STUDIES ON THE AVIATION INDUSTRY BASED ON INDUSTRIAL ORGANIZATION

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Dedications

This thesis is dedicated to

Dad, Jianlin Dong

Mom, Jie Ya

Sister, Jing Dong

Contents

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Chapter I

Cost Pass-through in the U.S. Aviation Industry

Abstract

This paper uses data from the 2000 to 2019 U.S. civil aviation industry to analyze the disparities in jet fuel cost pass-through among legacy, low-cost, and ultra-low-cost carriers. Different pricing mechanisms are determined by different business structures. We use empirical methods to study which category of carriers transfers more of the cost increase to final consumers when facing an increase in jet fuel costs. According to the findings, when faced with an increase in jet fuel costs, low-cost carriers are more likely than legacy carriers to increase flight ticket prices. Compared to legacy and low-cost carriers, ultra-low-cost carriers have the lowest pass-through.

Keywords— Cost pass-through, Low-cost carriers, Aviation industry, Fuel costs

1 Introduction

Since the introduction of the Airline Deregulation Act in 1978, a substantial number of low-cost carriers (LCCs) have emerged, altering the structure of the American airline industry. Up to now, there have been 39 low-cost carriers in the U.S. aviation industry.[1] The low-cost carriers, together with the legacy carriers, which have had a more comprehensive market presence since the 1960s, constitute the U.S. civil aviation industry. Each has its own relatively unique business model. Benefiting from low-cost carriers' "point-to-point" business strategy, there is an obvious cost difference between legacy airline companies with a "hub-and-spoke" business model and LCCs (including both low-cost carriers and ultra-low-cost carriers (ULCC)).[2] Legacy carriers' business strategy is to offer a wide range of high-quality services with relatively higher airfares. Low-cost carriers choose to use low-price strategies to attract more price-sensitive travellers, and their service quality and variety are inferior to those of legacy carriers. In the second quarter of 2008, jet fuel price was at its high point at 364 cents per gallon. During that quarter, jet fuel accounted for 29.13% of American Airlines' (legacy carrier) and 44.96% of JetBlue Airways' (low-cost carrier) total operating costs.[3] Due to cost structure differences, LCCs always offer lower airfare than legacy carriers for the same route.

As a critical component of an airline company's costs, jet fuel accounts for more than 40% of total operating costs when the jet oil price is at its high point. This would constitute the largest component of their operating cost.[4] When the jet fuel price is at the bottom level, on the other hand, the percentage is also quite high, in the range of 15% to 20%, which is still the second or third highest

[1]International Civil Aviation Organization(ICAO).
[2]A special type of low-cost carriers with even lower cost than regular LCC.
[3]Author's calculation based on airline companies' annual reports.
[4]Author's calculation based on airline companies' annual reports.

operating cost item for an airline company.[5] Changes in aircraft fuel prices will have a significant impact on airfare pricing. This makes it meaningful for us to investigate the influence of jet fuel price changes on the architecture of air ticket pricing in both of these business models.

Pass-through is defined as the ability of one company to transfer cost changes, usually an increase in costs, to the final consumers. In the aviation industry, jet fuel cost is the most important variable cost the company could pass on to the consumer.

When the price of jet fuel rises, on the one hand, a legacy carrier can modify its airfare to pass the cost increase onto travellers. For LCCs and ULCCs, which provide relatively less service, lower price is their competitive advantage to compete for market share. As a result, LCCs and ULCCs tend to maintain low airfare, implying that LCCs and ULCCs may have a lower pass-through than legacy carriers. On the other hand, compared with LCCs and ULCCs, legacy carriers are able to charge higher price premiums (Hazledine, 2011), which allows them to tolerate more cost rises while maintaining the same airfare. The lower (even zero) price margin (Fischer and Kamerschen, 2003) gives LCCs and ULCCs little room to absorb the cost increase without resulting in negative profits. Thus, legacy carriers can wrest greater market share from LCCs and ULCCs during the oil price-increasing period. Under this circumstance, LCCs and ULCCs have to raise the ticket price to remain profitable, meaning that LCCs may have a higher pass-through than legacy carriers. The aforementioned two different mechanisms affect the pass-through effect in opposite directions, leaving the net result ambiguous. This paper's objective is to use empirical data to test these predictions.

A pricing structure which is in line with the laws of the market can help consumers choose the most suitable airline while meeting their own needs. Aviation

[5] Author's calculation based on airline companies' annual reports.

companies can effectively make strategic adjustments under the premise of understanding competitors and their own pricing mechanisms (Burger and Fuchs, 2005). Studying the pass-through effect of jet fuel costs can help the aviation industry optimize costs, improve competitiveness and profitability, and improve the bidding mechanism. As a relatively mature market, the development of the U.S. aviation industry provides a reference for the aviation industry and carriers of other countries and regions. The findings are useful for those countries that still regulate airfare pricing.

The jet fuel pass-through effect of the U.S. aviation sector has been researched in the literature (Shi, 2017; Gayle and Lin, 2021). However, these studies did not take into account diverse airline business models, which makes their conclusions relatively general. Our paper fills this gap by assessing differences in jet fuel pass-through effects among legacy carriers, LCCs, and ULCCs. It, therefore, provides valuable insights into various pricing strategies among different airline business models. To the best of our knowledge, this is the first work to look into the differences in pass-through between the two categories of airline carriers. Although the U.S. airline industry has been deregulated, the article's findings could provide a basis for airline regulation in other regions, such as Europe and Asia.

This paper uses U.S. commercial aviation industry data from 2000 to 2019 to examine whether there is a difference in jet fuel cost pass-through among legacy carriers, low-cost carriers, and ultra-low-cost carriers. The findings demonstrate that low-cost carriers' (when we classify four ultra-low-cost carriers as low-cost carriers as well) jet fuel pass-through is higher than legacy carriers'. When facing a 10% increase in the industry-wide jet fuel price, legacy carriers' airfare increases by 0.172% in the same quarter, while low-cost carriers' airfare increases by 0.351%. Four quarters' cumulated pass-through for legacy carriers and low-cost carriers are 0.572% and 1.289%, respectively. We also find that low-cost carriers are more inclined to increase their airfares than ultra-low-cost carriers. When facing a 10% increase in the jet fuel price, the airfare increases of legacy carriers, low-cost carriers, and ultra-low-cost carriers are 0.725%, 0.911% and -0.971%, respectively. Firm-specific cost changes and single-trip results verify the above results.[6]

The remainder of the paper is organized as follows. Section 2 describes the current market context of the U.S. civil aviation industry. Section 3 presents a literature review, both theoretical and empirical, related to the cost pass-through effect and its impact on the commercial aviation industry. Pass-through information in the commercial aviation industry is provided in Section 4. Section 5 describes the data. Section 6 describes the methodology, while the results are reported in Section 7. We conclude in Section 8.

2 The U.S. Civil Aviation Industry

According to the business structure of the airline companies, U.S. civil aviation carriers are categorized into two groups: legacy carriers and low-cost carriers (Franke, 2004); the latter includes low-cost carriers and ultra-low-cost carriers (Bachwich and Wittman, 2017). Since 1949, the U.S. civil aviation business has had 39 low-cost airlines; however, following three waves of mergers and acquisitions and bankruptcies, there are only nine low-cost airlines left in the market today.[7] From 1990 to 2002, the market share of low-cost carriers in the U.S. domestic market grew from 9% to 25% (Ito and Lee, 2003). In 2021, the largest four low-cost carriers, Southwest Airlines, Spirit, JetBlue Airways, and Frontier, accounted for more than 31.9% of the domestic market.[8]

[6]Regression results provided in this section are all from industry-wide cost change with round-trip, firm-specific cost change and single-trip results are provided in Section 7.

[7]Global Air Transport Outlook to 2030 and trends to 2040 by ICAO.

[8]United States Department of Transportation, Bureau of Transportation Statistics, measured by domestic passenger miles, September 2020 to August 2021.

A legacy carrier is also known as a full-service or network carrier (Hazledine, 2011). Originally, legacy carriers referred, in particular, to the large carriers that began operations prior to the Airline Deregulation Act in 1978, which established a free market in commercial aviation in the U.S. As the industry has grown, the phrase "legacy carriers" has come to refer generally to large aviation groups who run the "hub-and-spoke" business model and provide full service to travellers.[9] The "hub-and-spoke" model connects minor destination airports using their hub airport, which is a central connection airport within a certain geographic area. The connecting flight passengers are required to change to a different aeroplane at the hub. Since they require a large airport as a connection, legacy carriers always rent the primary, newest or largest airport when there is more than one airport in that area. To connect all destinations to their hubs, legacy carriers normally run short-haul, medium-haul, and long-haul flights.

For example, American Airlines (AA) is a well-known legacy carrier with hubs in Charlotte, Chicago, Dallas/Fort Worth, London, Los Angeles, Miami, New York, Philadelphia, Phoenix, and Washington, D.C. If a passenger from Buffalo, New York wishes to fly with American Airlines to Detroit, Michigan, they must first fly to Chicago and then transfer to another flight bound for Detroit. This is because, for American Airlines, there are only five direct flight routes from Buffalo: Buffalo - Chicago, Buffalo - Dallas, Buffalo - Charlotte, Buffalo - Washington, D.C. and Buffalo - Philadelphia. These five cities are all hubs for American Airlines.

Most of the legacy carriers provide more than one class of seats and services on board. Delta Air Lines (DL), which is the second-largest airline group in the U.S. in 2019 and is also considered a legacy carrier company, may be used as an example.[10] Delta offers four different classes of service for most of its domestic and

[9] Definition source: Volaris Aviation Holding Company SEC 20-F filing.

[10] Based on the domestic market share of leading U.S. airlines from August 2019 to July 2020.

international flights: "Basic Economy", "Main Cabin", "Delta Comfort+", and "First Class". Additionally, two more comprehensive service classes are provided on selected long-haul international trips, namely "Delta Premium Select" and "Delta One", which provide more options for different types of travellers.[11]

Other notable features of legacy carriers include that to satisfy the needs of varied distances and types of flights, legacy carriers always hold multiple types of aircraft. Multiple types of frequent flyer programmes and relatively complicated mileage accumulation plans are another characteristic of most of the legacy carriers.

In contrast to legacy carriers, a low-cost carrier usually refers to a carrier running a "point-to-point" business network and focusing on short and medium-haul routes. "Point-to-point" companies are less likely to establish central transit hubs (Alderighi et al., 2007). Instead of routing passengers through their hub airports, they seek to deliver more nonstop flights directly from an origin to a destination.

Southwest Airlines (WN) is the largest low-cost carrier in the U.S. In 2019, 77% of its passengers took non-stop flights, and until the end of 2019, Southwest Airlines ran 704 non-stop city pairs.[12] Southwest Airlines serves nine nonstop destinations from Buffalo, including Baltimore, Denver, Ft. Lauderdale, Las Vegas, Orlando, Chicago, Phoenix, Ft. Myers, and Tampa. It has more direct flights between cities, indicating that "point-to-point" flights are preferred.

Since low-cost carriers are more concerned with efficiency, they frequently select secondary airports within a city to avoid wasting time due to congestion. For lower rental costs, old terminals are also better options compared with new ones. In addition, onboard service is normally abbreviated with no frills and lim-

[11]Delta Air Lines official website, on-board experience, https://www.delta.com/ca/en/onboard/overview.

[12]Southwest Airlines CO. 2019 annual report.

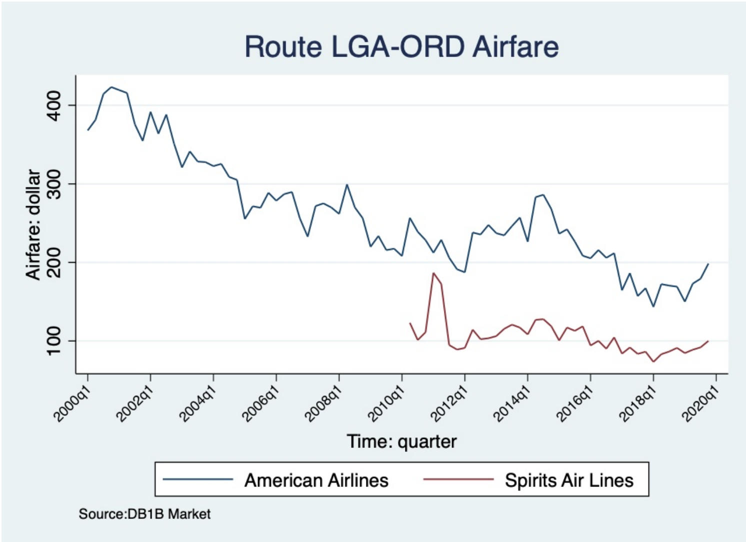
ited types of food and drink provided. The fare structure of low-cost carriers is also simple, especially for short-haul flights. To fit in more seats on one plane, most low-cost carriers do not offer first class and instead use Economy Plus to substitute the business seats. Southwest Airlines only has three categories of fare class: "Wanna Get Away", "Anytime" and "Business Select". These correspond to non-refundable economy class, refundable economy class, and business class, respectively. To reduce employee training and maintenance costs, low-cost carriers use homogeneous aircraft for the majority of their flights. The frequent flyer program is also relatively straightforward, and a low-cost carrier may even operate without any such program.

All of these disparities in business models between legacy carriers and low-cost carriers result in a large cost disparity. Low-cost carriers have the ability to offer 80% of the services provided by legacy carriers with only half of the total cost (Franke, 2004). Therefore, their target consumers are normally dissimilar to each other. Legacy carriers attract more business travellers through convenient connections and comprehensive services, while low-cost carriers' low-price strategy gives them a larger market share of price-sensitive customers.

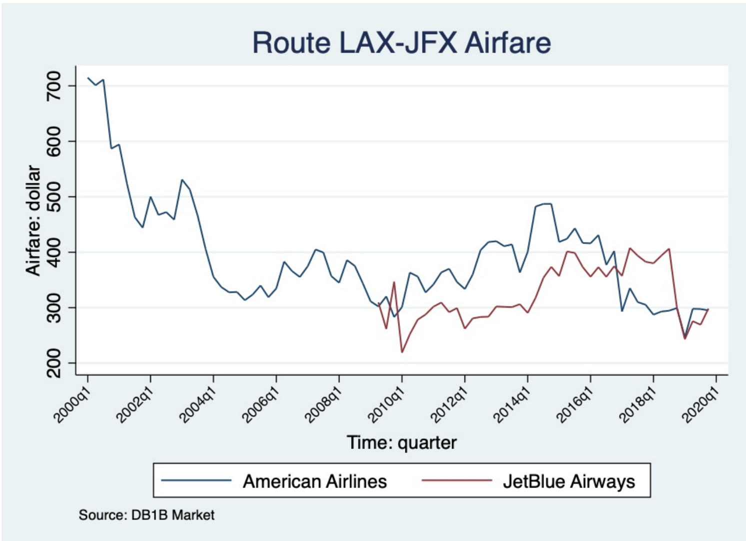
With the development of the aviation industry, a new category of airline companies with even lower costs than low-cost carriers, known as ultra-low-cost carriers (ULCCs), has emerged. In 2014, Frontier announced it was moving to an ultra-low-cost pricing initiative, and it was the first airline to announce it would run an ultra-low-cost business model. As low-cost carriers are increasingly getting into the long-haul market and are beginning to converge with the legacy carriers' business models, this causes the cost gap between these two categories of airline companies to shrink. However, the revenue-earning channel of ultra-low-cost carriers differs from the former two groups, as it is based on ancillary fees like on-board services and check-in baggage rather than flight ticket fare, resulting in a lower revenue level compared with the other two groups (Bachwich and Wittman, 2017). Since there are only four airlines that run an ultra-low-cost carrier business model in the U.S. (namely Allegiant, Frontier, Spirit, and Sun Country), the sample size is relatively small. Because of this, we focus mainly on the pass-through effect between legacy carriers and low-cost carriers.

In recent years, LCCs have relied on their price advantages to provide products that are differentiated from those of legacy airlines in the market, thus maintaining a relatively steady market share. According to market data, there is a significant price difference between the fares of low-cost airlines and the fares of legacy airlines. Figure 1 presents examples of two randomly selected markets in which both legacy carriers and LCCs are operating. In a short-haul market from LaGuardia Airport, New York (LGA) to O'Hare International Airport, Chicago (ORD), the average ticket price for the legacy carrier American Airlines (AA) is around \$200, while the price for the LCC, Spirits Air Lines (NK), is around \$100 (Figure 1(a)). American Airlines' airfare is 100% higher than Spirits'. Table 1 gives a random date (March 5, 2020) of price data for all four carriers who operate in this market. The pricing differences between legacy carriers and LCCs for single-trip and round-trip flights are enormous. Delta, American and United (all legacy carriers) single-trip airfares are 63%, 178% and 257% higher than Spirit's (low-cost carrier) airfare. The price differences for a round-trip are 110%, 174% and 77%, respectively. The same result can be found in the long-haul market; an example is from Los Angeles International Airport (LAX) to John F. Kennedy Airport, New York (JFK). The airfare trend for the two airlines is shown in Figure 1(b), and the random draw date prices are shown in Table 2, for which American Airlines is the legacy carrier, and JetBlue Airways is the representative for the LCC.

Figure 1: **Airfare differences between the legacy carriers and the LCCs**



(a) Route LGA-ORD Airfare



(b) Route LAX-JFK Airfare

Table 1: **LGA-ORD Ticket Price**

LaGuardia Airport, New York – O'Hare International Airport, Chicago		
	Single Trip (Mar.5 2020)	Round-trip (Mar.5-Mar.8 2020)
Spirit	$38	$125
Delta	$62	$263
American	$106	$343
United	$136	$222

Data source: Public ticketing website Travelocity[13]

Table 2: **LAX-JFK Ticket Price**

Los Angeles International Airport – John F. Kennedy International Airport, New York		
	Single Trip (Mar.5)	Round-trip (Mar.5-Mar.8)
JetBlue	$264	$567
Alaska	$264	$567
American	$311	$614
United	$795	$1,098

Data source: Public ticketing website Travelocity[14]

The price of jet fuel is mainly determined by market supply. International economic and political patterns result in fluctuating oil prices. For example, the price of jet fuel in the fourth quarter of 2019 was below 200 cents per gallon, which is roughly half the level in 2014 (Figure 2). Since all costs except fuel costs are fixed costs in the short term for airline companies, changes in fuel prices have become an important factor affecting changes in airfare, which is why it is the main consideration in our research.

[13]https://www.travelocity.ca.
[14]https://www.travelocity.ca.

Figure 2: **Jet Fuel Price**

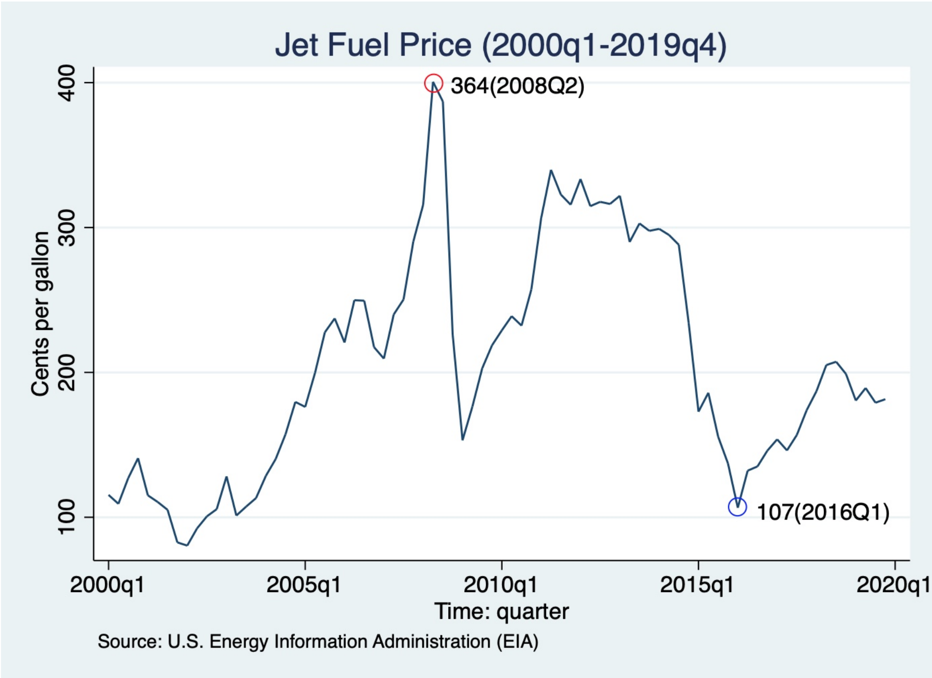


Figure 3: **Airfare and jet fuel price percentage change, LGA-ORD**

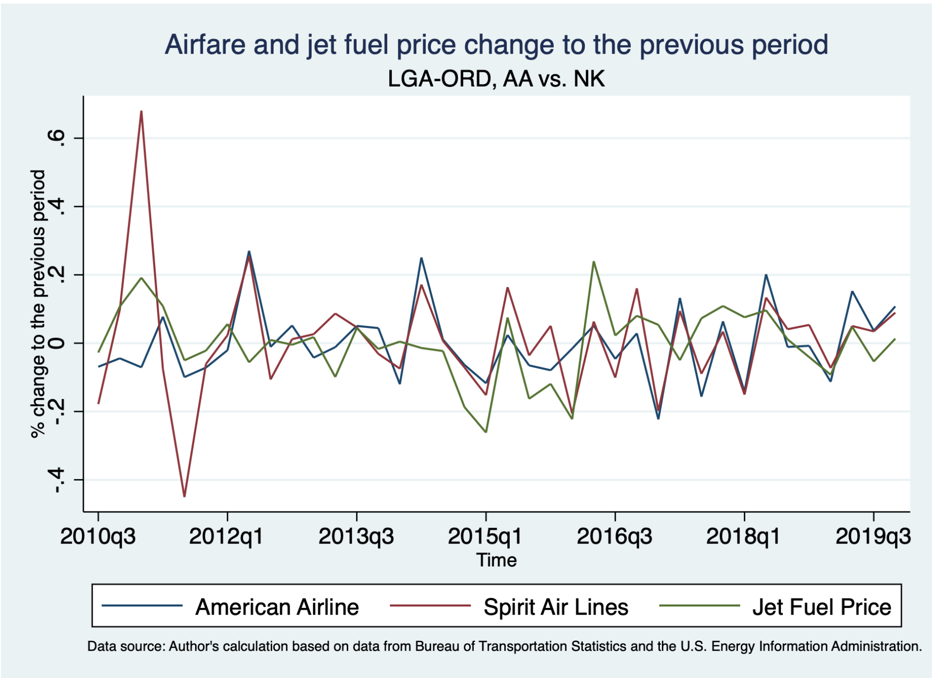
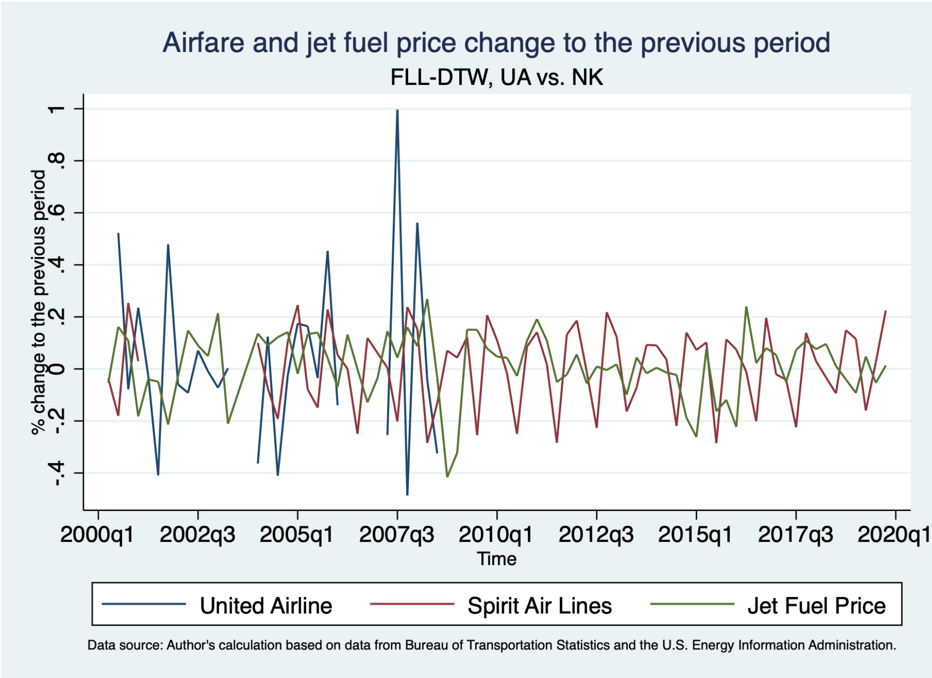


Figure 4: **Airfare and jet fuel price percentage change, FLL-DTW**



To illustrate the relationship between changes in oil prices and changes in flight fares, we take two random routes from our dataset as examples. The first route is from LaGuardia Airport, New York (LGA) to O'Hare International Airport, Chicago (ORD), operated by American Airlines (legacy carrier) and Spirit Airlines (low-cost carrier). The second route is from Fort Lauderdale-Hollywood International Airport, Broward County, Florida (FLL) to Detroit Metropolitan Wayne County Airport, Wayne County, Michigan (DTW) operated by United Airlines (legacy carrier) and Spirit Airlines (low-cost carrier). The airfare change and jet fuel price change from the previous period are shown in Figures 3 and 4, respectively. From both figures, we have similar trends in ticket prices between the two types of airlines. There is no significant difference in the magnitude of the airfare change between American Airlines and Spirit Airlines in Figure 3. According to DB1B statistics, in the 38 quarters that both carriers operate on this route, there are 26 quarters where the low-cost carrier has a larger magnitude of airfare change. Figure 4, on the other hand, demonstrates the opposite result. In the 24 quarters in which both United Airlines and Spirit Airlines operate in FLL-DTW, there are only eight quarters where the low-cost carrier has a higher percentage change in airfare than the legacy carrier. From the two figures, we can observe that oil price changes and airfare changes have a strong correlation. Yet, because of the randomness of the routes chosen, we cannot draw a conclusion about which type of carrier's airfare is more affected by jet fuel price fluctuations. In the following discussion, we will introduce more rigorous econometric models to explore this problem.

3 Literature Review

3.1 Cost pass-through effect

The focus of our research is the cost pass-through of the aviation industry. A number of empirical and theoretical studies have been conducted to investigate the cost pass-through effect. In general, the cost pass-through rates vary among industries due to the diversity of industry market structures, cost structures, and the sources of cost changes. The range of pass-through rates can vary from 0 to over 100%.

According to Walters et al. (2014), the pass-through effect is more significant when an industry-wide cost adjustment occurs rather than a cost change at a single firm. With the same degree of substitutability between products and the same number of companies in the market, the pass-through caused by industry-wide cost change is higher than the pass-through caused by firm-specific cost change, at roughly 9% to 30%. Furthermore, in a competitive market, the pass-through rate is also influenced by the relative elasticity of demand and supply, the curvature of the demand curve, and the slope of the marginal cost curve. To be more specific, a more elastic demand, with a less elastic supply market, will show a smaller pass-through rate, ceteris paribus. The reason is that under more elastic demand with less elastic supply, consumers are more sensitive to the price and will more easily switch to other suppliers. In the opposite extreme case, where perfectly inelastic demand is combined with perfectly elastic supply, the result will be a unit pass-through (Frontier Economics, 2006), which means the supplier can pass all its cost increases to final consumers. Also, both a concave demand curve and an upward-sloping marginal cost can generate a smaller pass-through. Market structure, on the other hand, has an essential impact, as a less concentrated market has a higher pass-through rate than a more concentrated market (Ritz, 2019).

In several disciplines, including international trade, public finance, and industrial organization, cost pass-through is regularly studied in empirical papers.

In the field of international trade, Goldberg and Knetter (1996) elaborated on how variations in the exchange rates affect the traded goods' final prices during the process of import and export and found an incomplete pass-through because some of the effects are cancelled out by destination-specific adjustments of markups over cost. Campa and Goldberg (2005) find that due to the diversity of monetary and exchange rate policies, the pass-through of exchange rates into import prices among OECD countries ranges from 46% in the short run to 64% in the long run. For example, the U.S. has a lower pass-through rate compared to other OECD countries, varying from 25% in the short run to 40% in the long run, whereas Germany has a higher pass-through, ranging from 60% to 80%.

In the realm of public finance, processing tax is always the most important cost factor that may be passed on to the final consumers. Seiler et al. (2019) find that there is almost a full "soda tax" pass-through on the retail price of sweetened beverages.[15] When considering the tax on diesel, the pass-through rate depends on the position of the tax in the industry chain. When taxed at the bulk terminal, which is the first procedure after the refinery factories, it reaches the greatest level (Kopczuk et al., 2016).

Cost volatility is the major cause of the final price changes in the sphere of industrial organization. Miller et al. (2017) use data from the U.S. Portland cement industry, which is a concentrated industry, and find that industry-wide cost changes are more than fully passed-through to cement prices and authenticate that competition reduces pass-through under the same conditions. In the electricity market, Fabra and Reguant (2014) discovered that a one-unit shock on emissions cost would lead the wholesale price of electricity to change by 0.8 units in general. When separating the data into peak-hours and non-peak-hours, the results of the emissions cost pass-through are 1 and 0.6 units, respectively.

From the different industries' empirical results, it can be deduced that cost pass-through depends not only on the demand and supply elasticities of an industry, but also on its cost structure. The percentage ranges from 0% to over 100%. Macroeconomic variables disturbances such as interest rates, tax rates, and global fuel refiner price changes play an important role in the product cost structure, which could lead to final price fluctuations. The relatively high proportion of jet fuel costs in an airline company's operating costs along with the frequent fluctuations in the worldwide oil price, merit an in-depth discussion in the following subsection.

3.2 The commercial aviation industry

There is some consensus in the literature that a majority of commercial aviation markets follow an oligopoly market structure with differentiated products. Both

[15] Soda tax is the tax applied on sugar or artificial sweetener-added beverages.

Koopmans and Lieshout (2016) and Walters (2014) find that firm-specific cost adjustments result in a lower pass-through rate (less than 50%) compared with industry-level cost changes (higher than 50%).

For the U.S. commercial aviation market, Duplantis (2011) discovered that when the capacity of the airline is flexible and can adjust according to the firm's strategy, the airline companies have the ability to transfer unit cost changes to the consumer. However, if the capacity is invariant, the pass-through rate is close to zero. Shi (2017) has more specific results on the pass-through rate, asserting that a 10% increase in the fuel cost will boost the final airfare by 1.2% in the same quarter and will cause a continuous effect for the following four quarters, with a total effect for the next four quarters adding up to 1.7%. Gayle and Lin (2021) confirm a positive pass-through from crude oil prices to airfare prices, and they show that there is a higher pass-through rate when the market is more competitive. Empirical studies for the European market show that when the cost changes come from the CO_2 emission allowance (European Union Emission Trading Scheme), it causes almost a unit pass-through (Toru, 2010).

There is also research that compares the operations of legacy carriers and LCCs. When the economy is in a slump, LCCs are stronger due to their flexible cost structure (Franke, 2004). Gillen and Lall (2004) use Southwest, Ryanair, and EasyJet to verify that the low-cost carrier business model, particularly the Southwest model, is difficult to duplicate by other carriers due to the source of their advantage. The uniqueness of the low-cost model makes the conversion from legacy carriers to low-cost carriers hard to implement (Daraban, 2012).

Considering the move into a new market, empirical evidence demonstrates that when LCCs start their business on a route where legacy carriers already operate, the airfare is dragged down even if the LCCs only account for a small market share (Ito and Lee, 2003; Hofer et al., 2008). Bachwich and Wittman (2017) find that ultra-low-cost carriers dragged the average airfare down more than low-cost carriers. In markets in which both low-cost carriers and legacy carriers operate, the LCC can reduce airfare by 7.7%, while the ULCC can reduce it by 20.5%.

Existing studies on the aviation industry pass-through base their findings on the entire aviation industry (Shi, 2017; Gayle and Lin, 2021). However, due to the difference in business structure and cost structure, different types of airlines could also have different strategies when they encounter rising costs. It is worth noting that the existing studies on legacy airlines and LCCs mostly compare their differences from a qualitative perspective or from the perspective of the threat of LCCs to legacy airlines (Frank, 2004; Ito and Lee, 2003; Gillen and Lall, 2004). They do not address the cost pass-through differences between the two categories of carriers. Our paper will fill these gaps by analyzing the empirical results of jet fuel cost pass-through for legacy carriers and LCCs.

4 Pass-through in the commercial aviation industry

The cost pass-through can be determined on a per-unit or per-percentage basis. Absolute pass-through is the amount of price increase in a currency unit when the cost increases by 1 unit of currency. For instance, in the civil aviation industry, the absolute jet fuel cost pass-through is measured as the increase in airfare (e.g., \$0.20) when the jet fuel price increases by \$1. Likewise, pass-through elasticity is the percentage increase in the final price (e.g., 0.2%) when the price of jet fuel increases by 1%.

The extent of the cost pass-through depends on many factors, including industry characteristics, market structure, the origin of the cost increase, the market's supply elasticity, the company's supply elasticity, the product's demand elasticity, and the company's cost structure, among others.

When facing a perfectly competitive market, the price is equal to the marginal cost. If a firm-specific cost changes due to the pricing mechanism of a perfectly competitive market, that firm cannot change the industry-wide product price. Therefore, it will stop producing when the marginal cost is higher than the market price, which generates zero pass-through (Bulow and Pfleiderer, 1983). When the entire industry faces growing costs, under perfectly elastic supply or perfectly inelastic demand, producers have the ability to pass the entire cost increase to the final consumers, which generates a unit pass-through (Zimmerman and Carlson, 2010). In other non-extreme scenarios with positive slope supply and negative slope demand, the pass-through rate will be less than one (Walters, 2014).

Another extreme scenario is a monopolistic market, in which case the pass-through rate is equal to 0.5 if the company has a constant marginal cost and linear demand because the slope of demand is half the slope of the marginal revenue curve. The pass-through rate varies as the form of the demand curve changes. Concave demand curves will generate a pass-through rate higher than 0.5, while a convex demand curve will have a rate of less than 0.5 (Walters, 2014).

Ten Kate and Niels (2005) examine the situation of an oligopoly market with Cournot competition. Under the assumptions of a homogeneous product, linear demand, and equal-sized firms, the pass-through rate depends on the number of firms in the market. For a market with N firms, the pass-through for firm-specific cost change and industry-wide cost change is $\frac{1}{N+1}$ and $\frac{N}{N+1}$, respectively. When generalizing the model to differentiated products, the pass-through starts to converge to the monopoly level and depends on the market structure. When companies are in an oligopoly market and competing in prices, cost pass-through varies from 0 to 100% depending on the degree of differentiation between products (Zimmerman and Carlson, 2010).

The civil aviation industry is a special industry that is difficult to categorize into the market segments listed above. For the aviation industry, many of the market structures can be observed at the same time. From our dataset, the number of carriers operating from an origin to a destination is between 1 and 14. If there is a new route or short-haul route, there may be only one service provider in the market, making the carrier a monopolist. For some popular and busy routes, there are normally more than eight or ten carriers, which makes it a more competitive market. The majority of airline routes are served by three to five carriers, which makes the market an oligopoly. Due to the small profit margins and considerable fixed costs, the majority of carriers maintain strong pricing rigidity (Ciliberto et al., 2019).

5 Data

The major data source we use in this paper is administrative data from the Airline Origin and Destination Survey (DB1B), which is collected by the Office of Airline Information of the Bureau of Transportation Statistics (BTS). It encompasses a 10% sample of airline tickets dataset from reporting carriers. DB1B consists of three sub-datasets: DB1B Coupon, DB1B Market, and DB1B Ticket. DB1B Coupon provides coupon-specific information for each domestic itinerary of the Origin and Destination Survey, such as the operating carrier, origin and destination airports, number of passengers, fare class, coupon type, trip break indicator, and distance. DB1B Market contains directional market characteristics of each domestic itinerary of the Origin and Destination Survey, such as the reporting carrier, origin and destination airport, prorated market fare, number of market coupons, market miles flown, and carrier change indicators. DB1B Ticket provides information on summary characteristics of each domestic itinerary on the Origin and Destination Survey, including the reporting carrier, itinerary fare, number of passengers, originating airport, roundtrip indicator, and miles flown. The time interval used in this paper is from the first quarter of 2000 to the fourth quarter of 2019. The relatively long time provides us with enough variation to investigate the pass-through effects of changes in fuel prices across different types of airline market structures.

The links between these three datasets are shown in Figure 5. Every ticket has a unique identifier (ItinID) for any specific year, which allows one to connect all three datasets. For instance, ItinID 20001214 is a piece of data information that is common for DBIB Ticket and DB1B Market datasets. In the DB1B Market, this ticket is comprised of two markets of flight, which are indicated by unique MktID 20001373 (ABQ-ACT) and MktID 20001374 (ACT-ABQ).[16] Then ItinID and MktID are used to track every single coupon in the DB1B Coupon dataset. MktID 20001373 contains two segments of a flight, ABQ-DFW and DFW-ABQ, and MktID 20001374 also contains two segments of a flight, ACT-DFW and DFW-ACT.[17] The DB1B dataset then provides detailed information for any single trip, which allows us to obtain precise information at the micro level.

To indicate the frequent routes, we also make use of a different information set, the T-100 Domestic Segment dataset, which gives administrative information on domestic non-stop segment data reported by U.S. air carriers, including carrier, origin, destination, available capacity, scheduled departures, and transported passengers. We use T-100 to provide monthly seats and carried passengers to generate quarterly seats and carried passengers for each route.

First, following Ciliberto and Tamer (2009), we merge DB1B Coupon with T-100 Domestic Segment dataset and restrict the frequent flights by having more

[16] ABQ: Albuquerque International Sunport, New Mexico; ACT: Waco Regional Airport, Texas.

[17] DFW: Dallas/Fort Worth International Airport, Texas.

Figure 5: **DB1B dataset relation example**

DB1B Ticket

ItinID	Coupons	Year	Quarter	Origin	OriginAirportID	OriginAirportSeqID	OriginCityMarketID	OriginCountry	OriginStateFips
20001214	4	2000	1	ABQ	10140	1014001	30140	US	35

DB1B Market

ItinID	MktID	MktCoupons	Year	Quarter	OriginAirportID	OriginAirportSeqID	OriginCityMarketID	OriginCountry	OriginStateFips
20001214	20001373	2	2000	1	10140	1014001	30140	ABQ	US
20001214	20001374	2	2000	1	10155	1015501	30155	ACT	US

DB1B Coupon

ItinID	MktID	SeqNum	Coupons	Year	OriginAirportID	OriginAirportSeqID	OriginCityMarketID	Quarter	Origin
20001214	20001373	1	4	2000	10140	1014001	30140	1	ABQ
20001214	20001373	2	4	2000	11298	1129802	30194	1	DFW
20001214	20001374	3	4	2000	10155	1015501	30155	1	ACT
20001214	20001374	4	4	2000	11298	1129802	30194	1	DFW

than 30 seats, and all of the flights travel with more than 15 passengers (to remove the impact of temporary routes) in one quarter to generate a reduced Coupon dataset, by doing so we drop the irregular flights.[18]

We merge the reduced DB1B Coupon dataset, which only includes regular flights, along with the DB1B Market and DB1B Ticket datasets to construct the final estimation dataset. To avoid outliers like mileage points redemption tickets, we delete tickets with airfares of less than \$50. To eliminate seat class influence, we only keep economy class for the empirical analysis. Since the division of fare class varies from carrier to carrier, we set the highest airfare to \$2000 for U.S. domestic flights to reduce the disparities. Only trips of fewer than six segments are taken into consideration. Other data decision processes include: (1) maintaining domestic (Lower 48 U.S. states) flights only; (2) keeping the flights for which the ticketing carrier is identical to the operating carrier only; (3) keeping credible airfare value tickets only.[19]

For jet fuel cost, we collect the data from both firm-specific and industry levels. Firm-specific fuel costs and gallons of fuel consumed data come from the BTS Air Carrier Financial Schedule P-12(a), which is reported by carriers monthly. The

[18]Flights with less than 30 seats per quarter account for 0.006% of total flights and flights carrying fewer than 15 passengers per quarter account for 0.08% of total flights.

[19]Detailed process of data decisions are shown in Appendix C.

BTS Air Carrier Financial Schedule P-12(a) provides statistics on fuel costs and gallons of fuel utilized by air carriers and the category of fuel use (domestic and international) for both scheduled and non-scheduled service. We use these monthly data to generate the quarterly fuel cost. Jet fuel refiner price to end-users, at the industry level, is from the U.S. Energy Information Administration (EIA), which provides quarterly jet fuel refiner prices to end-users from the first quarter of 1990.[20]

Other carriers' operating costs information is collected from the BTS Air Carrier Financial Schedule P-6. These data contain quarterly operating expenses, by objective grouping, for carriers with annual operating revenues of $20 million or more. The operating costs reported in this dataset include salaries, related fringe benefits, materials purchased, services purchased, landing fees, rentals, depreciation, amortization, and other operating expenses.

Data on the origin and destination city population sizes are collected from the United States Census Bureau Population and Housing Unit Estimates Program (PEP). Since the population census is conducted every ten years, only statistics for the years 2000 and 2010 are from the decennial census. For the remaining years, we use the estimated population sizes from the most recent decennial census for city, town and county. The strength of these data is that they supplement the data for the years without the census. However owing to the long time interval between censuses and the assumptions on which the estimate is based, there is an estimation error during the process. Since the actual size of the population is determined by the actual birth rate, mortality rate, and population migration, the deviation of the projections of these indicators may lead to a deviation in the estimation of the population.

Other data sources include the International Civil Aviation Organization

[20] http://api.eia.gov/series/?api_key=YOUR_API_KEY_HERE&series_id=STEO.JKTCUUS.Q.

(ICAO), which provides the list of low-cost carriers based on the ICAO definition, and the listed carriers' U.S. Securities and Exchange Commission (SEC) filing (10-Q, 10-K).[21][22]

6 Methodology

For testing whether a legacy carrier or a low-cost carrier has more ability to pass the fuel cost increase on to consumers, our empirical model takes the following form:

$$\begin{aligned} lnairfare_{ijt} = \alpha + \beta_0 lnFuelPrice_{it} + \sum_{k=1}^{3} \beta_k (lag_k lnFuelPrice_{it}) \\ +\gamma_0 lnFuelPrice_{it} * LCC_i + \sum_{k=1}^{3} \gamma_k (lag_k lnFuelPrice_{it}) * LCC_i \\ +[\delta X_{ijt} + \eta Y_{it} + \rho Z_{jt}] + \phi_i + \theta_t + \epsilon_{ijt} \end{aligned} \tag{1}$$

where i denotes the carrier, j denotes the market, t denotes time, and θ_t captures the year-quarter fixed effect.

We define the variable 'market' to the paired origin and destination route. For example, BOS-AUS (Boston Logan International Airport to Austin-Bergstrom International Airport) indicates one 'market', while AUS-BOS indicates a different market. For round-trip, we define "A-B, B-A" as a market, and this is distinguished from "B-A, A-B". The variable 'product' is defined by a flight operated by a specific carrier in a given 'market'. For instance, route BOS-AUS operated by American Airlines is a 'product', while route BOS-AUS operated by Southwest Airlines constitutes another 'product'.

[21] http://www.icao.int/sustainability/Pages/GATO2030.aspx.

[22] https://www.sec.gov/edgar.shtml.

We focus on airfare as the dependent variable. A product airfare is generated by the average ticket price of that product in a specific quarter t. The determinants of airfare normally include components such as the carrier's cost, the distance of travel, market competition, the convenience of the flight, and other factors (Shi, 2017).

$FuelPrice$ is the fuel cost variable, which can take two forms. When $FuelPrice$ takes the value of $JetFuelPrice$, it reflects the industry-wide refiner jet fuel price to the final consumers, while when $FuelPrice$ takes the value of $averagetotalcost$, it provides the firm-specific fuel consumption cost information.

The parameters we focus on are γ_0 and γ_k. When adopting a log-log specification, γ_0 represents the pass-through elasticity difference between legacy carriers and low-cost carriers for that quarter. γ_k shows whether there is an extension effect of the difference over the next three quarters when all other conditions are kept equal. We use three lags of the fuel cost data since some of the aviation companies use a hedging contract to lock in the jet fuel price for the next quarter or several quarters.[23] Normally, the hedge contract is used to hedge the next quarter's to next year's fuel consumption cost, and the contract is typically less than one year in length.

Whether the flight is operated by a legacy carrier or a low-cost carrier would also affect the airfare. To estimate the difference in jet fuel cost pass-through between legacy carriers and low-cost carriers, we generate a dummy variable LCC that equals 1 if the carrier is classified as a low-cost carrier by ICAO. It includes 11 LCCs in our dataset: JetBlue Airways, Independence Air, Frontier Airlines, AirTran Airways, Allegiant Air, Spirit Airlines, Sun Country Airlines, ATA Airlines, Mesa Airlines, Virgin America, and Southwest Airlines. LCC equals 0, indicating the carrier is one of the legacy carriers, which are Delta Airlines, American Airlines,

[23]The main results with different numbers of lag are shown in the Appendix Table D.33.

United Airlines, Northwest Airlines, Envoy Air, ExpressJet Airlines, US Airways, SkyWest Airlines, Continental Airlines, Endeavor Air, PSA Airlines, ExpressJet Airlines, America West Airlines, Horizon Air, and Air Wisconsin Airlines.

In the second part of our study, to verify whether the reactions of a low-cost carrier and an ultra-low-cost carrier are the same when facing rising aircraft oil prices, we regenerate three dummy variables, which are *Legacy carrier*, $LCC2$ and $ULCC$ to reflect the category of carriers. *Legacy carrier* equals one if the carrier is categorized as a legacy carrier and zero otherwise. $LCC2$ equals one if the carrier is classified as a low-cost carrier by ICAO and is not one of Spirit Airlines (NK), Allegiant Air (G4), Frontier Airlines (F9), or Sun Country Airlines (SY), and equals 0 otherwise. $ULCC$ equals one if the carrier is one of Spirit Airlines (NK), Allegiant Air (G4), Frontier Airlines (F9), or Sun Country Airlines (SY), and 0 otherwise. *Legacy carrier* is considered as the reference group in our regression.

Other independent variables that capture carriers, routes and time controls include salaries and benefits, flight distance group, market concentration indicator (HHI), merger and acquisition, bankruptcy, and whether the flight is convenient, as specified below. These variables are used to capture route and carrier effects.

The operating costs of the civil aviation industry include salaries and benefits, material costs, service costs, landing fees, rental costs, and depreciation and amortization costs. For most airline companies, salaries and benefits account for more than 25% of their operating costs and are either the largest or the second-largest operating cost component. As a result, we expect them to have an impact on airfare prices.

The airfare also depends on the distance of the travel. Normally, the farther the distance, the higher the airfare. *Distance group* is the variable we use to denote the flight flown distance. It is grouped by 500 miles and equals 1 if the flight is less than 500 miles, equals 2, indicating 500 to 999 miles of flight, equals 3, indicating 1000 to 1499 miles flight, and so on. The largest value is 10, which indicates the distance of flight is between 4500 and 4999 miles.

The market structure is represented by HHI, which ranges from 0 to 1. HHI is calculated by

$$HHI_{jt} = \sum (market\ share_{jt})^2 \tag{2}$$

where

$$market\ share_{ijt} = \frac{Passengers\ one\ airline\ carries_{ijt}}{market\ size_{jt}} \tag{3}$$

and $market\ size_{jt} = \sum Passengers\ carried\ by\ all\ airlines_{ijt}$. The data on passengers are from T-100. The higher the HHI, the more concentrated the market is. When a market has a high level of concentration, it has a small number of airlines operating in it (normally less than three). Airlines in high-concentration markets have more negotiating power and operate as oligopolies or duopolies, allowing them to charge a higher price than those in low-concentration markets or markets with robust competition. We predict that HHI will have a positive relationship with airfare.

Special events like mergers and acquisitions or filing for bankruptcy can also influence the operation of an airline company, thereby affecting the airfare. These kinds of events are often due to poor management or strategic adjustment; during these periods, carriers always lower the airfare. 'Merge' is a binary variable, which equals 1 if the quarter is during the period from the announcement of a merger and acquisition information to the trade closure, and equals 0 otherwise.[24] 'Bankruptcy' is also a binary variable that equals 1 to indicate the quarter when the carrier is going through bankruptcy, otherwise it equals 0.[25]

Whether the flight is convenient is also an important element that determines

[24] Airlines for America (A4A).

[25] Airlines for America (A4A).

the airfare. We generate the variable *inconvenience* (Gayle and Lin, 2021) by dividing the actual market miles flown by market nonstop miles to mirror the inconvenience of one product. The higher the *inconvenience*, the longer the flight would take or the more stops between the origin and the destination. For example, in the fourth quarter of 2019, the *inconvenience* of flight FLL-DTW (from Fort Lauderdale-Hollywood International Airport, Broward County, Florida to Detroit Metropolitan Wayne County Airport, Wayne County, Michigan) operated by American Airlines is around 1, indicating that the nonstop distance between these two airports equals the actual miles flown by American Airlines aircraft. In the same quarter, the *inconvenience* of FLL-DTW operated by Spirits Airlines is 1.7, which could be because it has a transit stop or is using a relatively further distance flight path.

For our econometric model, there are three potential econometric problems, endogeneity, autocorrelation, and group-wise heteroscedasticity.

Following Davis (2005), Bilotkach and Pai (2016), Gerardi and Shapiro (2009) and Shi (2017), HHI is always seen as an endogenous variable in the analysis of the airline industry since HHI measures market concentration, which is highly related to the pricing mechanism. To test the endogeneity of the variable HHI, we use the Durbin and Wu-Hausman test, and the p-value of the test equals 0, which rejects the null hypothesis that HHI is an exogenous independent variable. To solve this problem, we use the IV approach. Following Davis (2005), Bilotkach and Pai (2016), and Gerardi and Shapiro (2009), we use lagged HHI, a geometric average of the population between origin and destination cities, and an arithmetic average GDP between origin and destination cities as instrumental variables. Since HHI is an indicator of market concentration. Due to the high cost of exiting the aviation market, the airline industry has a relatively stable market structure over short time periods. Furthermore, the level of competition in the individual market from the preceding period typically continues, indicating that changes in the HHI may not occur frequently. Using the lagged HHI reduces the likelihood that it is correlated with any disturbances or factors captured in the error term. Population and GDP reflect the demands of the market, which affect airfares. The regression results of first stage estimation are shown in Appendix Tables D.19 - D.26.

Since we use quarterly data, there is a potential serial correlation because the level of a variable such as airfare affects its future level. The p-value of the Wooldridge test for autocorrelation in panel data equals 0, rejecting the null hypothesis of no first-order autocorrelation. Although the OLS estimator is unbiased, the estimator of standard errors is usually underestimated, which would overestimate the t-value and make insignificant results significant. OLS estimation ignores the information contained in the disturbance serial correlation, so it is not the most effective estimation method. We use the standard AR(1) disturbance approach to correct this potential problem. Due to the difficulty of interpreting the dynamic effect, we also introduce the dependent variable as one of the explanatory variables to correct the potential serial correlation.

Our model may not include all the variables that would have an influence on airfare, which could lead to heteroscedasticity. For example, the rental cost of aircraft and airport gates would also affect airfare, and these costs depend on both the company's negotiating power and business strategy. Since these costs do not account for a large share of an airline company's operating costs, we do not include them in our model. The absence of these explanatory variables could lead to heteroscedasticity. And since our data range from 2000 to 2019, varying degrees of financial crises and macroeconomic policy changes can also lead to changes in random influencing factors. According to the data's properties and the results of the modified Wald test for group-wise heteroscedasticity, there is heteroscedasticity in the data.[26] Standard errors are then clustered at the product level to deal with this problem.

7 Results

7.1 Summary statistics

In this section, we are going to test whether a legacy carrier or a low-cost carrier has more ability to pass the fuel cost increase on to consumers. The summary statistics of variables used in the regressions are listed in Table 3 with all price variables adjusted for inflation.[27] The airfare in the database for a round-trip treats two parts of the trip as a whole, while some of the studies evenly distributed the ticket price to both segments and mixed them with single-trip data. Since in reality, A-B airfare is normally different from B-A airfare, to be more accurate, we distinguished round-trip data from single-trip data. Because round-trip tickets account for a larger proportion of the database, we present round-trip travel summary statistics and regression results in the main text, while corresponding summary statistics and regression results for single-trip tickets are shown in the Appendix. The summary statistics for legacy carriers and LCCs are also shown separately in Appendix Table D.1.

From Table 3, the mean value of airfare of all products is \$245.71. The industry-wide jet fuel price ranges from \$0.8 per gallon to \$4.01 per gallon and the firm-specific average total jet fuel cost ranges from \$0.64 per gallon to \$11.75 per gallon, which is much wider than the industry-wide jet fuel price. In our round-trip data, low-cost carriers' products account for 20% of total products. The mean

[26] The p-value of the test is zero, and the null hypothesis of the test is homoscedasticity. Thus we conclude that our data have heteroscedasticity.

[27] CPI data are from the Federal Reserve Bank of St. Louis, quarterly data, Index 2015=100, seasonally adjusted.

value of HHI is 0.57. A market with an HHI greater than 0.25 is considered highly concentrated by the U.S. Department of Justice. This demonstrates that the majority of the airline markets are highly concentrated and can be classified as oligopolies. The mean of the inconvenience indicator is 1.2 with a standard deviation of 0.28, which means the majority of the airline products' actual flown miles are approximately equal to the market's straight-line non-stop distance.

Table 3: **Summary Statistics, Round-trip**

Variable	Mean	Std. Dev.	Min	Max
Airfare	245.71	90.89	45.96	2,595.89
JetFuelPrice	2.04	0.78	0.80	4.01
Avetotalcost	2.11	0.88	0.64	11.75
Salaries	821,555.60	667,724.70	1,489.09	2,302,571.00
LCC	0.20	0.40	0.00	1.00
Distance group	3.09	1.38	1.00	10.00
HHI	0.57	0.32	0.10	1.00
Merge_aqui	0.05	0.21	0.00	1.00
Bankruptcy	0.01	0.10	0.00	1.00
Inconveniece	1.20	0.28	0.96	3.68
GDP(million USD)	161.20	184.95	0.15	1380.23
N	3,300,297			
Market	57,430			
Product	220,888			

Data source: Author's calculation based on U.S. BTS DB1B data.

7.2 Legacy carriers and low-cost carriers

All of our regression results tables are organized as follows: Column (1) provides the baseline results, while Column (2) includes the lag of the dependent variable on the right-hand side of the estimated model to deal with serial correlation. Column (3) provides the point estimates under the alternative AR(1) approach, while Column (4) displays the AR(1) regression results after instrumenting the HHI variable.

Table 4 provides the regression results using the industry-wide jet fuel refiner price to end-users as the fuel cost variable.[28][29] From the benchmark regression in Column (1), the same quarter industry-wide jet fuel cost pass-through is 0.167% when facing a 10% increase in the jet fuel price. And the cumulative effect of all four quarters adds up to 0.559%. When industry-wide jet fuel cost rises by 10%, a low-cost carrier will increase airfare by 0.334% in the same quarter, which is double the legacy carrier's number. All four quarters' pass-through is at 1.28%. All of the preceding results are statistically significant at 1%.

[28]The baseline regression results without controls for industry-wide cost change and firm-specific cost change are shown in Appendix Tables D.4 and D.5.

[29]To capture the dynamic price adjustment of airfare and account for the persistence ofpricing, we also show the results with three lags of airfare ($\sum \lambda_m lag_m(airfare_{ij(t-m)})$, where m is the number of lags) on the right-hand side of (1) in Table D.31 and D.32. The AIC and BIC criterions show that include three lags of airfare is the best number of lags.

Table 4: **Regression results for round-trip (Industry-wide cost, Legacy vs. LCC)**

	(1)	(2)	(3)	(4)
lnJetFuelPrice	0.0167***	0.0275***	0.0179***	0.0172***
	[0.00161]	[0.00164]	[0.00159]	[0.00161]
lnJFPlag1	0.0564***	0.0370***	-0.00996***	0.0557***
	[0.00200]	[0.00228]	[0.00192]	[0.00200]
lnJFPlag2	0.0292***	0.00829***	0.0129***	0.0301***
	[0.00181]	[0.00209]	[0.00168]	[0.00182]
lnJFPlag3	-0.0464***	-0.0402***	0.0398***	-0.0467***
	[0.00145]	[0.00151]	[0.00144]	[0.00146]
lnJFP*LCC	0.0167***	0.0122***	-0.0461***	0.0179***
	[0.00225]	[0.00207]	[0.00256]	[0.00227]
lnJFPlag1*LCC	0.0236***	0.0230***	-0.00206	0.0256***
	[0.00270]	[0.00299]	[0.00333]	[0.00269]
lnJFPlag2*LCC	-0.0211***	-0.0237***	0.0174***	-0.0256***
	[0.00284]	[0.00313]	[0.00332]	[0.00288]
lnJFPlag3*LCC	0.0529***	0.0381***	-0.0484***	0.0538***
	[0.00242]	[0.00217]	[0.00253]	[0.00245]
N	2,177,590	2,177,590	2,078,771	2,141,757
Time FE	Y	Y	Y	Y
IV	N	N	N	Y

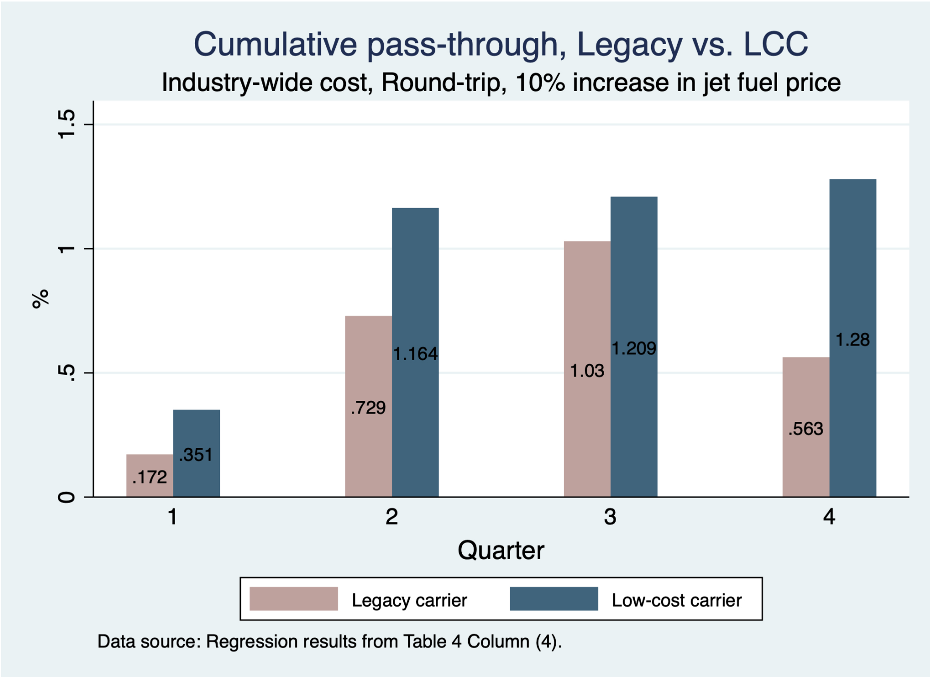
Notes: The dependent variable is the natural logarithm of airfare; Column (4) regression uses the IV approach, first-stage result is shown in Appendix Table D.19; Control variables include wage cost, route distance group, HHI, merger and acquisition condition, bankruptcy condition, inconvenience; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%; Complete regression results are shown in the Appendix Table D.15.

In Columns (2) and (3), we address the potential serial correlation problem by including the dependent variable's lag as an explanatory variable and the AR(1) disturbance. When we employ the lag of the dependent variable as an explanatory variable, the results (Column (2)) do not change much, with estimated parameters' signs unchanged and a smaller magnitude of pass-through compared with benchmark results. When using the AR(1) disturbance method instead, we have similar results for legacy carriers. However, the sign of $lnJFP * LCC$ is negative and the cumulative pass-through for four quarters is also negative, which is the opposite of our benchmark results. Whether a lagged dependent variable or AR(1) produces more robust results is determined by the data structure and properties of the dependent variable (Beck and Katz, 2011).[30] Since we cannot determine the speed of adjustment of the dependent variable, we cannot draw conclusions about which regression gives more accurate results.

The IV approach along with AR(1) results are shown in Column (4). When the fuel cost change is industry-wide, a 10% jet fuel price increase, ceteris paribus, would lead to a legacy carrier airfare raise of 0.172% in the same quarter, with a total influence of 0.563% across all four quarters. The parameters we are mostly interested in are the parameters for interactions between jet fuel cost and the LCC dummy variable, which identifies a low-cost carrier. *lnJFP * LCC* has a coefficient of 0.0179 in the same quarter, which means when the jet fuel price increases, the low-cost carrier will increase airfare more than legacy carriers in the same quarter. All four quarters' pass-through results summed up to 0.128 compared with 0.0563 for legacy carriers, which indicates that when the jet fuel price increases by 10%, legacy carriers will raise their airfare by 0.563% during the entire year, while LCC carriers would raise their prices by 1.28%. This pass-through for low-cost carriers is more than twice the size of the pass-through for legacy carriers. The cumulative pass-through for four quarters of legacy carriers and low-cost carriers is presented in Figure 6. After correction of endogeneity, we have similar results with the lagged dependent variable model and the AR(1) model. For the rest of our analysis, since the regressions with correction of serial correlation and endogeneity provide more accurate parameters and standard errors, we will concentrate mainly on the results of Column (4).

[30]The speeds of adjustment of the dependent variable would lead to different results of OLS regression, lagged dependent variable model regression, and AR(1) regression.

Figure 6: **Cumulative pass-through for legacy carriers and low-cost carriers (1)**



One of the likely explanations for LCCs' higher pass-through rate is their various business structures. Before the jet fuel price increase, because of the thin profit margin in the airline industry, especially with LCC's streamlined and special business structure, to maintain their low-price advantage, one of their strategies is to make small profits per customer but quick turnovers. This strategy requires LCCs to set airfare lower than legacy carriers, and to maintain smaller profit margins for the same products and also set low prices on their unique products. When facing an increase in oil prices, they need to increase their ticket prices more to make a positive profit, especially when other costs are difficult to change in a short period.

The other reason that would have an influence on the different pass-through rates could be the hedging strategy used by LCCs, which allows them, when facing a rising price of oil, to still enjoy relatively lower oil prices compared with firms with small hedging positions, not optimal hedging prices, or without a hedging position before 2009. Before 2009, LCCs were more willing to sign hedging contracts compared with legacy carriers. Southwest Airlines, as the largest LCC in the U.S. airline industry, realized a gain from their jet fuel hedging contract of more than 4 billion dollars from 2000 to 2008. During the same period, the hedging gains of American Airlines and Delta Airlines were 1.5 billion and 1.2 billion dollars, respectively. The high hedging income allowed Southwest to maintain a much lower average oil price than other carriers for a long period.[31] The combination of an effective hedging strategy and the LCC's unique business structure for cost reductions led to greater pricing flexibility compared to legacy carriers. After 2008, due to the violent fluctuations in oil prices, a large number of companies chose to give up hedging contracts and be fully exposed to fluctuations in fuel prices; the resulting cost difference is also decreasing. During this period, Southwest's hedging contracts brought consistent losses, which in turn induced comparative or even higher real jet fuel prices.

Since the results from the latter regression yielded that ultra-low-cost carriers generate negative pass-throughs and their data volumes are low, we removed them completely from the data and did the regression. The regression results are shown in Appendix Table D.27. We can see that the above results still hold when we keep only the legacy airlines and the low-cost carriers other than the four ultra-low-cost carriers. That is, low-cost carriers have a larger pass-through compared to legacy carriers.

Following Table D.15 in the Appendix, which contains the full results of Table 4, we can see that the most important operating costs, higher salaries and benefits for employees, and more concentrated markets, both have a positive influence on airfare. When an airline company engages in business activity such as mergers and acquisitions or filing for bankruptcy, this will have a negative effect on the price

[31] Average fuel prices of selected carriers are shown in the Appendix Table D.7.

of airline tickets. After an announcement of bankruptcy or a merger, the airline may temporarily reduce fares to stimulate demand and attract customers who may be reluctant to book with a struggling carrier. This may result in discounted airfare for a limited time. In the long run, the efficiency gain and economies of scale from the merger and the lower operating costs from the bankruptcy could also reduce the airfare. The higher inconvenience value indicates a longer time of flying or the higher numbers of inter-stops during the flight. At the same time, the higher inconvenience value may also decrease the demand for the product, since longer-distance flights usually come with higher airfare.

Table 5 presents the results when firm-specific fuel cost and its lagged value are used as explanatory variables, as well as different methods of oil saving or other factors that would cause differences in firm-specific fuel price. Similar to Table 4 we use four specifications: a benchmark regression, adding the lag of the dependent variable as an explanatory variable, using an AR(1) disturbance regression approach, and both an AR(1) disturbance regression and an IV approach for dealing with the endogeneity of the HHI control variable.[32]

[32]The regression results exclude ultra-low-cost carriers are shown in Appendix Table D.28. The single-trip industry-wide and firm-specific regression results using data without ultra-low-cost carriers are shown in Appendix Table D.29 and D.30.

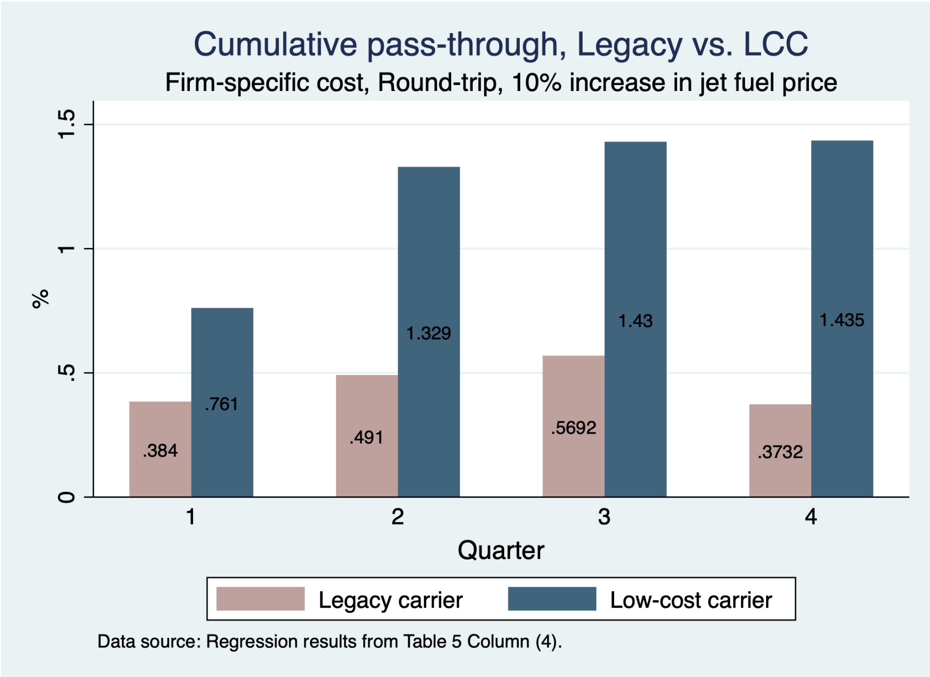
Table 5: **Regression results for round-trip (Firm-specific cost, Legacy vs. LCC)**

	(1)	(2)	(3)	(4)
lnavetotalcost	0.0371***	0.0432***	0.0542***	0.0384***
	[0.00174]	[0.00160]	[0.00135]	[0.00175]
lntcostlag1	0.0113***	-0.00932***	0.0116***	0.0107***
	[0.00168]	[0.00181]	[0.00143]	[0.00169]
lntcostlag2	0.00743***	0.00135	0.00416**	0.00782***
	[0.00156]	[0.00173]	[0.00138]	[0.00157]
lntcostlag3	-0.0206***	-0.0192***	0.0494***	-0.0196***
	[0.00164]	[0.00155]	[0.00130]	[0.00163]
lnavecost*LCC	0.0352***	0.0340***	-0.0635***	0.0377***
	[0.00277]	[0.00247]	[0.00314]	[0.00281]
lnavecostlag1*LCC	0.0547***	0.0429***	0.0140***	0.0461***
	[0.00304]	[0.00335]	[0.00397]	[0.00304]
lnavecostlag2*LCC	-0.00500	-0.0196***	0.0173***	0.00228
	[0.00334]	[0.00358]	[0.00397]	[0.00328]
lnavecostlag3*LCC	0.0232***	0.0162***	-0.0432***	0.0201***
	[0.00299]	[0.00263]	[0.00309]	[0.00302]
N	2,078,934	2,078,934	1,988,843	2,043,101
Time FE	Y	Y	Y	Y
IV	N	N	N	Y

Notes: The dependent variable is the natural logarithm of airfare; Column (4) regression uses IV approach, first-stage results are shown in the Appendix Table D.20; Control variables include wage cost, route distance group, HHI, merger and acquisition condition, bankruptcy condition, inconvenience; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%; Complete regression results are shown in the Appendix Table D.16.

In Table 5, Column (4) reveals that a 10% increase in oil price would lead to a legacy carrier's airfare increase of 0.384% in the same quarter, which is around double the effect when facing an industry-wide cost change, and the result is statistically significant at 1%. However, the lasting effect is smaller than the industry-wide cost change. The cumulative fuel cost pass-through for legacy carriers in all four quarters is 0.373%, which is less than the number obtained with the industry-wide cost change situation at 0.563%. This result is consistent with Walters (2014) who shows that when the cost change is industry-wide, there will

Figure 7: **Cumulative pass-through for legacy carriers and low-cost carriers (2)**



be a higher pass-through than a firm-specific cost change, since in an oligopoly, when the cost change is industry-wide, all of the competitors could adjust their prices to keep the industry profit margin stable. When one of the companies raises airfares because of its own increased fuel costs, it's easy for consumers to switch to other firms when the products don't differ much. Also, because of the high cost of exiting routes, airlines will choose to stabilize airfares to maintain market share.

On the other hand, LCC's airfare increase in the same quarter is 0.761% following a 10% increase in the firm-level fuel price, which is higher than the estimated number when considering the industry-wide fuel price increase. The cumulated pass-through is 1.435%, and it is significant at 1%. The results reveal that under both scenarios, LCCs are more inclined to increase ticket prices than legacy carriers. Due to the relatively smaller margins, increases in firm-specific costs will have a greater impact on low-cost carriers' pricing decisions. The cumulative pass-throughs for four quarters of legacy carriers and low-cost carriers are shown in Figure 7.

While all the carriers face the same cost increase due to the fluctuation of global fuel prices, LCCs are seeing a higher price increase than legacy companies, even though their main business strategy is to attract customers at a low price, with lower profit margins. This may result in squeezing the low-price advantage, thereby potentially losing the attraction to price-sensitive customers. When aviation fuel prices are rising globally, it is a good opportunity for legacy carriers to catch price-sensitive consumers. The business model of the LCCs is relatively weaker in this case. Legacy carriers, whose business strategy emphasis is not on low price but rather on transit convenience and service quality, choose to transfer the cost increase to consumers to reduce the losses it could cause. Firm-specific aircraft fuel price increases may be caused by failure of hedging or the change in the structure of owned or rented aircraft, which can lead to fuel consumption inefficiency. In this instance, even legacy carriers need to transfer part of the incremental cost to customers.

The single-trip regression model is provided in Appendix Tables D.6 and D.8, and corresponding figures of cumulative pass-through are presented in Appendix Figures E.1 and E.2. When facing a 10% industry-wide cost increase, legacy carriers and LCCs' pass-through for four quarters are 0.493% and 1.375% respectively. For firm-specific jet fuel increases, the numbers of pass-throughs are 1.648% and 3.035%. In the case of single-trip, our results show that the pass-through under a firm-specific cost increase is higher than under an industry-wide cost increase. Legacy airlines, in comparison to LCCs, are more likely to absorb the increase in fuel costs. And the pass-through is higher for both legacy carriers and LCCs when compared with the round-trip pass-through.

In this paper's analysis, the pass-through is an elasticity measurement. Under this precondition, and facing a cost increase of the same size, legacy carriers with higher average airfare have a lower pass-through rate and LCCs with lower average airfare have a higher pass-through rate. This would reduce the price difference between these two types of carriers' flights, which may lead to LCCs losing their competitive edge. However, if the price difference between the two is large enough before the cost and airfare change, low-cost airlines may still maintain their lower price status.

7.3 Legacy carriers, low-cost carriers and ultra-low-cost carriers

There are only four carriers, Spirit Airlines (NK), Allegiant Air (G4), Frontier Airlines (F9), and Sun Country Airlines (SY), that operate under the ultra-low-cost (ULCC) business strategy. In the analysis of pass-through among legacy, low-cost, and ultra-low-cost carriers, we redefine the dummy variable that denotes the category of an airline. The airline is ULCC if it is one of Spirit Airlines (NK), Allegiant Air (G4), Frontier Airlines (F9), and Sun Country Airlines (SY). If the airline is a low-cost carrier, it is classified as LCC2, with the exception of the four ultra-low-cost airlines.

The regression results for ultra-low-cost carriers are presented in Tables 6 and 7, following the same specifications used in Tables 4 and 5 for round-trip regression.[33] The cumulative pass-throughs are presented in Figures 8 and 9. Corresponding regression results for the single-trip approach are shown in Appendix Tables D.13 and D.14, and the cumulative pass-throughs from single-trip regression are shown in Appendix Figures E.3 and E.4.

For legacy carriers, whether the added fuel cost is industry-wide or firm-

[33] The baseline regression results without controls for industry-wide cost change and firm-specific cost change are shown in Appendix Tables D.11 and D.12.

specific, they would always transfer part of the increment to consumers. The same quarter's influence would be 0.268% and 0.617% corresponding to a 10% increase in fuel prices, while the four-quarter cumulative effects are 0.725% and 0.856%.

Low-cost carriers, excluding the four ULCCs, increased their airfare in the same quarter as the industry-wide jet fuel price increase, however, the pass-through is less than legacy carriers' at 0.126%. The sequential effect in all four quarters added up to 0.911%. When considering a firm-specific situation, higher aircraft fuel prices also lead to higher LCC airfare, but the same quarter pass-through is smaller than legacy carriers' 0.617%, at 0.573%. When considering all four quarters' results, a 10% firm-specific fuel cost increase will lead to airfare going up 1.2%, which is higher than legacy carriers.

ULCCs, on the other hand, are the least likely type of company to choose to raise the price of the ticket to compensate for the cost increase. The same quarter parameters are negative at -0.0579 and -0.0252 for industry-wide and firm-specific cost increases, which indicates that when jet fuel prices increase, ULCCs would choose to lower their airfare. The sequential effect of rising fuel prices in the next quarter is prominent and positive. The four quarters' cumulated effects are -0.097% and 0.005%, ceteris paribus, corresponding to a 10% increase in industry-wide fuel price or in firm-specific fuel price. Except for the third quarter, in which the result was not significant, the results were statistically significant at 1% in all other quarters. The single-trip data provide similar results in Tables D.13 and D.14 of the Appendix. The four quarters' cumulative pass-through for legacy carriers, low-cost carriers, and ultra-low-cost carriers corresponding to a 10% increase in industry-wide fuel price are 0.729%, 0.906% and -0.657%. The estimated results for 10% firm-specific fuel price increase are 2.409%, 2.861% and 1.302%. All regression results above are statistically significant at 1%.[34] Although ULCC has the lowest pass-through for the same quarter and the lowest pass-through for four quarters, the regression results are not uniform if we consider the cumulative pass-through of two quarters or three quarters.

We believe that since ultra-low-cost carriers' airfares include only the price of passenger boarding prices, in contrast, ultra-low-cost carriers have more additional products to sell to increase their revenue compared to legacy carriers and low-cost carriers, such as the sale of class baggage weight and in-flight services. These additional revenues are not counted in the price of the ticket. This makes it necessary for legacy carriers and low-cost carriers to offset the increase in costs by raising fares when fuel prices increase, but ultra-low-cost carriers can offset the increase in their costs by raising the prices of their additional services.

When we categorize U.S. airline companies into legacy carriers, low-cost carriers, and ultra-low-cost carriers, when facing an increase in jet fuel price, ultra-low-cost carriers have the lowest pass-through in the same quarter and have the lowest cumulative pass-through for four quarters.

[34] These results may have a bias since there are four ULCCs in the U.S. civil aviation industry and their products only account for 3.85% of the database. The small number of firms could include extreme cases and bias the results. But we can still conclude that based on our regression results, compared with legacy carriers and low-cost carriers, the ULCC is one type of airline company that absorbs most of the cost increases and tries to maintain the low price advantage.

Table 6: **Regression results for round-trip (Industry-wide cost, legacy, LCC and ULCC)**

	(1)	(2)	(3)	(4)
lnJetFuelPrice	0.0236***	0.0402***	0.0177***	0.0268***
	[0.00159]	[0.00166]	[0.00158]	[0.00160]
lnJFPlag1	0.0565***	0.0314***	-0.00936***	0.0553***
	[0.00200]	[0.00239]	[0.00192]	[0.00201]
lnJFPlag2	0.0289***	0.00200	0.0127***	0.0302***
	[0.00182]	[0.00219]	[0.00168]	[0.00183]
lnJFPlag3	-0.0416***	-0.0315***	0.0393***	-0.0398***
	[0.00144]	[0.00155]	[0.00143]	[0.00145]
lnJFP*LCC2	-0.00835***	-0.0217***	-0.0512***	-0.0142***
	[0.00217]	[0.00206]	[0.00270]	[0.00220]
lnJFPlag1*LCC2	0.0140***	0.0165***	-0.0150***	0.0192***
	[0.00275]	[0.00320]	[0.00351]	[0.00277]
lnJFPlag2*LCC2	-0.0232***	-0.0250***	0.0143***	-0.0329***
	[0.00291]	[0.00335]	[0.00350]	[0.00300]
lnJFPlag3*LCC2	0.0501***	0.0227***	-0.0543***	0.0465***
	[0.00249]	[0.00220]	[0.00267]	[0.00252]
lnJFP*ULCC	-0.0475***	-0.102***	0.0159*	-0.0847***
	[0.00639]	[0.00553]	[0.00637]	[0.00662]
lnJFPlag1*ULCC	0.116***	0.107***	0.0899***	0.114***
	[0.00701]	[0.00753]	[0.00817]	[0.00707]
lnJFPlag2*ULCC	-0.00597	-0.0165*	0.0403***	0.00849
	[0.00785]	[0.00808]	[0.00818]	[0.00767]
lnJFPlag3*ULCC	-0.0905***	-0.124***	-0.00556	-0.120***
	[0.00585]	[0.00557]	[0.00616]	[0.00599]
N	2,177,590	2,177,590	2,078,771	2,141,757
Time FE	Y	Y	Y	Y
IV	N	N	N	Y

Notes: The dependent variable is natural logarithm of airfare; Column (4) regression uses IV approach, first-stage result is shown in the Appendix Table D.21; Control variables including wage cost, route distance group, HHI, merger and acquisition condition, bankruptcy condition, inconvenience; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%; Complete regression results are shown in the Appendix Table D.17.

Table 7: **Regression results for round-trip (Firm-specific cost, legacy, LCC and ULCC)**

	(1)	(2)	(3)	(4)
lnavetotalcost	0.0542***	0.0674***	0.0545***	0.0617***
	[0.00170]	[0.00158]	[0.00135]	[0.00172]
lntcostlag1	0.0185***	-0.00534**	0.0117***	0.0201***
	[0.00168]	[0.00188]	[0.00143]	[0.00170]
lntcostlag2	0.00934***	0.00248	0.00330*	0.0105***
	[0.00156]	[0.00181]	[0.00138]	[0.00158]
lntcostlag3	-0.0113***	-0.00763***	0.0478***	-0.00668***
	[0.00160]	[0.00154]	[0.00130]	[0.00160]
lnavecost*LCC2	0.000487	-0.000635	-0.0692***	-0.00443
	[0.00279]	[0.00260]	[0.00355]	[0.00287]
lnavecostlag1*LCC2	0.0332***	0.0137***	-0.00619	0.0234***
	[0.00339]	[0.00393]	[0.00455]	[0.00345]
lnavecostlag2*LCC2	-0.00178	-0.0167***	0.0179***	-0.000199
	[0.00368]	[0.00417]	[0.00454]	[0.00373]
lnavecostlag3*LCC2	0.0213***	0.00407	-0.0445***	0.0157***
	[0.00329]	[0.00285]	[0.00350]	[0.00331]
lnavecost*ULCC	-0.0489***	-0.104***	0.0126*	-0.0869***
	[0.00626]	[0.00516]	[0.00613]	[0.00654]
lnavecostlag1*ULCC	0.133***	0.133***	0.0963***	0.128***
	[0.00640]	[0.00668]	[0.00750]	[0.00645]
lnavecostlag2*ULCC	-0.0172**	-0.0472***	0.0346***	0.00317
	[0.00649]	[0.00646]	[0.00747]	[0.00616]
lnavecostlag3*ULCC	-0.0909***	-0.112***	-0.00482	-0.125***
	[0.00551]	[0.00503]	[0.00589]	[0.00579]
N	2,078,934	2,078,934	1,988,843	2,043,101
Time FE	Y	Y	Y	Y
IV	N	N	N	Y

Notes: The dependent variable is natural logarithm of airfare; Column (4) regression uses IV approach, first-stage result is shown in the Appendix Table D.22; Control variables including wage cost, route distance group, HHI, merger and acquisition condition, bankruptcy condition, inconvenience; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%; Complete regression results are shown in the Appendix Table D.18.

Figure 8: **Cumulative pass-through for legacy, low-cost and ultra-low-cost carriers (1)**

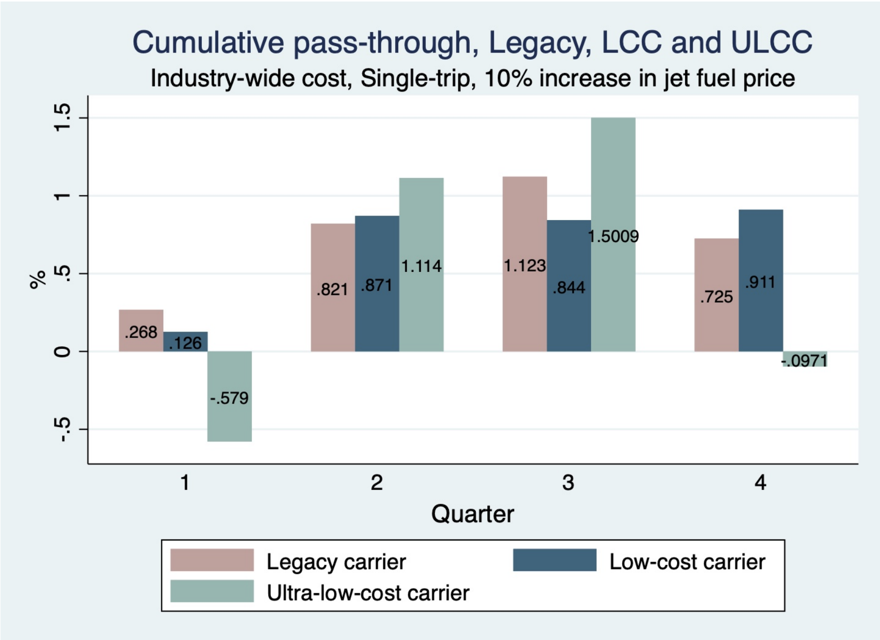
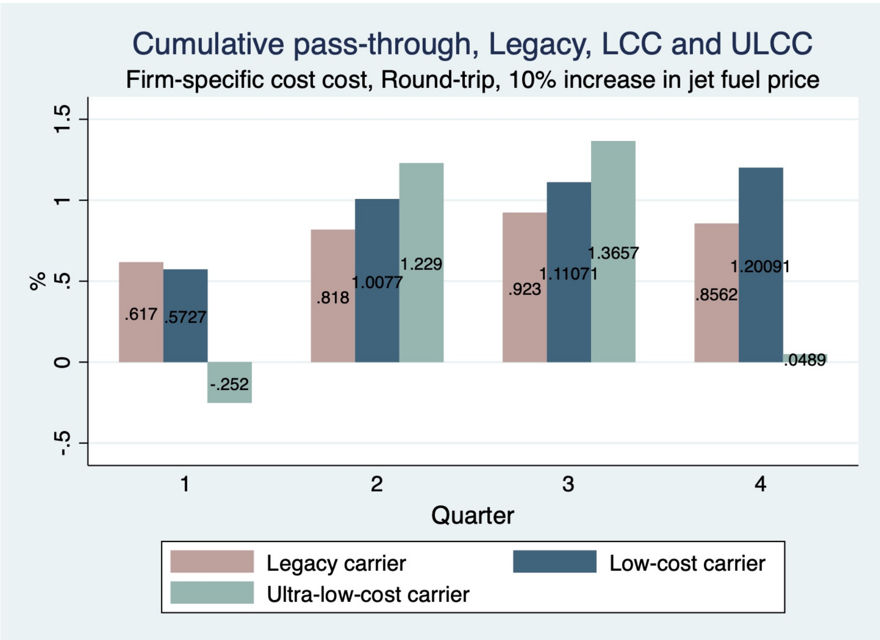


Figure 9: **Cumulative pass-through for legacy, low-cost and ultra-low-cost carriers (2)**



8 Conclusion

Jet fuel consumption accounts for the majority of an airline company's cost structure. Airline fares will change with the fluctuations of jet fuel prices. In this paper, we use 20 years of data related to the U.S. civil aviation industry to analyze the different reactions of legacy carriers, low-cost carriers, and ultra-low-cost carriers when facing industry-wide fuel cost increases and firm-specific cost increases. Our main contribution is using empirical analysis to find that no matter whether the jet fuel price rise is an industry-wide change or a firm-specific change, low-cost carriers are more willing to transfer the cost increase to consumers by raising the airfare than legacy carriers (relative pass-through). When separating the four ultra-low-cost carriers from low-cost carriers, we also find that ultra-low-cost carriers have the lowest pass-through compared with legacy carriers and low-cost carriers. The robustness check using single-trip data verifies the above conclusions. The above findings provide contributions to the authority's regulation of the civil aviation industry and also provide information to market participants including travellers, airline company shareholders, debtors, and investors.

Our study verifies the result from Ritz's(2019) empirical method that a more concentrated market leads to a higher price. Koopmans and Lieshout (2016) and Walters (2014) find that in theory, industry-wide cost change leads to higher pass-through. However, our study finds that firm-specific cost change in the U.S. aviation industry leads to higher pass-through than industry-wide cost change.

Our article also has some limitations. The classification of airlines became blurred after the deregulation of the U.S. airline industry than before. Many legacy carriers started to enter smaller markets, while some larger low-cost carriers such as Southwest Airlines also started to establish their own hubs and move closer to the legacy carriers' operating model. At the same time, due to the relatively small amount of data, the conclusions about ultra-low-cost carriers cannot be fully robust.

There are some further areas we can explore next. First, due to sample size limits, the results from ultra-low-cost carriers are not completely compelling. Next, the research could randomly draw comparable sizes of products from each of the categories of carriers to verify the results more accurately. Further, our analyses are based on the pass-through rate, which studies the percentage change in the airfare of different categories of carriers corresponding to a 1% increase in jet fuel price. Additional studies could use absolute value pass-through to figure out in currency units, when jet fuel price increases by one dollar, how much the resulting airfares increase or decrease for legacy carriers, low-cost carriers, and ultra-low-cost carriers.

Appendix

A List of datasets

1. Airline Origin and Destination Survey (DB1B)

   Data Source: United States Department of Transportation, Bureau of Transportation Statistics.

   Online Access: https://www.transtats.bts.gov/DatabaseInfo.asp?QO_VQ=EFI&Yv0x=D

   Dataset characteristic: 10% sample of airline tickets from reporting carriers, from 1993 to 2021, quarterly data.

2. T-100 Domestic Market (U.S. Carriers)

   Data Source: Air Carrier Statistics (Form 41 Traffic)- U.S. Carriers, United States Department of Transportation, Bureau of Transportation Statistics.

   Online Access: https://www.transtats.bts.gov/TableInfo.asp?gnoyr_VQ=FIL&QO_fu146_anzr=Nv4%20Pn44vr45&V0s1_b0yB=D

   Dataset characteristic: contains domestic market data reported by U.S. air carriers, including carrier, origin, destination, and service class for enplaned passengers, freight and mail when both origin and destination airports are located within the boundaries of the United States and its territories, from 1990 to 2021, monthly data.

3. Air Carrier Financial: Schedule P-6

   Data Source: Air Carrier Financial Reports (Form 41 Financial Data), United States Department of Transportation, Bureau of Transportation Statistics.

Online Access: https://www.transtats.bts.gov/TableInfo.asp?gnoyr_VQ=FME&QO_fu146_anzr=Nv4%20Pn44vr4%20Sv0n0pvny&V0s1_b0yB=D

Dataset characteristic: contains carriers' operating expenses, by objective grouping, for carriers with annual operating revenues of $20 million or more, and includes such items as salaries, benefits, materials purchased, services purchased, depreciation, amortization, food, and other operating expenses, from 1990 to 2021, quarterly data.

4. Air Carrier Financial: Schedule P-12(a)

   Data Source: Air Carrier Financial Reports (Form 41 Financial Data), United States Department of Transportation, Bureau of Transportation Statistics.

   Online Access: https://www.transtats.bts.gov/Fields.asp?gnoyr_VQ=FMH

   Dataset characteristic: contains fuel costs and gallons of fuel consumed, by air carrier and category of fuel use, including scheduled and non-scheduled service for domestic and international traffic regions, from 1990 to 2021, monthly data.

5. Jet Fuel Refiner Price to End Users

   Data Source: U.S. Energy Information Administration

   Online access: https://www.eia.gov/opendata/qb.php?category=1039856&sdid=STEO.JKTCUUS.Q

   Dataset characteristic: quarterly data.

6. Population and Housing Unit Estimates

   Data Source: United States Census Bureau

   Online access: https://www.census.gov/programs-surveys/popest.html

Dataset characteristic: contains national, state, and county total resident population and demographic components of population estimation, yearly data.

7. List of Low-Cost Carriers

   Data Source: International Civil Aviation Organization

   Online access: https://www.icao.int/sustainability/Documents/LCC-List.pdf

B List of variables

1. $airfare$: equals to average price of the product price in a specific quarter.

2. *JetFuelPrice*: spot market jet fuel price which is common to the industry.

3. *avetotalcost*: generated by aggregating the fuel consumption and expenditure from monthly to quarterly levels for each carrier.

4. $salarybenefit$: each carrier's quarterly cost on employees' salary and benefit.

5. *distancegroup*: a numerical type variable, which equals 1 if the flight distance is less than 500 miles, equals 2 if the distance of flight distance is between 500 and 999 miles, equals 3 if the distance of the flight is between 1000 to 1499, etc. The largest number of this variable is 10 which indicates the distance of flight is between 4500 and 4999 miles.

6. *mergeraqui*: equals 1 if the carrier experiences a merger transition in that period, otherwise equals 0.

7. *bankruptcy*: equals 1 if the carrier experiences bankruptcy in that period, otherwise equals 0.

8. *inconvenience*: generated by dividing the actual market miles flown by non-stop miles, the larger the number, the further distance or longer time the flight would take to the destination.

9. HHI: equals to the summation of market shares squared, a carrier's market share equals to passengers that the carrier has in that quarter divided by the total passengers in the market in the quarter.

C Process of data cleaning

1. Merge DB1B Coupon with T-100 Domestic Segment dataset and restrict the frequent flights by having more than 30 seats, and all of the flights travel with more than 15 passengers in one quarter to generate a reduced Coupon dataset. Flights with less than 30 seats per quarter account for 0.006% of total flights and flights carrying fewer than 15 passengers per quarter account for 0.08% of total flights.

2. Since our target is to investigate the U.S. domestic market, for the merged dataset from step 1, we keep an observation only if the flight is a U.S. reporting carrier flying between two U.S. points to make sure our data only includes domestic flights (which account for 99.96% of our original data).

3. Then we drop freight configuration (accounts for 0.03% of data from step 2) from the data and keep passenger configuration only.

4. To avoid outliers like mileage points redeemed tickets, we delete tickets with airfares of less than \$50, we set the highest airfare to \$2000 for U.S. domestic flights to reduce the disparities of really high price tickets (business class or first class). Tickets with less than \$50 account for 3.98% of total tickets; tickets higher than \$2000 account for 0.02% of total tickets.

5. Keep credible airfare value tickets only (accounts for 99.63% of data from step 4) to ensure the accuracy of the tickets' price value.

6. Keep the flights for which the ticketing carrier is identical to the operating carrier only (86.10% of the data from step 5). From this process, we delete flights with different ticketing carriers and operating carriers since this kind of flight is always part of the connection flight, and we do not have information on the profit-sharing structure.

7. Keep only economy class for the empirical analysis (accounts for 96.95% of the data from step 6).

D Tables

Table D.1: **Summary Statistics Grouped by Legacy and LCC Carriers (Round-trip)**

	(1) Legacy Carriers		(2) Low-cost Carriers	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Airfare	256.01	93.15	205.69	68.06
Avetotalcost	2.10	0.91	2.19	0.75
Salaries	853,525.88	664,826.50	697,286.71	664,419.00
Distance group	3.05	1.36	3.25	1.46
HHI	0.58	0.32	0.50	0.29
Merge_aqui	0.05	0.21	0.05	0.21
Bankruptcy	0.01	0.11	0.00	0.06
Inconvenience	1.21	0.28	1.18	0.28
N	2,624,978		675,319	

Source: Author's calculation based on U.S. BTS DB1B data.

Table D.2: **Summary Statistics – Single-trip**

Variable	Mean	Std. Dev.	Min	Max
Airfare	333.70	183.76	46.23	2756.31
JetFuelPrice	2.07	0.77	0.80	4.01
Avetotalcost	2.16	0.87	0.65	11.75
Salaries	831,152.10	675,074.90	1,489.09	2,302,571.00
LCC	0.24	0.43	0.00	1.00
Distance group	3.15	1.44	1.00	12.00
HHI	0.53	0.31	0.10	1.00
Merge_aqui	0.05	0.21	0.00	1.00
Bankruptcy	0.01	0.10	0.00	1.00
Inconveniece	1.21	0.30	0.96	3.84
N	2,934,019			
Market	52,271			
Product	223,260			

Source: Author's calculation based on U.S. BTS DB1B data.

Table D.3: **Summary Statistics Grouped by Legacy and LCC Carriers (Single-trip)**

	(1) Legacy Carriers		(2) Low-cost Carriers	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Airfare	362.69	194.71	241.82	98.69
Avetotalcost	2.15	0.90	2.19	0.75
Salaries	880,745.59	671,834.89	672,912.54	660,592.64
Distance group	3.10	1.41	3.32	1.51
HHI	0.55	0.31	0.49	0.29
Merge_aqui	0.05	0.22	0.04	0.20
Bankruptcy	0.01	0.11	0.00	0.06
Inconvenience	1.22	0.30	1.20	0.31
N	2,230,822		703,197	

Source: Author's calculation based on U.S. BTS DB1B data.

Table D.4: **Baseline regression results without controls (Industry-wide cost, legacy vs. LCC)**

	Round-trip	Single-trip
lnJetFuelPrice	0.0119***	-0.0486***
	[0.00159]	[0.00289]
lnJFPlag1	0.0547***	0.0671***
	[0.00200]	[0.00370]
lnJFPlag2	0.0298***	0.0396***
	[0.00181]	[0.00345]
lnJFPlag3	-0.0524***	-0.0464***
	[0.00145]	[0.00260]
lnJFP*LCC	0.0243***	0.113***
	[0.00219]	[0.00335]
lnJFPlag1*LCC	0.0252***	-0.0203***
	[0.00269]	[0.00434]
lnJFPlag2*LCC	-0.0251***	-0.0576***
	[0.00286]	[0.00431]
lnJFPlag3*LCC	0.0661***	0.113***
	[0.00251]	[0.00331]
N	2,177,590	1,726,244

Notes: The dependent variable is natural logarithm of airfare; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.5: **Baseline regression results without controls (Firm-specific cost, legacy vs. LCC)**

	Round-trip	Single-trip
lnavetotalcost	0.0339***	0.0305***
	[0.00168]	[0.00261]
lntcostlag1	0.0104***	0.0709***
	[0.00168]	[0.00277]
lntcostlag2	0.00776***	0.0162***
	[0.00156]	[0.00265]
lntcostlag3	-0.0240***	0.00218
	[0.00158]	[0.00245]
lnavecost*LCC	0.0386***	0.143***
	[0.00265]	[0.00380]
lnavecostlag1*LCC	0.0572***	-0.0115*
	[0.00304]	[0.00454]
lnavecostlag2*LCC	-0.00614	-0.0368***
	[0.00334]	[0.00464]
lnavecostlag3*LCC	0.0293***	0.107***
	[0.00304]	[0.00381]
N	2,078,934	1,645,281

Notes: The dependent variable is natural logarithm of airfare; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.6: **Regression results for single-trip (Industry-wide cost, legacy vs. LCC)**

	(1)	(2)	(3)	(4)
lnJetFuelPrice	-0.0302***	-0.0235***	-0.0139***	-0.0292***
	[0.00290]	[0.00291]	[0.00267]	[0.00291]
lnJFPlag1	0.0686***	0.0652***	0.00611	0.0659***
	[0.00370]	[0.00406]	[0.00328]	[0.00371]
lnJFPlag2	0.0375***	0.0180***	0.0247***	0.0427***
	[0.00346]	[0.00381]	[0.00293]	[0.00347]
lnJFPlag3	-0.0272***	-0.0251***	0.0617***	-0.0301***
	[0.00261]	[0.00269]	[0.00241]	[0.00262]
lnJFP*LCC	0.0820***	0.0671***	0.00619	0.0848***
	[0.00337]	[0.00323]	[0.00378]	[0.00339]
lnJFPlag1*LCC	-0.0215***	-0.0196***	-0.0117*	-0.0138**
	[0.00435]	[0.00473]	[0.00507]	[0.00434]
lnJFPlag2*LCC	-0.0478***	-0.0476***	-0.0134**	-0.0657***
	[0.00434]	[0.00471]	[0.00506]	[0.00436]
lnJFPlag3*LCC	0.0758***	0.0689***	-0.0284***	0.0829***
	[0.00330]	[0.00313]	[0.00373]	[0.00333]
lnSalary	0.106***	0.0812***	0.358***	0.0979***
	[0.00245]	[0.00195]	[0.000715]	[0.00246]
Distance_group	-0.00356*	-0.000131	0.0107***	-0.00397*
	[0.00176]	[0.00152]	[0.00102]	[0.00176]
HHI	0.0662***	0.0519***	0.0532***	0.154***
	[0.00296]	[0.00247]	[0.00199]	[0.00688]
Merge_aquisi	0.0143***	0.0111***	0.0361***	0.0140***
	[0.00126]	[0.00107]	[0.00121]	[0.00125]
Bankruptcy	-0.0237***	-0.0274***	-0.0487***	-0.0228***
	[0.00291]	[0.00292]	[0.00218]	[0.00291]
Inconvenience	0.100***	0.0869***	0.0902***	0.101***
	[0.00491]	[0.00412]	[0.00246]	[0.00489]
N	1,716,005	1,716,005	1,634,753	1,695,132
Time FE	Y	Y	Y	Y
IV	N	N	N	Y

Notes: The dependent variable is natural logarithm of airfare; Column (4) regression uses IV approach, first-stage result is shown in the Appendix Table D.23.; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.7: **Average price* per gallon of aircraft fuel for selective carriers**

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
AA	0.781	0.814	0.762	0.875	1.210	1.740	2.010	2.130	3.030	2.000
DL	0.674	0.686	0.669	0.818	1.157	1.714	2.040	2.210	3.160	2.150
WN	0.787	0.709	0.680	0.800	0.920	1.130	1.530	1.800	2.440	2.120
B6	0.962	0.756	0.723	0.850	1.060	1.610	1.990	2.180	3.080	2.080
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
AA	2.310	3.009	3.190	3.080	2.910	1.720	1.410	1.730	2.230	2.070
DL	2.330	3.060	3.250	3.000	3.470	1.900	1.490	1.680	2.200	2.020
WN	2.510	3.190	3.300	3.160	2.930	1.960	1.900	1.990	2.200	2.090
B6	2.290	3.170	3.210	3.140	2.990	1.930	1.410	1.720	2.240	2.090

Notes: The price includes related fuel taxes as well as effective fuel hedging gains and losses.

Table D.8: **Regression results for single-trip (Firm-specific cost, Legacy vs. LCC)**

	(1)	(2)	(3)	(4)
lnavetotalcost	0.0510***	0.0455***	0.0609***	0.0508***
	[0.00270]	[0.00256]	[0.00224]	[0.00271]
lntcostlag1	0.0728***	0.0572***	0.0588***	0.0730***
	[0.00277]	[0.00291]	[0.00248]	[0.00278]
lntcostlag2	0.0153***	0.00244	0.0160***	0.0175***
	[0.00265]	[0.00283]	[0.00242]	[0.00266]
lntcostlag3	0.0226***	0.0180***	0.0887***	0.0235***
	[0.00253]	[0.00248]	[0.00221]	[0.00253]
lnavecost*LCC	0.106***	0.0912***	0.00194	0.116***
	[0.00387]	[0.00364]	[0.00454]	[0.00393]
lnavecostlag1*LCC	-0.00854	-0.0162***	-0.0174**	-0.0241***
	[0.00454]	[0.00489]	[0.00594]	[0.00456]
lnavecostlag2*LCC	-0.0370***	-0.0342***	0.00290	-0.0367***
	[0.00466]	[0.00497]	[0.00594]	[0.00463]
lnavecostlag3*LCC	0.0803***	0.0696***	-0.00837	0.0835***
	[0.00382]	[0.00356]	[0.00448]	[0.00384]
lnSalary	0.0973***	0.0748***	0.362***	0.0895***
	[0.00254]	[0.00204]	[0.000719]	[0.00254]
Distance_group	-0.00395*	-0.000532	0.0138***	-0.00445**
	[0.00171]	[0.00149]	[0.00103]	[0.00171]
HHI	0.0713***	0.0563***	0.0572***	0.193***
	[0.00298]	[0.00251]	[0.00204]	[0.00680]
Merge_aquisi	0.00392**	0.00286**	0.0299***	0.00389**
	[0.00126]	[0.00108]	[0.00121]	[0.00126]
Bankruptcy	-0.0389***	-0.0396***	-0.0551***	-0.0385***
	[0.00295]	[0.00296]	[0.00220]	[0.00295]
Inconvenience	0.103***	0.0895***	0.0824***	0.104***
	[0.00473]	[0.00402]	[0.00250]	[0.00472]
N	1,635,825	1,635,825	1,562,732	1,614,952
Time FE	Y	Y	Y	Y
IV	N	N	N	Y

Notes: The dependent variable is natural logarithm of airfare; Column (4) regression uses IV approach, first-stage result is shown in the Appendix Table D.24.; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.9: **Summary Statistics Grouped by Legacy, LCC and ULCC (Round-trip)**

	(1) Legacy Carriers		(2) LCC2		(3) ULCC	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Airfare	256.01	93.15	216.37	62.85	159.65	70.40
Avetotalcost	2.10	0.91	2.16	0.75	2.31	0.76
Salaries	853,525.88	664,826.50	841,271.93	658,440.08	76,958.49	37,452.13
HHI	0.58	0.32	0.51	0.29	0.48	0.32
Merge_aqui	0.05	0.21	0.05	0.23	0.01	0.10
Bankruptcy	0.01	0.10	0.00	0.04	0.01	0.09
Distance group	3.05	1.36	3.20	1.50	3.44	1.27
Inconvenience	1.21	0.28	1.19	0.28	1.12	0.25
N	2,624,978		548,099		127,220	

Source: Author's calculation based on U.S. BTS DB1B data.

Table D.10: **Summary Statistics Grouped by Legacy, LCC and ULCC (Single-trip)**

	(1) Legacy Carriers		(2) LCC2		(3) ULCC	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Airfare	362.69	194.71	256.08	95.51	183.59	89.65
Avetotalcost	2.15	0.90	2.17	0.75	2.28	0.75
Salaries	880,745.59	671,834.89	818,608.84	659,529.09	78,109.99	40,791.36
HHI	0.55	0.31	0.50	0.28	0.46	0.32
Merge_aquisi	0.05	0.22	0.05	0.22	0.01	0.08
Bankruptcy	0.01	0.10	0.00	0.05	0.01	0.09
Distance group	3.10	1.41	3.27	1.55	3.53	1.31
Inconvenience	1.22	0.30	1.21	0.31	1.15	0.29
N	2,230,822		564,840		138,357	

Source: Author's calculation based on U.S. BTS DB1B data.

Table D.11: **Baseline regression results without controls (Industry-wide cost, Legacy , LCC, and ULCC)**

	Round-trip	Single-trip
lnJetFuelPrice	0.0181***	-0.0313***
	[0.00159]	[0.00286]
lnJFPlag1	0.0551***	0.0650***
	[0.00200]	[0.00370]
lnJFPlag2	0.0294***	0.0407***
	[0.00181]	[0.00345]
lnJFPlag3	-0.0474***	-0.0359***
	[0.00145]	[0.00259]
lnJFP*LCC2	0.000684	0.0672***
	[0.00218]	[0.00334]
lnJFPlag1*LCC2	0.0141***	-0.0339***
	[0.00274]	[0.00442]
lnJFPlag2*LCC2	-0.0271***	-0.0405***
	[0.00291]	[0.00439]
lnJFPlag3*LCC2	0.0655***	0.0917***
	[0.00253]	[0.00338]
lnJFP*ULCC	-0.0329***	-0.0180*
	[0.00629]	[0.00772]
lnJFPlag1*ULCC	0.117***	0.110***
	[0.00696]	[0.00911]
lnJFPlag2*ULCC	-0.00476	-0.155***
	[0.00777]	[0.00899]
lnJFPlag3*ULCC	-0.0812***	-0.00976
	[0.00580]	[0.00665]
N	2,177,590	1,726,244

Notes: The dependent variable is the natural logarithm of airfare; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.12: **Baseline regression results without controls (Firm-specific cost, Legacy , LCC, and ULCC)**

	Round-trip	Single-trip
lnavetotalcost	0.0432***	0.0493***
	[0.00166]	[0.00259]
lntcostlag1	0.0143***	0.0781***
	[0.00167]	[0.00277]
lntcostlag2	0.00902***	0.0176***
	[0.00156]	[0.00265]
lntcostlag3	-0.0197***	0.0107***
	[0.00157]	[0.00243]
lnavecost*LCC2	0.0123***	0.0897***
	[0.00278]	[0.00405]
lnavecostlag1*LCC2	0.0354***	-0.0340***
	[0.00338]	[0.00510]
lnavecostlag2*LCC2	-0.00294	-0.0102*
	[0.00367]	[0.00510]
lnavecostlag3*LCC2	0.0364***	0.0915***
	[0.00330]	[0.00416]
lnavecost*ULCC	-0.0321***	-0.00440
	[0.00616]	[0.00748]
lnavecostlag1*ULCC	0.136***	0.0637***
	[0.00628]	[0.00862]
lnavecostlag2*ULCC	-0.0153*	-0.103***
	[0.00640]	[0.00837]
lnavecostlag3*ULCC	-0.0842***	-0.0173**
	[0.00549]	[0.00620]
N	2,078,934	1,645,281

Notes: The dependent variable is the natural logarithm of airfare; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.13: **Regression results for single-trip (Industry-wide cost change, Legacy , LCC, and ULCC)**

	(1)	(2)	(3)	(4)
lnJetFuelPrice	-0.0193***	-0.000775	-0.0141***	-0.0120***
	[0.00287]	[0.00293]	[0.00267]	[0.00287]
lnJFPlag1	0.0661***	0.0594***	0.00718*	0.0616***
	[0.00370]	[0.00425]	[0.00328]	[0.00371]
lnJFPlag2	0.0395***	0.0121**	0.0246***	0.0476***
	[0.00346]	[0.00398]	[0.00293]	[0.00347]
lnJFPlag3	-0.0243***	-0.0157***	0.0609***	-0.0243***
	[0.00259]	[0.00274]	[0.00241]	[0.00260]
lnJFP*LCC2	0.0491***	0.00694*	0.00505	0.0367***
	[0.00331]	[0.00320]	[0.00398]	[0.00334]
lnJFPlag1*LCC2	-0.0347***	-0.0306***	-0.0356***	-0.0194***
	[0.00443]	[0.00505]	[0.00536]	[0.00444]
lnJFPlag2*LCC2	-0.0333***	-0.0301***	0.00239	-0.0640***
	[0.00441]	[0.00502]	[0.00535]	[0.00447]
lnJFPlag3*LCC2	0.0631***	0.0334***	-0.0417***	0.0644***
	[0.00336]	[0.00317]	[0.00394]	[0.00340]
lnJFP*ULCC	-0.0142	-0.125***	0.0412***	-0.0638***
	[0.00764]	[0.00722]	[0.00873]	[0.00791]
lnJFPlag1*ULCC	0.113***	0.139***	0.130***	0.119***
	[0.00910]	[0.0100]	[0.0115]	[0.00915]
lnJFPlag2*ULCC	-0.161***	-0.173***	-0.107***	-0.159***
	[0.00907]	[0.0100]	[0.0115]	[0.00908]
lnJFPlag3*ULCC	-0.00197	-0.0291***	0.0549***	-0.0348***
	[0.00662]	[0.00636]	[0.00844]	[0.00674]
lnsal_bene	0.0641***	0.0293***	0.359***	0.0540***
	[0.00100]	[0.000624]	[0.000716]	[0.000926]
distance_group	0.0341***	0.0369***	0.0104***	0.0455***
	[0.000755]	[0.000477]	[0.00102]	[0.000706]
HHI	0.0930***	0.0793***	0.0532***	0.202***
	[0.00258]	[0.00187]	[0.00198]	[0.00430]
merge_aquisi	0.00415***	-0.00238*	0.0373***	0.00264*
	[0.00123]	[0.000987]	[0.00121]	[0.00123]
bankruptcy	-0.0160***	-0.0166***	-0.0493***	-0.0121***
	[0.00291]	[0.00297]	[0.00219]	[0.00292]
inconvenience	0.00693*	-0.0170***	0.0898***	-0.0182***
	[0.00311]	[0.00207]	[0.00246]	[0.00293]
N	1,716,005	1,716,005	1,634,753	1,695,132
Time FE	Y	Y	Y	Y
IV	N	N	N	Y

Notes: The dependent variable is the natural logarithm of airfare; Column (4) regression uses IV approach, first-stage result is shown in the Appendix Table D.25.; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.14: **Regression results for single-trip (Firm-specific cost change, Legacy , LCC, and ULCC)**

	(1)	(2)	(3)	(4)
lnavetotalcost	0.0774***	0.0836***	0.0612***	0.0883***
	[0.00263]	[0.00251]	[0.00224]	[0.00266]
lntcostlag1	0.0864***	0.0712***	0.0590***	0.0919***
	[0.00279]	[0.00303]	[0.00248]	[0.00281]
lntcostlag2	0.0172***	0.000152	0.0150***	0.0213***
	[0.00266]	[0.00295]	[0.00242]	[0.00267]
lntcostlag3	0.0333***	0.0307***	0.0867***	0.0394***
	[0.00247]	[0.00246]	[0.00221]	[0.00247]
lnavecost*LCC2	0.0613***	0.0289***	-0.000974	0.0595***
	[0.00403]	[0.00386]	[0.00514]	[0.00413]
lnavecostlag1*LCC2	-0.0316***	-0.0503***	-0.0476***	-0.0522***
	[0.00510]	[0.00577]	[0.00683]	[0.00516]
lnavecostlag2*LCC2	-0.00984	-0.00104	0.0277***	-0.0179***
	[0.00511]	[0.00573]	[0.00683]	[0.00514]
lnavecostlag3*LCC2	0.0569***	0.0240***	-0.0188***	0.0558***
	[0.00416]	[0.00386]	[0.00508]	[0.00418]
lnavecost*ULCC	0.00713	-0.0848***	0.0553***	-0.0361***
	[0.00720]	[0.00677]	[0.00845]	[0.00748]
lnavecostlag1*ULCC	0.0608***	0.0763***	0.0712***	0.0579***
	[0.00855]	[0.00965]	[0.0107]	[0.00873]
lnavecostlag2*ULCC	-0.112***	-0.118***	-0.0515***	-0.103***
	[0.00881]	[0.00960]	[0.0106]	[0.00855]
lnavecostlag3*ULCC	0.00362	-0.0236***	0.0423***	-0.0295***
	[0.00621]	[0.00584]	[0.00811]	[0.00624]
lnSalary	0.0907***	0.0530***	0.363***	0.0838***
	[0.00118]	[0.000791]	[0.000720]	[0.00112]
Distance_group	0.0402***	0.0412***	0.0136***	0.0518***
	[0.000751]	[0.000484]	[0.00103]	[0.000701]
HHI	0.0948***	0.0809***	0.0573***	0.199***
	[0.00261]	[0.00192]	[0.00204]	[0.00431]
Merge_aquisi	-0.00276*	-0.00834***	0.0311***	-0.00505***
	[0.00125]	[0.00101]	[0.00121]	[0.00126]
Bankruptcy	-0.0351***	-0.0323***	-0.0556***	-0.0324***
	[0.00295]	[0.00300]	[0.00220]	[0.00295]
Inconvenience	-0.00155	-0.0222***	0.0822***	-0.0278***
	[0.00307]	[0.00209]	[0.00250]	[0.00290]
N	1,635,825	1,635,825	1,562,732	1,614,952
Time FE	Y	Y	Y	Y
IV	N	N	N	Y

Notes: The dependent variable is the natural logarithm of airfare; Column (4) regression uses IV approach, first-stage result is shown in the Appendix Table D.26.; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.15: **Full results of Table 4: Regression results for round-trip (Industry-wide cost, Legacy vs. LCC)**

	(1)	(2)	(3)	(4)
lnJetFuelPrice	0.0167***	0.0275***	0.0179***	0.0172***
	[0.00161]	[0.00164]	[0.00159]	[0.00161]
lnJFPlag1	0.0564***	0.0370***	-0.00996***	0.0557***
	[0.00200]	[0.00228]	[0.00192]	[0.00200]
lnJFPlag2	0.0292***	0.00829***	0.0129***	0.0301***
	[0.00181]	[0.00209]	[0.00168]	[0.00182]
lnJFPlag3	-0.0464***	-0.0402***	0.0398***	-0.0467***
	[0.00145]	[0.00151]	[0.00144]	[0.00146]
lnJFP*LCC	0.0167***	0.0122***	-0.0461***	0.0179***
	[0.00225]	[0.00207]	[0.00256]	[0.00227]
lnJFPlag1*LCC	0.0236***	0.0230***	-0.00206	0.0256***
	[0.00270]	[0.00299]	[0.00333]	[0.00269]
lnJFPlag2*LCC	-0.0211***	-0.0237***	0.0174***	-0.0256***
	[0.00284]	[0.00313]	[0.00332]	[0.00288]
lnJFPlag3*LCC	0.0529***	0.0381***	-0.0484***	0.0538***
	[0.00242]	[0.00217]	[0.00253]	[0.00245]
lnSalary	0.0311***	0.0212***	0.340***	0.0275***
	[0.00193]	[0.00135]	[0.000404]	[0.00194]
Distance_group	-0.0208***	-0.0136***	-0.00221**	-0.0208***
	[0.00173]	[0.00127]	[0.000789]	[0.00174]
HHI	0.0643***	0.0447***	0.0576***	0.142***
	[0.00216]	[0.00159]	[0.00131]	[0.00420]
Merge_aquisi	-0.00257**	-0.00200**	0.0263***	-0.00204*
	[0.000930]	[0.000710]	[0.000810]	[0.000927]
Bankruptcy	-0.0187***	-0.0174***	-0.0388***	-0.0184***
	[0.00133]	[0.00127]	[0.00121]	[0.00133]
Inconvenience	0.0880***	0.0699***	0.109***	0.0899***
	[0.00537]	[0.00384]	[0.00206]	[0.00541]
N	2,177,590	2,177,590	2,078,771	2,141,757
Time FE	Y	Y	Y	Y
IV	N	N	N	Y

Notes: The dependent variable is the natural logarithm of airfare; Column (4) regression uses IV approach, first-stage result is shown in the Appendix Table D.19; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.16: **Full regression results for Table 5: Regression results for round-trip (Firm-specific cost, Legacy vs. LCC)**

	(1)	(2)	(3)	(4)
lnavetotalcost	0.0371***	0.0432***	0.0542***	0.0384***
	[0.00174]	[0.00160]	[0.00135]	[0.00175]
lntcostlag1	0.0113***	-0.00932***	0.0116***	0.0107***
	[0.00168]	[0.00181]	[0.00143]	[0.00169]
lntcostlag2	0.00743***	0.00135	0.00416**	0.00782***
	[0.00156]	[0.00173]	[0.00138]	[0.00157]
lntcostlag3	-0.0206***	-0.0192***	0.0494***	-0.0196***
	[0.00164]	[0.00155]	[0.00130]	[0.00163]
lnavecost*LCC	0.0352***	0.0340***	0.0635***	0.0377***
	[0.00277]	[0.00247]	[0.00314]	[0.00281]
lnavecostlag1*LCC	0.0547***	0.0429***	0.0140***	0.0461***
	[0.00304]	[0.00335]	[0.00397]	[0.00304]
lnavecostlag2*LCC	-0.00500	-0.0196***	0.0173***	0.00228
	[0.00334]	[0.00358]	[0.00397]	[0.00328]
lnavecostlag3*LCC	0.0232***	0.0162***	-0.0432***	0.0201***
	[0.00299]	[0.00263]	[0.00309]	[0.00302]
lnSalary	0.0150***	0.0104***	0.340***	0.0123***
	[0.00202]	[0.00141]	[0.000400]	[0.00203]
Distance_group	-0.0206***	-0.0135***	0.00223**	-0.0206***
	[0.00174]	[0.00127]	[0.000793]	[0.00175]
HHI	0.0617***	0.0426***	0.0571***	0.136***
	[0.00224]	[0.00164]	[0.00135]	[0.00429]
Merge_aquisi	-0.00684***	-0.00535***	0.0240***	-0.00623***
	[0.000928]	[0.000707]	[0.000809]	[0.000925]
Bankruptcy	-0.0195***	-0.0179***	-0.0406***	-0.0194***
	[0.00134]	[0.00128]	[0.00121]	[0.00135]
Inconvenience	0.0856***	0.0685***	0.0943***	0.0876***
	[0.00537]	[0.00383]	[0.00208]	[0.00540]
N	2,078,934	2,078,934	1,988,843	2,043,101
Time FE	Y	Y	Y	Y
IV	N	N	N	Y

Notes: The dependent variable is the natural logarithm of airfare; Column (4) regression uses IV approach, first-stage result is shown in the Appendix Table D.20; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.17: **Full regression results for Table 6: Regression results for round-trip (Industry-wide cost, legacy, LCC and ULCC)**

	(1)	(2)	(3)	(4)
lnJetFuelPrice	0.0236***	0.0402***	0.0177***	0.0268***
	[0.00159]	[0.00166]	[0.00158]	[0.00160]
lnJFPlag1	0.0565***	0.0314***	-0.00936***	0.0553***
	[0.00200]	[0.00239]	[0.00192]	[0.00201]
lnJFPlag2	0.0289***	0.00200	0.0127***	0.0302***
	[0.00182]	[0.00219]	[0.00168]	[0.00183]
lnJFPlag3	-0.0416***	-0.0315***	0.0393***	-0.0398***
	[0.00144]	[0.00155]	[0.00143]	[0.00145]
lnJFP*LCC2	-0.00835***	-0.0217***	-0.0512***	-0.0142***
	[0.00217]	[0.00206]	[0.00270]	[0.00220]
lnJFPlag1*LCC2	0.0140***	0.0165***	-0.0150***	0.0192***
	[0.00275]	[0.00320]	[0.00351]	[0.00277]
lnJFPlag2*LCC2	-0.0232***	-0.0250***	0.0143***	-0.0329***
	[0.00291]	[0.00335]	[0.00350]	[0.00300]
lnJFPlag3*LCC2	0.0501***	0.0227***	-0.0543***	0.0465***
	[0.00249]	[0.00220]	[0.00267]	[0.00252]
lnJFP*ULCC	-0.0475***	-0.102***	0.0159*	-0.0847***
	[0.00639]	[0.00553]	[0.00637]	[0.00662]
lnJFPlag1*ULCC	0.116***	0.107***	0.0899***	0.114***
	[0.00701]	[0.00753]	[0.00817]	[0.00707]
lnJFPlag2*ULCC	-0.00597	-0.0165*	0.0403***	0.00849
	[0.00785]	[0.00808]	[0.00818]	[0.00767]
lnJFPlag3*ULCC	-0.0905***	-0.124***	-0.00556	-0.120***
	[0.00585]	[0.00557]	[0.00616]	[0.00599]
lnSalary	0.0239***	0.00873***	0.340***	0.0221***
	[0.000799]	[0.000390]	[0.000404]	[0.000708]
Distance_group	0.0342***	0.0332***	-0.00253**	0.0468***
	[0.000673]	[0.000346]	[0.000789]	[0.000610]
HHI	0.105***	0.0945***	0.0577***	0.224***
	[0.00190]	[0.00120]	[0.00131]	[0.00295]
Merge_aquisi	-0.00561***	-0.00697***	0.0277***	-0.00523***
	[0.000893]	[0.000637]	[0.000810]	[0.000893]
Bankruptcy	-0.0183***	-0.0155***	-0.0395***	-0.0175***
	[0.00132]	[0.00128]	[0.00121]	[0.00133]
Inconvenience	-0.0337***	-0.0393***	0.108***	-0.0546***
	[0.00344]	[0.00176]	[0.00205]	[0.00321]
N	2,177,590	2,177,590	2,078,771	2,141,757
Time FE	Y	Y	Y	Y
IV	N	N	N	Y

Notes: The dependent variable is natural logarithm of airfare; Column (4) regression uses IV approach, first-stage result is shown in the Appendix Table D.21; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.18: **Full regression results for Table 7: Regression results for round-trip**
(Firm-specific cost, legacy, LCC and ULCC)

	(1)	(2)	(3)	(4)
lnavetotalcost	0.0542***	0.0674***	0.0545***	0.0617***
	[0.00170]	[0.00158]	[0.00135]	[0.00172]
lntcostlag1	0.0185***	-0.00534**	0.0117***	0.0201***
	[0.00168]	[0.00188]	[0.00143]	[0.00170]
lntcostlag2	0.00934***	0.00248	0.00330*	0.0105***
	[0.00156]	[0.00181]	[0.00138]	[0.00158]
lntcostlag3	-0.0113***	-0.00763***	0.0478***	-0.00668***
	[0.00160]	[0.00154]	[0.00130]	[0.00160]
lnavecost*LCC2	0.000487	-0.000635	-0.0692***	-0.00443
	[0.00279]	[0.00260]	[0.00355]	[0.00287]
lnavecostlag1*LCC2	0.0332***	0.0137***	-0.00619	0.0234***
	[0.00339]	[0.00393]	[0.00455]	[0.00345]
lnavecostlag2*LCC2	-0.00178	-0.0167***	0.0179***	-0.000199
	[0.00368]	[0.00417]	[0.00454]	[0.00373]
lnavecostlag3*LCC2	0.0213***	0.00407	-0.0445***	0.0157***
	[0.00329]	[0.00285]	[0.00350]	[0.00331]
lnavecost*ULCC	-0.0489***	-0.104***	0.0126*	-0.0869***
	[0.00626]	[0.00516]	[0.00613]	[0.00654]
lnavecostlag1*ULCC	0.133***	0.133***	0.0963***	0.128***
	[0.00640]	[0.00668]	[0.00750]	[0.00645]
lnavecostlag2*ULCC	-0.0172**	-0.0472***	0.0346***	0.00317
	[0.00649]	[0.00646]	[0.00747]	[0.00616]
lnavecostlag3*ULCC	-0.0909***	-0.112***	-0.00482	-0.125***
	[0.00551]	[0.00503]	[0.00589]	[0.00579]
lnSalary	0.0308***	0.0158***	0.341***	0.0322***
	[0.000923]	[0.000470]	[0.000400]	[0.000836]
Distance_group	0.0368***	0.0345***	0.00186*	0.0497***
	[0.000682]	[0.000347]	[0.000792]	[0.000615]
HHI	0.105***	0.0974***	0.0574***	0.225***
	[0.00198]	[0.00124]	[0.00135]	[0.00301]
Merge_aquisi	-0.00737***	-0.00915***	0.0254***	-0.00713***
	[0.000899]	[0.000640]	[0.000809]	[0.000901]
Bankruptcy	-0.0216***	-0.0187***	-0.0412***	-0.0219***
	[0.00133]	[0.00128]	[0.00121]	[0.00133]
Inconvenience	-0.0398***	-0.0425***	0.0938***	-0.0616***
	[0.00347]	[0.00178]	[0.00208]	[0.00324]
N	2,078,934	2,078,934	1,988,843	2,043,101
Time FE	Y	Y	Y	Y
IV	N	N	N	Y

Notes: The dependent variable is the natural logarithm of airfare; Column (4) regression uses IV approach, first-stage result is shown in the Appendix Table D.22; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.19: **First-stage results of IV regression**
Industry-wide cost change, Round-trip, Legacy vs. LCC

	First-stage	G2SLS
L.HHI	0.50789***	-
	[0.00202]	-
lnPopulation	-0.04037***	-
	[0.00478]	-
lnGDP	-0.04018***	-
	[0.00426]	-
lnJetFuelPrice	-0.01347***	0.0172***
	[0.00083]	[0.00161]
lnJFPlag1	0.00283**	0.0557***
	[0.00113]	[0.00200]
lnJFPlag2	0.0089***	0.0301***
	[0.00106]	[0.00182]
lnJFPlag3	-0.00127	-0.0467***
	[0.00078]	[0.00146]
lnJFP*LCC	-0.00823***	0.0179***
	[0.00141]	[0.00227]
lnJFPlag1*LCC	0.00667***	0.0256***
	[0.00217]	[0.00269]
lnJFPlag2*LCC	-0.00078	-0.0256***
	[0.00219]	[0.00288]
lnJFPlag3*LCC	0.00380***	0.0538***
	[0.00137]	[0.00245]

Notes: The dependent variable is the natural logarithm of airfare; First-stage results of Table 4 Column (4); Control variables include wage cost, route distance group, HHI, merger and acquisition condition, bankruptcy condition, inconvenience; P-value for over-identification and under-identification equal to 0, Kleibergen-Paap Wald rk F statistic equals 21083.2; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.20: **First-stage results of IV regression**
Firm-specific cost change, Round-trip, Legacy vs. LCC

	First-stage	G2SLS
L.HHI	0.51469***	-
	[0.00208]	-
lnPopulation	-0.04063***	-
	[0.00463]	-
lnGDP	-0.028023***	-
	[0.00416]	-
lnavetotalcost	-0.00354***	0.0384***
	[0.00084]	[0.00175]
lntcostlag1	0.00771***	0.0107***
	[0.00093]	[0.00169]
lntcostlag2	0.00218**	0.00782***
	[0.00095]	[0.00157]
lntcostlag3	0.00121	-0.0196***
	[0.00078]	[0.00163]
lnavecost*LCC	-0.01065***	0.0377***
	[0.00172]	[0.00281]
lnavecostlag1*LCC	0.02323***	0.0461***
	[0.00254]	[0.00304]
lnavecostlag2*LCC	-0.01294***	0.00228
	[0.00254]	[0.00328]
lnavecostlag3*LCC	0.00766***	0.0201***
	[0.00167]	[0.00302]

Notes: The dependent variable is the natural logarithm of airfare; First-stage results of Table 5 Column (4); Control variables include wage cost, route distance group, HHI, merger and acquisition condition, bankruptcy condition, inconvenience; P-value for over-identification and under-identification equal to 0, Kleibergen-Paap Wald rk F statistic equals 20510.55; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.21: **First-stage results of IV regression**
Industry-wide cost change, Round-trip, Legacy, LCC and ULCC

	First-stage	G2SLS
L.HHI	0.58574***	-
	[0.00090]	-
lnPopulation	-0.05331***	-
	[0.00061]	-
lnGDP	-0.01845***	-
	[0.00048]	-
lnJetFuelPrice	-0.01247***	0.0268***
	[0.00085]	[0.00160]
lnJFPlag1	0.00314***	0.0553***
	[0.00114]	[0.00201]
lnJFPlag2	0.01064***	0.0302***
	[0.00104]	[0.00183]
lnJFPlag3	-0.00188**	-0.0398***
	[0.00080]	[0.00145]
lnJFP*LCC2	-0.0100***	-0.0142***
	[0.00150]	[0.00220]
lnJFPlag1*LCC2	0.00921***	0.0192***
	[0.00234]	[0.00277]
lnJFPlag2*LCC2	-0.00115	-0.0329***
	[0.00236]	[0.00300]
lnJFPlag3*LCC2	0.00348**	0.0465***
	[0.00148]	[0.00252]
lnJFP*ULCC	-0.00429**	-0.0847***
	[0.00219]	[0.00662]
lnJFPlag1*ULCC	0.0047	0.114***
	[0.00335]	[0.00707]
lnJFPlag2*ULCC	-0.01070***	0.00849
	[0.00337]	[0.00767]
lnJFPlag3*ULCC	0.00260	-0.120***
	[0.00209]	[0.00599]

Notes: The dependent variable is the natural logarithm of airfare; First-stage results of Table 6 Column (4); Control variables include wage cost, route distance group, HHI, merger and acquisition condition, bankruptcy condition, inconvenience; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.22: **First-stage results of IV regression**
Firm-specific cost change, Round-trip, Legacy, LCC and ULCC

	First-stage	G2SLS
L.HHI	0.59445***	-
	[0.00092]	-
lnPopulation	-0.05408***	-
	[0.00061]	-
lnGDP	-0.01735***	-
	[0.00048]	-
lnavetotalcost	-0.00141*	0.0617***
	[0.00077]	[0.00172]
lntcostlag1	0.00876***	0.0201***
	[0.00091]	[0.00170]
lntcostlag2	0.00367***	0.0105***
	[0.00091]	[0.00158]
lntcostlag3	0.00193***	-0.00668***
	[0.00075]	[0.00160]
lnavecost*LCC2	-0.01647***	-0.00443
	[0.00199]	[0.00287]
lnavecostlag1*LCC2	0.03214***	0.0234***
	[0.00304]	[0.00345]
lnavecostlag2*LCC2	-0.01856***	-0.000199
	[0.00306]	[0.00373]
lnavecostlag3*LCC2	0.00730***	0.0157***
	[0.00194]	[0.00331]
lnavecost*ULCC	-0.00788***	-0.0869***
	[0.00222]	[0.00654]
lnavecostlag1*ULCC	0.00205	0.128***
	[0.00327]	[0.00645]
lnavecostlag2*ULCC	-0.00393	0.00317
	[0.00317]	[0.00616]
lnavecostlag3*ULCC	-0.00028	-0.125***
	[0.00204]	[0.00579]

Notes: The dependent variable is the natural logarithm of airfare; First-stage results of Table 7 Column (4); Control variables include wage cost, route distance group, HHI, merger and acquisition condition, bankruptcy condition, inconvenience; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.23: **First-stage results of IV regression Industry-wide cost change, Single-trip, Legacy vs. LCC**

	First-stage	G2SLS
L.HHI	0.42840***	-
	[0.00228]	-
lnPopulation	-0.02957***	-
	[0.00597]	-
lnGDP	-0.04121***	-
	[0.00528]	-
lnJetFuelPrice	-0.02636***	-0.0292***
	[0.00103]	[0.00291]
lnJFPlag1	0.01116***	0.0659***
	[0.00146]	[0.00371]
lnJFPlag2	0.00330**	0.0427***
	[0.00137]	[0.00347]
lnJFPlag3	0.00520***	-0.0301***
	[0.00099]	[0.00262]
lnJFP*LCC	-0.00260*	0.0848***
	[0.00158]	[0.00339]
lnJFPlag1*LCC	-0.00171	-0.0138**
	[0.00240]	[0.00434]
lnJFPlag2*LCC	0.00778***	-0.0657***
	[0.00244]	[0.00436]
lnJFPlag3*LCC	-0.00672***	0.0829***
	[0.00157]	[0.00333]

Notes: The dependent variable is the natural logarithm of airfare; First-stage results of Table D.6 Column (4); Control variables include wage cost, route distance group, HHI, merger and acquisition condition, bankruptcy condition, inconvenience; P-value for over-identification and under-identification equal to 0, Kleibergen-Paap Wald rk F statistic equals 12025.42; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.24: **First-stage results of IV regression**
Firm-specific cost change, Single-trip, Legacy vs. LCC

	First-stage	G2SLS
L.HHI	0.43120***	-
	[0.00233]	-
lnPopulation	-0.03036***	-
	[0.00580]	-
lnGDP	-0.03132***	-
	[0.00528]	-
lnavetotalcost	-0.01427***	0.0508***
	[0.00103]	[0.00271]
lntcostlag1	0.01165***	0.0730***
	[0.00114]	[0.00278]
lntcostlag2	-0.00123	0.0175***
	[0.00116]	[0.00266]
lntcostlag3	0.00432***	0.0235***
	[0.00096]	[0.00253]
lnavecost*LCC	-0.00631***	0.116***
	[0.00186]	[0.00393]
lnavecostlag1*LCC	0.00771***	-0.0241***
	[0.00273]	[0.00456]
lnavecostlag2*LCC	0.00601**	-0.0367***
	[0.00275]	[0.00463]
lnavecostlag3*LCC	-0.00700***	0.0835***
	[0.00183]	[0.00384]

Notes: The dependent variable is the natural logarithm of airfare; First-stage results of Table D.8 Column (4); Control variables include wage cost, route distance group, HHI, merger and acquisition condition, bankruptcy condition, inconvenience; P-value for over-identification and under-identification equal to 0, Kleibergen-Paap Wald rk F statistic equals 11622.23; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.25: **First-stage results of IV regression**
Industry-wide cost change, Single-trip, Legacy, LCC and ULCC

	First-stage	G2SLS
L.HHI	0.53683***	-
	[0.00102]	-
lnPopulation	-0.06144***	-
	[0.00066]	-
lnGDP	-0.01344***	-
	[0.00055]	-
lnJetFuelPrice	-0.02511***	-0.0120***
	[0.00107]	[0.00287]
lnJFPlag1	0.01250***	0.0616***
	[0.00147]	[0.00371]
lnJFPlag2	0.00482***	0.0476***
	[0.00136]	[0.00347]
lnJFPlag3	0.00356***	-0.0243***
	[0.00101]	[0.00260]
lnJFP*LCC2	-0.00248	0.0367***
	[0.00170]	[0.00334]
lnJFPlag1*LCC2	0.00076	-0.0194***
	[0.00265]	[0.00444]
lnJFPlag2*LCC2	0.00691***	-0.0640***
	[0.00266]	[0.00447]
lnJFPlag3*LCC2	-0.00592***	0.0644***
	[0.00166]	[0.00340]
lnJFP*ULCC	0.00318	-0.0638***
	[0.00242]	[0.00791]
lnJFPlag1*ULCC	-0.00765	0.119***
	[0.00363]	[0.00915]
lnJFPlag2*ULCC	0.00104	-0.159***
	[0.00355]	[0.00908]
lnJFPlag3*ULCC	0.00048	-0.0348***
	[0.00224]	[0.00674]

Notes: The dependent variable is natural logarithm of airfare; First-stage results of Table D.13 Column (4); Control variables include wage cost, route distance group, HHI, merger and acquisition condition, bankruptcy condition, inconvenience; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.26: **First-stage results of IV regression**
Firm-specific cost change, Single-trip, Legacy, LCC and ULCC

	First-stage	G2SLS
L.HHI	0.54243***	-
	[0.00104]	-
lnPopulation	-0.06233***	-
	[0.00066]	-
lnGDP	-0.01268***	-
	[0.00056]	-
lnavetotalcost	-0.01074***	0.0883***
	[0.00095]	[0.00266]
lntcostlag1	0.01362***	0.0919***
	[0.00114]	[0.00281]
lntcostlag2	0.00037	0.0213***
	[0.00115]	[0.00267]
lntcostlag3	0.00492***	0.0394***
	[0.00094]	[0.00247]
lnavecost*LCC2	-0.00753***	0.0595***
	[0.00222]	[0.00413]
lnavecostlag1*LCC2	0.01277***	-0.0522***
	[0.00340]	[0.00516]
lnavecostlag2*LCC2	0.00458	-0.0179***
	[0.00341]	[0.00514]
lnavecostlag3*LCC2	-0.00981***	0.0558***
	[0.00215]	[0.00418]
lnavecost*ULCC	-0.00250	-0.0361***
	[0.00241]	[0.00748]
lnavecostlag1*ULCC	-0.00552	0.0579***
	[0.00358]	[0.00873]
lnavecostlag2*ULCC	0.00346	-0.103***
	[0.00339]	[0.00855]
lnavecostlag3*ULCC	-0.00017	-0.0295***
	[0.00217]	[0.00624]

Notes: The dependent variable is natural logarithm of airfare; First-stage results of Table D.14 Column (4); Control variables including wage and benefit cost, route distance group, HHI, merger and acquisition condition, bankruptcy condition, inconvenience; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.27: **Regression results for round-trip (Industry-wide cost, Legacy vs. LCC)**

	(1)	(2)	(3)	(4)
lnJetFuelPrice	0.0205***	0.0296***	0.0191***	0.0210***
	[0.00161]	[0.00164]	[0.00159]	[0.00161]
lnJFPlag1	0.0578***	0.0395***	-0.00966***	0.0569***
	[0.00200]	[0.00227]	[0.00194]	[0.00201]
lnJFPlag2	0.0296***	0.00941***	0.0153***	0.0309***
	[0.00181]	[0.00207]	[0.00168]	[0.00182]
lnJFPlag3	-0.0447***	-0.0392***	0.0374***	-0.0452***
	[0.00145]	[0.00151]	[0.00144]	[0.00146]
lnJFP*LCC	0.00483*	0.00393	-0.0512***	0.00642**
	[0.00222]	[0.00208]	[0.00269]	[0.00224]
lnJFPlag1*LCC	0.00935***	0.0107***	-0.0156***	0.0124***
	[0.00273]	[0.00303]	[0.00353]	[0.00274]
lnJFPlag2*LCC	-0.0199***	-0.0225***	0.0149***	-0.0269***
	[0.00289]	[0.00319]	[0.00352]	[0.00295]
lnJFPlag2*LCC	0.0560***	0.0434***	-0.0525***	0.0577***
	[0.00247]	[0.00224]	[0.00267]	[0.00250]
N	2,102,726	2,102,726	2,008,315	2,067,153
Time FE	Y	Y	Y	Y
IV	N	N	N	Y

Notes: The regression exclude ultra-low-cost carrier data. The dependent variable is the natural logarithm of airfare; Column (4) regression uses the IV approach; Control variables include wage cost, route distance group, HHI, merger and acquisition condition, bankruptcy condition, and inconvenience; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.28: **Regression results for round-trip (Firm-specific cost, Legacy vs. LCC)**

	(1)	(2)	(3)	(4)
lnavetotalcost	0.0341***	0.0406***	0.0526***	0.0356***
	[0.00172]	[0.00159]	[0.00136]	[0.00172]
lntcostlag1	0.00646***	-0.0118***	0.00866***	0.00611***
	[0.00166]	[0.00179]	[0.00144]	[0.00167]
lntcostlag2	0.00527***	0.000175	0.00271	0.00592***
	[0.00156]	[0.00172]	[0.00139]	[0.00157]
lntcostlag3	-0.0281***	-0.0244***	0.0439***	-0.0267***
	[0.00161]	[0.00154]	[0.00131]	[0.00161]
lnavecost*LCC	0.0170***	0.0249***	-0.0733***	0.0204***
	[0.00285]	[0.00263]	[0.00354]	[0.00291]
lnavecostlag1*LCC	0.0303***	0.0159***	-0.00462	0.0225***
	[0.00337]	[0.00372]	[0.00457]	[0.00340]
lnavecostlag2*LCC	0.00507	-0.00719	0.0195***	0.00766*
	[0.00366]	[0.00398]	[0.00456]	[0.00369]
lnavecostlag3*LCC	0.0326***	0.0253***	-0.0438***	0.0321***
	[0.00331]	[0.00294]	[0.00350]	[0.00332]
N	2,004,195	2,004,195	1,918,509	1,968,622
Time FE	Y	Y	Y	Y
IV	N	N	N	Y

Notes: The regression exclude ultra-low-cost carrier data. The dependent variable is the natural logarithm of airfare; Column (4) regression uses IV approach; Control variables include wage cost, route distance group, HHI, merger and acquisition condition, bankruptcy condition, and inconvenience; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.29: **Regression results for single-trip (Industry-wide cost, legacy vs. LCC)**

	(1)	(2)	(3)	(4)
lnJetFuelPrice	-0.0244***	-0.0196***	-0.0120***	-0.0235***
	[0.00291]	[0.00293]	[0.00270]	[0.00292]
lnJFPlag1	0.0684***	0.0655***	0.0101**	0.0655***
	[0.00371]	[0.00405]	[0.00333]	[0.00371]
lnJFPlag2	0.0359***	0.0170***	0.0252***	0.0415***
	[0.00345]	[0.00379]	[0.00296]	[0.00347]
lnJFPlag3	-0.0217***	-0.0208***	0.0608***	-0.0251***
	[0.00262]	[0.00270]	[0.00243]	[0.00263]
lnJFP*LCC	0.0705***	0.0616***	0.00502	0.0739***
	[0.00338]	[0.00327]	[0.00399]	[0.00340]
lnJFPlag1*LCC	-0.0440***	-0.0437***	-0.0395***	-0.0347***
	[0.00440]	[0.00477]	[0.00539]	[0.00440]
lnJFPlag2*LCC	-0.0253***	-0.0239***	0.00249	-0.0468***
	[0.00439]	[0.00476]	[0.00538]	[0.00444]
lnJFPlag2*LCC	0.0674***	0.0604***	-0.0385***	0.0763***
	[0.00339]	[0.00322]	[0.00394]	[0.00342]
N	1,643,637	1,643,637	1,566,782	1,622,872
Time FE	Y	Y	Y	Y
IV	N	N	N	Y

Notes: The regression exclude ultra-low-cost carrier data. The dependent variable is the natural logarithm of airfare; Column (4) regression uses the IV approach; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.30: **Regression results for single-trip (Firm-specific cost, Legacy vs. LCC)**

	(1)	(2)	(3)	(4)
lnavetotalcost	0.0496***	0.0445***	0.0612***	0.0491***
	[0.00269]	[0.00256]	[0.00226]	[0.00270]
lntcostlag1	0.0682***	0.0544***	0.0596***	0.0688***
	[0.00276]	[0.00289]	[0.00250]	[0.00277]
lntcostlag2	0.0131***	0.00102	0.0155***	0.0156***
	[0.00265]	[0.00282]	[0.00244]	[0.00266]
lntcostlag3	0.0218***	0.0176***	0.0848***	0.0231***
	[0.00255]	[0.00250]	[0.00224]	[0.00255]
lnavecost*LCC	0.0887***	0.0847***	-0.00187	0.102***
	[0.00414]	[0.00396]	[0.00516]	[0.00422]
lnavecostlag1*LCC	-0.0361***	-0.0502***	-0.0509***	-0.0538***
	[0.00506]	[0.00546]	[0.00687]	[0.00509]
lnavecostlag2*LCC	-0.00516	0.000837	0.0251***	-0.00899
	[0.00508]	[0.00545]	[0.00688]	[0.00510]
lnavecostlag3*LCC	0.0754***	0.0627***	-0.0147**	0.0822***
	[0.00422]	[0.00395]	[0.00510]	[0.00423]
N	1,562,885	1,562,885	1,494,253	1,542,120
Time FE	Y	Y	Y	Y
IV	N	N	N	Y

Notes: The regression exclude ultra-low-cost carrier data. The dependent variable is the natural logarithm of airfare; Column (4) regression uses the IV approach; Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.31: **Regression results for round-trip (with lag of airfare) (Industry-wide cost, Legacy vs. LCC)**

lnairfare	Legacy	Low-cost
lnJetFuelPrice	0.0290***	0.0011
	[0.00165]	[0.001985]
lnJFPlag1	0.0486***	0.0287***
	[0.00220]	[0.0029]
lnJFPlag2	0.036*	-0.0169***
	[0.00201]	[0.00313]
lnJFPlag3	-0.0521***	0.0234***
	[0.00149]	[0.00211]
N	2,141,757	

Notes: Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.32: **Regression results for round-trip (with lag of airfare) (Firm-specific cost, Legacy vs. LCC)**

lnairfare	Legacy	Low-cost
lnavetotalcost	0.0474***	0.0196***
	[0.001565]	[0.00237]
lncostlag1	-0.0047***	0.0483***
	[0.00176]	[0.00324]
lncostlag2	0.0084***	0.00867**
	[0.00170]	[0.00352]
lncostlag3	-0.0253***	-0.0071***
	[0.00149]	[0.00255]
N	2,043,101	

Notes: Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table D.33: **Regression results for round-trip with different lags of jet fuel price (Industry-wide cost, Legacy vs. LCC)**

lnairfare	Legacy	Low-cost
No lag		
lnJetFuelPrice	0.0254***	0.0570***
	[0.001441]	[0.00177]
One lag		
lnJetFuelPrice	0.0195***	0.0117***
	[0.0160]	[0.00227]
lnJFPlag1	0.0550***	0.0490***
	[0.00173]	[0.00228]
Two lags		
lnJetFuelPrice	0.0164***	0.0225***
	[0.0161]	[0.00228]
lnJFPlag1	0.0720***	0.044
	[0.00201]	[0.00272]
lnJFPlag2	-0.0137***	0.0389***
	[0.00148]	[0.00237]

Notes: Standard errors clustered at the product level are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

E Figures

Figure E.1: **Cumulative pass-through for legacy carriers and low-cost carriers (3)**

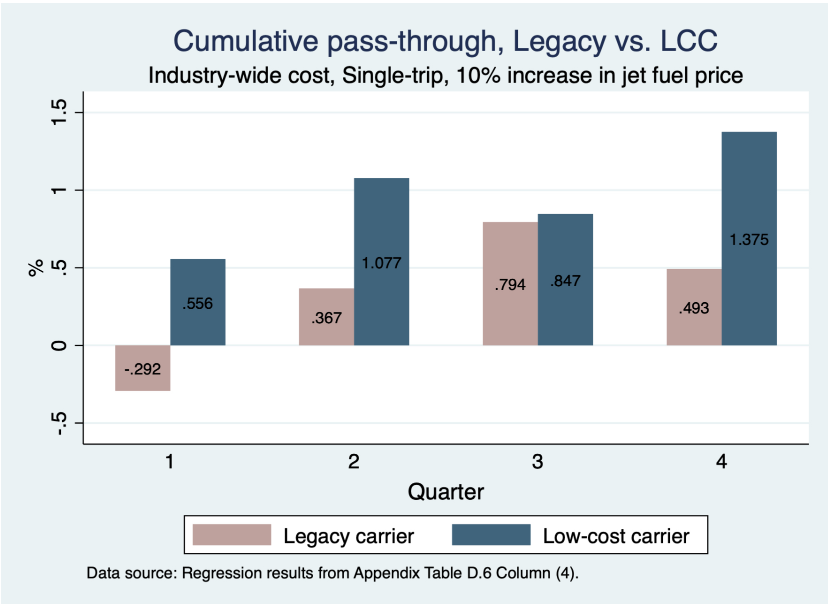


Figure E.2: **Cumulative pass-through for legacy carriers and low-cost carriers (4)**

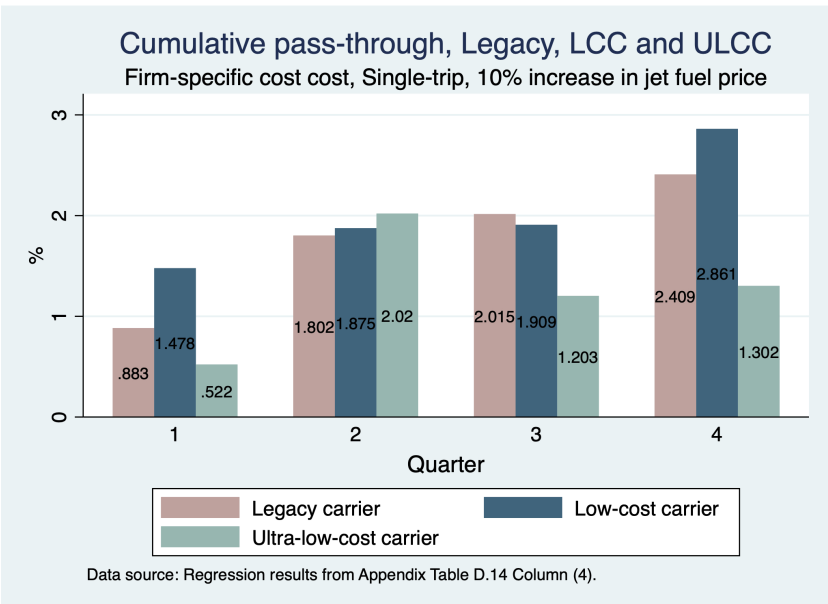


Figure E.3: **Cumulative pass-through for legacy, low-cost and ultra-low-cost carriers (3)**

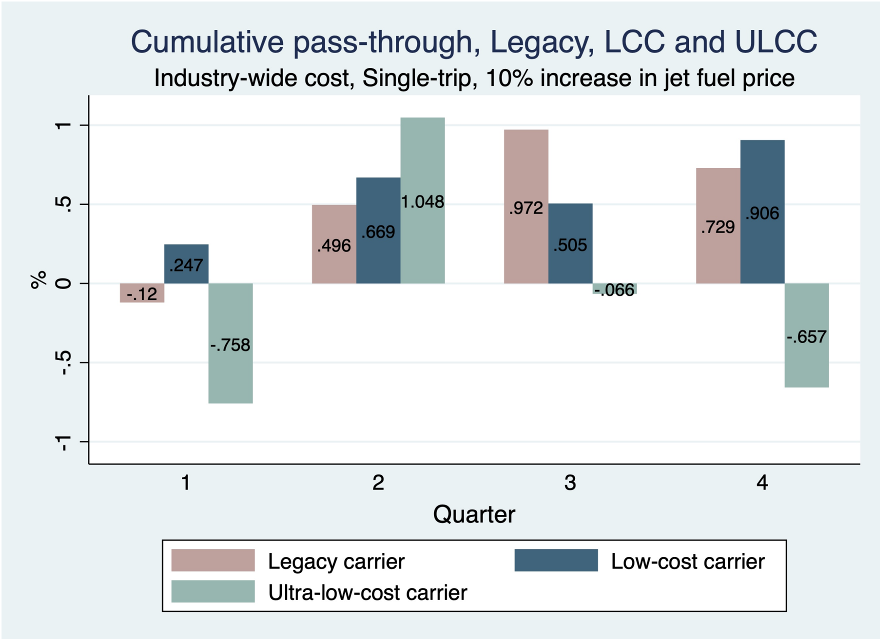
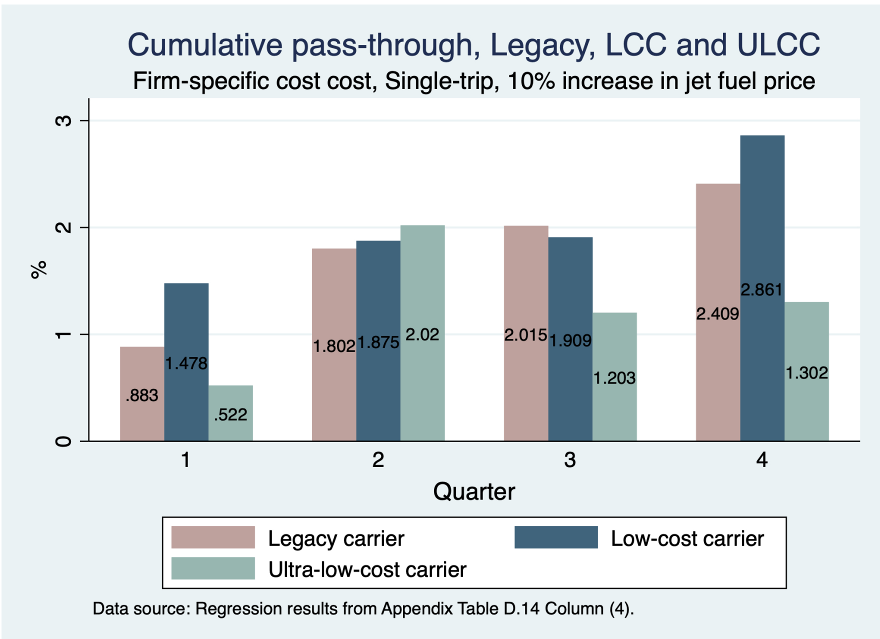


Figure E.4: **Cumulative pass-through for legacy, low-cost and ultra-low-cost carriers (4)**



Chapter II

Market performance comparison between China and U.S. commercial civil airline companies during COVID-19

Abstract

This paper uses the financial data analysis and event study approach to evaluate the market performance and financial performance of legacy carriers and low-cost carriers in China and the U.S. during the COVID-19 pandemic. Analysis of financial reports and ratios reveals that legacy carriers in both countries experience a greater revenue loss than low-cost carriers, while low-cost carriers keep more liquidity and better loan repayment capability during the pandemic. The cumulative average abnormal returns and average buy-and-hold abnormal returns to publicly traded airline stocks in the U.S. are significantly higher than those in China, both in the short-term and long-term event windows. In the short run, both Chinese and U.S. legacy carriers are more affected than low-cost carriers. State ownership has not significantly helped China's airline stocks mitigate negative shocks.

Keywords— COVID-19, Aviation industry, Legacy carrier, Low-cost carrier

1 Introduction

In the context of increasing economic globalization, any black swan event (especially a negative random shock) could rapidly impact all industries globally.[35] According to the World Bank Global Economic Prospects 2020, the world economy in 2020 faced the deepest recession since World War II, shrinking 5.2% in global GDP due to the COVID-19 pandemic. As an important part of this global economy, the airline industry was particularly affected since most of its activities were halted worldwide to prevent the virus from spreading. Domestic and international travel restrictions caused the commercial airline industry to lose around $371 billion in gross passenger operating revenue (ICAO, 2020).

On January 23, 2020, China became the first country to declare a lockdown policy and continuously implement strict travel control measures during the pandemic. During the week of implementing the lockdown policy, the China Southern Airlines (legacy carrier) stock and Juneyao Airlines (low-cost carrier (LCC)) stock plunged 8.53% and 11.78%, respectively.[36] Right after the lockdown, in February 2020, passenger volume experienced an 84.5% year-over-year (YOY) decline in the Chinese civil aviation industry.[37] In the U.S. market, after the first travel restriction was implemented on January 31, 2020, the stock prices of Delta Airlines (legacy carrier) went down by 5.22% and JetBlue Airways (LCC) went down by 3.97%. After the announcement of the global pandemic, the magnitude of the decline was extended to 28.45% and 34.29% for these two U.S. airline companies. This evidence highlights that the travel bans had a considerable negative effect on the airline industry and, thus, on investors in the airline industry.

[35] An event that is extremely rare and unexpected but has very significant consequences (Taleb, 2007).

[36] Bloomberg securities data.

[37] Statistics of Key Performance Indicators for China's Civil Aviation Industry in February 2020 from Civil Aviation Administration of China (CAAC), http://www.caac.gov.cn/en/HYYJ/SJ/202006/t20200629_203334.html

There are at least three reasons why comparing the U.S. and China experience helps us understand better how commercial airlines responded to Covid-19: (1) Geographically, China and the U.S. are both vast (compared to Europe) and have a relatively balanced distribution of cities and populations (compared to Australia), with aviation being the main mode of transportation in both countries. (2) While China was the first country to implement travel restrictions during the COVID-19 pandemic, the United States was the country with the largest absolute reported number of infections.[38] (3) The United States and China are the two largest economies in the world; the impact of the COVID-19 pandemic on them, especially on their aviation industry, profoundly affected the travel and trade industries worldwide.[39] This study compares the airlines' stock and financial performance of low-cost carriers versus legacy carriers within and between these two countries during the COVID-19 pandemic assessment.

For the comparison of the airline industries in these two countries, since the U.S. financial market is more efficient than the Chinese market (Zhou et al., 2002), we expect U.S. aviation stocks to be more affected by the pandemic than Chinese aviation stocks.[40] Considering COVID-19, which was defined by the WHO as a global pandemic on March 11, 2020, the 5-day average cumulative decline in Chinese and U.S. civil aviation stocks was 12.32% and 25.48%, while the 10-day average cumulative decline was 16.09% and 28.21%, respectively.[41]

While comparing the impact on the airline industry in the two countries, we look at each country's legacy carriers and low-cost carriers separately. For the comparison of two categories of airlines, theoretically, we do not know the differ-

[38] WHO Coronavirus (COVID-19) Dashboard, as of March 2022.

[39] By GDP in current USD from World Bank national accounts data in 2021. United States: 22,996,100.00 million USD, China: 17,734,062.65 million USD. https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?most_recent_value_desc=true

[40] Stock price can reflect more macro-economy, industry, and company information.

[41] Author's calculation based on Bloomberg historical stock price data.

ential magnitude of the impacts associated with the COVID-19 pandemic because of two countervailing forces. On the one hand, with larger market capitalization compared to low-cost carriers, we expect legacy carriers to have more consistent stock returns and better financial performance during the crisis.[42] On the other hand, low-cost carriers have a more flexible cost structure to offset the potential revenue loss, and with a lower proportion of international business in their total operating income, it is also possible that investors have more confidence in low-cost carriers.

China's three largest airlines, China Eastern Airlines, China Southern Airlines, and Air China, have 69.91%, 75.92% and 75.18% government ownership, respectively. Investors may expect state-owned companies to receive government support in times of economic hardship or crisis (Musacchio and Lazzarini, 2014; Dewenter and Malatesta, 2001). This expectation may reduce the volatility of state-owned companies' stocks because it reduces the risk of bankruptcy or severe financial distress. Stocks of state-owned enterprises may be less liquid due to their large scale and the presence of large government shareholders. Lower liquidity may lead to increased price volatility (Amihud, 2002). This makes it more meaningful to compare the performance of firms with a large percentage of government ownership with private firms during the pandemic and to see whether government ownership can mitigate the negative impact of a large proportion of international business.

From a methodological standpoint, this paper follows an event study and a financial ratio analysis. We use public-traded airline companies in each country to assess their abnormal returns, cumulative abnormal returns (CAR), and buy and hold abnormal returns (BHAR). We also use financial indicators during the pandemic to analyze the companies' performance during COVID-19. We use seven

[42]The average market capitalization of Chinese legacy carriers in 2019 was 65,852.32 million in CNY, and that of low-cost carriers was 34,857.85 million in CNY. The average market capitalization of U.S. legacy carriers in 2019 was 14,156.07 million in USD, and that of low-cost carriers was 7,821.36 million in USD.

listed airlines in the Chinese market, including five legacy carriers and two low-cost carriers.[43] In the U.S. market, we focus on eleven companies, including six legacy carriers and five low-cost carriers.[44]

For financial performance, we focus on the data from the statements of operating and balance sheets of each company, which come from the annual statements of the airlines published by the securities regulators. Profitability ratios, activity ratios, liquidity ratios, and solvency ratios, which can reflect the business's operating conditions, are taken into consideration.

First, we acknowledge the global COVID-19 pandemic as the study event and examine the short- and long-term impacts of the event on Chinese and U.S. airline stocks. Next, we choose a specific event in each of the two countries that has a significant negative impact (negative random shock) on the country's aviation industry for analysis. We assess each country's government stimulus packages (positive random shocks) to assess their countervailing responses.

Our results indicate that, in the short term, over one to ten days, Chinese low-cost carriers enjoy higher cumulative average abnormal returns than legacy carriers in response to new information in the market. When looking at the 50-day long-term event window, the results show that Chinese legacy carriers are more significantly affected by the negative random shock than low-cost carriers. In the U.S. market, legacy carriers are more negatively affected in the short term than low-cost carriers. And there is no statistically significant difference between U.S. low-cost and traditional airlines in the long run. The numbers and ratios from the financial reports show that legacy carriers prefer to keep high financial

[43] The legacy carriers are China Eastern Airlines, China Southern Airlines, Air China, China Express Airlines, and Hainan Airlines. The low-cost carriers are Spring Airlines and Juneyao Air.

[44] The legacy carriers are American Airlines, Delta Air Lines, Alaska Airlines, Hawaiian Airlines, United Airlines, and Skywest Airlines. The low-cost carriers are Spirit Airlines, JetBlue Airways, Southwest Airlines, Allegiant Airlines, and Mesa Airlines.

leverage even during the pandemic. Conversely, low-cost carriers are more inclined to hold assets with higher liquidity and maintain relatively better short-term and long-term liability repayment capabilities.

To the best of our knowledge, this is the first study to explore the difference in market performance and financial performance between legacy carriers and low-cost carriers during the COVID-19 pandemic. Our empirical conclusions provide markets' attitudes toward airlines with different business models when facing random shocks, especially negative random shocks. Our research results provide information on how airline companies operate under such circumstances, as well as relevant information on the markets' attitudes towards different airline models (legacy and low-cost models) operating under negative random shocks. Our research provides further insights into the differences between legacy and low-cost airlines. It lays the foundation for future research on the civil aviation industry.

The rest of the paper is organized as follows: Section 2 summarizes the literature related to our topic; Sections 3 and 4 discuss the data and methodology used in the analysis, while the results are shown in Section 5. We conclude in Section 6.

2 Literature review

COVID-19, a negative random shock that was completely unforeseen by all industries and countries, has had a huge negative impact on the global stock market in a short time (Bash, 2020). The declaration of COVID-19 as a global pandemic has had a significant negative effect on major Asian stock markets (AlAli, 2020).[45] G-20 countries' stock markets provided similar results with a negative effect at the

[45] The event date used in AlAli (2020) is March 11, 2020, on which date WHO announced COVID-19 as a global pandemic. The event windows he used are 5-days, 15-days and 30-days, which covers both short- and medium-run periods.

beginning of the pandemic. Further study of its long-run effects shows positive cumulative abnormal returns, which means the stock market gradually recovers from the shock (Singh et al., 2020).[46]

The evidence from specific countries like the U.S. (Chowdhury, 2020), China (He et al., 2020), and Australia (Rahman, 2021) is consistent with the study of global markets. Using the first COVID-19 case diagnosed in the U.S. (January 20, 2020) as the event date, Chowdhury (2020) shows that the cumulative abnormal return of the S&P500 in the event window-day [0,5] was -0.02477, while in the event window-day [6,10] it was -0.06551. The results of the Chinese stock market were smaller than in the U.S. case, with the cumulative abnormal return of the Shanghai A-share equal to -0.0025 in the event window-day [0,5] and -0.0020 in the event window-day [0,10].

The random shock affected different industries to varying degrees. The study, based on 2,895 listed firms in 18 industries in the Chinese A-market, demonstrates that, from the perspective of the industry, the outbreak of COVID-19 (January 23, 2020) had a significant negative effect on almost all of the industries (He et al, 2020). Traditional sectors such as transportation, mining, and agriculture were hit hardest (with same-day abnormal returns at -0.0109, -0.0389 and -0.0316). However, high-tech-related industries like information technology, education, and sports and entertainment reveal positive reactions to the pandemic, with same-day abnormal returns at 0.0246, -0.0305 and -0.0276. Although the same-day abnormal returns of the education and health industries are both negative, the cumulative abnormal returns in the medium run of 30 days are both positive, at 0.0031 and 0.0021, which are the highest positive cumulative abnormal returns among all 18 industries. Most of the existing studies are focused on one event only (the declaration of COVID-19 as a global pandemic on January 23, 2020) and

[46]Singh et al.(2020) use 30 countries' stock markets as their sample and the first registered case in each country as its event date, the event window is [-10, 20].

use 30 days as an event window (Chowdhury, 2020; He et al., 2020). Although long-term event studies provide the continuing impacts of the event on the stock market, a longer time window may include other concurrent events that also have a significant impact on the stock market, making the conclusions drawn more uncertain. Our study uses both short- and long-run event windows to address the potential impacts of the events.

The effect of COVID-19 on the stock markets is widely discussed across various countries (Zeren, 2020; Rahman, 2021; Chowdhury, 2020) and industry perspectives (Mazur, 2021; He et al., 2020). There are limited studies devoted to the aviation industry, which is one of the industries that is most affected by this global pandemic (He et al., 2020). Maneeop and Kotcharin (2020) studied 52 airline companies' stock performance after three representative events and found that investors became more sensitive to information with the development of the outbreak; the longer window period corresponds to a larger negative cumulative abnormal return. At the same time, airline stock turbulence is more pronounced in Western countries, including Australia, Canada, the U.K., and the U.S., than in other markets in the world.[47]

Some studies examine the impact of COVID-19 on the aviation industry from other perspectives, like employment and strategic autonomy. Sobieralski (2020) shows that the pandemic caused a 7% employment loss for the U.S. airline industry as a whole. The legacy carriers were hit the most since low-cost carriers and regional carriers do not generate as many jobs as the legacy carriers do. Albers

[47] The events they used are the first case reported outside China in Thailand (January 13, 2020), the outbreak in Italy (February 21, 2020), and the declaration of COVID-19 as a global pandemic (March 11, 2020). Although the study used a short-term event window and selected multiple events, some regional events were not sufficient to have a large impact on aviation stock price fluctuations in other countries. For example, no country has issued any travel restrictions because of the confirmation of the first case in Thailand; this is in the early days of the outbreak and has not yet attracted widespread global attention, so the impact of the incident on the aviation industry stocks in other countries is very limited.

(2020) shows that, unlike low-cost carriers, the European legacy carriers show a reduction in strategic autonomy after receiving government aid due to the pandemic.

For the airline industry, air crashes (Ho et al., 2013, Flouris and Walker, 2005) and epidemic infectious diseases (Loh, 2006) are two factors that are most likely to have a negative effect on the demand for the market, which then cause the stock prices to fluctuate. Air crashes are usually very sudden and more unpredictable than the spread of an epidemic, so they give the market different reaction times, resulting in different investor reactions. Although the spread of epidemics is also unpredictable, in the middle and late stages, health departments can give the public a relatively clear route of virus transmission and measures to prevent virus spread. This makes the spread of disease predictable, especially in the later stages, compared to air crashes.

The analysis of the influence of public health events on the airline industry follows the episode of SARS in 2003 and is more focused on the risk side. Loh (2006) finds that during the SARS, airline stocks were more volatile than other stocks in the market.

The studies on the influence of the air crash are focused on stock performance. It is widely acknowledged that fatalities from an air crash have a significant influence on the airline's stock performance. Ho et al. (2013) find that when the death toll is less than ten, the crashed airline suffers a stock price fall; the stock price of its rival rises. When the death toll is more than ten, both the crashed airline and rival airline stocks drop due to the anxiety about aviation safety spreading throughout the whole industry, including travellers and investors.

In addition to air crashes caused by mechanical failure or human operation error, air disasters caused by terrorist attacks, such as the September 11 attacks in the U.S., also result in lower trust by passengers and investors in the civil aviation industry. Flouris and Walker (2005) analyze the accounting and stock performance between Southwest Airlines, a representative low-cost carrier, and Continental and Northwest Airlines, representatives of legacy carriers, following the September 11 attacks. Their results indicate that Southwest had a better financial position in the aftermath compared to the other two carriers. It also has better stock performance, both with and without risk adjustments. Their conclusions suggest that the Southwest (LCC) business model is more trusted by investors in the stock market.[48] Our study compares the stock performance of legacy carriers and low-cost carriers, taking all publicly traded companies into consideration, which can provide more detailed results for these two types of carriers when facing negative random shocks.

To the best of my knowledge, this paper is the first to examine the performance differences between legacy carriers and low-cost carriers during a public health event. As global migration continues to rise along with increases in the frequency and incidence of infectious diseases in recent years, the impact of public health events such as SARS, H5N1 ("bird flu"), and the Coronavirus (COVID-19) on the civil aviation industry deserves our attention.

3 Accounting analysis

3.1 Accounting indicators and ratios

The major accounting indicators we choose are mainly from airlines' consolidated statements of operations and balance sheets. *Operating revenue*, *operating expense* and *net income* all reflect the current state of the business, particularly its prof-

[48]Compared with legacy carriers, the Southwest business model operates at lower operating costs. They use a relatively simple pricing structure to increase the seats on board, rent old terminals, and rent homogeneous flights to reduce maintenance and training costs. Flouris and Walker (2005) also show that the productivity of low-cost carriers is higher than that of legacy carriers.

itability over the previous year. The indicators from the balance sheet: *current asset, cash, current liability, non-current liability*, and *stockholders' equity* show the financial position of the firm, and we use them to calculate the financial ratios.

Given the particularity of the airline industry, some financial ratios that are commonly used to analyze the traditional manufacturing industry or financial industry are not suitable here. We pick the ratios that are more applicable to the airline industry (Morrell, 2018). The financial ratios are divided into four groups: activity ratio, liquidity ratio, solvency ratio, and profitability ratio.

Total asset turnover and the *operating ratio* are activity ratios. Total asset turnover indicates the efficiency of a firm's ability to generate revenue using its total assets (Gitman et al., 2015). The higher the total asset turnover, the more efficient a company is in asset use. An operating ratio is measured from a cost perspective to determine whether a company can keep a low cost when generating revenue. The higher the operating ratio, the more revenue the firm can generate with the unit operating expense (Morrell, 2018). The operational ratio and total asset turnover are computed using:

$$Total\ asset\ turnover = \frac{Revenue}{Average\ total\ asset}$$

where the average total asset is the arithmetic average of total asset from the previous year and this year, and

$$Operating\ ratio = \frac{Operating\ revenue}{Operating\ expense}$$

From liquidity ratios, we can have an intuitive understanding of a company's ability to pay short-term debt. Commonly used liquidity ratios are *current ratio*, *quick ratio*, and *cash ratio*. The current ratio equals 1, which means the current asset a company generates can cover the short-term debt (current liability). The higher the current ratio, the greater the degree of liquidity (Gitman et al., 2015). The quick ratio is similar to the current ratio except that the asset excludes inventory, which is the most difficult asset to liquidate in the short term from the current asset (Morrell, 2018). The higher the quick ratio, the greater the degree of liquidity. It is a more conservative measurement of liquidity than the current ratio. The cash ratio is the strictest liquidity ratio. A firm's cash ratio reflects its ability to pay back its current liability using only cash and cash equivalents like marketable securities, without selling other current assets. Liquidity ratios are calculated by:

$$Current\ ratio = \frac{Current\ asset}{Current\ liability}$$

$$Quick\ ratio = \frac{Cash + short\text{-}term\ marketable\ security + receivables}{Current\ liability}$$

$$Cash\ ratio = \frac{Cash + short\text{-}term\ marketable\ security}{Current\ liability}$$

The four solvency ratios are used in the analysis to show a firm's ability to pay long-term debt, including *debt to equity ratio*, *debt to asset ratio*, *financial leverage*, and *interest coverage*. The formulas for these ratios are:

$$Debt\ to\ equity = \frac{Debt}{Equity}$$

$$Debt\ to\ asset = \frac{Debt}{Asset}$$

$$Financial\ leverage = \frac{Asset}{Equity}$$

$$Interest\ coverage = \frac{EBIT}{Interest}$$

where *EBIT* is earnings before interests and taxes, some companies equate it to operating income. Debt to equity ratio, debt to asset ratio and financial leverage are convertible to each other. A higher debt to equity ratio, debt to asset ratio, or financial leverage indicates that outside finance accounts for more of a company's assets and lower solvency capability. Keeping a relatively low debt-to-equity ratio makes creditors' liabilities safe and payable. Interest coverage reflects a company's ability to pay back contractual interest. The greater the interest coverage, the greater the ability to repay. International Air Transportation Association (IATA) industry capital suggests an airline carrier's interest coverage be no less than 1.5 (Morrell, 2018).

Three profitability ratios indicate the ability to create earnings, taking into consideration the comparison: *net profit margin*, *return on asset*, and *return on equity*:

$$Net\ profit\ margin = \frac{Net\ income}{Net\ revenue}$$

$$Return\ on\ asset = \frac{Net\ income}{Average\ total\ asset}$$

$$Return\ on\ equity = \frac{Net\ income}{Average\ total\ equity}$$

where average total equity is the arithmetic average of total equity last year and this year. Net profit margin measures the profitability of a company after a company has deducted all its costs, including tax, interest, and preferred stock dividends. Return on asset is used to measure the overall management's success in generating profits with all its assets. Return on equity is an indicator to measure a firm's ability to generate profit for its common stock shareholders. For all three of these ratios, the higher the ratio, the better the profitability of a firm (Morrell, 2018; Gitman et al., 2015).

The data we use to perform the financial analysis are the financial and accounting data of airline companies. For Chinese airlines the data come from annual reports and quarterly reports from SSE disclosure and SZSE disclosure, while the data for U.S. airlines come from annual reports (10-K) from the U.S. Securities and Exchange Commission (SEC).[49][50][51][52]

3.2 Accounting performance

The accounting performance of Chinese airline carriers

Accounting data are important indicators for analyzing business conditions, and summarizing and evaluating the financial status and operating results of an enterprise.

The major accounting indicators of Chinese airline companies are listed in Table 3. In 2020, the entire civil aviation industry suffered from COVID-19. The average operating revenue dropped by 43.09% compared to 2019, with legacy carriers' net income falling by 47.90% and low-cost carriers' operating income falling by 38.28%.[53] The average year-over-year increases in operating revenue for legacy and low-cost carriers from 2017 to 2019 were 9.33% and 19.91%, respectively. Although the operating expenses are reduced at the same time, they are insufficient to compensate for the significant revenue loss. Of these seven listed companies, only China Express achieved positive net income in 2020. The remaining airlines face losses of 485 to 68,743 million CNY.[54] Net income of legacy carriers and low-cost airlines declined by 818.55% and 137.77%, respectively, from 2019 to 2020.

Comparing the average data for 2017-2019 with the data for 2019-2020 shows that compared to low-cost carriers, legacy carriers maintained more current assets, especially cash, during the pandemic. The growth rates of current liabilities of legacy and low-cost carriers both increased during the pandemic, legacy carri-

[49] http://english.sse.com.cn

[50] http://www.szse.cn/English/index.html

[51] https://sec.report

[52] The fiscal year of U.S. airline companies ends December 31 every year, except for Mesa Airlines, which has a fiscal year that ends September 30 every year.

[53] Author's calculation based on airline companies' 2019 and 2020 annual reports data.

[54] Airline companies' 2019 annual reports data.

ers increased from 9.14% to 22.42%, and low-cost carriers increased from 18.98% to 20.36%. The growth rate of non-current liabilities of legacy carriers decreased to 0.26% from 4.17% before the pandemic, and low-cost carriers decreased from 20.51% to 8.68%. From 2017 to 2019, the stockholders' equity of legacy carriers remained almost flat per year, and in 2020 it decreased by 33.90%. This is in contrast to low-cost airlines, which maintained a more pronounced average annual growth rate of 23.18% from 2017 to 2019. In 2020, the stockholders' equity decreased by 10.43% compared to 2019.

Table 4 calculates the major financial ratios of Chinese airlines. Total asset turnover is used to measure a company's ability to generate revenue using one unit of assets. Before COVID-19, legacy and low-cost carriers' average total asset turnovers were 0.57 and 0.60, which has been relatively stable in the last three years. The COVID-19 shock to the industry led to all companies' numbers dropping to 0.27 and 0.31, which means the efficiency of asset use shrank to half of what it was before. From 2017 to 2019, the operating ratio also kept an approximately fixed value for each firm, and the average number was around 107%. In 2020, the number was reduced to 85% on average. Both activity ratios for legacy and low-cost carriers declined from 2017 to 2019, and both declined to a similar extent.

When we analyze the liquidity ratios, which include the current ratio, quick ratio, and cash ratio, low-cost carriers perform better than legacy carriers in the ability to pay out short-term debt both before the COVID-19 pandemic and during the pandemic with higher liquidity ratios. From 2017 to 2019, the average current ratio, quick ratio, and cash ratio of legacy carriers were 0.75, 0.47, and 0.29. For low-cost carriers, these numbers are 0.91, 0.56, and 0.53. During the year 2020, both categories of airlines saw a decline in their liquidity ratios. Overall, legacy carriers' current, quick, and cash ratios in 2020 decreased by 0.27, 0.19, and 0.10, compared to their 2017 to 2019 averages, and low-cost carriers decreased by 0.25, 0.03, and 0.02, on average. The results could indicate potential short-term financial distress for legacy carriers, whereas low-cost carriers maintained comparatively better liquidity.

Low-cost carriers had better long-term solvency than legacy carriers from 2017 to 2019, with relatively smaller debt to equity, debt to asset, and financial leverage. Low-cost carriers' average debt to equity, debt to asset, and financial leverage for 2017 to 2019 are 1.25, 0.55, and 2.25, which are both lower than legacy carriers' 2.41, 0.70, and 3.40. In 2020, the average long-term solvency of legacy carriers improved significantly compared to previous years. The significant decrease in legacy carriers' solvency ratios on average is mainly due to the significant decrease in Hainan Airlines' solvency ratios. Among the five legacy airlines, Eastern Airlines, China Southern Airlines, and Air China saw increases in all three indicators, implying a weakening of their long-term solvency. From Table 7, the government share ownership of these three airlines is 69.91%, 75.92%, and 75.18% respectively. When a private company raises funds, creditors will act more carefully to inspect aspects of enterprise qualification and credit history. Compared with fully privatized enterprises, creditors prefer companies with state-owned equity, especially during the crisis, which creates a more favourable environment for the high leverage ratio of this type of company. Interest coverage is another indicator to analyze a firm's loan repayment ability. The higher the interest coverage, the easier it is for a company to repay the interest expense. It gives us the same conclusion as financial leverage does. Before COVID-19, legacy carriers had a lower rate at 1.95 than low-cost carriers at 6.26. In 2020, both categories of airlines' interest coverage became negative, which indicates that the companies do not have enough revenue to pay their outstanding interest expenses. The situation for low-cost carriers is relatively better. The legacy carriers' interest expense needed to pay exceeds 2.7

times their revenue; the number for low-cost carriers is 1.91.

The net profit margin, return on asset, and return on equity reflect the profitability of a company. Greater ratio values indicate better profitability. For all three indicators, low-cost carriers have better profitability and are less affected by travel restrictions caused by COVID-19. The most important factor could be the difference in the profit structure and business models of the two types of companies. Although the profit margins of the entire aviation industry are low, low-cost carriers can get relatively higher net profit margins due to their lower costs, and the damage from the pandemic is not as severe as for legacy airlines. The average net profit margin of legacy carriers before COVID-19 was 0.05, and that of low-cost carriers was 0.10. In 2020, the average net profit margin of legacy carriers was -0.56 and that of low-cost carriers was -0.06. Legacy carriers experienced a sharp decline in net profit margins and negative values by 2020. In contrast, low-cost carriers managed to maintain a positive net profit margin, although it decreased over the years. Return on assets and return on equity show similar patterns. This suggests that while both types faced profitability challenges, low-cost carriers managed slightly better.

Overall, Chinese low-cost carriers outperformed legacy carriers in terms of revenue generation, short-term solvency, long-term solvency, and profitability before the COVID-19 pandemic and suffered less during the pandemic.

Given that three of the legacy carriers have around 70-75% of state-owned stock (Table 7), it can be deduced that the state might be significantly exposed to the challenges facing these carriers, especially in 2020. State ownership might provide some buffer against financial distress due to potential government support. However, state-owned enterprises may encounter additional bureaucratic obstacles and be less agile in responding to market dynamics than completely private entities. Using the data in Tables 3 and 4, we find that China's legacy carriers did not perform better in the financial markets during the pandemic than low-cost carriers, which are without government ownership, because of their larger government ownership.

The accounting performance of U.S. airline carriers

Table 5 presents U.S. airline companies' financial data from their statements of operating and balance sheets. All airline companies' operating revenues have suffered. The influence on legacy carriers is greater than on low-cost carriers, which is the same as in the Chinese airline industry. The decrease in operating revenues of legacy and low-cost carriers in 2020 is 62.60% and 58.42%, which lead to 380.53% and 243.90% decreases in net income, respectively.

Both legacy and low-cost carriers held much more current assets, especially cash, during the outbreak of COVID-19 compared with the average level from 2017 to 2019. The average year-over-year increases of current assets from 2017 to 2019 are -0.32% and 3.33% for legacy and low-cost carriers, indicating that both types of companies maintain relatively stable current assets from 2017 to 2019. In 2020, current assets held by legacy and low-cost carriers increased by 74.45% and 122.73%, respectively, compared to 2019.

The decline in shareholders' equity is 81.50% of legacy carriers, which was much greater than the 10.81% of low-cost airlines. The change in average stockholders‘ equity for 2019 to 2020 for the legacy airlines is large, mainly due to the large value of the change in stockholders‘ equity for American Airlines compared to the other airlines, which is -5719.49%. If we exclude the impact of American Airlines, the decrease in stockholders‘ equity of 61.65% from 2019 to 2020 for traditional airline stocks is still much greater than for low-cost airlines.

Table 6 calculates the major financial ratios of U.S. airlines. From 2019 to 2020, the ability to generate income for both legacy and low-cost carriers declined.

The total asset turnover of legacy and low-cost carriers dropped from 0.77 and 0.70 in the 2017 to 2019 average to 0.27 and 0.29 in 2020. The 2017 to 2019 average operating ratios also declined from 1.14 and 1.16 to 0.70 and 0.81.

As was the case with Chinese airline companies, the short-term solvency of low-cost carriers, that is, their liquidity, was better than that of legacy carriers, both before and during the pandemic. From 2017 to 2019, the average current, quick, and cash ratios of legacy carriers were 0.66, 0.51, and 0.41, and of low-cost carriers were 0.90, 0.71, and 0.64. In 2020, these three liquidity ratios of legacy carriers increased to 1.00, 0.87, and 0.79, while those of low-cost carriers increased to 1.37, 1.23, and 1.12. Combining Table 5 with Table 3, both Chinese and U.S. low-cost carriers have better liquidity ratios than their respective countries' legacy carriers, and U.S. airlines have higher liquidity ratios overall than Chinese airlines.

Low-cost carriers in the U.S. have stronger long-term solvency than legacy carriers. Before the pandemic, the average debt-to-equity ratio for low-cost carriers was 2.15, which was lower than 2.72 for legacy carriers. Legacy carriers' average debt to equity increased to 13.29 in 2020, compared to 2.79 for low-cost carriers, indicating that legacy carriers' long-term debt is 13.29 times their equity and that paying back the long-term debt will be challenging.[55] Table 8 lists the top three types of holdings of U.S. airlines. U.S. airlines maintained higher financial leverage in the pandemic compared to Chinese airlines, despite the absence of large government holdings in U.S. legacy airlines. In other words, both in China and the U.S., legacy carriers are more likely to be funded by a negative shock such as COVID-19 compared to low-cost carriers.

Both before and during the pandemic, low-cost carriers had slightly better profitability than legacy carriers. In 2020, the profitability of legacy carriers was more severely impacted. The 2017 to 2019 average net profit margin of legacy

[55]The results exclude American Airlines' data. If we include American Airlines, legacy carriers' debt to equity is 9.41.

carriers is 0.09, and the corresponding number for low-cost carriers is 0.10. In 2020, the two numbers dropped to -0.45 and -0.23, respectively.

According to our results from financial reporting analysis, legacy carriers suffered more of their net income during the pandemic compared with low-cost carriers. Both types of carriers prefer to hold more liquid assets and liabilities in 2020. The ability to generate revenue is similar between the two types of carriers. In both China and the U.S., low-cost carriers have better short-term solvency, long-term solvency, and profitability. This phenomenon may be due to the fact that legacy carriers have a larger market capitalization or a broader scope of business than low-cost carriers and have higher credit in the market. In particular, three of the Chinese legacy carriers have large government holdings, increasing creditor confidence in their ability to settle their debts. The special corporate structure and cost structure of low-cost carriers make them more profitable than legacy carriers.

Most U.S. airline company stocks except Mesa (Table 8), over 70% or more, are held by investment advisors. The presence of a diversified ownership composition, particularly with significant institutional stakeholders, has the potential to mitigate the impact of market volatility on a stock (Xavier et al., 2006). Nevertheless, in the event of a shift in market attitude towards the industry or firm, along with corresponding adjustments made by these institutions, substantial fluctuations in stock prices may ensue.

Based on the analysis of financial data and ratios, we find that Chinese legacy carriers have not been less impacted by their state-owned holdings. Instead, the deterioration in all indicators is more severe compared to low-cost carriers. The U.S. legacy carriers also did not suffer from their larger market capitalization. However, most studies show that stocks of companies with larger market capitalization are less volatile in the face of shocks than stocks of companies with smaller market capitalization (Fama and French, 1993; Ang et al. 2006). Next, we use event analysis to further investigate whether legacy carrier stocks are less volatile than low-cost carriers in the face of COVID-19 shocks and whether state ownership of Chinese legacy carriers helps to minimize stock price volatility in the face of shocks.

4 Data

The main dataset used in the event study is comprised of airline companies' historical daily stock prices and market returns in the Chinese and U.S. markets. All airline companies' stock prices and market return data are from Datastream from Thomson Reuters, which provides historical financial databases including daily stock prices for 65 years across 175 countries. Based on the outbreak timeline of the COVID-19 pandemic and the estimated window used in this study, the time frame ranges from February 2019 to June 2020.

There are eight publicly traded airline companies in China.[56] Since Shandong Airlines' stocks are only traded in the B-share market, we excluded them from our sample.[57] The remaining seven airlines' stock prices make up our study sample for the Chinese airline stock dataset.

China Eastern Airlines is listed on three markets: the Shanghai Stock Exchange (SSE), the Hong Kong Stock Exchange (HKEX), and the New York Stock

[56]The legacy carriers are China Eastern Airlines, China Southern Airlines, Air China, China Express Airlines, Hainan Airlines, and Shandong Airlines. The low-cost carriers are Spring Airlines and Juneyao Air.

[57]B-share in the Chinese stock market means CNY special stocks. It is a stock that indicates the par value in CNY, subscribes and trades in foreign currencies, and is listed and traded on the domestic (Shanghai and Shenzhen) stock exchanges. The investors of B-shares need to hold legal foreign exchange to freely open accounts to buy and sell B-shares, which makes the investing process of B-shares more complicated than A-share shock (CNY ordinary shares). Due to restrictions on investor eligibility, differences in access to information, and transaction complexity, the B-share market is less efficient than the A-share market in China (Hu and Fan, 2020 Fifield and Jetty, 2008), which makes its stock price react more slowly to market information than in the A-share market. To keep our results more consistent, we exclude Shandong Airlines from our sample.

Exchange (NYSE). China Southern Airlines is listed on three markets: the SSE, the HKEX, and the NYSE. Air China is listed on two markets: the SSE and the HKEX. China Express Airlines is listed on the Shenzhen Stock Exchange (SZSE). Hainan Airlines is listed on the SSE A-share.[58] Spring Airlines is listed on the SSE. Juneyao Air is listed on the SSE. When a stock is traded in multiple markets, the price of the stock listed in the country (region) in which the company is located can best reflect the market information (negative random shock) of that country (region). We use SSE stock prices as China Eastern Airlines, China Southern Airlines, and Air China stock prices. The market capitalization information for 2019 is shown in Table 1. The average market capitalization of publicly traded Chinese legacy carriers and low-cost carriers is 65,852.32 million CNY and 34,857.85 million CNY respectively.

For the market return of the Chinese stock market, we use the CSI 300 Index. The CSI 300 Index is composed of 300 of the most representative securities in the SSE and SZSE with a large scale and good liquidity. It was officially released on April 8, 2005, to reflect the overall performance of securities listed on the SSE and SZSE. Since the stocks of the seven Chinese airlines in our study are listed on different stock exchanges, we chose this indicator that represents the overall performance of the two markets as the market return.

There is a 10% daily price limit in the SSE and SZSE, which means that except under certain special circumstances, the maximum daily rise and fall for one specific stock cannot exceed 10%.[59][60]

[58]Hainan Airlines' stocks are both traded in the A-share market and in the B-share market. Since the B-share market is significantly less efficient than the A-share market (Fifield and Jetty, 2008), we use the A-share market stock prices only.

[59]On the first day of listing new shares, there is no limit on the amount of increase or decrease. There is no increase or decrease limit on the day of listing of additional shares or the first day of trading of the suspension of the resumption of listing.

[60]The meltdown mechanisms in the Chinese and U.S. stock markets are slightly different, but because they are primarily concerned with extreme situations, they do not have a major impact on our research. The Chinese stock market implements circuit breakers that

The size factor and value factor used to calculate the Chinese stocks' expected return by the Fama-French 3-factor model are from the China Securities Market and Accounting Research Database (CSMAR), which provides data information covering 19 series of stocks, including companies, funds, bonds, industries, the economy, and commodity futures.[61]

For the U.S. market, there are thirteen publicly traded airline companies.[62] The date of the initial public offering of Frontier Airlines is April 1, 2021, and that of Sun Country Airlines is March 17, 2021. Both dates are later than our study time frame (from February 2019 to June 2020), so we exclude these two airline companies. The rest of the eleven airline companies' stock prices make up our study sample for the U.S. airline stock dataset.

American Airlines, Hawaiian Airlines, United Airlines, Skywest Airlines, JetBlue Airways, Allegiant Airlines, and Mesa Airlines are registered and traded on the NASDAQ Stock Exchange (NASDAQ). Delta Air Lines, Spirit Airlines, and Southwest Airlines are registered and traded on the NYSE. All U.S. airline companies are traded on a single market and have a unique historical daily stock price. The market capitalization information for U.S. airline carriers in 2019 is shown in Table 2. The average market capitalization of publicly traded U.S. legacy carriers and low-cost carriers is 14,156.07 million USD and 7,821.36 million USD respectively.

effectively suspend trading for a duration of 15 minutes if the CSI 300 Index experiences a movement of 5% from its closing value the day before. In the event that the index experiences a 7% movement from its closing value, trading activities for the remainder of the day will be suspended. Similar systems are in place in the United States stock market. In the situation where the S&P 500 experiences a decline of 7%, it activates a level 1 market-wide circuit breaker, resulting in a temporary suspension of trade for 15 minutes. In the event of additional decreases of 13% and 20%, level 2 and level 3 circuit breakers would be activated, resulting in extended pauses in trading activities.

[61] https://cn.gtadata.com/

[62] The legacy carriers are American Airlines, Delta Air Lines, Alaska Airlines, Hawaiian Airlines, United Airlines, and Skywest Airlines. The low-cost carriers are Spirit Airlines, JetBlue Airways, Southwest Airlines, Allegiant Airlines, Frontier Airlines, Sun Country Airlines, and Mesa Airlines.

The market return of the U.S. stock market we use is the S&P 500 Index. The companies in S&P 500 Index cover stocks on the NASDAQ and NYSE, and it contains a large number of companies and reflects a wide range of market changes, which makes it a good index for U.S. stock market returns. There is no daily price limit on the NYSE or NASDAQ. Although there is a circuit breaker mechanism in the U.S. stock market, the trigger conditions are relatively harsh compared with the 10% price limit.[63]

The U.S. market size factor and value factor for Fama-French 3-factor model are from the Kenneth R. French Data Library, which provides information including daily and weekly data on Fama-French 3 research factors, Fama-French 5 research factors, and factors for portfolio research.[64]

To track the policies of the two governments during the pandemic, we also use the International Monetary Fund Policy Tracker to COVID-19, U.S. Congress Legislation, the Civil Aviation Administration of China and the 2020 Chinese Government Work ReportState Council of China (2020).[65],[66],[67]

5 Methodology

5.1 Event date and event window selection

The event study structure is shown in Figure 1. From T_0 to T_1 is the estimation window used to calculate the stock's expected return. We use 150 trading days as the estimation window, which is from the 160^{th} trading day before the event date

[63]The U.S. circuit breaker is set to halt trading when the S&P 500 Index drops 7%, 13%, and 20% (Financial Industry Regulatory Authority (FINRA) Rulemaking, 2022).
[64]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[65]https://www.congress.gov
[66]http://www.caac.gov.cn/en/SY/
[67]https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19

to the 11^{th} trading day before the event date.[68][69]

This study focuses on both short- and long-run reactions to the stock market. For the short-run reaction, the event window is from one day before the event date to the third trading day after the event date. For the event date that is not a trading day, we use the next trading day after the event date as the real event date. For the long-run reaction, we considered 10, 20, 30, 40 and 50-day event windows.

Figure 1: **Event Study Timeline**

For the long-run event study, we use March 11, 2020, as the event date (Figure 2).[70] On March 11, 2020, the Director-General of the World Health Organization

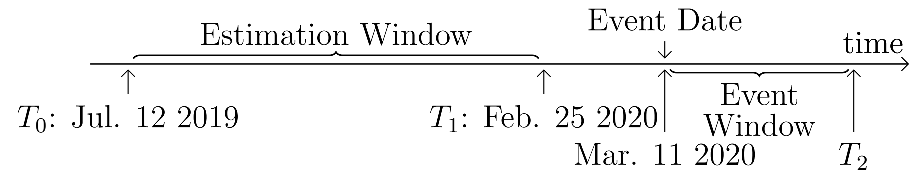
[68] If the estimation window is too short, it cannot reflect the relatively reliable price of a stock. If the estimation window is too long, while the accuracy increases, the likelihood that the period will contain other events that significantly affect the stock price will also increase. There is no strict rule for selecting the length of the estimation window. For the event study literature, the most commonly used estimation window is between 30 and 750 days (Holler, 2014). When the estimation window is longer than 100 days (150 days, 200 days, and 250 days), there are no significant differences in the abnormal return, ceteris paribus (Park, 2004). We use a relatively moderate length of time, 150 days, as our benchmark estimation window. We also use 90 days and 210 days for robustness checks, as shown in the Appendix. The choice among the 90, 150, and 210-day estimation windows, however, do not have significant differences when estimating the expected return.

[69] In the event study, some of the information (for example, major transactions, mergers and acquisitions, and bankruptcy) that would influence the stock price can be leaked in advance. The study of the performance of stocks in the days before the event dates is also necessary. The estimation window always ended five to ten days before the event date. Since in our study, the events barely include the information that can be leaked in advance, we chose five days before the event date as the end date of the estimation window.

[70] The T_0 shown in the figure is based on a 150-day estimation window in the Chinese market. The T_0 for the Chinese market 90 and 210 days estimation windows are Oct. 14, 2019, and Apr. 15, 2019, respectively. Due to the different legal holidays in China and the U.S. resulting in different trading days, the two T_0 are also slightly different. For the U.S. market, 90, 150 and 210 estimation window, T_0 is Oct. 10, 2019, Jul. 23, 2019, and

(WHO) Tedros said that "assessed that COVID-19 can be characterized as a pandemic". The announcement of COVID-19 as a global pandemic began to attract the attention of countries and began to strengthen the prevention and control of the pandemic. This event is a common event that influences both China and the U.S. transportation industry, especially the civil aviation industry.

Figure 2: **Long-run Event Study Timeline – China: March 11, 2020**



For the short-run event study, we chose two event dates for each country. They are (1) the event that may have the most significant impact on the civil aviation industry during the pandemic as the negative random shock; and (2) the government economic rescue plan for the pandemic of each country as the positive random shock.

The event dates chosen for China's airline companies are shown in Figure 3.[71] Event 1 is March 29, 2020, when the Civil Aviation Administration of China (CAAC) introduced a new measure, "Five One", considering international civil flights from or to China. The "Five One" policy is that "Each Chinese airline is only allowed to maintain one route to any specific country with no more than one flight per week; each foreign airline is only allowed to maintain one route to China with no more than one flight per week" (Civil Aviation Administration of China Notice, 2020).[72] This event happened in the middle stage of the pandemic. As

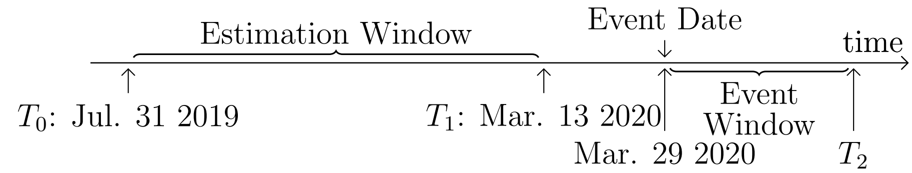
Apr. 26, 2019. The short-run T_0, T_1 and event date are the same as the date of the long run.

[71]The T_0 shown in the figure is based on a 150-day estimation window in the Chinese market. The T_0 for the Chinese market 90 and 210 days estimation windows are Oct. 31, 2019, and May. 7, 2019 respectively.

[72]http://www.caac.gov.cn/XWZX/MHYW/202003/t20200330_201811.html.

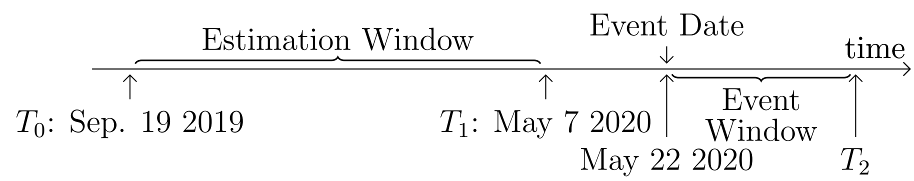
of 21:00 on January 25, 2020, except in Tibet, which has not found suspected or confirmed cases of COVID-19 infection, all provinces that have found new COVID-19 cases launched a first-level response to major public health emergencies.[73] As of March 29, 2020, 27 provinces had downgraded their emergency response levels.[74] Although the event occurred during the period when the outbreak had eased, this policy is a restrictive measure directed at the aviation industry. We expect more significant changes in airline stock prices.

Figure 3: **Short-run Event Study Timeline – China: March 29, 2020**



Event 2 is the proposed and implemented economic stimulus plan by the Chinese government on May 22, 2020 (Figure 4), including issuing special government bonds, local government special debt, and increasing the size of the fiscal deficit, which adds up to 4.2 trillion CNY (State Council of China, 2020).[75] We expect this government financial aid policy to have a positive influence on all industries, including the airline industry, strengthening investors' confidence.

Figure 4: **Short-run Event Study Timeline – China: May 22, 2020**



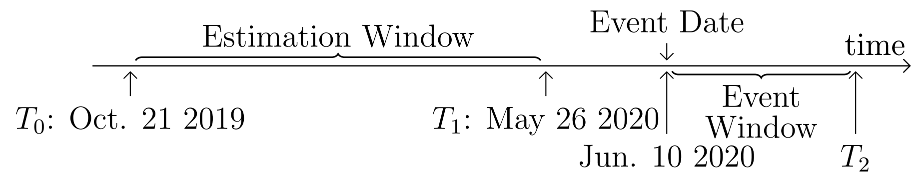
[73] http://news.haiwainet.cn/n/2020/0125/c3541083-31705784.html.

[74] http://english.www.gov.cn/news/.

[75] The T_0 shown in the figure is based on a 150-day estimation window in the Chinese market. The T_0 for the Chinese market 90 and 210 days estimation windows are Dec. 31, 2019, and Jun. 26, 2019, respectively.

The event dates chosen for U.S. airline companies are shown in Figures 5 and 6.[76] Event 1 is on June 10, 2020. On this date, JP Morgan downgraded two airline companies: JetBlue Airways was downgraded from Neutral to Underweight and United Airlines was downgraded from Overweight to Neutral.[77] This downgrading released the financial institutions' concerns about the civil aviation industry to the market. On June 10, 2020, JetBlue Airways and United Airlines stock prices fell by 11.12% and 11.02%, respectively. The second day fell by 12.03% and 16.11%, respectively.[78] We expect this downgrading to have a negative effect on all airline stocks.

Figure 5: **Short-run Event Study Timeline – U.S.: June 10 2020**



Event 2 is the most aggressive economic rescue plan from the U.S. government during the pandemic, named the Coronavirus Aid, Relief, and Economy Security Act ("CARES Act").[79] It was introduced on March 19, 2020, aiming to spend up to $2.3 trillion to help recover the market. We expect this CARES Act to affect several industries, boost market confidence and positively impact the airline industry's stocks.

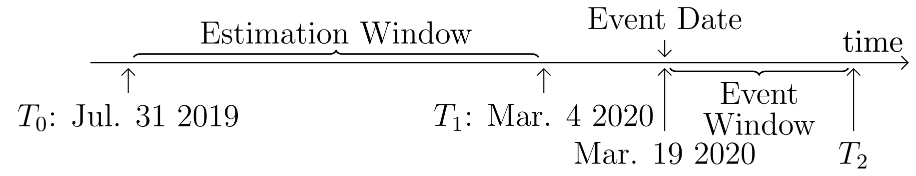
[76]The T_0 shown in Figures 5 and 6 are based on a 150-day estimation window in the U.S. market. In Figure 5, the T_0 for the U.S. market 90 and 210 days estimation windows are Jan. 16, 2020, and Jul. 26, 2019, respectively. In Figure 6, the T_0 for the U.S. market 90 and 210 days estimation windows are Oct. 24, 2019, and May 6, 2019, respectively.

[77]Bloomberg securities data and Benzinga Insights, https://www.benzinga.com/markets/penny-stocks/20/06/16221585/benzingas-top-upgrades-downgrades-for-june-10-2020.

[78]Bloomberg securities data.

[79]International Monetary Fund-Policy responses to COVID-19 https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19#U, U.S. Congress Text: S.3548 ? 116th https://www.congress.gov/bill/116th-congress/senate-bill/3548/text.

Figure 6: **Short-run Event Study Timeline – U.S.: March 19 2020**



5.2 Fama-French 3-factor model and Market model

The event study method for the stock market was initially developed by Fama et al. (1969) to evaluate the impact of a specific event like a stock split, a dividend paid, or a new information release on the stock's price. Under the semi-strong efficient market assumption, the company's stock price fluctuation could fully reflect the new information related to the company, industry, or the entire macroeconomy.[80]

There are several approaches to evaluating the stock return, for example the constant return model, market-adjusted model, market model, capital asset pricing model (CAPM), Fama-French 3-factor model and so on.[81],[82],[83] In this paper,

[80]The semi-strong efficient market hypothesis holds that prices adequately reflect all publicly available information about the company's operating prospects. This information includes transaction price, volume, earnings information, earnings forecasts, company management status, and other publicly disclosed financial information. If investors have quick access to this information, share prices should react quickly (Fama, 2017).

[81]The constant return model assumes that $E(R_{it}) = \bar{R}_i$, where $\bar{R}_i$ is the expected return equals the stock's historical average return. The constant return model does not account for the situation of macroeconomic changes; however, it provides similar results relative to more sophisticated models (Brown and Warner, 1985). We use the constant return model as a robustness check with the results shown in the Appendix.

[82]Market-adjusted model assumes that $E(R_{it}) = R_{mt}$, where R_{mt} is the market return. This model ignores the company's specific characteristics and assumes that the volatility of individual stocks is consistent with market volatility. This assumption holds when the β value (an index used to measure the price volatility of an individual stock or equity fund relative to the entire stock market. When β =1, it means that the return and risk of the stock are consistent with the return and risk of the broader market index; when $\beta > 1$, it means that the return and risk of the stock are greater than the return and risk of the large-cap index. The higher the β value, the greater the volatility of the stock relative to the performance evaluation benchmark, and vice versa. An individual stock's β value can be calculated by a market model or capital asset pricing model.) of a stock is close to 1.

[83]Since "the results of the studies may be sensitive to the specific CAPM restrictions,... the use of the CAPM has almost ceased" (MacKinlay, 1997, page19), we do not use the

we use the Fama-French 3-factor model and market model which are the most commonly used approaches in the airline industry event studies (Park, 2004, Ho et al., 2013) and which have good predictive power (Brenner, 1979).

We use the market model and the Fama-French 3-factor model, respectively, to compute the expected return $E(R_{it})$ for each stock.

First, from the definition of stock return in the market model, we can have R_{it} which is the expression for the return of the stock i at time t,

$$R_{it} = \alpha_i + \beta_i R_{mt} + u_{it} \tag{4}$$

where R_{mt} is the market return.

Then we predict the expected return $E(R_{it})$ using the estimated parameters $\hat{\alpha}_i$ and $\hat{\beta}_i$ obtained from equation (1),

$$E(R_{it}) = \hat{\alpha}_i + \hat{\beta}_i R_{mt} \tag{5}$$

Based on the market model and CAPM model, Fama and French (1992,1993) found that small-cap stocks have historically outperformed large-cap stocks even after adjusting the market risk. Thus, they introduced a size factor, SMB, which represents the difference in returns between small-cap and large-cap stocks. They also find that high book-to-market ratios stocks tend to outperform low book-to-market ratios stocks. They introduced the HML factor, which is the difference in returns between high book-to-market ratios stocks and low book-to-market ratios stocks.

The excess return ER_{it} of the stock i at time t

$$ER_{it} = R_{it} - R_{ft} \tag{6}$$

CAPM model in our study.

where R_{ft} is the market risk free rate.

Then we use the estimation window data to estimate the parameters $\hat{\beta_{it}}$, $\beta_{it,\hat{SMB}}$and $\beta_{it,\hat{HML}}$ for the calculation of excess return, using the equation

$$ER_{it} = \alpha_i + \beta_{it}(R_{mt} - R_{ft}) + \beta_{it,SMB}SMB + \beta_{it,HML}HML + \epsilon_t \tag{7}$$

The expected return $E(R_{it})$ calculated using Fama-French 3-factor model is

$$E(ER_{it}) = R_{ft} + \hat{\beta_{it}}(R_{mt} - R_{ft}) + \beta_{it,\hat{SMB}}SMB + \beta_{it,\hat{HML}}HML \tag{8}$$

The abnormal return AR_{it} is the difference between the actual return of the stock and the expected return calculated from (2) for the market model and (5) for the Fama-French 3-factor model,

$$AR_{it} = R_{it} - E(R_{it}) \tag{9}$$

The t-test statistic is given by

$$t_{AR_{it}} = \frac{AR_{it}}{S_{AR_i}}, \tag{10}$$

where

$$S^2_{AR_i} = \frac{1}{M-2}\sum_{t=T_0}^{T_1} AR^2_{it} \tag{11}$$

and where M indicates the number of returns during the estimation window.

To get the single stock cumulative abnormal return $CAR_{i,(t_1,t_2)}$ from time t_1 to t_2, we have

$$CAR_{i,(t_1,t_2)} = \sum_{t=t_1}^{t_2} AR_{it} \tag{12}$$

The t-statistic of the cumulative abnormal return is

$$t_{CAR_i} = \frac{CAR_i}{S_{CAR_i}} \tag{13}$$

where

$$S^2_{CAR} = LS^2_{AR_i} \tag{14}$$

L indicates the length of the event window.

The average abnormal return AAR_t of a group of stocks at time t is given by

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{it} \tag{15}$$

where N denotes the number of stocks in the group. The t-statistic of the average abnormal return is

$$t_{AAR_t} = \sqrt{N}\frac{AAR_t}{S_{AAR_t}} \tag{16}$$

where

$$S^2_{AAR_t} = \frac{1}{N-1}\sum_{i=1}^{N}(AR_{it} - AAR_t)^2 \tag{17}$$

The cumulative average abnormal return (CAAR) from time t_1 to t_2 is obtained by

$$CAAR_{i,(t_1,t_2)} = \frac{1}{N}\sum_{t=t_1}^{t_2} CAR_{it} \tag{18}$$

The t-statistic of the cumulative average abnormal return is

$$t_{CAAR_t} = \sqrt{N}\frac{CAAR_t}{S_{CAAR_t}} \tag{19}$$

where

$$S^2_{CAAR_t} = \frac{1}{N-1}\sum_{i=1}^{N}(CAR_{it} - CAAR_t)^2 \tag{20}$$

The buy-and-hold abnormal return (BHAR) provides similar results compared with CAR when the event window is short, while it is more consistent than CAR in the long length of the event window (Barber and Lyon, 1997). Compared with CAR, which is only a simple accumulation of returns, BHAR considers the impact of the return of the previous period on the return of the next period. The basis of the return for different periods has changed, that is, the BHAR considers the impact of the conformity effect on the abnormal return.

The $BHAR_{i,(t_1,t_2)}$ from time t_1 to t_2 is calculated by the equation below,

$$BHAR_{i,(t_1,t_2)} = \prod_{t=t_1}^{t_2}(1+R_{it}) - \prod_{t=t_1}^{t_2}[1+E(R_{it})] \tag{21}$$

The t-statistic of buy-and-hold abnormal returns is

$$t_{BHAR_i} = \frac{BHAR_i}{S_{BHAR}} \tag{22}$$

where

$$S^2_{BHAR} = LS^2_{AR_i}. \tag{23}$$

The average buy-and-hold abnormal return $ABHAR_t$ of a group of stocks at time t is given by

$$ABHAR_t = \frac{1}{N}\sum_{i=1}^{N} BHAR_{it} \tag{24}$$

The t-statistic of the average buy-and-hold abnormal return is

$$t_{ABHAR_t} = \sqrt{N}\frac{ABHAR_t}{S_{ABHAR_t}} \tag{25}$$

where

$$S^2_{ABHAR_t} = \frac{1}{N-1}\sum_{i=1}^{N}(BHAR_{it} - ABHAR_t)^2 \tag{26}$$

6 Results

6.1 Chinese airlines stocks' event studies results

COVID-19 is defined by the WHO as a global pandemic

On March 11, 2020, COVID-19 was officially identified as a global pandemic for the first time. This recognition can be viewed as the first warning of the virus threat to all countries around the world. As the main mode of passenger transportation, we anticipate a negative reaction from the worldwide civil aviation industry. Tables 9, 10, 11, and 12 show the information on short- and long-run cumulative average abnormal returns and average buy-and-hold abnormal returns of Chinese airline stocks for this occurrence.

Short-run event study results for Chinese airlines are presented in Table 9.[84] We use the three-day rolling average abnormal returns obtained from the 150-day estimation window and the Fama-French 3-factor model and its 95% confidence interval to draw Figure 11, and we find that the rolling average abnormal returns before the event are positive for both legacy and low-cost carriers, but the rolling average abnormal returns after the event are significantly reduced and mostly negative compared to those before the event.[85] The figure shows that this event

[84]The results in Table 9 are based on a 150-day estimation window and the Fama-French 3-factor model. The cumulative average abnormal returns of 90, 150, and 210 days based on the constant model, market-adjusted model, market model and Fama-French 3-factor model are shown in Appendix Tables A.1 and A.2. If the constant return model is used to estimate the expected return, the resulting 10-day short-run cumulative average abnormal returns were significantly greater than those obtained from the other two models. This is because the constant model does not consider the changes in the market affected by this event; it reflects the changes in stock prices relative to their historical prices. Since the entire market was negatively affected by the pandemic, the market model and the market-adjusted model are better at reflecting the movement of airline industry stocks relative to the overall market. The β-value calculated by the market model is close to 1, indicating that the volatility of airline industry stocks is closer to the overall market volatility, both the market model and the market-adjusted model can reflect relatively accurate results.

[85]The calculation of rolling average abnormal returns and tables are shown in Appendix B.

has a negative impact on China's aviation stocks. From Table 9 we can see that the same-day cumulative average abnormal returns for both legacy and low-cost carriers are positive, showing that the date on which WHO declared COVID-19 as a global outbreak did not have a negative impact on the stocks of Chinese airlines. The cumulative average abnormal returns for legacy carriers become negative on the second day of the event. From the second to the ninth day, the cumulative average abnormal returns for legacy carriers are all negative (-0.36%, -1.33%, -3.20%, -3.70%, -2.95%, -3.72%, -2.92%, -2.38%, and -0.88% respectively). The three- to seven-days results are statistically significant. The cumulative average abnormal returns of low-cost carriers are negative for event windows [1,4], [1,5] and [1,6] and statistically significant. The cumulative average abnormal returns for [1,2] and [1,3] are positive. In the short run, this event has a greater negative impact on Chinese legacy carriers than on Chinese low-cost carriers, especially in the first three days.

The main reasons could be: (1) investors' confidence in the legacy carrier business structure compared to low-cost carriers is lower during the special event period; (2) legacy carriers' revenue is more dependent on international flights than low-cost carriers. The operating revenues of legacy carriers are more dependent on international business than low-cost carriers. In 2019, international business accounted for 27.67% of legacy carriers' operating revenue on average and accounted for 25.92% of low-cost carriers operating revenue on average.[86] Due to the spread of the pandemic, countries have strengthened their entry inspection measures and restrictions, resulting in legacy carriers, which have higher proportions of international business, being more affected.

We also analyze the long-run impact of this event. Table 10 shows the cumulative average abnormal returns of the long-run event study. Table 11 presents the

[86] Author's calculation based on airline companies' 2019 annual reports data.

average buy-and-hold abnormal returns using equal weight of each airline stock. Table 12 presents the average buy-and-hold abnormal returns when the weight of each airline stock is assigned according to the market capitalization of that airline company.

When we consider a ten-day event window, the impact of the event on legacy and low-cost carriers is 1.62% and -0.37%. Lengthening the event window to 20, 30, 40, and 50 days, we find that the cumulative average abnormal returns for either legacy or low-cost carriers turned out to be positive and significant at the 1% level. Overall, the cumulative average abnormal returns for legacy carriers are larger compared to low-cost carriers. This result is largely due to the corresponding economic stimulus policies introduced by the Chinese government, coupled with the fact that the short-term impact of the event on equities stays around -3%, the impact of the economic stimulus on equities outweighs the long-term negative impact of the event. However, the drawback of the long-run practice study is that we cannot isolate other events that occur during the event window from the original event being analyzed that would have an impact on stock prices.

Together with Tables 10, 11, and 12, we find that defining COVID-19 as a global pandemic had a larger and more significant impact on legacy carriers than on low-cost carriers in the long run. Long-run cumulative average abnormal returns analysis, equal-weighted average buy-and-hold abnormal returns analysis, and market capitalization-weighted average buy-and-hold abnormal returns analysis provide similar results.

The equal-weighted average buy-and-hold abnormal returns of legacy carriers for [1,10], [1,20], [1,30], [1,40], and [1,50] event windows are 16.94%, 26.78%, 36.16%, 46.75%, and 50.39%. The numbers for low-cost carriers are 12.03%, 22.70%, 29.80%, 43.06%, and 44.32%. The average buy-and-hold abnormal returns calculated by weighted market capitalization are similar to the average buy-and-hold abnormal returns calculated by equal weights. However, both methods show that the event has a significant and larger positive effect on Chinese legacy carrier stocks than on Chinese low-cost carriers in the long run. The Legacy carriers show significance earlier (from the 20-day window) and have consistently higher average cumulative and buy-and-hold abnormal return values than the low-cost carriers. This could imply that investors or the market perceive legacy carriers to be better positioned to weather the effects of the pandemic or capitalize on the eventual recovery.

CAAC introduces "Five One" policy

On March 29, 2020, the Civil Aviation Administration of China introduced the "Five One" policy. The policy states that each airline company can only keep one route to a destination country, and the route can hold for at most one flight per week. This policy is specific to international civil airline routes, thus we expect that it will have a greater influence on carriers with a higher percentage of international business compared with those emphasizing domestic business. The event study results are shown in Table 13.[87] Through Table 13 and Figure 12, we find that the introduction of the policy-induced positive cumulative average abnormal returns for legacy carriers on the event date and the cumulative average abnormal returns of both legacy and low-cost carriers are positive before the event date. However, after the event date, the cumulative average abnormal returns of both of them decrease; both legacy and low-cost carriers have negative cumulative average abnormal returns in the short time period [1,10].

Through Figure 12, we find that low-cost carriers are more significantly negatively affected by this policy than legacy carriers. Although they have larger and

[87] The cumulative abnormal returns of 90, 150, and 210 days based on the constant model, market model, market-adjusted model and Fama-French 3-factor model are shown in Appendix Tables A.3 and A.4.

broader international business operations compared to low-cost carriers.[88] This may be due to the fact that several Chinese provinces and cities had already introduced relevant travel control policies prior to this policy, and the number of international flights in and out of China had already declined significantly from normal times.

Although the results show negative cumulative average abnormal returns, as we expected, the ten-day cumulative average abnormal return is only -3.71%. The potential explanation could be that the travel restrictions before the “five one” policy had already reduced flight frequency and lowered market confidence in airline stocks.

Chinese government special subsidy on COVID-19

As COVID-19 has had a major impact on people’s lives and on production in various industries around the world, governments and financial departments have enacted policies to stimulate the economy or to support related industries. On May 22, 2020, the first national fiscal policy target for COVID-19 was proposed and released in the 2019 Chinese government work report. Specific content includes (1) issuing one trillion CNY of special government bonds for anti-pandemic measures and transfers to local governments, mainly for public health and other infrastructure construction (including utilities and hospitals) and anti-pandemic related expenditures; (2) planning to issue 3.75 trillion CNY of special government bonds for local governments; (3) planning a deficit rate in 2020 to be 3.6% or more, which is 0.8% higher than last year, with a quota of 3,760 billion CNY, (4) maintaining the policy of lowering the value-added tax rate and corporate pension insurance rates, as well as deferring income tax payments for small and micro

[88] In 2019, international business revenue averaged 27.67% of the legacy carrier’s total revenue and 25.92% of the low-cost carrier’s total revenue. Author’s calculation based on airline companies’ 2019 annual reports data.

enterprises and individuals until next year.

This fiscal policy has a direct and significant positive effect on the airline industry on the event date (Table 14).[89] The cumulative average abnormal return of legacy carriers is 3.39% and that of low-cost carriers is 2.63% on the event date. They are statistically significant at the 1% and 5% levels, respectively. The policy has consistently had a positive impact on airline stock prices in the short run, with ten-day cumulative average abnormal returns for legacy and low-cost carriers of 21.89% and 24.83% respectively. Although the policy was aimed at setting macroeconomic targets and did not directly subsidize the airline industry, nor did it relax travel restrictions on the airline industry, the short-run positive effect is significant, especially for low-cost carriers, which have a small capitalization compared with legacy carriers. From Figure 13, we can also see that the rolling average abnormal returns after the event date are significantly higher than those before the event date.

6.2 U.S. airlines stocks' event studies results

COVID-19 is defined by the WHO as a global pandemic

Event study results of the event that COVID-19 is defined by the WHO as a global pandemic for U.S. airline stocks returns are presented in Tables 15, 16, 17, and 18.[90] On the event date, the cumulative average abnormal returns of legacy and low-cost carriers are 1.95% and -1.41%. For both legacy and low-cost carriers, the cumulative average abnormal returns are negative and statistically significant until the event window [1,9]. Overall, legacy carriers are slightly more affected

[89] The cumulative abnormal returns of 90, 150, and 210 days based on the constant model, market model, and market-adjusted model are shown in Appendix Tables A.5 and A.6.

[90] The short-run cumulative abnormal returns of 90, 150, and 210 days based on the constant model, market model, market-adjusted model and Fama-French 3-factor model are shown in Appendix Tables A.7 and A.8.

than low-cost carriers, with smaller cumulative average abnormal returns besides the [1,3] event window. The WHO designation of COVID-19 as a global pandemic has had a significant negative impact on the entire U.S. airline industry stock in the short run, especially on legacy airlines. The same result is reflected in the rolling average of abnormal returns in Figure 14. From the figure, we see that legacy and low-cost carriers' stocks fluctuate more consistently before the event and begin to differ more after the event.

Long-run event study cumulative average abnormal returns are shown in Table 16. [1,10], [1,20], [1,30], [1,40], and [1,50] results of legacy carriers are 2.74%, -24.04%, -24.55%, -29.16%, and -19.00% respectively. Compared with legacy carriers, low-cost carriers are more negatively influenced in the long run. The corresponding results are 2.26%, -17.96%, -26.98%, -32.39%, and -24.24%, which are all statistically significant except for the [1,10] event window.

Fifty-day average buy-and-hold abnormal returns of U.S. carriers are up to -24% as a result of the event. More specifically, the average buy-and-hold abnormal returns of legacy carriers with equal weight for [1,10], [1,20], [1,30], [1,40] and [1,50] event windows are -2.74%, -24.04%, -24.55%, -29.16%, and -19.00%. The numbers for low-cost carriers are 2.26%, -17.96%, -26.98%, -32.39%, and -24.24%. When we use the company's market capitalization as the weight, the [1,10] event window results become negative. The average buy-and-hold abnormal returns for legacy carriers are -5.08%, -26.58%, -26.58%, -31.04%, and -26.13%. The results of low-cost carriers are -4.41%, -22.97%, -29.80%, -35.11%, and -32.13%. Except for the [1,10] results, all the results are significant at the 1% level.

U.S. economic stimulus plan: Coronavirus Aid, Relief and Economy Security Act

The U.S. economic stimulus plan "Coronavirus Aid, Relief, and Economic Security Act" ("CARES Act") was imposed on March 19, 2020. Unlike previous bills targeting mainly virus testing and health care related to COVID-19, the CARES Act also includes aid for large and medium-sized businesses, which includes 510 billion USD to prevent corporate bankruptcy by providing loans, guarantees, and backstopping (Senate and House of Representatives of the United States of America, 2020). This bill is undoubtedly powerful support for all industries, especially the civil aviation industry, which suffered heavy losses during COVID-19.

The cumulative average abnormal returns on the bill introduction date of legacy and low-cost carriers are 2.53% and -5.74% respectively. On March 20, 2020, the Committee meeting date, all companies started to have positive and significant abnormal returns (Table 19).[91]

For legacy carriers, there was a significant negative return leading up to the event date, with -8.12% from 10 days before to a day before the event and even more pronounced at -13.68% for the 5 days leading up to the event. On the event day itself, there's a small positive cumulative average abnormal return. After the event, the cumulative average abnormal returns were notably positive and statistically significant. This suggests that the relief act had a positive impact on the stock returns of legacy carriers in the short-run post-announcement. Just like the legacy carriers, low-cost carriers saw significant negative returns leading up to the event, with -25.50% and -25.76% returns for the 10-day and 5-day windows, respectively. Following the event, there was a consistent positive trend, implying that the act had a beneficial effect on these airlines too.

[91] The cumulative average abnormal returns of 90, 150, and 210 days based on the constant model, market model, market-adjusted model and Fama-French 3-factor model are shown in Appendix Tables A.9 and A.10.

The magnitude of these returns was fairly close, with legacy carriers showing a slightly higher peak on [1,4] (39.86% vs. 36.06% for low-cost carriers). By event window [1,5], the returns were similar (38.14% for legacy vs. 38.17% for low-cost carriers). Both legacy and low-cost carriers saw a decline in the magnitude of their positive cumulative average abnormal returns over the 10-day post-event window, but legacy carriers had a slightly higher cumulative average abnormal returns of 10.11% compared to 6.74% for low-cost carriers by Day [1,10]. In conclusion, while both legacy and low-cost carriers saw positive returns after the event (except for the event day for low-cost carriers), legacy carriers generally exhibited stronger positive cumulative average abnormal returns immediately after the event. However, as days went by, the difference in returns between the two types of carriers narrowed, with both showing significant positive returns over the ten days following the event. Also, through Figure 15, we find that the positive stimulus from that economic stimulus lasted only 5 days and did not continue to stimulate stock prices.

JP Morgan downgraded two airline companies

Table 20 shows the cumulative average abnormal returns results of the event, which is that JP Morgan downgraded JetBlue and Spirit.[92] Leading up to the event, from 10 days before to one day before, [-10,-1], legacy carriers experienced a positive cumulative average abnormal return of 34.67%, significant at the 5% level. A similar positive trend is observed in the 5 days leading up to the event, with cumulative average abnormal returns of 31.88%. Low-cost carriers also showed a positive cumulative average abnormal return of 24.72%, but it was not statistically significant. However, in the 5 days leading up, the cumulative average abnormal returns of 23.01% were significant at the 10% level.

[92]The cumulative average abnormal returns of 90, 150, and 210 days based on the constant model, market model, market-adjusted model and Fama-French 3-factors model are shown in Appendix Tables A.11 and A.12.

On the event day, legacy carriers faced a drastic drop of around 8.79%, significant at the 1% level. Low-cost carriers also experienced a decline in cumulative average abnormal returns, but at a slightly lesser magnitude than legacy carriers, at -8.64%, significant at the 5% level. The majority of the stocks were hit by this downgrade and showed negative abnormal returns, which indicates that the capital markets have lost confidence in the aviation industry. JetBlue and Spirit received a relatively large negative impact at -10.23% and -13.09% of the same day abnormal return, the results are statistically significant at 5%.[93]

After the event, legacy carriers' cumulative average abnormal returns fluctuated with initial rebounds in the short term (Days [1,2] to [1,4]) showing positive and significant returns. However, by Day 1-10, they faced a notable negative cumulative average abnormal return of 8.42%, significant at the 1% level. Low-cost carriers, similar to legacy carriers, showed initial short-term rebounds. By the 10th day, the cumulative average abnormal returns dropped to -3.91%, which was significant at the 10% level.

The results reveal that the downgrade of JP Morgan had a significant negative effect on the stock prices of both legacy and low-cost carriers in the short term, specifically on the day of the event. Although there were temporary recoveries ([1,2] to [1,6]) observed immediately after the event, the overall impact on both types of carriers remained detrimental in the longer term ([1,8] to [1,10]), spanning up to a period of 10 days. Legacy airlines, specifically, saw a more pronounced and enduring adverse effect compared to low-cost carriers.

From Figure 16, we see that the rolling average abnormal return is already declining from -2. We cannot rule out the possibility that information about downgrading firms will be leaked in advance, thus affecting market sentiment in advance.

[93] Author's calculation is based on Bloomberg historical stock price data.

6.3 Comparison results between China and the U.S. for event date March 11, 2020

We have analyzed the short- and long-term impact of the WHO recognition of COVID-19 as a global pandemic on Chinese and U.S. airline stocks, and we can draw the following conclusions from this comparison: 1. In the short run, Chinese legacy carriers are more affected than low-cost carriers, while the same is true for the U.S. 2. In the long run, Chinese airline stocks are not negatively affected by this event, while U.S. legacy carriers are slightly more affected than the country's low-cost carriers, but the difference is not significant. 3. In both the short and long term, U.S. airlines' abnormal returns are much larger in absolute terms than those of Chinese airline stocks.

We also integrated legacy and low-cost carriers for the Chinese and U.S. markets and analyzed them in Table 21. Both Chinese and U.S. airline stocks exhibited positive cumulative average abnormal returns leading up to the event, though the strength and significance varied. Chinese airlines had a stronger positive trend compared to U.S. airlines. Post-event, both markets experienced negative returns. However, the decline was much steeper and more prolonged for U.S. airlines compared to their Chinese counterparts. For the long-run analysis (Table 22), Chinese airline stocks displayed remarkably strong performance in the weeks after the event, with a consistent and statistically significant upward trend. In contrast, U.S. airline stocks exhibited a consistent downturn, and this declining trend was statistically significant. It seems the U.S. airline sector might have been perceived as more adversely affected by the pandemic's implications.

This wide difference between Chinese and U.S. companies' abnormal returns could be explained by four reasons. The first is that the price limit of the SSE and SZSE stocks restricts the market's reaction to the event, while without the price change limit, U.S. stocks can reflect the reactions of investors more efficiently. The second reason is the difference in market efficiency. In general, the U.S. financial market is more developed and can reflect market information more accurately than the Chinese financial market (Zhou et al, 2002), which means U.S. stock prices will more accurately and completely reflect investor attitudes toward information. The third possible reason is the event date. This announcement happened around two months after the virus outbreak in China, during which Chinese investors already had continuously negative expectations during that time. On the contrary, in the U.S., the early stage of the outbreak did not attract enough attention from the government and the public, so investors were more optimistic about market expectations. Chinese companies' state ownership could be the fourth reason. China's three largest airlines are all nearly 70% government-owned, while U.S. airlines are mostly institutionally owned. State ownership often brings stability in terms of financial backing and support. This could also be an explanation for the more moderate impact on China's airline stocks than on U.S. airline stocks.

By comparing Figures 11-16, we find that the stock fluctuations of the two categories of U.S. airlines were very convergent prior to our selected events, while the stock price fluctuations of China's legacy and low-cost airlines were not.

In general, the event of officially acknowledging COVID-19 as a global pandemic had a negative impact on the civil aviation industries of the two countries in the short run and had a negative impact on U.S. aviation industries in the long run. The impact on U.S. airlines is particularly significant.

7 Conclusion

COVID-19 spans from the 2019 outbreak to the present. It has seriously affected the global economic development of almost all industries in the world, especially the global passenger transport industry. In this research, we evaluate the stock and accounting performance of Chinese and U.S. publicly traded airlines during the COVID-19 pandemic using financial ratio analysis and an event study.

From the evidence on accounting performance analysis, the two countries' results are similar in general. In both countries, low-cost carriers are associated with higher liquidity and solvency capabilities compared to legacy carriers. The equity structure differs, U.S. legacy carriers do not have state-owned stock like Chinese legacy carriers. Investors and creditors in both countries place more trust in debt repayment during crises than in low-cost carriers. Legacy carriers in both countries have a large volume of capital, together with their operating strategy and business model, which gives the market a signal that they have a stronger ability to resist shocks than low-cost carriers. On the contrary, low-cost carriers in both countries have a relatively more flexible cost structure when facing a global crisis like COVID-19; their low-cost model has not made them more robust in capital markets.

We use both long-run and short-run event studies to analyze the impact of COVID-19-related policy on Chinese and U.S. legacy and low-cost carriers' stock performance. The cumulative average abnormal returns and average buy-and-hold abnormal returns from negative random shocks to publicly traded airline stocks in the U.S. are significantly higher than those for publicly traded airline stocks in China, both in the long and short event windows. In the short run, both Chinese and U.S. legacy carriers are more affected than low-cost carriers. In the long run, neither Chinese legacy carriers nor low-cost carriers are negatively affected by the random shock; U.S. low-cost carriers are more affected than legacy carriers. For the respective stimulus policies of the two countries, Chinese low-cost carriers are more positively affected than legacy carriers. The opposite is true in the U.S. The results show that the large government ownership of Chinese airlines does not make them less vulnerable to negative market shocks than private firms.

The above results can be attributed to (1) the difference in the effectiveness of the stock markets of the two countries, with U.S. stock prices responding more promptly and better to market information. When comparing both countries, it is evident that stock prices in the U.S. exhibit a higher degree of response and accuracy in response to new market information. In contrast, China's stock markets are comparatively more recent and experiencing ongoing growth. There may still exist instances where the integration of market information into stock prices is not as prompt or effective as observed in the U.S. (2) the 10% price limit on the rise and fall of stocks on the Shanghai and Shenzhen Stock Exchanges; these circuit breakers are designed to prevent extreme price volatility in the stock market. However, these limitations can sometimes suppress the natural price discovery process. If a stock's intrinsic value suggests it should rise or fall by more than 10% based on certain news or events, the imposed limit might prevent it from reaching its natural price on that day. This can lead to pent-up demand or supply, resulting in sudden and sharp price changes once the limits are lifted or on the subsequent trading days. This might not fully represent the stock's actual value and can pose challenges for investors who rely on timely price adjustments. and (3) the large percentage of government ownership of the three legacy Chinese airlines. This can lead to discrepancies between a company's stock price and its intrinsic value, as the company might not always act in the best interest of profit maximization or shareholder value. It also usually signals to investors that the companies may receive financial or policy support from the government in the event of a shock.

Our results conclude that legacy is not more negatively affected in all event studies due to its more international operations. Low-cost carriers are also not more affected due to their smaller market capitalization. The impact of the stocks in the event studies depends on a number of factors, such as the selection of the event and whether there were other events around the time of the event that significantly affected the stock price.

The main limitation of this paper is the multiple-event issue. Sometimes, multiple significant events might occur close in time. This can make it challenging to isolate the impact of a single event, especially for long-run event study. And there are some further areas we can explore in the future. A more comprehensive study of the impact of state ownership in the Chinese stock market can be done using more industries that contain both state-owned and private companies.

8 Tables

Table 1: **Chinese airline companies' market capitalization in 2019**

Company	Market capitalization
Legacy Carriers	
China Eastern Airlines	85,080.60
China Southern Airlines	78,928.50
Air China	128,797.60
China Express Airlines	7,317.10
Hainan Airlines	29,137.80
Low-cost Carriers	
Spring Airlines	40,223.50
Juneyao Air	29,492.20

Notes: The data is for the fiscal year ended December 31, 2019; In millions of CNY.

Table 2: **U.S. airline companies' market capitalization in 2019**

Company	Market capitalization
Legacy Carriers	
American Airlines	12,280.80
Delta Air Lines	37,589.30
Alaska Airlines	8,333.30
Hawaiian Airlines	1,350.90
United Airlines	22,129.70
Skywest Airlines	3,252.40
Low-cost Carriers	
Spirit Airlines	2,759.40
JetBlue Airways	5,279.00
Southwest Airlines	28,019.10
Allegiant Air	2,837.40
Mesa Airlines	211.90

Notes: The data is for the fiscal year ended December 31, 2019, except for Mesa Airlines, the fiscal year of Mesa Airlines ended September 30, 2019; In millions of USD.

Table 3: **Major financial data of China airline companies**

	2017	2018	2019	2020	2017-2019 Ave. YOY	2019-2020 YOY
Legacy carriers						
Operating revenue	84,495	94,858	97,832	50,967	9.33%	-47.90%
Operating expense	76,996	89,084	90,211	62,197	4.01%	-31.05%
Net income	5,320	2,219	3,015	(21,667)	-1.16%	-818.55%
Current asset	20,353	24,257	22,960	30,255	4.93%	31.77%
Cash	10,951	10,829	6,859	9,877	-0.84%	43.99%
Current liability	58,065	71,119	74,830	91,609	9.14%	22.42%
Noncurrent liability	60,903	54,745	80,461	80,672	4.47%	0.26%
Stockholders' equity	57,820	61,850	62,798	41,508	1.03%	-33.90%
Low-cost carriers						
Operating revenue	11,691	13,740	15,776	9,737	19.91%	-38.28%
Operating expense	10,733	13,014	14,870	11,063	21.20%	-25.61%
Net income	1,307	1,371	1,425	(538)	9.21%	-137.77%
Current asset	5,298	7,230	7,183	7,322	12.20%	1.93%
Cash	3,186	3,359	4,671	5,512	14.69%	18.02%
Current liability	5,566	7,766	9,237	11,118	18.98%	20.36%
Noncurrent liability	6,230	4,787	8,023	8,719	20.51%	8.68%
Stockholders' equity	8,624	11,463	13,993	12,533	23.18%	-10.43%

Notes: In CNY million, except year-over-year change (%); Data source: Financial reports of listed airline companies from Shanghai Stock Exchange, Shanghai Stock Exchange and companies' official websites; According to financial practices, negative numbers are displayed in parenthesis. In the legacy airline category, Hainan Airlines' 2019-2020 year-over-year net income decreased by -9201.08% due to its lower earnings in 2019 and higher losses in 2020. Excluding this data, the other four legacy airlines have a 2019-2020 year-over-year net income decline of -705.16%. China Express Airlines was publicly traded in March 2018 and its 2018 annual report contains only partial accounting information for 2016, so we exclude China Express Airlines' data when calculating the average growth rate from 2017 to 2018.

Table 4: **Major financial ratios of Chinese airline companies**

	2017	2018	2019	2020
Legacy carriers				
Total asset turnover	0.65	0.54	0.50	0.27
Operating ratio	1.10	1.04	1.06	0.83
Current ratio	0.99	0.77	0.50	0.48
Quick ratio	0.64	0.47	0.30	0.28
Cash ratio	0.41	0.27	0.19	0.19
Debt to equity	2.49	2.24	2.52	0.54
Debt to asset	0.71	0.68	0.71	0.81
Financial leverage	3.44	3.24	3.52	1.54
Interest coverage	2.69	1.77	1.40	-2.70
Net profit margin	0.07	0.02	0.04	-0.56
Return on asset	0.05	0.02	0.02	-0.09
Return on equity	0.14	0.05	0.07	-0.08
Low-cost carriers				
Total asset turnover	0.60	0.62	0.57	0.31
Operating ratio	1.09	1.06	1.06	0.88
Current ratio	0.96	0.97	0.80	0.66
Quick ratio	0.61	0.49	0.57	0.53
Cash ratio	0.58	0.46	0.54	0.51
Debt to equity	1.37	1.11	1.26	1.63
Debt to asset	0.58	0.53	0.55	0.61
Financial leverage	2.37	2.11	2.26	2.63
Interest coverage	5.43	6.86	6.49	-1.91
Net profit margin	0.11	0.10	0.09	-0.06
Return on asset	0.07	0.06	0.05	-0.02
Return on equity	0.15	0.12	0.10	-0.04

Notes: Data source: Author's calculation based on financial reports data of listed airline companies from Shanghai Stock Exchange, Shanghai Stock Exchange and companies' official websites.

Table 5: **Major financial data of the U.S. airline companies**

	2017	2018	2019	2020	2017-2019 Ave. YOY	2019-2020 YOY
Legacy carriers						
Operating revenue	22,539	24,101	25,103	9,387	5.61%	-62.60%
Operating expense	19,885	21,994	22,455	14,648	7.14%	-34.77%
Net income	1,392	1,404	1,793	(5,030)	3.49%	-380.53%
Current asset	4,658	4,281	4,720	8,234	-0.32%	74.45%
Cash	693	706	1,101	3,653	8.79%	231.80%
Current liability	8,587	9,126	9,776	8,577	8.87%	-12.26%
Noncurrent liability	14,971	16,854	17,984	26,775	8.26%	48.88%
Stockholders' equity	4,424	5,029	5,726	1,059	5.65%	-81.50%
Low-cost carriers						
Operating revenue	6,592	7,059	7,383	3,070	-0.61%	-58.42%
Operating expense	5,568	6,231	6,435	4,318	1.59%	-32.90%
Net income	1,027	601	697	(1,003)	-2.22%	-243.90%
Current asset	1,598	1,708	1,973	4,395	3.33%	122.73%
Cash	543	704	935	3,005	12.65%	221.23%
Current liability	2,134	2,385	2,719	2,513	3.76%	-7.59%
Noncurrent liability	2,976	3,285	3,504	6,471	2.58%	84.66%
Stockholders' equity	3,406	3,491	3,640	3,247	0.63%	-10.81%

Notes: In USD million, except year-over-year change (%); Data source: Financial reports of listed airline companies from the U.S. Securities and Exchange Commission and companies' official websites; According to financial practices, negative numbers are displayed in parenthesis. Mesa Airlines was publicly traded in August 2018 and its 2018 annual report does not contain accounting information for 2016, so we exclude Mesa Airlines' data when calculating the average growth rate from 2017 to 2018.

Table 6: **Major financial ratios of U.S. airline companies**

	2017	2018	2019	2020
Legacy carriers				
Total asset turnover	0.81	0.79	0.73	0.27
Operating ratio	1.15	1.11	1.14	0.70
Current ratio	0.72	0.63	0.61	1.00
Quick ratio	0.56	0.49	0.48	0.87
Cash ratio	0.45	0.39	0.38	0.79
Debt to equity	-9.15	-57.68	-82.63	9.41
Debt to asset	0.77	0.77	0.77	0.89
Financial leverage	-8.15	-56.68	-81.63	10.41
Interest coverage	9.17	7.41	10.01	-10.19
Net profit margin	0.09	0.07	0.08	-0.45
Return on asset	0.07	0.05	0.06	-0.11
Return on equity	-0.04	-1.22	-2.20	-2.11
Low-cost carriers				
Total asset turnover	0.72	0.70	0.68	0.29
Operating ratio	1.18	1.12	1.17	0.81
Current ratio	0.97	0.92	0.82	1.37
Quick ratio	0.72	0.74	0.67	1.23
Cash ratio	0.64	0.68	0.59	1.12
Debt to equity	2.40	2.03	2.01	2.79
Debt to asset	0.66	0.66	0.66	0.73
Financial leverage	3.40	3.03	3.01	3.79
Interest coverage	11.04	7.65	9.41	-5.42
Net profit margin	0.13	0.07	0.09	-0.23
Return on asset	0.10	0.05	0.06	-0.06
Return on equity	0.26	0.14	0.18	-0.22

Notes: Data source: Author's calculation based on financial reports data of listed airline companies from U.S. Securities and Exchange Commission and companies' official websites. American Airlines' stockholders' equity has been negative since 2017, making several financial ratios (especially long-term solvency ratios) differ significantly from other airlines. After removing the data of American Airlines, the average debt-to-equity ratio from 2017 to 2020 of legacy carriers is 2.75, 2.68, 2.73, and 13.29. The financial leverages are 3.75, 3.68, 3.73, and 14.29. The returns on equity are 0.28, 0.20, 0.22, and -2.11.

Table 7: **China airline companies top three ownership type**

Carrier	Proportion (%)	Carrier	Proportion (%)
Legacy carriers		***Low-cost carriers***	
China Eastern Airlines		**Spring Airlines**	
Government	69.91	Corporation	58.72
Other	14.34	Investment advisor	7.19
Investment advisor	8.92	Brokerage	4.9
China Southern Airlines		**Juneyao Air**	
Government	75.92	Holding Company	60.96
Investment advisor	11.77	Corporation	16.83
Brokerage	7.07	Investment advisor	7.1
Air China			
Government	75.18		
Corporation	14.88		
Investment advisor	7.35		
China Express Airlines			
Corporation	66.02		
Hedge fund manager	5.57		
Individual	4.83		
Hainan Airlines			
Corporation	59.97		
Other	31.46		
Government	5.23		

Notes: Data source: Bloomberg securities data and airline companies' annual report to SSE and SZSE; The data is by December 29, 2019.

Table 8: **U.S. airline companies top three ownership type**

Carrier	Proportion (%)	Carrier	Proportion (%)
Legacy carriers		***Low-cost carriers***	
American Airlines		**Spirit Airlines**	
Investment advisor	82.63	Investment advisor	84.91
Hedge fund manager	7.78	Hedge fund manager	7.88
Pension fund	2.42	Pension fund	3.96
Delta Air Lines		**JetBlue Airways**	
Investment advisor	81.5	Investment advisor	78.04
Hedge fund manager	8.94	Hedge fund manager	15.21
Bank	3.29	Pension fund	2.08
Alaska Airlines		**Southwest Airlines**	
Investment advisor	84.56	Investment advisor	88.35
Hedge fund manager	6.6	Hedge fund manager	3.36
Pension fund	3.91	Bank	2.59
Hawaiian Airlines		**Allegiant Air**	
Investment advisor	85.02	Investment advisor	60.47
Hedge fund manager	5.74	Individual	17.7
Individual	2.35	Hedge fund manager	17.52
United Airlines		**Mesa Airlines**	
Investment advisor	70.22	Investment advisor	49.11
Hedge fund manager	23.22	Hedge fund manager	28.26
Pension fund	2.01	Individual	4.43
Skywest Airlines			
Investment advisor	84.69		
Hedge fund manager	7.34		
Individual	2.83		

Notes: Data source: Bloomberg securities data and airline companies' SEC 10-K form; The data is by December 29, 2019; The third type of Skywest Airlines is unclassified and account for 5.27%, we use the fourth type 'Individual' in the table.

Table 9: **Short-run event study**
– China airline stocks' CAARs on March 11, 2020

Event: COVID-19 is defined by the WHO as a global pandemic.

Window	CAAR	t-stat	p-value
Legacy carriers			
[-10,-1]	17.73%**	5.730	0.000
[-5,-1]	11.16%	1.683	0.096
[0,0]	6.65%*	1.924	0.058
[1,1]	-0.36%	-0.730	0.468
[1,2]	-1.33%	-0.916	0.362
[1,3]	-3.20%***	-3.193	0.002
[1,4]	-3.70%***	-3.070	0.003
[1,5]	-2.95%*	-1.908	0.060
[1,6]	-3.72%***	-2.748	0.007
[1,7]	-2.92%*	-1.342	0.183
[1,8]	-2.38%	-0.660	0.511
[1,9]	-0.88%	-0.333	0.740
[1,10]	2.62%	1.154	0.252
Low-cost carriers			
[-10,-1]	17.97%	0.527	0.600
[-5,-1]	13.41%	-0.060	0.953
[0,0]	4.56%	1.052	0.296
[1,1]	-0.12%	-0.342	0.733
[1,2]	0.37%	1.314	0.192
[1,3]	0.25%	0.120	0.904
[1,4]	-1.33%***	-3.716	0.000
[1,5]	-1.33%***	-2.731	0.008
[1,6]	-0.89%***	-4.343	0.000
[1,7]	-3.43%	-0.558	0.578
[1,8]	-3.18%	-0.562	0.576
[1,9]	-3.12%	-0.486	0.628
[1,10]	-0.37%	-0.060	0.952

The expected returns are based on the Fama-French 3-factor model and the estimation window is 150 days. *The result is significant at 10% level, **the result is significant at 5% level, ***the result is significant at 1% level.

Table 10: **Long-run event study – China airline stocks' CAARs on March 11, 2020**

Event: COVID-19 is defined by the WHO as a global pandemic.

Window	CAAR	t-stat	p-value
Legacy carriers			
[1,10]	2.62%	0.459	0.647
[1,20]	15.18%***	3.128	0.002
[1,30]	29.68%***	5.790	0.000
[1,40]	43.51%***	5.866	0.000
[1,50]	60.47%***	11.902	0.000
Low-cost carriers			
[1,10]	-0.37%	-0.028	0.978
[1,20]	14.44%*	1.695	0.092
[1,30]	27.18%**	2.129	0.035
[1,40]	40.09%**	2.163	0.032
[1,50]	54.87%***	3.472	0.001

The expected returns are based on the Fama-French 3-factor model and the estimation window is 150 days. *The result is significant at 10% level, **the result is significant at 5% level, ***the result is significant at 1% level.

Table 11: **Long-run event study**
– China airline stocks' ABHARs on March 11, 2020

Event: COVID-19 is defined by the WHO as a global pandemic.			
Window	ABHAR	t-stat	p-value
Legacy carriers			
[1,10]	16.94%***	28.767	0.000
[1,20]	26.78%***	9.051	0.000
[1,30]	36.16%***	9.023	0.000
[1,40]	46.75%***	9.498	0.000
[1,50]	50.39%***	9.997	0.000
Low-cost carriers			
[1,10]	12.03%***	29.409	0.000
[1,20]	22.70%***	8.690	0.000
[1,30]	29.80%***	4.438	0.000
[1,40]	43.06%***	4.676	0.000
[1,50]	44.32%***	5.200	0.000

Average buy-and-hold return is calculated by equal weight of each company. The expected returns are based on the Fama-French 3-factor model and the estimation window is 150 days. *The result is significant at 10% level, **the result is significant at 5% level, ***the result is significant at 1% level.

Table 12: **Long-run event study – China airline stocks' ABHARs on March 11, 2020**

Event: COVID-19 is defined by the WHO as a global pandemic.

Window	ABHAR	t-stat	p-value
Legacy carriers			
[1,10]	17.51%***	26.792	0.000
[1,20]	24.53%***	7.748	0.000
[1,30]	33.19%***	7.765	0.000
[1,40]	44.73%***	8.899	0.000
[1,50]	47.09%***	8.876	0.000
Low-cost carriers			
[1,10]	11.97%***	28.914	0.000
[1,20]	23.10%***	8.741	0.000
[1,30]	30.84%***	4.539	0.000
[1,40]	44.48%***	4.774	0.000
[1,50]	45.63%***	5.292	0.000

The weights of the average buy-and-hold return are assigned according to the market capitalization of each airline. The expected returns are based on the Fama-French 3-factor model and the estimation window is 150 days. *The result is significant at 10% level, ** the result is significant at 5% level, *** the result is significant at 1% level.

Table 13: **Short-run event study – China airline stocks' CAARs on March 29, 2020**

Event: CAAC introduce "Five One" policy.

Window	CAAR	t-stat	p-value
Legacy carriers			
[-10,-1]	12.57%	0.279	0.781
[-5,-1]	8.47%	-0.126	0.900
[0,0]	0.74%	0.711	0.479
[1,1]	0.83%*	1.756	0.082
[1,2]	-1.22%	-1.526	0.131
[1,3]	-1.99%**	-2.109	0.038
[1,4]	-1.27%	-1.284	0.202
[1,5]	-1.13%	-0.980	0.330
[1,6]	-3.41%***	-2.816	0.006
[1,7]	-3.77%***	-2.836	0.006
[1,8]	-3.54%**	-2.048	0.044
[1,9]	-3.00%	-1.645	0.103
[1,10]	-3.71%**	-2.117	0.037
Low-cost carriers			
[-10,-1]	10.01%	0.225	0.823
[-5,-1]	6.10%	0.060	0.952
[0,0]	0.55%	0.914	0.363
[1,1]	-1.66%***	-4.882	0.000
[1,2]	-3.12%*	-2.631	0.096
[1,3]	-4.05%*	-1.651	0.072
[1,4]	-4.94%	-1.331	0.187
[1,5]	-4.69%	-1.244	0.217
[1,6]	-0.70%	-0.160	0.873
[1,7]	-1.80%	-0.401	0.690
[1,8]	-1.83%	-0.423	0.674
[1,9]	-5.06%*	-1.895	0.061
[1,10]	-2.32%**	-2.541	0.013

The expected returns are based on the Fama-French 3-factor model and the estimation window is 150 days. *The result is significant at 10% level, **the result is significant at 5% level, ***the result is significant at 1% level.

Table 14: **Short-run event study – China airline stocks' CAARs on May 22, 2020**

Event: Chinese government special subsidy on COVID-19.

Window	CAAR	t-stat	p-value
Legacy carriers			
[-10,-1]	14.80%	0.678	0.500
[-5,-1]	8.05%	0.700	0.486
[0,0]	3.39%***	2.684	0.009
[1,1]	0.46%	1.497	0.138
[1,2]	1.83%***	6.062	0.000
[1,3]	5.18%***	8.160	0.000
[1,4]	6.04%***	8.548	0.000
[1,5]	8.93%***	5.770	0.000
[1,6]	9.94%***	4.543	0.000
[1,7]	11.76%***	5.352	0.000
[1,8]	13.23%***	9.290	0.000
[1,9]	14.37%***	13.616	0.000
[1,10]	21.89%***	32.334	0.000
Low-cost carriers			
[-10,-1]	13.28%	0.346	0.730
[-5,-1]	6.47%	0.226	0.822
[0,0]	2.63%**	2.329	0.022
[1,1]	0.67%***	6.214	0.000
[1,2]	2.97%***	3.934	0.000
[1,3]	7.57%***	5.920	0.000
[1,4]	8.38%***	6.968	0.000
[1,5]	12.44%***	4.729	0.000
[1,6]	12.65%***	5.578	0.000
[1,7]	14.32%***	5.923	0.000
[1,8]	18.06%***	6.837	0.000
[1,9]	20.33%***	5.874	0.000
[1,10]	24.83%***	6.812	0.000

The expected returns are based on the Fama-French 3-factor model and the estimation window is 150 days. *The result is significant at 10% level, **the result is significant at 5% level, ***the result is significant at 1% level.

Table 15: **Short-run event study – U.S. airline stocks' CAARs on March 11, 2020**

Event: COVID-19 is defined by the WHO as a global pandemic.

Window	CAAR	t-stat	p-value
Legacy carriers			
[-10,-1]	-1.79%***	-0.054	-0.027
[-5,-1]	-3.31%***	3.001	0.002
[0,0]	1.95%**	2.076	0.041
[1,1]	-8.45%***	-9.018	0.000
[1,2]	-12.09%***	-9.127	0.000
[1,3]	-2.85%*	-1.759	0.082
[1,4]	-17.30%***	-9.232	0.000
[1,5]	-35.23%***	-16.815	0.000
[1,6]	-35.30%***	-15.384	0.000
[1,7]	-23.81%***	-9.607	0.000
[1,8]	-15.48%***	-5.843	0.000
[1,9]	-6.05%**	-2.152	0.034
[1,10]	2.74%	0.924	0.358
Low-cost carriers			
[-10,-1]	-2.67%	-0.825	0.412
[-5,-1]	7.54%***	3.288	0.001
[0,0]	-1.41%	-1.373	0.173
[1,1]	-6.50%***	-6.341	0.000
[1,2]	-5.43%***	-3.743	0.000
[1,3]	-6.21%***	-3.495	0.001
[1,4]	-13.66%***	-6.664	0.000
[1,5]	-21.13%***	-9.218	0.000
[1,6]	-32.37%***	-12.893	0.000
[1,7]	-24.51%***	-9.039	0.000
[1,8]	-18.37%***	-6.335	0.000
[1,9]	-3.80%	-1.235	0.220
[1,10]	2.26%	0.696	0.488

The expected returns are based on the Fama-French 3-factor model and the estimation window is 150 days. *The result is significant at 10% level, **the result is significant at 5% level, ***the result is significant at 1% level.

Table 16: **Long-run event study – U.S. airline stocks' CAARs on March 11, 2020**

Event: COVID-19 is defined by the WHO as a global pandemic.			
Window	CAAR	t-stat	p-value
Legacy carriers			
[1,10]	2.74%	0.164	0.870
[1,20]	-24.04%**	-2.393	0.018
[1,30]	-24.55%**	-2.464	0.015
[1,40]	-29.16%**	-2.156	0.033
[1,50]	-19.00%*	-1.847	0.067
Low-cost carriers			
[1,10]	2.26%	0.184	0.854
[1,20]	-17.96%**	-2.586	0.011
[1,30]	-26.98%**	-2.354	0.020
[1,40]	-32.39%**	-2.091	0.038
[1,50]	-24.24%**	-2.202	0.029

The expected returns are based on the Fama-French 3-factor model and the estimation window is 150 days. *The result is significant at 10% level, **the result is significant at 5% level, ***the result is significant at 1% level.

Table 17: **Long-run event study – U.S. airline stocks' ABHARs on March 11, 2020**

Event: COVID-19 is defined by the WHO as a global pandemic.

Window	ABHAR	t-stat	p-value
Legacy carriers			
[1,10]	-5.08%	-0.885	0.377
[1,20]	-26.58%***	-6.703	0.000
[1,30]	-26.58%***	-6.663	0.000
[1,40]	-31.04%***	-7.297	0.000
[1,50]	-26.13%***	-5.908	0.000
Low-cost carriers			
[1,10]	-4.41%	-1.457	0.147
[1,20]	-22.97%***	-5.550	0.000
[1,30]	-29.80%***	-7.354	0.000
[1,40]	-35.11%***	-5.410	0.000
[1,50]	-32.13%***	-6.480	0.000

Average buy-and-hold return is calculated by equal weight of each company. The expected returns are based on the Fama-French 3-factor model and the estimation window is 150 days. *The result is significant at 10% level, **the result is significant at 5% level, ***the result is significant at 1% level.

Table 18: **Long-run event study**
– U.S. airline stocks' ABHARs on March 11, 2020

Event: COVID-19 is defined by the WHO as a global pandemic.

Window	ABHAR	t-stat	p-value
Legacy carriers			
[1,10]	-6.38%	-1.102	0.272
[1,20]	-21.23%***	-4.361	0.000
[1,30]	-28.31%***	-7.184	0.000
[1,40]	-38.16%***	-7.788	0.000
[1,50]	-34.36%***	-6.685	0.000
Low-cost carriers			
[1,10]	1.50%	0.355	0.723
[1,20]	-23.22%***	-5.607	0.000
[1,30]	-28.24%***	-6.843	0.000
[1,40]	-39.40%***	-5.765	0.000
[1,50]	-36.22%***	-6.753	0.000

The weights of the average buy-and-hold return are assigned according to the market capitalization of each airline. The expected returns are based on the Fama-French 3-factor model and the estimation window is 150 days. *The result is significant at 10% level, ** the result is significant at 5% level, *** the result is significant at 1% level.

Table 19: **Short-run event study**
– U.S. airline stocks' CAARs on March 19, 2020

Event: U.S. Coronavirus Aid, Relief and Economy Security Act.

Window	CAAR	t-stat	p-value
Legacy carriers			
[-10,-1]	-8.12%***	-0.087	-0.075
[-5,-1]	-13.68%***	0.000	0.000
[0,0]	2.53%*	1.852	0.067
[1,1]	10.29%***	7.518	0.000
[1,2]	16.52%***	8.540	0.000
[1,3]	29.67%***	12.520	0.000
[1,4]	39.86%***	14.567	0.000
[1,5]	38.14%***	12.469	0.000
[1,6]	32.40%***	9.668	0.000
[1,7]	22.76%***	6.288	0.000
[1,8]	25.41%***	6.567	0.000
[1,9]	17.51%***	4.267	0.000
[1,10]	10.11%**	2.337	0.022
Low-cost carriers			
[-10,-1]	-25.50%***	-6.500	0.000
[-5,-1]	-25.76%***	-9.287	0.000
[0,0]	-5.74%***	-4.627	0.000
[1,1]	7.93%***	6.392	0.000
[1,2]	14.04%***	8.002	0.000
[1,3]	29.61%***	13.779	0.000
[1,4]	36.06%***	14.533	0.000
[1,5]	38.17%***	13.757	0.000
[1,6]	32.53%***	10.704	0.000
[1,7]	17.71%***	5.394	0.000
[1,8]	22.17%***	6.318	0.000
[1,9]	16.40%***	4.407	0.000
[1,10]	6.74%*	1.718	0.089

The expected returns are based on the Fama-French 3-factor model and the estimation window is 150 days. *The result is significant at 10% level, **the result is significant at 5% level, ***the result is significant at 1% level.

Table 20: **Short-run event study – U.S. airline stocks' CAARs on June 10, 2020**

Event: JP Morgan downgraded two airline companies.

Window	CAAR	t-stat	p-value
Legacy carriers			
[-10,-1]	34.67%**	2.169	0.033
[-5,-1]	31.88%**	2.136	0.035
[0,0]	-8.79%***	-14.051	0.000
[1,1]	-6.87%***	-16.295	0.000
[1,2]	3.63%**	2.162	0.033
[1,3]	3.18%**	2.097	0.039
[1,4]	3.53%*	1.983	0.050
[1,5]	2.48%	1.119	0.266
[1,6]	2.55%	1.179	0.241
[1,7]	-0.24%	-0.114	0.910
[1,8]	-2.99%	-1.065	0.290
[1,9]	-4.26%*	-1.902	0.060
[1,10]	-8.42%***	-3.977	0.000
Low-cost carriers			
[-10,-1]	24.72%	1.608	0.111
[-5,-1]	23.01%*	1.697	0.093
[0,0]	-8.64%**	-2.430	0.017
[1,1]	-5.98%***	-6.054	0.000
[1,2]	3.94%***	3.486	0.001
[1,3]	4.18%**	2.107	0.038
[1,4]	4.58%*	1.742	0.085
[1,5]	3.01%	1.227	0.223
[1,6]	3.29%	1.344	0.182
[1,7]	0.05%	0.020	0.984
[1,8]	-1.50%	-0.621	0.536
[1,9]	-0.18%	-0.089	0.929
[1,10]	-3.91%*	-1.713	0.090

The expected returns are based on the Fama-French 3-factor model and the estimation window is 150 days. *The result is significant at 10% level, **the result is significant at 5% level, ***the result is significant at 1% level.

Table 21: **Short-run event study – China and U.S. airline stocks' CAARs on March 11, 2020**

Event: COVID-19 is defined by the WHO as a global pandemic.

Window	CAAR	t-stat	p-value
China airlines			
[-10,-1]	17.80%***	5.104	0.000
[-5,-1]	11.80%***	3.140	0.002
[0,0]	6.05%***	6.306	0.000
[1,1]	-0.29%	-0.826	0.410
[1,2]	-1.28%	-1.385	0.168
[1,3]	-2.61%**	-2.568	0.011
[1,4]	-3.04%***	-4.339	0.000
[1,5]	-2.51%***	-3.303	0.001
[1,6]	-2.93%***	-2.971	0.003
[1,7]	-3.09%*	-1.763	0.080
[1,8]	-2.63%	-1.125	0.262
[1,9]	-1.54%	-0.767	0.444
[1,10]	1.74%	0.945	0.346
U.S. airlines			
[-10,-1]	-3.43%	-1.535	0.127
[-5,-1]	7.10%***	5.495	0.000
[0,0]	0.42%	0.352	0.725
[1,1]	-7.56%***	-5.021	0.000
[1,2]	-9.06%**	-2.385	0.018
[1,3]	-4.38%	-0.993	0.322
[1,4]	-15.64%***	-3.688	0.000
[1,5]	-28.82%***	-4.258	0.000
[1,6]	-33.97%***	-8.450	0.000
[1,7]	-24.13%***	-4.352	0.000
[1,8]	-16.79%***	-3.287	0.001
[1,9]	-5.03%	-1.204	0.231
[1,10]	2.52%	0.656	0.513

The expected returns are based on the Fama-French 3-factor model and the estimation window is 150 days. *The result is significant at 10% level, **the result is significant at 5% level, ***the result is significant at 1% level.

Table 22: **Long-run event study**
– – China and U.S. airline stocks' CAARs on March 11, 2020

Event: COVID-19 is defined by the WHO as a global pandemic.

Window	CAAR	t-stat	p-value
China airlines			
[1,10]	1.74%	0.945	0.346
[1,20]	14.94%***	8.957	0.000
[1,30]	28.94%***	18.097	0.000
[1,40]	42.51%***	23.021	0.000
[1,50]	58.85%***	28.963	0.000
U.S. airlines			
[1,10]	2.52%	0.656	0.513
[1,20]	-21.27%***	-4.325	0.000
[1,30]	-25.66%***	-5.162	0.000
[1,40]	-30.63%***	-4.401	0.000
[1,50]	-21.38%***	-3.972	0.000

The expected returns are based on Fama-French 3-factor model and the estimation window is 150-days. *The result is significant at 10% level, **the result is significant at 5% level, ***the result is significant at 1% level.

9 Figures

Figure 7: China airline stocks' rolling average returns with 95% confidence interval

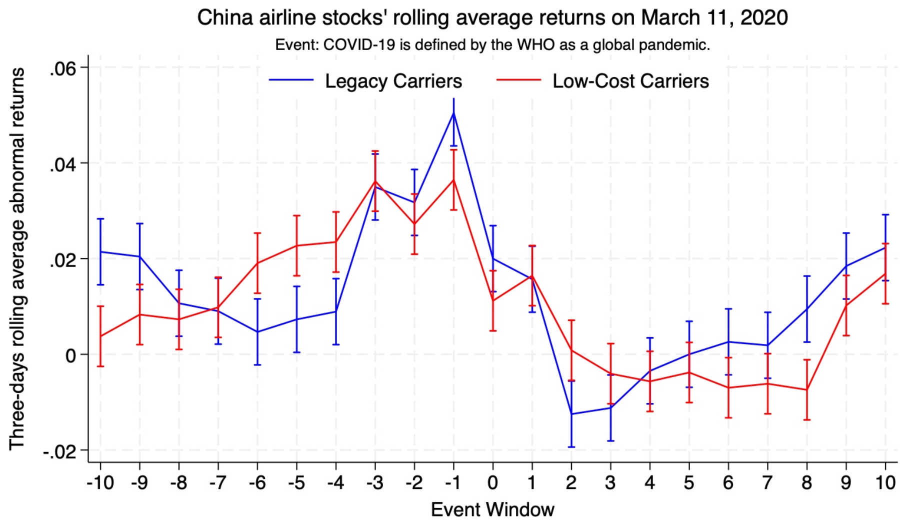


Figure 8: China airline stocks' rolling average returns with 95% confidence interval

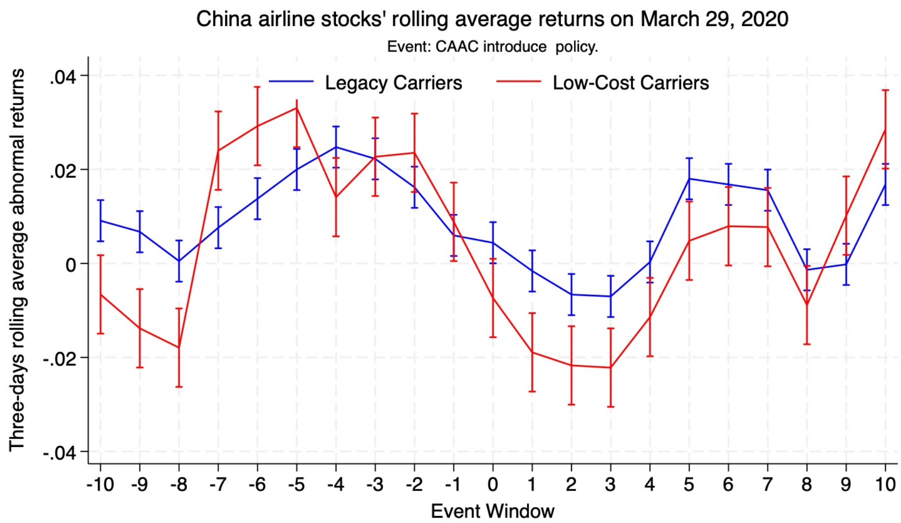


Figure 9: China airline stocks' rolling average returns with 95% confidence interval

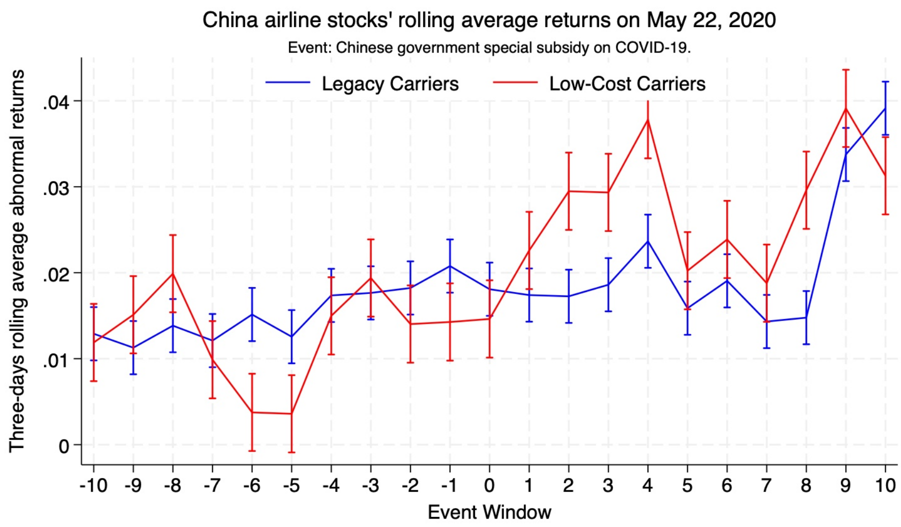


Figure 10: U.S. airline stocks' rolling average returns with 95% confidence interval

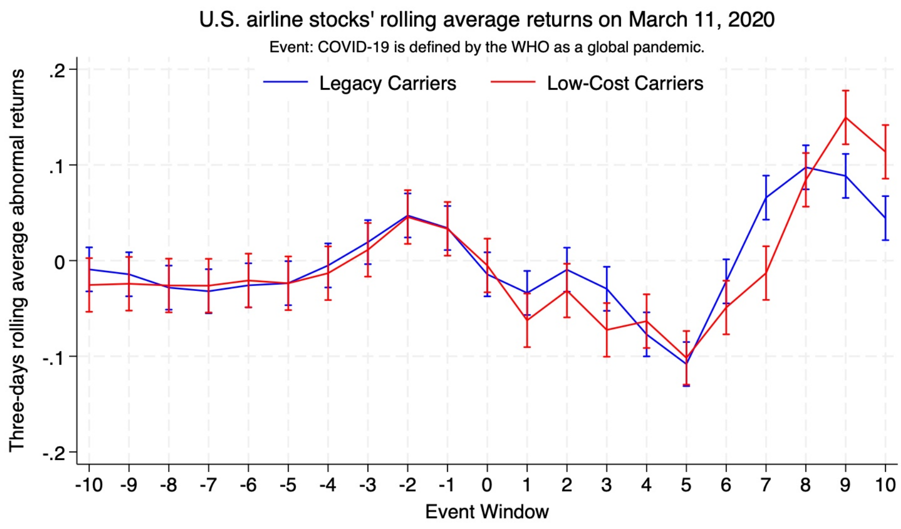


Figure 11: U.S. airline stocks' rolling average returns with 95% confidence interval

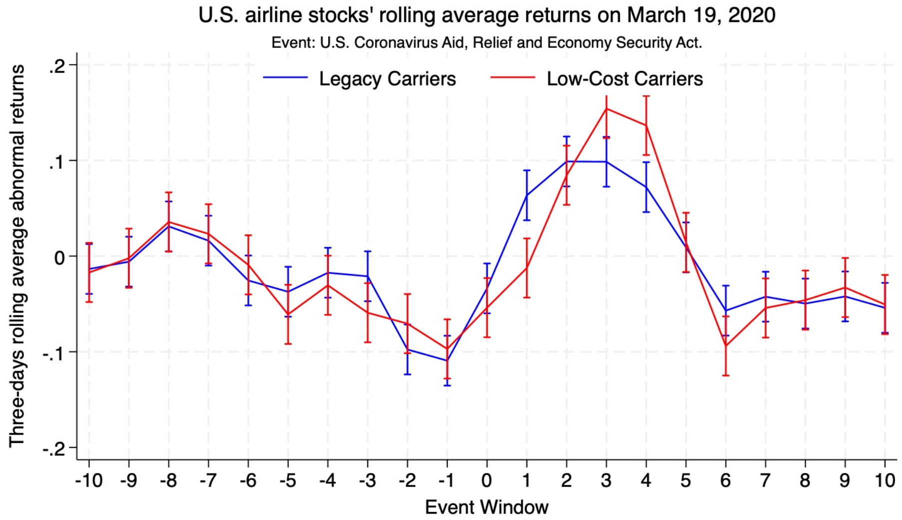
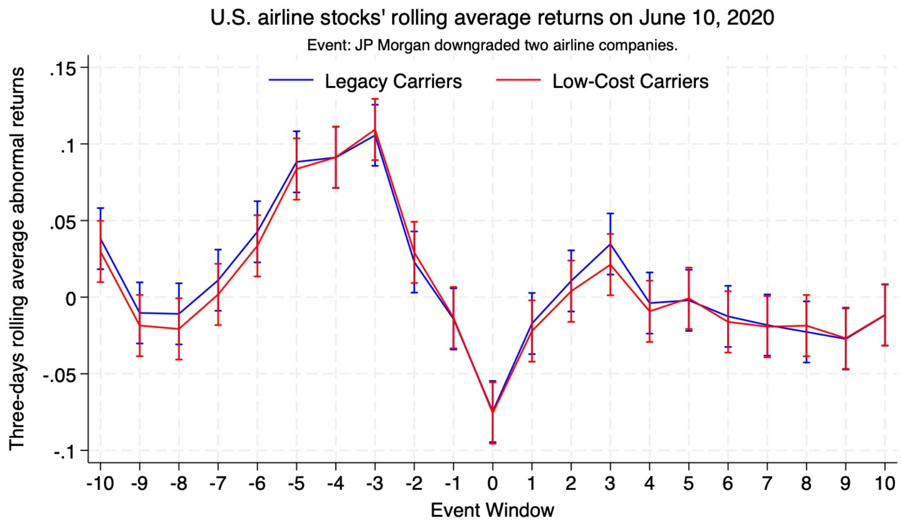


Figure 12: U.S. airline stocks' rolling average returns with 95% confidence interval



Appendix

A Tables

Table A.1: **Chinese airline stocks' CAAR on March 11, 2020**

Event: COVID-19 is defined by the WHO as a global pandemic.

Window	Constant model			Market-adjusted	Market model			Fama-French 3-factors model		
	90 days	150 days	210 days	model	90 days	150 days	210 days	90 days	150 days	210 days
Legacy carriers										
[-10,-1]	2.44%***	2.95%	3.57%	3.12%**	4.18%**	4.62%**	4.74%**	17.29%**	17.73%**	17.84%**
[-5,-1]	3.74%***	3.99%	4.30%	3.79%	4.25%	4.48%	4.55%	10.81%	11.16%	11.36%
[0,0]	3.47%	3.52%	3.58%	4.79%**	5.18%**	5.20%**	5.18%**	6.59%*	6.65%*	6.72%*
[1,1]	-4.16%	-4.11%***	-4.05%***	-2.25%***	-1.73%***	-1.71%***	-1.75%***	-0.34%	-0.36%	-0.37%
[1,2]	-6.28%	-6.17%***	-6.05%***	-2.96%**	-2.04%	-2.00%	-2.06%	-0.79%	-1.33%	-1.29%
[1,3]	-10.50%	-10.35%***	-10.17%***	-2.90%	-0.94%	-0.91%	-1.06%	-2.83%**	-3.20%***	-3.37%***
[1,4]	-12.33%	-12.13%***	-11.88%***	-4.25%**	-2.09%	-2.02%	-2.17%	-2.79%***	-3.70%***	-3.85%***
[1,5]	-15.53%***	-15.28%***	-14.97%***	-5.47%**	-2.79%	-2.70%	-2.89%	-2.08%*	-2.95%*	-3.03%*
[1,6]	-18.75%***	-18.45%***	-18.07%***	-7.40%***	-4.34%***	-4.23%***	-4.43%***	-2.89%***	-3.72%***	-3.66%***
[1,7]	-16.16%**	-15.80%***	-15.37%***	-6.60%***	-3.85%***	-3.66%***	-3.81%***	-5.00%*	-2.92%*	-2.93%*
[1,8]	-19.10%	-18.70%***	-18.20%***	-6.20%***	-2.60%**	-2.42%***	-2.64%***	-2.96%	-2.38%	-2.28%
[1,9]	-16.39%	-15.94%***	-15.38%***	-6.18%***	-3.09%**	-2.83%**	-2.97%**	-1.44%	-0.88%	-0.83%
[1,10]	-11.50%	-11.00%***	-10.37%***	-3.98%**	-1.40%	-1.05%	-1.11%	2.07%	2.62%	2.68%

Notes: *The result is significant at 10% level, ** the result is significant at 5% level, *** the result is significant at 1% level.

Table A.2: **Chinese airline stocks' CAAR on March 11, 2020 - Continued**

Event: COVID-19 is defined by the WHO as a global pandemic.

Window	Constant model			Market-adjusted	Market model			Fama-French 3-factors model		
	90 days	150 days	210 days	model	90 days	150 days	210 days	90 days	150 days	210 days
Low-cost carriers										
[-10,-1]	1.81%	1.29%	1.14%	1.34%	3.45%***	2.79%***	2.14%***	17.79%	17.97%	16.77%
[-5,-1]	4.96%	4.70%	4.63%	4.44%	5.45%	5.14%	4.84%	13.76%	13.41%	12.55%
[0,0]	1.40%	1.35%	1.34%	2.61%	3.01%	2.85%	2.69%	4.78%	4.56%	4.33%
[1,1]	-3.52%***	-3.57%***	-3.58%***	-1.71%***	-1.22%***	-1.42%***	-1.63%***	-0.16%	-0.12%	-0.23%
[1,2]	-6.09%***	-6.19%***	-6.22%***	-3.00%***	-2.10%***	-2.46%***	-2.84%***	0.43%	0.37%	0.10%
[1,3]	-10.39%***	-10.55%***	-10.59%***	-3.13%***	-1.37%***	-2.11%***	-2.88%***	0.31%	0.25%	0.03%
[1,4]	-13.85%***	-14.06%***	-14.12%***	-6.22%***	-4.20%***	-5.03%***	-5.90%***	-1.45%***	-1.33%***	-1.67%***
[1,5]	-17.65%***	-17.92%***	-17.99%***	-8.17%***	-5.64%***	-6.68%***	-7.76%***	-1.25%***	-1.33%***	-1.92%***
[1,6]	-20.84%***	-21.16%***	-21.24%***	-10.18%***	-7.26%***	-8.45%***	-9.69%***	-0.59%***	-0.89%***	-2.16%***
[1,7]	-14.02%***	-14.39%***	-14.49%***	-5.27%***	-2.42%***	-3.54%***	-4.70%***	-3.06%	-3.43%	-4.59%
[1,8]	-18.79%***	-19.21%***	-19.33%***	-6.80%***	-3.24%***	-4.67%***	-6.15%***	-2.63%	-3.18%	-4.48%
[1,9]	-17.11%***	-17.58%***	-17.71%***	-7.93%***	-4.57%***	-5.86%***	-7.20%***	-2.62%	-3.12%	-4.09%
[1,10]	-13.06%***	-13.59%***	-13.73%***	-6.69%***	-3.55%***	-4.71%***	-5.89%***	0.20%	-0.37%	-1.21%

Notes: *The result is significant at 10% level, ** the result is significant at 5% level, *** the result is significant at 1% level.

Table A.3: **Chinese airline stocks' CAAR on March 29, 2020**

Event: CAAC introduce "Five One" policy.

Window	Constant model			Market-adjusted model	Market model			Fama-French 3-factors model		
	90 days	150 days	210 days		90 days	150 days	210 days	90 days	150 days	210 days
Legacy carriers										
[-10,-1]	-7.69%	-7.19%	-7.13%	-3.12%***	-3.10%**	-2.34%**	-2.08%**	11.37%	12.57%	12.85%
[-5,-1]	2.21%**	2.47%**	2.49%**	0.52%***	0.64%***	0.81%***	0.96%***	8.59%	8.47%	8.48%
[0,0]	-1.85%**	-1.80%**	-1.80%**	-0.89%	-0.90%	-0.80%	-0.77%	0.73%	0.74%	0.74%
[1,1]	-0.32%	-0.27%	-0.26%	-0.65%	-0.62%	-0.59%	-0.56%	0.83%*	0.83%*	0.91%*
[1,2]	-0.80%**	-0.70%*	-0.69%**	-0.84%***	-0.81%**	-0.71%*	-0.65%*	-1.50%*	-1.22%	-1.12%
[1,3]	-0.07%	0.09%	0.10%	-1.72%**	-1.63%**	-1.56%*	-1.48%**	-1.94%**	-1.99%**	-1.79%*
[1,4]	-0.94%	-0.74%	-0.72%	-2.03%**	-1.94%*	-1.79%	-1.68%	-1.71%	-1.27%	-0.98%
[1,5]	0.33%	0.58%	0.61%	-3.04%***	-2.88%**	-2.80%**	-2.65%**	-1.19%	-1.13%	-0.84%
[1,6]	2.70%***	3.01%***	3.04%***	-0.21%	-0.04%	0.12%	0.29%	-3.03%***	-3.41%***	-3.62%**
[1,7]	2.45%***	2.80%***	2.84%***	-0.79%*	-0.61%	-0.42%	-0.21%	-3.40%***	-3.77%***	-3.97%**
[1,8]	0.79%	1.20%	1.24%	-1.83%	-1.65%	-1.37%	-1.14%	-3.00%**	-3.54%**	-3.80%**
[1,9]	-1.72%	-1.26%	-1.22%	-3.92%**	-3.74%*	-3.38%	-3.13%*	-2.36%	-3.00%	-3.32%*
[1,10]	-0.67%	-0.16%	-0.11%	-4.80%	-4.55%**	-4.25%**	-3.96%**	-3.29%**	-3.71%**	-4.01%**

Notes: *The result is significant at 10% level, ** the result is significant at 5% level, *** the result is significant at 1% level.

Table A.4: **Chinese airline stocks' CAAR on March 29, 2020 - Continued**

Event: CAAC introduce "Five One" policy.

Window	Constant model			Market-adjusted	Market model			Fama-French 3-factors model		
	90 days	150 days	210 days	model	90 days	150 days	210 days	90 days	150 days	210 days
Low-cost carriers										
[-10,-1]	-7.03%	-8.37%	-9.01%	-4.65%	-2.26%	-3.85%	-4.47%	9.08%	10.01%	9.75%
[-5,-1]	0.41%	-0.26%	-0.58%	-2.38%	-1.22%	-1.80%	-1.96%	6.94%	6.10%	5.63%
[0,0]	-1.93%***	-2.06%***	-2.13%***	-1.18%***	-0.94%***	-1.13%***	-1.21%***	0.79%	0.55%	0.39%
[1,1]	1.02%***	0.89%***	0.83%***	0.47%**	0.70%***	0.59%**	0.56%**	-1.66%***	-1.66%***	-1.82%***
[1,2]	1.02%	0.75%	0.62%	0.54%	1.01%	0.75%	0.66%	-3.12%***	-3.12%***	-0.26%
[1,3]	-2.71%*	-2.31%	-2.12%	0.40%	1.09%	0.78%	0.70%	-4.05%*	-4.05%*	-1.25%*
[1,4]	-2.53%	-2.00%	-1.74%	-0.57%	-1.49%	-1.02%	0.88%	-4.94%*	-4.94%*	-2.06%***
[1,5]	-3.51%*	-2.84%	-2.52%	-0.96%	-0.18%	-0.31%	-0.41%	-4.53%	-4.69%	-1.82%**
[1,6]	-5.34%***	-4.54%***	-4.15%***	1.12%	-2.49%	-1.84%	-1.68%	-0.13%	-0.70%	1.82%
[1,7]	-5.15%***	-4.21%***	-3.76%**	0.38%	-1.98%	-1.21%	-1.02%	-1.23%	-1.80%	0.80%
[1,8]	3.38%*	2.31%	1.79%	-1.00%	0.84%	-0.09%	-0.35%	-1.20%	-1.83%	0.85%
[1,9]	-1.71%	-2.91%	-3.49%	-5.88%	-3.80%	-4.89%	-5.21%	-4.34%*	-5.06%*	-2.39%***
[1,10]	1.13%	-0.21%	-0.86%	-5.20%	-2.90%	-4.02%*	-4.31%*	-1.49%**	-2.32%**	0.23%

Notes: *The result is significant at 10% level, ** the result is significant at 5% level, *** the result is significant at 1% level.

Table A.5: **Chinese airline stocks' CAAR on May 22, 2020**

Event: Chinese government special subsidy on COVID-19.

Window	Constant model			Market-adjusted model	Market model			Fama-French 3-factors model		
	90 days	150 days	210 days		90 days	150 days	210 days	90 days	150 days	210 days
Legacy carriers										
[-10,-1]	-0.24%	-0.94%	-0.67%***	-1.34%	-0.14%	-0.54%	-0.15%***	15.54%	14.80%	14.94%
[-5,-1]	0.55%	0.20%	0.33%***	0.15%	0.75%	0.55%	0.75%***	8.44%	8.05%	8.23%
[0,0]	-0.40%	-0.47%	-0.44%**	1.76%	1.85%	1.91%	1.97%**	3.36%***	3.39%***	3.46%***
[1,1]	-0.92%***	-0.99%***	-0.96%**	-1.19%***	-1.07%***	-1.12%***	-1.08%**	0.52%	0.46%	0.45%
[1,2]	0.16%	0.02%	0.08%**	-1.38%***	-1.13%***	-1.27%***	-1.20%**	1.98%***	1.83%***	1.83%***
[1,3]	1.20%**	0.99%*	1.07%	0.22%	0.59%	0.44%	0.55%	5.41%***	5.18%***	5.13%***
[1,4]	0.81%	0.53%	0.64%	-0.59%	-0.10%	-0.31%	-0.16%	6.38%***	6.04%***	5.96%***
[1,5]	2.54%*	2.19%	2.33%***	0.73%	1.35%	1.09%	1.27%***	9.34%***	8.93%***	8.88%***
[1,6]	4.88%**	4.46%**	4.62%	0.24%	1.01%	0.59%	0.78%***	10.66%***	9.94%***	9.88%***
[1,7]	5.64%***	5.15%***	5.34%***	0.55%	1.44%	0.97%	1.20%***	12.47%***	11.76%***	11.78%***
[1,8]	5.64%***	5.08%***	5.30%**	0.42%	1.43%	0.91%	1.18%**	13.95%***	13.23%***	13.27%***
[1,9]	5.35%***	4.72%***	4.96%**	0.02%	1.16%	0.60%	0.91%*	15.05%***	14.37%***	14.49%***
[1,10]	11.99%***	11.29%***	11.56%*	6.05%	7.31%***	6.69%***	7.03%	22.59%***	21.89%***	22.08%***

Notes: *The result is significant at 10% level, ** the result is significant at 5% level, *** the result is significant at 1% level.

Table A.6: **Chinese airline stocks' CAAR on May 22, 2020 - Continued**

Event: Chinese government special subsidy on COVID-19.

Window	Constant model			Market-adjusted	Market model			Fama-French 3-factors model		
	90 days	150 days	210 days	model	90 days	150 days	210 days	90 days	150 days	210 days
Low-cost carriers										
[-10,-1]	-0.76%	-2.09%	-0.0250553	-3.38%	-0.65%	-1.67%	-0.0198016	14.23%	13.28%	12.78%
[-5,-1]	-0.14%	-0.81%	-0.0101534	-1.30%	0.08%	-0.43%	-0.0059258	6.91%	6.47%	6.30%
[0,0]	-1.07%	-1.20%	-0.0124489	0.93%	1.46%**	1.32%*	0.01200902	2.73%**	2.63%**	2.53%**
[1,1]	-0.78%***	-0.91%***	-0.0095153	-1.20%***	-0.95%***	-1.05%	-0.0107221	0.79%***	0.67%***	0.60%***
[1,2]	1.33%**	1.06%	0.00981064	-0.52%	-0.12%	-0.30%	-0.0031321	3.20%***	2.97%***	2.88%***
[1,3]	3.61%***	3.21%**	0.03081861	2.17%	2.92%***	2.62%*	0.02552702	7.88%***	7.57%***	7.37%***
[1,4]	3.19%***	2.66%**	0.02489694	1.18%	2.16%**	1.77%	0.01682503	8.79%***	8.38%***	8.12%***
[1,5]	6.22%***	5.56%**	0.0534635	3.65%	4.88%**	4.39%	0.04279243	12.95%***	12.44%***	12.15%***
[1,6]	8.45%***	7.65%***	0.07401762	2.90%	4.10%**	3.54%	0.03510571	13.15%***	12.65%***	12.45%***
[1,7]	9.09%***	8.16%***	0.07869868	2.94%	4.38%**	3.73%	0.03678054	14.96%***	14.32%***	14.11%***
[1,8]	11.26%***	10.20%***	0.09864824	4.82%*	6.53%***	5.78%**	0.05695455	18.83%***	18.06%***	17.77%***
[1,9]	12.00%***	10.80%***	0.10425995	5.31%	7.29%***	6.43%*	0.06319893	21.25%***	20.33%***	19.99%***
[1,10]	15.78%***	14.46%***	0.14037743	8.33%**	10.52%***	9.58%**	0.09450791	25.87%***	24.83%***	24.49%***

Notes: *The result is significant at 10% level, ** the result is significant at 5% level, *** the result is significant at 1% level.

Table A.7: **U.S. airline stocks' CAAR on March 11, 2020**

Event: COVID-19 is defined by the WHO as a global pandemic.

Window	Constant model			Market-adjusted	Market model			Fama-French 3-factors model		
	90 days	150 days	210 days	model	90 days	150 days	210 days	90 days	150 days	210 days
Legacy carriers										
[-10,-1]	-22.27%***	-22.61%***	-23.16%***	-16.37%***	-8.38%***	-11.60%***	-12.37%***	-0.59%	-1.79%***	-1.72%***
[-5,-1]	-4.28%	-4.46%	-4.73%	-1.48%	2.40%	0.84%	0.46%	9.59%***	-3.31%***	-3.39%***
[0,0]	-5.54%***	-5.57%***	-5.63%***	-0.80%	3.18%***	1.46%	1.26%	3.89%**	1.95%**	1.94%**
[1,1]	-22.40%***	-22.43%***	-22.49%***	-13.03%***	-5.52%***	-8.80%***	-9.13%***	-4.96%***	-8.45%***	-8.56%***
[1,2]	-12.14%***	-12.21%***	-12.32%***	-12.21%***	-11.57%***	-11.79%***	-11.91%***	-11.50%***	-12.09%***	-11.66%***
[1,3]	-19.93%***	-20.03%***	-20.20%***	-8.16%***	1.88%	-2.45%	-2.96%	-2.00%	-2.85%*	-2.56%
[1,4]	-26.30%***	-26.44%***	-26.66%***	-20.67%***	-14.98%***	-17.37%***	-17.77%***	-14.56%***	-17.30%***	-17.19%***
[1,5]	-55.41%***	-55.59%***	-55.86%***	-44.75%***	-34.86%***	-39.07%***	-39.67%***	-29.55%***	-35.23%***	-34.86%***
[1,6]	-52.66%***	-52.87%***	-53.20%***	-42.62%***	-32.85%***	-36.97%***	-37.62%***	-30.89%***	-35.30%***	-35.83%***
[1,7]	-47.58%***	-47.82%***	-48.21%***	-33.35%***	-20.03%***	-25.68%***	-26.51%***	-17.87%***	-23.81%***	-24.53%***
[1,8]	-44.72%***	-44.99%***	-45.44%***	-27.70%***	-11.90%***	-18.62%***	-19.58%***	-8.62%***	-15.48%***	-16.77%***
[1,9]	-21.21%***	-21.52%***	-22.01%***	-13.72%***	-4.86%	-8.49%***	-9.24%***	-2.35%**	-6.05%**	-7.05%**
[1,10]	-9.80%	-10.14%*	-10.69%**	-3.61%	4.61%	1.29%	0.51%	6.04%*	2.74%	1.88%

Notes: *The result is significant at 10% level, ** the result is significant at 5% level, *** the result is significant at 1% level.

Table A.8: **U.S. airline stocks' CAAR on March 11, 2020 - Continued**

Event: COVID-19 is defined by the WHO as a global pandemic.

Window	Constant model			Market-adjusted	Market model			Fama-French 3-factors model		
	90 days	150 days	210 days	model	90 days	150 days	210 days	90 days	150 days	210 days
Low-cost carriers										
[-10,-1]	-20.08%***	-19.47%***	-19.96%***	-12.95%***	-8.08%**	-9.60%***	-10.26%***	-2.00%	-2.67%	-4.28%
[-5,-1]	-3.46%	-3.15%	-3.39%	-0.03%	2.33%	1.60%	1.27%	7.53%***	7.54%***	6.35%***
[0,0]	-8.51%***	-8.45%***	-8.50%***	-3.65%***	-0.98%	-2.15%**	-2.31%**	-0.23%	-1.41%	-1.69%
[1,1]	-19.07%***	-19.00%***	-19.05%***	-9.58%***	-4.48%***	-6.78%***	-7.05%***	-4.06%***	-6.50%***	-6.76%***
[1,2]	-7.84%***	-7.71%***	-7.81%***	-7.66%***	-7.34%***	-7.34%***	-7.44%***	-5.55%***	-5.43%***	-6.09%***
[1,3]	-23.89%***	-23.71%***	-23.85%***	-11.75%***	-5.03%***	-7.94%***	-8.37%***	-3.18%***	-6.21%***	-7.11%***
[1,4]	-23.63%***	-23.38%***	-23.58%***	-17.51%***	-13.84%***	-15.25%***	-15.59%***	-12.27%***	-13.66%***	-14.42%***
[1,5]	-42.42%***	-42.12%***	-42.36%***	-31.14%***	-24.65%***	-27.30%***	-27.81%***	-18.96%***	-21.13%***	-22.77%***
[1,6]	-48.15%***	-47.78%***	-48.07%***	-37.36%***	-31.01%***	-33.53%***	-34.07%***	-29.85%***	-32.37%***	-33.02%***
[1,7]	-45.72%***	-45.30%***	-45.64%***	-30.62%***	-21.90%***	-25.44%***	-26.13%***	-20.88%***	-24.51%***	-25.22%***
[1,8]	-42.63%***	-42.14%***	-42.53%***	-24.62%***	-14.26%***	-18.49%***	-19.30%***	-14.00%***	-18.37%***	-18.81%***
[1,9]	-16.78%***	-16.23%***	-16.67%***	-8.18%**	-2.65%	-4.55%	-5.19%	-1.95%	-3.80%	-4.40%
[1,10]	-9.25%	-8.64%*	-9.13%*	-1.83%	3.20%	1.61%	0.94%	3.84%	2.26%	1.52%

Notes: *The result is significant at 10% level, ** the result is significant at 5% level, *** the result is significant at 1% level.

Table A.9: **U.S. airline stocks' CAAR on March 19, 2020**

Event: U.S. Coronavirus Aid, Relief and Economy Security Act.

Window	Constant model			Market-adjusted	Market model			Fama-French 3-factors model		
	90 days	150 days	210 days	model	90 days	150 days	210 days	90 days	150 days	210 days
Legacy carriers										
[-10,-1]	-66.90%***	-68.06%***	-68.72%***	-46.17%***	-39.25%***	-40.61%***	-40.43%***	-36.20%***	-8.12%***	-7.81%***
[-5,-1]	-54.50%***	-55.08%***	-55.40%***	-44.75%***	-41.37%***	-42.05%***	-41.98%***	-38.85%***	-13.68%***	-12.86%***
[0,0]	2.93%	2.82%	2.75%	2.13%	2.46%*	2.32%*	2.25%	2.90%*	2.53%*	2.37%*
[1,1]	5.26%***	5.15%***	5.08%***	9.27%***	10.20%***	10.07%***	10.15%***	10.56%***	10.29%***	10.30%***
[1,2]	8.31%***	8.08%***	7.95%***	14.92%***	16.61%***	16.34%***	16.46%***	17.86%***	16.52%***	16.45%***
[1,3]	32.01%***	31.66%***	31.46%***	28.90%***	29.80%***	29.38%***	29.12%***	31.13%***	29.67%***	29.19%***
[1,4]	43.60%***	43.14%***	42.88%***	39.01%***	40.15%***	39.59%***	39.24%***	41.17%***	39.86%***	39.32%***
[1,5]	47.96%***	47.38%***	47.05%***	36.79%***	37.53%***	36.83%***	36.21%***	40.51%***	38.14%***	36.93%***
[1,6]	39.30%***	38.61%***	38.21%***	31.18%***	32.73%***	31.89%***	31.32%***	33.29%***	32.40%***	31.68%***
[1,7]	33.46%***	32.65%***	32.19%***	21.66%***	23.18%***	22.19%***	21.45%***	23.63%***	22.76%***	21.88%***
[1,8]	34.25%***	33.32%***	32.80%***	23.71%***	25.82%***	24.70%***	23.95%***	25.67%***	25.41%***	24.59%***
[1,9]	21.59%***	20.55%***	19.96%***	15.14%***	18.20%***	16.95%***	16.28%***	18.39%***	17.51%***	16.75%***
[1,10]	17.01%***	15.85%***	15.19%**	7.95%*	11.10%**	9.71%**	8.90%**	11.38%**	10.11%**	9.22%**

Notes: *The result is significant at 10% level, ** the result is significant at 5% level, *** the result is significant at 1% level.

Table A.10: **U.S. airline stocks' CAAR on March 19, 2020 - Continued**

Event: U.S. Coronavirus Aid, Relief and Economy Security Act.

Window	Constant model			Market-adjusted	Market model			Fama-French 3-factors model		
	90 days	150 days	210 days	model	90 days	150 days	210 days	90 days	150 days	210 days
Low-cost carriers										
[-10,-1]	-56.57%***	-56.94%***	-57.40%***	-34.47%***	-27.54%***	-29.31%***	-29.16%***	-23.11%***	-25.50%***	-26.16%***
[-5,-1]	-41.57%***	-41.75%***	-41.98%***	-31.14%***	-27.79%***	-28.65%***	-28.59%***	-24.06%***	-25.76%***	-26.35%***
[0,0]	-5.55%***	-5.59%***	-5.64%***	-6.22%***	-6.05%***	-6.09%***	-6.14%***	-5.38%***	-5.74%***	-5.89%***
[1,1]	2.59%	2.56%	2.51%	6.74%***	7.78%***	7.51%***	7.57%***	8.30%***	7.93%***	7.90%***
[1,2]	5.86%**	5.78%**	5.69%**	12.74%***	14.57%***	14.10%***	14.19%***	16.60%***	14.04%***	13.99%***
[1,3]	31.88%***	31.77%***	31.63%***	29.18%***	29.56%***	29.47%***	29.30%***	31.71%***	29.61%***	29.25%***
[1,4]	39.58%***	39.43%***	39.25%***	35.53%***	35.96%***	35.86%***	35.62%***	37.59%***	36.06%***	35.66%***
[1,5]	46.92%***	46.74%***	46.51%***	36.44%***	35.99%***	36.12%***	35.69%***	40.58%***	38.17%***	37.10%***
[1,6]	38.49%***	38.27%***	38.00%***	31.19%***	31.60%***	31.51%***	31.11%***	32.27%***	32.53%***	31.93%***
[1,7]	27.29%***	27.03%***	26.71%***	16.44%***	16.50%***	16.51%***	15.99%***	17.09%***	17.71%***	16.97%***
[1,8]	29.31%***	29.01%***	28.64%***	19.86%***	20.47%***	20.34%***	19.81%***	19.98%***	22.17%***	21.43%***
[1,9]	19.03%***	18.70%***	18.28%***	13.81%**	15.47%***	15.07%***	14.61%***	15.60%***	16.40%***	15.74%***
[1,10]	12.44%**	12.07%**	11.61%**	4.74%	6.24%	5.89%	5.33%	6.57%*	6.74%*	6.03%

Notes: *The result is significant at 10% level, ** the result is significant at 5% level, *** the result is significant at 1% level.

Table A.11: **U.S. airline stocks' CAAR on June 10, 2020**

Event: JP Morgan downgraded two airline companies.

Window	Constant model			Market-adjusted	Market model			Fama-French 3-factors model		
	90 days	150 days	210 days	model	90 days	150 days	210 days	90 days	150 days	210 days
Legacy carriers										
[-10,-1]	29.63%**	26.97%*	26.31%*	22.18%	25.66%*	23.77%*	22.94%*	38.82%*	26.05%*	24.29%*
[-5,-1]	24.06%**	22.73%**	22.40%**	19.76%*	21.32%**	20.37%**	19.96%**	34.80%**	22.08%**	20.87%**
[0,0]	-8.41%***	-8.68%***	-8.74%***	-8.61%***	-7.94%***	-8.11%***	-8.19%***	-8.34%***	-7.91%***	-8.14%***
[1,1]	-13.10%***	-13.36%***	-13.43%***	-8.02%***	-5.58%***	-5.75%***	-5.93%***	-6.42%***	-5.49%***	-5.79%***
[1,2]	-0.96%	-1.49%	-1.62%	2.96%*	5.57%***	5.21%***	4.95%***	4.19%**	5.02%***	4.41%**
[1,3]	3.50%	2.70%	2.50%	4.59%*	7.25%***	6.76%***	6.49%**	4.05%**	6.73%***	6.04%**
[1,4]	6.86%*	5.80%	5.53%	5.62%*	8.18%***	7.51%***	7.19%**	4.48%**	7.56%***	6.92%**
[1,5]	6.61%	5.28%	4.95%	4.07%	7.11%**	6.30%*	5.94%*	5.21%*	7.44%**	6.07%
[1,6]	5.55%	3.96%	3.56%	2.97%	6.57%**	5.58%*	5.12%*	4.09%**	6.27%**	5.59%*
[1,7]	1.66%	-0.20%	-0.66%	-1.57%	2.64%	1.50%	0.97%	1.52%	2.34%	1.61%
[1,8]	-0.68%	-2.81%	-3.34%	-4.75%	-0.19%	-1.52%	-2.13%	-0.94%	-0.16%	-0.80%
[1,9]	-2.08%	-4.48%	-5.07%	-6.33%*	-1.29%	-2.82%	-3.53%	-2.29%	-1.86%	-2.67%
[1,10]	-9.20%**	-11.87%***	-12.53%***	-12.25%	-5.94%**	-7.62%	-8.42%***	-6.55%***	-6.99%	-7.92%***

Notes: *The result is significant at 10% level, ** the result is significant at 5% level, *** the result is significant at 1% level.

Table A.12: **U.S. airline stocks' CAAR on June 10, 2020 - Continued**

Event: JP Morgan downgraded two airline companies.

Window	Constant model			Market-adjusted	Market model			Fama-French 3-factors model		
	90 days	150 days	210 days	model	90 days	150 days	210 days	90 days	150 days	210 days
Low-cost carriers										
[-10,-1]	37.65%*	34.79%	34.69%	25.59%	27.00%*	25.35%	25.26%	22.78%	24.72%	23.94%
[-5,-1]	30.51%*	29.08%*	29.03%*	23.92%*	24.39%*	23.57%*	23.53%*	21.00%*	23.01%*	22.61%
[0,0]	-9.06%**	-9.35%**	-9.36%**	-9.03%**	-8.38%	-8.55%**	-8.59%**	-8.84%**	-8.64%**	-8.65%***
[1,1]	-13.98%***	-14.27%***	-14.28%***	-8.59%***	-5.73%***	-5.90%***	-6.06%***	-6.25%***	-5.98%***	-6.21%***
[1,2]	-1.89%	-2.46%**	-2.48%**	1.69%	4.45%***	4.11%***	3.95%***	4.17%***	3.94%***	4.46%***
[1,3]	-0.20%	-1.06%	-1.09%	2.05%	4.89%**	4.39%**	4.23%**	4.45%**	4.18%**	4.65%**
[1,4]	3.06%	1.92%	1.88%	2.91%	5.40%*	4.74%*	4.59%*	5.00%*	4.58%*	4.86%*
[1,5]	1.68%	0.25%	0.20%	1.39%	4.46%*	3.63%	3.45%	1.60%	3.01%	3.25%
[1,6]	1.80%	0.08%	0.03%	0.94%	4.42%*	3.43%	3.22%	3.30%	3.29%	2.80%
[1,7]	-2.00%	-4.00%*	-4.07%*	-2.79%	1.35%	0.19%	-0.06%	0.06%	0.05%	-0.63%
[1,8]	-2.45%	-4.74%**	-4.82%**	-4.40%***	-0.10%	-1.42%	-1.68%	-1.86%	-1.50%	-2.89%
[1,9]	-0.29%	-2.86%	-2.95%	-3.17%**	1.39%	-0.10%	-0.37%	-0.14%	-0.18%	-1.12%
[1,10]	-7.46%***	-10.32%***	-10.42%***	-8.26%***	-2.20%	-3.86%	-4.22%*	-2.98%*	-3.91%*	-4.61%**

Notes: *The result is significant at 10% level, ** the result is significant at 5% level, *** the result is significant at 1% level.

B Rolling average returns

We also calculated the three-day centred rolling average abnormal return (AAR) for each event using the abnormal returns obtained through the Fama-French 3-factor model and the estimation window is 150 days.

The three-day rolling AAR is calculated by:

$$\textit{3-day Rolling } AAR_N = \frac{AR_{N\text{-}1} + AR_N + AR_{N+1}}{3}$$

$$\textit{3-day Rolling } AAR_N = \frac{AR_{N\text{-}1} + AR_N + AR_{N+1}}{3}$$

3-day Rolling AA

Where AR_N is the abnormal return on day N, $AR_{N\text{-}1}$ is the abnormal return one day prior to day N, and AR_{N+1} is the abnormal return one day post to day N. Results are shown in Tables B.13-18, and the corresponding graphs are presented in Figures 11-16.

Table B.13: **China airline stocks' rolling average returns on March 11, 2020**

time	Legacy Carriers	Low-cost Carriers
-10	2.14%	0.38%
-9	2.04%	0.83%
-8	1.07%	0.73%
-7	0.90%	0.98%
-6	0.47%	1.90%
-5	0.73%	2.27%
-4	0.89%	2.35%
-3	3.50%	3.62%
-2	3.17%	2.72%
-1	5.05%	3.65%
0	2.00%	1.12%
1	1.57%	1.64%
2	-1.25%	0.08%
3	-1.12%	-0.41%
4	-0.35%	-0.57%
5	0.00%	-0.38%
6	0.26%	-0.70%
7	0.19%	-0.62%
8	0.95%	-0.74%
9	1.84%	1.02%
10	2.23%	1.69%

We test whether the rolling average abnormal returns for days 1-10 for legacy and low-cost carriers are significantly different, and the p-value from the test is 0.260.

Table B.14: **China airline stocks' rolling average returns on March 29, 2020**

time	Legacy Carriers	Low-cost Carriers
-10	0.91%	-0.66%
-9	0.67%	-1.38%
-8	0.05%	-1.79%
-7	0.76%	2.40%
-6	1.38%	2.92%
-5	2.00%	3.31%
-4	2.47%	1.41%
-3	2.22%	2.27%
-2	1.62%	2.35%
-1	0.60%	0.88%
0	0.44%	-0.74%
1	-0.16%	-1.89%
2	-0.66%	-2.17%
3	-0.70%	-2.22%
4	0.03%	-1.14%
5	1.80%	0.48%
6	1.68%	0.79%
7	1.56%	0.77%
8	-0.14%	-0.89%
9	-0.02%	1.02%
10	1.68%	2.85%

We test whether the rolling average abnormal returns for days 1-10 for legacy and low-cost carriers are significantly different, and the p-value from the test is 0.047.

Table B.15: **China airline stocks' rolling average returns on May 22, 2020**

time	Legacy Carriers	Low-cost Carriers
-10	1.29%	1.19%
-9	1.13%	1.51%
-8	1.38%	1.99%
-7	1.21%	0.99%
-6	1.51%	0.38%
-5	1.26%	0.36%
-4	1.74%	1.50%
-3	1.77%	1.94%
-2	1.82%	1.40%
-1	2.08%	1.43%
0	1.81%	1.46%
1	1.74%	2.26%
2	1.73%	2.95%
3	1.86%	2.93%
4	2.37%	3.78%
5	1.59%	2.02%
6	1.91%	2.39%
7	1.43%	1.88%
8	1.48%	2.96%
9	3.38%	3.91%
10	3.91%	3.13%

We test whether the rolling average abnormal returns for days 1-10 for legacy and low-cost carriers are significantly different, and the p-value from the test is 0.010.

Table B.16: **U.S. airline stocks' rolling average returns on March 11, 2020**

time	Legacy Carriers	Low-cost Carriers
-10	-0.92%	-2.55%
-9	-1.43%	-2.42%
-8	-2.83%	-2.60%
-7	-3.20%	-2.62%
-6	-2.58%	-2.08%
-5	-2.36%	-2.37%
-4	-0.51%	-1.32%
-3	1.93%	1.13%
-2	4.72%	4.55%
-1	3.40%	3.32%
0	-1.44%	-0.51%
1	-3.38%	-6.24%
2	-0.95%	-3.13%
3	-2.95%	-7.24%
4	-7.71%	-6.33%
5	-10.82%	-10.16%
6	-2.17%	-4.90%
7	6.58%	-1.31%
8	9.75%	8.44%
9	8.85%	14.96%
10	4.44%	11.37%

We test whether the rolling average abnormal returns for days 1-10 for legacy and low-cost carriers are significantly different, and the p-value from the test is 0.677.

Table B.17: **U.S. airline stocks' rolling average returns on March 19, 2020**

time	Legacy Carriers	Low-cost Carriers
-10	-1.34%	-1.71%
-9	-0.58%	-0.22%
-8	3.11%	3.57%
-7	1.62%	2.33%
-6	-2.55%	-0.92%
-5	-3.73%	-6.09%
-4	-1.74%	-3.05%
-3	-2.11%	-5.92%
-2	-9.76%	-7.06%
-1	-10.93%	-9.71%
0	-3.37%	-5.39%
1	6.35%	-1.25%
2	9.89%	8.45%
3	9.86%	15.42%
4	7.21%	13.65%
5	0.91%	1.44%
6	-5.70%	-9.39%
7	-4.24%	-5.42%
8	-4.96%	-4.60%
9	-4.22%	-3.29%
10	-5.41%	-5.06%

We test whether the rolling average abnormal returns for days 1-10 for legacy and low-cost carriers are significantly different, and the p-value from the test is 0.49.

Table B.18: **U.S. airline stocks' rolling average returns on June 10, 2020**

time	Legacy Carriers	Low-cost Carriers
-10	3.82%	2.98%
-9	-1.03%	-1.85%
-8	-1.09%	-2.08%
-7	1.11%	0.18%
-6	4.27%	3.35%
-5	8.83%	8.36%
-4	9.12%	9.13%
-3	10.56%	10.94%
-2	2.29%	2.92%
-1	-1.42%	-1.34%
0	-7.46%	-7.56%
1	-1.72%	-2.21%
2	1.06%	0.39%
3	3.47%	2.12%
4	-0.38%	-0.93%
5	-0.21%	-0.07%
6	-1.26%	-1.61%
7	-1.82%	-1.93%
8	-2.27%	-1.86%
9	-2.73%	-2.68%
10	-1.17%	-1.15%

We test whether the rolling average abnormal returns for days 1-10 for legacy and low-cost carriers are significantly different, and the p-value from the test is 0.10.

Chapter III

U.S. Airline Industry Merger Simulation Analysis

Abstract

This paper examines the evolution of airfare ticket prices following the merger of the market with and without low-cost carriers. Using demand estimation and merger simulation methods, we examine how the presence of low-cost airlines in mergers influences the post-merger price through four mergers in the U.S. airline industry in the late 2000s and early 2010s. Our analysis reveals that the post-merger ticket increase is notably less pronounced in markets where low-cost airlines operate as opposed to markets without low-cost carriers. This suggests that low-cost carriers generate considerable competitive pressure, effectively limiting the ability of merged entities to raise prices and thereby protecting consumer welfare.

Keywords— Low-cost carriers, Merger and acquisition, Aviation industry

1 Introduction

From the perspective of consumers' welfare, it may be affected by airline mergers in terms of airfares and flight options. Mergers may reduce competition as a result of their increased market power. The majority of merged enterprises will increase product prices (Gaudet and Salant, 1992; Kim and Singal, 1993; Werden and Froeb, 1994; Nevo, 2000; Ashenfelter, 2013; Erdős, 2022). On the other hand, merger efficiency gains may result in cost savings that are passed on to consumers (Farrell and Shapiro, 1990). Mergers may also result in alterations to available routes, frequencies, and destinations. This could lead to more direct flights or improved connections for some passengers but fewer options for others, particularly if the merger eliminates routes that overlapped before the merger. Inter-firm mergers typically result in a decrease in the variety of products available to consumers (Atalay et al., 2020; Ashenfelter, 2013). Both adjustments reduce customer welfare.

From the perspective of the market and regulators, the civil aviation sector is characterized by its capital-intensive nature and substantial fixed costs (Morrell, 2018). Mergers have the potential to generate economies of scale and synergies (Cabral, 2017) since the consolidated organization may distribute expenses across a broader scope, resulting in decreased marginal costs, administrative resource savings, and increased productivity (Andrade, 2001; Feldman and Hernandez, 2022). This phenomenon can lead to financial benefits for airlines and potentially result in reduced tickets for consumers.

Mergers within the U.S. airline industry encompass a broad spectrum of economic, policy, competitive, and consumer welfare considerations. Understanding these mergers has significant importance for a wide range of participants, including policymakers, as well as the general populace of travellers. By analyzing these mergers, we may anticipate likely results and make more informed decisions regarding the future trajectory of the civil airline sector.

From an antitrust regulatory perspective, before mergers and acquisitions, antitrust regulators would typically evaluate the potential post-merger changes in market prices, product types, etc., to assess that the transactions would not impair social welfare.

Often, antitrust authorities scrutinize mergers and acquisitions involving companies that manufacture substitute products (horizontal mergers).[94] After executing a merger and acquisition, many corporations lessen the degree of competition in their markets while increasing their market share.[95]

A low-cost carrier is an airline with a different business model than traditional airlines, intending to capitalize on economies of scale and expand routes. In general, low-cost carriers accomplish cost efficiencies by streamlining operations, applying point-to-point travel routes, and not providing additional services.

Due to the reduction in competition, we expect that the consolidation between legacy airlines could result in higher fares, particularly on overlapping routes. In contrast, the market may perceive low-cost carriers to have reduced operating costs and a history of price fluctuations, thereby making fares more competitive, particularly for mergers involving low-cost carriers. Given the various characteristics and implications of traditional and low-cost carriers' business models, their respective mergers may affect competition, prices, service offerings, and overall market structures differently.

The U.S. airline industry has undergone a few mergers and acquisitions since the implementation of the Deregulation Act in 1978, resulting in significant changes to the industry landscape. Meanwhile, the emergence of low-cost airlines has like-

[94] A horizontal merger is between two companies operating in the same industry, often as direct competitors and manufacturing substitute products. A vertical merger is between companies in the same supply chain but manufacturing at different levels.

[95] U.S. Department of Justice and the Federal Trade Commission: Horizontal Merger Guidelines: https://www.justice.gov/sites/default/files/atr/legacy/2007/08/14/hmg.pdf.

wise changed the industry's competitive landscape. To study the role of low-cost airlines in airline mergers, this study focuses on four notable mergers in this industry: the mergers between Delta Air Lines and Northwest Airlines, United Airlines and Continental Airlines, US Airways and American Airlines, and Southwest Airlines and AirTran Airways. By performing demand estimation and merger simulation, we examine the impact of mergers in the U.S. airline industry by assessing the price and market share changes pre- and post-merger for markets with or without low-cost carriers.

In this paper, we use the merger simulation method (Peters, 2006; Yamamoto, 2019) to evaluate the effect of these four mergers. First, the demand estimates are used to determine how consumers respond to price changes. Then, supply estimations are utilized to assess how firms set prices based on costs and the competitive environment. After estimating demand and supply, the estimated parameters can be input into a merger simulation model to predict the prices and market share after the merger. The model can predict how the merged companies will modify their prices based on changes in the competitive environment and potential cost savings. We assume a Bertrand competition market.

The merger simulation results show that the airfare increase is more pronounced in markets without low-cost carriers than in markets with low-cost carriers. The simulated price increases for routes without low-cost carrier participation range from 1.40% to 7.82% in the merger simulation. For routes with low-cost carrier participation, the simulated fare increases ranged from 0.62% to 4.89%. This indicates that low-cost carriers generate substantial competitive pressure, effectively limiting the ability of merged entities to increase prices and thus protecting the welfare of consumers. Simultaneously, the presence of low-cost carriers has resulted in an expansion in customer options, mitigating the potential decline in options that consumers may encounter during airline consolidations.

The main contribution of this paper is to analyze the role of low-cost airlines in airline mergers. In practical application, the duration of many mergers can extend to two to three years. During this time frame, various factors, including shifts in the global economy, alterations in national macroeconomic policies, and adjustments in the business strategies of other firms within the industry, would influence the pricing dynamics of the merged carriers' products. The elements influencing post-merger price effects are eliminated from evaluation through merger simulation. Our analysis focuses solely on the impact of the merger itself on the two merging carriers and other competing carriers. This enables the application of the findings in other economic contexts.

In particular, for future antitrust authorities to analyze airline mergers, they can use the existence of low-cost airlines in the market as a basis for judging the merger's impact on market competition and consumer welfare. Specific recommendations included retaining and encouraging low-cost carriers to operate in the market; more stringent scrutiny of mergers on routes where there are no low-cost carriers based on antitrust considerations; consumer welfare protections through incentives for low-cost carriers to enter more routes; and monitoring of post-merger commodity prices in markets where there are no low-cost carriers, among other things.

The rest of this paper is structured as follows: Section 2 describes the mergers in the airline sector and is subject to analysis. Section 3 presents a comprehensive examination of the theoretical and empirical literature related to mergers and acquisitions, specifically focusing on those within the aviation industry. The data used is outlined in Section 4. The methodology employed is discussed in Section 5, while the findings derived from the research are provided in Section 6. Conclusions are presented in Section 7.

2 Mergers and acquisitions in the U.S. civil aviation industry

This paper uses four merger cases from the late 2000s and early 2010s. We examine the merger between the legacy carriers first and then study the merger between the two low-cost carriers. While it is true that the trend towards consolidation during this period created an environment in which airlines felt the need to merge to remain competitive, not every merger was a direct response to a previous merger. Therefore, we believe that we can look at these merger cases independently.

2.1 Merger between Delta Air Lines and Northwest Airlines

Delta Air Lines and Northwest Airlines announced a merger agreement on April 15, 2008.[96] On October 29, 2008, the U.S. Department of Justice approved the merger application after finding that the merger would not substantially harm competition and would result in some increase in operating efficiencies.[97] The merger was formally completed on October 31, 2008. Northwest became a subsidiary of Delta.[98] Before the merger, Delta and Northwest were the third and fifth largest airlines in the U.S., with 2007 revenue passenger miles (RPM) of 169.4 billion and 138.9 billion, respectively.[99][100]

Before the merger, both airlines' hubs were centred on the East Coast and

[96] https://www.sec.gov/Archives/edgar/data/1058033/000110465908025369/a08-10921_1ex2d1.htm.

[97] https://www.justice.gov/archive/atr/public/press_releases/2008/238849.htm.

[98] https://www.sec.gov/Archives/edgar/data/27904/000095012309025381/g19787exv10w2.htm.

[99] Revenue passenger miles is calculated by $RPM = number\ of\ paying\ passengers * distance\ traveled\ in\ miles$, which is an index used to quantify the volume of passenger traffic.

[100] Delta and Northwest 2007 annual reports.

Central (Ohio and Tennessee), primarily including Hartsfield-Jackson Atlanta International Airport, Minneapolis-Saint Paul International Airport, Salt Lake City International Airport, etc.[101] After the merger, Los Angeles International Airport and Seattle-Tacoma International Airport, the company's primary West Coast airports and transit airports for routes to Asia, also became major hubs. This has allowed the combined company to not only enhance its network connectivity in the centre and east but also complete the major airports in the west, allowing for more comprehensive coverage of the merged company's route framework.

2.2 Merger between United Airlines and Continental Airlines

On May 2, 2010, United Airlines and Continental Airlines announced the agreement and plan of merger among UAL Corporation, Continental Airlines, Inc., and JT Merger Sub Inc..[102] The U.S. Department of Justice approved this merger on August 27, 2010, and the deal closed on October 1, 2010.[103] On November 30, 2011, the merged company United Continental Holdings received the single operating certification from the Federal Aviation Administration (FAA). According to the Bureau of Transportation Statistics, United and Continental began reporting jointly in January 2012.

In 2009, the year before their merger arrangement, United and Continental were the third and fourth largest airline companies in the U.S., with 100.3 and 77.7 billion RPM, respectively.[104] In 2009, United operated its domestic and international flights based on five hub airports: Chicago O'Hare International Airport,

[101] Delta and Northwest 2007 annual reports.
[102] https://www.sec.gov/Archives/edgar/data/100517/000095015710000587/ex2-1.htm.
[103] https://www.sec.gov/Archives/edgar/data/100517/000119312510222185/dex991.htm.
[104] United and Continental 2009 annual reports.

Denver International Airport, Los Angeles International Airport, San Francisco International Airport, and Washington Dulles International Airport, which are located in the southwestern, central, and northeastern United States, respectively. The three hubs of Continental were Newark Liberty International Airport, Houston George Bush International Airport, and Cleveland Hopkins International Airport, which are located in the eastern and southern parts of the United States. The integration of hubs facilitated the implementation of strategic network planning, capitalizing on the advantages of United's and Continental's pre-existing networks to provide enhanced connectivity and access to additional destinations. Following the successful merger, United Airlines emerged as the world's largest airline at the time, surpassing Delta Air Lines in terms of total miles flown.[105]

2.3 Merger between American Airlines and US Airways

The announcement of the merger between American Airlines and US Airways was made on February 14, 2013.[106] On November 12, 2013, the U.S. Department of Justice filed an antitrust lawsuit to block the proposed merger, considering that the merger would adversely affect competition throughout the industry. The main concerns were that the merger would harm consumers by reducing competition and increasing fares on routes where the two carriers overlapped before the merger and that the merger could result in the two carriers controlling too many gates at specific airports, limiting expansion opportunities for other carriers.[107]

The U.S. Department of Justice agreed to the merger of the two companies on

[105] https://www.bbc.com/news/10095080.

[106] U.S. Securities and Exchange Commission (SEC) Public Information: https://www.sec.gov/Archives/edgar/data/4515/000119312513060746/d487000dex21.htm.

[107] https://www.justice.gov/opa/pr/justice-department-files-antitrust-lawsuit-challenging-proposed-merger-between-us-airways-and.

November 12, 2013, after the two airlines agreed to give up a number of slots, notably at Reagan National Airport in Washington, D.C., and at LaGuardia Airport in New York. The Department of Justice argued that, based on this, the merger would not result in a monopoly on several routes by the airlines. Also, since the merged company was required to sell some slots to Southwest and JetBlue, this not only kept the market competitive but also introduced low-cost airlines on some routes in favour of consumer rights (Park, 2020).[108] On December 9, 2013, the two companies completed the deal to finalize the merger and became the world's largest airline at the time, operating more than 6,700 flights a day.[109]

2.4 Merger between Southwest Airlines and AirTran Airways

On September 27, 2010, Southwest Airlines announced its plans to acquire AirTran Airways.[110] Since they are both low-cost carriers with little overlap in routes, they have less of a competition-reducing effect on the markets in which they operate. On April 26, 2011, Southwest received antitrust approval from the U.S. Department of Justice for its acquisition of AirTran.[111] The FAA formally issued a Single Operating Certificate (SOC) to the merged company, marking the completion of the merger.[112]

Before the merger, Southwest operated primarily on a point-to-point model and did not have traditional hubs; its primary service area was in the central

[108] https://www.justice.gov/opa/pr/justice-department-requires-us-airways-and-american-airlines-divest-facilities-seven-key.

[109] American Airlines Group Inc. 2013 annual report.

[110] U.S. Securities and Exchange Commission Public Information :https://www.sec.gov/Archives/edgar/data/92380/000119312510217176/dex991.htm.

[111] https://www.justice.gov/opa/pr/statement-department-justice-antitrust-division-its-decision-close-its-investigation.

[112] https://www.southwestairlinesinvestorrelations.com/news-and-events/news-releases/2012/01-03-2012.

and western U.S., while AirTran operated the Atlanta airport as its hub and primarily served the central and eastern U.S.[113][114] Their route networks were largely complementary rather than overlapping, allowing Southwest to expand its route coverage to the east.[115]

3 Literature Review

For the consolidation of firms in different industries, the literature has focused on changes in different outcomes, including product prices, product types, consumer welfare, and producer profits (Barton and Sherman, 1984; Berry and Waldfogel, 2001; Ashenfelter et al., 2013; Dafny et al., 2019).

The effects of horizontal mergers have also been widely discussed, including in the airline industry. The consolidation of airlines has major implications for various facets of the airline industry, including the merged airlines, competing firms, airport operations, and travellers. There is a large literature that has examined different aspects of mergers and acquisitions in the aviation sector as a result of the abundance of data that is available (e.g., Mechanic, 2002; Richard, 2003; Peters, 2006; Luo, 2014; Vaze et al., 2017).

Many existing studies have found that corporate mergers in the airline industry lead to increased airfares (Mechanic, 2002; Peters, 2006; Luo, 2014) and decreased consumer welfare (Richard, 2003) due to increased market power.

Using a merger case example from a little further back in time, Peters (2006) conducts a merger simulation using six airline merger cases in the industry during the 1980s. The focus was on comparing the results of estimated price changes with actual price changes. His study finds that price increases are significant in markets

[113] Southwest Airlines 2010 annual report.
[114] AirTran Airways 2010 annual report.
[115] Southwest Airlines 2012 annual report.

where both firms operated simultaneously before the merger, but the increases vary widely across mergers. Peters also finds that the price growth resulting from the merger simulation can be used to a large extent to estimate the actual post-merger price growth.

There have also been several studies on different aspects of the merger cases we researched. For example, Luo (2014) uses the DiD methodology to study the Delta and Northwest mergers. Luo finds that routes where the two companies overlapped before the merger had more price increases after the merger compared to other routes. Yamamoto (2019) similarly investigates the merger of Delta and Northwest. He uses data on mergers in the U.S. airline industry to discuss whether different merger approaches would impact product prices and consumer welfare differently. The reality is that in the merger of Delta and Northwest, Northwest merged with Delta to become a company under it. The authors hypothesize two other hypothetical scenarios: (1) Delta becoming a subsidiary of Northwest, or (2) both brands remaining after the merger. Comparing these two scenarios to the actual situation, Yamamoto finds that companies' profits and consumer surplus are higher when firms merge into one instead of remaining independent.

The studies on the United Airlines and Continental merger found that the merger led to an around 8% increase in airfare in the direct flight market (Shen, 2017). When separating travellers into business and leisure travellers, it was found that the company increased the fares for business travellers after that merger (Fan, 2020). Vaze et al. (2017) find that although the merger of United and Continental led to an increase in fares, the increased frequency of flights after the merger, particularly non-stop flights, increased consumer welfare relative to the pre-merger period.

Bontemps et al.'s (2021) study of the merger of American Airlines and US Airways found that the decline in fuel prices during that merger period led to a corresponding drop in airfares. However, the merger reduced the magnitude of the decline in airfares and fuel prices to some extent. Their study also found that consumer demand for direct flights increased during this period. Regarding the merger between American and US, the antitrust authorities considered that their merger would harm competition. Therefore, while agreeing to the merger, American and US Airlines were required to engage in divestitures, which consisted mainly of American and US relinquishing or transferring 67 pairs of landing and takeoff slots at Reagan Airport, as well as a number of other slots at New York's LaGuardia Airport. Park (2020) finds that this divestiture can increase consumer welfare by $112 million per year.

Southwest merged with its largest low-cost competitor (Salam and McMullen, 2013), AirTran Airways, in 2011. Le (2016) finds elevated fares in markets where the two airlines overlapped pre-merger.

Some studies analyze the merger's impacts from a corporate standpoint. For instance, Khezrimotlagh et al. (2022) broke down the advantages of mergers into production and consumption efficiency. They calculated efficiency scores for eight airlines involved in four mergers in the U.S. civil aviation industry between 2005 and 2018, demonstrating that mergers led to overall efficiency gains, with legacy airlines experiencing greater gains than low-cost airlines. This is notably true for legacy airlines regarding saleable seats and service-related consumption efficiency.

Most of the existing literature analyzes all routes for two airline mergers and does not examine the role of low-cost airlines in the merger. The main contribution of this paper is to analyze the role of low-cost carriers in airline mergers by decomposing the routes of merging carriers into with and within low-cost carriers.

4 Data

The primary data we use is from the Bureau of Transportation Statistics (BTS), the Airline Origin and Destination Survey (DB1B), which includes a 10% sample of the dataset of airline tickets from carriers. The information covered by DB1B data consists of the operating carrier, origin and destination airports, number of passengers, fare class, coupon type, trip break indicator, and distance. The DB1B dataset comprises three sub-datasets, namely DB1B Coupon, DB1B Market, and DB1B Ticket. We aggregate the three sub-datasets with the same unique identifier (ItinID) for each ticket in all three sub-datasets. The data include airfare price, distance travelled, number of ticket travellers, the origin and destination locations and airports for each ticket.

For each merger, we use the four quarters before the date when the Department of Justice approved the merger of the two companies as the pre-merger period and use this period for each market demand estimate. The four mergers covered in this paper, Delta and Northwest, United and Continental, American and US, and Southwest and AirTran, have pre-merger periods from 2007 Q2 to 2008 Q1, from 2009 Q4 to 2010 Q3, from 2012 Q1 to 2012 Q4, and from 2009 Q3 to 2010 Q2, respectively.

The T-100 Domestic Segment information is used to identify the frequently travelled routes. The T-100 dataset provides administrative data on domestic non-stop segment information supplied by air carriers in the United States. This includes details such as the carrier name, origin and destination cities, airports of the flights, and available capacity. The T-100 data is used to derive monthly seat and passenger counts, which are then aggregated to provide quarterly seat and passenger counts for each specific route.

Following Ciliberto and Tamer (2009), we use the T-100 Domestic Segment dataset to identify and keep frequent flights. A frequent flight is defined as a flight with more than 30 seats and 15 passengers in a given quarter.[116] Subsequently, the remaining flights are merged with the DB1B Coupon data, creating a dataset that only includes flights classified as frequent. With this step, we eliminated the effect of some temporary flights on the data. Following that, the same identifier, namely a unique identifier (ItinID), is used across all three datasets to combine the three sub-datasets into a comprehensive dataset, including the whole of the route information.

We made some data choices to obtain the final dataset after eliminating outlier values and other data anomalies. Given the focus of our research on route pricing, it is essential to ensure that the ticketing carrier aligns with the operating carrier. Hence, we excluded instances in which the ticketing carrier and the operating airline differed for direct flights, as well as circumstances in which the operating carrier and the ticketing carrier could not be matched for non-direct flights.

In instances where airlines alone operate flights without issuing tickets, resulting in a difference between the ticketing carrier and the flying carrier, we have implemented the following measures. First, we retained routes operated by subsidiaries that the parent company ticketed. Another situation is that small regional airlines fly with multiple ticketing companies. For instance, Endeavour Air, a subsidiary of Delta Air Lines, operates all flights ticketed by Delta Air Lines. In this case, we consider the ticketing carrier to be the same as the operating carrier, and both are considered Delta Air Lines. Second, we determine route attribution based on their actual ticketing carrier for regional carriers that do not correspond to any parent company. For example, in the second quarter of 2009, Silver Airways, a regional carrier, flew 96.43% of its flights ticketed by Continental Airlines and 3.57% ticketed by United Airlines, in which case we determined the route attribution

[116]Flights with fewer than 30 seats per quarter account for 0.006% of total flights, and flights carrying fewer than 15 passengers per quarter account for 0.08% of total flights.

based on the actual ticketing carrier.[117]

To keep fares within reasonable limits and to exclude outliers such as gift tickets or member program mileage redemption tickets, we keep the data for ticket prices between \$50 and \$2000.[118] We only keep domestic (Lower 48 U.S. states) flights and credible airfare value tickets.

Since our study focuses on inter-carrier mergers, we retain only those markets where the two carriers overlapped before the merger. In the realm of merger studies, scholars and regulatory authorities have primarily directed their attention towards overlapping markets. This emphasis arises from the recognition that the merging of two carriers operating within an overlapping market raises the likelihood of a potential decline in competition. Such a decline can result in various issues, including elevated airfares, diminished service quality, restricted consumer options, and the potential establishment of a monopoly.

The legacy carriers operating during the study periods are American Airlines, Alaska Airlines, Continental Air Lines, Delta Air Lines, Northwest Airlines, United Air Lines, and US Airways.[119] According to IACO's definition of low-cost airlines, low-cost airlines still operating in the U.S. aviation market as of 2008 include Air Tran Airways, Allegiant Air, ATA Airlines, Go!, Frontier Airlines, JetBlue Airways, Midwest Airlines, Southwest Airlines, Spirit Airlines, Sun Country Airlines, Ted, USA 3000, ViaAir, and Virgin America.[120] [121]

Jet fuel costs and fuel consumed data are from the BTS Air Carrier Financial Schedule P-12(a), which carriers report monthly. The BTS Air Carrier Financial Schedule P-12(a) provides statistics on fuel costs, gallons of fuel utilized by air

[117]Excluding special cases, the number of cases in which the ticketing carrier differed from the operating carrier amounted to 5.06% of the total data.

[118]Data exceeding this range accounted for 4.91% of the total data volume.

[119]U.S. Department of Transportation, Bureau of Transportation Statistics.

[120]ATA ceased operations in 2008. Ted ceased operations in 2009. Midwest ceased operations in 2010. USA 3000 ceased operations in 2012.

[121]https://www.icao.int/sustainability/documents/lcc-list.pdf.

carriers, and categories of fuel use.

The market size is defined as the geometric mean of the population of the cities where the two originating airports are located. The population data was acquired from the Population and Housing Unit Estimates Program (PEP) of the U.S. Census Bureau.[122] The Population and Housing Evaluation Program is carried out decennially. During years in which a census is conducted, such as 2010, the program relies on data from the decennial census to provide statistical information. In subsequent years, we employed the projected population figures of cities, towns, and counties based on the last decennial census.

5 Methodology

5.1 Demand estimation

The airline market can be seen as a differentiated product market. Following Nason (1981), Berry (1994), and Coldren et al. (2003), a unit demand specification nested logit model with a discrete choice framework can be used to describe the market demand of the airline industry.

The term 'market' is defined as a route consisting of an origin and destination, whereby the origin and destination are distinct airports. For example, BOS-LAX (Boston Logan International Airport to Austin-Los Angeles International Airport) indicates one 'market', while LAX-BOS indicates a different market. The market is indexed by t, where $t = 1, ..., T$. The variable 'product' refers to a flight operated by a certain airline inside a specified market. For example, the BOS-LAX route offered by Delta Air Lines can be seen as one distinct product, while the BOS-LAX route provided by Southwest Airlines is another. The product is indexed by j, where $j = 1, ..., J_t$. We define the market in which low-cost carriers operate as a

[122] https://www.census.gov/programs-surveys/popest.html.

market with ‘low-cost carriers’, otherwise as a ‘market’ without low-cost carriers.

In each market t, consumer i can choose either to buy a single unit of their most preferred product $j = 1, ..., J_t$ (in market BOS-LAX, decide to fly with Delta or Southwest) or they buy the outside good $j = 0$ (travel by railway or by road trip) (Figure 1). In the context of the airline industry, consumers have the option to choose from a range of flights that provide service from point A to point B. Alternatively, they may also consider other forms of transportation, such as driving, taking a train, or opting for a ship journey.

Figure 13: **Nest of the market**

$$
\begin{tikzcd}[column sep=small]
& \text{Market: O-D} \arrow[dl, no head] \arrow[dr, no head] & \\
\text{Flight} & & \text{Outside goods}
\end{tikzcd}
$$

The utility of consumer i from product j in market t can be specified as U_{ijt}. To maximize each consumer’s utility, we have

$$\max_{j \in \{0, \ldots, J_t\}} \{U_{ijt} = x_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt} + \upsilon_{it}(\lambda) + \lambda\epsilon_{ijt}\} \tag{28}$$

where x_{jt} is a K-dimensional (row) vector of observable product characteristics, including the distance of the route, whether the route’s origin and destination airports are carrier hubs, and whether it is a non-stop flight. Corresponding to this, β_i is a K-dimensional (column) of individual-specific coefficients for each different product characteristic.

The airfare of product j in market t is indicated by p_{jt}. The corresponding parameter α_i can be seen as an individual-specific marginal utility of price.

The unobservable (by econometricians, but observed by consumers and airline carriers) product characteristics of product j in market t are captured by ξ_{jt}. This may include brand reputation, loyalty programs, service quality, etc. To indicate these unobservable characteristics, we include carrier and time-fixed effects.

A nest to differentiate air travel products from outside goods is indicated by υ_{it}. And λ is the nested logit parameter between 0 and 1. (1) If λ approaches 0, products are approaching being perfectly substitutable in the nest; (2) if λ approaches 1, the model converges to a simple logit model, and the products in the nest are independent; (3) if $\lambda \in (0,1)$, it constructs a nested logit model. ϵ_{ijt} captures all other consumer-specific tastes and preferences.

The proportion of consumers choosing product j among the set of products $j \in 1, ..., J$ in market t in nest g is given by:

$$s_{j|gt}(x_t, p_t, \xi_t; \theta_d) = \frac{e^{\delta_{jt}/\lambda}}{\sum_{k=1}^{J} e^{\delta_{kt}/\lambda}}$$

with $\delta_{jt} = x_{jt}\beta - \alpha p_{jt} + \xi_{jt}$, which is the mean utility of product j, and $\theta_d \equiv (\tilde{\beta}, \tilde{\alpha}, \tilde{\lambda})$ are the estimated parameters from (1). We define it as within_share.

Let $D_t = \sum_{k=1}^{J} e^{\delta_{kt}/\lambda}$, the proportion of consumers who choose to fly is

$$s_{gt}(x_t, p_t, \xi_t; \theta_d) = \frac{D_t^{\lambda}}{1 + D_t^{\lambda}}$$

The overall market share of product j in market t is:

$$\begin{aligned} s_{jt}(x_t, p_t, \xi_t; \theta_d) &= s_{j|gt}(x_t, p_t, \xi_t; \theta_d) * s_{gt}(x_t, p_t, \xi_t; \theta_d) \\ &= \frac{e^{\delta_{jt}/\lambda} D_t^{\lambda-1}}{1 + D_t^{\lambda}} \end{aligned}$$

And the share of the outside goods is

$$\begin{aligned} s_{0t}(x_t, p_t, \xi_t; \theta_d) &= 1 - s_{gt}(x_t, p_t, \xi_t; \theta_d) \\ &= 1 - \frac{D_t^{\lambda}}{1 + D_t^{\lambda}} \\ &= \frac{1}{1 + D_t^{\lambda}} \end{aligned}$$

Following Berry (1994),

$$
\begin{aligned}
\frac{s_{jt}}{s_{0t}} &= \frac{s_{gt} * s_{j|gt}}{s_{0t}} \\
&= \frac{\frac{D_t^{\lambda}}{1+D_t^{\lambda}} * \frac{e^{\delta_{jt}/\lambda}}{D_t}}{\frac{1}{1+D_t^{\lambda}}} \\
&= D_t^{\lambda-1} e^{\delta_{jt}/\lambda} \\
&= \frac{1}{D_t^{1-\lambda}} (e^{\delta_{jt}/\lambda})^{1-\lambda} (e^{\delta_{jt}/\lambda})^{\lambda} \\
&= (s_{j|gt})^{1-\lambda} (e^{\delta_{jt}/\lambda})^{\lambda}
\end{aligned}
$$

By taking the natural logarithm on both sides of this equation, one defines the linear estimating equation of market demand:

$$
\begin{aligned}
ln(s_{jt}) - ln(s_{0t}) &= (1-\lambda) lns_{j|gt} + \lambda(\delta_{jt}/\lambda) \\
&= \delta_{jt} + (1-\lambda) lns_{j|gt} \\
&= x_{jt}\beta - \alpha p_{jt} + \xi_{jt} + (1-\lambda) lns_{j|gt}
\end{aligned}
\tag{29}
$$

5.2 Supply side

The airline market competition can be seen as static Nash-Bertrand pricing conduct (Peters, 2006; Jou et al., 2008).[123] To characterize the supply side of the

[123]Firstly, airlines engage in intense price competition, especially in markets where multiple carriers offer similar routes and services, aiming to maximize their own profit while maintaining or growing their market share. Secondly, Although airline services can be considered somewhat homogeneous (as they transport passengers from point A to point B), there is a degree of product differentiation. This differentiation comes from factors such as flight timings, customer service, baggage policies, in-flight amenities, frequent flyer programs, and other value-added services. This allows airlines to have some pricing power, as consumers may be willing to pay higher prices for preferred service characteristics, aligning with the Bertrand model's scenario for differentiated products. Thirdly, Airlines operate in an environment of strategic interdependence. This scenario is a core aspect of the Nash-Bertrand Competition, where firms must consider the potential reactions of their rivals when setting prices. Lastly, with its high fixed costs and regulatory barriers, we do not see as frequent entry and exit as some other industries might. This somewhat static landscape, at least in the short to medium term.

airline market, we use f to indicate the carriers, where $f = 1, ..., F$. The potential market size in market t is M_t. The potential market size is defined as the geometric mean of the population of the cities where the two originating airports are located.

The market share of product j in market t is s_{jt}, and the quantity of product j sold in market t is q_{jt}. In the airline industry, q_{jt} indicates the number of passengers in market t. Then we have $s_{jt} = \frac{q_{jt}}{M_t}$.

Define C_{ft} as the fixed cost of firm f in market t. The marginal cost of product j in market t is mc_{jt}. The profit of firm f in market t is:

$$\Pi_{ft} = \sum_{j \in J_f} (p_{jt} - mc_{jt}) s_{jt}(x_t, p_t, \xi_t; \theta_d) M_t - C_{ft}$$

To find the competitive equilibrium, the first-order condition to maximize profit is:

$$\frac{\partial \Pi_{ft}}{\partial p_{jt}} = s_{jt}(x_t, p_t, \xi_t; \theta_d) + \sum_{k \in J_f} (p_{kt} - mc_{kt}) \frac{\partial s_{kt}(x_t, p_t, \xi_t; \theta_d)}{\partial p_{jt}} = 0$$

The partial derivative of market share with respect to price can be written as:

$$\frac{\partial s_{kt}(p)}{\partial p_{jt}} = S_{jkt}(p)$$

where $j, k = 1, ..., J$.

We define the pre-merger ownership Ω a $J * J$ matrix,

$$\Omega_{jkt} = \begin{cases} 1, & if j, k \in J_f \\ 0, & otherwise. \end{cases}$$

Let pre-merger Ω be the element-by-element product of $S_{jkt}(p)$ and Ω_{jkt}

$$\Omega_{jkt}^{pre} = \begin{cases} -\frac{\partial s_{kt}(p)}{\partial p_{jt}}, & if j,k \in J_f \\ 0, & otherwise. \end{cases}$$

where$\frac{\partial s_{kt}(p)}{\partial p_{jt}}$ is given by

$$\frac{\partial s_{kt}(p)}{\partial p_{jt}} = \begin{cases} s_{jt}(\frac{\alpha}{p_{jt}})[\frac{1}{\lambda}(1 - s_{j|gt}) + s_{j|gt(1-s_{gt})}], & if j = k \\ s_{jt}s_{k|gt}(\frac{\alpha}{p_{jt}})(1 - s_{gt} - \frac{1}{\lambda}), & if j \neq k. \end{cases}$$

The first-order condition can be written as

$$s_t(x_t, p_t, \xi_t; \theta_d) - \Omega_t^{pre}(x_t, p_t, \xi_t; \theta_d)(p_t - mc_t) = 0$$

The markup and implied estimated marginal cost are:

$$p_t - mc_t = (\Omega_t^{pre})^{-1} s_t$$

$$mc_t = p_t - (\Omega_t^{pre})^{-1} s_t$$

5.3 Post-merger prediction

The industry structure post-merger is defined by Ω_t^{post}. When we assume an unchanged marginal cost, the equilibrium price in the post-merger market can be predicted by

$$p_t^{post} = mc_t^{pre} - (\Omega_t^{post})^{-1} s_t(p^{post}) \tag{30}$$

According to the pre- and post-merger conditions, the market share of each carrier can be calculated by:

$$s_{ft}^{pre} = \sum_{j \in J_f} s_{jt}(x_t, p_t, \xi_t; \theta_d)$$

$$s_{ft}^{post} = \sum_{j \in J_f} s_{jt}(x_t, p_t^{post}, \xi_t; \theta_d) \tag{31}$$

6 Results

6.1 Summary statistics

Tables 1, 2, and 3 display the summary statistics for all overlapping markets for merger 1 (Delta Air Lines and Northwest Airlines), considering markets with and without low-cost carriers. For all overlapping markets, on average, airfare is \$369.31. In markets with low-cost carriers, the average airfare is lower, at \$333.62 compared to \$389.38 in markets without low-cost carriers.

The average number of products per market and carriers per market for low-cost carrier markets are 7.26 and 5.28, respectively. The lower average number of products per market (4.51) and carriers per market (3.47) indicate that markets without low-cost carriers exhibit reduced competitiveness.

The corresponding summary statistics for merger 2 (United Airlines and Continental Airlines) are displayed in Tables 4, 5, and 6. In markets with no low-cost carrier, the average airfare is \$351.91, the products per market are 6.64, and the carriers per market are 4.23. We similarly find lower average fares (\$299.45) and more competition (products per market are 10.12 and carriers per market are 5.91) in markets where low-cost carriers are present relative to markets where they are not.

The market summary statistics of merger 3 (US Airways and American Airlines) are presented in Tables 7, 8, and 9 and exhibit comparable findings to the aforementioned mergers. The average airfares for the markets with and without low-cost carriers are \$338.64 and \$370.69, respectively. The presence of low-cost carriers also increased competition in the market, with average products per market increasing from 6.77 to 10.35 and carriers per market increasing from 3.61 to 5.07.

Overall, these tables suggest that the presence of low-cost carriers in a market significantly impacts airfare and competition, typically leading to lower prices and more options for consumers.

Since merger 4 (Southwest Airlines and AirTran Airways) deals with low-cost carriers, we do not distinguish between their overlapping markets and whether they contain low-cost carriers. The summary statistics of variables are displayed in Table 10. The average airfare in the overlapping markets is \$273.29, which is lower than the previously discussed markets. The product per market and carriers per market are also markedly higher than the averages for previous cases where no low-cost carriers were present, which were 11.04 and 6.21, respectively.

Additionally, factors such as market passengers, product passengers, market size, and market distance also vary in the different market scenarios.

6.2 Demand estimation

Table 11 presents the results of demand estimation using a unit demand one-level nested logit model applied to merger 1 (Delta Air Lines and Northwest Airlines) for all overlapping markets and following equation (2). The dependent variable is M_ls, representing each product's market-level share.

The negative coefficient of -0.0149 suggests that a \$1 increase in airfare leads to approximately a 1.49% decrease in market share, holding all else constant. It is significant at 1%. As anticipated, an increase in airfare prices corresponds to a decrease in demand, in accordance with the principles of the law of demand. Consequently, this leads to a reduction in market share.

The positive coefficient of within_share 0.582 indicates that all else being equal, a 1% increase in within_share (presumably the airline's current market share) results in a 0.582% increase in market share.

The estimated parameters for market distance, Hub_origin, Hub_dest, and direct are all positive. This might suggest that longer routes are less competitive, or it could reflect the fact that consumers prefer direct flights over connections for long-haul travel. The coefficients of Hub_origin and Hub_dest are 0.435 and 0.291, suggesting that if the origin or destination is a hub for the carrier, it increases the route's market share. This result is also in line with our expectations. The coefficient of 0.962 suggests that a direct flight (as opposed to flights with connections) increases market share, holding all else constant. This is expected as passengers typically prefer direct flights for the convenience of not having to change planes.

The first-stage regression employs instrumental variables such as the number of competitors in the market, scheduled departures, and fuel costs to estimate the impact of these factors on airfare. These variables do not directly affect the utility a passenger derives from a flight. The coefficient of N_rival exhibits a negative relationship, indicating that increased competition generally leads to decreased airfares. Conversely, reduced departure frequencies and elevated fuel costs result in higher airfares. All three are significant, providing a reasonable justification for their use as instruments.

Comparing the demand estimation for merger 1 (Delta Air Lines and Northwest Airlines) overlapping markets in Tables 11, 12, and 13, we can see that the sign of most of the estimated parameters meets our expectations and is statistically significant. The estimated parameter for airfare is more negative in markets without low-cost carriers (-0.0126) than in markets with low-cost carriers (-0.00580), implying that demand is more sensitive to price changes in markets without low-cost carriers. In Delta and Northwest's overlapping markets without low-cost carriers, consumers do not have the option to switch to a cheaper airline when prices increase, so a slight increase in airfare can significantly decrease demand. On the other hand, in markets with low-cost carriers, consumers have more options. They can switch to a low-cost carrier when prices increase instead of cancelling their travel plans. Therefore, demand in these markets is less sensitive to price changes.

Tables 14, 15, and 16 display the regression results on the demand for merger 2 (United Airlines and Continental Airlines) overlapping markets. The results are separated into three scenarios, as in the previous case: the overall market, markets with low-cost carriers, and markets without low-cost carriers. In all three scenarios, airfare has a negative and significant impact on market share, which is intuitive because demand for the service typically decreases as airfare increases. The coefficients capture the elasticity of demand. In the overall market, a 1% increase in airfare leads to approximately a 2.05% decrease in market share. This elasticity increases when low-cost carriers are present at 2.69% and when they are not at 3.19%. Comparing these elasticities, we see that the absolute value of the elasticity is largest in markets where low-cost carriers do not operate. This implies that consumers are most sensitive to changes in airfare in markets where low-cost carriers do not operate. However, in markets where low-cost carriers operate (Table 15), the elasticity is higher than in all markets but lower than in markets where low-cost carriers do not operate. This suggests that the presence of low-cost carriers increases consumers' sensitivity to price changes. The coefficients of within_share are all positive and less than 1, which is consistent with our expectation.

Demand estimation results for merger 3 (US Airways and American Airlines) overlapping markets are shown in Tables 17, 18, and 19. In all overlapping markets (Table 17), the airfare coefficient is -0.0226. This suggests that a 1% increase in airfare would lead to a decrease in demand by 2.26%. This is statistically significant at 1%.

The more competition there is in the market (i.e., the presence of low-cost carriers), the more sensitive passengers are to changes in airfare. This is reflected in the larger (in absolute value) airfare coefficients observed when low-cost carriers are present. In markets with low-cost carriers, the airfare coefficient is -0.0173, indicating that a 1% increase in airfare would result in a 1.73% decline in demand. This statistically significant result indicates a strong inverse relationship between price and demand. Compared to the overall market scenario, the magnitude of the airfare coefficient is smaller. The airfare coefficient is -0.0179 in markets without low-cost carriers. This scenario has a higher elasticity than the one with low-cost carriers, indicating that in the presence of low-cost carriers, passengers are less sensitive to changes in airfare. This result is in line with our two previous merger cases. However, in the results for the US and American scenarios, the parameter difference between the two scenarios is not as pronounced as in the previous two mergers.

The demand estimation results for merger 4 (Southwest Airlines and AirTran Airways) are presented in Table 20. The results show a negative relationship with market-level share, as the coefficient is -0.0240 and is statistically significant at 1%. Since this parameter estimate is less than one, we can say that the demand for flight routes is inelastic with respect to airfare.

In general, from all four merger estimation results, we find that the negative effect of airfare, which indicates the demand for flight in the above markets is inelastic, does reduce the market share of a route, potentially opening opportunities for rival airlines to compete more effectively. The results align with prior literature (Yamamoto, 2019).

6.3 Pre- and post-merger price and market share comparison

The impact of merger 1 (between Delta Air Lines (DL) and Northwest Airlines (NW)) on price and market share is simulated in Tables 21 and 22, following equations (3) and (4).

After the merger, the prices of the combined carriers (DL and NW) increased by 3.06 percent and 3.63 percent, respectively, as shown in Table 21. This suggests that, because of the merger's reduction in competition, the airlines have more pricing power, which they use to increase fares. In contrast, the prices of competing airlines (AA, AS, B6, CO, FL, SY, UA, US, and WN) have remained relatively stable, with minor price increases ranging from 0.00 to 0.12%. The negligible increase in rival carriers' prices may indicate that they have not substantially altered their pricing strategies in response to the Delta and Northwest merger, or it may be the result of the influence of other market factors that were not accounted for in the simulation.

Table 22 provides a simulation of the effects of the merger on market share. It is noteworthy that Delta and Northwest's market shares decreased after the merger by 0.002 and 0.012 percentage points, respectively. This may result from some customers transferring to competing airlines in response to the price increases. In contrast, rival carriers' market shares have increased by between 0.001 and 0.018 percentage points. This indicates that some customers may have shifted to these carriers due to the merger, most likely because of their stable prices. In conclusion, while the merger between Delta and Northwest appears to have given them greater pricing power, it may have resulted in minor market share losses as consumers shifted to competing airlines. Meanwhile, competing carriers have maintained stable prices and experienced modest gains in market share.

The simulations show distinct differences in market responses depending on the presence or absence of low-cost carriers (Tables 23, 24, 25, and 26).

In the presence of low-cost carriers, the price increase for the merged carriers (DL and NW) post-merger is somewhat moderate (2.63% for DL and 4.89% for NW). However, in the absence of low-cost carriers, the price increase is more pronounced (4.74% for DL and 5.33% for NW). This suggests that low-cost carriers provide significant competitive pressure, effectively limiting the merged entities' ability to raise prices. Thus, the presence of low-cost carriers can help protect consumers from substantial price increases following a merger.

The presence or absence of low-cost carriers also significantly impacts market share distribution. With low-cost carriers in the market, consumers have a broader range of choices, and it appears they gravitate towards more cost-effective options when facing price increases from the merged entity. This is evident as low-cost carriers such as B6, FL, and WN experienced higher growth in market share compared to other rival carriers. On the other hand, in the absence of low-cost carriers, the increase in market share is more evenly distributed among the remaining legacy carriers. This implies that in a market without low-cost carriers, consumers are likely to redistribute themselves among the remaining legacy carriers, which could potentially increase these carriers' market power.

Tables 27 through 32 demonstrate a simulated analysis of the changes in airline prices and market shares before and after merger 2 (United Airlines (UA) and Continental Airlines (CO)). The changes are compared in all overlapping markets and subdivided based on whether low-cost carriers operate in the markets or not.

Table 27 shows that the post-merger prices of both United and Continental have increased, with relative changes of 1.99% and 2.19%, respectively. The effect of the merger on the prices of the rival carriers is minimal, as evidenced by the minor relative changes in their prices, all of which are under 0.1%. The post-merger market shares (Table 28) for both United and Continental show a slight decline, with differences of -0.019 and -0.008, respectively. Contrarily, most rival carriers experienced a slight increase in their market shares post-merger.

For the markets with low-cost carriers, post-merger, both merged carriers, United and Continental, show a marginal increase in prices: Continental by 0.91% and United by 0.78%. The price change for rival carriers is negligible, with the highest being Southwest at 0.07%. This suggests that the merger had a minimal impact on ticket prices in the presence of low-cost carriers, probably due to the competitive pressure of these low-cost carriers.

In the absence of low-cost carriers, the price increase for Continental and United is notably higher at 1.47% and 1.40%, respectively. The increase in prices for rival carriers is still minimal. This could mean that the absence of low-cost carriers allows the merged entity to exercise greater market power, resulting in higher consumer prices.

Tables 30 and 32 show the market share simulation of the Continental and United merger. In markets with low-cost carriers, the merged carriers experience a decrease in market share post-merger. Continental's market share decreased by 0.010, and United's decreased by 0.013. Most rival carriers see a slight increase in their market share, with Southwest showing the largest gain of 0.012. This suggests the merger may have made rival carriers more appealing to customers, possibly due to pricing or service factors, or that the market was already highly competitive.

In markets without low-cost carriers, the market share decrease for Continental and United is less significant, at 0.004 and 0.017, respectively. However, rival carriers such as DL, AA, and US gain substantially more market share compared to the scenario with low-cost carriers. This observation implies that the absence of low-cost carriers leads to a reduction in competition, thereby increasing the appeal of other rival carriers.

Based on the findings of the simulation analysis, it can be inferred that the consolidation of Continental and United Airlines has resulted in a minimal upward change in their respective prices, possibly attributable to a decrease in competitive forces between the two companies. Nevertheless, the merger's influence on competing carriers' pricing actions is minimal. This observation indicates the merged entity took on the cost of the price increase instead of transferring it to consumers via elevated prices offered by other airlines. This analysis posits that the merger between Continental and United Airlines resulted in internal adjustments pertaining to prices and market shares. However, the overall impact on the broader industry seems insignificant. Consumers may have encountered limited direct repercussions in relation to price fluctuations among competing carriers. However, they may have also experienced indirect consequences as they modified their preferences in reaction to shifts in the merged carriers' prices and market shares.

The two tables presented above are simulations showing the impact of a hypothetical merger between US Airways (US) and American Airlines (AA). They provide details about price changes and market shares for the merged entity and rival carriers before and after the merger.

Tables 33 through 38 provide a comparison of ticket prices and market share simulations pre- and post-merger of merger 3 (American Airlines and US Airways). From Tables 33 and 34, for the merged carriers (AA and US), post-merger prices have increased by 1.83% and 0.75%, respectively. Similar to the previous two merger cases, the rival carriers mostly saw negligible changes in their prices. For the merged entity (AA and US), there's a slight decrease in market shares (-0.012 for AA and -0.004 for US). Conversely, most rival carriers saw a slight increase in their market shares, likely benefiting from the slight decrease in the merged entity's market share.

In the market scenario where low-cost carriers operate (Tables 35 and 36), both price and market share simulations suggest that the impact of the merger on the market is limited. Similar to the all-markets scenario, the prices for the merged carriers (AA and US) increased slightly post-merger (1.41% for AA and 0.62% for US). This price increase is smaller than the overall market, which might be attributed to competition from low-cost carriers. For the rival carriers, price changes are as small as in the all-markets scenario. The market shares of AA and US decreased slightly post-merger (-0.009 for AA and -0.006 for US). The market shares of most rival carriers increased slightly, indicating that they were able to capture some of the market share lost by the merged entity. This indicates that competition from low-cost carriers might have offset some potential market power from the merger.

In the market scenario without low-cost carriers, the price and market share simulations indicate a more noticeable impact of the merger (Tables 37 and 38). AA and US saw significant increases in their prices post-merger: 7.82% for AA and 3.30% for US. This increase is larger compared to the scenario with low-cost carriers, which shows that the merged entity could exercise more market power and raise prices without competition from low-cost carriers. The price changes for rival carriers (AS, DL, and UA) are relatively small, suggesting they maintained their pricing despite the merger. The market shares of AA and US decreased post-merger, -0.022 for AA and -0.003 for US. The loss of customers is possibly due to increased prices. For the rival carriers, market shares rose.

Tables 39 and 40 depict the price and market share simulation results for merger 4 (Southwest Airlines and AirTran Airways). Since Southwest and AirTran are low-cost carriers, there are no markets in which they are located that do not have low-cost carriers' participation, so we analyze only the full overlapping markets.

Post-merger, the average price of both merged carriers, FL and WN, has increased by 1.78% and 0.86%, respectively. The relative changes in the prices of rival carriers are negligible (below 0.10%). Compared with pre-merger, post-merger market share of both merged carriers has decreased slightly (FL by 0.009 and WN by 0.002). The market shares of rival carriers have slightly increased. Among the rival carriers, NK showed the most substantial gain of 0.007 in market share. However, its market share was relatively small before the merger, so the increase of 0.007 in market share does not change the market structure significantly.

In summary, these price and market share simulation result tables (from Tables 21 to 40) highlight low-cost carriers' moderating role in the airline industry. Their presence appears to keep prices in check, even in the event of a merger between two major carriers. It adds to the competitiveness of the market, affecting market share distributions. The absence of low-cost carriers allows merged entities to increase prices and lose fewer customers to rival carriers. These simulations illustrate the importance of competition in the industry, not only for price control but also for maintaining a balanced market share distribution.

6.4 Minimum required efficiency

Minimum required efficiency within the domain of merger analysis refers to the minimum level of cost savings or other efficiency improvements that a merger must generate. This is necessary to offset any potential negative impacts on competition, thus ensuring that the merger has a neutral or positive effect on consumer welfare. We can apply it to validate the conclusions drawn from the merger simulation.

Minimal required efficiency (mre) is the amount by which the post-merger costs of the merging firms must decrease to protect consumers from price increases, where $p_t^{post}(mre) = p_t^{pre}$.

From the post-merger condition, $p_t^{post} - mc_t^{post} = (\Omega_t^{post})^{-1} s_t(p^{post})$, we can solve for the post-merger marginal cost and thus get $mre = 1 - \frac{mc_t^{post}}{mc_t^{pre}}$. The minimum required efficiency estimation results are shown in Tables 41, 42, 43, and 44.

Tables 41, 42, and 43 show that markets with low-cost carriers have lower minimum required efficiency at 9.8%, 1.3% and 1.5%, respectively, compared with markets without low-cost carriers at 10.8%, 2.4% and 9.8%. These results suggest that even a small increase in efficiency could be sufficient to offset any negative effects of the merger. This is because the competition from low-cost carriers is likely to limit any potential anti-competitive behaviour by the merged entity. The higher minimum required efficiency in markets without low-cost carriers indicates that the merged entity would have to produce substantial efficiency gains to prevent negative consumer effects. Without low-cost carriers' competition, the merged entity may be able to increase prices without losing many customers.

7 Conclusion

This article employs demand estimation and merger simulation methodologies to analyze the influence of low-cost airlines on merger outcomes in the U.S. airline industry. The study focuses on four prominent merger cases within this industry: the merger between Delta Air Lines and Northwest Airlines, the merger between United Airlines and Continental Airlines, the merger between US Airways and American Airlines, and the merger between Southwest Airlines and AirTran Airways. The findings indicate that the presence of low-cost carriers in the market could have a significant impact on reducing the possible negative consequences of a merger in terms of competition. The existence of low-cost carriers constrains the merging entity's capacity to raise rates and acquire market share. On the contrary, in the event of low-cost carriers being absent, the merged business exhibits higher market power, leading to larger price increases and decreased market share fluctuations.

Based on the conclusions drawn from the simulations, we make the following recommendations: firstly, it is essential to maintain the presence of low-cost airlines in the industry. Low-cost carriers are important in maintaining competitive pricing within the airline sector. Policy interventions facilitating the entry and long-term viability of low-cost carriers play a crucial role in promoting competitive fares within the market.

Furthermore, antitrust authorities need to evaluate the market presence of low-cost carriers as a crucial factor in their evaluation of mergers concerning antitrust issues. Routes that do not have low-cost carriers could face more significant fare escalations following a merger, necessitating a more thorough examination.

Moreover, it is important to consider the protection of consumer welfare. Low-cost carriers not only provide competitive pricing but also impose constraints on the ability of other airlines to raise fares while simultaneously expanding the range of product options available to consumers. Therefore, the presence of these carriers directly influences the welfare of consumers. The implementation of policies that encourage airline diversity can protect consumer welfare. The promotion of low-cost carriers to expand their operations in routes that are predominantly served by established airlines can serve as a means to mitigate the effects of reduced competition resulting from a merger.

This study highlights the significance of low-cost carriers in maintaining competition within the aviation industry. We believe that policymakers could leverage this role of low-cost airlines by implementing measures aimed at preserving and, when feasible, enhancing the competitive pressures exerted by these carriers.

This research, however, has certain limitations, as the actual effects of a merger can differ depending on the particular route or market in consideration. Additionally, it should be noted that the above simulations do not account for any advantages resulting from the merger, such as enhanced operational efficiency, expanded flight choices, and other potential synergies that could also impact prices and market shares.

8 Tables

Table 1: **Summary Statistics**
All overlapping markets for Delta Air Lines and Northwest Airlines

Variable	Mean	Std. Dev.	Min	Max
Airfare	369.31	212.92	52.37	1,997.21
Market passengers	660.80	1,505.95	20.00	26,690.00
Product passengers	104.53	448.88	10.00	20,460.00
Market size	648,397.50	615,211.10	41,742.25	5,483,307.00
Market distance	1,883.76	684.07	227.00	3,869.00
Products per market	5.50	2.77	2.00	16.00
Carriers per market	4.12	1.54	2.00	10.00
Low-cost carrier	0.09	0.28	0.00	1.00
Hub_origin	0.14	0.35	0.00	1.00
Hub_destination	0.13	0.33	0.00	1.00
Direct	0.12	0.34	0.00	1.00
Total Number of Market	1,256			
Observations	6,751			

Data source: Author's calculation based on U.S. BTS DB1B and T-100 data.

Table 2: **Summary Statistics**
Overlapping markets with low-cost carriers operates in
for Delta Air Lines and Northwest Airlines

Variable	Mean	Std. Dev.	Min	Max
Airfare	333.62	194.31	52.37	1,700.30
Market passengers	930.49	1,431.76	30.00	11,760.00
Product passengers	121.93	393.24	10.00	7,310.00
Market size	613,834.50	470,883.70	88,495.71	5,483,307.00
Market distance	2,025.18	679.23	339.00	3,843.00
Products per market	7.26	2.91	3.00	16.00
Carriers per market	5.28	1.44	3.00	10.00
Low-cost carrier	0.24	0.43	0.00	1.00
Hub_origin	0.13	0.33	0.00	1.00
Hub_destination	0.11	0.32	0.00	1.00
Direct	0.16	0.24	0.00	1.00
Total Number of Market	347			
Observations	2,430			

Data source: Author's calculation based on U.S. BTS DB1B and T-100 data.

Table 3: **Summary Statistics**
Overlapping markets without low-cost carriers operates in for Delta Air Lines and Northwest Airlines

Variable	Mean	Std. Dev.	Min	Max
Airfare	389.38	220.19	53.55	1,997.21
Market passengers	509.13	1,525.46	20.00	26,690.00
Product passengers	94.74	477.09	10.00	20,460.00
Market size	667,834.70	682,392.70	41,742.25	5,483,307.00
Market distance	1,804.23	673.94	227.00	3,869.00
Products per market	4.51	2.12	2.00	12.00
Carriers per market	3.47	1.16	2.00	7.00
Hub_origin	0.15	0.35	0.00	1.00
Hub_destination	0.13	0.34	0.00	1.00
Direct	0.06	0.24	0.00	1.00
Total Number of Market	995			
Observations	4,321			

Data source: Author's calculation based on U.S. BTS DB1B and T-100 data.

Table 4: **Summary Statistics**
Overlapping markets for United Airlines and Continental Airlines

Variable	Mean	Std. Dev.	Min	Max
Airfare	319.92	180.23	35.74	2,151.44
Market passengers	1,219.54	1,598.24	20.00	24,900.00
Product passengers	130.64	428.88	10.00	16,900.00
Market size	724,544.20	581,306.60	20,807.23	5,575,485.00
Market distance	2,079.24	609.90	191.00	3,953.00
Products per market	8.76	4.21	2.00	24.00
Carriers per market	5.25	1.42	2.00	9.00
Low-cost carrier	0.15	0.36	0.00	1.00
Hub_origin	0.18	0.39	0.00	1.00
Hub_destination	0.18	0.38	0.00	1.00
Direct	0.06	0.23	0.00	1.00
Total Number of Market	1,739			
Observations	18,212			

Data source: Author's calculation based on U.S. BTS DB1B and T-100 data.

Table 5: **Summary Statistics**
Overlapping markets with low-cost carriers operates in for United Airlines and Continental Airlines

Variable	Mean	Std. Dev.	Min	Max
Airfare	299.45	161.03	44.72	2,151.44
Market passengers	1,386.43	1,689.66	30.00	24,900.00
Product passengers	130.03	398.05	10.00	16,900.00
Market size	742,779.10	586,759.40	82,771.62	5,545,549.00
Market distance	2,143.91	590.68	337.00	3,953.00
Products per market	10.12	4.05	3.00	24.00
Carriers per market	5.91	1.20	3.00	9.00
Low-cost carrier	0.25	0.43	0.00	1.00
Hub_origin	0.15	0.36	0.00	1.00
Hub_destination	0.16	0.37	0.00	1.00
Direct	0.05	0.22	0.00	1.00
Total Number of Market	874			
Observations	11,103			

Data source: Author's calculation based on U.S. BTS DB1B and T-100 data.

Table 6: **Summary Statistics**
Overlapping markets without low-cost carriers operates in for United Airlines and Continental Airlines

Variable	Mean	Std. Dev.	Min	Max
Airfare	351.91	202.58	35.74	2,131.27
Market passengers	958.88	1,404.93	20.00	12,400.00
Product passengers	131.58	473.06	10.00	8,430.00
Market size	696,064.60	571,564.60	20,807.23	5,575,485.00
Market distance	1,978.24	625.57	191.00	3,869.00
Products per market	6.64	3.51	2.00	22.00
Carriers per market	4.23	1.09	2.00	7.00
Hub_origin	0.23	0.42	0.00	1.00
Hub_destination	0.19	0.39	0.00	1.00
Direct	0.06	0.25	0.00	1.00
Total Number of Market	1.047			
Observations	7,109			

Data source: Author's calculation based on U.S. BTS DB1B and T-100 data.

Table 7: **Summary Statistics**
Overlapping markets for US Airways and American Airlines

Variable	Mean	Std. Dev.	Min	Max
Airfare	350.90	182.92	25.95	2,050.00
Market passengers	1,757.65	3,204.68	20.00	70,720.00
Product passengers	174.06	669.40	10.00	20,220.00
Market size	813,689.40	740,239.80	39,732.19	5,669,639.00
Market distance	1,964.34	628.35	178.00	3,982.00
Products per market	8.98	4.43	2.00	35.00
Carriers per market	4.52	1.01	2.00	8.00
Low-cost carrier	0.16	0.36	0.00	1.00
Hub_origin	0.21	0.41	0.00	1.00
Hub_destination	0.20	0.40	0.00	1.00
Direct	0.06	0.24	0.00	1.00
Total Number of Market	2,088			
Observations	22,844			

Data source: Author's calculation based on U.S. BTS DB1B and T-100 data.

Table 8: **Summary Statistics**
Overlapping markets with low-cost carriers operates in for US Airways and American Airlines

Variable	Mean	Std. Dev.	Min	Max
Airfare	338.64	173.45	25.95	2,014.78
Market passengers	2,012.69	3,469.91	30.00	70,720.00
Product passengers	177.26	638.23	10.00	20,220.00
Market size	760,535.30	665,369.10	96,416.11	5,669,639.00
Market distance	2,045.10	610.44	370.00	3,982.00
Products per market	10.35	4.14	3.00	27.00
Carriers per market	5.07	0.77	3.00	8.00
Low-cost carrier	0.25	0.44	0.00	1.00
Hub_origin	0.19	0.40	0.00	1.00
Hub_destination	0.19	0.39	0.00	1.00
Direct	0.06	0.23	0.00	1.00
Total Number of Market	1,079			
Observations	14,106			

Data source: Author's calculation based on U.S. BTS DB1B and T-100 data.

Table 9: **Summary Statistics**
Overlapping markets without low-cost carriers operates in for US Airways and American Airlines

Variable	Mean	Std. Dev.	Min	Max
Airfare	370.69	195.64	28.03	2,050.00
Market passengers	1,345.92	2,671.81	20.00	31,450.00
Product passengers	168.88	716.86	10.00	19,580.00
Market size	899,497.50	840,232.00	39,732.19	5,669,639.00
Market distance	1,833.96	634.93	178.00	3,869.00
Products per market	6.77	3.95	2.00	35.00
Carriers per market	3.61	0.62	2.00	5.00
Hub_origin	0.24	0.43	0.00	1.00
Hub_destination	0.23	0.42	0.00	1.00
Direct	0.06	0.24	0.00	1.00
Total Number of Market	1,265			
Observations	8,738			

Data source: Author's calculation based on U.S. BTS DB1B and T-100 data.

Table 10: **Summary Statistics**
Overlapping markets for Southwest Airlines and AirTran Airways

Variable	Mean	Std. Dev.	Min	Max
Airfare	273.29	154.15	38.25	1,811.74
Market passengers	2,021.95	2,424.37	90.00	20,060.00
Product passengers	188.81	656.00	10.00	10,930.00
Market size	765,615.10	543,193.30	140,811.30	3,444,985.00
Market distance	1,905.02	646.12	638.00	3,671.00
Products per market	11.04	4.18	2.00	24.00
Carriers per market	6.21	1.25	2.00	9.00
Low-cost carrier	0.35	0.48	0.00	1.00
Hub_origin	0.20	0.40	0.00	1.00
Hub_destination	0.17	0.37	0.00	1.00
Direct	0.06	0.23	0.00	1.00
Total Number of Market	214			
Observations	2,537			

Data source: Author's calculation based on U.S. BTS DB1B and T-100 data.

Table 11: **Demand estimation for Delta Air Lines and Northwest Airlines overlapping markets**

	First-stage	2SLS
Airfare	-	-0.0149***
	-	[0.00218]
Within_share	-7.222**	0.582***
	[2.515]	[0.0361]
Market_distance	0.0706***	0.000875***
	[0.00402]	[0.000152]
Hub_origin	45.98***	0.435**
	[7.528]	[0.156]
Hub_dest	32.77***	0.291*
	[7.912]	[0.144]
Direct	16.13	0.962***
	[11.10]	[0.171]
N_rival	-12.40***	
	[2.093]	
Departures	-0.114*	
	[0.0569]	
Fuelcost	1.216**	
	[0.375]	
Time FE		Y
Carrier FE		Y
N		6,751

Notes: Standard errors are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%. The model passes underidentification test and overidentification test of all instruments. The F statistic for weak identification test is 12.742.

Table 12: **Demand estimation for Delta Air Lines and Northwest Airlines overlapping markets (with low-cost carriers operates in)**

	First-stage	2SLS
Airfare	-	-0.00580**
	-	[0.00187]
within_share	-14.05***	0.593***
	[3.529]	[0.0343]
Market_distance	0.0606***	0.000155
	[0.00593]	[0.000116]
Hub_origin	48.54***	-0.0891
	[11.68]	[0.127]
Hub_dest	17.98	-0.108
	[12.44]	[0.102]
Direct	37.78*	0.851***
	[16.81]	[0.142]
N_rival	-5.266	
	[3.092]	
Departures	-0.0191	
	[0.0781]	
Fuelcost	1.786**	
	[0.579]	
Time FE		Y
Carrier FE		Y
N		2,430

Notes: Standard errors are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%. The model passes the underidentification test and overidentification test of all instruments. The F statistic for the weak identification test is 12.465.

Table 13: **Demand estimation for Delta Air Lines and Northwest Airlines overlapping markets (without low-cost carriers operates in)**

	First-stage	2SLS
Airfare	-	-0.0126***
	-	[0.00326]
within_share	-4.366	0.633***
	[3.475]	[0.0438]
Market_distance	0.0766***	0.000842***
	[0.00535]	[0.000247]
Hub_origin	39.06***	0.334
	[9.787]	[0.182]
Hub_dest	37.62***	0.292
	[10.19]	[0.184]
Direct	5.145	0.881***
	[14.50]	[0.192]
N_rival	-10.53**	
	[3.560]	
Departures	-0.178*	
	[0.0794]	
Fuelcost	0.868	
	[0.503]	
Time FE		Y
Carrier FE		Y
N		4,320

Notes: Standard errors are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%. The model passes the underidentification test and overidentification test of all instruments. The F statistic for the weak identification test is 4.218.

Table 14: **Demand estimation for United Airlines and Continental Airlines overlapping markets**

	First-stage	2SLS
Airfare	-	-0.0205***
	-	[0.00167]
within_share	-5.360***	0.729***
	[1.133]	[0.0224]
Market_distance	0.0563***	0.00119***
	[0.00228]	[0.0000944]
Hub_origin	65.63***	1.184***
	[3.339]	[0.132]
Hub_dest	51.64***	0.887***
	[3.425]	[0.111]
Direct	23.33***	0.733***
	[5.857]	[0.123]
N_rival	-12.81***	
	[1.053]	
Departures	-0.0263	
	[0.0254]	
Fuelcost	-0.0263	
	[0.0254]	
Time FE		Y
Carrier FE		Y
N		18,211

Notes: Standard errors are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%. The model passes the underidentification test and overidentification test of all instruments. The F statistic for the weak identification test is 20.204.

Table 15: **Demand estimation for United Airlines and Continental Airlines overlapping markets (with low-cost carriers operates in)**

	First-stage	2SLS
Airfare	-	-0.0269***
	-	[0.00449]
within_share	-4.202***	0.739***
	[1.275]	[0.0359]
Market_distance	0.0537***	0.00138***
	[0.00264]	[0.000235]
Hub_origin	63.25***	1.614***
	[4.071]	[0.301]
Hub_dest	46.48***	1.074***
	[4.026]	[0.232]
Direct	18.36**	0.0960
	[7.008]	[0.200]
N_rival	-7.543***	
	[1.331]	
Departures	-0.00405	
	[0.0293]	
Fuelcost	0.860*	
	[0.421]	
Time FE		Y
Carrier FE		Y
N		11,102

Notes: Standard errors are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%. The model passes the underidentification test and overidentification test of all instruments. The F statistic for the weak identification test is 9.006.

Table 16: **Demand estimation for United Airlines and Continental Airlines overlapping markets (without low-cost carriers operates in)**

	First-stage	2SLS
Airfare	-	-0.0319**
	-	[0.0119]
within_share	-7.785***	0.590***
	[2.160]	[0.0982]
Market_distance	0.0566***	0.00206**
	[0.00414]	[0.000656]
Hub_origin	62.35***	1.784*
	[5.731]	[0.759]
Hub_dest	52.21***	1.569*
	[6.098]	[0.636]
Direct	27.22**	2.001***
	[10.12]	[0.436]
N_rival	-6.151*	
	[2.592]	
Departures	-0.0584	
	[0.0457]	
Fuelcost	0.179	
	[0.690]	
Time FE		Y
Carrier FE		Y
N		7,109

Notes: Standard errors are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%. The model passes the underidentification test and overidentification test of all instruments. The F statistic for the weak identification test is 1.792.

Table 17: **Demand estimation for US Airways and American Airlines overlapping markets**

	First-stage	2SLS
Airfare	-	-0.0226***
	-	[0.00188]
within_share	-10.42***	0.597***
	[0.975]	[0.0265]
Market_distance	0.0597***	0.00142***
	[0.00200]	[0.000111]
Hub_origin	51.95***	0.959***
	[2.852]	[0.119]
Hub_dest	59.59***	1.117***
	[2.887]	[0.133]
Direct	23.54***	0.578***
	[5.208]	[0.122]
N_rival	-14.70***	
	[1.280]	
Departures	-0.0564*	
	[0.0259]	
Fuelcost	0.692**	
	[0.230]	
Time FE		Y
Carrier FE		Y
N		22,844

Notes: Standard errors are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%. The model passes the underidentification test and overidentification test of all instruments. The F statistic for the weak identification test is 16.881.

Table 18: **Demand estimation for US Airways and American Airlines overlapping markets (with low-cost carriers operates in)**

	First-stage	2SLS
Airfare	-	-0.0173***
	-	[0.00255]
within_share	-9.891***	0.671***
	[1.162]	[0.0306]
Market_distance	0.0577***	0.00103***
	[0.00243]	[0.000146]
Hub_origin	53.61***	0.838***
	[3.519]	[0.148]
Hub_dest	59.51***	0.865***
	[3.584]	[0.163]
Direct	22.33***	0.129
	[6.378]	[0.122]
N_rival	-12.94***	
	[1.934]	
Departures	-0.0170	
	[0.0311]	
Fuelcost	-0.524	
	[0.273]	
Time FE		Y
Carrier FE		Y
N		1,4106

Notes: Standard errors are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%. The model passes the underidentification test. The Chi-square value of the overidentification test of all instruments is 4.075. The F statistic for the weak identification test is 12.200.

Table 19: **Demand estimation for US Airways and American Airlines overlapping markets (without low-cost carriers operates in)**

	First-stage	2SLS
Airfare	-	-0.0179***
	-	[0.00157]
within_share	-11.43***	0.727***
	[1.751]	[0.0222]
Market_distance	0.0618***	0.000642***
	[0.00347]	[0.0000980]
Hub_origin	52.36***	0.0827
	[4.918]	[0.0921]
Hub_dest	59.75***	0.226*
	[4.940]	[0.104]
Direct	25.62**	0.744***
	[8.883]	[0.0878]
N_rival	-12.12***	
	[3.549]	
Departures	-0.124**	
	[0.0461]	
Fuelcost	1.455***	
	[0.425]	
Time FE		Y
Carrier FE		Y
N		8,738

Notes: Standard errors are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%. The model passes the underidentification test and the overidentification test of all instruments. The F statistic for the weak identification test is 8.617.

Table 20: **Demand estimation for Southwest Airlines and AirTran Airways overlapping markets**

	First-stage	2SLS
Airfare	-	-0.0240***
	-	[0.00697]
within_share	-7.337**	0.683***
	[2.442]	[0.0731]
Market_distance	0.0539***	0.00112**
	[0.00497]	[0.000358]
Hub_origin	56.50***	1.198**
	[7.491]	[0.434]
Hub_dest	52.42***	1.029*
	[8.114]	[0.414]
Direct	13.82	0.268
	[13.19]	[0.330]
N_rival	-8.436***	
	[2.505]	
Departures	-0.0284	
	[0.0533]	
Fuelcost	0.174	
	[0.721]	
Time FE		Y
Carrier FE		Y
N		2,537

Notes: Standard errors are reported in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%. The model passes underidentification test. The Chi-square value of overidentification test of all instruments is 5.473. The F statistic for weak identification test is 3.101.

Table 21: **Price simulation for**
Delta Air Lines and Northwest Airlines all overlapping markets

Carriers	Pre-merger Price	Post-merger Price	Relative Changes
Merged carriers			
DL	363.481	374.590	3.06%
NW	411.308	426.233	3.63%
Rival carriers			
AA	387.581	387.905	0.08%
AS	733.003	733.317	0.04%
B6	272.161	272.492	0.12%
CO	367.460	367.825	0.10%
FL	212.618	212.839	0.10%
SY	258.968	258.973	0.00%
UA	399.158	399.549	0.10%
US	415.596	415.921	0.08%
WN	251.524	251.756	0.09%

Notes: Unweighted averages by firm.

Table 22: **Market share simulation for**
Delta Air Lines and Northwest Airlines all overlapping markets

Carriers	Pre-merger Market Share	Post-merger Market Share	Differences
Merged carriers			
DL	0.402	0.400	-0.002
NW	0.284	0.272	-0.012
Rival carriers			
AA	0.297	0.312	0.015
AS	0.076	0.090	0.014
B6	0.115	0.133	0.018
CO	0.294	0.306	0.012
FL	0.334	0.341	0.007
SY	0.207	0.208	0.001
UA	0.205	0.222	0.017
US	0.330	0.343	0.013
WN	0.342	0.352	0.010

Notes: Unweighted averages by firm.

Table 23: **Price simulation for Delta Air Lines and Northwest Airlines overlapping markets (with low-cost carriers operate in)**

Carriers	Pre-merger Price	Post-merger Price	Relative Changes
Merged carriers			
DL	311.854	320.059	2.63%
NW	411.365	431.497	4.89%
Rival carriers			
AA	336.803	337.126	0.10%
AS	953.071	953.336	0.03%
B6	272.161	273.038	0.32%
CO	283.496	283.983	0.17%
FL	212.618	213.204	0.28%
SY	258.968	258.983	0.01%
UA	404.855	405.135	0.07%
US	313.309	313.687	0.12%
WN	251.524	252.136	0.24%

Notes: Unweighted averages by firm.

Table 24: **Market share simulation for Delta Air Lines and Northwest Airlines overlapping markets (with low-cost carriers operate in)**

Carriers	Pre-merger Market Share	Post-merger Market Share	Differences
Merged carriers			
DL	0.299	0.294	-0.005
NW	0.124	0.111	-0.013
Rival carriers			
AA	0.26	0.265	0.005
AS	0.009	0.009	0
B6	0.115	0.133	0.018
CO	0.185	0.191	0.006
FL	0.334	0.341	0.007
SY	0.207	0.208	0.001
UA	0.098	0.102	0.004
US	0.246	0.252	0.006
WN	0.342	0.353	0.011

Notes: Unweighted averages by firm.

Table 25: **Price simulation for Delta Air Lines and Northwest Airlines overlapping markets (without low-cost carriers operate in)**

Carriers	Pre-merger Price	Post-merger Price	Relative Changes
Merged carriers			
DL	381.602	399.701	4.74%
NW	411.291	433.222	5.33%
Rival carriers			
AA	413.275	413.841	0.14%
AS	586.290	586.911	0.11%
CO	418.281	418.905	0.15%
UA	396.717	397.401	0.17%
US	455.892	456.418	0.12%

Notes: Unweighted averages by firm.

Table 26: **Market share simulation for Delta Air Lines and Northwest Airlines overlapping markets (without low-cost carriers operate in)**

Carriers	Pre-merger Market Share	Post-merger Market Share	Differences
Merged carriers			
DL	0.434	0.433	-0.001
NW	0.335	0.321	-0.014
Rival carriers			
AA	0.317	0.338	0.021
AS	0.120	0.148	0.028
CO	0.369	0.385	0.016
UA	0.249	0.275	0.026
US	0.365	0.383	0.018

Notes: Unweighted averages by firm.

Table 27: **Price simulation for United Airlines and Continental Airlines all overlapping markets**

Carriers	Pre-merger Price	Post-merger Price	Relative Changes
Merged carriers			
CO	331.631	338.882	2.19%
UA	348.537	355.483	1.99%
Rival carriers			
AA	323.413	323.588	0.05%
AS	347.505	347.523	0.01%
B6	258.625	258.670	0.02%
DL	308.999	309.305	0.10%
F9	266.248	266.396	0.06%
FL	205.532	205.620	0.04%
US	392.521	392.778	0.07%
VX	479.422	479.475	0.01%
WN	260.456	260.690	0.09%
YX	214.955	214.966	0.01%

Notes: Unweighted averages by firm.

Table 28: **Market share simulation for United Airlines and Continental Airlines all overlapping markets**

Carriers	Pre-merger Market Share	Post-merger Market Share	Differences
Merged carriers			
CO	0.289	0.281	-0.008
UA	0.267	0.248	-0.019
Rival carriers			
AA	0.169	0.180	0.011
AS	0.032	0.034	0.002
B6	0.329	0.333	0.004
DL	0.279	0.298	0.019
F9	0.185	0.192	0.007
FL	0.169	0.175	0.006
US	0.251	0.266	0.015
VX	0.185	0.189	0.004
WN	0.272	0.284	0.012
YX	0.014	0.015	0.001

Notes: Unweighted averages by firm.

Table 29: **Price simulation for United Airlines and Continental Airlines overlapping markets (with low-cost carriers operate in)**

Carriers	Pre-merger Price	Post-merger Price	Relative Changes
Merged carriers			
CO	306.095	308.887	0.91%
UA	331.014	333.600	0.78%
Rival carriers			
AA	307.674	307.742	0.02%
AS	365.152	365.168	0.00%
B6	258.625	258.659	0.01%
DL	288.678	288.782	0.04%
F9	266.248	266.361	0.04%
FL	205.532	205.599	0.03%
US	358.619	358.704	0.02%
VX	479.422	479.462	0.01%
WN	260.456	260.634	0.07%
YX	214.955	214.963	0.00%

Notes: Unweighted averages by firm.

Table 30: **Market share simulation for United Airlines and Continental Airlines overlapping markets (with low-cost carriers operate in)**

Carriers	Pre-merger Market Share	Post-merger Market Share	Differences
Merged carriers			
CO	0.195	0.185	-0.010
UA	0.206	0.193	-0.013
Rival carriers			
AA	0.125	0.13	0.005
AS	0.022	0.024	0.002
B6	0.329	0.333	0.004
DL	0.204	0.211	0.007
F9	0.185	0.192	0.007
FL	0.169	0.175	0.006
US	0.219	0.225	0.006
VX	0.185	0.189	0.004
WN	0.272	0.284	0.012
YX	0.014	0.015	0.001

Notes: Unweighted averages by firm.

Table 31: **Price simulation for United Airlines and Continental Airlines overlapping markets (without low-cost carriers operate in)**

Carriers	Pre-merger Price	Post-merger Price	Relative Changes
Merged carriers			
CO	345.780	350.879	1.47%
UA	358.715	363.747	1.40%
Rival carriers			
AA	345.797	345.955	0.05%
AS	326.916	326.924	0.00%
DL	324.069	324.294	0.07%
US	413.116	413.298	0.04%

Notes: Unweighted averages by firm.

Table 32: **Market share simulation for United Airlines and Continental Airlines overlapping markets (without low-cost carriers operate in)**

Carriers	Pre-merger Market Share	Post-merger Market Share	Differences
Merged carriers			
CO	0.340	0.336	-0.004
UA	0.301	0.284	-0.017
Rival carriers			
AA	0.227	0.242	0.015
AS	0.047	0.048	0.001
DL	0.327	0.347	0.020
US	0.269	0.284	0.015

Notes: Unweighted averages by firm.

Table 33: **Price simulation for US Airways and American Airlines all overlapping markets**

Carriers	Pre-merger Price	Post-merger Price	Relative Changes
Merged carriers			
AA	315.582	321.347	1.83%
US	341.229	343.772	0.75%
Rival carriers			
AS	344.288	344.299	0.00%
B6	340.898	340.920	0.01%
DL	354.743	354.871	0.04%
F9	219.667	219.751	0.04%
NK	180.244	180.249	0.00%
SY	210.692	210.723	0.01%
UA	372.664	372.814	0.04%
WN	276.821	276.917	0.03%

Notes: Unweighted averages by firm.

Table 34: **Market share simulation for US Airways and American Airlines all overlapping markets**

Carriers	Pre-merger Market Share	Post-merger Market Share	Differences
Merged carriers			
AA	0.181	0.169	-0.012
US	0.276	0.272	-0.004
Rival carriers			
AS	0.068	0.070	0.002
B6	0.115	0.117	0.002
DL	0.233	0.241	0.008
F9	0.282	0.286	0.004
NK	0.070	0.070	0.000
SY	0.118	0.121	0.003
UA	0.268	0.277	0.009
WN	0.285	0.290	0.005

Notes: Unweighted averages by firm.

Table 35: **Price simulation for US Airways and American Airlines overlapping markets (with low-cost carriers operate in)**

Carriers	Pre-merger Price	Post-merger Price	Relative Changes
Merged carriers			
AA	310.044	314.411	1.41%
US	351.138	353.302	0.62%
Rival carriers			
AS	359.741	359.762	0.01%
B6	340.898	340.929	0.01%
DL	356.282	356.391	0.03%
F9	219.667	219.787	0.05%
NK	180.244	180.252	0.00%
SY	210.692	210.736	0.02%
UA	369.04	369.178	0.04%
WN	276.821	276.961	0.05%

Notes: Unweighted averages by firm.

Table 36: **Market share simulation for US Airways and American Airlines overlapping markets (with low-cost carriers operate in)**

Carriers	Pre-merger Market Share	Post-merger Market Share	Differences
Merged carriers			
AA	0.117	0.108	-0.009
US	0.207	0.201	-0.006
Rival carriers			
AS	0.089	0.090	0.001
B6	0.115	0.117	0.002
DL	0.212	0.217	0.005
F9	0.282	0.287	0.005
NK	0.070	0.070	0.000
SY	0.118	0.121	0.003
UA	0.230	0.236	0.006
WN	0.285	0.291	0.006

Notes: Unweighted averages by firm.

Table 37: **Price simulation for US Airways and American Airlines overlapping markets (without low-cost carriers operate in)**

Carriers	Pre-merger Price	Post-merger Price	Relative Changes
Merged carriers			
AA	321.521	346.668	7.82%
US	328.188	339.019	3.30%
Rival carriers			
AS	297.927	297.938	0.00%
DL	352.025	352.775	0.21%
UA	379.767	380.630	0.23%

Notes: Unweighted averages by firm.

Table 38: **Market share simulation for US Airways and American Airlines overlapping markets (without low-cost carriers operate in)**

Carriers	Pre-merger Market Share	Post-merger Market Share	Differences
Merged carriers			
AA	0.253	0.231	-0.022
US	0.354	0.351	-0.003
Rival carriers			
AS	0.013	0.013	0.000
DL	0.263	0.280	0.017
UA	0.322	0.341	0.019

Notes: Unweighted averages by firm.

Table 39: **Price simulation for Southwest Airlines and AirTran Airways all overlapping markets**

Carriers	Pre-merger Price	Post-merger Price	Relative Changes
Merged carriers			
FL	197.245	200.747	1.78%
WN	273.369	275.708	0.86%
Rival carriers			
AA	309.942	309.996	0.02%
B6	261.507	261.520	0.00%
CO	260.522	260.543	0.01%
DL	261.166	261.225	0.02%
F9	248.291	248.293	0.00%
NK	132.834	132.914	0.06%
UA	368.039	368.155	0.03%
US	376.200	376.285	0.02%
YX	120.847	120.867	0.02%

Notes: Unweighted averages by firm.

Table 40: **Market share simulation for Southwest Airlines and AirTran Airways all overlapping markets**

Carriers	Pre-merger Market Share	Post-merger Market Share	Differences
Merged carriers			
FL	0.167	0.158	-0.009
WN	0.225	0.223	-0.002
Rival carriers			
AA	0.215	0.217	0.002
B6	0.392	0.393	0.001
CO	0.095	0.096	0.001
DL	0.206	0.210	0.004
F9	0.016	0.016	0.000
NK	0.044	0.051	0.007
UA	0.218	0.222	0.004
US	0.133	0.138	0.005
YX	0.036	0.038	0.002

Notes: Unweighted averages by firm.

Table 41: **Minimum required efficiency for Delta Air Lines and Northwest Airlines overlapping markets**

	Unweighted	Weighted by market size
All Markets	6.8%	4.2%
Markets with LCC	9.8%	5.8%
Markets without LCC	10.8%	6.7%

Table 42: **Minimum required efficiency for United Airlines and Continental Airlines overlapping markets**

	Unweighted	Weighted by market size
All Markets	3.6%	2.2%
Markets with LCC	1.3%	0.7%
Markets without LCC	2.4%	1.5%

Table 43: **Minimum required efficiency for US Airways and American Airlines overlapping markets**

	Unweighted	Weighted by market size
All Markets	1.8%	1.0%
Markets with LCC	1.5%	1.0%
Markets without LCC	9.8%	5.7%

Table 44: **Minimum required efficiency for Southwest Airlines and AirTran Airways Airlines overlapping markets**

	Unweighted	Weighted by market size
All Markets	1.9%	1.6%

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