AIR CARGO: CARRIERS, COST, AND COMPETITION

by

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ABSTRACT

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Under the Supervision of Professor James H. Peoples, Jr.

This dissertation examines the cost structure of U.S. air carriers participating in the freight transport sector. From 1991 to 2021, events such as the 9/11 terrorist attacks, the global financial crisis, and the COVID-19 pandemic have coincided with various events directly impacting the air freight transport industry. During this 30-year period, air transport has developed and implemented global tracking systems, engaged in labor negotiations, and weathered supply-chain shocks all of which warrant comprehensive evaluation of the U.S. air freight transport industry from the cost perspective. Chapter 1 of this thesis explores existence of natural monopoly and economies of scope among U.S. air carriers which transport both passengers and freight. Chapter 2 examines allocative efficiency and Chapter 3 measures productivity growth among U.S. air carriers which transport freight only.

PEOPLES! Mom, Dad, Ole, Simon, Natalie, Eisley, and Daisy Booper

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1 Moving Boxes (and People) by Air

Abstract

This study examines the cost structure of U.S. air carriers. Recent widespread business and personal Internet usage has facilitated unprecedented levels of global connectivity at an unprecedented pace. Thus emerged a rich, complex digital marketplace for e-commerce. E-commerce, reaching peak popularity during the COVID-19 outbreak, eliminates the need for face-to-face interaction between buyer and seller. Regardless, e-commerce exchanges involving physical goods still require transport and delivery. E-commerce consumer expectations concerning physical transport and delivery, perhaps unsurprisingly, seem to reflect the relative ease and speed associated with the sale itself. Given these expectations, the high value, low volume[1] nature of goods typically purchased online (consumer electronics, pharmaceuticals/supplements), as well as the frequently great distances between buyers and sellers, aviation seems the most appropriate transport mode[2] for the task. However, the question remains as to which type(s) of air carriers are best suited to meet e-commerce's demand cost-effectively. In examining the cost structures of U.S. air carriers, the study finds that combination air carriers are most often natural monopolies over simulated output levels and rarely natural monopolies over specialist[3] output levels.

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[1] ACI-Air Cargo NA Committee (2019); Abeyratne (2018); evidence from the commodity flow survey in Figs. 1-1 and 1-2

[2] Most used modes of freight transportation include truck, maritime, rail, and aviation (including truck air) as defined by the Oak Ridge National Laboratory 2021 for the U.S. Bureau of Transportation Statistics

[3] Specialists as referred to in this text are air carriers which specialize in a single transportation service, i.e. while Fed Ex is a freight specialist transporting only freight and no passengers, Spirit Airlines is a passenger specialist transporting only passengers and no freight.

1.1 Introduction

COVID-19 has reignited and further complicated the age-old dispute concerning air transport's correlation with economic growth. Recent studies identify passenger air transport[4] as a major contributor to COVID-19's rapid, global spread[5] and recommend conscientious travel restrictions protective of economic activity. Although travel restrictions, "stay at home" orders, and social distancing measures were implemented by over 100 countries,[6] these efforts failed to prevent economic distress. Even so, the U.S. economy not only recovered from the COVID-19-induced shutdown of its most prolific employer, the service sector, but also exceeded pre-pandemic real GDP levels.[7] At issue is what contributed to this GDP rebound. To address this issue, consider e-commerce. Almost overnight, workers deemed "non-essential" were confined to their homes from which they either continued their previous work, supervised their children's newly virtual education, started microbusinesses,[8] improved their homes, or consumed virtual entertainment. Irrespective of any given "non-essential" worker's elected pursuit, concurrent explosive e-commerce growth[9] suggests said pursuits likely involved demand-/supply-side online market participation.

Thus evolved a virtual marketplace accessible via the internet to any consumer and any producer at any place, at any time. However, e-commerce does not eliminate transaction costs

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[4] Efficient transport for this service requires operating with high passenger volumes, high flight frequency, and high airport density.

[5] Sokadjo & Atchade, 2020; Y. Zhang et al., 2020; L. Zhang et al., 2020; Lau et al., 2020

[6] Pew Research Center reports people around the world faced major travel restrictions resulting in understandably lower passenger traffic in April 2020.

[7] Bureau of Economic Analysis, Real Gross-Domestic Product 2012Q1-2022Q1

[8] The Brookings Institution reports American entrepreneurs started 2.8 million more online microbusinesses, discrete domain name and active website, in 2020 than in 2019.

[9] Data from the U.S. Dept. of Commerce and analysis by DigitalCommerce360 reveal explosion in e-commerce quarterly growth rate from 20.4% in Q1.2020 to 53.4% in Q2.2020 after which it remained above pre-pandemic levels until Q2.2021.

but rather outsources them to the transportation and delivery sector. Notably high value, lightweight imports such as consumer electronics and pharmaceuticals/supplements are best suited for air freight transportation as shown in Figures 1-1 and 1-2. Although air freight rates tend to exceed those of other modes, aviation's speed and reach render it ideal for high value, low weight products expected to travel long distances in short amounts of time also shown in Figures 1-1 and 1-2. The pandemic-induced explosion in e-commerce demand among Americans and across the globe gave rise to a complementary explosion in freight transportation demand. Recent evidence on cargo carriers' capacity shows e-commerce's short-term scalability may have outpaced the ability of air freight transportation services as well as transportation services at large to match consumer demand.[10] Air carriers attempted to meet e-commerce's demand via fleet expansion and alteration but ultimately failed to surpass the very supply pressures they had hoped to ease.[11] Given the enhanced demand for cargo services, combination air carriers, those which carry freight and passengers within a given year, sought to alleviate the record-breaking low, COVID-19 induced passenger volumes by increasing freight volumes. This carrier group[12] is composed of the following high passenger volume carriers: American Airlines, Delta Airlines, Southwest Airlines, United Airlines, and the following

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[10] New York Times reports supply-chain shortages (August 2021).

[11] IATA emphasizes air cargo's integral role in the financial survival of air carriers. Barron's reports Alaska Air converts aircrafts for greater freight service capacity during the global pandemic., Barron's reports on U.S. airline recovery from the COVID-19 pandemic., American Shipper reports on air cargo's role in alleviating air carrier financial struggles amidst the COVID-19 pandemic.

[12] The following airlines carrying both passengers and freight during the relevant time period are excluded from the analysis due to incomplete information: Air Transport International, Omni Air International LLC, Air Wisconsin Airlines Corp, ExpressJet Airlines LLC d/b/a (doing business as) aha!, JetBlue Airways, Atlas Air Inc., National Air Cargo Group Inc d/b/a National Airlines, US Airways Inc., Eastern Airlines f/k/a (formerly known as) Dynamic Airways, LLC, Island Air Hawaii, Mesa Airlines Inc., Spirit Air Lines, Swift Air, LLC d/b/a Eastern Air Lines d/b/aEastern, Executive Airlines, Frontier Airlines Inc., Colgan Air, USA Jet Airlines Inc., Avjet Corporation, Continental Air Lines Inc., Envoy Air, ExpressJet Airlines Inc., Mesaba Airlines, Republic Airline, Shuttle America Corp., SkyWest Airlines Inc.

companies: Hawaiian Airlines, Alaska Airlines, Sun Country,[13] Tatundak Outfitters Ltd,[14] Mesa, Atlas, ATI, and Endeavor. A critical question is whether these combination carriers benefit cost-wise from economies of joint production induced by the potential cost complementarity between passenger and freight flows derived from their commonly shared labor, fuel, and capital inputs.[17] Then, given a combination carrier does indeed benefit from economies of joint production, is that carrier able to compete with freight specialists FedEx and UPS as far as total costs with respect to output are concerned?

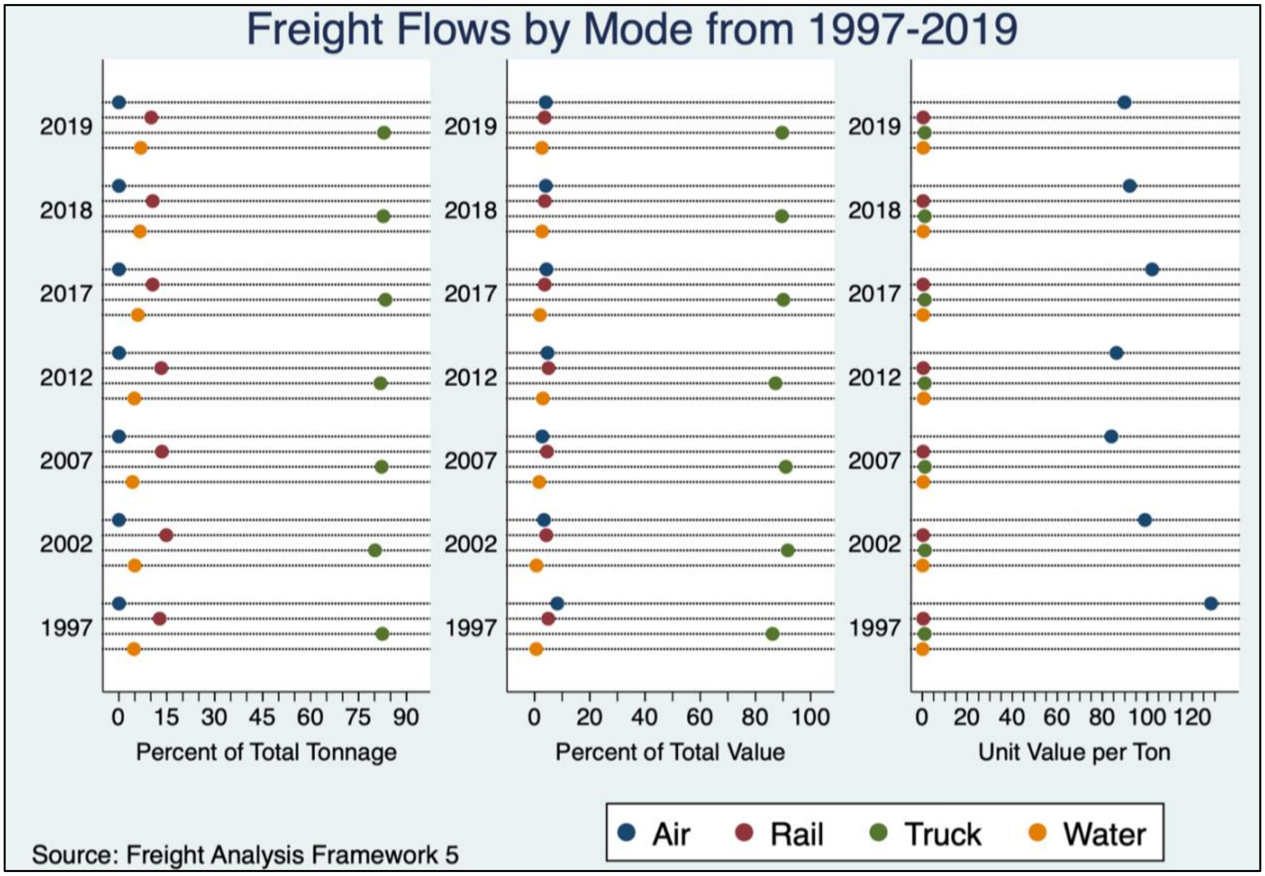

Figure 1-1 Freight Flow Tonnage and Value by Mode

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[13] d/b/a MN Airlines

[14] d/b/a Everts Air Alaska/Cargo

[17] Of particular interest is the aircraft (capital input). statistics defines 4 main Aircraft configurations, as defined in the U.S. Bureau of Transportation data, include passenger, freight, combination, and seaplane.

A brief background presentation of the major combination carriers reveals they have been providing freight service prior to the growth of air freight specialists that began following the 1977 air cargo deregulation act. Legacy carriers such as Delta and United have transported cargo since carrier operations began in 1924 and 1922, respectively. American Airlines claims to have provided the "first scheduled air cargo service in the world" in the fall of 1944. Then in 1964, United became the "first US passenger airline to offer non-stop transcontinental all-cargo service". By 1973, even Southwest Airlines diversified its transportation services and officially created a separate cargo department in 1990. Soon after, Delta became the "first airline to offer its own air express service" in 1975. Fast-forward to the COVID-19 pandemic and all four carriers, survivors of the many airline mergers and bankruptcies occurring in the meantime, announced all-cargo only flights.[18] It stands to reason then that given the longevity of Delta, United, American, and Southwest, other "passenger" airlines seeking a more sustainable business model may see cost benefits from expanding into cargo services. Indeed, there may be market space for more players since, according to the U.S. Department of Homeland Security (DHS), passenger aircrafts transport approximately 25% of all domestic air cargo.[19]

While this group of carriers consistently provided both freight and passenger services since as early as 1964, the freight component of their operation remained a relatively small part of the transport services. For instance, information presented in Fig. 1-3 shows, other than for 1994, freight's share of combination revenue rarely exceeded 20 percent from 1990 to 2014.

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[18] American Airlines announces cargo-only flights to keep business moving during the COVID-19 pandemic. American Shipper reports United Airlines brings back cargo-only flights to manage financial duress incurred by the COVID-19 pandemic, Transport Topics reports Southwest begins first ever cargo-only flights in its operational history to combat drop in passenger traffic from the COVID-19 pandemic,, Delta announces cargo-only flights between the U.S. and Europe during the COVID-19 pandemic.

[19] The Department of Homeland Security details shipping facts and security measures specific to air cargo.

However, freight service increased dramatically by 2021 as combination air carriers transported an average of 984 million revenue ton miles of freight and mail (**RFTM**) in 1990 and that number increased 68% to 1.68 billion **RFTM**. Such gains in freight transport service, though may just reflect an overall increase in air transport services. Freight-share information presented in Fig. 1-3, however, shows this growth in air-freight transport outpaced the change in passenger service following 2014, as freight's share of air transport service in the US increased regularly from 2015 to 2021, reaching 30 percent of all revenue-ton-miles for combination carriers in 2020. Freight's increasing share of business has provided these combination carriers with a source of additional revenue growth, however, it is not obvious, a priori, whether expanding services to include increasing amounts of freight hauled is costly. For instance, coordinating freight service to match with passenger service could limit the amount of freight hauled such that combination carriers are shipping freight appreciably below capacity levels. Even though such cost analysis would provide critical information on the economic viability of combination freight and passenger air services there is an absence of research that directly examines whether it is cost effective to combination air carriers to offer greater service to customers shipping freight. Although several previous studies (Gillen et al. 1990; Kiesling & Hansen 1993; Keeler & Formby 1994; Jara-Diáz et al. 2013) have estimated the cost structures of passenger, all-cargo, and combination carriers in their respective market spaces (freight and passenger), few have analyzed all three together. Not only does this study estimate the cost structures for all three types of carriers, but also allows carrier type to vary over time which to the best of my knowledge has not been done before.

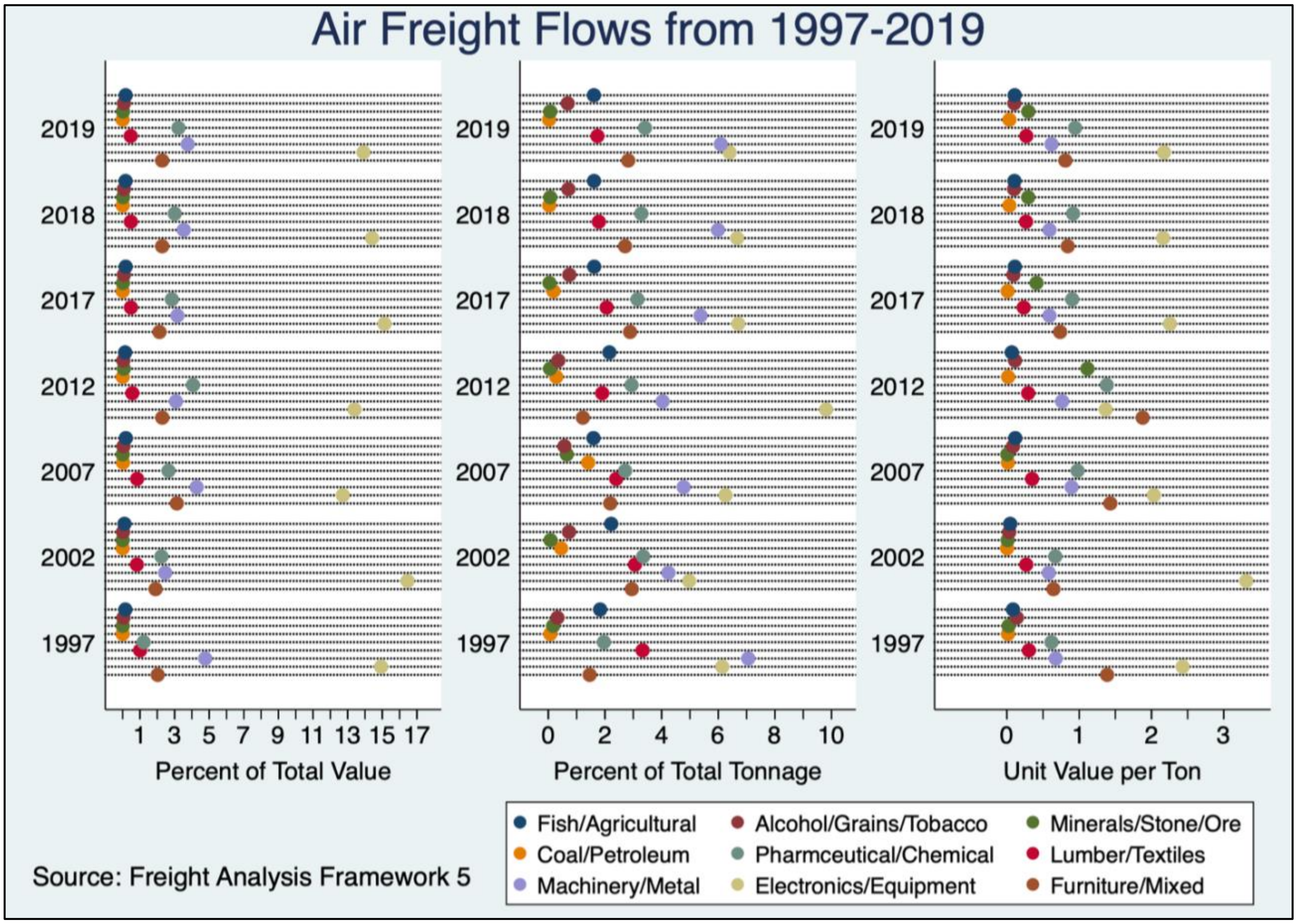

Figure 1-2 Top Commodities Transported by Air

This analysis contributes to our understanding of combination air carrier service by examining cost efficiency of U.S. combination air carriers from 1991 to 2021 relying on the rich expanse of data collected and published by the Bureau of Transportation Statistics (BTS). First, I estimate the combination carrier market-level, translog cost function via the seemingly unrelated regression (SUR) technique. Using the resultant parameter estimates, I perform 999 total cost simulations over 999 simulated passenger and freight output levels per carrier per year to determine the presence of natural monopoly[20] in the market for combined passenger

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[20] Presence of natural monopoly indicates the industry in question operates more cost effectively with fewer larger firms rather than several smaller firms.

and freight services by testing the simulations for multi-product subadditivity. Findings show combination air carriers satisfying the condition for multi-product subadditivity nearly 90 percent of the time in the 1990s reaching a satisfaction rate of nearly 100 percent of the time in the 2010s. I interpret these results as an indication of cost complementarity between passenger and freight/mail services that may contribute to the persistent offering of these two services by well-known firms such as United, Delta, and Southwest.

While air carrier cost structure, both freight and passenger, is thoroughly investigated in the relevant literature detailed in the comprehensive literature review provided in Jara-Diáz et al. 2013, combination carrier cost structure seems to be overlooked. Inconsistent carrier classification could obfuscate the combination carrier sized gap in the transportation literature which has yet to reach a consensus where carrier criterion correspondent to consistent, carrier classification is concerned. In any case, no previous work to the best of my knowledge, has allowed carrier classification to vary over time. By estimating cost functions for each type of carrier, the classic test for multiproduct economies of scope can be performed relative to empirical market activity as opposed to simulated market activity.

These findings add to the literature, inform the industry, and contribute to broader understanding of air transportation's impact on economic growth. If combination air carriers can cost-effectively expand further into freight, the demand for e-commerce may be satisfied more sufficiently and the historical burden of air carrier bankruptcy[21] may be somewhat alleviated.

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[21] Airlines for America reports over 30 airline filings for bankruptcy in the last 30 years.

Section II discusses the theoretical framework on subadditivity and economies of scope to identify the conditions needed to satisfy these cost concepts.

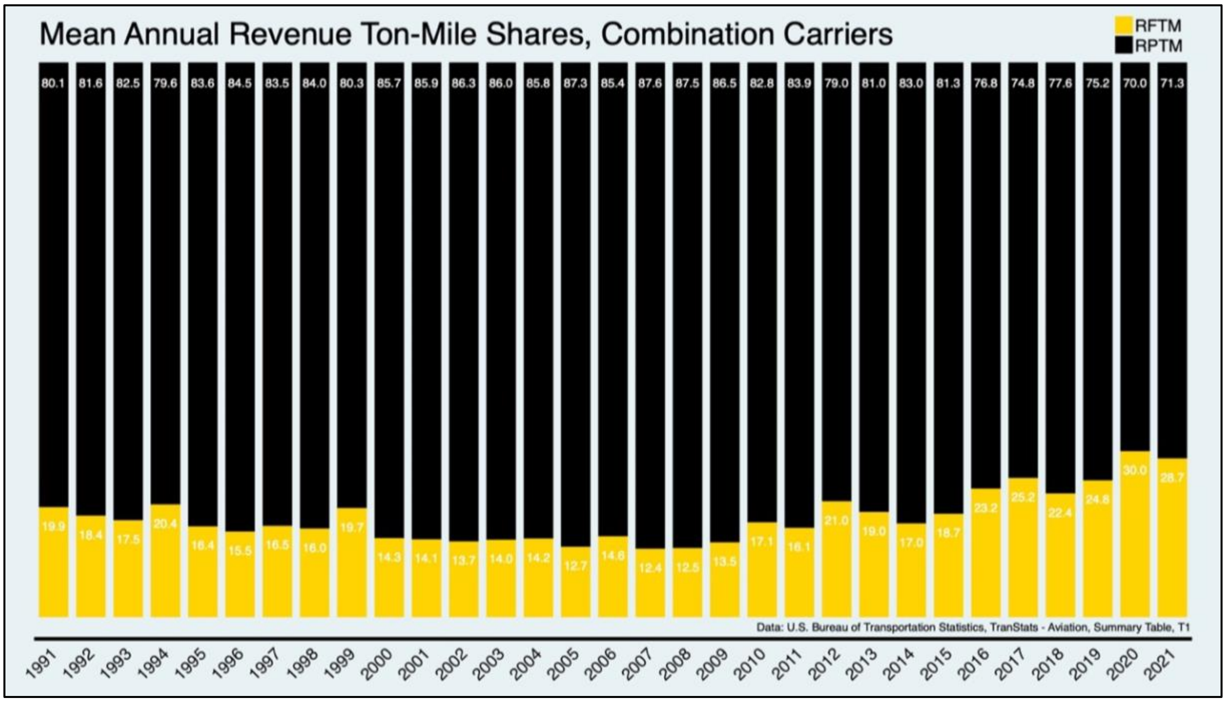

Figure 1-3 Composition of output, revenue ton-miles, completed and reported by U.S. combination air carriers. Segment-level data sourced from U.S. DOT, Bureau of Transportation Statistics, TranStats database, Aviation, Summary Table T1.

Further, understanding the condition for subadditivity and economies of scope provide guidelines for empirically testing whether it is cost effective for combination carriers to expand their operations to include greater amounts of freight transport services. Section III reviews airline cost analyses with emphasis on each study's dataset and empirical approach. Section IV presents details on the dataset used to test for subadditivity and economies of scope, and section V describes the empirical approaches used for these tests. Section VI presents the translog cost function results. Parameter estimates from this estimation are used to provide simulations to test for subadditivity and economies of scope. Section VII presents the simulations used to test whether the combination air carrier sector exhibits characteristics consistent with a of natural monopoly (i.e., satisfies the condition of subadditivity) and this section also presents the simulations used to test for economies of scope. Concluding remarks are presented in Section VIII.

1.2 Cost Concepts and Natural Monopoly

This study seeks to evaluate economies of joint production between freight and passenger air transport services. Given economies of joint production between freight and passenger services do exist, at issue is whether specialist carriers, those providing either freight or passenger services only, enjoy cost advantages from joint service provision. An analysis of economies of scale and scope provides a theoretical foundation that contributes to examination of these queries and to development of hypotheses as related to the possibility that the combination air carrier sector exhibits attributes consistent with a natural monopoly.

Economies of scale and its relationship to subadditivity will be presented first for a theoretical single-product firm. The concept of economies of scale and subadditivity effectively illuminate the cost structure of the single-product firm as it clearly defines the relationship between cost and output. Extended to the multi-product case, however, that relationship between cost and output is blurred by the additional output(s). Overall, a scale analysis may reveal the multiproduct firm's average cost decreases with respect to an increase in *total* output but the question remains as to how to most cost-effectively increase that *total* output. Should the multi-product firm provide more freight services or more passenger services? What combination of freight services and passenger services minimizes total cost? Multiproduct subadditivity can answer these questions but fails to provide insight into whether the firm should even be producing multiple outputs jointly. Herein lies the need for economies of scope which shows whether the multiproduct firm would be better off from the cost perspective if split into two specialist firms.

Of course service diversification (passenger and freight) is not the only way to achieve scale or scope in the air transport industry but it does remain the least investigated. The literature is rich with sources of scale, most famous is the returns to scale gained from the transition to the hub-and-spoke from the point-to-point route structure (Oum et al. 1990, Antoniou 1991, Starr & Stinchcombe 1992, etc.). Scale gains from changes to route structure, however, are eventually exhausted as density adjusts to the change in network size (Starr & Stinchcombe 1992). Other potential sources of scale such as increased fuel efficiency, aircraft rental, labor outsourcing, and improved aircrafts (Donatelli, 2012) are thus far empirically unsupported for analysis as most airline data is not currently granular enough to analyze such input variation across and within firms. As far as sources of scope are concerned, much debate remains over how to distinguish one air transport product from another. Jara-Diaz 2013, et al. suggests various service-level stratification.[22] The most agreed upon differentiation is between passenger and freight services but to the best of my knowledge no study has empirically disentangled passenger from freight service output and measured each in identical units. Passenger services are typically measured in revenue passenger-miles, the product of passengers transported for revenue and miles transported whereas freight services are typically measured as the product of freight tonnage transported for revenue and miles transported. Thereby, I convert passengers to tons using the U.S. Bureau of Transportation Statistics proxy for passenger weight of 200 pounds per passenger. Using the theory of multiproduct

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[22] trunk vs. local, domestic vs. international, and short vs. long haul services

economies of scope and subadditivity detailed below following Sharkey (1982) and Berg & Tschirhart (1988) as applied to the empirical analysis of freight and passenger services measured in tons, this study attempts to fill that gap.

A single-product firm with a cost function *C(q)* enjoys economies of scale when the average cost of producing output, λq, is less than the average cost of producing output level $q < \lambda q$ as shown in Eq. 1.

Equation 1-1

$$\frac{C(\lambda q)}{\lambda q} < \frac{C(q)}{q},\ \forall\lambda \text{ s.t. } 1 < \lambda \leq (1+\varepsilon) \text{ where } \varepsilon > 0$$

Thus, scale economies (diseconomies) exist when the average cost of production declines (increases) with respect to an increase in output. Mathematically, when the first derivative of average cost with respect to output is less (greater) than zero there exists economies (diseconomies) of scale. Consider then a monopolist with cost function $C(q_M)$ and convex, average cost function as shown by Eq. 2 where constants *a* and *b* are greater than zero.

Equation 1-2

$$\mathrm{TC} = q_M(q_M - a)^2 + \frac{a q_M}{b.}$$

$$\frac{C(q_M)}{q_M} = (q_M - a)^2 + \frac{a}{b}$$

Scale economies (diseconomies) can be easily determined by setting the first derivative of Eq. 2 equal to zero and solving it for q_M as in Eq. 3. For values of $q_M < a$, $\frac{d\left(\frac{C(q_M)}{q_M}\right)}{dq_M} < 0$ suggesting the monopolist cost curve exhibits scale economies. For values of $q_M > a$, $\frac{d\left(\frac{C(q_M)}{q_M}\right)}{dq_M} > 0$ suggesting the monopolist cost curve exhibits scale diseconomies. Figure 1-4 presents a graphical depiction of the monopolist's average cost curve with regions labeled as exhibiting scale economies and diseconomies.

Equation 1-3

$$\frac{d\left(\frac{C(q_M)}{q_M}\right)}{dq_M} = 2q_M - 2\mathrm{a}$$

$$0 = 2q_M - 2\mathrm{a}$$

$$\mathrm{q_M} = \mathrm{a}$$

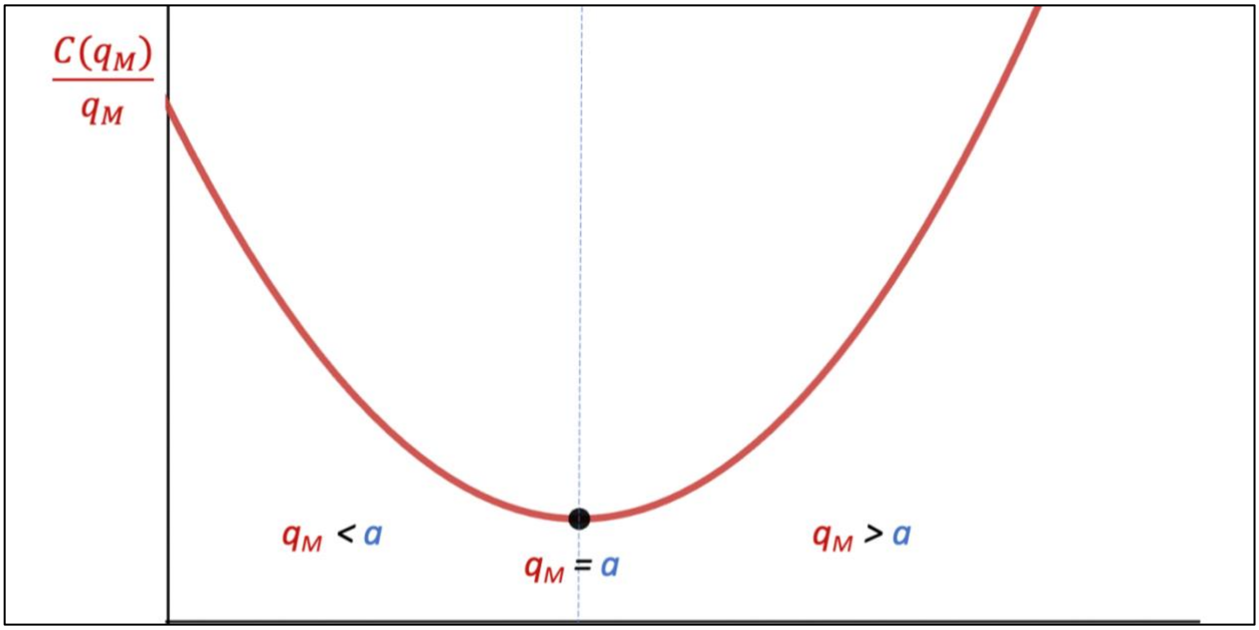

Figure 1-4 The single-product monopolist's cost curve (Eq. 2) depicting values of output for which there are scale economies/diseconomies.

Now consider a duopoly in which two identical firms' costs are defined as a function of q_D such that the convex, market average cost function takes the form presented by Eq. 4.

Equation 1-4

$$\frac{\mathrm{C}(q_D)}{q_D} = (\mathrm{q_D} - 2\mathrm{a})^2 + \frac{\mathrm{a}}{\mathrm{b}}$$

Scale economies (diseconomies) for the duopoly can be determined again using the first derivative method as shown in Eq. 5. For values of $q_D < 2a$, $\frac{d\left(\frac{C(q_D)}{q_D}\right)}{dq_D} < 0$ suggesting the duopoly cost curve exhibits scale economies. For values of $q_D > 2a$, $\frac{d\left(\frac{C(q_D)}{q_D}\right)}{dq_D} > 0$ suggesting the duopoly cost curve exhibits scale diseconomies.

Equation 1-5

$$\frac{d\left(\frac{C(q_D)}{q_D}\right)}{dq_D} = 2q_D - 4\mathrm{a}$$

$$0 = 2q_D - 4\mathrm{a}$$

$$\mathrm{q_D} = 2\mathrm{a}$$

Figure 1-5 combines both the monopoly and duopoly average cost curves which intersect where $\mathrm{q^M} = \mathrm{q^D} = \frac{3a}{2}$.

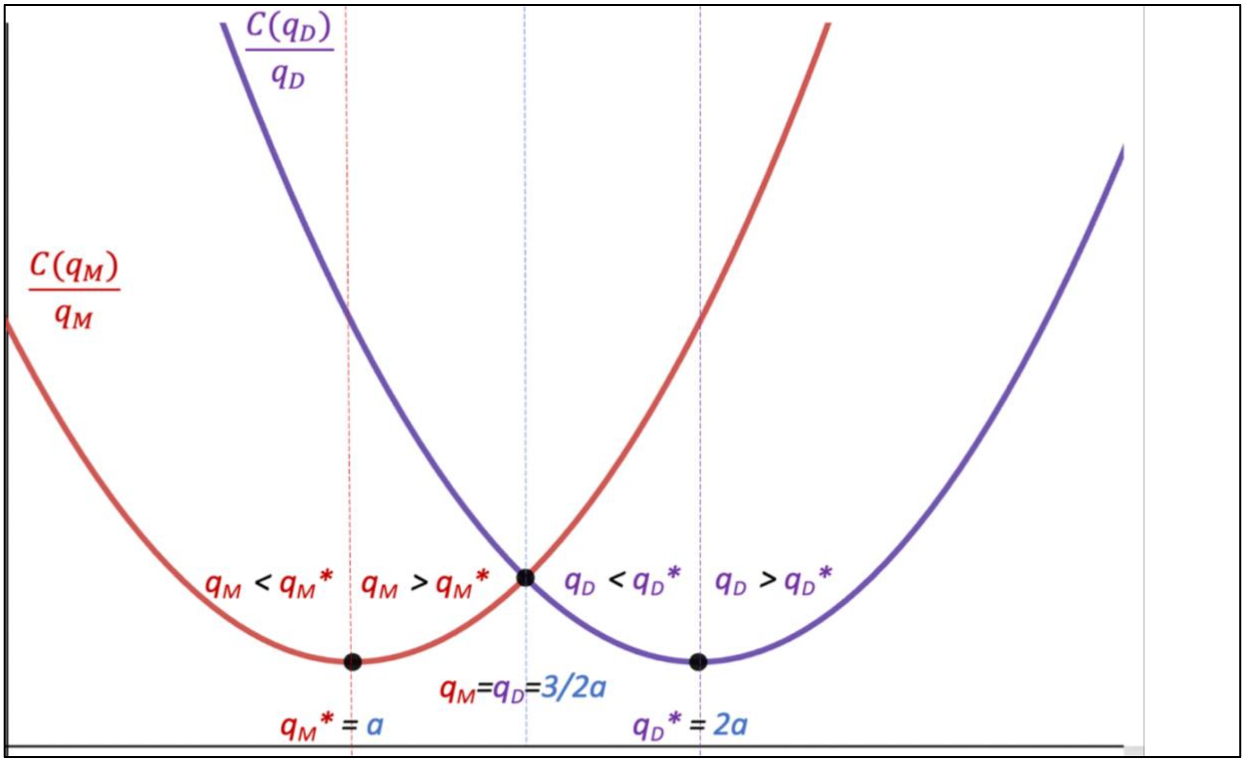

Figure 1-5: The single product-monopolist's average cost curve (Eq. 2, red) overlayed with the duopoly average cost curve (Eq. 4, purple) depicting values of output for which there are scale economies/diseconomies.

Notice the region between *a* and 3/2*a*: although the monopolist is producing output with scale *diseconomies* and the duopoly is producing output with scale economies, the monopolist's average costs are below the duopoly's average costs. Thus, the monopolist producing output between *a* and 3/2*a* at diseconomies of scale is considered more cost efficient than a duopoly would produce in the same interval. Indeed, this exercise shows a firm can operate in the decreasing returns to scale range (the region between *a* and 3/2*a*) and still satisfy the condition of subadditivity which may serve to illuminate the cost structures of the air transport industry in which differing carrier types see variable average costs.

In the case of single-output production it may be concluded that subadditivity adds a new dimension to, but is not a radical departure from, the traditional association of natural monopoly and economies of scale. Subadditivity is an essential concept, however, for the understanding of multiple output natural monopoly. In the multiproduct case, economies of scale are neither necessary nor sufficient for natural monopoly as shown by the following exposition. For a multiple output cost function, subadditivity holds at an output level *Q* if

Equation 1-6

$$\mathrm{C}(Q) \leq \sum_{i=1}^{k} C(q_i) \ where \ \sum_{i=1}^{k} q_i = \mathrm{Q}$$

A cost function sub additive for all *Q* may be characterized by satisfying Eq. 7.

Equation 1-7

$$\mathrm{C}(q_1) + \mathrm{C}(q_2) \geq \mathrm{C}(Q) \qquad \forall \text{ output vectors } \mathrm{q_i}$$

The key to multiproduct subadditivity is the characterization of the economies of joint production. Although subadditivity in one dimension is implied by economies of scale or declining average costs, it will be seen that general subadditivity as outlined in the empirical approach is closely related to certain convexity conditions.

The most direct and intuitive measure of the economies of joint production is provided by the definition of the economies of scope, which is only subadditivity applied to a restricted set of output vectors.

Definition: *C* exhibits economies of scope if

Equation 1-8

$$C(q_1) + C(q_2) \geq C(q_1 + q_2) \text{ where } q_1 \text{ and } q_2 \text{ are different outputs}$$

Factor inputs shareable by the air carriers to provide freight and passenger services

Include the (1) aircraft, (2) labor—maintenance crew and flight crew, (3) fuel, (4) other inputs—logistics systems and routes. Sharing an aircraft should promote cost complementarity by increasing load factors thereby decreasing average costs. Scheduling a flight for passengers allows a combination carrier to haul freight while increasing total cost at a decreasing rate because for labor and fuel additional freight increases total costs at a decreasing rate (decreasing marginal cost) since the flight is already transporting passengers and may only need to increase crew and fuel at a disproportionately lower rate compared to increasing crew and fuel for the specialist that only transports freight of passenger. The disproportionate increase is due to the use of a shared input. Any given scheduled flight includes an assigned aircraft and operating crew both of which can jointly transport passengers and freight. Furthermore, logistical costs, in addition to the aircraft's fixed cost, may not be impacted by the carriage of freight on a primarily passenger flight. Although aircraft cost complementarity may contribute to potential cost advantage for combo carriers, its impact to be significant, cost complementarity must outweigh any logistical advantages enjoyed by specialist carriers.

Specialist carriers seeking to provide an additional service may face barriers to entry. For example, integrators[23] such as FedEx and UPS operate on predictable, nightly schedules which may prove incongruous with passenger demand. Regardless, an important indication of

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[23] Integrators are all-cargo carriers which dictate their own flight and delivery schedules rather than allowing them to be driven by demand.

economies of scope is cost complementarity as anecdotally described above and analytically described below by the following definition:

Definition: *C* satisfies cost complementarity if

Equation 1-9

$$\mathrm{C}(y_i) \text{ is continuous and differentiable,}$$

$$\mathrm{li}m_{y_i \to y-} \to \mathrm{C}(y_i) = \mathrm{C}(y_i) = \mathrm{li}m_{y_i \to y+} \mathrm{C}(y_i)$$

$$\mathrm{li}m_{y_i \to y-} \frac{C(y_i) - C(y)}{y_i - y} = \mathrm{li}m_{y_i \to y+} \frac{C(y_i) - C(y)}{y_i - y} \ \forall y_i \in Y$$

$$\text{and } \frac{\partial^2 C(y_i)}{\partial y_1 \, \partial y_2} \leq 0$$

1.3 Review of Airline Cost Analyses

The literature has yet to reach a consensus on how to apply cost concepts such as scale, scope, and subadditivity to the air transport industry. Traditional determinations of scale, scope, and subadditivity as outlined in the preceding section, foundational theory as presented by Berg & Tschirhart (1988) do not allow for multidimensional output. However, the transport industry produces multidimensional output[24], spanning both distance and volume. Thus, transportation economists such as Jara-Díaz et al. (2013), Kiesling & Hansen (1993) have attempted to establish universal measures of cost concepts as they apply to the air transport industry. Existing empirical work employing the translog cost function for its flexible interpretation (Chaudary & Mufti, 1999) typically finds increasing returns to density (**RTD**) and constant returns to scale (**RTS**) from varying total cost and variable cost function estimations (Jara-Díaz et al., 2013). While many of these works estimate air transport cost via the translog cost

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[24] Cargo (typically measured in tons of freight, number of passengers) multiplied by the distance in miles or kilometers transported

function, they are distinguishable by their output variable constructions adding further disparity to their cost concept calculations.

Returns to density measures the cost function's response to changes in flows holding network size, points served (**PS**), and route structure, origin-destination pairs (**OD**), all constant. Returns to scale measures the cost response to proportional changes in output and network size holding density constant. The common calculations of **RTD** and **RTS** in this context are as follows:

Equation 1-10

$$\mathrm{RTD} = \left[\sum_i y_i \frac{\partial C}{\partial y_i}\right]^{-1} \qquad \mathrm{RTS} = \left[\sum_i y_i \frac{\partial C}{\partial y_i} + PS \frac{\partial C}{\partial PS}\right]^{-1}$$

Several studies represent output, denoted by y_i produced by firm *i* in Eq. 1, as a multilateral index constructed from carrier reported revenue[25] freight ton-miles and revenue passenger miles including Caves et al. (1984), Caves & Christensen (1988), Kumbhakar (1990), Windle (1991), Oum & Yu (1998). Caves et al. (1984) and Windle (1991) find increasing returns to density as well as constant and increasing returns to scale, respectively. Gillen et al. (1990) also finds constant returns to scale and increasing returns to density; however, rather the multilateral index for output, the authors account for three types of output in the following form: scheduled revenue passenger-kilometers, scheduled revenue freight ton- kilometers, and chartered revenue ton-kilometers.[26] Keeler & Formby (1994) and Johnston & Ozment (2013) represent output using available[27] freight ton-miles and available seat-miles. Using this measure for output, Keeler & Formby find constant returns to scale and increasing returns to

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[25] Not all air transport traffic contributes to carrier revenue.

[26] Revenue ton miles is an aggregate of freight, mail, and passengers measured in tons multiplied by miles transported.

[27] Available refers to aircraft capacity multiplied by multiplied by the distance in miles or kilometers transported.

density whereas Johnston & Ozment find moderate economies of scale. Liu & Lynk (1999) in addition to Creel & Farrell (2001) only consider revenue passenger miles and both find increasing returns to scale and density.

Economies of scope, which denotes the presence of cost advantages derived from the joint production of two or more outputs, is examined far less frequently as applied to the airline industry. It can be determined from the parameter estimate on the interaction between two outputs or it can be calculated from the total cost figures as shown in Eq. 2. Gillen et al. (1990) and Keeler & Formby (1994) both evaluate economies of scope using the parameter estimate method. Gillen et al. (1990) finds diseconomies of scope for the joint provision of scheduled and chartered service. Keeler & Formby (1994) find economies of scope for the joint ***availability*** of freight and passenger services by defining output in terms of capacity rather than output produced.

However, Jara-Díaz et al. (2013) claim these indices fail to reflect true firm behavior such as frequent mergers, acquisitions, and alliances in the air transport industry. To resolve this issue, the authors propose three new indices: corrected returns to density (**RTD'**), multiproduct degree of economies of scale (**S**), and economies of spatial scope (**SC**). **RTD'** measures cost response to proportional change in flows and network size holding route structure constant, **S** measures cost response to change in flows allowing route structure to vary, and **SC** measures cost response to change in flow types (hub-spoke/circular, trunk/local, domestic/international) allowing network size to vary. **RTD'**, **S**, and **SC** are computed as follows:

Equation 1-11

$$\mathrm{RT}D' = \left[\sum_j \alpha_j \eta_j\right]^{-1} \qquad \mathrm{S} = \left[\sum_j \gamma_j \eta_j\right]^{-1} \qquad \mathrm{SC} = \frac{C(Y^A, PS^A) + C(Y^B, PS^B) - C(Y^{A+B}, PS^{A+B})}{C(Y^{A+B}, PS^{A+B})}$$

where α_j represents the elasticity of aggregate output with respect to an output component, η_j represents elasticity of cost with respect to an output component, and superscripts A and B represent differing flow types.

Jara-Díaz et al. (2013) compute their new cost indices **RTD'**, **S**, and **SC** and compare them to the standard **RTD** and **RTS** examined in previous, related research.[28] Overall, Jara-Díaz et al. (2013) find **RTD**< **RTD'**<**S** and develop new measures of spatial scope. Their results are consistent with theory and effectively apply a more nuanced approach to calculating returns to scale, scope and density of estimates from existing research. Limitations include no new empirical analyses or datasets employed to evaluate the new indices. In this sense, the revaluations rely on original cost estimations which may include assumptions inconsistent with the updated indices. Nonetheless, Jara-Díaz et al. (2013) presents a thorough analysis and update of the existing empirical work on the air transport industry from the cost perspective.

Differing entirely in approach from the studies described in Jara-Díaz et al. (2013), Hofer & Eroglu (2010) explore cost concept economies of scope from a revenue perspective. Hofer & Eroglu investigate the impact of economies of scope derived from dual service output, passenger, and cargo, on passenger airline ticket pricing behavior in the US domestic airline industry. They motivate the connection between economies of scope and dual output by citing evidence from the airline management literature, game theoretic economic literature, and the cost structural economic literature. Continued dual service provided by airlines, theoretical cost advantages in an oligopolistic marketplace, and increased profitability via lower operating costs

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[28] Caves et al. (1984), Caves and Christensen (1988), Gillen et al. (1990), Kumbhakar (1990), Windle (1991), Oum Zhang (1991), Keeler and Formby (1994), Baltagi et al. (1995), Oum and Yu (1998), Liu and Lynk (1999), Creel and Farell (2001), and Johnston and Ozment (2013).

all point to economies of scope derived from dual service output. However, none of the research, according to Hofer & Eroglu, directly tests and identifies economies of scope derived from dual service output in the passenger airline industry.

Hofer & Eroglu extend the dual service-scope correlation going as far as to suggest dual service carriers enjoy relatively lower marginal passenger service costs driven by concurrent cargo service provision. They then allege these dual- service carriers pass the cost savings along to their passengers by offering lower fares. In this way, Hofer and Eroglu propose dual service carriers enjoy a comparative advantage over their single service counterparts. Despite the integral role marginal costs appear to play in this framework, no cost estimation was conducted. Rather the authors elected to estimate determinants of passenger volume as well as passenger fares. Data for the analysis is sourced from the Bureau of Transportation Statistics (BTS) including variables such as unit price (fare), number of passengers, weight of cargo, distance between O&D pairs, fraction of tourists, routing circuity, general load factor, airline operating cost, firm financial health, route competitive characteristics, and demographic characteristics of airports. The computation of these variables, from the raw BTS data, remains unclear. The authors used the data to construct the following equations to be estimated:

Equation 1-12

$$ln\,\#passengers = \alpha_0 + \alpha_1\, ln\, fare + \alpha_2\, ln\, miles + \alpha_3\mathrm{circuity} + \alpha_4\mathrm{tourist} + \alpha_5\mathrm{finhealth} + \alpha_6\mathrm{loadfactor} + \alpha_7\mathrm{airlinecost} + \alpha_8\, ln\, population + \alpha_9\, ln\, income + \alpha_{10}\, ln\, freight + \alpha_{11}\, ln\, mail + \sum f\mathrm{irm} + \sum time + \mathrm{u}$$

Equation 1-13

$$lnfare = \beta_0 + \beta_1 ln\#passengers + \beta_2 lnmiles + \beta_3 lncircuity + \beta_4 lntourist + \beta_5 lnfinhealth + \beta_6\mathrm{loadfactor} + \beta_7\mathrm{airlinecost} + \beta_8 lnroute + \beta_9 lnairport + \beta_{10}\mathrm{routesshare} + \beta_{11}\mathrm{airportshare} + \beta_{12} lnfreight + \beta_{13} lnmail + \beta_{14}[lnfreight]^2 + \beta_{15}[lnmail]^2 + \sum f\,irm + \sum t\,ime + \mathrm{v}$$

The authors conclude their findings show greater belly cargo volumes result in lower passenger fares due to economies of scope derived from dual output service. However, there is a point past which greater belly cargo volumes exhaust economies of scope. Additionally, they find legacy carriers benefit more from providing dual service than do low-cost carriers. Cargo volume also seems to have greater negative impact on fares when the carrier has lower route market share, long-haul market participation, and tourist market participation. Even though, all Hofer and Eroglu's findings confirmed their hypotheses, one exception remained. Load factor, they found, does not have a moderating effect on passenger fares. Cost estimation is necessary to identify a relationship between dual service and scope.

In sum, while this review of past research presents mixed findings on economies of scale, (some report increasing returns to scale while others report constant returns to scale) theory presented in the preceding section indicates the possibility of a natural monopoly if the conditions of subadditivity are met, and such conditions can arise even if the industry exhibits constant or increasing average costs. Furthermore, the returns to scale studies use aggregate measures of output rather than separately examine cost changes associated with different types of output (e.g., passenger and freight). For the purposes of this study making the latter distinction is critical to examining whether it is cost effective for companies to jointly provide both services. In addition, those same studies focus on different output flows when examining whether the cost structure of this industries satisfies the condition of economies of scope. While the work of Hofer & Eroglu, does examine economies of scope when jointly offering passenger and freight service, that work examines this concept from the demand side. Hence, there is a gap in the literature as far as empirical tests of subadditivity and empirical tests of economies of scope between freight and passenger service as presented in Eq. 2.

1.4 Empirical Approach and Data

1.4.1 Empirical Approach

This study seeks answers to its queries via a 2-pronged approach: (1) translog total cost function estimation, implemented frequently in the relevant empirical literature summarized in Jara-Díaz et al. (2013), of three separate carrier operations including combination, passenger, and cargo carriers (2) empirical tests of economies of scope and subadditivity, implemented in related cost studies such as Shin & Ying (1992) and Bitzan (1999, 2001). The empirical approach part (1) differs from those outlined in Jara-Diaz et al. 2013 in that it requires differentiation among carrier types: combination, passenger, and cargo. The empirical approach part (2) although obviously applied to other cost studies has yet to be applied identically in the empirical air transport literature. In other words, the existing air transport economies of scope studies do not employ a total cost estimation of economies of scope but defer instead to the translog cost interaction parameter estimate of various output combinations. This study interprets the interaction parameter estimate of the freight and passenger output combination alone to indicate cost complementarity. For the purposes of this study making the latter distinction is critical to examining whether it is cost effective for companies to jointly provide both services. What follows is the set up and subsequent description of the 2-pronged empirical approach.

Air carriers can be sorted into three, general classifications on an annual basis as follows: carriers providing both revenue freight-ton and revenue passenger-ton transport services (combination), carriers providing only revenue freight-ton transport services (cargo), and carriers providing only revenue passenger-ton transport services (passenger). The distinction proves important in more consistent cost estimation for several reasons.

While combination carrier fleets have historically been comprised of three of the four BTS defined aircraft configurations[29], Budd & Ison (2017) finds combination carriers direct investment toward new-wave passenger aircrafts. The passenger aircrafts produced over the last 20 years feature ample cargo bellies. Ample enough, according to Budd & Ison, that combination carriers can undercut cargo carrier freight rates (excluding integrators) and still earn up to 30% profit. Zhang & Zhang (2002) attribute the combination carrier's cost advantage to their distinct production process. Freight service provided by combination carriers mirrors the frequent, consistent, consumer rush of passenger service as opposed to the global, international trade riddled freight service provided by cargo carriers. Although cargo carriers enjoy larger freight load factors, carriers with lower load factors and greater flight density (integrators and combination carriers) appear to have more adequately met explosive, e-commerce/technology driven demand for expedient, low-volume, high-value freight transport. Let air carriers be sorted into three distinct groups on annual basis according to Table 3.

Each carrier faces total annual operating expenses defined as the function of input costs, output quantities, output characteristics, and technological advancement. Annual input costs include labor (salaries and benefits), fuel (aircraft oil and fuel), capital (depreciation, amortization, maintenance materials, rentals, property & equipment), and other transportation related expenses (in-flight entertainment, limousine/car service, etc.).

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[29] Passenger, freighter, and combi (very small percentage of the fourth configuration: seaplane)

Outputs include revenue freight ton-miles **RFTM** (revenue freight tonnage • revenue aircraft miles flown) and passenger freight ton-miles **RPTM** (revenue passengers transported • 0.1 tons • revenue aircraft miles flown). The BTS estimates each passenger + luggage to be the equivalent of 200 pounds, 0.1 tons. While many air carrier cost studies measure freight output by **RFTM**, few to none measure passenger output by **RPTM**. Passenger output is typically measured without the conversion to tons thus revenue seat miles, **RPM** (revenue passengers transported • revenue aircraft miles flown). Since passenger transport service is sold in denominations of seats, **RSM** as a measure of output for revenue analysis logically follows.

As far as cost analyses in the literature are concerned **RSM** seems to have achieved the desired outcome. However, this cost analysis seeks to investigate the relationship between jointly transported freight output and passenger output flown on the same input, the aircraft. An aircraft faces capacity constraints in terms of raw tonnage to be safe to fly. Thus, it follows that ton-miles serve as the logical unit for measuring operational cost incurred by both passenger traffic and freight traffic.

Table 1-1 Carrier Classifications – Variable with Respect to Time (Year)

	RFTM > 0	**RPTM > 0**
RFTM > 0	Cargo	Combination
RPTM > 0	Combination	Passenger

Therefore, an air carrier either produces a single product (**RPTM** or **RFTM)** multiple products (**RPTM** and **RFTM).** When combination carriers provide both **RPTM** and **RFTM** on the same aircraft, the aircraft can be considered a shared input (Panzar & Willig, 1981). Sharing an aircraft also implies shared fuel and labor inputs excluding employees specializing in the service of a single output such as flight attendants to **RPTM.** Given the presence of a shared input, Panzar & Willig (1981) prove the existence economies of scope between those two inputs.

Scheduling a flight for passengers allows a combo carrier to additionally haul freight while increasing total cost at a decreasing rate because for labor and fuel, additional freight increases total costs at a decreasing rate (decreasing marginal cost) since the flight is already transporting passengers and may only need to increase crew and fuel at a disproportionately lower rate compared to increasing crew and fuel for the specialist that only transports freight of passenger. The disproportionate increase is due to the use of a shared input.

The flight already has a crew and aircraft assigned to the flight and these inputs can transport both passengers and freight. Further, the cost of logistics systems and aircraft might not increase when additionally hauling freight since the company is transporting passengers anyway. Thus, this study identifies the presence of a shared input and empirically tests for economies of scope to provide evidence for Panzar & Willig's theory. Keeping that set up in mind, the empirical approach part (1) follows.

First, I estimate a translog cost function for combination, passenger, and cargo carriers from 1991 to 2021, post-deregulation, generally defined as in Eq. 1- 14.

Equation 1-14

$$\mathrm{C} = \mathrm{f}(\mathrm{P}, \mathrm{Y}, \mathrm{M}, \mathrm{T})$$

where *C*, total cost is a function of *P*, input prices, *Y,* output, *M*, movement characteristics, and *T*, the number of years since 1991. Inputs include labor, fuel, capital and other.[30]

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[30] Other expenses include landings fees, rentals, service expenses, and transport related expenses.

Output[31] is measured in revenue freight- and/or passenger-ton-miles, the product of tonnage and miles transported for revenue. Movement characteristics include average load factor[32], average stage length[33], points served[34], and fleet size. *T* is a time trend included to capture unexplained technological change. Equation 15 features a second order Taylor series expansion of Eq. 14 around the mean values of output, factor input prices, technical characteristics and time.

Logarithmic transformation of Eq. 15 and parameterization of its partial derivatives yields Eq. 16, the relevant translog cost specification:[35]

Equation 1-15

$$\begin{aligned}
\mathrm{C} = \mathrm{f}(\mathrm{P},\mathrm{Y},\mathrm{M},\mathrm{T}) = {} & \frac{\bar{\mathrm{C}}}{0!} + \frac{\frac{\partial \mathrm{C}}{\partial \mathrm{P}}}{1!}(\mathrm{P}-\bar{\mathrm{P}}) + \frac{\frac{\partial \mathrm{C}}{\partial \mathrm{Y}}}{1!}(\mathrm{Y}-\bar{\mathrm{Y}}) + \frac{\frac{\partial \mathrm{C}}{\partial \mathrm{M}}}{1!}(\mathrm{M}-\bar{\mathrm{M}}) + \frac{\frac{\partial \mathrm{C}}{\partial \mathrm{T}}}{1!}(\mathrm{T}-\bar{\mathrm{T}}) + \frac{\frac{\partial^2 \mathrm{C}}{\partial \mathrm{P}^2}}{2!}(\mathrm{P}-\bar{\mathrm{P}})^2 + \frac{\frac{\partial^2 \mathrm{C}}{\partial \mathrm{P}\,\partial \mathrm{Y}}}{2!}(\mathrm{P}-\bar{\mathrm{P}})(\mathrm{Y}-\bar{\mathrm{Y}}) + {} \\
& \frac{\frac{\partial^2 \mathrm{C}}{\partial \mathrm{P}\,\partial \mathrm{M}}}{2!}(\mathrm{P}-\bar{\mathrm{P}})(\mathrm{M}-\bar{\mathrm{M}}) + \frac{\frac{\partial^2 \mathrm{C}}{\partial \mathrm{P}\,\partial \mathrm{T}}}{2!}(\mathrm{P}-\bar{\mathrm{P}})(\mathrm{T}-\bar{\mathrm{T}}) + \frac{\frac{\partial^2 \mathrm{C}}{\partial \mathrm{Y}^2}}{2!}(\mathrm{Y}-\bar{\mathrm{Y}})^2 + \frac{\frac{\partial^2 \mathrm{C}}{\partial \mathrm{Y}\,\partial \mathrm{P}}}{2!}(\mathrm{Y}-\bar{\mathrm{Y}})(\mathrm{P}-\bar{\mathrm{P}}) + \frac{\frac{\partial^2 \mathrm{C}}{\partial \mathrm{Y}\,\partial \mathrm{M}}}{2!}(\mathrm{Y}-\bar{\mathrm{Y}})(\mathrm{M}-\bar{\mathrm{M}}) + {} \\
& \frac{\frac{\partial^2 \mathrm{C}}{\partial \mathrm{Y}\,\partial \mathrm{T}}}{2!}(\mathrm{Y}-\bar{\mathrm{Y}})(\mathrm{T}-\bar{\mathrm{T}}) + \frac{\frac{\partial^2 \mathrm{C}}{\partial \mathrm{M}^2}}{2!}(\mathrm{M}-\bar{\mathrm{M}})^2 + \frac{\frac{\partial^2 \mathrm{C}}{\partial \mathrm{M}\,\partial \mathrm{P}}}{2!}(\mathrm{M}-\bar{\mathrm{M}})(\mathrm{P}-\bar{\mathrm{P}}) + \frac{\frac{\partial^2 \mathrm{C}}{\partial \mathrm{M}\,\partial \mathrm{Y}}}{2!}(\mathrm{M}-\bar{\mathrm{M}})(\mathrm{Y}-\bar{\mathrm{Y}}) + \frac{\frac{\partial^2 \mathrm{C}}{\partial \mathrm{M}\,\partial \mathrm{T}}}{2!}(\mathrm{M}-\bar{\mathrm{M}})(\mathrm{T}-\bar{\mathrm{T}}) + {} \\
& \frac{\frac{\partial^2 \mathrm{C}}{\partial \mathrm{T2}}}{2!}(\mathrm{T}-\bar{\mathrm{T}})^2 + \frac{\frac{\partial^2 \mathrm{C}}{\partial \mathrm{T}\,\partial \mathrm{P}}}{2!}(\mathrm{T}-\bar{\mathrm{T}})(\mathrm{P}-\bar{\mathrm{P}}) + \frac{\frac{\partial^2 \mathrm{C}}{\partial \mathrm{T}\,\partial \mathrm{Y}}}{2!}(\mathrm{T}-\bar{\mathrm{T}})(\mathrm{Y}-\bar{\mathrm{Y}}) + \frac{\frac{\partial^2 \mathrm{C}}{\partial \mathrm{T}\,\partial \mathrm{M}}}{2!}(\mathrm{T}-\bar{\mathrm{T}})(\mathrm{M}-\bar{\mathrm{M}}) + \mathrm{R}
\end{aligned}$$

Factor-share equations, as shown by Eq. 17, are simply the derivative of the cost function with respect to the relevant factor. Thus $\alpha_L, \alpha_k, and\ \alpha_O$ represent labor, capital, and other's share of total cost respectively. As in previous studies using the translog cost function, I estimate the cost function and factor-share equations simultaneously as a system of seemingly unrelated regressions.

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[31] *Inclusion of output in any given cost function invites endogeneity concerns. See Appendix Table 1A-2 for the 3SLS estimation of the cost function in which output, RFTM, is instrumented with freight prices and RPTM, is instrumented with passenger ticket prices following the procedure applied to rail in Bitzan & Keeler 2003. The estimates are very similar to the un-instrumented results suggesting output is exogenous to the cost function.*

[32] Ratio of tonnage transported to aircraft capacity

[33] Ratio of departures performed and aircraft miles flown

[34] Number of airports served

[35] Traditionally research using the translog cost function avoids taking the log of the normalized mean if the time trend is used to depict unexplained technical change. This study follows that convention.

All but one factor-share equation are estimated to avoid singularity in the estimated covariance matrix (Takada et al*.,* 1995). Share equation parameter estimates satisfy the following conditions of homogeneity and symmetry shown in Eq. 18 and calculated for the sample in the Appendix Table 1A-1.

Equation 1-16

$$\ln C = \alpha_0 + \textstyle\sum_i \alpha_i \ln\left(\frac{P_i}{\bar{P}_\iota}\right) + \beta_Y\, ln\frac{Y}{\bar{Y}} + \textstyle\sum_n \gamma_n ln\left(\frac{M_n}{\bar{M}}\right) + \delta_T T + \frac{1}{2}\textstyle\sum_{ij} \phi_{ij} ln\left(\frac{P_i}{\bar{P}_\iota}\right) ln\left(\frac{P_j}{\bar{P}_j}\right) + \textstyle\sum_i \phi_{iY} ln\left(\frac{P_i}{\bar{P}_\iota}\right) ln\frac{Y}{\bar{Y}} +$$

$$\textstyle\sum_{in} \phi_{in} ln\left(\frac{P_i}{\bar{P}_\iota}\right) ln\left(\frac{M_n}{\bar{M}}\right) + \textstyle\sum_i \phi_{\mathrm{iT}} ln\left(\frac{P_i}{\bar{P}_\iota}\right)\mathrm{T} + \frac{1}{2}\phi_{YY}\left(ln\frac{Y}{\bar{Y}}\right)^2 + \textstyle\sum_n \phi_{Yn} ln\frac{Y}{\bar{Y}} ln\left(\frac{M_n}{\bar{M}}\right) + \phi_{YT} ln\frac{Y}{\bar{Y}}T + \frac{1}{2}\textstyle\sum_{nl} \phi_{nl} ln\left(\frac{M_n}{\bar{M}}\right) ln\left(\frac{M_l}{\bar{\mathrm{M}}}\right) +$$

$$\textstyle\sum_n \phi_{nT} ln\left(\frac{M_n}{\bar{M}}\right) T + \frac{1}{2}\phi_{TT} T^2 + \mu$$

Equation 1-17

$$\frac{\partial lnC}{\partial ln\left(\frac{P_i}{\bar{P}_\iota}\right)} = \alpha_i + \textstyle\sum_j \phi_{ij} ln\left(\frac{P_j}{\bar{P}_l}\right) + \textstyle\sum_Y \phi_{iY} ln\frac{Y}{\bar{Y}} + \textstyle\sum_n \phi_{in} ln\left(\frac{M_n}{\bar{M}}\right) + \phi_{\mathrm{iT}}\,\mathrm{T}$$

Equation 1-18

$$\textstyle\sum_i \alpha_i = \theta,\quad \textstyle\sum_i \phi_{ij} = \textstyle\sum_j \phi_{ij} = 0,\quad \textstyle\sum_i \phi_{iY} = \textstyle\sum_i \phi_{in} = \textstyle\sum_i \phi_{iT} = 0,\quad \phi_{ij} = \phi_{ji}$$

Following the theory outline in the previous section, cost function estimations are necessary to test for subadditivity and economies of scope. The empirical approach part (2) follows:

Equation 1-19

$$\mathrm{C}(y_f + y_p) < \mathrm{C}(\alpha y_f + (1-\alpha)y_p) + \mathrm{C}\left((1-\alpha)y_f + \alpha y_p\right)$$

where $0 < \alpha < 1$. Satisfaction $\forall\alpha$ indicates a single firm is the least expensive way to produce any given combination of freight and passenger services. To empirically test whether or not carriers satisfy this condition, I simulate 999 freight and passenger service output combinations for each carrier each year which comes out to around 1.1 million inequalities. Then, I calculate the fraction out of 999 that each carrier satisfies the subadditivity inequality and find the average across carriers for each year which is presented in the results section.

Multiproduct cost function subadditivity is more stringent than multiproduct economies of scope, which can be generally defined as follows:

Equation 1-20

$$\mathrm{C}(y_f + y_p) < \mathrm{C}(y_f) + \mathrm{C}(y_p)$$

Equation 1-21

$$C_i(y_f + y_p) < C_j(y_f) + C_k(y_p)$$

where *i* denotes a combination carrier, *j* denotes a cargo carrier, and *k* denotes a passenger carrier. Satisfaction of Eq. 20 suggests joint provision of freight and passenger services is less costly than separate provision of freight and passenger services at the output levels currently produced by the firm in question. Satisfaction of Eq. 21 suggests a combination carrier can jointly provide the same level of freight service provided by a cargo carrier and the same level of passenger service provided by a passenger carrier at total cost than the sum of the specialists' total costs.

Empirically, I identify carriers from each group, combination, passenger, and cargo, that consistently report from 2012 to 2021. Combination carriers include Everts Air Cargo, Atlas Air Inc., Air Transport International, Endeavor Air Inc., American Airlines Inc., Alaska Airlines Inc., Delta Airlines Inc., Hawaiian Airlines Inc. MN Airlines, United Air Lines Inc., Southwest Airlines Inc., and Mesa Airlines Inc. Cargo carriers include UPS, ABX Air Inc., FedEx, Gulf and Caribbean Cargo, Kalitta Air LLC, Aloha Air Cargo, Kalitta Charters II, Lynden Air Cargo Airlines, Amerijet International, Northern Air Cargo Inc., and Asia Pacific. Passenger carriers include Allegiant Air, United Express, and SkyWest Airlines Inc. Then, for each combination carrier, I simulate their total costs using each output combination as offered by any two specialists. As there are three unique passenger carriers, three unique specialist passenger output levels, and eleven unique cargo carriers & eleven unique specialist cargo output levels, each combination carrier undergoes 33 scope simulations coming out to 396 in total. I then calculate the fraction of combinations for which combination carriers satisfy economies of scope exploiting within and without variation.

1.4.2 Data

The empirical analyses of in the US air transport industry uses data from individual airline Form 41 financial reports and T-100 traffic data reported by large, certificated U.S. air carriers to the U.S. Department of Transportation for years 1991-2021. Information on all-cargo companies' total costs, prices of factor inputs, outputs, and movement characteristics are taken from these reports. Specifically, *Total Cost* is computed as the given value of *Operating Expense* as given by Form 41, Schedule P-6.

Table 1-2 Variable Construction

Variable	**Source**	**Item(s)**		**Construction**
Labor Price	P-1(a)	Number of full-time equivalent employees	fteemp	$\frac{sal\_ben}{fteemp} \cdot \frac{\mathrm{GDP_i}}{100}$
	P-6	Salaries and Benefits	sal_ben	
	BEA	GDP – Chain-type Price Index for Intermediate Input	GDP_i	
Fuel Price	P-6	Aircraft fuel and oil expense	fuel	$\frac{fuel}{gall} \cdot \frac{\mathrm{GDP_i}}{100}$
	T2	Aircraft fuels issued	gall	
Capital Price	P-6	Amortization	amort	$\frac{(amort+deprec+mat)}{ra\_ho} \cdot \frac{\mathrm{GDP_i}}{100}$
		Depreciation	deprec	
		Materials	rent	
	T1	Revenue airborne hours	ra_ho	
Lease Price	P-6	Landing fees	land_f	$\frac{(land_f+serv+rent+trans\_exp)}{ra\_ho} \cdot \frac{GDP_i}{100}$
		Service expenses	serv	
		Rentals	rent	
		Transport related expenses	trans_exp	
	T1	Revenue airborne hours	ra_ho	
Airports	T3	Origin Airport ID	or_id	bysort year unique_carrier: count(or_{id})
Fleet	T2	Aircraft Type	air_c	bysort year unique_carrier or_id: count(air_c)
Stage	T1	Revenue aircraft miles flown	rmf	$\frac{rmf}{dep}$
		Revenue aircraft departures performed	dep	

Load - Freight	T1	Revenue ton-miles - freight Revenue ton-miles - mail Available ton-miles	rtm_f rtm_m atm	$\frac{rtm_f+rtm_m}{atm}$
Load - Passenger	T1	Revenue ton-miles - passenger	rtm_p	$\frac{rtm_p}{atm}$

Input prices include those for labor, fuel, capital and other nonlabor factor inputs. *Capital Price* is computed as the ratio of the sum of *Depreciation*, *Amortization,* and *Materials* as given by Form 41, Schedule P-6 to *Air Hours* taken from Form 41, Table T1. *Fuel Price* is computed as the ratio of *Fuel Cost* taken from Form 41, Schedule P-6 to *Gallons Consumed* taken from Form 41, Table T2. *Labor Price* is computed as the ratio of *Salaries and Benefits* taken from Form 41, Schedule P-6 to *Full Time Equivalent Employees* as given by Form 41, Schedule P-1(a). Prices for *Other Non-Labor Factor Inputs* is computed as the ratio of the sum of *Landing Fees*, *Transport-Related Expenses*, *Service-Related Expenses*, *Other Expenses*, and *Rentals* as given by Form 41, Schedule P-6 to *Air Hours* taken from Form 41, Table T1. *Revenue Ton-Miles* is a commonly used output measure in the air cargo industry. Information on total *Revenue Ton-Miles* for the year is taken from Form 41, Table T1.

Table 5: (1) payroll sizes have increased over time, which is indicative of a growth sector; (2) real fuel prices increased after 9/11 and peaked by 2013; (3)**fuel usage varies in a relatively tight range which may indicate use of fuel efficient aircraft; (4) points served increased notably from 2000 to 2018 and fell-off during the pandemic; (5) fleet size increases throughout the sample period until the pandemic; (6) stage length has generally increased, which has economies of scale implications; (7) revenue freight ton miles has made notable gains following 2013, which is consistent with the notion that companies are taking advantage of consumer demand associated with the rise of e-commerce. (8) Freight load factor varies in a

narrow range; (9) revenue passenger ton miles reveals a positive trend until the pandemic (see 2020's big drop); (10) passenger load factors vary in a narrow range until the pandemic (see 2020's big drop); (11) the number of competitors have dropped significantly since the great recession and stayed low, which is consistent with the notion of a noncompetitive market structure that is associated with decreasing average cost as seen in Table 4.

Table 1-3 Descriptive Statistics by Service Type

	Cargo	Combination	Passenger
Labor	92,008	71,853	62,570
Fuel	1.46	1.42	1.65
Capital	1,741	650	747
Other	3,809	885	1,034
FTE Employees	9,499	13,974	1,823
Gallons of Fuel	144,108,067	499,578,967	77,244,464
Points Served	125	141	145
Fleet	37	59	19
Passenger	0.59	87.08	99.94
Freight	99.35	10.01	0.01
Combi	0.06	2.76	0.01
Seaplane	0.00	0.16	0.04
Stage Length	1,451	1,222	914
RFTM	3.9e+09	1.2e+09	0.000
RPTM	0.000	6.6e+09	1.2e+09
LOAD_F	0.52	0.08	0.00
LOAD_P	0.00	0.44	0.54
Carriers	21	38	19

Table 1-4 Average Cost per Ton Mile by Carrier Type

	Cargo	Combination	Passenger
1991	0.31	1.04	0.88
1992	0.41	0.99	1.05
1993	0.48	0.91	2.33
1994	0.50	0.89	1.06
1995	0.47	0.84	1.22
1996	0.41	0.84	0.95
1997	1.77	0.80	0.88
1998	0.66	0.72	0.92
1999	0.66	0.72	0.89
2000	1.00	0.77	2.34
2001	1.25	0.72	0.75
2002	1.04	0.64	0.98
2003	1.04	0.68	1.85
2004	0.33	0.66	1.36
2005	0.39	0.76	1.37
2006	0.36	0.75	1.27
2007	0.49	0.83	1.35
2008	0.68	0.94	1.72
2009	0.66	0.77	2.43

2010	0.63	1.49	1.15
2011	0.72	1.77	0.71
2012	0.76	1.03	2.40
2013	1.48	0.67	2.84
2014	1.88	0.50	2.78
2015	1.63	0.65	2.51
2016	2.14	0.47	2.89
2017	2.18	0.42	2.67
2018	2.67	0.49	3.02
2019	2.81	0.67	7.27
2020	1.20	0.68	4.30
2021	0.63	0.62	2.69

Table 1-5 Annual Descriptive Statistics -Combination Carriers

	Labor	Fuel	Capital	Other	FTE Employees	Gallons of Fuel	Points	Stage
1991	64,645	1.23	1,011	1,185	16,565	450,441,705	132	1,172
1992	61,170	1.04	984	1,344	18,469	519,725,392	134	1,222
1993	59,297	0.93	793	1,018	14,422	479,327,385	102	1,084
1994	61,878	0.89	785	1,024	11,771	411,262,056	106	1,207
1995	61,774	0.84	793	985	12,082	424,684,121	110	1,110
1996	61,777	0.90	727	966	11,317	407,125,423	120	1,090
1997	64,450	0.87	882	1,060	11,816	430,408,457	107	1,078
1998	60,400	0.67	593	750	12,159	428,425,765	110	1,012
1999	64,169	0.80	701	793	13,184	457,846,176	109	1,125
2000	67,008	1.06	715	784	13,892	489,197,849	114	1,132
2001	68,127	1.07	695	985	14,131	464,822,139	121	1,138
2002	68,183	1.31	631	715	13,292	426,953,921	121	1,187
2003	72,292	1.17	572	668	11,002	371,462,814	147	1,205
2004	70,017	1.43	506	697	10,942	402,763,657	144	1,206
2005	68,074	1.82	506	761	11,211	434,951,856	150	1,185
2006	68,566	2.11	514	813	10,828	431,827,334	145	1,238
2007	66,877	2.15	545	785	10,960	416,710,260	140	1,271
2008	64,746	2.90	551	888	10,888	415,807,573	144	1,238
2009	71,981	1.73	506	925	12,539	473,153,850	159	1,184
2010	80,985	1.84	520	884	12,444	488,837,095	174	1,218
2011	81,016	2.17	510	970	14,348	566,374,057	186	1,212
2012	84,011	2.41	476	1,019	15,387	608,653,926	180	1,215
2013	83,622	2.91	556	863	16,107	652,821,151	180	1,321
2014	86,200	1.91	497	746	17,668	717,012,609	191	1,322
2015	88,513	1.43	536	759	21,068	789,953,581	191	1,368
2016	91,693	0.99	598	868	19,531	772,821,293	198	1,489
2017	90,827	1.01	539	731	20,725	823,515,727	215	1,496
2018	94,898	1.25	571	759	19,468	785,385,119	198	1,399
2019	106,017	1.37	724	1,039	22,550	885,776,754	141	1,576
2020	98,896	1.09	845	994	21,500	503,540,425	132	1,783
2021	94,244	1.35	612	747	19,666	655,019,731	151	1,579

Table 1-6 Annual Descriptive Statistics - Combination Carriers, cont'd

	Fleet	Passenger	Freight	Combi	Seaplane	RFTM	RPTM	LOAD_F	LOAD_P	Carriers
1991	72	86.36	9.32	4.32	0.00	1.1e+09	4.1e+09	0.09	0.41	33
1992	73	85.65	10.38	3.98	0.00	1.3e+09	5.0e+09	0.09	0.42	34
1993	64	84.04	11.48	4.48	0.00	9.7e+08	4.7e+09	0.11	0.43	39
1994	57	82.59	13.50	3.92	0.00	8.9e+08	4.2e+09	0.11	0.41	44
1995	55	86.01	10.41	3.57	0.00	8.8e+08	4.5e+09	0.09	0.42	43
1996	51	88.41	8.27	3.32	0.00	8.2e+08	4.4e+09	0.08	0.41	45
1997	52	86.38	10.27	3.35	0.00	1.1e+09	4.6e+09	0.09	0.43	46
1998	49	85.32	10.25	4.44	0.00	1.2e+09	4.6e+09	0.08	0.45	48
1999	52	84.00	12.44	3.56	0.00	1.3e+09	5.0e+09	0.10	0.42	44
2000	49	87.61	8.79	3.60	0.00	1.3e+09	5.4e+09	0.08	0.46	43
2001	55	88.81	9.72	1.18	0.29	1.2e+09	5.2e+09	0.08	0.46	41
2002	53	91.98	6.85	1.17	0.00	8.5e+08	5.3e+09	0.07	0.43	39
2003	54	89.95	8.42	1.63	0.00	7.2e+08	4.8e+09	0.07	0.45	41
2004	50	90.73	7.55	1.72	0.00	7.9e+08	5.3e+09	0.07	0.50	44
2005	51	91.69	6.42	1.89	0.00	8.0e+08	6.1e+09	0.06	0.47	41
2006	48	90.59	7.29	2.12	0.00	8.6e+08	6.2e+09	0.07	0.48	43
2007	45	90.39	7.58	2.04	0.00	7.5e+08	6.1e+09	0.06	0.49	45
2008	45	90.47	7.40	2.14	0.00	7.6e+08	6.2e+09	0.06	0.50	43
2009	55	88.47	9.01	2.52	0.00	7.8e+08	7.2e+09	0.06	0.47	35
2010	55	86.21	11.17	2.62	0.00	1.2e+09	7.4e+09	0.08	0.45	35
2011	64	86.94	10.23	2.83	0.00	1.3e+09	8.7e+09	0.08	0.45	34
2012	72	83.77	12.62	3.60	0.00	1.4e+09	9.4e+09	0.09	0.45	30
2013	70	82.28	10.81	3.44	3.48	1.4e+09	1.0e+10	0.09	0.46	28
2014	75	88.52	9.29	2.19	0.00	1.6e+09	1.1e+10	0.07	0.47	26
2015	80	83.81	10.41	2.49	3.29	1.8e+09	1.3e+10	0.08	0.47	23
2016	81	85.68	11.86	2.46	0.00	1.8e+09	1.2e+10	0.09	0.41	24
2017	81	83.65	13.86	2.49	0.00	2.3e+09	1.3e+10	0.10	0.42	22
2018	72	85.89	12.55	1.56	0.00	2.2e+09	1.3e+10	0.08	0.43	27
2019	78	83.21	15.43	1.36	0.00	2.4e+09	1.5e+10	0.08	0.40	22
2020	95	82.15	15.74	2.11	0.00	2.2e+09	5.9e+09	0.11	0.24	22
2021	92	81.92	16.12	1.96	0.00	2.7e+09	9.6e+09	0.12	0.31	22

The data sources used for this study also include information necessary to compute the cost shares of each factor input. Cost share information for these four inputs is critical for estimating cost functions. Output and movement characteristics are included in this analysis to account for cost changes attributable to non-input-price cost determinants. *Revenue Ton-Miles* (**RTM**) is used to measure output levels and captures the potential of economies of scale associated with transporting greater cargo volumes. Movement characteristics include air cargo companies' *Stage Length*, *Load Factor* and *Points served*. *Stage Length* is the aeronautical distance flown per route. Longer *Stage Lengths* contribute to lower costs because they require fewer costly take-offs and landings. *Load Factor* for air cargo transport is defined as *Revenue Ton-Miles* divided by *Available Ton-Miles*. *Load Factors* are included to show that many operational costs (e.g., flight crew, maintenance, fuel) do not increase proportionally with the freight tonnage on a flight. *Points served* is included as a proxy for firm size and is included to account for the potential a more extensive network presents with the potential economies of network size present. Data used to construct the movement characteristic variables is taken from the T-100 traffic data reports.

1.5 Results

1.5.1 Translog Total Cost Estimation

Cost results in Table 7 feature inelastic, statistically significant, positive first-order input price parameter estimates varying in magnitude across carrier types. These parameters also represent average cost shares per input. The magnitude of the first-order labor price parameter estimate is greatest for combination carriers followed by cargo and passenger carriers. First-order fuel and capital price parameter estimate magnitudes are greatest for passenger carriers followed by cargo and combination carriers. Cargo carrier first-order other price parameter estimate magnitude exceeds those for both passenger and combination carriers. Although combination and cargo first-order **RFTM** parameter estimates are both positive, the combination estimate is lesser in magnitude and lower in significance than the cargo estimate. This result is unsurprising considering annual average **RFTM** output shares for cargo carriers exceed those of combination carriers by more than 60%. Combination and passenger first-order **RPTM** parameter estimates are both positive, significant at the 1% level but disparate in magnitude suggesting relatively greater combination cost responsiveness to **RPTM** fluctuation. Both parameter estimates for **RFTM** and **RPTM** are less than one indicating increasing returns to scale.

Average stage length results of variable magnitude indicate statistically significant cost savings across all carrier types. Cargo costs benefit most from longer average stage lengths, followed by passenger and combination costs respectively. Load factor results indicate cost savings across all carrier types yet fail to boast the statistical significance achieved by input prices, output, and average stage length. Fluctuations in freight load factors impact cargo cost at the 5% level failing to impact combination cost at any relevant significance level. Alas, worry not combination carriers, passenger load factors deliver, at the 1% level, statistically more significant cost savings than those received by passenger carriers.

Table 1-7 Translog Total Cost Estimation Results by Carrier Type

	Combination	Passenger	Cargo
Labor	0.249***	0.175***	0.211***
	(0.0045)	(0.00915)	(0.00808)
Fuel	0.139***	0.185***	0.155***
	(0.00474)	(0.0103)	(0.00956)
Other	0.341***	0.348***	0.387***
	(0.00294)	(0.00928)	(0.00868)
Capital	0.271***	0.292***	0.246***
	(0.00266)	(0.00866)	(0.00565)
RFTM	0.102**		0.783***
	(0.0372)		(0.0474)
RPTM	0.954***	0.684***	
	(0.0379)	(0.0562)	
Stage Length	-0.963***	-0.727***	-0.650***
	(0.0526)	(0.114)	(0.117)
LOAD_F	-0.0456		-1.064***
	(0.0376)		(0.251)
LOAD_P	-0.481***	-0.254	
	(0.078)	(0.224)	
Points Served	0.106*	0.101	0.363***
	(0.043)	(0.0779)	(0.0758)
Fleet	0.133***	0.107	0.196**
	(0.0366)	(0.057)	(0.061)
Time	-0.0381***	-0.0178	0.113***
	(0.00476)	(0.012)	(0.00895)
Labor Sq.	0.102***	0.0373***	0.0508***

	(0.00354)	(0.00645)	(0.0032)
Fuel Sq.	0.0470***	0.0487***	0.0668***
	(0.00169)	(0.0027)	(0.00357)
Other Sq.	0.166***	0.108***	0.145***
	(0.00207)	(0.00615)	(0.00299)
Capital Sq.	0.140***	0.0989***	0.116***
	(0.00216)	(0.00688)	(0.00333)
RFTM Sq.	0.163***		0.148***
	(0.0269)		(0.0349)
RPTM Sq.	0.235***	0.0606***	
	(0.0248)	(0.0168)	
Stage Sq.	0.250***	0.789***	0.600***
	(0.0555)	(0.139)	(0.171)
LOAD_F Sq.	0.152***		0.239
	(0.0309)		(0.673)
LOAD_P Sq.	0.00624	-0.781	
	(0.071)	(0.474)	
Points Served Sq.	0.0292	0.140**	0.0454
	(0.0279)	(0.0465)	(0.0779)
Fleet Sq.	-0.0162	0.214	0.218**
	(0.0519)	(0.133)	(0.0832)
	Combination	**Passenger**	**Cargo**
Time Sq.	0.00365***	0.00711***	-0.00471***
	(0.000306)	(0.000718)	(0.000568)
*Labor*Fuel*	-0.0191***	-0.0227***	-0.0171***
	(0.00156)	(0.00237)	(0.00251)
*Labor*Other*	-0.0557***	-0.0132**	-0.0276***
	(0.00236)	(0.00487)	(0.0024)
*Labor*Capital*	-0.0270***	-0.00136	-0.00609**
	(0.00207)	(0.00541)	(0.00227)
*Labor*RFTM*	-0.00832**		0.0057
	(0.00284)		(0.0037)
*Labor*RPTM*	-0.00131	-0.00845**	
	(0.00256)	(0.00316)	
*Labor*Stage*	0.0119**	-0.0149	-0.0678***
	(0.00415)	(0.00768)	(0.00844)
*Labor*LOAD_F*	0.0105***		-0.0670***
	(0.00293)		(0.0192)
*Labor*LOAD_P*	0.0163***	-0.00902	
	(0.0046)	(0.0147)	
*Labor*Points Served*	-0.0233***	0.0110*	0.0079
	(0.00301)	(0.00461)	(0.00601)
*Labor*Fleet*	0.0291***	-0.000175	-0.00314
	(0.0031)	(0.00612)	(0.00648)
*Labor*Time*	0.00160***	0.00351***	0.000579
	(0.00026)	(0.000505)	(0.000458)
*Fuel*Other*	-0.0129***	-0.0118***	-0.0286***
	(0.00109)	(0.00236)	(0.00251)
*Fuel*Capital*	-0.0150***	-0.0143***	-0.0211***
	(0.000995)	(0.00231)	(0.00196)
*Fuel*RFTM*	0.0138***		0.00627
	(0.00294)		(0.00441)
*Fuel*RPTM*	-0.00873**	0.0159***	
	(0.00272)	(0.00302)	
*Fuel*Stage*	0.0396***	0.0383***	0.0430***
	(0.00395)	(0.00778)	(0.00997)
*Fuel*LOAD_F*	-0.0141***		0.0394

	(0.003)		(0.0224)
*Fuel*LOAD_P*	0.00105	0.0282	
	(0.0049)	(0.0166)	
*Fuel*Points Served*	0.00366	0.0017	-0.0214**
	(0.00319)	(0.00511)	(0.00705)
*Fuel*Fleet*	-0.0167***	-0.00276	-0.00677
	(0.00326)	(0.00688)	(0.00763)
*Fuel*Time*	0.00379***	0.00205***	0.00250***
	(0.000277)	(0.000551)	(0.00055)
*Other*Capital*	-0.0977***	-0.0833***	-0.0891***
	(0.00155)	(0.00481)	(0.00237)
*Other*RFTM*	0.0015		-0.00807*
	(0.00186)		(0.00399)
*Other*RPTM*	0.00381*	-0.0012	
	(0.00165)	(0.00305)	
*Other*Stage*	-0.0351***	0.00259	0.0135
	(0.0028)	(0.00759)	(0.00907)
*Other*LOAD_F*	-0.0031		0.00952
	(0.00191)		(0.0206)
*Other*LOAD_P*	-0.00913**	-0.0234	
	(0.00295)	(0.0148)	

	Combination	**Passenger**	**Cargo**
*Other*Points Served*	0.0105***	-0.0181***	0.00973
	(0.00194)	(0.00464)	(0.00647)
*Other*Fleet*	-0.00641**	0.00535	0.0114
	(0.002)	(0.00615)	(0.00695)
*Other*Time*	-0.00199***	-0.00236***	-0.000355
	(0.000168)	(0.000498)	(0.0005)
*Capital*RFTM*	-0.00701***		-0.00391
	(0.00166)		(0.00259)
*Capital*RPTM*	0.00623***	-0.00629*	
	(0.0015)	(0.00286)	
*Capital*Stage*	-0.0164***	-0.0259***	0.0113
	(0.0025)	(0.007)	(0.00592)
*Capital*LOAD_F*	0.00673***		0.0181
	(0.00171)		(0.0134)
*Capital*LOAD_P*	-0.00818**	0.00426	
	(0.00268)	(0.014)	
*Capital*Points Served*	0.00914***	0.00541	0.00378
	(0.00176)	(0.00435)	(0.0042)
*Capital*Fleet*	-0.00602***	-0.00241	-0.00148
	(0.00182)	(0.00582)	(0.00451)
*Capital*Time*	-0.00340***	-0.00319***	-0.00273***
	(0.000153)	(0.000471)	(0.000327)
*RFTM*RPTM*	-0.164***		
	(0.0232)		
*RFTM*Stage*	0.0682		-0.263***
	(0.0349)		(0.0598)
*RPTM*Stage*	-0.118**	-0.270***	
	(0.0365)	(0.0378)	
*RFTM*LOAD_F*	-0.158***		-0.0301
	(0.0281)		(0.114)
*RPTM*LOAD_P*	-0.110**	0.292***	
	(0.0398)	(0.0885)	
*RPTM*LOAD_F*	0.165***		
	(0.025)		
*RFTM*LOAD_P*	0.110**		

	(0.0375)		
*RFTM*Points Served*	0.0117		-0.0359
	(0.0253)		-0.0371
*RFTM*Fleet*	-0.00208		-0.129**
	(0.0279)		-0.0432
*RPTM*Points Served*	0.0173	-0.0139	
	(0.0264)	(0.0199)	
*RPTM*Fleet*	-0.0268	-0.0642**	
	(0.027)	(0.024)	
*RFTM*Time*	0.000745		0.00468*
	(0.00178)		(0.00233)
*RPTM*Time*	-0.00109	0.00995***	
	(0.00168)	(0.00259)	
*Stage*LOAD_F*	-0.0558		0.231
	(0.0359)		(0.254)
*Stage*LOAD_P*	0.0991	0.192	
	(0.0648)	(0.184)	
*Stage*Points Served*	-0.204***	-0.0611	-0.0469
	(0.0277)	(0.055)	(0.0741)
*Stage*Fleet*	0.142***	0.173*	0.204*
	(0.0301)	(0.0729)	(0.0814)
	Combination	**Passenger**	**Cargo**
*Stage*Time*	0.0154***	-0.0137*	-0.00975
	(0.00245)	(0.00627)	(0.00581)
*LOAD_F*LOAD_P*	-0.166***		
	(0.039)		
*LOAD_F*Points Served*	-0.03		0.4
	(0.0242)		(0.205)
*LOAD_F*Fleet*	0.0064		-0.197
	(0.0285)		(0.194)
*LOAD_P*Points Served*	-0.140**	0.0227	
	(0.0489)	(0.0984)	
*LOAD_P*Fleet*	0.0686	-0.0338	
	(0.0515)	(0.156)	
*LOAD_F*Time*	-0.00443*		0.0268*
	(0.00188)		(0.0121)
*LOAD_P*Time*	-0.000856	0.0186	
	(0.00297)	(0.011)	
*Points Served*Fleet*	0.0379	-0.0523	0.146*
	(0.0286)	(0.0555)	(0.0648)
*Points Served*Time*	-0.00308	-0.00139	-0.0123**
	(0.0019)	(0.00382)	(0.00385)
*Fleet*Time*	0.00178*	-0.000961	-0.00276
	(0.000781)	(0.00299)	(0.00176)
Constant	22.04***	18.93***	19.77***
	(0.0421)	(0.11)	(0.0717)
R-Squared	0.9731	0.921	0.9328
N	953	336	481

Airports, i.e. points served, impact neither combination nor passenger costs no matter the significance level. In contrast, at the 5% level, cargo costs increase when the number of airports cargo carriers service increases. Fleet size statistically significantly increases combination carrier costs at the 1% level but does not bear a statistically significant influence on passenger and cargo costs. Time, the proxy for technological advancement, provides statistically significant cost savings to combination carriers at the 1% level, no statistically significant cost savings to passenger carriers, and statistically significant cost growth to cargo carriers at the 1% level. Combination carriers experience a much larger decline in cost over time the passenger only service, however freight only service experiences an even larger cost reduction overtime indicating a possible advantage associated with operating as a specialist, at least for freight service.

Various second-order parameter estimates, though reported for all carrier types, carry no relevance here save for the **RFTM**-**RPTM** interaction parameter estimate from the combination carrier cost specification. Negative and statistically significant at the 1%, the RFTM-RPTM result suggests combination carriers reap the benefits of cost complementarity and provides evidence for at least one input shareable by freight and passenger service.

1.5.2 Cost-Concept Tests

Table 1-8 and Figure 1-6 show the average satisfaction rates at which combination carriers satisfy returns to network size, returns to density, and subadditivity. Table 1-8 also includes annual mean degrees go which economies of scope is satisfied. Returns to network size remain below 50% from 1991 to 1999. Between 2000 and 2012, returns to network size frequently exceed 50% and occasionally exceed 60%. Following 2012, returns to network size typically remain below 50%. Returns to density sees somewhat of an opposing trend such that between 1991 and 1999, rates frequently exceed 50% and occasionally exceed 60%. Between 2000 and 2014, rates rarely exceed 50%. Following 2014, returns to density rates bear similarity to returns to network size rates. Subadditivity rates fluctuate between 91% and 95% for all years save for 98% in 2020 and 97% in 2021. Degree to which firms satisfy economies of scope is lower from 1991 to 1999 relative to 2000 to 2021 with spikes in 2011, 2014, and 2019.

Table 1-8 Cost Concepts - Combination Carriers

	Returns to Network Size	Returns to Density	Economies of Scope (degree)	Subadditivity
1991	0.48	0.45	36	0.93
1992	0.41	0.48	124	0.93
1993	0.48	0.58	8	0.91
1994	0.46	0.62	312	0.92
1995	0.44	0.61	8	0.92
1996	0.49	0.59	21	0.93
1997	0.44	0.64	14	0.93
1998	0.45	0.57	11	0.93
1999	0.46	0.59	224	0.93
2000	0.50	0.61	12	0.93
2001	0.50	0.50	292	0.93
2002	0.50	0.56	307	0.93
2003	0.49	0.41	428	0.94
2004	0.51	0.49	350	0.94
2005	0.50	0.42	324	0.94
2006	0.50	0.37	345	0.94
2007	0.53	0.40	442	0.94
2008	0.54	0.38	446	0.94
2009	0.53	0.40	600	0.94
2010	0.53	0.33	456	0.94
2011	0.62	0.46	1006	0.95
2012	0.54	0.46	415	0.92
2013	0.48	0.39	762	0.93
2014	0.48	0.33	1537	0.94
2015	0.47	0.53	482	0.92
2016	0.47	0.47	579	0.90
2017	0.44	0.50	506	0.91
2018	0.45	0.55	486	0.91
2019	0.50	0.44	2166	0.93
2020	0.47	0.53	509	0.98
2021	0.56	0.56	594	0.97
Total	0.49	0.50	306	0.93

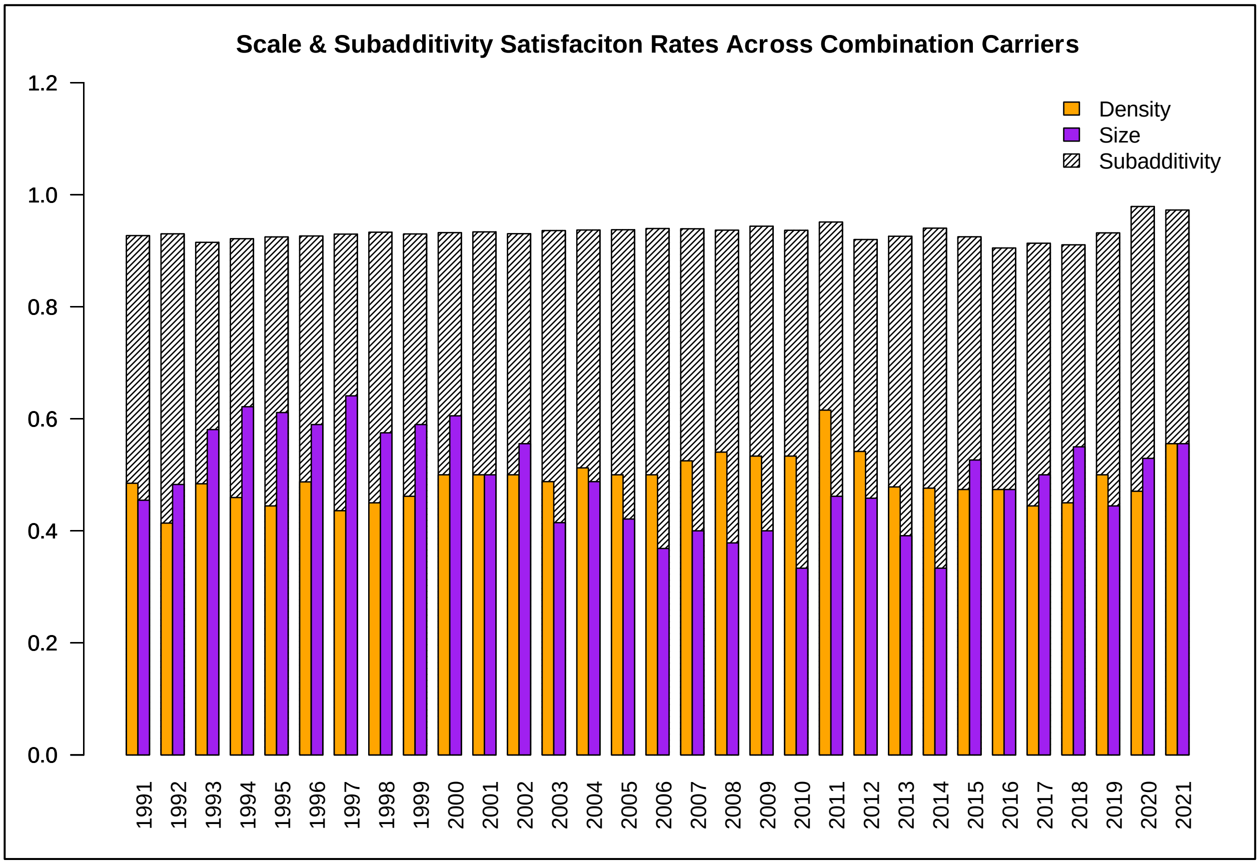

Figure 1-6 Mean Rates at which Combination Carriers Satisfy Economies of Density, Size, and Subadditivity

Table 1-9 and Figure 1-7 show the average satisfaction rates at which each of 12 select combination carriers satisfy economies of scope relative to specialist passenger and freight carriers. While rates fluctuate within firms, across firm rates are typically increasing with overall decreases in 2013 and 2017. In these cases, no firm satisfies economies of scope beyond 54.5% whereas in the theoretical economies of scope simulation, the average firm satisfies economies of scope between passenger and freight services every single year between 1991 and 2021.

Table 1-9 Economies of Scope, Carrier Cases

Economies of Scope, Carrier Cases

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Evert	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.061	0.061
Atlas	0.061	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.030	0.061
ATI	0.061	0.000	0.030	0.030	0.030	0.091	0.061	0.061	0.061	0.121
Endeavor	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
American	0.152	0.121	0.121	0.121	0.091	0.061	0.061	0.091	0.121	0.121
Alaska	0.121	0.061	0.061	0.061	0.061	0.030	0.030	0.061	0.030	0.030
Delta	0.091	0.061	0.061	0.061	0.061	0.030	0.030	0.030	0.091	0.061
Hawaiian	0.121	0.091	0.121	0.121	0.121	0.091	0.091	0.121	0.121	0.121
MN	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.030	0.121
United	0.091	0.061	0.121	0.091	0.091	0.061	0.091	0.121	0.091	0.091
Southwest	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Mesa	0.000	0.000	0.000	0.091	0.182	0.091	0.121	0.000	0.182	0.545
Total	0.061	0.038	0.048	0.053	0.058	0.043	0.045	0.045	0.068	0.111

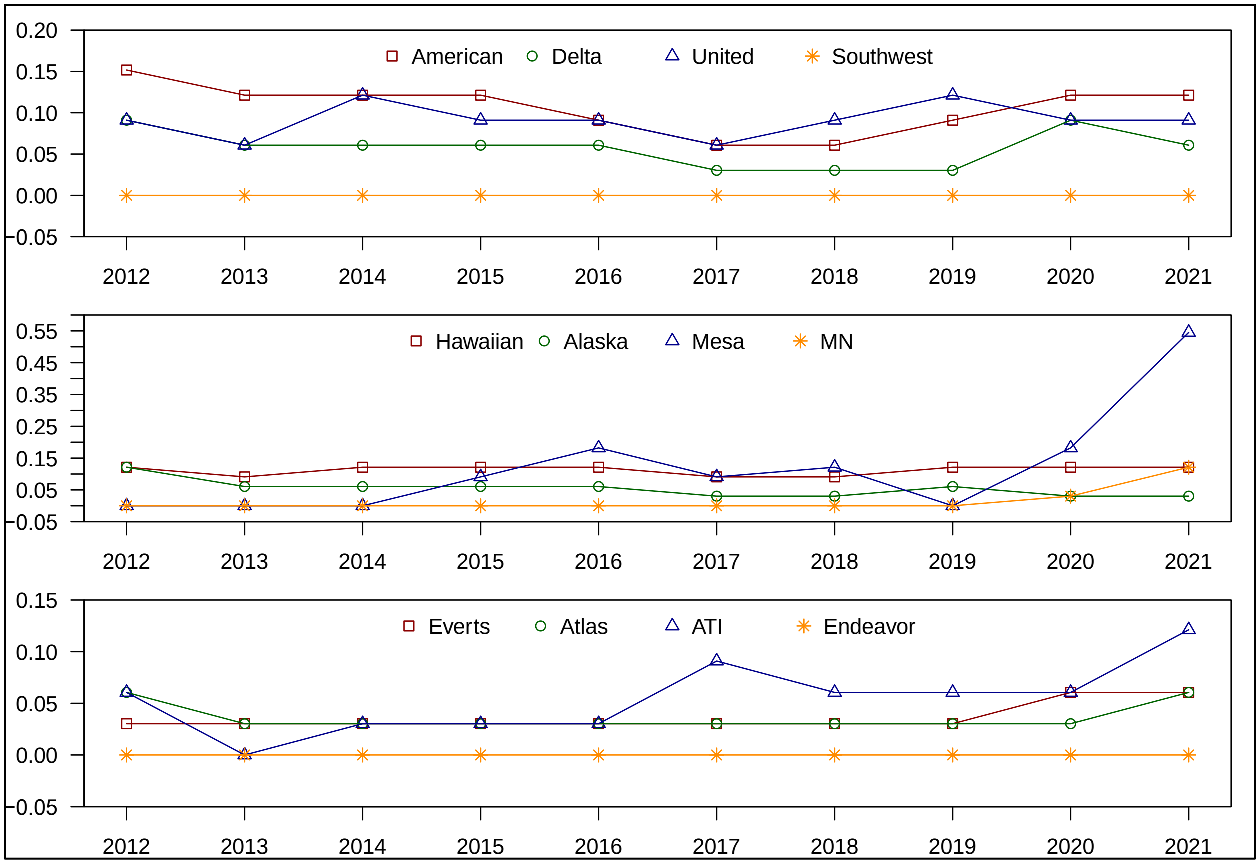

Figure 1-7 Air Carrier Cases: Economies of Scope (Passenger & Freight)

1.6 Concluding Remarks

Combination carriers satisfy economies of scope between passenger & freight services and subadditivity at a rate of nearly 100% when only their cost curve is considered. When considering the cost curve of the specialist, combination carriers only satisfy economies of scope between passenger & freight services at a rate of at most 54%. American Airlines announcement of an all-cargo arm coincides with consistent gains in economies of scope and increasing freight-tons transported until the outbreak of COVID-19 caused a 75% drop in passenger traffic. Given the entanglement of their transport services, freight traffic suffered alongside passenger traffic potentially prompting American Airlines decision to divide the two services.

These findings suggest combination carriers occupy a niche market. While they are unable to compete with the output of the specialist, particularly the freight specialist, combination carriers enjoy cost complementarity from providing both passenger and freight service, are more cost effective as a single unit than if they were to split their current operations between two firms, and benefit from economies of joint production.

Returns to network size have become more important to the combination carrier than returns to density. As suggest by Swan (2002), the shift in importance from returns to density to returns to network size could explain the continued mergers among combination air carriers post 9/11. Mergers expand network size of course but also involve combined logistical systems resulting in greater, more reliable flight frequency somewhat resembling the consistent schedule kept by freight leaders FedEx and UPS.

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1.8 Appendix

Table 1-A 1 Regularity Conditions for Translog Cost Function

Regularity Conditions		**Carrier Type**		
(I) Monotonicity		Cargo	Combination	Passenger
Input Prices	*Labor*	100%	100%	100%
	Capital	100%	98%	100%
	Fuel	95%	98%	92%
	Other	99%	100%	100%
Output		100%	94%	100%
(II) Concavity		100%	99%	100%
Observations		481	953	336

Table 1-A 2 3SLS Translog Cost Function Estimation Instrumenting Output with Producer Price Indices

Combination			Passenger			Freight		
Variable	Coefficient	SE	Variable	Coefficient	SE	Variable	Coefficient	SE
lpl	0.240	0.008	lpl	0.164	0.018	lpl	0.240	0.015
lpg	0.142	0.006	lpg	0.192	0.013	lpg	0.158	0.010
lpo	0.345	0.004	lpo	0.351	0.011	lpo	0.372	0.010
lpk	0.273	0.003	lpk	0.293	0.010	lpk	0.230	0.010
lrtm_f	0.105	0.035	lrtm_p	0.695	0.052	lrtm_f	0.785	0.043
lrtm_p	0.954	0.035	lstage	-0.742	0.105	lstage	-0.639	0.107
lstage	-0.942	0.049	lload_p	-0.275	0.205	lload_f	-0.972	0.229
lload_f	-0.052	0.035	lairports	0.102	0.072	lairports	0.403	0.069
lload_p	-0.489	0.073	lroutes	0.118	0.053	lroutes	0.198	0.055
lairports	0.109	0.040	time	-0.016	0.011	time	0.110	0.008
lroutes	0.127	0.034	hpl	0.044	0.012	hpl	0.066	0.006
time	-0.036	0.004	hpg	0.048	0.003	hpg	0.065	0.004
hpl	0.108	0.006	hpo	0.110	0.007	hpo	0.152	0.004
hpg	0.047	0.002	hpk	0.103	0.009	hpk	0.128	0.005
hpo	0.168	0.003	hrtm_p	0.059	0.016	hrtm_f	0.139	0.032
hpk	0.139	0.003	hstage	0.748	0.129	hstage	0.546	0.158
hrtm_f	0.162	0.025	hload_p	-0.740	0.436	hload_f	0.424	0.629
hrtm_p	0.235	0.023	hairport	0.130	0.043	hairport	0.070	0.072
hstage	0.252	0.052	hroute	0.242	0.122	hroute	0.295	0.077
hload_f	0.150	0.029	time2	0.007	0.001	time2	-0.005	0.001
hload_p	0.007	0.066	plpg	-0.023	0.004	plpg	-0.012	0.003
hairport	0.031	0.026	plpo	-0.016	0.007	plpo	-0.036	0.004
hroute	-0.004	0.048	plpk	-0.005	0.008	plpk	-0.018	0.004
time2	0.003	0.000	plrtm_p	-0.011	0.006	plrtm_f	0.014	0.007
plpg	-0.018	0.003	plstage	-0.019	0.015	plstage	-0.073	0.016

plpo	-0.060	0.004	plload_p	0.009	0.029	plload_f	-0.076	0.035
plpk	-0.030	0.003	plport	0.017	0.009	plport	0.008	0.011
plrtm_f	-0.010	0.005	plrout	-0.004	0.012	plrout	-0.016	0.012
plrtm_p	-0.005	0.005	plt	0.005	0.001	plt	0.000	0.001
plstage	0.025	0.008	pgpo	-0.011	0.003	pgpo	-0.030	0.003
plload_f	0.010	0.005	pgpk	-0.014	0.003	pgpk	-0.024	0.003
plload_p	0.022	0.009	pgrtm_p	0.017	0.004	pgrtm_f	0.007	0.005
plport	-0.026	0.006	pgstage	0.041	0.010	pgstage	0.039	0.010
plrout	0.031	0.006	pgload_p	0.019	0.021	pgload_f	0.041	0.023
plt	0.002	0.000	pgport	-0.002	0.006	pgport	-0.021	0.007
pgpo	-0.014	0.002	pgrout	-0.001	0.009	pgrout	-0.007	0.008
pgpk	-0.015	0.001	pgt	0.001	0.001	pgt	0.002	0.001
pgrtm_f	0.014	0.003	popk	-0.083	0.006	popk	-0.086	0.003
pgrtm_p	-0.007	0.003	portm_p	0.000	0.004	portm_f	-0.012	0.005
pgstage	0.037	0.005	postage	0.004	0.009	postage	0.019	0.011
pgload_f	-0.013	0.004	poload_p	-0.029	0.017	poload_f	0.013	0.025
pgload_p	-0.001	0.006	poport	-0.020	0.005	poport	0.009	0.008
pgport	0.004	0.004	porout	0.006	0.007	porout	0.018	0.008
pgrout	-0.017	0.004	pot	-0.003	0.001	pot	0.000	0.001
pgt	0.004	0.000	pkrtm_p	-0.005	0.004	pkrtm_f	-0.009	0.004
popk	-0.094	0.002	pkstage	-0.025	0.009	pkstage	0.015	0.010
portm_f	0.002	0.003	pkload_p	0.001	0.017	pkload_f	0.022	0.023
portm_p	0.005	0.002	pkport	0.005	0.005	pkport	0.004	0.007
postage	-0.041	0.004	pkrout	-0.002	0.007	pkrout	0.005	0.008
poload_f	-0.003	0.003	pkt	-0.003	0.001	pkt	-0.002	0.001
poload_p	-0.011	0.004	rtm_pstage	-0.257	0.035	rtm_fstage	-0.253	0.055
poport	0.012	0.003	rtm_pload_p	0.294	0.082	rtm_fload_f	-0.033	0.107
porout	-0.007	0.003	rtm_pport	-0.011	0.018	rtm_fport	-0.012	0.034
pot	-0.002	0.000	rtm_prout	-0.054	0.022	rtm_frout	-0.149	0.040
pkrtm_f	-0.006	0.002	rtm_pt	0.009	0.002	rtm_ft	0.003	0.002
pkrtm_p	0.007	0.002	stageload_p	0.205	0.170	stageload_f	0.232	0.235
pkstage	-0.020	0.003	stageport	-0.038	0.051	stageport	-0.074	0.069
pkload_f	0.006	0.002	stagerout	0.134	0.068	stagerout	0.222	0.075
pkload_p	-0.009	0.003	staget	-0.011	0.006	staget	-0.010	0.005
pkport	0.010	0.002	load_pport	0.006	0.091	load_fport	0.367	0.190
pkrout	-0.007	0.002	load_prout	-0.071	0.144	load_ft	0.026	0.011
pkt	-0.003	0.000	load_pt	0.019	0.010	load_frout	-0.123	0.179
rtm_frtm_p	-0.162	0.022	timeport	-0.002	0.004	portrout	0.142	0.060
rtm_fstage	0.077	0.033	portrout	-0.053	0.051	timerout	-0.003	0.002

rtm_pstage	-0.123	0.034	timerout	-0.002	0.003	timeport	-0.011	0.004
rtm_fload_f	-0.158	0.026	_cons	18.917	0.101	_cons	19.744	0.065
rtm_pload_p	-0.112	0.037						
rtm_pload_f	0.164	0.023						
rtm_fload_p	0.109	0.035						
rtm_fport	0.009	0.024						
rtm_frout	-0.004	0.026						
rtm_pport	0.023	0.025						
rtm_prout	-0.031	0.025						
rtm_ft	0.001	0.002						
rtm_pt	-0.001	0.002						
stageload_f	-0.063	0.033						
stageload_p	0.104	0.060						
stageport	-0.210	0.026						
stagerout	0.142	0.028						
staget	0.015	0.002						
load_fload_p	-0.167	0.036						
load_fport	-0.029	0.023						
load_frout	0.007	0.027						
load_pport	-0.151	0.046						
load_prout	0.082	0.048						
load_ft	-0.004	0.002						
load_pt	-0.001	0.003						
portrout	0.037	0.027						
timeport	-0.003	0.002						
timerout	0.002	0.001						
_cons	22.024	0.039						

2 Allocative Efficiency in the US Air Cargo Industry*

Abstract

Providing affordable service is critical to the success of air cargo companies, especially given the potential of increase in competition from airline companies in the passenger service sector. Operating efficiently is key to offering an affordable service in this increasingly competitive business environment. This study estimates a cost function specified to include shadow input prices as an approach to examine whether air cargo carriers have been able to satisfy allocative efficiency. Findings suggest US all-cargo air companies use an allocatively efficient combination of all labor and nonlabor inputs included in this study. I interpret these findings as suggesting that these companies generally operate in a cost-effective manner with integrators like FedEx and UPS leading the way with lower load factors and higher frequency flight schedules.

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*NOTE: A similar essay using different data appears as the chapter: *Allocative Efficiency in the U.S. Air Cargo Industry*, with James Peoples, in Urban Economics, Real Estate, Transportation and Public Policy, edited by Donald Siegel and Jeffrey Cohen, World Scientific Publishers (Forthcoming book chapter 2022)

2.1 Introduction

Arguably some of the most iconic factor inputs are employed by air transportation service companies. For instance, it is not unusual for documentaries and films to feature the accomplishments and tragedies of aircraft pilots.[36] Public attention toward air transportation inputs is not limited to labor as aircraft failures and the roll-out of new aircrafts typically make news headlines.[37] Operationally, these factor inputs along with jet fuel critically contribute to the success of air transportation service companies. Historically however, success in this industry has been proven quite challenging. Air transportation companies are required to comply with union- and federally-imposed work rules, to manage idle aircrafts due to overcapacity, and to negotiate operations in the presence of volatile fuel prices. These factor market idiosyncrasies contribute to difficulty satisfying cost minimization and allocative efficiency conditions and thus play a role in preventing air transport companies from generating meaningful profits.

Past research investigating allocative efficiency in the air transport service sector is bifurcated into research examining this market during the years near the 1978 airline deregulation act and examining the years significantly following the passage of this act. Findings examining allocative efficiency immediately preceding and following the airline passenger deregulation act find air transport companies employed an inefficiently high level of labor relative to capital and fuel (Kumbhakar, 1992). In contrast to those early results, analysis using more recent data finds passenger airline companies use an inefficiently low amount of

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[36] Famous examples of luminary pilots are Charles Lindbergh, Amelia Earhart, the Tuskegee airmen, and Chesley 'Sully' Sullenberger

[37] Aircraft tragedies include Turkish Airline flight 981 (1974), American Airlines flight 191 (1979) and Air India Express flight 812 (2010).

labor relative to fuel, capital and other inputs (Bitzan and Peoples, 2014). These latter results are interpreted as indicating passenger airlines employ too much of nonlabor inputs. While these findings provide valuable insight on air transport companies' ability to satisfy the condition for cost minimization/allocative efficiency, these studies focus exclusively on the passenger service sector of the air transportation market. The other major sector of this market includes air cargo companies, who face similar input market challenges as passenger service companies. Furthermore, cost analysis of this sector of the airline service industry is important in part because air cargo services have become an ever increasingly key component to the economy due to their role in the supply chain of product distribution. This essay contributes to our understanding of the scope of allocative efficiency in the air transport market by testing whether all-cargo air companies are able operate in a manner that satisfies the condition of cost minimization.

The succeeding section of this essay presents institutional background on the factor input market for the air cargo transportation sector so as to identify potential sources of allocative inefficiency. Section 3 presents a theoretical and empirical model of firm cost minimization as well as a method for examining allocative efficiency. Specifically, I use the approach developed by Atkinson and Halverson that assumes firms minimize "shadow costs" taking into account the different prices firms pay for labor and nonlabor input services in comparison to their market prices (Atkinson and Halverson 1984). Section 4 presents the data used for the analysis, and presentation of the empirical results are provided in section 5. Concluding remarks and a discussion of the results and their implications are reported in the last section.

2.2 Background

The air transport sector is characterized as historically operating below capacity and operating within the limits of union negotiated and federally mandated work-rules. Past analysis of overcapacity in the air cargo sector centers on the actual measure of this operations' outcome (Baltagi et al. 1998). For instance, research that utilizes the engineering measure of load factor rarely if ever finds air cargo companies operating at full capacity, since the industry average for load factors rarely exceeds 70 percent of aircraft freight potential (Baltagi et al. 1998). Thus, from an engineering perspective, air cargo carriers consistently operate below capacity. A shortcoming associated with using load factor as a measure of air cargo capacity is that it does not account for the possibility of rising marginal costs at higher levels of output. An alternative to using load factors is the use of the minimum average cost as the definition of capacity (Klein, 1960 and Hickman, 1964). For example, Baltagli et al. reveals the potential for air cargo carriers to operate at capacity when using minimum average cost in place of the load factor (Baltagi et al. 1998). Nonetheless, operating at minimum average cost output levels remains a challenge in this industry given its sensitivity to variations in global and regional demands. Indeed, as recent as March 2020 the International Air Transport Association (IATA) reported a 15.2 percent year-on-year drop in demand for air cargo freight shipped. Furthermore, in the future, air cargo carriers are likely to face greater competition for freight services as more cargo shifts to passenger planes and back onto the sea.[38] High value goods such as electronics have also

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[38] Even though operating at full capacity has historically been a challenge the combination of disrupted supply chains and a drastic decline in air passenger travel has positively impacted cargo-only airlines. Both rates and yields have gone up. In fact, the cargo load factor increased by 11.5% year-on-year in April 2020 and reached an all-time high since 1990. This unusual increase suggests that the air cargo market has been currently undersupplied. Hence, it seems that, so far, the pandemic has had a positive impact on some cargo airlines. In fact, revenue ton-

become smaller, eliminating the need for transportation via dedicated air freighters and opening up the possibility of transportation via passenger aircrafts. Operating below full capacity contributes to allocative inefficiency because air cargo companies pay (lease) for the services of their aircrafts without receiving commensurate productivity from this factor input (capital). Paying input prices that match marginal productivity is the underpinning of an allocatively efficient use of inputs.

Work-rules intended to provide a healthy work environment could also have unintended consequences which influence allocative efficiency in the air cargo industry. This essay identifies three separate work-rules that can potentially affect air cargo carriers' ability to satisfy the condition of allocative efficiency by using inputs in a cost-minimizing manner. The three labor practices I focus on are:

(1) deadheading,

(2) hours of service regulation, and

(3) scope provisions (clause).

Deadheading occurs when employees such as pilots are compensated for non-flight activity. While this provision is intended to compensate employees for the inconvenience associated with commuting to airports where there is an immediate shortage of labor, the labor activity associated with this commute does not contribute to productivity (flying a plane). Hence, compensation does not correspond accurately with wage. On the other hand, the ability to

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miles (RTM) increased by 13.86% from 2019 to 2020, as air cargo companies RTM reached $18,687.95 million by for 2020. Normally, about 50% of the world's air cargo is carried in the bellies of passenger aircraft, which have been all but idled due to the coronavirus crisis presenting air cargo companies with an unexpected demand for their services. However, post pandemic operations are likely to present passenger carriers the opportunity to compete for cargo service as they increasingly use more of their aircraft fleet.

transport workers to a high-need airport helps the air cargo company avoid the costly effect of paying for idle planes due to an immediate shortage of flight and maintenance personnel. Hours of service regulation are intended to improve flight safety by limiting flight time. However, when flight crews meet the maximum hours limitation, air companies face the immediate shortage of vital personnel, requiring the use of deadheading to avoid grounding some of their fleet. The scope provision, which is negotiated by labor unions and prohibits air cargo companies from outsourcing routes to carriers that are presumably using aircrafts better suited for the routes in question. The effect on allocative efficiency is not obvious *a priori* because negotiated fees for this type of code-sharing may not depict cost minimization if the principal (the company outsourcing) doesn't have complete information on the actual productivity associated with the 3rd party's service. In general, it does not appear that air transport companies likely suffered significant efficiency challenges from operating within the guidelines of union negotiated and government mandate work rules. Evidence examining the cost of labor in this sector reveal worker productivity has increase by 80 percent from 1990 to 2010 (Donatelli, 2012). In addition, Hirsch (2006) reports labor cost as a percent of available seat miles fell from 4.7 percent per mile to 3.17 percent per mile from 1990 to 2005.

The potential factor input distortion associated with operating at overcapacity and within the limits of work rules is captured in the following mathematical representation of the comparison between an optimal input mix and the input mix associated with potential market distortions due to operating with unused capacity and employing workers in a manner that satisfies the conditions of union-negotiated and federally-mandated work rules.

Standard economic theory indicates cost minimization occurs when companies employ factor inputs efficiently by equating the ratios of factor input marginal productivities with factor input prices across all factor inputs. For example, assume a hypothetical carrier faces no constraints in the labor market and is thereby able to satisfy the condition for cost minimization depicted by Eq. 2-1.

Equation 2-1

$$\frac{MP_L}{MP_K} = \frac{P_L}{P_K}$$

where MP_L and MP_K are the marginal product of labor and capital, respectively, P_L and P_K are input prices. This same cost minimizing condition can be shown graphically as the point of tangency between a firm's isoquant for producing a particular output level and an isocost line based on input prices as shown in Fig. 2-1. Optimization using observed input prices without overcapacity and restrictive work rules is represented graphically by point A in Fig. 2-1, where the combination of L* units of labor and K* units of capital minimizes the cost of producing $\bar{q}$ units of output at a cost of C using an isocost line based on observed input prices such that

Equation 2-2

$$\mathrm{C} = P_L^* L^* + P_K^* K^*$$

However, given the possibility that adherence to work-rules can alter the productivity of inputs and/or the costs of employing additional units of each input, air cargo companies may experience difficulty satisfying the aforementioned condition of allocative efficiency. This concept is depicted graphically in Fig. 2-1 by showing that the actual isocost curve a company adhering to work rules could prove steeper than the cost-minimizing isocost depicted by Eq. 2-2. For example, if deadheading results in employees such as pilots receiving compensation for non-flight activity, then the shadow price of nonlabor inputs increases, all else equal. The curve,

Equation 2-3

$$C' = P_L' L' + P_K' K'$$

depicts the steeper isocost curve derived when paying the higher shadow price *P´*. Thus, the actual input combination used by this hypothetical company is depicted by point *B* in Fig. 2-1, which when compared to point *A*, indicates the firm uses an allocatively inefficiently high amount of nonlabor inputs relative to labor.

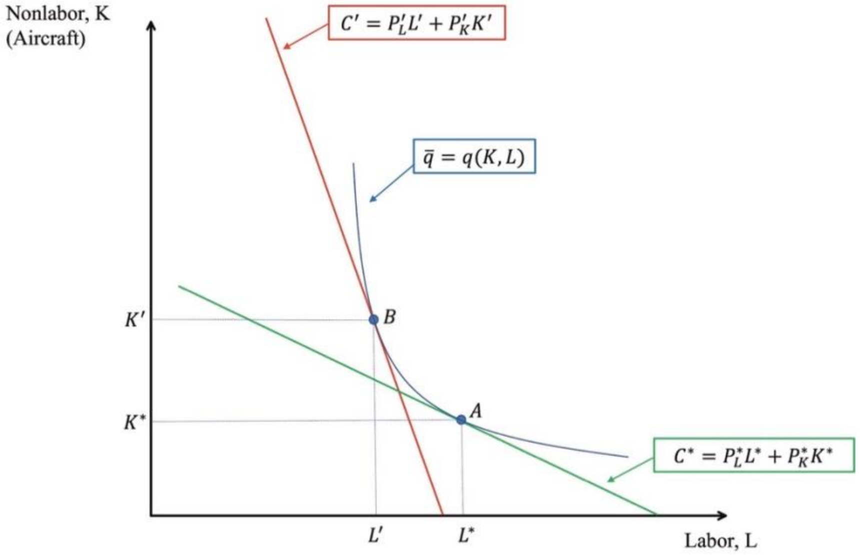

Figure 2-1 Overinvestment in nonlabor inputs in the presence of restrictive work rules.

As mentioned earlier in this essay, operating in an industry facing restrictive work-rules is not the only potential source of misallocation of factor inputs. Although operating at overcapacity may contribute to a steeper isocost curve, dominant firms such as FedEx and UPS incorporate overcapacity into their business models. Both integrators operate according to consistent, daily schedules which results in increased flight frequency and lower load factors. This outcome is depicted in Fig. 2-2, where point *B* is the allocatively efficient combination of inputs at output capacity $\bar{q}$. This input combination is efficient if the company is operating at overcapacity with lower load factors and greater flight frequency to accommodate express delivery and volatile demand. For ease of comparison with the restrictive work-rule example, I use the cost minimizing equation to explain overinvestment in capital due to restrictive work rules. Hence, for Eq. 2-2, point *A* depicts the actual output level achieved using an allocatively efficient combination of inputs, *(L*, K*)*. In comparison, the combination of inputs used at the higher output level $\bar{\bar{q}}$ is depicted by point *D* where one may assume efficient output should be in the absence of overcapacity. The hypothetical all-cargo air company which operates according to a business model reminiscent of integrators FedEx and UPS, may appear to overinvest in capital relative to labor as depicted by the amount of nonlabor inputs available at capacity *K´* but indeed compensates for the apparent overinvestment with greater flight frequency which is not captured in the common capacity measure, the load factor.

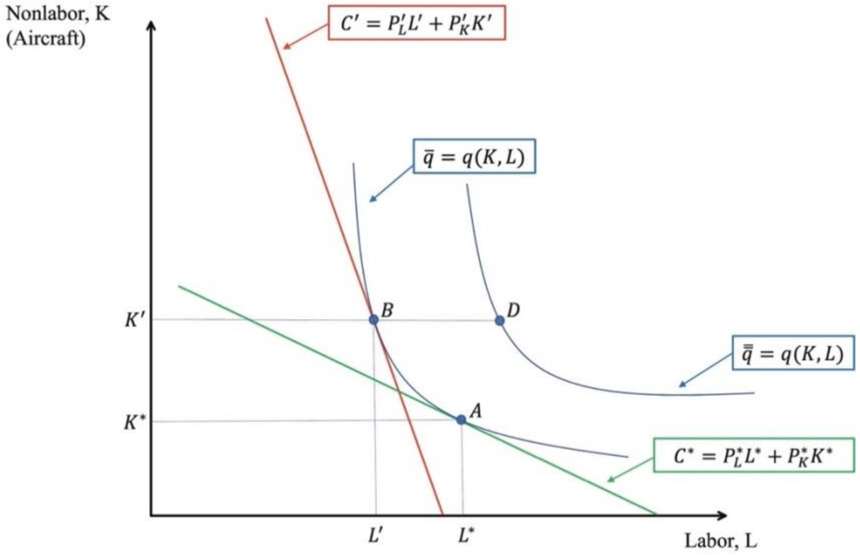

Figure 2-2 Overinvestment in nonlabor inputs in the presence of excess capacity.

Although Figs. 2-1,2 suggest overinvestment in nonlabor inputs associated with restrictive work rules and overcapacity, this essay shows how allocative efficiency may occur when air cargo companies adhere to restrictive work rules and operate business models which incorporate greater flight frequency. Operating at over capacity with greater flight frequency provides the conditions for air cargo companies using an allocatively efficient combination of inputs despite the relative idleness of their aircrafts during the day.

Figure 2-2 allows for a mathematical examination of an optimal input mix if restrictive work rules and overcapacity alter the apparent unit costs of using inputs. Following Fig. 2-2, the marginal productivity ratios are set equal to the shadow price ratios (rather than the observed input price ratios) as follows in Eq. 2-4,

Equation 2-4

$$\frac{MP_L}{MP_K} = \frac{P_L^*}{P_K^*}$$

Equation 2-4 implies the marginal product of a dollar's worth of labor is equal to the marginal product of a dollar's worth of nonlabor input at each inputs' true unit cost. If the shadow price of using nonlabor inputs P_K^* is lower than the observed price of nonlabor inputs P_K' due to the restrictive work rules but the shadow price of labor P_L^* is equal to the observed price of labor P_L' , then the equality in Eq. 2-4 implies that the marginal product of a dollar's worth of labor is more than the marginal product of a dollar's worth of nonlabor inputs at observed input prices as shown in Eq. 2-5,

Equation 2-5

$$\text{If } \frac{MP_K}{w_{K^*}} > \frac{MP_K}{w_K}, \text{ and } \frac{MP_L}{w_{L^*}} = \frac{MP_L}{w_L} \text{ then } \frac{MP_L}{w_L} > \frac{MP_K}{w_K}$$

Equation 2-5 suggests that the firm is using less labor relative to nonlabor inputs than it would if it optimized based on observed input prices.[39]

Equations 2-1 to 5 and Figs. 2-1,2 provide guidance for empirically examining factor input allocative efficiency by highlighting the need to empirically compute the input factor of proportionality (the factor that shows how much shadow input price deviates from actual input price) to attain information on the magnitude of the price distortion, and consequently the overutilization or underutilization of various inputs.

2.3 Data

Table 2-1 Descriptive Statistics

Year	**Input Prices**				**Points Served**	**Fleet Composition**			**Stage Length**	**RFTM**	**Load Factor**	**Carriers**
	Labor	Capital	Other	Fuel		Passenger	Freight	Combi				
1991	62,543	548	503	0.69	111	0.000	100.000	0.000	1,357	9.1e+08	0.50	17
1992	63,393	533	763	0.66	127	0.694	99.306	0.000	1,187	1.0e+09	0.54	16
1993	62,714	651	1,289	0.78	163	0.060	99.940	0.000	1,246	2.2e+09	0.53	17
1994	63,226	628	1,422	0.83	157	0.000	100.000	0.000	1,352	2.5e+09	0.54	19
1995	71,677	1,650	1,980	0.67	156	0.000	100.000	0.000	1,335	2.3e+09	0.57	20
1996	80,783	1,698	2,376	0.83	151	0.000	100.000	0.000	1,360	2.5e+09	0.59	24
1997	61,775	17,937	46,641	1.20	148	0.000	100.000	0.000	1,365	2.3e+09	0.61	22
1998	55,060	2,716	5,161	0.52	136	0.036	99.964	0.000	1,360	2.3e+09	0.58	22
1999	63,015	1,967	4,426	0.59	155	0.000	100.000	0.000	1,333	2.3e+09	0.56	23
2000	59,488	1,182	2,199	0.79	151	0.000	99.880	0.120	1,248	2.4e+09	0.54	27
2001	67,409	1,180	2,027	1.02	131	0.735	99.265	0.000	1,272	2.2e+09	0.48	26
2002	95,885	1,302	1,857	1.74	123	0.000	100.000	0.000	2,187	3.2e+09	0.51	24
2003	113,968	1,190	1,362	1.04	125	0.000	100.000	0.000	1,458	4.4e+09	0.56	24
2004	113,038	788	1,525	1.02	136	0.000	100.000	0.000	1,583	5.4e+09	0.60	23
2005	111,941	796	1,689	1.30	140	0.370	99.630	0.000	1,603	5.3e+09	0.60	24
2006	99,378	753	1,527	1.60	120	0.000	100.000	0.000	1,695	4.5e+09	0.59	25
2007	108,405	839	1,621	2.20	136	0.000	100.000	0.000	1,651	4.9e+09	0.57	23
2008	101,928	908	1,843	2.71	126	0.000	100.000	0.000	1,486	4.5e+09	0.55	23
2009	109,584	1,093	1,792	1.41	125	0.000	100.000	0.000	1,488	4.1e+09	0.51	22
2010	100,573	1,094	1,922	2.55	107	0.000	99.965	0.000	1,588	4.5e+09	0.52	21
2011	105,234	1,281	2,815	2.91	124	0.549	99.451	0.000	1,587	5.5e+09	0.55	20
2012	111,657	1,320	2,216	2.36	111	0.725	99.275	0.000	1,459	4.2e+09	0.50	20
2013	103,209	2,379	3,452	2.40	120	0.000	100.000	0.000	1,455	4.2e+09	0.49	21
2014	99,460	991	3,185	2.40	119	2.009	96.652	1.339	1,423	4.5e+09	0.48	20
2015	106,345	1,005	3,195	1.50	114	1.367	98.633	0.000	1,369	4.6e+09	0.49	20
2016	99,909	1,143	4,592	1.34	118	1.103	98.897	0.000	1,243	4.5e+09	0.44	20
2017	102,996	1,061	3,005	1.97	132	5.078	94.632	0.290	1,304	5.2e+09	0.47	19

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[39] It should be noted that if an employer does not sell their goods and services in a perfectly competitive industry, the inequalities presented in Eq. 2-5 can become distorted (Morrison, 1993). It should also be noted that the presentation of Eq. 2-5 assumes firms satisfy the condition of cost minimization with regards to shadow factor input prices.

2018	103,247	1,167	3,158	1.75	133	3.636	96.364	0.000	1,274	5.5e+09	0.47	17
2019	112,632	1,086	3,204	1.48	74	2.084	97.916	0.000	1,352	5.4e+09	0.44	18
2020	102,343	1,030	1,780	0.84	71	0.000	100.000	0.000	1,489	5.9e+09	0.42	18
2021	111,183	1,047	1,386	1.37	64	0.000	100.000	0.000	1,589	6.8e+09	0.46	18

2.4 Empirical Approach

The airline cost function used to analyze allocative efficiency in the US air cargo sector includes the cost determinants presented in the data section as well a time trend. The generalized airline cost function that depicts this cost association as follows in Eq. 2-6,

Equation 2-6

$$C^A = \mathrm{f}(P_L, P_F, P_K, P_O, Q, LOAD, StgLength, PtsServed, Fleet, T)$$

where C^A is the firm's actual costs, P_L is price of labor, P_F is price of fuel, P_K is price of capital[40], P_O is price of other[41], Q is output (*Revenue Ton-Miles*), *LOAD* is *Load Factor* (*Revenue Ton-Miles/Available Ton-Miles*), *Stg Length* is *Stage Length*, *Pts Served* is *Number of Airports Served*, and *T* is time trend.

As previously shown by Atkinson & Halvorsen (1984) and Oum & Zhang (1995), I can test for allocative efficiency by estimating the firm's cost function with an embedded shadow cost function. If adherence to work rules and operating at overcapacity alter the costs of using various inputs, the effective price of using an input will vary from its market price. Firms are expected to base their input hiring decisions on these unobserved shadow prices, and therefore, minimize total shadow costs. I can specify the firm's shadow cost function as follows in Eq. 2-7,

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[40] Including P_K in the cost function assumes a long run model, since capital is usually a fixed factor in the short run (Morrison, 2012).

[41] The price of other includes the price of all inputs excluding labor, capital, and fuel. It is calculated as a residual per hour of operation.

Equation 2-7

$$C^S = C^S(Q, P^*, M, T)$$

where C^S is the firm's shadow costs, Q is the firm's output as measured by *Revenue Ton-Miles* (RTM)[42], P^* is a vector of shadow prices, M is a vector of movement characteristics which includes *Load Factors*, *Number of Airports Served, Fleet* and *Stage Length*, and T is a vector of technological characteristics. Input shadow prices, P^*, are equal to the market input price multiplied by a factor of proportionality (Lau and Yotopolous, 1971) as follows in Eq. 2-8,

Equation 2-8

$$P_i^* = k_i P_i$$

The factor of proportionality, k_i, shows the relationship between the true input prices and market prices paid by firms for inputs as follows in Eq. 2-9,

Equation 2-9

$$k_i = \frac{P_i^*}{P_i}$$

If $k_i > 1$, it suggests that the firm's shadow price for the respective input is greater than its market price and thus indicates the respective input is likely underutilized. Alternatively, if $k_i < 1$, the respective input is likely overutilized. Atkinson and Halvorsen (1984) show that applying Shepard's Lemma to the shadow cost function yields input demands as follows in Eq. 2-10,

Equation 2-10

$$\frac{\partial C^S}{\partial P_i^*} = x_i$$

Therefore, total actual cost can be represented as follows in Eq. 2-11,

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[42] *Inclusion of output in any given cost function invites endogeneity concerns. See Appendix Table 1A-2 for the 3SLS estimation of the cost function in which output, RFTM, is instrumented with freight prices and RPTM, is instrumented with passenger ticket prices following the procedure applied to rail in Bitzan & Keeler 2003. The estimates are very similar to the un-instrumented results suggesting output is exogenous to the cost function.*

Equation 2-11

$$C^A = \sum_i P_i \, x_i = \sum_i P_i \frac{\partial C^S}{\partial P_i^*}$$

As shown by Atkinson and Halvorsen (1984), the share of shadow costs accounted for by any given input is defined in Eq. 2-12 as follows,

Equation 2-12

$$S_i^S = \frac{k_i P_i x_i}{C^S}$$

Equation 2-12 implies,

Equation 2-13

$$x_i = \frac{S_i^S C^S}{k_i P_i}$$

Then, the total actual cost function can be represented as follows in Eq. 2-14,

Equation 2-14

$$C^A = \sum_i P_i \frac{S_i^S C^S}{k_i P_i} = C^{S \sum_i \frac{S_i^S}{k_i}}$$

Taking the natural logarithm of Eq. 2-14 results in Eq. 2-15 as follows,

Equation 2-15

$$lnC^A = lnC^S + \sum_i l\,n \frac{S_i^S}{k_i}$$

Thus, the shadow cost function can be estimated as an embedded part of the total cost function. Using the translog functional form, the shadow cost function[43] can be written as follows in Eq. 2-16,

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[43] One potential challenge with the translog is the inclusion of explanatory variables with values of zero, since the log of these values are undefined. Cohen and Morrison (2003) show the generalized Leontiff is a way to circumvent this issue. Nonetheless, all variables used in this study have values greater than zero.

Equation 2-16

$$lnC^S = \alpha_0 + \sum_i \alpha_i \, lnk_iP_i + \sum_o \beta_o \, lnQ_o + \sum_n \gamma_n \, lnT_n + \sum_h \gamma_h \, lnM_h + \frac{1}{2}\sum_{ij} \phi_{ij} \, lnk_iP_i lnk_jP_j + \sum_{io} \phi_{io} \, lnk_iP_i lnQ_o + \sum_{in} \phi_{in} lnk_iP_i lnT_n + \sum_{ig} \phi_{ig} lnk_iP_i lnM_g + \frac{1}{2}\sum_{op} \phi_{op} lnQ_o lnQ_p + \sum_{on} \phi_{on} lnQ_o lnT_n + \sum_{oh} \phi_{oh} lnQ_o lnM_h + \frac{1}{2}\sum_{nl} \phi_{nl} lnT_n lnT_l + \sum_{nh} \phi_{nh} lnT_n lnM_h + \frac{1}{2}\sum_{hg} \phi_{hg} lnM_g lnM_h$$

where all cost determinants are normalized by their sample mean values. Imposing symmetry and homogeneity conditions yields the following parameter restrictions in Eq. 2-17,

Equation 2-17

$$\sum_i \alpha_i = 1, \sum_i \phi_{ij} = \sum_j \phi ji = 0, \sum_i \phi_{io} = \sum_n \phi_{in} = \sum_o \phi_{io} = \sum_h \phi_{ih} \, , \phi_{ij} = \phi_{ji}$$

To get the shadow cost share equations, Shepard's lemma is used and the translog shadow cost function with respect to shadow prices is differentiated from the actual translog cost function as follows in Eq. 2-18,

Equation 2-18

$$\frac{\partial lnC^S}{\partial lnk_iP_i} = \frac{\partial lnC^S}{\partial C^S} \cdot \frac{\partial C^A}{\partial lnk_iP_i} \cdot \frac{\partial k_iP_i}{\partial lnk_iP_i} = \frac{x_ik_iP_i}{C^S} = S_i^S$$

s.t.

$$S_i^S = \alpha_i + \sum_j \phi_{ij} lnk_jP_j + \sum_o \phi_{io} lnQ_o + \sum_h \phi_{ih} lnM_h + \sum_n \phi_{in} lnT_n$$

Since all cost determinants are normalized by their sample mean values, the input price parameters derived when estimating Eq. 2-16 represent the respective input's share of total shadow cost at the mean. Similarly, the parameter estimates of the actual cost function specified in its translog form present the respective input's share of the total actual cost at the mean. The parameter estimate on output in the actual cost equation indicates economies of scale at the mean. A parameter estimate less than one identifies increasing returns to scale whereas a parameter estimate greater than one identifies decreasing returns to scale.

From Eqs. 2-15, 2-16, 2-18 I can obtain the following total cost function as follows in Eq. 2-19,

Equation 2-19

$$lnC^A = \alpha_0 + \sum_i \alpha_i lnk_i P_i + \sum_o \beta_o lnQ_o + \sum_n \gamma_n lnT_n + \sum_h \gamma_h lnM_h + \frac{1}{2}\sum_{ij} \phi_{ij} lnk_i P_i lnk_j P_j + \sum_{io} \phi_{io} lnk_i P_i lnQ_o + \sum_{in} \phi_{in} lnk_i P_i lnT_n + \sum_{ig} \phi_{ig} lnk_i P_i lnM_g + \frac{1}{2}\sum_{op} \phi_{op} lnQ_o lnQ_p + \sum_{on} \phi_{on} lnQ_o lnT_n + \sum_{oh} \phi_{oh} lnQ_o lnM_h + \frac{1}{2}\sum_{nl} \phi_{nl} lnT_n lnT_l + \sum_{nh} \phi_{nh} lnT_n lnM_h + \frac{1}{2}\sum_{hg} \phi_{hg} lnM_g lnM_h + \sum_i \ln \frac{\alpha_i + \sum_j \phi_{ij} lnk_j P_j + \sum_o \phi_{io} lnQ_o + \sum_h \phi_{ih} lnM_h + \sum_n \phi_{in} lnT_n}{k_i}$$

As in other applications of the translog cost function, I jointly estimate total costs with factor share equations in a seemingly unrelated system of equations. In order to obtain factor share equations, note that the share of expenditures on a respective factor is as follows in Eq. 2-20,

Equation 2-20

$$S_i^A = \frac{P_i x_i}{C^A}$$

Like Atkinson and Halverson (1984), I can put this in terms of shadow share equations using Eqs. 2-9, 2-10 as shown by Eq. 2-21,

Equation 2-21

$$S_i^A = \frac{\frac{S_i^S}{k_i}}{\frac{\sum_i S_i^S}{k_i}}$$

Then, substituting with Eq. 2-14 I get Eq. 2-22 as follows,

Equation 2-22

$$S_i^A = \frac{\frac{\alpha_i + \sum_j \phi_{ij} lnk_j P_j + \sum_o \phi_{io} lnQ_o + \sum_h \phi_{ih} lnM_h + \sum_n \phi_{in} lnT_n}{k_i}}{\sum_i \frac{\alpha_i + \sum_j \phi_{ij} lnk_j P_j + \sum_o \phi_{io} lnQ_o + \sum_h \phi_{ih} lnM_h + \sum_n \phi_{in} lnT_n}{k_i}}$$

Since the factor shares sum to one, a single cost share equation is omitted to obtain a nonsingular covariance matrix. Given the total cost function is homogeneous of degree zero in factors of proportionality, a single factor of proportionality, labor, is normalized to one. Thus, all other factors of proportionality are measured relative to labor. Any statistically significant factor price distortion value less than one suggests overinvestment in input x_i relative to input x_j and any value significantly greater than one indicates underinvestment in input x_i relative to input x_j . Assuming air cargo companies choose inputs to minimize total costs based on input shadow prices, the factor of proportionality derived from maximum likelihood estimation captures deviations from cost minimization based on the actual input price. Empirically, the factor of proportionality is a parameter estimable by its presence in the cost function as a component of the shadow input price k_iP_i. Therefore, the MLE approach allows estimation of nonlinearity introduced when taking the product of the factor of proportionality and the actual price. It should be noted that the stochastic frontier approach used to estimate the production function is an alternative estimation technique that can be used to approximate allocative efficiency and to address the possibility of measurement error caused by a nonrandom, technical efficiency component in the error term. I view ML estimation of the shadow cost system over the stochastic frontier estimation of the production function due to the advantages of estimating a cost function over a production function. Past research identifies a lower probability of measurement error in estimating cost functions due to the greater reliability of input prices relative to input quantities. Additionally, production function estimation elicits endogeneity between input quantities and output as well as multicollinearity between inputs

(Bitzan and Peoples, 2019). In contrast, Shephard (1970) observes that cost function estimation easily avoids the endogeneity issues associated with production function estimation.

Moreover, if shadow cost estimation results fail to reject the hypothesis of allocative efficiency, the nonrandom technical efficiency component will not be present in the error term. Parameter estimates from the cost equation can be used to compute factor input demand elasticities as well as elasticities of factor input substitution. Examining these elasticities fills a void in allocative efficiency analysis, in part, because the parameter size for factor proportionality does not provide any insight on the magnitude of input price distortion. Computing these elasticities also contributes to our understanding of allocative efficiency because these measures indicate the potential magnitude of input misallocation due to artificially high input prices and exogenous limitations on input use, such as restrictions outlined in work-rule agreements. For instance, high elasticity of substitution suggests the potential for significant input misallocation because companies are more likely to substitute toward alternative inputs in response to restrictive work rules. Own and cross factor price elasticity are calculated using Eqs. 2-23, 2-24 as shown below,

Equation 2-23

$$\varepsilon_{ii} = \frac{\phi_{ii}}{S_i} + S_i - 1, \forall i$$

Equation 2-24

$$\varepsilon_{ij} = \frac{\phi_{ij}}{S_i} + S_j, \forall i \neq j$$

where ϕ_{ii}, ϕ_{ij} are parameter estimates from the ML estimation of Eq. 2-19 and S_i, S_j are factor input shares.

2.5 Results

Translog cost analysis requires the cost function satisfy the following regularity conditions:

(1) factor input price concavity,

(2) monotonicity in output, and

(3) homogeneity in input prices.

Table 2-2 Regularity conditions

Condition	Observations Satisfied
Monotonicity in output	100%
Concavity in input prices	
Labor	100%
Capital	100%
Fuel	95%
Other	99%

Therefore, Table 2-2 contains the percent of observations for which each regularity condition is met. Condition (1) is satisfied for labor, capital, fuel and other non-labor inputs prices for 100, 100, 95 and 99 percent of the observations. Condition (2) is satisfied for all observations. Condition (3) is imposed via constrained estimation.

*Table 2-3 Regression results. The notation *** indicates significance at 1% level, ** indicates significance at 5% level and * indicates significance at 10% level.*

	Cost Function SUR		Cost Function NLSUR	
	(1)		(2)	
Variables	Coefficient	z-stat	Coefficient	z-stat
Capital	0.246***	43.543	0.26034***	29.68
Capital Sq.	0.116***	34.882	0.1331073***	20.55
Capital*Fleet	-0.001	-0.327	-0.002704	-0.55
Capital*LOAD_F	0.018	1.350	0.0294114*	1.94
Capital*Points Served	0.004	0.902	0.0035568	0.77

Capital*RFTM	-0.004	-1.511	-0.0038773	-1.36
Capital*Stage	0.011*	1.908	0.0123662*	1.71
Capital*Time	-0.003***	-8.331	-0.0030908***	-7.87
Constant	19.775***	275.683	19.78203***	270.67
Fleet	0.196***	3.214	0.1914142***	3.09
Fleet Sq.	0.218***	2.617	0.2104915**	2.49
Fleet*Time	-0.003	-1.563	-0.002576	-1.44
Fuel	0.155***	16.247	0.1440674***	10.91
Fuel Sq.	0.067***	18.709	0.0578735***	7.46
Fuel*Capital	-0.021***	-10.730	-0.0218149***	-5.83
Fuel*Fleet	-0.007	-0.887	-0.005045	-0.74
Fuel*LOAD_F	0.039*	1.762	0.0305391	1.52
Fuel*Other	-0.029***	-11.377	-0.0234833***	-6.81
Fuel*Points Served	-0.021***	-3.037	-0.018221***	-2.85
Fuel*RFTM	0.006	1.422	0.0050135	1.27
Fuel*Stage	0.043***	4.313	0.0375024***	3.88
Fuel*Time	0.003***	4.542	0.0021677***	3.95
Labor	0.211***	26.143	0.20662***	13.89
Labor Sq.	0.051**	15.433	0.0470808***	10.15
Labor*Capital	-0.006***	-2.679	-0.0091083***	-2.83
Labor*Fleet	-0.003	-0.484	-0.0026892	-0.42
Labor*Fuel	-0.017***	-6.824	-0.0125753***	-3.85
Labor*LOAD_F	-0.067***	-3.490	-0.0667887***	-3.48
Labor*Other	-0.028***	-11.500	-0.0253972***	-8.21
Labor*Points Served	0.008	1.315	0.0070735	1.2
Labor*RFTM	0.006	1.541	0.0053492	1.47
Labor*Stage	-0.068***	-8.028	-0.0636799***	-6.96
Labor*Time	0.001	1.264	0.0005756	1.25
LOAD_F	-1.064***	-4.237	-1.096414***	-4.29
LOAD_F Sq.	0.239	0.355	0.2276411	0.33
LOAD_F*Fleet	-0.197	-1.016	-0.1563199	-0.79
LOAD_F*Points Served	0.400*	1.946	0.4011444*	1.92
LOAD_F*Time	0.027**	2.208	0.0286974**	2.31
Other	0.387***	44.612	0.3889726***	34.7
Other Sq.	0.145***	48.585	0.1510647***	25.14
Other*Capital	-0.089***	-37.579	-0.1021842***	-16.34
Other*Fleet	0.011	1.637	0.0104382	1.6
Other*LOAD_F	0.01	0.463	0.0068381	0.35
Other*Points Served	0.01	1.504	0.0075907	1.25
Other*RFTM	-0.008**	-2.021	-0.0064854*	-1.73
Other*Stage	0.013	1.484	0.0138114	1.56
Other*Time	0	-0.709	0.0003475	0.67
Points Served	0.363***	4.795	0.358046***	4.65
Points Served Sq.	0.045	0.582	0.0368003	0.46
Points Served*Fleet	0.146**	2.259	0.1534594**	2.33
Points Served*Time	-0.012***	-3.202	-0.0120639***	-3.09

RFTM	0.783***	16.535	0.7907398***	16.39
RFTM Sq.	0.148***	4.240	0.1480673***	4.17
RFTM*Fleet	-0.129***	-2.978	-0.1326055***	-3.02
RFTM*LOAD_F	-0.03	-0.264	-0.0333308	-0.29
RFTM*Points Served	-0.036	-0.968	-0.0329601	-0.87
RFTM*Stage	-0.263***	-4.407	-0.2620616***	-4.32
RFTM*Time	0.005**	2.005	0.0043017*	1.8
Stage	-0.650***	-5.552	-0.6788386***	-5.64
Stage Sq.	0.600***	3.507	0.6195671***	3.57
Stage*Fleet	0.204**	2.502	0.2055491**	2.48
Stage*LOAD_F	0.231	0.911	0.1864888	0.72
Stage*Points Served	-0.047	-0.632	-0.0612845	-0.81
Stage*Time	-0.010*	-1.678	-0.0090269	-1.53
Time	0.113***	12.644	0.113143***	12.43
Time Sq.	-0.005***	-8.291	-0.004741***	-8.2
Capital Factor			0.8663024***	5.21
Fuel Factor			0.991427***	8.27
Other Factor			1.237627***	7.61
R-squared	93.28		99.943	
Wald Tests			Statistic	P-value
Fuel/Labor = 1			0.65	0.4218
Capital/Labor = 1			0.01	0.943
Other/Labor = 1			2.14	0.1439

Table 2-3 contains results from the constrained SUR estimation excluding shadow prices of Eq. 2-19 as well as the constrained NLSUR estimation including shadow prices of Eq. 2-19. With R-squares of 93.28 (SUR) and 99.94 (NLSUR), both specifications explain a substantial amount of variation in air freight operational cost.

The parameter estimates from the constrained SUR specification excluding shadow prices represent the mean factor input *actual* cost shares showing fuel, labor, capital and other nonlabor inputs account for 15.5%, 21.1%, 24.6%, and 38.7% of total *actual* cost. These estimated factor input shares align with their respective raw mean values reported in Table 2-1. The parameter estimates from the constrained NLSUR specification including shadow prices represent the mean factor input *shadow* cost shares showing fuel, labor, capital and other nonlabor inputs account for 14.4%, 20.7%, 26.0%, and 38.9% of total *shadow* cost. All distortion factors are statistically significant in the estimation of total shadow cost and all fail to reject the null hypothesis that they are equal to one via the Wald test. The coefficient on output is less than one indicating that at the mean, US air cargo companies experience increasing returns to scale which aligns with operation well below full capacity.

Table 2-4 Own and Cross Input-Price Elasticities (SUR estimation)

Input Price	**Elasticity**	**Input Price**	**Elasticity**
E_{LO}	0.257	E_{KF}	0.070
E_{LK}	0.186	E_{FL}	0.101
E_{LF}	0.074	E_{FO}	0.203
E_{OL}	0.140	E_{FK}	0.110
E_{OK}	0.016	E_{LL}	-0.548
E_{OF}	0.082	E_{FF}	-0.415
E_{KL}	0.217	E_{KK}	-0.281
E_{KO}	0.025	E_{OO}	-0.238

The input price, cross second-order term coefficient estimates are mostly statistically significant for both the SUR and NLSUR specifications. I use the *actual* cost function estimates (SUR) to compute the capital, labor, fuel and other nonlabor input own-, cross-price demand elasticities reported in Table 2-4. Own-price demand is inelastic for all inputs. The inelastic own-price demand for labor suggests low probability of job loss which is consistent with the high mean salaries reported in Table 2-1. Presumably, price variation in fuel significantly influences carrier ability to provide transport services. The cross-price demand in addition to the elasticity of substitution for all inputs reveal all inputs are somewhat substitutable to one another. A more fuel-efficient aircraft requires less fuel, a more automated aircraft requires fewer laborers, and so on and so forth.

Table 2-3 also includes the estimated factors of proportionality. Labor, relative to capital and other nonlabor factor inputs, satisfies the condition for allocative efficiency according to the relevant Wald statistics which show both the labor/capital and labor/other factors of proportionality fail to differ from one. Despite the labor/fuel factor of proportionality Wald test which statistically differs from one, the parameter estimate of the factor itself is statistically insignificant in the cost function estimation. Therefore, all-cargo carriers seem to efficiently allocate their inputs.

2.6 Conclusion

The air transport industry is a critical component of a vibrant economy, especially in an increasingly interconnected world economy. Given the competitiveness of alternative modes of transportation and the expanding role of communications networks as vehicles of information transmission, providing an affordable transport service is vital to the success of air transport companies. Satisfying the condition of allocative efficiency (cost minimization) then is important as an objective for success in this industry. While much of the research on cost minimization and allocative efficiency in the airline industry primarily examines the passenger sector, there is a dearth of research examining allocative efficiency in the all-cargo air transport sector. Increasing demand for this service due in part to the rise of e-commerce indicates a cost analysis of this sector in particular seems more than relevant. Indeed, growing demand for air cargo service has facilitated interest from traditional passenger service carriers who are increasingly using the cargo bellies of the aircraft to transport freight and enhance competition in this transportation services sector.

This essay contributes to our understanding of the scope of allocative efficiency in the air transport market by testing whether all-cargo air companies are able operate in a manner that satisfies the condition of cost minimization. I consider the potential influence of air cargo companies adhering to union-negotiated and federally-mandated work rules and the potential influence of these companies operating with excess capacity. My analysis indicates adhering to work rules and operating at below full capacity can achieve allocative efficiency perhaps due to the greater returns to density from flight frequency rather than high load factors (Swan, 2002). Empirical findings derived by estimating the shadow cost function indicate US all-cargo air companies use an allocatively efficient combination of labor, fuel capital, and other inputs. I interpret these findings as suggesting that these companies operate in a cost-effective manner. I also interpret these findings as indicating that adherence to work rules doesn’t necessarily promote exorbitant costs given their ability to satisfy the condition allocative efficiency with respect to the use of labor in combination with fuel and other nonlabor inputs.

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3 Tech on Deck: Productivity in the U.S. All-Cargo Industry*

Abstract

This essay investigates productivity and cost patterns in the all-cargo US air transport sector. I empirically test the productivity growth influence of changes in unexplained technology, air operations movement characteristics, and factor input prices. Findings show productivity trends depicting negative growth for the 1992-2013 sample, then shifting measurably such that productivity trends depict positive growth for the 2014-2021 sample. The post 2013 growth was fueled by changes in unexplained technological advancements. I interpret this finding as an indication of the importance of technological innovation as a performance enhancer in this transport sector. Findings also reveal a lack of productivity change associated with changes in input prices and movement characteristics. I interpret input price findings as indicating increases in factor input prices such as wages and fuel prices are commensurate with enhanced labor and fuel productivity. The movement characteristic findings are attributable to a lack of sustained increases in load factors, stage length, network size and carrying more volume over the network (density).

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*NOTE: A similar essay using different data appears as the chapter: *Productivity and Cost Patterns in the All-Cargo US Airline Sector,* with James Peoples, in The International air Cargo Industry: A Modal Analysis, Emerald Publishing edited by James Nolan and James Peoples (Forthcoming book chapter, 2022) pp: 83-116.

3.1 Introduction

Air cargo profitability is strongly tied to the vagaries of domestic and international economies. Thus, a firm's survival in the air cargo sector relies in part on its ability to maintain a high level of productivity. Exogenous factors, such as regulatory change, have contributed to the maintenance of high productivity levels. While much attention has been paid to deregulation of the air passenger service industry, it is the air cargo transport service which was the initial sector of the air transport industry to experience economic deregulation. Congress passed the air cargo deregulation act in November of 1977 a full year before the more publicized 1978 air passenger deregulation act.[44] Prior to deregulation, transport rates were set based on average industry costs, which reduced incentives to control cost and contributed to inefficient operations (Oster, 1984). Past research reports significant limitations on industry performance associated with entry restrictions and rate regulation. Evidence shows capacity shortages for prime-time, evening cargo capacity as well as stifling development of integrated surface and air transportation services prior to deregulation (Oster et al. 1984, Keys, 1980).

Deregulation of air cargo transportation services removed the prior requirement of a 25-mile radius around an airport for freight forward shipments. Firms were then legally able to integrate surface and air transportation services in-house, which promoted the development of FedEx and UPS as major integrated carriers (Oster et al. 1984).[45] This innovative change contributed to nontrivial growth in intermodal transport of parcels as shipments from integrators, such as FedEx and UPS, increased from 5.4 percent of domestic shipment value in

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[44] The US air cargo deregulation act's legal name is Public Law 95-163.

[45] Prior to deregulation freight forwarders could charter cargo aircrafts but were prohibited from providing transport service using their own aircraft fleet (Oster, 1984). Freight forwarders are intermediary companies between the consignor of goods and the point of distribution.

1977 to 14.5 percent by 2012 (Button, 2014). Post deregulation gains were not limited to integrators as the air cargo sector output measured by revenue ton miles increased from around 11 percent per year prior to deregulation to 26 percent the year immediately following deregulation (Moore, 2002).

While analysis of air cargo productivity immediately following deregulation reveals limiting rate and entry restrictions' association with enhanced efficiency, industry events succeeding deregulation further contributed to changes in the productivity of this sector. For instance, in response to the 9/11 security breach, the US government collaborated with air cargo companies to develop an enhanced tracking system which contributed to a significantly more efficient supply chain system (Kaplan, 2017). More recently consumer demand for high-value, low-volume products has increased the need for air cargo carriers to efficiently transport these new types of products.[46] Hence, identifying potential contributing and limiting factors of recent productivity trends helps to further understand the all-cargo air company's ability to efficiently meet growing demand for its services.

This essay expands analysis of productivity gains in the US air cargo sector by using information well past the enactment of the 1977 deregulation act to empirically examine operating costs and productivity trends in the all-cargo US air transportation sector with emphasis on factors that contribute to lower unit costs and greater productivity. Identification

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[46] Evidence of increasing demand for air cargo services is depicted by revenue ton miles in this sector increasing by 35 percent from 2003 to 2019. Source: OST_R | BTS | Transtats.

of contributing factors to productivity gains reveals areas in which the industry has met efficiency needs as well as areas which require further work to promote productivity gains. The remainder of this essay presents a conceptual framework for the analysis of productivity trends in the US air cargo transportation sector. Section 2 discusses the relevant economic literature. Section 3 provides the data sources used for analysis. Section 4 presents the empirical approach used to estimate the industry cost function and the technique used to distinguish the effects of technology and factor input prices on productivity. Section 5 reports the cost estimate findings and productivity trends. Concluding comments are presented in Section 6.

3.2 Factors Influencing Air Cargo Productivity

Standard producer theory posits that, factors affecting costs of operation are key determinants of firms' productivity. Past research identifies load factors, stage length, number of airports served and economies of scale as cost factors that are potential contributors to productive air transport operations (Kanafani and Hansen, 1985; Banker and Johnston, 1993**;** Bitzan and Peoples, 2014). Since airlines have high fixed costs associated with aircraft purchasing, unit costs decline in the presence of higher load factors. Further, many flight-operation expenses such as flight crew, maintenance and fuel do not increase proportionally with freight tonnage (Bitzan and Peoples, 2014).

However, the business model for UPS and FedEx, the two integrators in this transport sector, emphasizes moving cargo quickly which contributes to their airplanes departing with a less-than-full-load and therefore a lower load factor (Donatelli, 2012). Thus, while gains from flying with high load factors can promote productivity growth, the dominant companies in this sector use a business model the limits their ability to take advantage of this productivity growth opportunity. Integrators' business model not only influences potential gains associated with flying with high load factors, but this model also influences these companies' ability to take advantage of the productivity enhancing attributes associated with flying longer stage length. Stage length enhances productivity growth because the increase in operating expenses attributed to longer stage length is less than proportional to the increase in available ton miles, increasing stage length lowers unit costs, all else equal (Tsoukalas et al. 2008). Essentially, longer stage lengths allow the fixed cost of each flight to be spread over more available ton miles. In addition, average variable costs should also decline since the cost of many variable inputs, such as maintenance, fuel, boarding security and landing fees do not vary proportionately with distance (Bitzan and Peoples, 2014). However, the opportunity to derive gains from longer stage lengths may not be as prevalent in the air cargo sector as in the combination passenger-cargo sector since integrators such as FedEx and UPS operate many short-haul flights to and from their hubs to sort and consolidate cargo.

The extensive network of these integrators, though, may present these companies the potential to benefit from economies of network size as they are better able to collect larger quantities of freight without increasing staff and capital proportionally. The number of points served in a point-to-point system serves as a proxy for firm size (Bitzan and Peoples, 2014). Thus, within the conceptual framework of producer theory, a larger number of airports served influences the shape of the firm's average cost curve. Despite the potential for larger firms to benefit from economies of network size, there is also the potential for diseconomies beyond the minimum, optimal number of airports served because an expansive network can become more difficult to coordinate efficient transfer of shipments even with a hub-and-spoke system (Kanafani and Hansen). In tandem with network size, large carriers can also benefit from economies of scale. For example, ground property and equipment, general overhead, maintenance labor, and maintenance materials as well as overhead inputs which all have fixed cost components, are likely to be associated with increasing returns to scale (Banker and Johnston, 1993). However, productivity gains associated with scale of operations may also have limits because efficiently transporting parcels and packages may become challenging in the presence of a potential bottleneck in the supply chain.

Subsequent to deregulation, the switch from a point-to-point system to a hub-and-spoke system enabled carriers to take advantage of these productivity enhancing properties.[47] All-cargo carriers who operate a hub-and-spoke network can provide frequent service between numerous airport pairs. These airport pairs include both short and long stages. Cross-feeding between spokes allows a hub-and-spoke operator to realize higher load factors than it would if each route were operated separately as in the point-to point network system. Therefore, load factors are larger on both short- and long-haul stages. As the number of routes emanating from a hub grows, the scale of operation expands exponentially by increasing the number of originating-and-destination markets served (Wheeler, 1989). In other words, a hub with 9 spokes serves 45 originating-and-destination markets whereas a hub with 18 spokes serves not 90, but 171 markets. In general, the number of originating-and-destination markets served by a hub is equal to $\frac{(N-1)N}{2}$, where N is equal to the total number of cities in the network including the hub. Although the hub-and-spoke system presents significant efficiency opportunities through economies of scale, there are potential efficiency limitations associated with such a network system. Periods of peak demand can congest the system and delay product distribution to consignees (Wheeler). In sum, even though the hub-and-spoke system enhances the productivity effect of stage length, scale of operations and ability to operate with high load factors, its augmenting effect is limited.

Developments in technical and communications equipment that improve logistics and supply chain efficiency can diminish the limitations of the hub-and-spoke system. Indeed,

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[47] FedEx, one of the sector’s dominant carriers, initially instituted the switch to the hub-and-spoke system.

technical innovation thrived following the shift to the hub-and-spoke distribution system as air cargo companies invested in computerized information systems (Button, 2014). Computerized information systems allow for efficient freight tracking and system-wide performance monitoring (Forster and Regan, 2003). Air cargo companies incorporated interorganizational information systems (IOS) which integrate the industry by sharing information electronically, lowering costs and yielding higher on-time performance. In particular, the cargo community systems (CCS) developed during the 1980s and 1990s by a consortium of carriers, airport authorities, industry associations and 3rd party providers allows transmission of documentation and tracking information among forwarders, carriers, consignees and shippers (Forster and Regan, 2003). In addition to IOS, value-added networks (VAN) emerged in the 1990s to provide a more general trade network with additional services such as currency exchange, control, and data integrity (Forster and Regan, 2003).

More recently, air carriers have adopted transportation management systems (TMS). TMS employ software in the planning and execution of good transport. This system monitors the location and supply of products from manufacturers in addition to inventory information at distribution centers. Real-time access to such information enhances productivity as it reveals optimal supply chain coordination.

While technical advancements such as the hub-and-spoke distribution system and computerized tracking systems shift the average cost curve, factor input prices also make an impact. Unit prices and price volatility of key inputs such as fuel, personnel, and aircrafts can heavily influence air cargo carrier productivity. In particular, fuel accounts for about 40% to

50% of air-operating costs for a single flight.[48] Although fuel consumption data shows stable jet fuel prices in the 1990s, the beginning of the 21st century saw not only a surge but also large fluctuations in jet fuel prices. By the 2010s, jet fuel prices stood at 6 times the levels seen in the 1990s.[49] Such wide swings in fuel prices may hinder consistent productivity growth of air cargo operations.

Lucrative wage negotiations may also inhibit a low-cost, high-productivity operation. Salary and benefits contract settlements for the average air transport worker can contribute to relatively high labor costs. As Hirsch (2006) reports, average total air transport worker compensation increased from $73,244 in 1990 to $82,098 in 2005 (in 2005 dollars). In comparison, the average total compensation in 2005 for US workers $26.46 per hour, which is approximately 47,654,46 for fulltime workers.[50] Capital expenses, such as aircraft purchasing, also prove non-trivial for all-cargo air carriers. Examination of prevalent short-haul and long-haul aircrafts purchased by FedEx (such as the 2013, short-haul workhorse Cessna 208B which has a price tag of $2.5 million in 2020 dollars) underscores the massive capital expense necessary to compete in the air cargo sector.[51] FedEx also relies heavily on the Boeing 767 for long-haul service, which has a price tag of $220 million in 2020 dollars.

Even though relatively high unit input prices inflate operating costs, they do not necessarily inflate the rate at which said operating costs increase. In the presence of high price

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[48] Source on fuel share of operating cost taken from Jet Fuel Prices, 1990-2019 | The Geography of Transport Systems (transportgeography.org)

[49] *Source: US Energy Information Administration, U.S. Gulf Coast Kerosene-Type Jet Fuel Spot Price FOB, USD per gallon.*

[50] Source for average compensation of US workers in 2005: https://www.bls.gov/news.release/archives/ecec_03142006.pdf

[51] Even though the Cessna 208b accounts for the large number of short-haul carriers in FedEx's fleet, they discontinued purchasing this aircraft and have instead placed a recent of for 50 of the $6.85 million Cessna SkyCouriers, which they expect to receive by 2022.

inputs, the cost change rate may decline if input prices are commensurate with physical productivity enhanced by technical innovation. Indeed, relatively high prices for fuel are indicative of high performance for this input, as higher quality fuel features cost-saving chemical properties such as a low freeze point which allows for more optimal, long-range flight profiles and a clean-burning capability which may reduce maintenance cost (US Department of Energy, 2020). Donatelli (2012) reports empirical evidence of jet fuel's increasing efficiency as he shows fuel productivity measured by fuel consumption per average ton mile grows annually at 1.5 and 3.65 percent, respectively for the two dominant integrators (FedEx and UPS) and all other air cargo carriers from 1990 to 2010. Additionally, large companies such as FedEx and UPS can reduce their exposure to fuel price volatility by negotiating offtake agreements for long contract periods (US Department of Energy).[52]

All-cargo airline workers and all-cargo aircrafts reportedly exhibit high physical productivity. Airline worker productivity coincides with declining, full-time equivalent employees needed per unit of output as measured by revenue ton miles. In part, the introduction of automated reservation systems for cargo processing accounts for increased worker productivity (Morrell, 2011).[53] Findings in support of Morrell's observation report 80 percent growth in worker productivity from 1990 to 2010 (Donatelli). Additionally, Hirsch (2006) finds labor cost as a percent of available seat miles fell from 4.7 cents per mile to 3.27 cents per mile from 1990 to 2005. Aside from labor productivity gains, investment in fuel

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[52] The offtake agreement is the agreement pursuant to which the purchaser buys all or a substantial portion of the output from the facility and provides the revenue stream supporting a project financing.

[53] Morrel reports air cargo communication system (CCS) and Global freight Exchange (GF-X) increased labor productivity by making it easier for companies to share cargo information, automate shipment tracking and prepare airplane load sheets automatically.

efficient aircrafts that allow for high-volume, freight transport also enable productivity gains (Donatelli). Past findings on air cargo productivity as measured by average ton miles per aircraft per day reveal an annual average growth rate of 3.5 percent from 1990 to 2010 for the two dominant integrators, FedEx, and UPS. In contrast, Donatelli's findings report average annual productivity gains of 20 percent from 1990 to 2010 as measured by average ton miles per day.

The difference between these productivity findings can partly be attributed to more frequent short stage lengths flown by the dominant integrators. Nonetheless, growing aircraft productivity is commensurate with the high purchase price of cargo aircrafts.

In sum, *a priori*, the productivity influence of factor input prices is not obvious. Additionally, the potential for diseconomies of scale and network size suggests possible limits associated with providing an expansive service. Furthermore, low aircraft utilization due to scheduling flights primarily during the night limits the productivity enhancing attributes of other movement characteristics such as load factors and stage length. In contrast to the potential limitation of these movement characteristics, this essay's brief review of technical innovations in the all-cargo air transportation sector reveals the potential for productivity growth during the years prior to and following the turn of the century. Furthermore, these innovations may enhance productivity resulting from factor input use and operational expansion. Despite the role of technical innovation as a facilitator of productivity growth, there is a dearth of research examining all-cargo air cost and productivity trends. Although to the best of my knowledge, at least two studies empirically examine the performance of all-cargo air carriers. Those studies separately analyze productivity growth and trends. Using the DOT's Bureau of Transportation Services' data on eight US all-cargo carriers from 2003 to 2013, Balliauw et al. (2016) estimates a log-log productivity equation with total factor productivity (TFP) as the dependent variable and revenue ton kilometers (RTK), load factor and stage length as explanatory variables.[54] Findings reveal the level of output (RTK) and the average stage length have a significant, positive impact on productivity levels.[55] These findings may suggest the presence of economies of scale in air cargo operations. On the other hand, findings do not reveal a statistically significant load factor-productivity level association, nor do they reveal a statistically significant difference in annual TFP levels compared to the 2013 benchmark year. The lack of annual change in TFP suggests an absence of notable productivity growth over the sample observation period. Separate calculations of TFP by company suggests non-integrators were more susceptible to changes in market conditions.

Using the same data source as Balliauw et al., Donatelli calculates the single and multi-factor productivity index for eleven US all-cargo carriers.[56] He also considers the possibility of differing productivity outcomes base on integrator status by bifurcating multifactor productivity growth for integrators and non-integrators. Single factor productivity findings suggest fuel consumption, labor productivity and aircraft productivity growth for both groups of all-cargo air companies. Multiple factor productivity findings reveal revenue ton miles aggregate productivity for the two integrators has hovered around 1.0 ton-mile per dollar, with a constant annual growth rate totaling 11 percent over the 20-year sample. In contrast, revenue ton miles

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[54] Balliauw et al.'s study uses the multilateral index procedure developed by Caves, et al. (1982) to compute the TFP index.

[55] The productivity equation used in this study excludes airports served because it is considered a decision variable under management control.

[56] The multifactor productivity index used in the Donatelli study. This index is the difference between the growth rate of real revenue ton miles ($\Delta Q/Q$) and the sum of the weighted average of factor inputs (labor fuel, capital and intermediates) where an input's cost shares are used as a weight.

aggregate productivity increased by 102 percent over the same sample period for non-integrators.

Even though findings from past research examining productivity trends for all-cargo highlights the importance of productivity determinants, such as load factor, inputs, stage length, and output as measured by revenue ton miles, past analyses have not empirically examined the contribution of technology to productivity growth, nor have they directly estimated the influence of the full complement of individual non-technology determinants on productivity. Although the Balliauw study includes non-technology factors such as stage length, and load factors in its analysis, the potential influence of factor inputs is excluded. In contrast, Donatalli includes factor inputs in productivity growth determinants, but fails to include the non-technology determinants considered in the Balliauw study. This study builds on both Balliauw and Donatelli's analyses by including both technological and non-technological productivity determinants as well as factor input prices in the analysis of productivity growth trends.

3.3 Data

Data used in this essay is the same data analyzed in essays 1 and 2 for all-cargo carriers. Figures 3-1 and 3-2 show average annual time trends and nonparametric breakpoints for key variables including output, load factor, stage length, airports, and input prices.

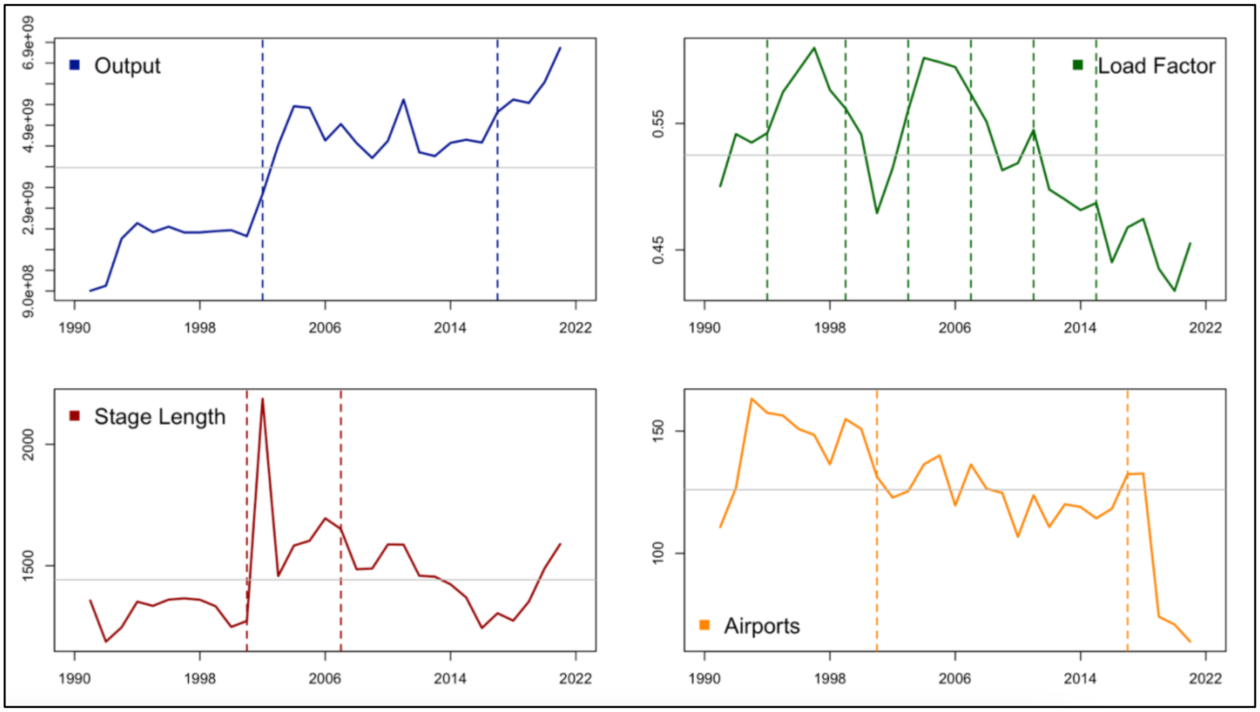

Figure 3-1 All-cargo carrier mean annual output, load factor, stage length, and number of airports (points served) from 1991 to 2021.

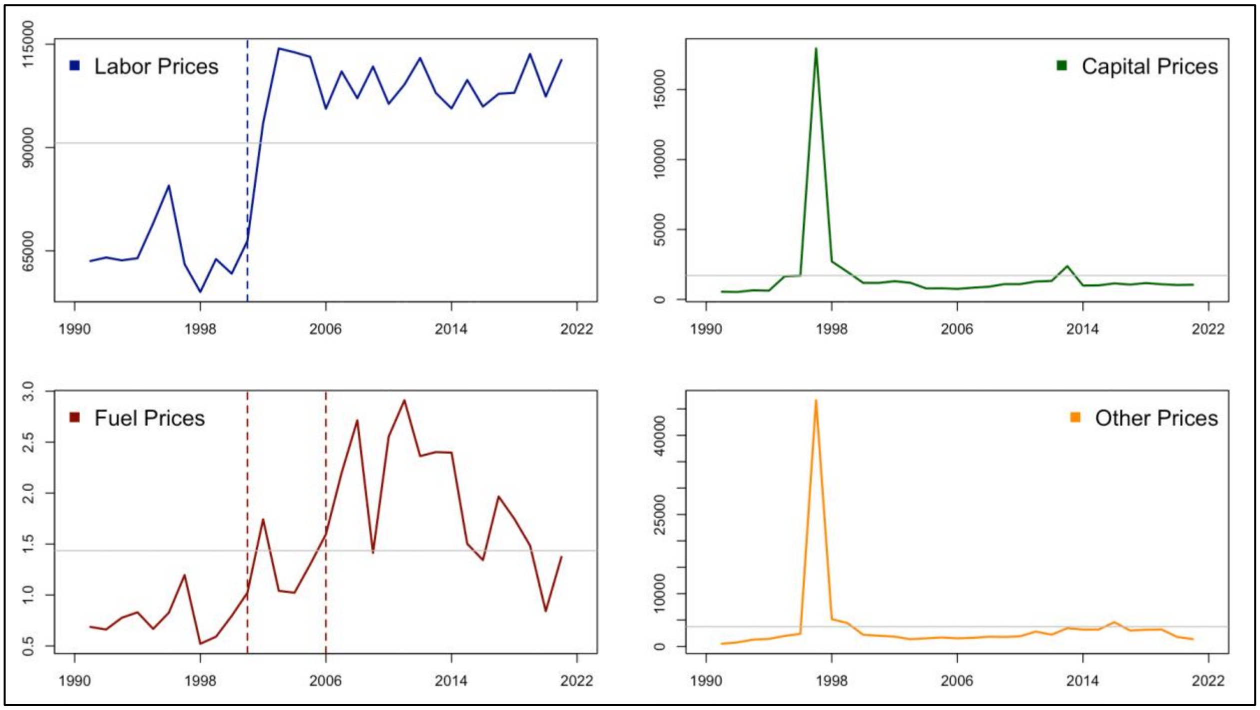

Figure 3-2 All-cargo carrier mean input prices of labor, capital, fuel, and other.

3.4 Empirical Approach

To account for variations in cost determinants over time and across companies I model total cost in the air cargo industry via a translog cost function and employ the Seemingly Unrelated Regression (SUR) estimation technique to measure potential productivity growth. In particular, the goal of this essay is to evaluate productivity growth arising from scale economies, movement characteristics (such as stage length) and technical efficiency rather than said growth arising allocative efficiently (when a firm chooses an optimal combination of inputs). Scale effects such as density and network size precipitated by firms navigating their long run average cost curves as well as unexplained technological change precipitated by shifts in the cost function are integral to this investigation of productivity gains made in the air cargo industry between 1992 and 2021.

While early studies examining productivity gains rely primarily on estimation of production functions, more recent analysis has benefitted from duality theory findings which show productivity technology is identifiable by the estimation of a cost function. My study estimates a flexible long-run cost function to investigate productivity trends in the US air cargo industry in line with past research (Wilson and Zhou, 1997; and Gollop and Roberts, 1981, 1983, Bitzan and Peoples, 2014). In the current deregulated environment faced by firms in the air cargo industry, it is reasonable to assume that firms are able to optimally adjust their capital stock to output changes. The generalized cost function is specified as follows:

Equation 3-1

$$\mathrm{C} = \mathrm{C}(P_i, Y, MoveChar, T) \text{ where i} = \mathrm{K, L, F, O}$$

Where , **P**ᵢ is a vector of factor prices such that P_L, P_K, P_F and P_M respectively denote the price of labor, capital, fuel and other inputs; Y denotes output[57] (e.g. revenue freight ton miles), **MoveChar** is a vector of movement characteristics of all cargo air companies (e.g., load factors, average length of haul, number of airports served, fleet size), and T is a time trend that is included to capture unexplained technological change.

A Taylor series expansion with a remainder (R) is used to approximate this cost function (Friedlander and Spady, 1980). For the generalized cost function depicted by Equation 3-1, a second order Taylor series expansion around the mean values of output, factor input prices, technical characteristics and time is specified as follows:

---

[57] *Inclusion of output in any given cost function invites endogeneity concerns. See Appendix Table 1A-2 for the 3SLS estimation of the cost function in which output, RFTM, is instrumented with freight prices and RPTM, is instrumented with passenger ticket prices following the procedure applied to rail in Bitzan & Keeler 2003. The estimates are very similar to the un-instrumented results suggesting output is exogenous to the cost function.*

Equation 3-2

$$\mathrm{C} = \mathrm{C}(\mathbf{P}_{\boldsymbol{i}}, \mathrm{Y}, \mathrm{Move}\mathbf{Char}, \mathrm{T}) \;= \frac{C(\bar{P}_i, \bar{Y}, \overline{\mathbf{MoveChar}}, T)}{0!} + \sum_i \frac{\frac{\partial C}{\partial P_i}}{1!}(P_i - \bar{P}_i) + \frac{\frac{\partial C}{\partial Y}}{1!}(Y - \bar{Y}) + \frac{\frac{\partial C}{\partial \mathbf{MoveChar}}}{1!}\left(\mathbf{MoveChar} - \overline{\mathbf{MoveChar}}\right) +$$

$$\frac{\frac{\partial C}{\partial T}}{1!}(T - \bar{T}) + \sum_i \sum_j \frac{\left(\frac{\partial^2 C}{\partial P_i \partial P_j}\right)}{2!}(P_i - \bar{P}_i)\left(P_j - \bar{P}_j\right) + \sum_i \frac{\left(\frac{\partial^2 C}{\partial P_i \partial \mathrm{Y}}\right)}{2!}(P_i - \bar{P}_i,)(Y - \bar{Y}) + \sum_i \frac{\left(\frac{\partial^2 C}{\partial P_i \partial GU}\right)}{2!}(P_i - \bar{P}_i,)(\mathrm{GU} - \overline{GU}) +$$

$$\sum_i \frac{\left(\frac{\partial^2 C}{\partial P_i \partial t}\right)}{2!}(P_i - \bar{P}_i)(t - \bar{t}) + \frac{\left(\frac{\partial^2 C}{\partial Y \partial Y}\right)}{2!}\left((Y - \bar{Y})\right)^2 + \sum_i \frac{\left(\frac{\partial^2 C}{\partial \mathrm{Y} \partial P_i}\right)}{2!}(P_i - \bar{P}_i,)(Y - \bar{Y}) + \frac{\left(\frac{\partial^2 C}{\partial Y \partial \mathbf{MoveChar}}\right)}{2!}(Y - \bar{Y})\big(\mathbf{MoveChar} -$$

$$\overline{\mathbf{MoveChar}}\big) + \frac{\left(\frac{\partial^2 C}{\partial Y \partial t}\right)}{2!}(Y - \bar{Y})(T - T) \;\; + \frac{\frac{\partial^2 C}{\partial GU^2}}{2!}\left(\mathbf{MoveChar} - \overline{\mathbf{MoveChar}}\right)^2 + \frac{\left(\frac{\partial^2 C}{\partial \mathrm{GU} \partial P_i}\right)}{2!}\left(\mathbf{MoveChar} - \overline{\mathbf{MoveChar}}\right)(P_i -$$

$$\bar{P}_i) \;\; + \frac{\left(\frac{\partial^2 C}{\partial \mathbf{MoveChar} \partial \mathrm{Y}}\right)}{2!}(Y - \bar{Y})\left(\mathbf{MoveChar} - \overline{\mathbf{MoveChar}}\right) + \frac{\left(\frac{\partial^2 C}{\partial\ \mathbf{TechChar} \partial T}\right)}{2!}\left(\mathbf{MoveChar} - \overline{\mathbf{MoveChar}}\right)(T - \bar{T}) + \frac{\frac{\partial^2 C}{\partial T^2}}{2!}(T - \bar{T})^2 \;\; +$$

$$\frac{\left(\frac{\partial^2 C}{\partial t \partial P_i}\right)}{2!}(T - \bar{T})(P_i - \bar{P}_i) + \frac{\left(\frac{\partial^2 C}{\partial T \partial \mathrm{Y}}\right)}{2!}(T - \bar{T})(Y - \bar{Y}) + \frac{\left(\frac{\partial^2 C}{\partial T \partial\ \mathbf{MoveChar}}\right)}{2!}(T - \bar{T})\left(\mathbf{MoveChar} - \overline{\mathbf{MoveChar}}\right) + R$$

This Taylor series approximation is then transformed by taking the logarithms of the variables and substituting the partial derivatives with parameters. After applying the symmetry of second derivatives (for example, $\frac{\partial^2 C}{\partial P_i \partial \mathrm{Y}} = \frac{\partial^2 C}{\partial \mathrm{Y} \partial P_i}$), simplifying and rearranging the terms, the resulting equation gives the translog cost function specified as follows, which includes dummies for air cargo companies with FedEx as the benchmark comparison firm:[58]

Equation 3-3

$$\ln\mathrm{C} = \alpha_0 + \sum_i \alpha_i ln\left(\frac{P_i}{\bar{\bar{P}}_i}\right) + \beta_Y \ln\frac{\mathrm{Y}}{\bar{Y}} + \sum_n \gamma_n ln\left(\frac{MoveChar_n}{\overline{MoveChar}}\right) + \delta_{T\mathrm{T}} + \frac{1}{2}\sum_{ij} \phi_{ij} ln\left(\frac{P_i}{\bar{\bar{P}}_i}\right) ln\left(\frac{P_j}{\bar{\bar{P}}_j}\right) + \sum_i \phi_{iY} ln\left(\frac{P_i}{\bar{\bar{P}}_i}\right) ln\frac{\mathrm{Y}}{\bar{Y}} +$$

$$\sum_{in} \phi_{in} ln\left(\frac{P_i}{\bar{\bar{P}}_i}\right) ln\left(\frac{MoveChar_n}{\overline{MoveChar}}\right) + \sum_i \phi_{i\mathrm{T}} ln\left(\frac{P_i}{\bar{\bar{P}}_i}\right)\mathrm{T} + \frac{1}{2}\phi_{YY}\left(ln\frac{\mathrm{Y}}{\bar{Y}}\right)^2 + \sum_n \phi_{Yn} ln\frac{\mathrm{Y}}{\bar{Y}} ln\left(\frac{MoveChar_n}{\overline{MoveChar}}\right) + \phi_{YT}\ln\frac{\mathrm{Y}}{\bar{Y}}\mathrm{T} +$$

$$\frac{1}{2}\sum_{nl} \phi_{nl} ln\left(\frac{MoveChar_n}{\overline{MoveChar}}\right) ln\left(\frac{MoveChar_l}{\overline{MoveChar}}\right) + \sum_n \phi_{nT} ln\left(\frac{MoveChar_n}{\overline{MoveChar}}\right) T + \frac{1}{2}\phi_{TT}\, T^2 +$$

Using Shephard’s Lemma to obtain conditional factor demands, the derivative of the log of total costs with respect to the log of input prices yields factor share equations:

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[58] Traditionally research using the translog cost function avoids taking the log of the normalized mean if the time trend is used to depict unexplained technological change. This study follows that convention.

Equation 3-4

$$\frac{\partial lnC}{\partial ln\left(\frac{P_i}{\overline{\overline{P_\iota}}}\right)} = \alpha_i + \sum_j \phi_{ij} ln\left(\frac{P_j}{\overline{\overline{P_J}}}\right) + \sum_Y \phi_{iY} ln\frac{\mathrm{Y}}{\bar{Y}} + \sum_n \phi_{in} ln\left(\frac{MoveChar_n}{\overline{MoveChar}}\right) + \phi_{\mathrm{iT}}\,\mathrm{T}$$

Since at the industry mean $P_i = \overline{P_\iota}$, $\mathrm{Y} = \bar{Y}$, $\mathrm{MoveChar} = \overline{MoveChar}$, $\mathrm{T} = 0$, then $\frac{\partial lnC}{\partial ln\left(\frac{P_i}{\overline{\overline{P_\iota}}}\right)} = \alpha_i$. Thus $\alpha_L, \alpha_k, and\ \alpha_O$ represent labor, capital and other's share of total cost respectively. In addition, Equation 3-5 represents economies of scale.

Equation 3-5

$$\beta_Y + \sum_j \phi_{iY} ln\left(\frac{P_i}{\overline{\overline{P_\iota}}}\right) + \phi_{YY} ln\frac{Y}{\bar{Y}} + \sum_n \phi_{Yn} ln\left(\frac{MoveChar_n}{\overline{MoveChar}}\right) + \phi_{YT}\,\mathrm{T}$$

Further, ϕ_{in} and ϕ_{iT} represents the respective explained and unexplained technology effect on the factor inputs. In terms of technical change, the model can also identify whether technology is factor using or factor saving for different factors of production. That is, I can look at time-factor price interaction terms to identify the impacts of input price changes on technical change and the changing input shares associated with technical change. Positive time-factor price interactions suggest an increase in the factor share over time (factor using) and a hindrance on technical change associated with price increases for that factor. On the other hand, negative time-factor price interactions suggest a decrease in factor share over time (factor saving) and a benefit to technical change associated with price increases of that factor because an increasing price of that factor encourages substitution to other factors of production associated with technical progress.

Unexplained technical change's second order productivity effects are not limited its labor-saving and labor using attributes, as technical change also influences productivity associated with scale and movement characteristics. A positive sign for the estimated coefficient on the time-output interaction term suggest unexplained technological change minifies scale, while a positive estimated coefficient suggest unexplained technological changes augments the scaling of operations. Similarly, a positive coefficient on time-movement characteristic variables suggests unexplained technological change introduces a negative productivity bias for these characteristics, whereas a negative coefficient on these interaction terms suggests a positive bias.

As in previous studies using the translog cost function, I estimate these factor-share equations jointly with the cost function in a system of seemingly unrelated regressions. Share equations are estimated for all the inputs excluding one to avoid singularity in estimated covariance matrix in the errors (Takada *et al.,* 1995). Furthermore, the parameter estimates in the share equations also need to satisfy the following conditions of homogeneity and symmetry with the following parameter restrictions:

Equation 3-6

$$\sum_i \alpha_i = 1, \quad \sum_i \phi_{ij} = \sum_j \phi_{ij} = 0, \quad \sum_i \phi_{iQ} = \sum_i \phi_{in} = \sum_i \phi_{iT} = 0, \quad \phi_{ij} = \phi_{ji}$$

Using this approach allows identifying cost changes, and therefore productivity changes, that result from scale effects, changes in technical change associated with movement characteristics, unexplained technological changes, and changes in input prices. Gollop and Roberts (1981) and Wilson and Zhou (1997) show that the reduction in average costs over time can be separated into a portion that is attributed to movements along the firm's long run average cost curve (scale economies) and a portion that is attributed to shifts in the firm's long run average cost curve (technical change and price changes):

Equation 3-7

$$\text{Decrease in AC} = -\frac{dlnAC}{dT} = \text{Decreasing AC from Scale Economies} + \text{Decreasing AC from Tech. Change}$$

where:

$$\text{Decreasing ACfrom Scale Economies} = \left(1 - \varepsilon_Q\right)\frac{dln\frac{Y}{\overline{Y}}}{dT} \text{ and } \varepsilon_Q = \frac{\partial lnC}{\partial lnY}$$

$$\text{Decreasing AC from Tech. Change} = -\frac{\partial lnC}{\partial T}$$

While this approach is convenient in identifying productivity changes for many industries, it is not sufficient in identifying productivity changes in the all-cargo airline transport sector where increases in traffic over a given network size or expansion of the firm's overall network contribute to increases in output. As Keeler (1974) observe, there are two types of potential scale economies in transport industries: (1) returns to density, and (2) returns to firm size. Returns to density are those returns to scale that result from carrying more traffic over a given network size, while returns to size are returns to scale that result from carrying more traffic due to an expanded network. Returns to density can be assessed by examining the elasticity of costs with respect to output, while holding network size constant. Returns to firm size can be assessed by examining the sum of the elasticities of costs with respect to output and firm size.

Expressions for the productivity gains realized due to economies of density, economies of network size, changes in firm characteristics, changes in factor input prices and technical change over time, are derived by initially defining the rate of change in total costs over time specified by Equation 3-8 below.

Equation 3-8

$$\frac{dlnTC}{dT} = \frac{\partial lnC}{\partial ln\frac{Y}{\overline{Y}}}\frac{\partial ln\frac{Y}{\overline{Y}}}{\partial T} + \frac{\partial lnC}{\partial lnNS}\frac{\partial lnNS}{\partial T} + \sum\nolimits_n \frac{\partial lnC}{\partial ln\left(\frac{MoveChar_n}{\overline{MoveChar}}\right)}\frac{\partial ln\left(\frac{MoveChar_n}{\overline{MoveChar}}\right)}{\partial T} + \sum\nolimits_i \frac{\partial lnC}{\partial ln\left(\frac{P_i}{\overline{\overline{P_i}}}\right)}\frac{\partial ln\left(\frac{P_i}{\overline{\overline{P_i}}}\right)}{\partial T} + \frac{\partial lnC}{\partial T}$$

where NS is network size.

Equation 3-9 is used to derive the rate of change in average cost by subtracting the rate of change in output over time from the rate of change in total costs, as depicted below:

Equation 3-9

$$\frac{dlnAC}{dT} = \frac{\partial lnC}{\partial ln\frac{Y}{\bar{Y}}}\frac{\partial ln\frac{Y}{\bar{Y}}}{\partial T} - \frac{\partial ln\frac{Y}{\bar{Y}}}{\partial T} + \frac{\partial lnC}{\partial lnNS}\frac{\partial lnNS}{\partial T} + \sum\nolimits_n \frac{\partial lnC}{\partial ln\left(\frac{MoveChar_n}{\overline{MoveChar}}\right)}\frac{\partial ln\left(\frac{MoveChar_n}{\overline{MoveChar}}\right)}{\partial T} + \sum\nolimits_i \frac{\partial lnC}{\partial ln\left(\frac{P_i}{\bar{P}_i}\right)}\frac{\partial ln\left(\frac{P_i}{\bar{P}_i}\right)}{\partial T} + \frac{\partial lnC}{\partial T}$$

Duality theory indicates that productivity growth is depicted as the negative of this rate of change in average costs. Thus, productivity growth is computed using the following equation:

Equation 3-10

$$\text{Productivity growth} = -\frac{dlnAC}{dT} = \left(1 - \frac{\partial lnC}{\partial ln\frac{Y}{\bar{Y}}}\right)\frac{\partial ln\frac{Y}{\bar{Y}}}{\partial T} - \frac{\partial lnC}{\partial lnNS}\frac{\partial lnNS}{\partial T} - \sum\nolimits_n \frac{\partial lnC}{\partial ln\left(\frac{MoveChar_n}{\overline{MoveChar}}\right)}\frac{\partial ln\left(\frac{MoveChar_n}{\overline{MoveChar}}\right)}{\partial T} - \sum\nolimits_i \frac{\partial lnC}{\partial ln\left(\frac{P_i}{\bar{P}_i}\right)}\frac{\partial ln\left(\frac{P_i}{\bar{P}_i}\right)}{\partial T} - \frac{\partial lnC}{\partial T}$$

Since Equation 3-10 does not specify the productivity effect associated with the returns to density I separate cost changes that result from increases in the network with density (i.e., output/network size) held constant (in terms of returns to firm size) from cost changes that result from increased output with network size held constant (in terms of returns to density). The first step in separating these effects is to separate the change in output that is the result of a change in network size from the change in output that is independent of changes in network size:

Equation 3-11

$$\frac{\partial ln\frac{Y}{\bar{Y}}}{\partial T} = \frac{\partial ln\frac{Y}{\bar{Y}}}{\partial lnNS}\frac{\partial lnNS}{\partial T} + \left(\frac{\partial ln\frac{Y}{\bar{Y}}}{\partial T} - \frac{\partial ln\frac{Y}{\bar{Y}}}{\partial lnNS}\frac{\partial lnNS}{\partial T}\right)$$

holding density constant, $\frac{\partial ln\frac{Y}{\overline{Y}}}{\partial lnNS} = 1$. This implies,

Equation 3-12

$$\frac{\partial ln\frac{Y}{\overline{Y}}}{\partial T} = \frac{\partial lnNS}{\partial T} + \left(\frac{\partial\, n\frac{Y}{\overline{Y}}}{\partial} - \frac{\partial lnNS}{\partial T}\right)$$

In Equation 3-12, the first term on the left-hand side represents the rate of change of output and the first term on the right-hand side represents the rate of change of network size, while the second term represents the rate of change of density. Equation 3-12 can be used in combination with Equation 3-10 to define productivity growth due to changes in density, firm size, movement characteristics, factor input prices and technical change as depicted in Equation 3-13 below:

Equation 3-13

$$-\frac{dlnAC}{dT} = \left(1 - \frac{\partial\, nC}{\partial\, n\frac{Y}{\overline{Y}}} - \frac{\partial lnC}{\partial lnNS}\right)\frac{\partial lnNS}{\partial T} + \left(1 - \frac{\partial lnC}{\partial ln\frac{Y}{\overline{Y}}}\right)\left(\frac{\partial ln\frac{Y}{\overline{Y}}}{\partial T} - \frac{\partial lnNS}{\partial T}\right) - \sum_n \frac{\partial lnC}{\partial ln\left(\frac{MoveChar_n}{\overline{MoveChar}}\right)} \frac{\partial ln\left(\frac{MoveChar_n}{\overline{MoveChar}}\right)}{\partial T} - \sum_i \frac{\partial lnC}{\partial ln\left(\frac{P_i}{\overline{\overline{P_\iota}}}\right)} \frac{\partial ln\left(\frac{P_i}{\overline{\overline{P_\iota}}}\right)}{\partial T} - \frac{\partial lnC}{\partial T}$$

In Equation 3-13, the first term represents productivity growth resulting from a change in firm size, the second term represents productivity growth resulting from a change in density, the third term represents productivity growth resulting from changes in firm characteristics, and the last term represents productivity growth resulting from technical change.

In this study I model productivity growth resulting from each of these effects for the industry average in each year of my data. Thus, decreases in average cost from the previous year are separated into these components by using cost function parameter estimates and industry averages of explanatory variables. Changes in average cost are computed for the mean firm in each year of my data. Specifically, decreases in average cost from the previous year are separated into these components by using cost function parameter estimates and industry averages of independent variables. A two-year average of independent variables is used to measure changes due to technical change, returns to density, and returns to firm size for any given year (YR), as follows:[59]

Equation 3-14

$$\text{Decreasing AC from unexplained technological change in year T} = -\left.\frac{\partial lnC}{\partial T}\right|_{YR_t} =$$

$$-\left[\delta_T + \textstyle\sum_i \phi_{\mathrm{iT}}\left(\frac{\ln\left(\frac{P_i}{\bar{P}_i}\right)(\mathrm{YR_t})+\ln\left(\frac{P_i}{\bar{P}_i}\right)(\mathrm{YR_{t-1}})}{2}\right) + \phi_{YT}\left(\frac{ln\frac{\mathrm{Y}}{\bar{Y}}(YR_t)ln\frac{\mathrm{Y}}{\bar{Y}}+(YR_{t-1})}{2}\right) + \phi_{nT}\left(\frac{ln\frac{MoveChar_n}{\overline{MoveChar}}(YR_t)ln\frac{MoveChar_n}{\overline{MoveChar}}+(YR_{t-1})}{2}\right) + \right.$$

$$\left.\phi_{TT}\left(\frac{t+(t-1)}{2}\right)\right]$$

where P_i denotes factor input prices. Including input prices in the equation allows for analysis of unexplained technological change while holding input prices constant.

Equation 3-15

$$Decreasing\ AC\ from\ change\ in\ \ movement\ characteristics\ in\ year\ t\ = \left(-\left.\frac{\partial lnC}{\partial ln\frac{MoveChar_n}{\overline{MoveChar}}}\right|_{YR_t}\right)\left(\left.\frac{\partial ln\frac{MoveChar_n}{\overline{MoveChar}}}{\partial t}\right|_{YR_t}\right)$$

$$=\left[-\left\{\gamma_n + \textstyle\sum_i \phi_{in}\left(\frac{\ln\left(\frac{P_i}{\bar{P}_i}\right)(\mathrm{YR_t})+\ln\left(\frac{P_i}{\bar{P}_i}\right)(\mathrm{YR_{t-1}})}{2}\right) + \phi_{Yn}\left(\frac{ln\frac{\mathrm{Y}}{\bar{Y}}(YR_t)+ln\frac{\mathrm{Y}}{\bar{Y}}(YR_{t-1})}{2}\right) + \phi_{nl}\left(\frac{ln\frac{MoveChar_n}{\overline{MoveChar}}(YR_t)+ln\frac{MoveChar_n}{\overline{MoveChar}}(YR_{t-1})}{2}\right) + \right.\right.$$

$$\left.\left.\phi_{nT}\left(\frac{t+(t-1)}{2}\right)\right\}\right]\left[\left(ln\,\frac{MoveChar_n}{\overline{MoveChar}}\,(YR_t) - ln\,\frac{MoveChar_n}{\overline{MoveChar}}\,(YR_{t-1})\right)\right]$$

Equation 3-16

$$Decreasing\ AC\ from\ Density\ Economies\ in\ year\ t = \left(1 - \left.\frac{\partial lnC}{\partial ln\frac{\mathrm{Y}}{\bar{Y}}}\right|_{YR_t}\right)\left(\left.\frac{\partial ln\frac{\mathrm{Y}}{\bar{Y}}}{\partial T}\right|_{YR_t} - \left.\frac{\partial lnNS}{\partial T}\right|_{YR_t}\right) = \left[1 - \right.$$

$$\left\{\beta_{\frac{\mathrm{Y}}{\bar{Y}}} + \textstyle\sum_i \phi_{i\frac{\mathrm{Y}}{\bar{Y}}}\left(\frac{\ln\left(\frac{P_i}{\bar{P}_i}\right)(\mathrm{YR_t})+\mathrm{lnP_i}(\mathrm{YR_{t-1}})}{2}\right) + \phi_{\frac{\mathrm{YY}}{\bar{Y}\bar{Y}}}\left(\frac{ln\frac{\mathrm{Y}}{\bar{Y}}(YR_t)+ln\frac{\mathrm{Y}}{\bar{Y}}(YR_{t-1})}{2}\right) + \textstyle\sum_n \phi_{\frac{\mathrm{Y}}{\bar{Y}}n}\left(\frac{lnMovechar_n(YR_t)+lnMovechar_n(YR_{t-1})}{2}\right) + \right.$$

$$\left.\left.\phi_{\frac{\mathrm{Y}}{\bar{Y}}T}\left(\frac{T+(T-1)}{2}\right)\right\}\right]\left[\left(ln\,\frac{\mathrm{Y}}{\bar{Y}}\,(YR_t) - ln\,\frac{\mathrm{Y}}{\bar{Y}}\,(YR_{t-1})\right) - \left(lnNS(YR_t) - lnNS(YR_{t-1})\right)\right]$$

---

[59] Gollop and Roberts (1981) and Bitzan and Peoples (2014) also used a two-year average of independent variables in measuring productivity effects due to scale and technical changes in the U.S. Electric Power Industry. Note that the notation YR_t denotes observation year at time 't'.

Equation 3-17

$$Decreasing\ AC\ from\ Size\ Economies\ (\mathrm{NS})\ in\ year\ t = \left(1 - \left.\frac{\partial lnC}{\partial ln\frac{\mathrm{Y}}{\bar{\bar{Y}}}}\right|_{YR_t} - \left.\frac{\partial lnC}{\partial lnNS}\right|_{YR_t}\right)\left(\left.\frac{\partial lnNS}{\partial T}\right|_{YR_t}\right) = \qquad \Bigg[1 -$$

$$\Bigg\{\beta_{\frac{\mathrm{Y}}{\bar{\bar{Y}}}} + \textstyle\sum_i \phi_{i\frac{\mathrm{Y}}{\bar{\bar{Y}}}}\left(\frac{\ln\left(\frac{P_i}{\bar{\bar{P}}_{\imath}}\right)(\mathrm{YR_t})+\ln\left(\frac{P_i}{\bar{\bar{P}}_{\imath}}\right)(\mathrm{YR_{t-1}})}{2}\right) + \phi_{\frac{\mathrm{YY}}{\bar{\bar{Y}}\bar{\bar{Y}}}}\left(\frac{ln\frac{\mathrm{Y}}{\bar{\bar{Y}}}(YR_t)+ln\frac{\mathrm{Y}}{\bar{\bar{Y}}}(YR_{t-1})}{2}\right) + \textstyle\sum_n \phi_{\frac{\mathrm{Y}}{\bar{\bar{Y}}}n}\left(\frac{lnMovechar_n(YR_t)+lnMovechar_n(YR_{t-1})}{2}\right) +$$

$$\phi_{\frac{\mathrm{Y}}{\bar{\bar{Y}}}T}\left(\frac{T+(T-1)}{2}\right)\Bigg\} - \Bigg\{\gamma_{NS} + \textstyle\sum_i \phi_{iNS}\left(\frac{\ln\left(\frac{P_i}{\bar{\bar{P}}_{\imath}}\right)(\mathrm{YR_t})+\ln\left(\frac{P_i}{\bar{\bar{P}}_{\imath}}\right)(\mathrm{YR_{t-1}})}{2}\right) + \phi_{\frac{\mathrm{Y}}{\bar{\bar{Y}}}NS}\left(\frac{ln\frac{\mathrm{Y}}{\bar{\bar{Y}}}(YR_t)+ln\frac{\mathrm{Y}}{\bar{\bar{Y}}}(YR_{t-1})}{2}\right) +$$

$$\textstyle\sum_n \phi_{nNS}\left(\frac{lnMovewchar_n(YR_t)+lnMovechar_n(YR_{t-1})}{2}\right) + \phi_{NST}\left(\frac{T+(T-1)}{2}\right)\Bigg\}\Bigg]\left(lnNS(YR_t) - lnNS(YR_{t-1})\right)$$

where, NS ϵ **t**.

Equation 3-18

$$Decreasing\ AC\ from\ factor\ input\ price\ changes\ in\ year\ T = -\left.\frac{\partial lnC}{\partial\left(\frac{P_i}{\bar{\bar{P}}_{\imath}}\right)}\right|_{YR_t} = \left(-\left.\frac{\partial lnC}{\partial ln\left(\frac{P_i}{\bar{\bar{P}}_{\imath}}\right)}\right|_{YR_t}\right)\left(\left.\frac{\partial ln\left(\frac{P_i}{\bar{\bar{P}}_{\imath}}\right)}{\partial t}\right|_{YR_t}\right) =$$

$$\Bigg[-\Bigg\{\alpha_i + \textstyle\sum_i \phi_{ij}\left(\frac{\ln\left(\frac{P_i}{\bar{\bar{P}}_{\imath}}\right)(\mathrm{YR_t})+\ln\left(\frac{P_i}{\bar{\bar{P}}_{\imath}}\right)(\mathrm{YR_{t-1}})}{2}\right) + \phi_{iY}\left(\frac{ln\frac{\mathrm{Y}}{\bar{\bar{Y}}}(YR_t)+ln\frac{\mathrm{Y}}{\bar{\bar{Y}}}(YR_{t-1})}{2}\right) + \phi_{in}\left(\frac{ln\frac{MoveChar_n}{\overline{\overline{MoveChar}}}(YR_t)+ln\frac{MoveChar_n}{\overline{\overline{MoveChar}}}(YR_{t-1})}{2}\right) +$$

$$\phi_{iT}\left(\frac{t+(t-1)}{2}\right)\Bigg\}\Bigg]\left[\left(ln\left(\frac{P_i}{\bar{\bar{P}}_{\imath}}\right)(YR_t) - ln\left(\frac{P_i}{\bar{\bar{P}}_{\imath}}\right)(YR_{t-1})\right)\right]$$

3.5 Results

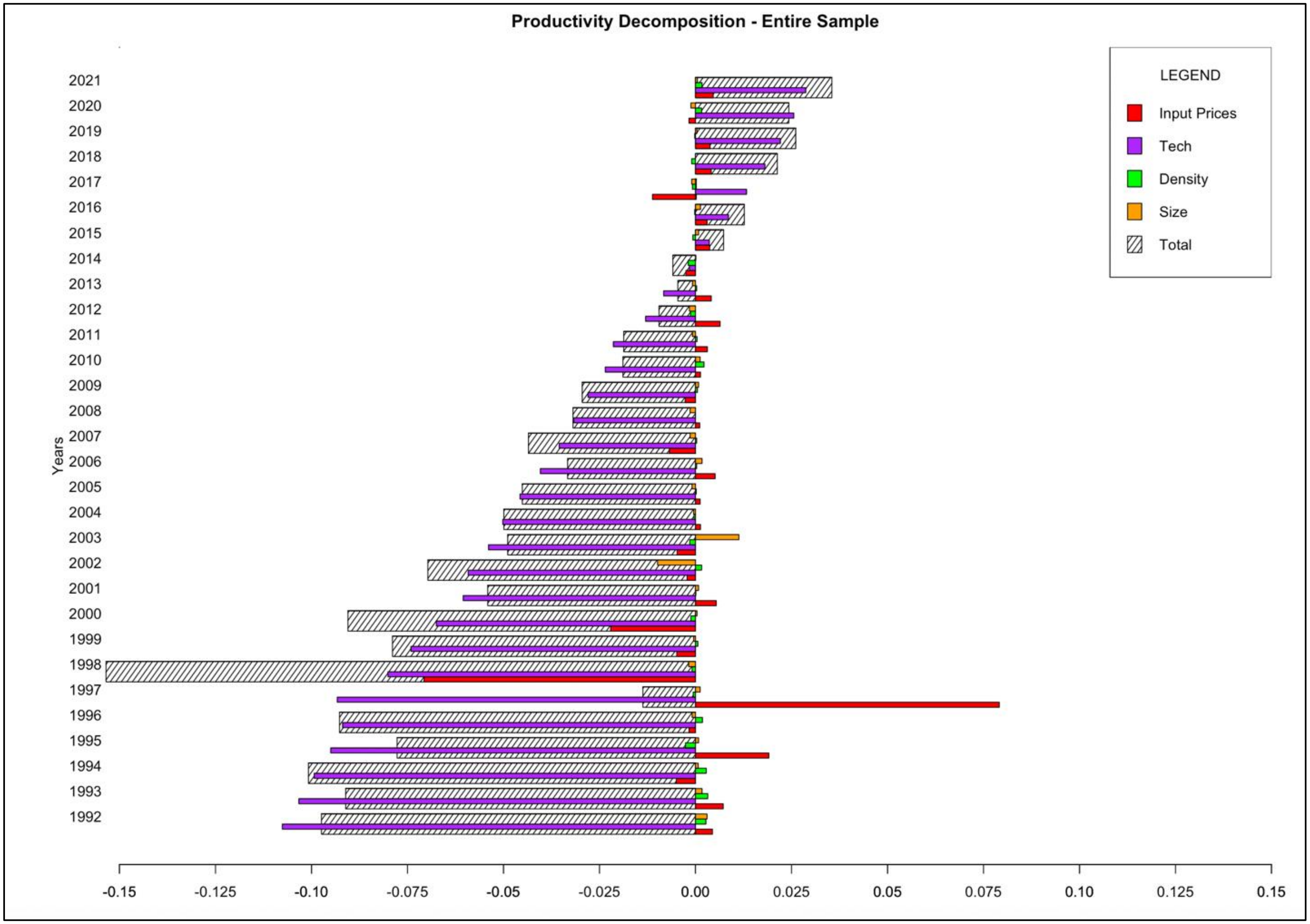

Figure 3-3 Productivity decomposition for all-cargo carriers from 1992 to 2021.

Table 3-1 Annual changes in productivity by component.

Year	Movement Characteristics					Input Prices					Tech	Productivity
	Points Served	Fleet	Load Factor	Stage Length	Total	Labor	Capital	Other	Fuel	Total		
1992	0.001	0.001	0.001	0.002	0.006	0.000	0.000	0.004	-0.001	0.004	-0.108	-0.097
1993	0.003	0.004	-0.001	-0.001	0.005	0.001	0.002	0.006	-0.002	0.007	-0.103	-0.091
1994	0.001	0.003	-0.001	0.000	0.003	0.000	0.000	-0.004	-0.001	-0.005	-0.099	-0.101
1995	0.000	-0.002	-0.001	0.001	-0.002	0.001	0.010	0.005	0.003	0.019	-0.095	-0.078
1996	0.000	0.002	0.000	-0.001	0.001	0.000	-0.002	0.002	-0.001	-0.002	-0.092	-0.093
1997	0.001	0.000	0.000	0.000	0.001	-0.002	0.029	0.046	0.006	0.079	-0.093	-0.014
1998	-0.003	0.000	0.000	0.001	-0.003	0.001	-0.028	-0.041	-0.004	-0.071	-0.080	-0.154
1999	-0.001	-0.001	0.002	0.000	0.000	0.001	-0.004	-0.001	-0.001	-0.005	-0.074	-0.079
1992-1999	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.003	0.000	0.004	-0.092	-0.087
2001	0.001	0.003	-0.002	0.000	0.001	-0.002	0.000	0.005	0.002	0.005	-0.060	-0.054
2002	0.000	0.001	0.001	-0.010	-0.008	-0.001	0.001	-0.003	0.000	-0.002	-0.059	-0.070
2003	-0.001	-0.003	0.002	0.012	0.010	0.001	0.001	0.000	-0.006	-0.005	-0.054	-0.049
2004	-0.001	-0.001	0.001	0.000	-0.001	0.000	-0.003	0.002	0.002	0.001	-0.050	-0.050
2005	0.000	0.000	0.000	-0.001	-0.001	0.000	0.000	0.001	0.001	0.001	-0.046	-0.045
2006	0.001	0.001	0.000	0.001	0.002	0.000	0.000	0.000	0.004	0.005	-0.040	-0.033
2007	0.000	0.001	0.000	-0.001	-0.001	0.000	-0.001	-0.001	-0.005	-0.007	-0.036	-0.043
2008	0.001	0.000	0.000	-0.003	-0.001	0.001	0.000	0.000	0.000	0.001	-0.032	-0.032
2009	0.000	0.000	0.000	0.000	0.001	0.000	0.000	-0.001	-0.003	-0.003	-0.028	-0.029
2010	0.000	0.002	0.000	0.001	0.003	0.000	0.000	0.000	0.002	0.001	-0.024	-0.019
2001-2010	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.043	-0.042
2012	-0.001	-0.001	0.000	-0.001	-0.003	0.000	0.001	0.001	0.005	0.006	-0.013	-0.009
2013	0.000	0.001	-0.001	-0.001	0.000	0.000	0.006	0.001	-0.003	0.004	-0.008	-0.005
2014	0.000	-0.001	-0.001	0.000	-0.002	0.001	-0.006	0.003	0.000	-0.003	-0.002	-0.006
2015	0.000	-0.001	0.000	0.001	0.000	0.000	-0.001	0.001	0.003	0.004	0.004	0.007
2016	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.004	-0.001	0.003	0.009	0.013
2017	0.000	-0.001	0.000	-0.001	-0.002	0.000	-0.002	-0.006	-0.003	-0.011	0.013	0.000
2018	0.000	-0.001	0.000	0.000	-0.001	0.000	0.000	0.003	0.001	0.004	0.018	0.021
2019	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.004	0.022	0.026
2020	0.000	0.001	0.000	-0.001	0.000	0.001	0.002	-0.003	-0.002	-0.002	0.026	0.024
2021	0.000	0.001	0.001	0.000	0.002	0.000	0.002	0.001	0.002	0.005	0.029	0.035
2012-2021	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.002	0.010	0.011

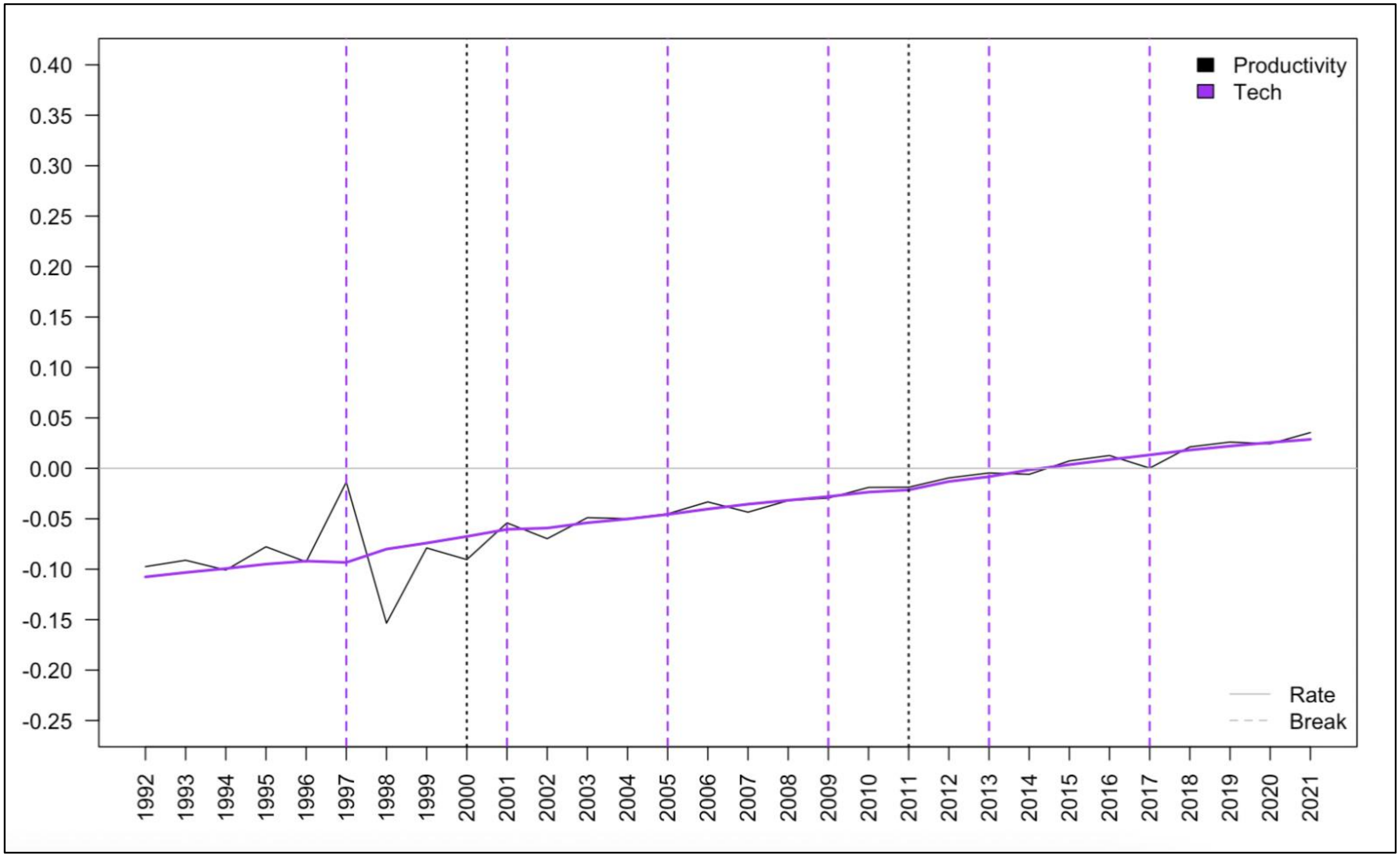

Figure 3-4 Productivity and unexplained technological change trends from 1992 to 2021 with structural breakpoints.

3.6 Conclusion

The continued rise in e-commerce purchases have contributed to consistent growth in the air cargo industry as shown in Figure 3-3 and Table 3-1. While such growth generates greater revenue for all-cargo air companies, increasing competition from passenger carriers transporting freight in the belly of the aircraft presents a source of competition that can erode all-cargo companies' revenue gains associated with increasing demand for air freight service. Faced with stepped-up competition, maintaining a low-cost operation by maintaining strong productivity growth is critical to the market success of all-cargo air transport companies. This study examines performance of all-cargo air transport companies in the US by using results from estimating the translog cost function to compute productivity growth trends.

Findings on productivity growth reveal two distinct productivity patterns for the 1992 to 2021 observation sample. These annual changes in growth rates were consistently negative prior to 2014 reaching positive growth thereafter, with most of the growth occurring after 2014.

Empirical findings from this study also reveal the importance of technological innovation as a driver for growth in this transport sector. These findings show total productivity growth closely resembles productivity growth attributable to unexplained technological change as shown in Figure 3-3 and Figure 3-4, while there is an absences of productivity growth attributable to changes in movement characteristics and changes in density and network size. I note that the lack of a productivity effect associated with movement characteristics and firm density and network size does not indicate that these determinants are not an important source of potential productivity growth. Rather, using an operations model that promotes express delivery by constraining aircraft utilization limits the productivity enhancing attributes of movement characteristics such as longer stage lengths and higher load factors. Nonetheless, any limits on productivity attributable to stage length and load factors are likely offset by higher return yields associated with adherence to express operations.

With regard to the lack of productivity growth associated with the density and network size, changes in these movement characteristics were negligible for this observation sample. Findings on the interaction of the time trend and stage length did reveal that unexplained technological change does enhance stage length's productivity growth influence. My empirical findings also show an absence of a productivity growth effect associated with changes in factor input prices. Relatively low mean prices for capital and other factor inputs for the post 2002 sample observation period relative to the post 2003 sample observation period contribute to an absence of a productivity erosion associated with consumption of these inputs. However, price of labor and fuel are measurably higher for the post 2003 sample, and these price gains are not associated with declining productivity. The price results for these to inputs is consistent with the notion that higher wages and fuel prices indicate compensation for greater performance.

Further, the interaction of the time trend and wages suggest unexplained technological change is associated with labor cost savings. In addition, the interaction of the time trend and the price of nonlabor inputs other than capital and fuel suggests technological advancement enhances the use of these inputs. I interpret this finding to indicate air cargo companies use more modernized customer services systems as well as accounting and management systems, given that outsourcing the use of these systems are the primary factor inputs for the other input category. In contrast to the unexplained technology findings for labor and nonlabor inputs other than capital and fuel, findings for the parameter estimate on the interaction variable for time trend and fuel prices is positive and suggest unexplained technological change is fuel using. This finding is consistent with the trend of air cargo companies increasingly investing in more fuel-efficient aircraft. Compared to less efficient aircraft used in the past, these newer planes can travel greater distances for every gallon consumed. Hence, companies can afford to consume more fuel because the average cost per rtm declines with usage as shown in Donatelli (2012).

In sum, to my knowledge this study is the first to include empirical analysis of technological innovation as a contributor to productivity growth in the all-cargo airline sector. Directly testing its productivity influence suggest continued investment in performance enhancing technology is critical to continued productivity gains. The significance of such cost-saving investment is highlighted by the need of all-cargo companies to be able to compete in an increasingly competitive market for air freight service.

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