (*Bankrupt*), and a dummy variable equal to one if a carrier is healthy and else zero (*Healthy*), control variables, and fixed effects. We run the regressions in columns (1) and (2) on markets with a past total-passenger-growth over the last two years above the second tercile and those in columns (3) and (4) on markets with a growth below the first tercile. We calculate a carrier's annual ticket fare inflation in a market as the log difference between its average fare in the market over the current quarter and the corresponding fare over the same quarter one year ago. The control variables are *LogMilesFlown*, *RoundTrip*, *NetworkSize*, and *MultiMarketContact* (see Table A.1 in the appendix for their definitions). To be concise, we do not report the coefficients and *t*-statistics of the control variables. We use dynamic market-time and static carrier fixed effects and cluster at the market-carrier and market-time level. The plain numbers are estimates and those in round brackets *t*-statistics. The bottom rows also report the adjusted R-squared and number of observations (in 1,000s). The sample period is 1993 to 2023.

Carrier-Level Annual Inflation Regressions				
	High Passenger Growth		Low Passenger Growth	
	(1)	(2)	(3)	(4)
NonZombie	–1.304***		–2.026***	
	(–5.077)		(–11.784)	
NonSubDistressed		–0.799***		–2.333***
		(–2.973)		(–13.050)
Bankrupt		–2.127***		–1.546***
		(–6.822)		(–5.807)
Healthy		–1.651***		–0.701***
		(–6.018)		(–3.205)
Carrier Controls	✓	✓	✓	✓
Market-Time FE	✓	✓	✓	✓
Carrier FE	✓	✓	✓	✓
Cluster Mkt Carrier	✓	✓	✓	✓
Cluster Mkt Time	✓	✓	✓	✓
Adj. R^2	0.23	0.23	0.22	0.22
Observations (in 1,000s)	1,041	1,041	969	969

Table 6. The Ticket Fare Inflation of Different Carriers in Zombie Markets: IV Regressions

In this table, we report the results from carrier-level two-stage least squares (2SLS) regressions of annual ticket-fare inflation on either an instrumentalized dummy variable equal to one if a carrier is not a zombie and else zero ($NonZombie^{IVed}$) or an instrumentalized dummy variable equal to one if a carrier is distressed but not a zombie and else zero ($NonSubDistressed^{IVed}$) and a dummy variable equal to one if a carrier is healthy and else zero (*Healthy*), control variables (in columns (3) and (4)), and fixed effects. While Panel A shows the results from the second stage, Panel B reports those from the first. We calculate a carrier's annual ticket fare inflation in a market as the log difference between its average fare in the market over the current quarter and the corresponding fare over the same quarter one year ago. We use as instrument the average of the product of a bank's 2018 tier ratio and the concurrent drop in its loan loss reserve taken over all banks funding a carrier. The control variables are *LogMilesFlown*, *RoundTrip*, *NetworkSize*, and *MultiMarketContact* (see Table A.1 in the appendix for their definitions). To be concise, we do not report the coefficients and t-statistics of the control variables. We use dynamic market-time and static carrier fixed effects and cluster at the market-carrier and market-time level. The plain numbers are estimates and those in round brackets t-statistics. The bottom row also gives the number of observations (in 1,000s), the overall and within adjusted R-squared, and the results from various 2SLS diagnostic tests, including the Kleibergen-Paap rk LM statistic, the Cragg-Donald F statistic, and Kleibergen-Paap rk Wald F statistic. The sample period is 2019 to 2023.

Panel A: Second-Stage Carrier-Level Regressions				
	Annual Inflation			
	(1)	(2)	(3)	(4)
$NonZombie^{IVed}$	–4.46***		–5.21***	
	(–11.55)		(–11.50)	
$NonSubDistressed^{IVed}$		–3.78***		–4.36***
		(–10.57)		(–10.44)
Healthy		3.83***		3.67***
		(10.81)		(9.80)
Cluster Mkt Carrier	✓	✓	✓	✓
Cluster Mkt Time	✓	✓	✓	✓
Panel B: First-Stage Carrier-Level Regressions				
	Non Zombie	NonSub Distressed	Non Zombie	NonSub Distressed
	(1)	(2)	(3)	(4)
Tier 1_{2018} × Loss Reserve Drop	1.01***	1.05***	0.98***	1.03***
	(9.00)	(29.38)	(9.48)	(24.89)
Cluster Mkt Carrier	✓	✓	✓	✓
Overall Adj. R^2	0.873	0.968	0.880	0.970
Within Adj. R^2	0.624	0.940	0.660	0.947
Kleibergen-Paap rk LM	2,898	3,738	3,051	3,898
rk LM Test p-value	(0.000)	(0.000)	(0.000)	(0.000)
Cragg-Donald F	156,807	869,288	118,113	695,333
Kleibergen-Paap rk Wald F	32,734	171,236	25,307	117,619
10% Max IV Size	16.380	16.380	16.380	16.380
Carrier Controls			✓	✓
Market-Time FE	✓	✓	✓	✓
Carrier FE	✓	✓	✓	✓
Observations (in 1,000s)	179	179	163	163

Table 7. The Effect of Zombie Threats on Non-Zombie Ticket-Fare Inflation

This table reports non-zombie-carrier regressions of annual ticket-fare inflation on an indicator equal to one when a zombie carrier threatens to enter a market and else zero, *ZombieThreat*, or on interactions between *ZombieThreat* and a dummy variable equal to one if a carrier is distressed but not a zombie and else zero (*NonSubDistressed*), a dummy variable equal to one if a carrier is in Chapter 11 and else zero (*Bankrupt*), and a dummy variable equal to one if a carrier is healthy and else zero (*Healthy*), controls, and fixed effects. We calculate a carrier's annual ticket fare inflation in a market as the log difference between its average fare in the market over the current quarter and the corresponding fare over the same quarter one year ago. The control variables are *LogMilesFlown*, *RoundTrip*, *NetworkSize*, and *MultiMarketContact* (see Table A.1 in the appendix for their definitions). In columns (2) and (4), we further add dummy variables indicating the presence of each carrier in a market ("In-Market Variables"). To be concise, we do not report the coefficients and t-statistics of the control variables. Columns (1) to (4) include dynamic market-carrier and static time fixed effects, while columns (5) to (8) replace the static time with dynamic carrier-quarter fixed effects. We further include dynamic origin-time and destination-time fixed effects in columns (2) and (4). We exclude zombie carriers from the regressions. The plain numbers are estimates and those in round brackets t-statistics. The bottom rows also report the adjusted R-squared and number of observations (in 1,000s). The sample period is 1993 to 2023.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ZombieThreat	–0.26***	–0.40***			–0.41***	–0.43***		
	(–3.28)	(–3.44)			(–5.04)	(–3.68)		
NonSubDistressed × *ZombieThreat*			–1.30***	–1.48***			–0.91***	–0.84***
			(–12.65)	(–9.82)			(–8.25)	(–5.03)
Bankrupt × *ZombieThreat*			1.10***	–0.77***			0.52**	–0.34
			(5.90)	(–3.37)			(2.13)	(–1.13)
Healthy × *ZombieThreat*			0.60***	0.58***			–0.06	–0.11
			(5.31)	(4.28)			(–0.50)	(–0.76)
Carrier Controls		✓		✓		✓		✓
Mkt-Carrier FE	✓	✓	✓	✓	✓	✓	✓	✓
Carrier-Time FE					✓	✓	✓	✓
Dest-Time FE		✓		✓		✓		✓
Origin-Time FE		✓		✓		✓		✓
Time FE	✓	✓	✓	✓				
In Market Variables		✓		✓				
Cluster Mkt Carrier	✓	✓	✓	✓	✓	✓	✓	✓
Cluster Mkt Time	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.05	0.13	0.05	0.14	0.06	0.15	0.06	0.15
Observations	6,885	4,841	6,885	4,841	6,885	4,841	6,885	4,841

Table 8. The Service Quality of Different Carriers in Zombie Markets

In this table, we report the results from carrier-level regressions of the arrival delay, the log number of daily flights, the share of cancellations, and the quarterly log change in the share of jet engine (rather than turboprop) aircrafts on either a dummy variable equal to one if a carrier is not a zombie and else zero (*NonZombie*) or a dummy variable equal to one if a carrier is distressed but not a zombie and else zero (*NonSubDistressed*), a dummy variable equal to one if a carrier is in Chapter 11 and else zero (*Bankrupt*), and a dummy variable equal to one if a carrier is healthy and else zero (*Healthy*), control variables, and fixed effects. We calculate the arrival delay as the log of one plus the non-negative arrival delay in minutes and the share of cancellations as one minus the ratio of operated-to-scheduled flights. The control variables are *LogMilesFlown*, *RoundTrip*, *NetworkSize*, and *MultiMarketContact* (see Table A.1 in the appendix for their definitions). To be concise, we do not report the coefficients and *t*-statistics of the control variables. We use dynamic market-time and static carrier fixed effects and cluster at the market-carrier and market-time level. The plain numbers are estimates and those in round brackets *t*-statistics. The bottom rows also report the adjusted R-squared and number of observations (in 1,000s). The sample period is 1993 to 2023.

Service-Level Regressions								
	Log Delay		Log Number Daily Flights		Cancellation Ratio		Jet Engine Change	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NonZombie	–0.02***		–0.04***		–0.03***		0.10*	
	(–2.73)		(–2.95)		(–8.05)		(1.93)	
NonSubDistressed		–0.05***		–0.05***		–0.03***		0.16**
		(–5.46)		(–3.20)		(–5.91)		(2.12)
Bankrupt		–0.01		–0.07***		–0.04***		–0.07**
		(–0.50)		(–3.50)		(–5.76)		(–2.05)
Healthy		0.02		–0.00		–0.03***		0.11**
		(1.53)		(–0.19)		(–8.88)		(2.29)
Carrier Controls	✓	✓	✓	✓	✓	✓	✓	✓
Market-Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Carrier FE	✓	✓	✓	✓	✓	✓	✓	✓
Cluster Mkt Carrier	✓	✓	✓	✓	✓	✓	✓	✓
Cluster Mkt Time	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.51	0.51	0.53	0.53	0.13	0.13	0.09	0.09
Observations (in 1,000s)	105	105	91	91	118	118	111	111

Table 9. The Real Outcomes of Different Carriers in Zombie Markets

In this table, we report the results from carrier-level regressions of the price-cost ratio, the Lerner mark-up, passenger growth, and market share growth on either a dummy variable equal to one if a carrier is not a zombie and else zero (*NonZombie*) or a dummy variable equal to one if a carrier is distressed but not a zombie and else zero (*NonSubDistressed*), a dummy variable equal to one if a carrier is in Chapter 11 and else zero (*Bankrupt*), and a dummy variable equal to one if a carrier is healthy and else zero (*Healthy*), control variables, and fixed effects. The price-cost ratio is a carrier's fare over its estimated cost of serving that market, where the cost the carrier-quarter operating cost per available seat-mile (constructed using T-100 available seat miles) multiplied by market distance. We calculate the Lerner-style markup as the difference between a carrier's fare and its estimated cost of serving that market divided by the fare. Passenger growth is the log difference in a carrier's total passengers from two quarters prior to the focal quarter to two quarters after, whereas market share growth is the log difference in the passenger-weighted market share over the same period. The control variables are *LogMilesFlown*, *RoundTrip*, *NetworkSize*, and *MultiMarketContact* (see Table A.1 in the appendix for their definitions). We use dynamic market-time and static carrier fixed effects and cluster at the market-carrier and market-time level. The plain numbers are estimates and those in round brackets *t*-statistics. The bottom rows also report the adjusted R-squared and number of observations (in 1,000s). The sample period is 1993 to 2023.

Real Outcome Regressions								
	Price-Cost Ratio		Lerner Mark-Up		Passenger Growth		Market Share Growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NonZombie	–0.01**		–0.08***		–0.22***		–0.03***	
	(–2.31)		(–58.51)		(–52.26)		(–44.38)	
NonSubDistressed		–0.03***		–0.10***		–0.21***		–0.03***
		(–14.44)		(–62.51)		(–46.29)		(–38.86)
Bankrupt		–0.14***		–0.13***		–0.40***		–0.05***
		(–41.58)		(–61.29)		(–53.93)		(–51.19)
Healthy		0.20***		0.01***		–0.09***		–0.01***
		(62.99)		(2.70)		(–13.44)		(–12.20)
Carrier Controls	✓	✓	✓	✓	✓	✓	✓	✓
Market-Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Carrier FE	✓	✓	✓	✓	✓	✓	✓	✓
Cluster Mkt Carrier	✓	✓	✓	✓	✓	✓	✓	✓
Cluster Mkt Time	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.77	0.77	0.74	0.74	0.18	0.18	0.33	0.33
Observations (in 1,000s)	1,153	1,153	1,153	1,153	1,091	1,091	1,091	1,091

Table 10. The Future Exit Rates of Different Carriers in Zombie Markets

In this table, we report the results from carrier-level regressions of a dummy variable equal to one if a carrier exits the market over the coming four (eight) [twelve] quarters and else zero on either a dummy variable equal to one if a carrier is not a zombie and else zero (*NonZombie*) or a dummy variable equal to one if a carrier is distressed but not a zombie and else zero (*NonSubDistressed*), a dummy variable equal to one if a carrier is in Chapter 11 and else zero (*Bankrupt*), and a dummy variable equal to one if a carrier is healthy and else zero (*Healthy*), control variables, and fixed effects. We assume that a carrier exits a market if it serves the market over the prior four quarters but not over the next four. The control variables are *LogMilesFlown*, *RoundTrip*, *NetworkSize*, and *MultiMarketContact* (see Table A.1 in the appendix for their definitions). To be concise, we do not report the coefficients and *t*-statistics of the control variables. We use dynamic market-time and static carrier fixed effects and cluster at the market-carrier and market-time level. The plain numbers are estimates and those in round brackets *t*-statistics. The bottom rows also report the adjusted R-squared and number of observations (in 1,000s). The sample period is 1993 to 2023.

Future Exit Regressions						
	One-Year-Ahead Exit		Two-Year-Ahead Exit		Three-Year-Ahead Exit	
	(1)	(2)	(3)	(4)	(5)	(6)
NonZombie	0.03***		0.04***		0.06***	
	(37.76)		(46.70)		(54.10)	
NonSubDistressed		0.03***		0.05***		0.07***
		(35.94)		(56.26)		(64.50)
Bankrupt		0.01***		0.04***		0.06***
		(8.72)		(17.61)		(23.90)
Healthy		0.04***		0.01***		0.01***
		(30.83)		(7.71)		(4.17)
Carrier Controls	✓	✓	✓	✓	✓	✓
Market-Time FE	✓	✓	✓	✓	✓	✓
Carrier FE	✓	✓	✓	✓	✓	✓
Cluster Mkt Carrier	✓	✓	✓	✓	✓	✓
Cluster Mkt Time	✓	✓	✓	✓	✓	✓
Adj. R^2	0.07	0.07	0.13	0.14	0.18	0.19
Observations (in 1,000s)	1,153	1,153	1,153	1,153	1,153	1,153

Table 11. The Efficiency of Different Carriers in Zombie Markets

In this table, we report the results from carrier-level regressions of the capacity utilization ratio ("load factor"), the quarterly change in the vintage age of a carrier's fleet, the speed-cost efficiency ratio, and MTOW-load factor product on either a dummy variable equal to one if a carrier is not a zombie and else zero (*NonZombie*) or a dummy variable equal to one if a carrier is distressed but not a zombie and else zero (*NonSubDistressed*), a dummy variable equal to one if a carrier is in Chapter 11 and else zero (*Bankrupt*), and a dummy variable equal to one if a carrier is healthy and else zero (*Healthy*), control variables, and fixed effects. We calculate the capacity utilization ratio as the average load factor, the speed-cost efficiency ratio as the difference between log average speed and log average cost per passenger, and MTOW-load factor product as the product of average maximum take-off weight (MTOW) and capacity utilization. The control variables are *LogMilesFlown*, *RoundTrip*, *NetworkSize*, and *MultiMarketContact* (see Table A.1 in the appendix for their definitions). To be concise, we do not report the coefficients and *t*-statistics of the control variables. We use dynamic market-time and static carrier fixed effects and cluster at the market-carrier and market-time level. The plain numbers are estimates and those in round brackets *t*-statistics. The bottom rows also report the adjusted R-squared and number of observations (in 1,000s). The sample period is 1993 to 2023.

	Efficiency Regressions							
	Capacity Utilization		Plane Vintage Change		Speed-Cost Efficiency		MTOW x Load	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NonZombie	0.01***		–0.38*		0.04***		1.51***	
	(7.19)		(–1.65)		(9.77)		(5.45)	
NonSubDistressed		0.01***		–0.28		0.01**		1.44***
		(2.60)		(–0.99)		(2.24)		(4.32)
Bankrupt		0.01***		0.15		–0.03***		–0.61
		(4.00)		(0.42)		(–4.27)		(–1.09)
Healthy		0.02***		–0.82***		0.13***		2.76***
		(10.63)		(–2.76)		(25.64)		(7.73)
Carrier Controls	✓	✓	✓	✓	✓	✓	✓	✓
Market-Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Carrier FE	✓	✓	✓	✓	✓	✓	✓	✓
Cluster Mkt Carrier	✓	✓	✓	✓	✓	✓	✓	✓
Cluster Mkt Time	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	0.68	0.68	0.02	0.02	0.92	0.92	0.53	0.53
Observations (in 1,000s)	118	118	111	111	96	96	108	108

A.1 Appendix: Variable Definitions

Table A.1. Variable Definitions

In this table, we offer the definitions of all variables used in our empirical work. While Panel A focuses on the D1B1 variables, Panel B concentrates on the T100 variables.

Variable Name	Variable Definition
	Panel A: The D1B1 Variables
TicketFare	The average fare charged by a carrier in a market (in $).
AnnualInflation	The natural log of the ratio of the average fare charged by a carrier in a market in the current quarter to the corresponding average fare in the same quarter one year ago.
AnnualMarketInflation	The natural log of the ratio of the average fare charged by all carriers in a market in the current quarter to the corresponding average fare in the same quarter one year ago.
ZombieShare	The passenger-weighted share of zombie carriers in a market (see *Non-Zombie* for the zombie definition).
DummyNonZombieMarket	A dummy variable equal to one if a market features only zombie carriers and else zero (see *NonZombie* for the zombie definition).
NonZombie	A dummy variable equal to one if a carrier is not a zombie and else zero. A zombie is a carrier with (i) an interest coverage ratio below one; (ii) a z-score below 1.80; (iii) an interest rate (interest expense-to-total debt) below that paid by investment grade carriers; and (iv) not in Chapter 11.
NonSubDistressed	A dummy variable equal to one if a carrier is a non-subsidized distressed carrier and else zero. A non-subsidized distressed carrier fulfills zombie conditions (i), (ii), and (iv), but not (iii) (see *NonZombie* for the conditions).
Bankrupt	A dummy variable equal to one if a carrier is bankrupt and else zero. A bankrupt carrier is in Chapter 11.
Healthy	A dummy variable equal to one if a carrier is healthy and else zero. A healthy carrier is neither a zombie, non-subsidized distressed, nor bankrupt carrier (see *NonZombie*, *NonSubDistressed*, and *Bankrupt* for the conditions).
ZombieThreat	A dummy variable equal to one if a market is threatened by zombie entry and else zero. A market is threatened if a zombie carrier (i) already operates at one of its endpoints; (ii) just established service at the other endpoint; and (iii) does not serve the market over prior quarters.
NumberCarriers	The number of carriers in a market.
RegionalPopulation	The geometrical mean of origin and destination airport population.
LogRegionalPopulation	The natural log of *LogRegionalPopulation*.
MilesFlown	The average number of miles flown by a carrier in a market.
LogMilesFlown	The natural log of *MilesFlown*
LogMeanMilesFlown	The natural log of the average miles flown by all carriers in a market.

(continued on next page)

Table A.1. Variable Definitions (cont.)

Variable Name	Variable Definition
	Panel A: The D1B1 Variables (cont.)
RoundTrip	The fraction of round trip flights by a carrier in a market.
MeanRoundTrip	The fraction of round trip flights by all carriers in a market.
SWNonStop	A dummy variable equal to one if Southwest offers non-stop flights in a market and else zero.
NetworkSize	The fraction of routes out of the origin airport served by a carrier.
MultiMarketContact	The fraction of routes in which a carrier competes with a rival averaged over all of the carrier's rivals in a market.
	Panel B: The T100 Variables
Delay	The average non-negative arrival delay of a carrier in a market (in minutes).
LogDelay	The natural log of *Delay*.
NumberDailyFlights	The average number of daily flights by a carrier in a market.
LogNumberDailyFlights	The natural log of *NumberDailyFlights*.
CancellationRatio	One minus the ratio of operated-to-scheduled flights.
JetEngineChange	The quarterly log change in the fraction of jet engine aircrafts used by a carrier in a market.
CapacityUtilization	The average of enplaned-to-total seats of a carrier in a market.
PlaneVintageChange	The quarterly log change in the average vintage age of a carrier's fleet in a market. The vintage age of an aircraft is the difference between the current quarter and its maiden flight quarter.
SpeedCostEfficiency	The difference between a carrier log average speed, calculated as the natural log of total distance flown to total elapsed time, and its log average cost per passenger, calculated as operating cost per seat mile multiplied by the route distance scaled by capacity utilization, in a market.
MTOWxLoad	The product of a carrier's average maximum take-off weight (MTOW) and its *CapacityUtilization* in a market.
PriceCostRatio	The ratio of a carrier's average fare to the product of its operating cost per seat mile and the route distance in a market.
LernerMarkUp	The ratio of the difference between a carrier's average fare and the product of its operating cost per seat mile and the route distance to its average fare in a market.
PassengerGrowth	The log percent change in a carrier's total passengers from two quarters before to two quarters after the focal quarter in a market.
MarketShareGrowth	The percent point change in a carrier's passenger-weighted market share from two quarters before to two quarters after the focal quarter in a market.
OneYearAheadExit	A dummy variable equal to one if a carrier exits a market over the next four quarters and else zero. An exit occurs if the carriers serves the market over each of the prior four quarters but over none of the subsequent.
TwoYearAheadExit	A dummy variable equal to one if a carrier exits a market over the next eight quarters and else zero (see *OneYearAheadExit* for the exit definition).
ThreeYearAheadExit	A dummy variable equal to one if a carrier exits a market over the next twelve quarters and else zero (see *OneYearAheadExit* for the exit definition).