Airline Non-Price Competition Between FSC and LCC Carriers: Varying Airline Optimization Strategies

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Abstract

The goal of this paper is to extend the discourse surrounding certain topics in terms of airline optimization which is defined in this paper as the ability of an airline to efficiently transport goods and passengers as well as accrue revenue from its airplanes relative to its total capacity to transport goods and accrue revenue. Previous literature deals heavily with the differences between LCC and FSC carriers as well as the importance of both customer satisfaction and operational efficiency for the ability of an airline to compete. The analysis of this paper is in the form of a panel-regression performed on a dataset obtained from the T1 Airline Summary Statistics form maintained by the Bureau of Transportation Statistics. This data demonstrates the relationship between dependent variables represented by certain metrics of airline success, revenue passengers enplaned, revenue passenger miles and revenue ton miles, with independent variables that reflect optimization in terms of both payload and passenger transport. These variables are influenced by factors such as certain measures of timeliness competition defined in this analysis as ramp inefficiency and departure efficiency.

JEL Classification: L93; D22; R4; L13

Keywords: Aviation; Optimization; Airline Efficiency; Firm Competition; Customer Satisfaction

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I Introduction

The domestic US airline industry is incredibly large and complex. In 2023 alone the Bureau of Transportation statistics reported that the US airline industry carried 763 million passengers and 22.653 billion pounds of freight or mail on 7.978 million departures (Airline Activity: National Summary 2024). As such it is obvious there is a high degree of coordination, efficiency and optimization required to maintain firm success in the airline industry. Covid-19 provided a unique challenge to this large and interconnected industry which has time and time again proven itself vulnerable to the greater economic trends of the world (Fraher 2014, Kim and Gu 2004, Efthimiou 2008). Faced with historic low levels of air travel demand, passenger airlines without the source of revenue upon which they typically rely were forced to adapt to new levels of passenger demand in order to survive. One way they were able to do so was to turn to sources of revenue not impacted by passenger travel regulation; freight and mail transport. The main goal of this research is to evaluate whether there exists relationships between airline revenue optimization, airline efficiency and airline success and, if they do exist, how they vary between the two differing airline carrier strategies. These relationships will also be examined before and after the onset of the Covid-19 pandemic to determine the presence of any long-term impacts on the industry.

The initial intuition which sparked this research topic came from many conversations with United pilots during Covid who, instead of being furloughed as many other pilots had been, reported a high volume of wide-body aircraft flights relative to present demand and a higher volume of freight per flight relative to present demand. These conversations provided merely circumstantial evidence and necessitated further investigation which led me into an interview with the United Airlines directors Brian Landry-Wilson and Perry Lewis in an attempt to discern the validity of my potential research questions[1]. When it comes to the airline industry, just as research suggests, director Brian Landry-Wilson confirmed that the entire domestic US industry was forced to adapt to a major “shock to the system [of airline transport]”. This shock occurred with the onset of the Covid-19 pandemic and had caused changes some at the time saw as permanent, long run changes to air travel demand. One of these changes is what director Perry Lewis called a shock to “business travel demand which is recovering but still not to its pre-pandemic level” in a market where cargo transport demand remained virtually unaffected by pandemic travel restrictions. This interview sparked a research question focused on the shifting of airline assets and strategy to adapt to changing levels and types of demand. How did airlines attempt to maintain a revenue stream without high passenger demand during Covid? Did they shift focus to other streams of revenue such as freight and mail carrying? Are there any visible long-term impacts that, even now years after the end of pandemic restrictions, are visible within the industry?

These research questions will serve as the foundation of this thesis but there is, however, another angle of these questions that necessitates analysis. Full service carriers (FSCs) and Low cost carriers (LCCs) are the two main carrier strategies of which the domestic US industry is comprised. A full service carrier operates on a hub-and-spoke model in which multiple regional hubs are established to ferry large numbers of passengers outside of smaller hubs to a point where large-scale transport is more efficient per passenger. These hubs are inherently sources of intense competition given their interconnectedness to the greater air transport system (Feng et al. 2022). LCCs operate in various degrees of point-to-point models of operation. These airlines,

[1] See appendix A for further details on the nature of the interview

though they have isolated regional hubs in many instances, spend less effort ferrying passengers to these hubs and instead use smaller, cost-effective aircraft to transport a smaller number of passengers from point to point. Given the strict divide in method of operation, another research question arises: are there differences in the way that FSCs and LCCs reacted to Covid and are there differences in their strategies of payload optimization that are reflective of their greater strategies of operation? These research questions build most closely upon the similar research of Adrangi and Hamilton which concluded a positive relationship of market concentration and airline firm performance.

This research occurs over the past 21 years of available data from the Bureau of Transportation Statistics or BTS; 2003-2023. For the purposes of this research, optimization is defined in a multitude of ways. An optimized firm uses its inputs of capital and labor to their highest level of effectiveness. In the airline industry, an optimized carrier is therefore one that optimizes the use of its airplanes both in its ability to carry cargo and passengers, and a carrier that optimizes the use of its personnel, not only in the form of pilots but in the form of ground crews that make the systems of the airline industry run efficiently (Rubin et al. 2005). There is no such measure of labor optimization present in this analysis but there are additional measures of ramp inefficiency and departure efficiency which are reflective of the reliability of a carrier and the ability of an airline to satisfy the timeliness desire of passengers (Hutter and Pfennig 2023). These two measures, rather than indicating aircraft optimization, are intended to describe the efficiency of airlines and their systems.

The main independent variables of analysis are payload efficiency, passenger efficiency, freight efficiency, mail efficiency, ramp inefficiency, departure efficiency and two dummy variables for FSC carriers and Covid. The dependent variables are revenue passengers enplaned, revenue passenger miles and revenue ton miles which have been chosen since they are indicative of the success or failure of an airline to accrue revenue from either of its two main sources; passengers and cargo. The central hypothesis of this research is that an airline which optimizes its aircraft to carry both passengers and freight or mail will have a positive relationship with revenue passengers enplaned, revenue passenger miles and revenue ton miles. While the actual mechanisms of this optimization remain unclear both in theory and practice, the purpose of this research thesis is to identify relationships within areas of performance so as to suggest that payload optimization is actually an indication of a healthily functioning passenger carrying airline.

This thesis is structured to review literature surrounding the discussion of carrying airline strategies in section two followed by a discussion of the theories of price and non-price competition in section three. The fourth section describes the dataset used for analysis in this research, the methods by which it was obtained and trimmed, and the distributions and descriptives of the variables of interest within the dataset. The fifth section reviews the empirical methodology followed by a discussion of the regression results in the sixth section and the conclusions reached by this research in the seventh and final section.

II Literature Review

The airline industry today is characterized by vicious competition both in the form of price and non price competition. It did not, however, always exist in such a state. Deregulation of the domestic market began in the United States with the Deregulation Act of 1978 (Abdi, Li and Càmara-Turull 2023). Absent the previous restrictions on price, capacity, entry and flight frequency, (Abdi, Li and Càmara-Turull 2023; Xiaowen et al. 2010; Hannigan et al. 2015) the airline industry was propelled into a free market system ripe with changing power dynamics (Cohen 2000; Adrangi and Hamilton 2023; Seong-Jong and Fowler 2014). Airlines that previously found competition only from other major carriers were now faced to compete with smaller low cost carriers who proved to have many advantages over their larger competitors in regional markets (Sun 2017; Hannigan et al. 2015).

The first of these advantages was the market strategy of LCCs. Many LCC carriers isolate small markets consisting of a handful of select individual routes and operate under a point-to-point system. LCC carriers can offer customers cheap, reliable, consistent service within a region or between a handful of cities which was a major threat to major airlines following deregulation (Ren 2021). The FSCs model of operation, hub-and-spoke, operates on the idea of economies of scale (Nasrollahi and Abdi 2023; Adrangi and Hamilton 2023). When demand for travel for a particular city is high in multiple different regions, it is more cost effective to transport all of these passengers to a central location, a hub, before transporting them all on a single flight to the final destination. This saves money on the multiple individual flights that it would take to transport all passengers from the initial point of origin to the desired destination for each passenger and first arose as a major strategy during the post-deregulation period (Rubin and Joy

2005). There is the threat of competition from LCC firms, however, on individual routes which has been shown to actually encourage FSC efficiency (Xiaowen et al. 2010).

The services necessary to maintain a large hub-and-spoke operation are incredibly expensive. Not only is a high level of capital required, both in the form of personnel needed to fly aircraft, manage the boarding process, load cargo and baggage and serve the passengers, but also in the form of equipment needed to maintain aircraft. Baggage carts, ramp vehicles, cargo loaders and the airplanes themselves are not only necessary for the swift operation of any airline but also expensive to purchase up front and maintain. Absent the cost of capital and maintenance, there is also a cost of real estate. Airlines need landing slots, hangars and gate slots in order to access passengers and run their airline and, unlike privately run airlines, these services are provided by privately owned firms within publicly owned airports (Chun-Hung 2023). These costs are a prime example of why following the airline deregulation act, major carriers faced intense competition from smaller operations on a regional basis who did not require large, expensive hubs to maintain an efficient operation. Major carriers, therefore, need to maintain efficiency of operations and maximize the use of their airplanes in order to offer services that compete with LCC carriers in smaller short-haul markets where the point-to-point method of operation is most effective (Ren 2021).

When faced with competition against LCC firms, many FSC carriers react by adopting an airline-within-airline (AWA) model. This model exists in many specific markets throughout the world and consists of a partnership between a regional LCC and larger FSC firm (Gil, Kim and Zanarone 2022). This can also manifest, as with many US carriers, as an airline directly created by an FSC to operate as an LCC partner (Khan et. al 2022). Two examples of this are American Eagle and United Express. One of the main concerns of the partnership between FSC and LCC firms is collusion in the forms of wages and pricing. This can result in the labor market from recruiting pipelines between regional carriers and FSC firms (Dimick 2023; Yang 1995; Masur and Posner 2023) or in air transport markets without sufficient levels of competition. This can happen as the result of a merger of two airlines which share similar routes (Bos, Iwan, and Marco 2023; Moss 2019).

In domestic markets, FSC carriers partner with smaller regional carriers and maintain contracts for capital, landing slots, pilots, passengers and/or cargo. In international markets, FSC carriers partner with other international carriers as well as smaller LCC carriers to form airline alliances. The same coordination of assets within these alliances allows traditionally expensive-to-operate FSC carriers to utilize the airport real estate, capital and systems efficiency which would otherwise necessitate sunk cost investment (Xiaowen et al. 2010). Much research has been done on the impact of high sunk capital costs on the airline industry (Dissanaike, Jayasekera and Meeks 2022) and its role in inhibiting competition and encouraging oligopic market structures heavily characterized by collision.

When entrance is possible and not prevented by capital cost barriers to entry, LCC firms pose a threat to any existing FSC or LCC carriers. The entrance of an LCC firm has been shown to force already existing airlines to lower costs (Sancho-Esper 2019) and potentially concede market concentration (Ren 2021; Batkeyev et al. 2019). This is evidence of price competition rather than non-price competition. There is also research which suggests the use of electronic transaction methods can shift market structure from oligopic to monopolistic or perfectly competitive (Aziz 2023) which could further explain the degradation of traditional oligopic structure in the airline industry.

Price competition often results if an LCC threatens to isolate a particular route or hub or corner market share within that route (HÃschelrath and MÃller 2013). Non-price competition often results if LCC and FSC firms are already operating with efficiency making price-competition unprofitable. In this instance carriers must resort to traditional oligopic non-price competition (Rubin and Joy 2005). The use of both could be due to a variety of factors, namely the duopoly that exists between FSC and LCC firm competition. Firms face competition both within their own class of service and between the two classes of service. Non-price competition may be the most effective tactic to compete against firms of a similar class (Dastidar 2017) but is less effective than price-competition against firms of a separate class (Batkeyev et al. 2019; HÃschelrath and MÃller 2013).

Although the traditional notion of a perfect oligopoly can be challenged by the presence of price-competition, non-price competition does still have a very palpable presence within the airline industry. In order to maintain market share airlines need loyal customers who are willing to continue to support their brand and purchase their services instead of choosing to support an airline of either a similar or different service class (Min and Min 2015). Most airlines have loyalty reward programs, offer inflight amenities, offer credit cards and reward mileage points or even bundle their air transport services with hotels and rental car companies (Rubin and Joy 2005). The quality and presence of these services does vary between LCC and FSC carriers (Min and Min 2015). In-flight amenities are often more rare and of worse quality on LCC flights. Research suggests that these differences in non-price competition are representative of the customer bases of these respective airline types. LCC customers care more about the cheap price of their ticket than the service they receive (Kim and Hwang 2019). As such they are more likely to react positively to customer loyalty programs and services out of surprise for being offered amenities or services they did not expect to receive (Batarlienė and Slavinskaitė 2023). FSC customers on the other hand are choosing to pay a higher price for their ticket under the assumption they will receive amenities and service (Kim and Hwang 2019). This makes FSC customers more likely to react negatively to customer loyalty programs and services if they fail to meet expectations (Batarlienė and Slavinskaitė 2023).

The question remains, however, as to how price and non-price methods of competition relate to our central research questions on optimization and efficiency. Literature suggests major differences between the general operating strategies of FSC and LCC firms (Qiang 2020). Not only do they operate on different scales, with different pricing and service qualities, but they operate with different capital and with different goals (Negotiation and corporate strategy 2019). The hypothesis of this research is that FSC firms will exhibit more often payload optimization because FSC operations are more costly and expansive. They require more capital to run smoothly, operate with more aircraft out of larger hubs and operate with larger aircraft capable of carrying higher volumes of passengers and payload on larger short-haul and long-haul markets. As such, FSC carriers are hypothesized to have more systems of efficiency which would make payload optimization more feasible. In terms of non-price competition, FSC firms are more often than LCC firms undercut in terms of price and service class by competing airlines. Additionally, economies of scale suggests that larger operations exhibit higher efficiency, which can be applied to the size and scope of FSC operations in contrast to smaller LCC operations (Hutter and Pfennig 2023). For these reasons, it is hypothesized that FSC firms will need to maintain higher levels of efficiency and departure reliability in order to maintain customer satisfaction and customer loyalty and compete with non-price means.

III Theoretical Foundations

As previously mentioned, it would be ideal to examine the airline industry in a vacuum of perfectly oligopic competition such that non-price competition was the only form of competition. This is unrealistic, though, as it is also common for airlines to compete for market share by competitive pricing to corner certain markets or isolate routes. Due to the unavailability of pricing data in the BTS database, this research will focus solely on non-price competition as a form of competition between airlines. Non-price competition will be analyzed through the lens of customer satisfaction. Customer satisfaction is represented by the metrics of ramp inefficiency and departure reliability. These two components, timeliness and reliability, form a large part of the opinion of a customer towards an airline and their willingness to return as a customer (Nasrollahi and Abbi 2023).

Non-price competition is visible in many aspects within the airline industry even with the presence of price competition. There is extreme product differentiation across the duality of FSC and LCC carriers and although FSC and LCC carriers undoubtedly compete amongst each other, their level of service and price are incredibly different. This means carriers must carefully choose a customer base, either low-maintenance low price or high-maintenance high price, and differentiate their product with respect to that customer base in order to maintain customer satisfaction (Adrangi and Hamilton 2023, Dwesar and Sahoo 2022, Kim and Hwang 2019).

In terms of firm efficiency there are two major competing models that describe two different mechanisms of the relationships between efficiency and firm performance. The results of this research are described with muted analysis of causal mechanisms through perspectives of each theoretical mode. The first model is the Structure Conduct Performance paradigm referred to as SCP. This paradigm was first proposed by Harvard economist Edward Mason in 1925. His work was further improved upon by Harvard economist Edward Chamberlain and Joan Robinson who separately published on this topic in 1933. It is the interaction of these three economists' work, as well as extensive research done since such as the work of Joe Bain at UCLA in the late 30s and early 40s, which form the foundation of the theory of structure conduct performance (Panhans 2023).

The foundational concept of this model is that a market that is more highly concentrated reflects an environment which drives out weaker firms and encourages better performance in firms within the market (Cohen and Mazzeo 2004, Clarke 1992, Lelissa and Kuhil 2018, Delorme et al. 2002). In this sense the direction of causation suggests that optimization and efficiency cause increased performance because of the structure and concentration of the market within which the firm operates. Research has been done to apply the principles of SCP to various other industries, for example the baking industry by Cohen and Mazzeo in 2004, but this has yet to be done within the airline industry.

The independent variables of this paper’s analysis are payload efficiency, passenger efficiency, freight efficiency, mail efficiency, ramp inefficiency and departure efficiency. They are hypothesized to have a relationship with the dependent variables revenue passengers enplaned, revenue passenger miles and revenue ton miles. From the perspective of the SCP paradigm, a more highly concentrated airline industry will encourage optimization and efficiency within FSC and LCC firms. Therefore it is also hypothesized that airlines with better metrics of optimization and efficiency operate with more success than airlines that do not have the same degree of optimization across these metrics.

The Demsetz model offers an alternative theory to the SCP paradigm and argues that it is the efficiency of individual firms which leads to superior performance within an industry rather than the efficiency imposed by market concentration (Demsetz 1973; Maltsev and Yudanov 2023). This model could be thought of as similar to natural selection. The mechanism of causation is reversed in comparison to the SCP model, such that performance causes a need for optimization and efficiency at risk of firm failure (Demsetz 1973). This model would suggest that any relationship between revenue passengers enplaned, revenue passenger miles or revenue ton miles with optimization metrics would be due to the carrier's size (Maltsev and Yudanov 2023). Airlines with more revenue passengers enplaned, revenue passenger miles or revenue ton miles operate on a larger scale, and any firms that operate on a larger scale have an increased necessity to be efficient. Analysis of causation in this paper’s analysis will be limited and the results of this paper’s regression will consider possible relationships between the independent and dependent variables that could coincide with both models.

IV Data

The data set that has been compiled for this thesis consists of T-1 summary statistic data obtained from the Bureau of Transportation Statistics. The T-1 form is created by the BTS from the submission of T-100 forms after the completion of each flight. These flight report summaries include data on total payloads, passengers carried, passenger capacity, freight carried, mail carried and distance traveled dating back to January, 1977. The BTS uses this flight data to calculate other monthly metrics of airline performance by summing up the total values for an airline reported in the T100 form each month. These sums are then transferred into the T-1 form and have been used to create the efficiency and optimization measures that serve as the independent variables as well as the measures of airline performance that serve as the dependent variables for this analysis.

The optimization measures were generated as a set of ratios between each airline's reported revenue from passengers, freight and mail relative to their available capacity to accrue revenue from carrying passengers, freight or mail. These are titled passenger, freight and mail efficiency and reflect each airline's ability to optimize revenue stream from multiple different sources in their aircraft each month. Additionally, although they are not used in the final regression analysis, ratios of the revenue from each of these sources out of total revenue from all sources were generated in order to gain a better understanding of how each of these categories accounts for total airline revenue. These are titled passenger, freight and mail margin. The final optimization variable created from the available data is titled payload efficiency which is the ratio of total revenue ton miles relative to total available revenue ton miles.This variable was created to reflect total cargo optimization for an airline holding freight and mail optimization constant and vice versa. These four independent variables serve as the main indicators of an airline's optimization strategy.

In order to measure an airline's ability to compete and satisfy customers, something that is separate from an airline’s ability to optimize its use of aircraft, two additional variables were created. The first is the natural log of ramp delay. This variable is the natural log of the difference in time an aircraft spends in the air compared to total time the passenger spends in the plane. This approach was chosen instead of creating a ratio, as was done with the optimization measures, because a ratio of time in the air to total time in the aircraft would include an underlying relationship with the distance and length of the flight. As the ramp inefficiency measure becomes lower, it is indicative of an airline which is consistently more efficient and less often experiences ramp delays. Ramp delays are often not in the control of an airline, and can often result instead from traffic congestion at a busy airport, a closed runway, weather or even security issues that would force an aircraft to return to the gate or hold in place. Even though these events are outside of the control of the airline, it is a major assumption of this paper that these situations are common enough, weather and ramp congestion in particular, to be calculated into an airline's efficiency strategy. If, as an arbitrary example, an airline chooses to operate out of the northeast, an airline better optimized to this environment with more experienced flight crews, flight planning departments and maintenance will be able to better predict and react to the weather conditions in that environment to maximize air transport efficiency for its passengers. The second variable which has been created to measure efficiency is named departure efficiency. This variable is a ratio between an airline’s total scheduled miles each month and the actual flown miles each month. This ratio accounts for an airline's reliability as far as cancelation that may occur due to weather, maintenance or a misallocation of resources which leaves a gate without a plane. It does, however, have the possibility to include positive bias if an airline decides to fly more flights per month than was initially scheduled. A lower ratio indicates a decrease in an airline's monthly miles in comparison to its total scheduled miles and a lower level of departure reliability. These two efficiency measures were created to understand the relationship of airline performance and certain metrics of non-price competitiveness, timeliness and reliability, which severely impact customer satisfaction and loyalty (Kim et al 2023, Batarlienė and Slavinskaitė 2023). The variables of interest within this dataset are reported in tables 1 and 2 below alongside their description and the ratio used to calculate them.

Table 1

Independent and dependent variable descriptions

Name	Description	Type	Formula
Dependent Variables			
lnpax_enplaned	Natural log of enplaned passengers	Float	ln(rev_pax_enp)
lnpax_miles	Natural log of passenger miles	Float	ln(rev_pax_miles)
lnton_miles	Natural log of ton miles	Float	ln(rev_ton_miles)
Independent Variables			
Payload_eff	Payload efficiency	Float	ton_miles / avl
Pax_eff	Passenger efficiency	Float	pax_miles / avl
Mail_eff4	Mail efficiency	Float	(ton_miles_mail / avl)^(0.25)
Freight_eff	Freight efficiency	Float	ton_miles_freight / avl
Dep_eff	Departure Efficiency	Float	miles_flown / miles_sch
lnramp_ineff	Ramp inefficiency	Float	Hrs_ramp - Hrs_air
Dummy Variables			
FSC	Indicator of an FSC carrier	Float	-
Covid	Indicator of the onset of Covid-19	Float	-
Interaction Control			
Payload_Pax	Payload-Passenger interaction control	Float	Payload_eff * Pax_eff
Cargo_eff4	Freight-Mail efficiency interaction control	Float	Freight_eff * Mail_eff

** "avl" indicates avl_ton_miles or avl_pax_miles for Payload_eff, Pax_eff, Mail_eff and Freight_eff and was omitted out of interest of spacing*

Table 2

Revenue Margin Variable Descriptions

Name	Description	Type	Formula
Revenue Margin Variables			
Pax_marg	Margin revenue from passenger transport	Float	ton_miles_pax / ton_miles
Mail_marg	Margin revenue from mail transport	Float	ton_miles_mail / ton_miles
Freight_marg	Margin revenue from freight transport	Float	ton_miles_freight / ton_miles

After trimming the BTS T1 dataset to contain the variables of interest, it still contained a multitude of issues that made the analysis of this question difficult and would have made any potential regression results unreliable. Firstly, the dataset contains reports from all domestic US airlines. In order to truly examine the trends of interest, this dataset needed to be trimmed down to a handful of airlines that reflect the majority of domestic market share and the large FSC and LCC firms that adhere to the theories this research is founded on. As such, the dataset was trimmed to contain only a handful of FSC and LCC airlines that capture the high majority of domestic US airline transport. In the US, there are only 3 major FSC carriers: Delta Airlines, American Airlines and United Airlines who comprised in 2023 17.8%, 17.2% and 16.0% of the domestic US market according to the BTS (Airline Domestic Market Share 2024). These were included in the trim. There is a much larger count of relevant LCC carriers since they often operate on a regional basis and have smaller total market share. The LCC carriers included in the dataset are Southwest airlines, Alaska, JetBlue, Spirit Airlines, Frontier, SkyWest, Hawaiian, Envoy, Allegiant and Endeavor who comprised 17.2%, 6.3%, 5.2%, 5.1%, 3.6%, 2.3% and 1.7% of the US domestic market respectively (BTS 2023). Envoy, Allegiant and Endeavor airlines are not in the top ten largest airlines by market share and therefore comprise some unknown proportion of the remaining 7.6% of US domestic market share at individual values less than 1.7%. They were included for regional presences in the American Southwest, Southeast and Midwest mainly. Although many of these LCC airlines do have hubs from which the majority of their operations occur, they are considered LCCs for their quality, pricing, regional presence, low domestic market share and lack of a system of major hubs throughout the country characteristic of a larger FSC hub-and-spoke airline. After the T-1 forms were trimmed to contain only these airlines, an FSC dummy variable was created which would be later used to identify statistical significance between these two groups.

The next challenge that was faced with the usage of this dataset was inconsistencies with reporting. Before 2003, airlines reported how much of their revenue was accrued from first class passenger tickets and coach tickets in two separate categories. This presented an excellent opportunity to analyze the optimization of airline revenue between these groups given their differences in ticket sale strategies and pricing. However, starting in January 2003 to the end of the dataset in December 2023, all airlines reported passenger revenue as 100% first class ticket revenue in the T1 form. This issue in the dataset reporting renders the analysis of first class and coach revenue inconsistent and inaccurate since the accuracy of the reporting is only viable before 2003 which is obviously outside the scope of the pandemic. Inaccurate reporting impacted a handful of other variables as well, namely revenue aircraft miles flown and revenue aircraft miles scheduled which were unfortunately not reported by any airlines prior to 2003. These reporting issues necessitated a decision to cut any observations prior to January 2003. Following the trim, a dummy variable was created with respect to the timeline of Covid-19. This dummy variable, aptly named 'Covid', was created to indicate if a given observation from an airline is reported before or after March, 2020. Although Covid restriction did not begin officially until mid-march of 2020, the reported observations of that entire month are skewed which is why it was included in entirety as a Covid month. Covid restrictions loosened up and reconstricted multiple times during 2021 and 2022. The reason that all observations after March 2020 are included is to test the hypothesis that permanent changes to the airline industry have persisted past the end of Covid restrictions.

The three dependent variables of interest are total revenue passengers per month, total passenger miles and total revenue tons. The natural log of these variables was taken to normalize the weighting of their magnitude, and the three dependent variables of interest for the three main regressions are lnpax_enp, lnpax_miles and lnton_miles. These three variables were chosen as dependent variables because of their significance to the success of any operating airline.

In addition to these variables, two interaction control variables were added to the dataset, Payload_Pax and Cargo_eff, that were introduced with the intent of controlling for the interactions between payload and passenger efficiencies as well as freight and mail efficiencies. The decision to include these variables was made due to their high correlation, greater than 0.3, amongst each other. The descriptive statistics for all variables of interest following the trim are reported in table 3.

Table 3

Descriptive Statistics

Variable	Mean	Median	Min	Max	Std. Dev	Obs
lnpax_enp	13.031	13.2566	0.693	16.556	1.892	21,142
lnpax_miles	20.401	20.676	6.397	23.305	1.779	21,146
lnton_miles	18.209	18.387	6.349	21.011	1.792	21,221
Payload_eff	0.605	0.606	0.111	0.954	0.124	21,221
Pax_eff	0.778	0.808	0	0.964	0.122	21,171
Mail_eff4	0.159	0.183	0	0.986	0.142	21,221
Freight_eff	0.051	0.014	0	0.463	0.067	21,221
Dep_eff	0.998	0.996	0.001	2	0.056	21,221
lnramp_ineff	13.031	13.257	0.693	16.556	1.892	21,142
FSC	0.446	0	0	1	0.497	21,221
Covid	0.191	0	0	1	0.393	21,221
Payload_Pax	0.480	0.492	0	0.911	0.139	21,171
Cargo_eff4	0.0146	0.00269	0	0.187	0.0227	21,221
Pax_marg	0.897	0.969	0	1	0.149	21,221
Mail_marg	0.00833	0.00193	0	1	0.0226	21,221
Freight_marg	0.0955	0.0226	0	1	0.137	21,221

The dataset functions mostly as designed following the set trims and calculations. At first glance, the ratios and margins lie between 0 and 1 and instead of having unfathomably large values for passengers, passenger miles and ton miles, the dependent variables lie on a much more reasonable scale. One issue that was presented was unfathomably low values for the mail efficiency ratio. This skewed the weighting of the magnitude of coefficients and statistical significance in the first regressions that were performed as well as the heteroskedasticity.

Initially, the natural log of this ratio was taken to create a new variable, lnmail_eff, but this introduced challenges of its own. An unproportionately high number of LCC months occurred absent the transport of any mail, which cut down the number of observations present in the regressions of interest to 13,465. No FSC observations were cut, meaning 9,465 of the 13,465 were FSC. This introduced bias to the regression analysis and necessitated change. Instead of transforming the mail efficiency variable with natural log, the cubed root was taken instead. This transformation manages to still constrict the mail efficiency ratio between zero and one and removes many of the aforementioned problems with magnitude and heteroskedasticity within the data. This new ratio was used to recalculate the cargo efficiency interaction control variable. They are named Mail_eff4 and Cargo_eff4 and are included in table 3 instead of Mail_eff and Cargo_eff.

The descriptive statistics further demonstrate how, across the FSC and LCC groupings, there are various notable differences. FSC carriers on average and at the median have higher enplaned passengers, revenue passenger miles, revenue ton miles, mail margin, mail efficiency, freight margin, freight efficiency and ramp inefficiency. LCC carriers have on average and at the median higher payload efficiency and passenger margin. The predicted and observed relationships within this dataset have been tested for statistical significance using t-tests. The results are shown in the table below.

Table 4

T-tests of significance across FSC grouping grouping

Variable	FSC	LCC	t
lnpax_enp	13.30	12.81	-18.87
lnpax_mil	21.19	19.76	-63.47
lnton_mil	19.13	17.47	-75.32
Payload_eff	0.59	0.62	19.49
Pax_eff	0.777	0.778	0.353
Mail_eff4	0.28	0.06	-1.8E+02
Freight_eff	0.099	0.013	-1.2E+02
Dep_eff	0.99	1.0	7.47
lnramp_ineff	7.58	7.25	-12.85
Payload_Pax	0.46	0.49	15.03
Cargo_eff4	0.030	0.002	-1.1E+02
Pax_marg	0.81	0.97	94.99
Mail_marg	0.016	0.002	-44.31
Freight_marg	0.178	0.027	-94.83

Table 5

T-tests of significance across Covid

Variable	Before	After	t
lnpax_enp	13.1	12.9	4.03
lnpax_mil	20.43	20.27	5.09
lnton_mil	18.23	18.12	3.46
Payload_eff	0.61	0.57	19.86
Pax_eff	0.79	0.69	56.73
Mail_eff4	0.16	0.14	8.68
Freight_eff	0.049	0.058	-6.87
Dep_eff	0.999	0.988	10.76
lnramp_ineff	7.397	7.403	-0.15
Payload_Pax	0.49	0.41	32.03
Cargo_eff4	0.014	0.018	-9.30
Pax_marg	0.91	0.86	19.38
Mail_marg	0.008	0.012	-10.92
Freight_marg	0.086	0.132	-19.25

With a 95% confidence interval and the usage of t = +- 1.96, all of the t-tests indicate statistically significant differences across both FSC and Covid groupings. The two exceptions to this are passenger efficiency across the FSC grouping and ramp inefficiency across the Covid grouping. These tests of significance confirm in greater detail many of the relationships described within the literature review and theoretical foundations. FSC carriers have larger operations and carry more passengers and cargo over a greater mileage. FSC carriers are more optimized for mixed-strategy transportation of specifically freight and mail but are outperformed by LCCs in terms of overall payload efficiency. This is likely due to differences in overall cargo capacity per flight. LCC carriers who typically operate smaller aircraft do not need to carry as much freight to fill up cargo capacity, and will subsequently receive less revenue per flight from cargo even if their efficiency per flight is high. Additionally, FSCs are shown here to be more ramp inefficient which is unexpected under the assumption that larger FSC operations at a wider variety and number of airports are more efficient than smaller LCC operations.

From the lens of the Covid grouping, the tests indicate that airlines did in fact shift airline optimization more towards mixed-strategy cargo transport after the onset of Covid-19. The data indicates that mail and freight have become more significant margins of revenue compared to passenger revenue margins which have decreased. The data also suggests that there is no significant difference in airline timeliness in terms of ramp inefficiency that could have resulted in these shifting margins through non-price competition mechanisms. Departure reliability, however, did decrease with statistical significance. There are also statistically significant decreases in enplaned passengers, passenger miles and ton miles across the Covid grouping.This suggests that leftward demand shocks for air transport both in terms of passenger and cargo transport did in fact exist and have yet to rebound as of December 2023.

While the predicted relationships do correspond to the hypothesis of this research, there are limitations to this dataset and the relationships being described within it. The dataset in hand does an excellent job of analyzing certain components of airline optimization and efficiency but there are additional variables that would have improved the analysis. While the dependent variables central to this research are measures indicative of revenue and specific sources of revenue, it must be stated that revenue does not necessarily equal success (Adrangi and Hamilton 2023). Any increase in revenue met with equal or greater increases in cost would be considered unsuccessful. Given this, financial indicators that have been left out of this dataset prevent the analysis of costs, namely fuel and personnel, as well as profit. These would be excellent indicators of efficiency from a financial perspective.

Another mode of airline efficiency not included in this data set is efficiency of personnel. If data could have been made available so as to discern the number of personnel working in different categories within an airline, there would be a greater understanding as to the specific mechanisms of shifting optimization within the two competing airline models. Although the BTS provides labor employment data, it is reported quarterly rather than monthly, and is plagued by many of the same reporting reliability errors as the T1 form. These factors made the labor data unfeasible to integrate into the present dataset.

In addition to the t-tests which were performed across groupings, the next step in determining the structure of the main regression analysis was the construction of a correlation matrix. Within this matrix it was discovered that payload efficiency and passenger efficiency have high correlation of greater than 0.3. An interaction control variable named Payload_Pax was constructed as a result. Freight efficiency and mail efficiency were also found to have similarly high correlation of greater than 0.3. An interaction control variable named Cargo_eff was constructed as a result. The correlation matrix is shown in table 6.

Table 6
Variable correlation Matrix

Variable	1	2	3	4	5	6	7	8	9	10	11
1. lnpax_enp	1										
2. lnpax_miles	.91	1									
3. lnton_miles	.87	.99	1								
4. Payload_eff	.31	.25	.22	1							
5. Pax_eff	.36	.36	.30	**.61**	1						
6. Mail_eff4	.18	.45	.49	-.17	-.07	1					
7. Freight_eff	-.23	.10	.18	-.26	-.25	**.68**	1				
8. Dep_eff	-.06	-.04	-.03	.07	.08	0.02	.006	1			
9. lnramp_ineff	.97	.83	.80	.25	.23	.12	-.28	-.10	1		
10. FSC	.13	.4	.46	-.13	-.002	.77	.64	-.05	.09	1	
11. Covid	-.02	-.03	-.02	-.14	-.36	-.06	.05	-.07	.001	-.04	1

**the bolded values indicate the high correlation values which spurred the decision to include interaction control variables*

The results of this correlation matrix continue to confirm the hypothesized relationships across both FSC and Covid groupings. The matrix indicates a positive correlation between enplaned passengers, passenger miles, ton miles, mail margin, mail efficiency, freight margin, freight efficiency and ramp inefficiency with the FSC dummy variable. The opposite is true for overall payload efficiency, passenger margin, passenger efficiency and departure efficiency. This reinforces a number of hypotheses first discussed following the t-tests. Once again, this correlation suggests that FSC carriers are larger. The operations of these three airlines in terms of total passengers, revenue miles and ton miles are larger than the combined operations of the ten LCC firms in this analysis. Once again, these values of correlation suggest FSC carriers are more optimized for mixed-strategy operations and less optimized for passenger operations. FSC correlates negatively both with passenger margins and passenger efficiency, suggesting that the LCC strategy is both more reliant/focused and efficient at passenger transport. In contrast to this, the correlation values here suggest that FSC carriers are more efficient in terms of freight and mail transport and accrue a higher margin of revenue from these operations than LCC firms do. One major reason for this, which will be analyzed in greater detail in the next section, is the heavy use of wide-body aircraft by FSC carriers. Typically, only FSC carriers operate these large aircraft which have the ability to transport greater amounts of cargo and passengers over greater distances.

These correlation values also indicate that FSCs, which have much larger operations under a hub-and-spoke model, are more ramp inefficient. This contradicts an earlier hypothesis which suggested economics of scale may make larger FSC operations more efficient. FSC carriers have more resources, larger operations, more personnel and perform operations over a wider variety of environments and regions in the United States. Whether or not this scale of operation is cost effective remains outside the scope of this analysis, but regardless of cost effectiveness, it is not beneficial for airline timeliness in comparison with LCC carriers.

The relationships across the second grouping, Covid, also demonstrate the presence of certain relationships, namely a positive relationship of Covid and mail margin, mail efficiency, freight margin and freight efficiency. All other factors, overall payload efficiency, passenger margin, passenger efficiency, and departure efficiency, have a negative relationship with Covid. Once again, this suggests a shift in airline optimization towards mixed-strategy transport in which mail and freight became a more important source of revenue when passenger demand was facing a massive negative shock. However, while this suggests mixed-strategy optimization between passenger and freight improved, it also suggests that operational efficiency declined in terms of reliability. Ramp inefficiency is correlated at 0.001 and will be considered here as non-correlation in either direction. Departure efficiency on the other hand correlates negatively with Covid likely a result of the high volume of flight cancelation upon the onset of Covid.

IV.I Additional Data Analysis: Wide-body Aircraft Usage

Given that the main dataset for this thesis was a summary dataset created by the BTS from transformation performed on the T100 form, I decided to do a separate but smaller analysis of the variables within the T100 form to look for any relevant patterns. The T100 dataset was created from flight reporting dating from January, 1977 to December, 2023. In order to isolate trends relevant to the discussion of the pandemic, the dataset was trimmed to include only observations in the past ten years of available data from January 2014 to December 2023. The dataset contains flights from every single US commercial airline each month, and therefore contains a large amount of irrelevant data since many of these airlines operate with a negligible market share or operate outside of the larger commercial airline industry. Upon examining the contents of the dataset, it became clear that not much additional analysis could be performed. There was, however, one incredible variable of interest that can offer insight to the restructuring of airline strategy during the pandemic. Since the data is reported on a flight by flight basis rather than monthly, each observation reports the type of aircraft that was flown. As mentioned previously, there are vast differences in the fleets operated by LCC and FSC carriers given their vastly different operating strategies and areas of operation. One such difference is the sole usage of wide-body aircraft by FSC and not LCC firms who tend to focus on operations conducted with a single model of aircraft (Negotiation and corporate strategy 2019). A wide-body aircraft can be classified two separate ways; firstly by wake turbulence metrics and secondly by the presence of two internal rows rather than a single internal row characteristic of a narrow-body aircraft. The latter will be used for the purposes of this analysis.

In order to discern the usage of wide-body aircraft, the relevant domestic US market needs to be isolated. The T100 form reports data for domestic US airlines both in international and domestic markets. Only the T100 domestic will be considered. In order to further isolate the market of interest the T100 forms would need to be trimmed to specific commercial airlines. This was done in a different manner than the T1 data set was. Instead of trimming directly for airlines of interest, I wanted the analysis done within the T100 dataset to be an analysis of wide-body aircraft usage in comparison to narrow-body aircraft usage by any airline which had the capability to operate either. Therefore the dataset was trimmed to only contain flights performed by certain wide-body and narrow body aircraft.

Of the aircraft of both types that were selected, all variants and models of the listed base aircraft aircraft were selected for analysis and specific detail or number of the multiple variants for each aircraft will not be disclosed alongside the base model. The narrow-body aircraft that were selected were the Boeing 717, 727, 737, 737 MAX, 757, Airbus A318/19/20/21, and McDonald Douglas DC9, MD80 and MD90. The Airbus A220 is becoming incredibly popular as a narrow-body aircraft in the domestic market but was unavailable given the time period of analysis. The Boeing 757 is considered a wide-body aircraft due to its wake turbulence metrics although it contains only one internal row. Because of this it has been included in the narrow body designation. The wide-body aircraft that were selected were the Boeing 767, 777, 787 and Airbus A330, A340, A350, A380, McDonald Douglas Dc10, and MD11.

In conjunction with the main hypothesis of this research that airlines optimized revenue streams from cargo payloads during Covid, a secondary goal of this research is to analyze the relationship of Covid with the usage of wide-body aircraft. Because they have the capacity to fly further distances and carry a greater volume of cargo, it is hypothesized that greater airline payload optimization occurs alongside more frequent usage of wide-body aircraft relative to total flights flown. In order to test if this increase in wide-body usage is statistically significant a dummy variable was created to indicate if a flight happens during the period of March 2020 to April 2022 which was the end of the final peak of Covid cases in the US. A t-test was performed across this group and the results are shown table 7.

Table 7
T-test Wide-body aircraft usage

T-test of significance	Wide_avg
Covid restriction	0.1504
Null	0.1164
t-score	-9.6E+02

Although it is only a small portion of the analysis of this thesis, the data from the T100 forms suggests that wide-body aircraft usage increased during the Covid-19 pandemic with statistical significance. This suggests, albeit does not prove, that airlines had the capacity to shift towards freight and mail as alternate sources of revenue during the pandemic due to the increased performance characteristics of operations using wide-body aircraft. These relationships also suggest that, as hypothesized previously, the efficiency of wide-body aircraft made them viable targets for improvements in airline optimization during a period of demand shock similar to the one experienced upon the onset of Covid. There are limitations to these conclusions, though, namely the disproportionate impact of Covid restrictions on passenger only or mixed-strategy airlines in contrast to cargo only airlines which use wide-body aircraft for cargo-only operations. Additionally, because the dataset was not trimmed to contain only specific FSC and LCC airlines, these results are generalized across the entire industry instead of the specific firms of interest.

V Empirical Methodology

The methodology of analysis in this thesis is a series of three demeaned ordinary least squares panel regressions with dummy variables. The dependent variables are the natural log of revenue passengers enplaned, the natural log of revenue passenger miles and the natural log of revenue ton miles. The independent variables are payload-passenger interaction control, freight mail interaction control, payload efficiency, passenger efficiency, freight efficiency, the cubed root of mail efficiency, the natural log of ramp efficiency, departure efficiency, the FSC dummy variable and the Covid dummy variable. The payload-passenger interaction and freight-mail interaction control variables were included due to these variables high correlations, above 0.3, with each other, which may have otherwise experienced an increase in explanatory strength or a detraction of explanatory strength. The final trimmed data set contains 21,221 observations. Payload_Pax, lnramp_ineff, Pax_eff, lnpax_miles and lnpax_enp are missing 50, 79, 50, 75 and 79 observations respectively. Given the low number of missing observations the panel regression is balanced. The three regressions are structured in figure 1.

Figure 1

Description of the three main regressions

$$Lnpax\_enp = \beta 0 + \beta 1(a) + \beta 2(b) + \beta 3(c) + \beta 4(d) + \beta 5(e) + \beta 6(f) + \beta 7(g) + \beta 8(h) + \beta 9(i) + \beta 10(j) + \varepsilon$$

$$Lnpax\_miles = \Theta 0 + \Theta 1(a) + \Theta 2(b) + \Theta 3(c) + \Theta 4(d) + \Theta 5(e) + \Theta 6(f) + \Theta 7(g) + \Theta 8(h) + \Theta 9(i) + \Theta(j) + \varepsilon$$

$$Lnton\_miles = \omega 0 + \omega 1(a) + \omega 2(b) + \omega 3(c) + \omega 4(d) + \omega 5(e) + \omega 6(f) + \omega 7(g) + \omega 8(h) + \omega 9(i) + \omega 10(j) + \varepsilon$$

B0, Θ0 and ω0 are constant terms

ε is the error term

(a) = Payload_Pax; Payload-passenger interaction control

(b) = Cargo_eff4; Freight-mail efficiency interaction control

(c) = Payload_eff; Payload efficiency

(d) = Pax_eff; Passenger efficiency

(e) = Freight_eff; Freight efficiency

(f) = Mail_eff4; Cubed root of mail efficiency

(g) = lnramp_ineff; natural log of ramp inefficiency

(h) = Dep_eff; departure efficiency

(i) = FSC

(j) = Covid

The main objective of these regressions is to analyze the impact of optimization and efficiency measures both across carrier strategy groupings and time groupings. One of the limitations of the OLS approach is the possibility that the T1 data would be more applicable for a time series, fixed effects, diff-in-diff or two-way fixed effects regression analysis. The time series, fixed effects, diff-in-diff analyses were not possible given the way that the data has been recorded per unit time. These three regression techniques are unable to be used when time is represented as a non-integer or when there are multiple observations per unit of time. Both of these are true of the T1 dataset. A two-way fixed effects regression model could have been useful for determining mechanisms of causation within the relationships described in this data. However, this mechanism requires an instrumental variable which would need to be defined as any variable which affects the dependent variable through any mechanism other than the independent variables present in the two-stage regression. There was no such variable present in the T1 dataset and the correlation matrix serves as proof of this.

In choosing OLS as the method of analysis, there are many assumptions about the distribution of the data that could prove to limit the effectiveness of the results. One such assumption made when using OLS estimators is the independence of the dependent variables from the residuals. If there is an underlying relationship between the dependent variable and the residuals, this is an indication of an incomplete model. This could be due to omitted variable bias, in which a particular variable which has a high degree of explanatory power is not included. The relationship between this omitted variable and the dependent variable can be hidden instead within the calculated relationship of the dependent variable and the residuals or any of the independent variables and the residuals.

The opposite of omitted variable bias is commonly referred to as the ‘kitchen sink approach’ in which too many variables are just simply thrown into one giant regression in an attempt to explain every little detail of the relationship between the independent and dependent variables.

With a large number of variables which may have been included without any theoretical justification, the actual driving force of the relationship between the independent and dependent variables can become unclear. Additionally, some of the variables which may have been included could fall prey to multicollinearity, in which the standard errors of the coefficients for certain independent variables can be inflated reducing the accuracy and efficiency of the regression results.

Testing these assumptions is known as testing for heteroskedasticity, or constant variance of residuals. A hypothesis test is established in which the null hypothesis is the constant variance of residuals, after which a chi squared test is performed. Upon the rejection of the null hypothesis at a 95% confidence interval, it is assumed the residuals are not heteroskedastic, and exhibit changing variance in relation to the dependent variable. In this instance, there is evidence of an underlying relationship between the dependent variables and residuals which is indicative of an imperfect or incomplete model. The tests for heteroskedasticity for each regression have been included in the results section where it will be discussed.

An additional assumption made when using an OLS estimator is that the relationship between the independent and dependent variables is linear. If this assumption proves incorrect, the parameters of the relationship of the independent variables with the dependent variables could be inaccurate leading to over or underestimation of the relationship between the independent and dependent variables and an underlying relationship between the dependent variable and residuals. This could lead to the standard errors of the predicted coefficients being inflated which could in turn lead to questions regarding the accuracy and efficiency of the OLS mechanism as an estimator.

One way to address this concern is to refer to the skewness of the distribution of the independent variables included in an OLS regression. If the distribution of the independent or dependent variables is skewed heavily in either direction, the regression results may inefficiently and inaccurately estimate regression coefficients in an attempt to explain with linearity a relationship which is inherently non-linear. The values for skewness of the distribution of independent and dependent variables in the T1 dataset are provided in table 8.

Mail efficiency, one of the key variables of interest, has significant leftward skewness. This skewness is high enough to question the accuracy and efficiency of OLS as an estimator of its coefficient. Because of this, the cubed root of Mail_eff was taken to generate Mail_eff4 which is included in place of Mail_eff in the final regressions. Mail_eff4 was used to recalculate the freight-mail interactions control, Cargo_eff, because of its leftward skewness. In comparison to regressions tested before the inclusion of Mail_eff4 and Cargo_eff4, the final regressions have higher r-squared values and lower mean squared error. Additionally, the chi2 value for the tests of heteroskedasticity drastically lowered, though they are still statistically significant, further suggesting improvement in the model. The skewness of the variables included in the final regressions are in table 8 with the improvements in skewness highlighted in bold.

Table 8

Independent variable skewness before and after adjustments for robustness

Skewness	a	b	c	d	e	f	g	h	i	j
Before	-.62	**11.3**	-.58	-2.61	**47.6**	1.37	-0.53	4.59	0.22	1.57
After	-.62	**2.00**	-.58	-2.61	**0.12**	1.37	-0.53	4.59	0.22	1.57

** The improvements in skewness resulting from translating mail efficiency to its cubed root and cargo efficiency to include this measure of mail efficiency are highlighted in bold*
*** a-j refer to the variable nomenclature as set forth in figure one*
**** b represents Cargo_eff before robustness changes and Cargo_eff4 afterwords*
***** e represents Mail_eff before robustness changes and Mail_eff4 afterwords*

Though the skewness of the variables included are still far from perfect, using the quarter root of mail efficiency to calculate Mail_eff4 and Cargo_eff4 improved the skewness of one of the key variables of interest and its interaction control variable. This improved r squared, lowered mean squared error and lowered homoscedasticity. These improvements are indicative of improvements in accuracy and efficiency of the regression results.

VI Results

VI.I Regression of Revenue Passengers Enplaned

The results of the first regression are shown in figure 2 and table 9 in which the natural log of passengers enplaned serves as the dependent variable and the payload-passenger interaction control variable, freight-mail efficiency interaction control variable, payload efficiency, passenger efficiency, the cubed root of mail efficiency, freight efficiency, the natural log of ramp inefficiency, departure inefficiency, the FSC dummy variable and the Covid dummy variable serve as independent variables labeled a-j respectively.

Figure 2

Description of the first regression

$$Lnpax\_enp = \beta0 + \beta1(a) + \beta2(b) + \beta3(c) + \beta4(d) + \beta5(e) + \beta6(f) + \beta7(g) + \beta8(h) + \beta9(i) + \beta10(j) + \varepsilon$$

B0 is the constant term

ε is the error term

Table 9

Regression regression results with lnpax_enp as the dependent variable

lnpax_enp	a	b	c	d	e	f	g	h	i	j	$\beta0$
Coefficient	-0.04	-16.6	0.475	2.11	1.43	5.29	0.94	0.57	-0.10	0.12	3.37
Sign	-	-	+	+	+	+	+	+	+	+	+
t-score	-0.27	-38.8	3.98	31.0	38.8	37.7	533	11.9	-10.5	16.2	48.2
P > |t|	.791	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Accuracy and Efficiency Measures	
R-squared	0.9601
Root MSE	0.37721
Observations	21,138
Chi Squared	1,912
Prob > chi2	0.000

For starters, all of the regression coefficients are statistically significant except for the payload-passenger interaction control variable coefficient. The regression coefficients indicate positive relationships between the dependent variable, natural log of enplaned passengers, with payload efficiency, passenger efficiency, mail efficiency, freight efficiency, ramp efficiency, departure efficiency and the FSC dummy variable. This regression indicates a negative relationship only with the two interaction control variables and the FSC dummy variable. These relationships support the hypothesis of this research. There is an underlying positive relationship between enplaned passengers and all measures of mixed-strategy optimization as well as reliability and ramp efficiency.

The r-squared of this regression model is high, suggesting around 96% explanatory power of changes in the natural log of enplaned passengers. The chi squared, unfortunately, is also high at 1,912. This suggests with statistical significance the presence of homoscedasticity in which there is an unaccounted for underlying relationship between the dependent variable and the residuals. This suggests that, while the explanatory power of this model is high, there is an underlying relationship which describes the movement of the natural log of passengers enplaned which has not been included.

From the perspective of the SCP model, these relationships suggest that airlines which are more optimized for mixed-strategy operations and are more efficient and reliable carriers will attract more customers. This optimization could allow for airlines to price more competitively given an alternate source of revenue. This would be a mechanism by which airlines could capture market share through optimization and compete given a high market concentration. Additionally, from an SCP perspective, increases in reliability could allow an airline to be more non-price competitive by capturing market share and maintaining customer loyalty through attraction to its quality of service in terms of reliability and ramp efficiency. The positive relationship between ramp inefficiency suggests that, as previously determined, larger airline operations with larger numbers of enplaned passengers are inherently more inefficient.

From a Demsetz model perspective, these relationships can be explained through alternate mechanisms of causation. It is also intuitive to expect that airlines with more enplaned passengers need to be optimized in terms of mixed-strategy operations to cover the costs of the size of their operation. Additionally, non-price competition functions like natural selection from a Demsetz perspective. Firms who are unable to non-price compete in terms of reliability and ramp efficiency will fail to acquire and hold market share.

The Covid indicator variable suggests that there is a positive relationship between passengers enplaned and the outbreak of Covid with all other metrics held constant. This result is contrary to the intuition that Covid restriction permanently caused a negative shift in air travel demand and suggests instead that, while the values of enplaned passengers declined with significance upon the onset of Covid, the ratio of this decline relative to the capital optimization of airlines increased. The distribution of the enplaned passengers, that is whether they are first class or coach, would provide greater insight to this puzzling conclusion. Regardless of the model of analysis, SCP or Demsetz, the positive regression coefficients support the hypotheses of this research.

The negative regression coefficients, on the other hand, raise some interesting questions regarding mechanisms of airline optimization. Both the payload-passenger and freight-mail interaction control variables are negative although it is necessary to mention again that the payload-passenger interaction control variable is not statistically significant. The direction of the relationships, nonetheless, suggest a tradeoff in efficiency between each of the pairs of interacting variables. In layman's terms this would mean that increasing payload efficiency would have a negative impact on passenger efficiency and vice versa. This also suggests that efforts taken to increase freight efficiency will have a negative impact on mail efficiency and vice versa.

One of the initial hypotheses of this research was that passenger or mixed-strategy airlines shifted optimization towards the transport of cargo following the onset of Covid and that this shift was indicative of greater metrics of success. While it would be ideal to claim that shifts towards airline optimization are beneficial at all times and in all magnitudes, these two negative relationships confirm the naivety of this claim. There is an obvious tradeoff in the shifting of sources of revenue which explains why, if at all, airline cargo optimization happened after the onset of Covid when traditional passenger revenue was diminished. This tradeoff likely results from two sources: capital equipment and capital labor. Payload efficiency, freight efficiency and mail efficiency all rely on heavy equipment, coordination with warehouse staff and a large degree of specialized manual labor. It would make intuitive sense that any investment into these categories in order to more efficiently pursue cargo revenue would detract from an airline's ability to efficiently transport passengers which is also inherently capital and labor intensive. This switch is further complicated by the fact that the specialized capital and labor for each of these processes can oftentimes be unique only to the process of freight loading, mail loading or passenger loading, explaining also why there is a tradeoff between freight and mail efficiency.

VI.II Regression of Revenue Passenger Miles

The results of the second regression are shown in figure 3 and table 10 in which the natural log of passengers miles serves as the dependent variable and the payload-passenger interaction control variable, freight-mail efficiency interaction control variable, payload efficiency, passenger efficiency, the cubed root of mail efficiency, freight efficiency, the natural log of ramp inefficiency, departure inefficiency, the FSC dummy variable and the Covid dummy variable serve as independent variables labeled a-j respectively.

Figure 3

Description of the second regression

$$Lnpax\_miles = \Theta 0 + \Theta 1(a) + \Theta 2(b) + \Theta 3(c) + \Theta 4(d) + \Theta 5(e) + \Theta 6(f) + \Theta 7(g) + \Theta 8(h) + \Theta 9(i) + \Theta(j) + \varepsilon$$

Θ0 is the constant term

ε is the error term

Table 10

Regression regression results with lnpax_miles as the dependent variable

lnpax_miles	a	b	c	d	e	f	g	h	i	j	*Θ0*
Coefficient	1.19	-20.9	-0.76	2.99	2.44	12.67	0.78	0.68	0.14	0.25	10.65
Sign	+	-	-	+	+	+	+	+	+	+	+
t-score	5.36	-31.2	-4.05	28.2	42.5	57.8	295	9.10	9.78	21.5	97.7
P > |t|	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Accuracy and Efficiency Measures	
R-squared	0.8897
Root MSE	0.58908
Observations	21,141
Chi Squared	3096.68
Prob > chi2	0.000

The main nuance between enplaned passengers and passenger miles is that it scales the worth of each passenger relative to how far the airline transports them. A passenger traveling further will pay more for the services of the airline. The conclusions suggested by this regression are similar to those of the first. There is a positive relationship between passenger miles and passenger efficiency, mail efficiency, freight efficiency, ramp inefficiency, departure efficiency, the FSC dummy variable and the Covid dummy variable. All of the coefficients are statistically significant.

The r-squared of this regression model is high, suggesting around 89% explanatory power of changes in the natural log of passenger miles. The chi squared, unfortunately, is also high at 3096.68. This suggests with statistical significance the presence of homoscedasticity in which there is an unaccounted for underlying relationship between the dependent variable and the residuals. While the explanatory power of this model is high, there is certainly an underlying relationship which describes the movement of the natural log of passengers enplaned which has not been included in this model.

From an SCP model perspective, these positive coefficients support many of the same conclusions as the last regression. It is a possibility that an airline which has optimized its strategy through the efficient transport of passengers, mail and freight will have opportunities for increased passenger miles. This model suggests that airlines optimized in these areas of efficiency will have a greater capability to capture market share with competitive pricing and diversified streams of revenue particularly in environments with high market concentration. Additionally, these relationships suggest that airlines which have maximized reliability will have an increased ability to compete through non-price means; acquiring market share through customer satisfaction and loyalty. The ramp inefficiency relationship suggests that a larger number of passenger miles, and therefore a larger operation, has a positive relationship with inefficiency. From an SCP model perspective this would detract from an airline's ability to satisfy their customer and compete via non-price means.

From a Demsetz model perspective, these relationships suggest that airlines which operate on a larger scale with more passenger miles necessitate passenger, freight and mail efficiency to operate. Additionally, this model suggests that airlines with larger operations must be reliable in order to sufficiently compete with non-pricing means and maintain market share.

Unlike the suggestions of tradeoff present in the relationships of the interaction control variables in the first regression, this regression suggests that payload and passenger efficiency do not exhibit trade offs but rather strengthen each other. This interaction control variable coefficient is also statistically significant unlike in the previous regression which increases the legitimacy of this claim. This positive relationship suggests that, in terms of passenger miles, optimizing payload and passenger capacity mutually benefit each other. Unlike the passenger-payload interaction control variable, the variable controlling freight and cargo interaction remains negative and statistically significant, once again suggesting the presence of a tradeoff between freight and mail efficiency.

The sign of the coefficient for the FSC dummy variable has been reversed and retains statistical significance. This suggests that, while FSC firms carry less passengers in total they carry their passengers further. Long-haul flights, typically operated only by FSC firms with the access to longer range narrow-body or wide-body aircraft, provide the bulk of intuition surrounding this result. The sign of the coefficient for the Covid dummy variable remains positive, suggesting once again that revenue passenger miles have increased following the onset of the pandemic with all other metrics held constant. This is evidence of optimization of resources following the onset of Covid and supports one of the central hypotheses of this research.

One confusing result is the negative coefficient for the payload efficiency variable considering the positive coefficients for both freight and mail efficiency. Given the method with which these three variables were calculated, it is likely that much of the relationship between payload efficiency and passenger miles is explained in variations in freight and mail efficiency and vice versa. Nonetheless, this coefficient is statistically significant, and suggests that holding all other measures of optimization and efficiency constant, there is a tradeoff between payload optimization and passenger miles regardless of the type of cargo. This relationship suggests a tradeoff of passenger miles with inefficient use of payload capacity since this relationship assumes freight and mail efficiency are held constant.

VI. III Regression of Revenue Ton Miles

The results of the third regression are shown in figure 4 andtable 11 in which the natural log of ton miles serves as the dependent variable and the payload-passenger interaction control variable, freight-mail efficiency interaction control variable, payload efficiency, passenger efficiency, the cubed root of mail efficiency, freight efficiency, the natural log of ramp inefficiency, departure inefficiency, the FSC dummy variable and the Covid dummy variable serve as independent variables labeled a-j respectively.

Figure 4

Description of the third regression

$$Lnton\_miles = \omega 0 + \omega 1(a) + \omega 2(b) + \omega 3(c) + \omega 4(d) + \omega 5(e) + \omega 6(f) + \omega 7(g) + \omega 8(h) + \omega 9(i) + \omega 10(j) + \varepsilon$$

ω0 is the constant term

ε is the error term

Table 11

Regression regression results with lnton_miles as the dependent variable

lnton_miles	a	b	c	d	e	f	g	h	i	j	ω0
Coefficient	3.04	-19.3	-2.17	1.64	2.36	15.2	0.78	0.89	0.11	0.25	9.10
Sign	+	-	-	+	+	+	+	+	+	+	+
t-score	14.2	-30.7	-12.1	16.2	42.4	73.2	307	12.4	7.59	23.1	87.2
P > |t|	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Accuracy and Efficiency Measures	
R-squared	0.8969
Root MSE	0.57076
Observations	21,166
Chi Squared	2625.73
Prob > chi2	0.000

This regression demonstrates the relationship between a different dependent variable, the natural log of ton miles, with the independent variables payload efficiency, passenger efficiency, mail efficiency, freight efficiency, ramp efficiency, departure efficiency and the FSC dummy variable. Ton miles is similar to passenger miles in the sense that it is a measure of tons of revenue cargo carried, scaled for the worth of each ton of cargo relative to how far the airline transports them. Just as with a passenger, a ton of cargo traveling further will be worth more to transport. The conclusions suggested by this regression are similar to those of the second. There is a positive relationship between revenue ton miles and passenger efficiency, mail efficiency, freight efficiency, ramp inefficiency, departure efficiency, the FSC dummy variable and the Covid dummy variable. All of the coefficients are statistically significant.

The r-squared of this regression model is high, suggesting around 90% explanatory power of changes in the natural log of enplaned passengers. The chi squared, unfortunately, is also high at 2625.73. This confirms with statistical significance the presence of homoscedasticity in which there is an unaccounted for underlying relationship between the dependent variable and the residuals. While the explanatory power of this model is high, there is certainly an underlying relationship which describes the movement of the natural log of ton miles which has not been included in this model.

From an SCP model perspective, the positive coefficients support many of the same conclusions as the last regression. It is a possibility that an airline which has optimized its strategy through the efficient transport of passengers, mail and freight will have opportunities for increased ton miles. This model suggests that airlines optimized in these areas of efficiency will have a greater capability to capture market share with competitive pricing and diversified streams of revenue in the freight market. This is a different conclusion from the previous two regressions. In this case, both price and non-price competition relate not to the ability of an airline to capture the market share reflected by individual passengers, but rather by larger cargo contracts and the companies which offer them.

With this in mind, these relationships suggest that airlines which have maximized reliability will have an increased ability to compete through non-price means; acquiring market share in the cargo transport market perhaps through satisfying their cargo customers in the reliability with which they transport cargo. No research has been done on customer satisfaction of larger cargo contract holders in the airline industry. The ramp inefficiency relationship suggests that a larger number of ton miles, and therefore a larger operation, has a positive relationship with inefficiency. From an SCP model perspective a lower ramp efficiency would detract from an airline's ability to satisfy their customer, with whom they hold a cargo contract, and compete via non-price means with other cargo transporting airlines.

From a Demsetz model perspective, these relationships suggest that airlines which operate on a larger scale with more ton miles necessitate passenger, freight and mail efficiency to operate. Additionally, this model suggests that airlines with larger operations must be reliable in order to sufficiently compete with non-pricing means and maintain market share.

This regression suggests once again that payload and passenger efficiency do not exhibit trade offs but rather strengthen each other. This interaction control variable coefficient is also statistically significant unlike in the first regression. This positive relationship suggests that, in terms of ton miles, optimizing payload and passenger capacity mutually benefit each other. Similar to the last regression, the variable controlling for freight and cargo interaction remains negative and statistically significant, once again suggesting the presence of a tradeoff between freight and mail efficiency. This negative coefficient suggests that the tradeoff between freight and mail efficiency affects cargo transport as well as passenger transport. This is likely due to the unique capital needs of freight and mail transport that vary between the two although any further specifics of this variation remain a mystery to me.

The sign of the coefficient for the FSC dummy variable remains positive and is statistically significant. This suggests that FSC firms carry more revenue ton miles with all other metrics held constant. This is different from the assertion that FSC firms carry more revenue tons and instead is a positive indication of the presence of mixed-strategy optimization in FSC carriers. The sign of the coefficient for the Covid dummy variable remains positive, suggesting once again that revenue passenger miles have increased following the onset of the pandemic with all other metrics held constant. This relationship further supports the hypothesis that mixed-strategy optimization rose in prominence with statistical significance following the onset of Covid.

VII Conclusion

The results of these regressions are unique in the sense that they comment on two separate discussions within airline industry literature. The first component is optimization strategies and the second is non-price competition. Comparison among the variables of interest across groupings as well as the main regressions supported the initial hypotheses of this research. Airlines that optimize in the form of mixed-strategy such that passenger, freight and mail efficiency are jointly targeted are also airlines characterized by higher levels of revenue passengers enplaned, revenue passenger miles and revenue mile tons. Additionally, the analysis supports the hypotheses that FSC firms are larger, more mixed-strategy optimized and more efficient per capita. In terms of non-price competition, however, FSC were more ramp inefficient and less departure reliable than LCC carriers. This is likely due to the large size of FSC carriers that can serve both to afford opportunities to increase optimization measures but certainly increases strain on the systems of efficiency in place within an airline.

It is also concluded that passengers enplaned, passenger revenue miles and revenue ton miles have decreased with statistical significance following the onset of the Covid-19 pandemic but have increased when optimization and efficiency measures are held constant. This conclusion suggests that long-term impacts to travel demand did ensue following the onset of Covid but also that airlines reacted to these changes with increased mixed-strategy optimization. Further research should be done to analyze if the significant decreases in passenger travel demand are disproportionately accounted for by low cost or high cost travel demand. This could provide insight to the permanent impacts of the onset of Covid-19 on the airline industry.

There is also evidence in all three regressions which suggests a massive tradeoff between freight and mail efficiency. The specifics of the mechanism of this relationship are unknown and should be researched further though it is hypothesized here this tradeoff is due to differences in the specialized capital or labor personnel necessary for the possibility of freight and mail efficiency within an airline. Contrary to the tradeoff between freight and mail efficiency, it is concluded that payload and passenger efficiency exhibit mutual reinforcement rather than a tradeoff. The only data indicative of a tradeoff between these two variables is present in the first regression and has no statistical significance. This result suggests that airlines should pursue mixed-strategy optimization in which both payload and passenger optimization are priorities.

These conclusions serve to support the central hypothesis that, firstly, airlines which are better optimized for mixed-strategy operations are more successful. All metrics of payload and passenger optimization maintained positive relationships with revenue passengers enplaned, revenue passenger miles and revenue ton miles. The mechanism by which this success either results from optimization as described in the SCP paradigm model or causes optimization as described in the Demsetz model remains unclear. Further research should be done to analyze the validity of these mechanisms within the airline industry. This research additionally concludes that optimization became a more prominent tactic following the onset of Covid-19 likely due to the scarcity of passenger revenue.

The discussions within this research contribute to discussions within economics literature surrounding airline efficiency, the differences between FSC and LCC models, customer satisfaction and the impacts of Covid-19 on the airline industry. Further research should be done to analyze the tradeoffs of freight and mail efficiency discovered in this research. A tradeoff between these two modes of efficiency, hypothesized in this research as a result of differences in the specialized capital or labor personnel necessary for the possibility of freight and mail efficiency, would limit the viability of optimization of an airline within the cargo industry and could limit the effectiveness of mixed-strategy optimization. Further research could shed light on these limitations as well as the source of it. Further research should also be done to analyze if, as hypothesized, these increases in passenger travel demand are disproportionately accounted for by low cost travel demand increases. There are still mixed opinions within airline and economics literature as to the existence of long-term or permanent impacts of the Covid-19 pandemic or a lack thereof. Finally, identifying the specific causal mechanism of the relationship between optimization measures and airline success should be examined. Both SCP paradigm and Demsetz model perspectives were considered in this research and provide logical, intuitive explanations for the mechanism by which optimization increased airline success.

In the interview which sparked this research, I naively asked United directors Brian Landry-Wilson and Perry Lewis why United had, in contrast to the actions of every other domestic US airline, seemingly doubled down, purchased additional wide-body aircraft during a liquidity crisis and continued to fly their pilots routinely in a move I likened to a poker bluff. Their answer was simple: “we prefer to think of it less as a gamble and more so a long term strategy”. The calmness of their response reflected the immense volumes of thought which had gone into this decision that I had, on the surface, deemed careless. It seems very clear that United’s prediction of long term rebounding in airline travel demand coupled with controversial investments into mixed-strategy cargo optimization capabilities in the form of wide-body aircraft, cargo contracts and pilot currency were in fact calculated moves which certainly do, as this research suggests, have the ability to pay off immensely.

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A Appendix

The interview with United directors Brian Landry-Wilson and Perry Lewis was conducted on January 19th remotely over zoom. United airline's Eric Lane is responsible for the organization of the interview for which I am unequivocally grateful. As mentioned in the introduction and conclusion sections, the interview ranged from discussion over more generalized airline industry trends to very specific strategy decisions made by United airlines in the wake of the onset of Covid-19.