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Essays on Air Cargo Cost Structures, Airport Traffic, and Airport Delays: Panel Data Analysis of the U.S. Airline Industry

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Essays on Air Cargo Cost Structures, Airport Traffic, and Airport Delays: Panel Data Analysis of the U.S. Airline Industry

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Transportation Science

by

Paulos Ashebir Lakew

Dissertation Committee:
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2014

DEDICATION

to my parents, Ashebir Lakew and Ethiopia Gebreyesus

to my sister, Ruth

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ABSTRACT OF THE DISSERTATION

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By

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Professor Jan K. Brueckner, Chair

The present thesis is comprised of four essays that address important gaps in passenger- and cargo-airline research. Seminal studies in airline economics that rely on cross-section methods make critical homogeneity assumptions and preclude time-specific effects. The essays in this thesis use panel data, which allow for certain assumptions made by cross-sectional studies to be relaxed, while shedding light on the intertemporal features of air transport.

The first chapter investigates the cost structure of air cargo carriers by applying a total cost model used in passenger-airline studies. Using quarterly panel data (2003-2011) on the domestic operations and costs of FedEx Express and UPS Airlines, empirical results indicate that the air cargo industry exhibits increasing returns to traffic density and constant returns to scale. Accounting for carrier-specific differences in cost structure and network size, FedEx is found to be more cost efficient than UPS (a finding that is reversed when network size is not controlled). Individually, UPS exhibits substantial economies of density and constant returns to scale while FedEx's cost structure is characterized by weak economies of density and constant returns to scale. Both carriers exhibit economies of size.

The next three chapters embody papers that use quarterly panel data of city-level air traffic, airline delay, and socioeconomic variables. Spanning 10 years (2003-2012), the panel structure of the data permits the use of fixed effects to control for city-specific heterogeneity.

The second chapter presents a paper prepared for the Airport Cooperative Research Program (ACRP). The study demonstrates the within-city traffic impacts of urban size, employment composition, and wages, providing new insights into the determinants of passenger and air cargo traffic. The essay also confirms that airport traffic is proportional to population, and that service-sector employment and higher wages induce passenger travel and goods movement. A city's share of manufacturing employment, however, only impacts air cargo traffic. Passenger enplanements exhibit more sensitivity to the proportion of urban workers providing non-tradable services, compared to the share of workers in tradable service jobs.

The third chapter, co-authored with Andre Tok, examines the determinants of air cargo traffic in California. The study uses a shorter 7-year panel (2003-2009), and shows that service and manufacturing employment impact the volume of outbound air cargo. Total (domestic) air cargo traffic is found to grow faster than (proportionally to) population, while wages play a significant role in determining both total and domestic air cargo movement. Metro-level air cargo tonnage are also forecasted for the years 2010-2040, indicating that California's total (domestic) air cargo traffic will increase at an average rate of 5.9 percent (4.4 percent) per year in that period.

The final chapter is co-authored with Volodymyr Bilotkach, and it provides the first evidence on the impact of airline delays on urban-sectoral employment. Controlling for unobserved city-specific differences, the empirical estimates of the effects of air traffic on total employment are comparable to previously reported measures. However, service-sector employment is found to be less sensitive to air traffic than other studies suggested. New evidence confirming that delays have a negative impact on employment is also provided, a finding that is robust to various model specifications.

Chapter 1

The Cost Structures of FedEx Express and UPS Airlines

In view of the air cargo industry's considerable growth in transported cargo and express services, this study investigates the cost structures of the leading integrated carriers, FedEx Express and United Parcel Services (UPS) Airlines, to find empirical evidence on economies of traffic density and economies of scale in the integrated air cargo industry.[1] Much of the air cargo literature is naturally adapted from studies on passenger airlines, which suggest that (1) costs per passenger-mile decrease with traffic density on individual airline routes (2) both major and local carriers exhibit constant returns to scale (Caves, Christensen, and Tretheway [31]; Gillen, Oum, and Tretheway [46]; Brueckner and Spiller [20]). Air cargo analysis by Kiesling and Hansen [54] has shown that increasing returns to traffic density and decreasing returns to scale held for FedEx Express in the 1980's and early 1990's.

[1]Integrated carriers provide all-inclusive parcel shipping services, from forwarding and flying to ground handling. Considering the dominant presence of FedEx Express and UPS Airlines amongst integrators, both in terms of traffic volume and revenues, the two carriers are assumed to represent the entire integrated industry in this paper.

Analyzing quarterly time-series data from 2003 to 2011, this paper shows that the domestic (United States and Canada) integrated industry exhibits increasing returns to density and constant returns to scale. The combined effect of economies of density and economies of scale on the carriers' cost structure is captured by *economies of size*, a measure introduced to the air cargo literature by Kiesling and Hansen [54]. Controlling for carrier-specific differences in network and input-price attributes, this study shows that the integrators exhibit increasing returns to size.

Although the air cargo industry was deregulated a year before the passage of the Airline Deregulation Act (November 9, 1977), its deregulation has not sparked nearly as much research interest as deregulation of the passenger airline industry. Despite the thinness of the air cargo literature, and the limited knowledge of the industry due to sparse data, there has been a gradual shift of attention towards it in the past decade. Still, the industry's distinctive cost structure and success in servicing a range of domestic and international markets remains unappreciated. Some of the earliest works that address economies of density and scale in the air cargo industry are by Smith[83] and Carron [30]. Since deregulation, cost-structure studies of the passenger airline industry continued to examine the nature of density and scale economies. Caves et al. [31] found that there are substantial economies of density for carriers of all sizes. They showed that total cost increases 80 percent as rapidly as total traffic, holding the number of points served fixed. They also found that constant returns to scale held for major and local carriers. The latter conclusion, however, negated previous beliefs about cost differentials between major (trunk) and local carriers, assuring that local carriers could compete with airlines that operate larger networks. Brueckner and Spiller [20] found stronger estimates of economies of density by taking a more disaggregated approach that uses a structural model of hub-and-spoke airline competition.

Recognizing the need for a similar empirical analysis of the air cargo industry, Kiesling and Hansen [54] characterized the cost structure of the largest integrated air cargo carrier at that time, FedEx Express (then Federal Express, Inc). They showed that FedEx Express, and conceivably the rest of the all-cargo carriers in the industry, exhibits substantial economies of density and diseconomies of scale. The authors also introduced a third aspect of the industry's cost structure, economies of size, that combines the effects of economies of density and economies of scale. They found that FedEx Express exhibits constant returns to size, implying that costs rise in proportion to output when the network size is adjusted in step. This result supported their view that FedEx Express could expand its output and network size without sacrificing efficiency, an outcome that presumably requires network size to increase less than in proportion to output so as to exploit economies of density. Therefore, economies of size captures the effects of increasing output levels while adjusting the number of airports served (points served), assuming that output and points served are functionally related.

FedEx Express has expanded its operations and markets at a remarkable pace since Kiesling and Hansen's [54] study. Just as Caves et al. [31] reexamined the widely held beliefs about the cost advantages of major carriers in the passenger airline industry, the following analysis will attempt to characterize the current cost structures of the two most dominant air cargo carriers, FedEx Express (FedEx hereafter) and UPS Airlines (UPS hereafter). The broader implications of this study will also be useful for policy-related questions regarding cost efficiencies in the air cargo industry. Specifically, the study will provide a baseline framework to understand the cost factors that are involved in network-size and traffic-allocation decisions. Considering that the current understanding of the air cargo industry is mostly based on analogies drawn to passenger airlines, it is important to distinguish the unique characteristics of air cargo operations and to fill the corresponding literature gaps along the way.

While studying the cost structure of the entire air cargo industry would be a useful exercise, the distinctive operational characteristics of FedEx and UPS require an analysis focusing on them alone. Specifically, integrated carriers consolidate the supply chain of cargo transportation, from the consignor to the consignee, according to their own schedule. Other dedicated air cargo or passenger-cargo (combination and belly freight) carriers mostly offer chartered services for shippers, forwarders, and third-party logistics providers. Moreover, data from the U.S. Department of Transportation (DOT) show that FedEx and UPS respectively transported 53 and 29 percent of the total domestic cargo tons enplaned by U.S. carriers over the past decade. Together, the two carriers also accounted for just over 90 percent of all international air freight ton-miles in 2008 (see Morrell [61], p. 99). With operating revenues over $1 billion, FedEx and UPS are the only cargo carriers officially classified as Group III carriers by the DOT, further distinguishing them from the rest of the air cargo industry. Therefore, this study will primarily focus on these two carriers to represent the integrated air cargo industry.

It should be noted that, despite the many perceived similarities between FedEx and UPS, the carriers have fundamental differences in demand, network characteristics, and operations that affect their cost structures. FedEx specializes in expedited delivery of business-related small packages and letters, using a large air fleet on feeder, point-to-point, and hub-and-spoke networks. UPS operates a multimodal network of trucks and air freighters for delivery of packages to businesses and personal customers. A sizable portion of UPS's traffic is transported by ground vehicles. Thus, while there is a need to analyze the integrated industry, a proper study must shed light on the differences between the firms.

1.1 Background

Air freighters used a single hub city (airport) for sorting in the early stages of the air cargo industry (Noviello et al., [67]). Over the years, increasing demands have led carriers to incorporate more hubs into their networks. Both FedEx and UPS now operate nine domestic hubs that are dispersed across the U.S. and Canada. FedEx is based at Memphis International Airport, its largest hub (*Superhub*). The other domestic hubs for FedEx are Fort Worth Alliance, Indianapolis International, Newark Liberty International, Oakland International, Ted Stevens Anchorage International, Piedmont Triad International (Greensboro), Miami International, and Toronto Pearson International (Canada). UPS operates from its Louisville International Airport hub (*Worldport*) as well as the following additional domestic hubs: Philadelphia International, Los Angeles/Ontario International, Dallas-Fort Worth International, Chicago Rockford International, Bradley International (Hartford), Miami International, Columbia Metropolitan (South Carolina), and Hamilton International (Canada).[2]

Even though air cargo carriers operate hub-and-spoke networks like passenger airlines, the nature of their hub-and-spoke systems is different. Air freighters typically transfer a larger proportion of their traffic through a relatively small number of hubs in their network. Parcels being transported are not sensitive to multiple stops and circuity, so they can be flown in a manner that allows carriers to operate their hub-and-spoke system most efficiently (Kiesling and Hansen [54]). However, flying cargo naturally involves other costly operations that are not characteristic of transporting passengers. These operations include transshipment, pallet assembly and disassembly, and the handling of parcels during aircraft changes. Demand asymmetry is also inherent in air cargo networks since, unlike passengers, goods being transported do not make round-trip flights. Goods are generally flown one-way, from manufacturers to retailers, and to consumers (Zhang and Zhang [89]).

Air cargo network structures and hub location have been studied using a variety of approaches. O'Kelly and Miller [68] provided a detailed review of passenger-airline and air cargo network designs. The authors evaluated research on hub-and-spoke assignments, spoke-to-spoke connections that bypass hubs, and the interconnectivity of hubs. A more pertinent study by Kuby and Gray [55] also challenged the traditional understanding of hub-and-spoke

[2] See Bowen [17] for major-hub timelines for FedEx and UPS.

networks, with particular attention paid to FedEx. Kuby and Gray showed that FedEx does not serve all cities with direct flights to and from hub cities; instead feeder aircraft are used to service smaller cities while also making intermediate stops at other points in the carrier's network before flying to a hub. Their work provides the underlying framework that will be used to measure the network size of the integrated carriers in this study. More recently, Bowen [17] provided a comprehensive overview of the spatial network characteristics of FedEx and UPS.

The air cargo industry has changed considerably since Kiesling and Hansen's [54] study. Air express, in particular, has been the driving force of the industry as it meets the speed and reliability demands of today's supply chain management. Owing to the increase in international trade and the recovery from the 2007-2010 financial crisis, domestic air cargo traffic is expected to grow annually by 2.9 percent through 2029 (*Boeing World Air Cargo Forecast, 2010-2011*).

Accordingly, the primary focus of this study will be on air cargo services of the leaders in this industry, FedEx and UPS. Air cargo is defined as the sum of air freight, air mail, and air express in this study.[3]

1.2 Conceptual Framework

To start, definitions of economies of scale and density in the context of air cargo transportation are needed:

[3]Air freight, a large component of air cargo, is generally used in reference to heavier parcels (excluding air mail, air express, and passenger bags) that are transported by air. Air mail is composed of letters and small packages that are flown for postal services of the government. While air mail may also be sent through express services (e.g. overnight express), air express mostly refers to small packages (usually weighing less than 100 pounds) that are either time-sensitive or have a high carriage priority (Tsao [88]).

Degree of returns to density: the proportional increase in output resulting from a proportional increase in all inputs, controlling for network size (points served), average stage length, load factor, and input prices. Returns to density can be measured by taking the inverse of the elasticity of total cost with respect to output (Caves et al. [31]). *Economies (diseconomies) of density* exist if doubling output holding points served fixed less than (more than) doubles total cost.

Degree of returns to scale: the proportional increase in output resulting from proportional increases in all inputs and points served, controlling for average stage length, load factor, and input prices. Returns to scale can be measured by taking the inverse of the sum of the elasticity of total cost with respect to output and the elasticity of total cost with respect to points served (Caves et al. [31]). *Economies (diseconomies) of scale* exist if doubling both output and points served less than (more than) doubles total cost, controlling for average stage length and input prices.

Degree of returns to size: the proportional increase in output as a result of a proportional increase in all inputs, controlling for average stage length, load factor, and input prices. Output and points served are assumed to be functionally related. Returns to size can be measured by taking the inverse of the elasticity of total cost with respect to output, without controlling for network size (points served) (Kiesling and Hansen [54]). *Economies (diseconomies) of size* exist if doubling output without holding points served constant less than (more than) doubles total cost.

1.2.1 Total Cost Model

To provide a comprehensive analysis of FedEx Express and UPS, a total cost model is specified as follows:

$$TC = f(Q, P, W, Z), \tag{1.1}$$

where TC is total cost (sum of operating expenses and capital costs of operating property and equipment), Q is output (aggregate of freight and mail revenue ton-miles (RTM)), P is the number of airports served (points served), W includes the prices of production inputs (fuel, labor, and materials), and Z controls for the average payload-weighted distance between segment airports (average stage length) and the average utilization of fleet capacity (load factor). Load factor is calculated as the ratio of payload ton-miles used to available ton-miles. Controlling for load factor in this model provides the added benefit of understanding the cost effects of increased route-level traffic (Caves et al. [31]). Carrier-dummy variables are included in the model to avoid coefficient biases arising from a carrier's unmodeled cost and network features that are constant over time.

The following Cobb-Douglas cost function is specified as an approximation to a more general function:

$$TC_{it} = Q_{it}^{\beta_Q} P_{it}^{\beta_P} W_{it}^{\beta_W} Z_{it}^{\phi} e^{u_i + \varepsilon_{it}}, \tag{1.2}$$

where i indicates the carrier and t refers to the quarter time period. The β coefficients pertain to the main variables of interest and ϕ denotes the coefficients for the control variables (average stage length and load factor). Taking the log transformation of the Cobb-Douglas cost function above yields

$$lnTC_{it} = \beta_Q lnQ_{it} + \beta_P lnP_{it} + \beta_W lnW_{it} + \phi lnZ_{it} + u_i + \varepsilon_{it}, \tag{1.3}$$

where u_i gives the carrier-specific intercept and the error terms ε_{it} are assumed to be homoscedastic and uncorrelated.

Previous studies have cautioned that capital inputs for airlines may not be adjusted optimally from quarter to quarter and have estimated short-run variable cost models (Caves et al. [31]; Gillen et al. [46]). However, a long-run total cost model has been selected for this study based on evidence that integrated carriers rely heavily on capital and are able to comfortably vary working capital with output. Earlier studies claimed that FedEx, for example, is able to optimally reroute up to 30 percent of its aircraft on a given night to meet its express-service demands (Chan and Ponder [35]). Bowen [17] also addressed the transitory nature of FedEx's and UPS's networks by calculating the proportion of network segments that were only flown once by the carriers in 2010 (33 percent for FedEx and 22 percent for UPS).

A more generalized Translog cost function specification would be preferred to make inferences about second-order effects, as done in Caves et al. [31] and Gillen et al. [46]. However, due to insufficient variation in this study's time-series data, the analysis is restricted to the first-order effects obtained by a Cobb-Douglas technology specification. As noted by Kiesling and Hansen [54], the limited variation in the data suggests that the second-order effects on the coefficients would also be small.

The coefficients on average stage length and load factor, Z_{it}, are expected to have negative signs. The expectation for average stage length can be justified by arguing that, for a given number of revenue ton-miles, total costs should be lower when this output is generated over longer stage lengths, which are less costly to fly on a per-mile basis than shorter stage lengths. In the absence of this control, one ton carried 1000 miles will effectively be indistinguishable from 1000 tons carried one mile, a failure that would bias the estimated coefficients. The load-factor coefficient is also expected to have a negative sign since, for a given amount of revenue ton-miles, costs are expected to be lower if this output is flown from origin to destination on fewer flights.

Economies of density captures the effect on total cost of an increase in output holding points served fixed, a change that raises traffic density. Economies of density are expected to exist if, for example, costs decline as carriers add flights to a route or increase capacity in existing markets by using larger aircraft (see Shah and Brueckner [81]; for an analytical model).

When economies of density are present, cost should rise less than proportionally to the increase in traffic, so that $\beta_Q < 1$. The degree of returns to density (RTD) is then equal to the inverse of the elasticity of total cost with respect to output (keeping points served constant):

$$RTD = \frac{1}{\beta_Q} \tag{1.4}$$

Economies of density are exhibited if $\frac{1}{\beta_Q} > 1$, with $\frac{1}{\beta_Q} < 1$ indicating diseconomies of density.

Economies of scale capture the effect on total cost of equiproportional increases in output and points served. The degree of returns to scale (RTS) is equal to the inverse of the sum of the elasticities of total cost with respect to output and points served:

$$RTS = \frac{1}{\beta_Q + \beta_P} \tag{1.5}$$

If $\frac{1}{\beta_Q+\beta_P} > 1$, economies of scale exist, whereas diseconomies of scale exist if $\frac{1}{\beta_Q+\beta_P} < 1$. Which inequality holds depends on the magnitude of β_P relative to β_Q. Assuming that $\beta_Q < 1$, so that economies of density exist, economies of scale ($\beta_Q + \beta_P < 1$) require $\beta_P < 1 - \beta_Q > 0$. In other words, cost cannot increase too rapidly with points served holding output constant, with an upper bound imposed on β_P.

To understand this idea, consider a stylized cost function $QC\left({}^{Q}\!/_{P}\right)$, where C is unit cost as a function of traffic volume on each route segment, equal to ${}^{Q}\!/_{P}$, with economies of density yielding $C' < 0$. Including a fixed cost of $K(P)$, total costs are then $K(P) + QC\left({}^{Q}\!/_{P}\right)$. If C is a constant function and $K(P) = \alpha P$, then doubling Q and P doubles cost, indicating constant returns to scale, whereas if $K''(P) < 0$, then costs less than double, indicating economies of scale. Computing the relevant elasticities shows that $K''(P) < 0$ is equivalent to $\beta_P < 1 - \beta_Q$. Note that the cost effect of a higher P holding Q fixed has two components: the higher cost of serving more points; the cost increases from spreading a fixed output across more routes, which arises because density on each route falls. The elasticities associated with these combined effects must be less than $1 - \beta_Q$ for economies of scale to exist.

Kiesling and Hansen [54] took an approach similar to that of Caves et al. [31], specifying a cost model for FedEx based on time-series data from 1986 to 1992. Following airline industry studies, they speculated on three aspects of the air cargo industry's economic structure: economies of density, scale, and size. The authors argued that the degree of returns to size determines if FedEx can maintain its efficiency (keeping cost per unit of output constant) as it grows. If, for example, strong economies of density exist along with diseconomies of scale, efficiency can be maintained if the network expands less than in proportion to output, so that density rises. They confirmed their *a priori* expectations by showing that FedEx exhibits significant economies of density, diseconomies of scale, and constant economies of size.

Kiesling and Hansen [54] specified a Cobb-Douglas form of a total cost function after developing a model that includes prices of input factors used in production, such as labor, fuel and oil, materials and services, and capital. They measured output as the total revenue ton-miles of freight and mail. Although the authors stated that a Translog functional form would be preferred, they did not have enough observations given the number of variables (sufficient degrees of freedom) to estimate the model.

Of the three model variations they investigated, the first included all of the defined variables, for which they confirmed the expected signs of the coefficients, with statistical significance for most. The second model dropped the statistically insignificant control variables. As anticipated, they found substantial returns to density and decreasing returns scale in the first and second models. However, the degrees of decreasing returns to scale they estimated (0.62 and 0.54 in the first two models) were unexpectedly high. As a plausible (but still insufficient) explanation, the authors suggested that the strong diseconomies of scale may have resulted from increasing unit costs of sorting that arise when points are added to a fixed-density network. Overall, the findings affirmed the authors' assumption that, on a given network, increasing output has little effect on total system costs, and second, that costs of complicated hub operations, such as sorting, increase as the number of airports served increases (controlling for traffic density). The authors also relate their findings of strong economies of density to the efficiency of serving a given set of points by one carrier, shedding light on the dominant position of FedEx in the all-cargo industry. At the time of their study, Kiesling and Hansen [54] mentioned that UPS does not directly compete with FedEx as a cargo airline, but instead provides a wide range of services that compete with those of FedEx. This led the authors to suggest that economies of scope should be investigated between air express and other cargo services offered by multimodal firms such as UPS and the U.S. Post Office.

In the third model, to determine the degree of returns to size, Kiesling and Hansen [54] dropped the points-served variable and found that the output elasticity increased substantially to 0.97. The inverse of this elasticity (approximately one) implied constant returns to size, which they expected for FedEx's mature network. Strong economies of density, by itself, implied that FedEx could make substantial unit cost savings by increasing output on its existing network. Constant returns to size, however, indicates that an increase in output along with a proportionally smaller increase in points served would not reduce efficiency. Table 1.1 summarizes Kiesling and Hansen's findings.

Table 1.1: Kiesling and Hansen's (1993) Results for FedEx, 1986 - 1992

	Model 1	Model 2	Model 3
Degree of returns to scale	0.62	0.54	
Degree of returns to density	2.36	4.07	
Degree of returns to size			1.04

Source: Kiesling and Hansen [54]

Consistent with past findings, this study expects both FedEx and UPS to exhibit increasing returns to density and constant or decreasing returns to scale. For a given route, increasing output should have little effect on total cost since this increase can be accommodated by carrying more cargo on existing flights. The hub-and-spoke configuration of air cargo networks also facilitates the efficient sorting of shipments, allowing ground-distribution and transshipment costs to decrease with traffic density (O'Kelly and Miller [68]). Constant or decreasing returns to scale are expected for both carriers since establishing new hub operations can be very costly, even while flying operations and airport ground access can be replicated inexpensively (Kiesling and Hansen [54]).

The nature of returns to size, however, are expected to be different for the two carriers. FedEx has maintained a mature network during the period of this analysis, and is therefore likely to exhibit constant returns to size. In other words, even though there may be economies of traffic density on FedEx's existing network, the increase in traffic volume brought by adding new airports to the carrier's network would be offset by the cost of adding those airports. In contrast, evidence showing the growth of UPS's network implies that the carrier should exhibit economies of size since the additional traffic revenues generated by new airport-pair markets would more than counteract the cost of adding new airports to its network.

1.3 Data

The data for this study consist of nine years of quarterly observations for FedEx and UPS, from 2003 to 2011. The data are primarily collected from two sources: the *Form 41 Financial Schedule* and the *Form 41 Traffic T-100 Segment (U.S. Carriers)* tables [24, 25], which are both found on the DOT's Bureau of Transportation Statistics (BTS) website.

The *Form 41 Financial Schedule* tables include quarterly balance sheet, cash flow, employment, income statement, fuel cost and consumption, and operating-expense data. The *T-100* data are provided monthly at the carrier-origin-destination-aircraft type level. The reported data in the *T-100* tables include scheduled and performed departures, aircraft capacity (payload), distance between origin and destination airports (stage length), and transported freight and mail volumes (in pounds) by certified U.S. carriers. The traffic data have been aggregated to the quarter level for this study. The *T-100* tables contain complete data for both FedEx and UPS starting from 2002 Quarter 4. Quarter 1 of 2003 is chosen as the start date for this study to avoid data discrepancies that might exist during the traffic-reporting changes that took place in 2001-2002.

This study is will be based on the domestic operations of FedEx and UPS, bearing in mind the compatibility issues between the traffic and cost data for international operations. The selected *T-100* traffic tables provide data reported by U.S. carriers on domestic operations (U.S. and Canada origin and destination) and international operations when at least one point of service is a domestic origin or destination. However, the cost data (from the *Form 41 Financial Schedule*), only provides one indicator (carrier region) to specify the world region for which carriers providing *scheduled* services report their operations. These regions are Domestic (for U.S. and Canada), Atlantic (for Europe), Pacific (for Asia), and Latin America (for Central and South America). Carriers providing *non-scheduled* services specify their operating regions as either Domestic or International. Like the *T-100* international-traffic data, the latter operating region includes operations where one airport is domestic and the other is foreign (see the *BTS T-100 Traffic Reporting Guide* [21]). Therefore, the cost data do not distinguish operating costs incurred on *non-scheduled* flights from a domestic airport to a foreign airport from those costs incurred on *non-scheduled* flights between two foreign points. Considering that both FedEx and UPS provide *scheduled* and *non-scheduled* services between international points, the reporting discrepancies between the *T-100* traffic data and the *Form 41 Financial Schedule* preclude a fully reliable analysis of the international operations and cost characteristics of the carriers in this study. Specifically, output measures would be understated and operations from foreign hubs would be ignored.[4]

[4]The author thanks Anming Zhang and *Form 41 Financial Schedule* data managers at BTS for their insights into this data-compatibility issue.

1.3.1 Description of Variables

Based on the cost categories reported by carriers to the FAA, total cost (TC) is calculated as the sum of the operating expenses (fuel and oil, employee salaries and benefits, materials and services, landing fees and rental costs) and capital costs of operating property and equipment (Kiesling and Hansen [54]). Capital costs are computed as fifteen percent of the following property- and equipment-cost categories obtained from the carriers' balance sheets: flight equipment, ground property and equipment (less depreciation), land, construction, and capital leases of property (less amortization).

Three categories of input are considered in this study: labor, fuel, and materials. The labor price is captured by the carrier-average wage of pilots, copilots and maintenance employees. Expenses on flight personnel and maintenance labor are averaged over the number of pilots, copilots and maintenance workers reported by the carriers in the *Form 41 Financial Schedule* tables. Considering that UPS's labor force is highly unionized, the fact that only pilots amongst FedEx's employees are unionized makes the choice of this employment category a convenient one (Morrell [61], p. 250). The maintenance-worker category is also selected for having complete data and for being representative of FedEx's non-unionized labor. Due to reporting differences between FedEx and UPS, total employment data for UPS found in the tables (*Schedule P-1(a)* and *Schedule P-10*) are significantly low. UPS only reports employee statistics for flight-related employees, whereas FedEx includes statistics for all employees involved in ground and air operations. Therefore, the exclusion (or underreporting) of these employment categories (e.g. transport-related, general managers, cargo handling) would overstate the price of labor for UPS if it were simply calculated as the ratio of the firm's expenses on salaries and benefits to the total number of full-time equivalent employees.

The fuel price is constructed by dividing total air-fuel expenses by the total fuels issued for revenue and non-revenue operations. The price of material inputs is accounted for in the model by the price of purchased materials (assumed to be constant across the carriers), for which a quarterly Producer Price Index (PPI) is used as a proxy. PPI data, specifically constructed for scheduled air-transportation, were obtained from the U.S. Bureau of Labor Statistics databanks.

On the traffic side, output is measured by aggregating the freight and mail tons flown on a carrier's network to the quarter level. Although analyzing freight and mail outputs separately would be preferred, mail volumes transported by the carriers are inappreciable; 70 percent of intra-US mail is borne by passenger carriers (Morrell [61], p. 77).

Points served has been constructed to measure the core network size of the carriers. FedEx operates its hub-and-spoke and point-to-point networks in conjunction with a complicated network of stopovers and feeder points (Kuby and Gray [55]; Johnson and Gaier [52]). While spoke cities are served by FedEx, these cities also facilitate the consolidation (distribution) of FedEx's feeder traffic en route to (from) the hubs. Although UPS also operates a hub-and-spoke network, trucks are used to transport the carrier's feeder traffic to regional consolidation hubs (e.g. LA/Ontario International). Outside of their core network, FedEx and UPS have very fluid network structures to meet the demands of their priority and time-definite delivery guarantees. Therefore, in light of the basic differences in the carriers' networks, and considering the fluidity in their network structures, the following approach is taken to measure the core network size of the carriers. The underlying idea is to drop feeder and stopover points, which would otherwise cloud the real network size of the carriers. Hence, a quarter-specific hub dummy variable is first constructed to identify FedEx and UPS hubs in the *T-100* data. An airport with at least twelve direct flights per quarter (weekly flights) to or from these hubs is then counted as a single point served. Lastly, the average distance between takeoffs and landings is weighted by the payload tons available between those points to measure average stage length.

A balanced panel, with both carriers in the sample (72 carrier-quarter observations), is then constructed for these variables, which allows specification of intercept shifts for the carriers and for the quarters and years in the time series.

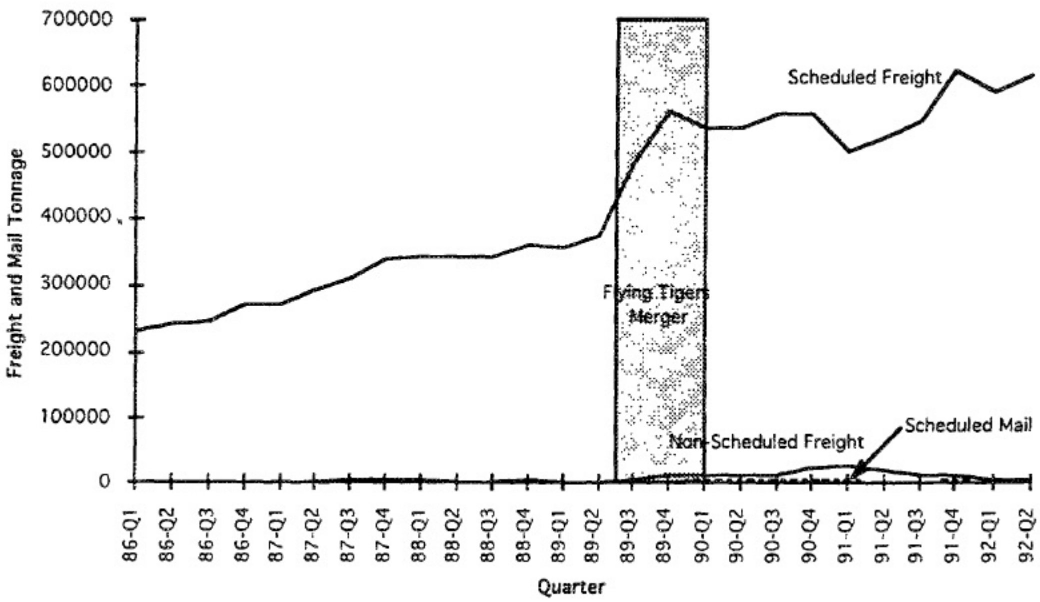
1.3.2 Summary of Descriptive Data

FedEx's cost structure, networks, and services have changed considerably in the past twenty years. This change has come as a result of both the transformation of the cargo industry's time-definite express sector, with increased demands from e-commerce and globally integrated "just-in-time" (JIT) systems, and significant growth and automation within the company.[5] Figure 1.1 illustrates the patterns of domestic air freight and mail volumes for two time periods, 1986-1992 and 2003-2011, for FedEx and UPS. Figure 1.1(a) pertains to FedEx in the first time period, while Figure 1.1(b) includes the air freight and mail volumes for UPS for a side-by-side comparison with FedEx in the second time period. The second figure (b) uses data from the DOT's BTS *Form 41 Traffic T-100 Segment* tables for freight and mail tonnage. The *T-100* segment-level data for FedEx and UPS are only available as far back as 2002, and volumes reported for 2002 are not complete. Therefore, this study will only look at the time period from 2003 to 2011.

[5] JIT is a logistical philosophy introduced to the U.S. in 1997. It provides efficient customer service by reducing inventory through the use of air cargo transportation. See Zhang and Zhang [89] for discussions on JIT and liberalization of air cargo services in international aviation.

Figure 1.1: Domestic Freight and Mail Tonnage

(a) FedEx (1986 - 1992): *Source: Kiesling and Hansen [54]*



(b) FedEx and UPS (2003 - 2011):

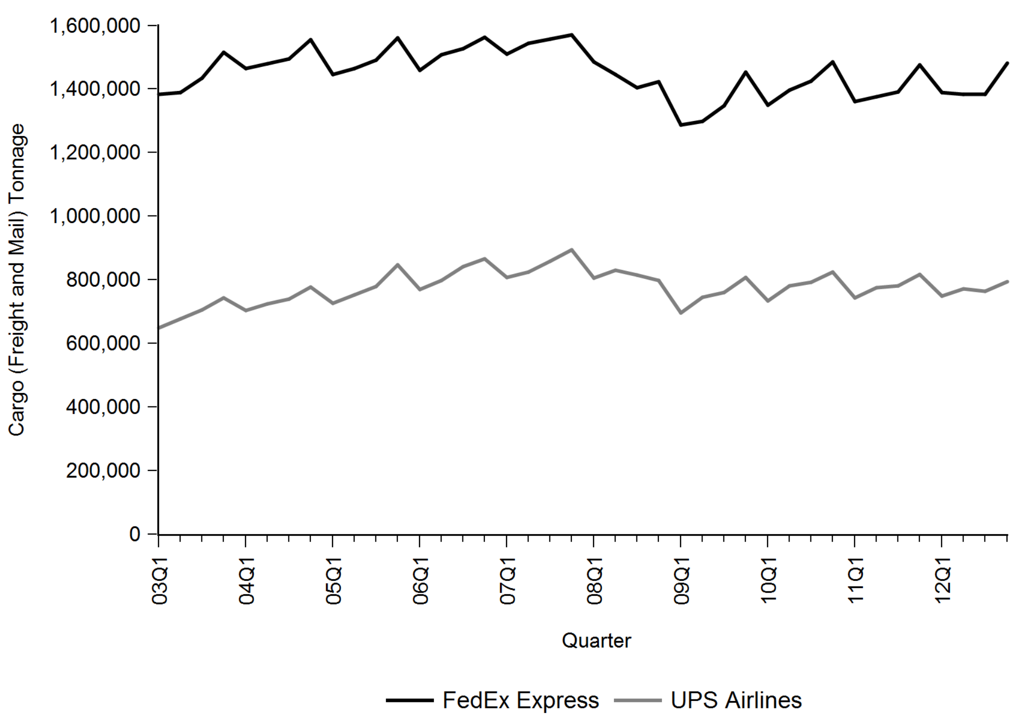
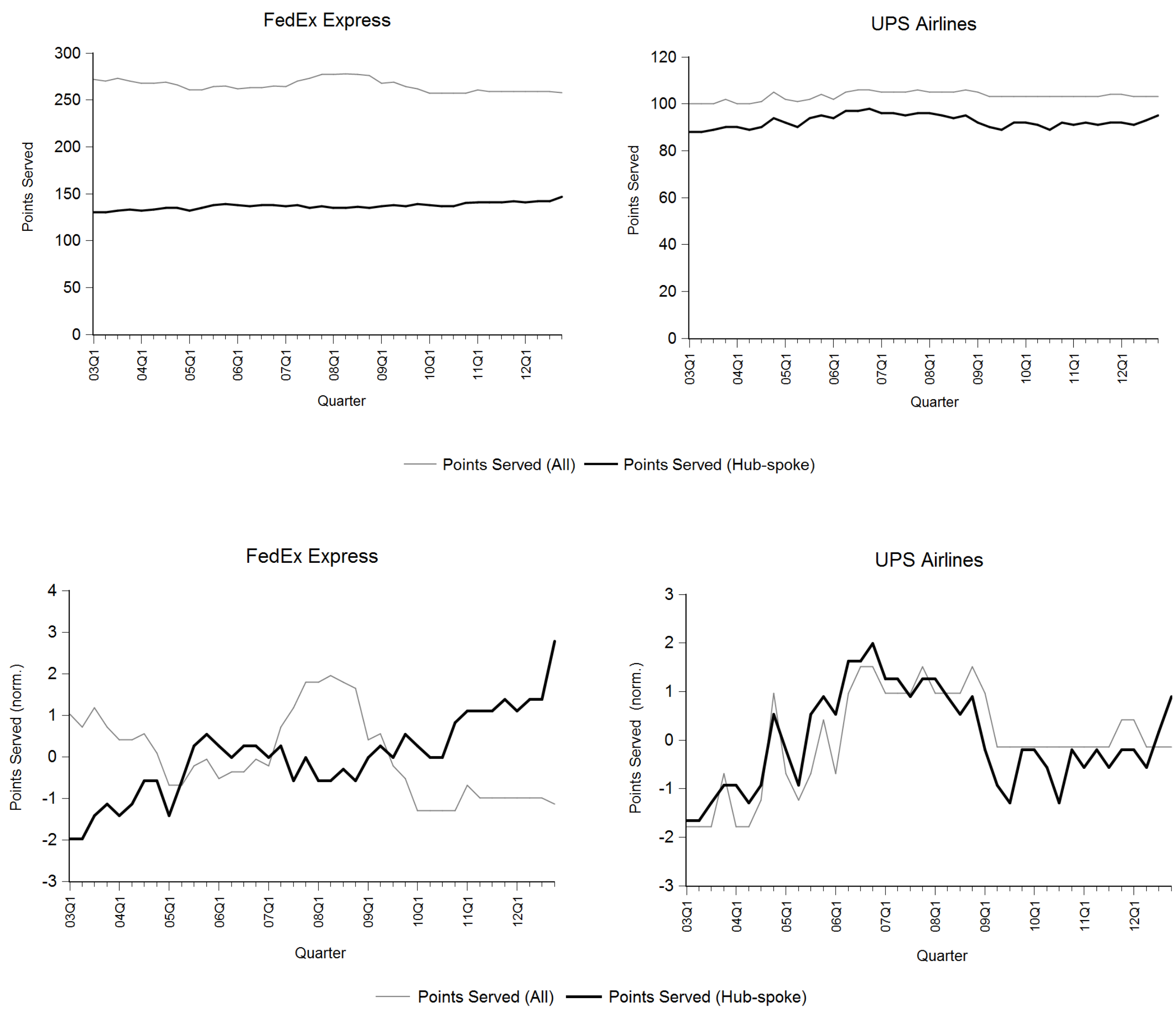


Figure 1.1(a) shows the increase in domestic freight and mail tonnage resulting from FedEx's acquisition of Flying Tigers in February, 1989. FedEx and Flying Tigers operations were merged by August of that year. As noted by Kiesling and Hansen [54], the merger induced a 50-percent increase in freight and mail tonnage almost immediately. Figure 1.1(b) illustrates the sporadic growth in freight and mail volume (both scheduled and non-scheduled) of FedEx and UPS in the second time period. The substantial increase in FedEx's transported-cargo volume across the ten-year difference between the two time periods is apparent in the two figures. Morrell [61] discusses the introduction of Air Cargo Communication Systems (CCS) and other technological improvements in air-cargo transportation that took place in the early 2000's (p. 187). In addition to the *technology bubble* of the late 1990's, these advancements possibly facilitated the sharp rise in cargo volumes (observed in the figures) through automation and reduced transfer and delay times. The significant increase in UPS's domestic cargo (around 200,000 tons of freight and mail) can also be seen in the second figure. Both carriers appear to have recovered steadily after the 2008 recession, following similar patterns of increases and decreases.

The domestic airports served (points served) are shown in Figure 1.2. It is apparent that FedEx regularly serves more than twice as many domestic airports as UPS, and that the variation in points served is modest. It is interesting to note the difference in the network structure between the two carriers. The black line represents the points that are flown to (or from) hubs at least 12 times a quarter. This measure of points served is chosen for the present study. The gray line depicts the number of airports that are served at least 12 times a quarter by the carriers, without any requirement for a hub connection. The top two panels in Figure 1.2 initially show that FedEx has a sizable network of airports served beyond the primary spokes of the hubs, as evidenced by the large gap between the black and gray line. UPS, on the other hand, seems to operate under 20 airports in addition to those that are connected to the carrier's hubs. The lower two graphs of the figure present the standardized measures (normal scores) of points served to further clarify the network differences between the carriers. Again, the trend in UPS's core network (hub-and-spoke) is the main driver of the carrier's entire network, as can be seen from the close association of the black and gray lines. FedEx's fringe networks (not hub-related) are apparently disjoint from the rest of the carrier's core network. The lower-left panel depicts the reason why this study has chosen to avoid the non-hub related airports of the carrier: to maintain consistency in measuring the network size between the two carriers and to avoid noisy data from feeder services. Moreover, it is interesting to see that FedEx's core network exhibits a gradual growth in size while the total network size does not show a clear pattern.

Figure 1.2: FedEx and UPS Domestic Points Served



A comparison of the summary quarterly financial statistics shows the significant change that FedEx has experienced in its cost structure. Table 1.2 summarizes the domestic quarterly statistics for two time periods (1986 - 1992 and 2003 - 2011) of this study. Total cost, labor price and fuel price are adjusted for inflation using the BLS Consumer Price Index (CPI) quarterly deflator, normalized to 2003Q1.

The substantial changes shown in Figure 1.1 and in the summary statistics in Table 1.2 suggest that there is a need for re-evaluating FedEx's current cost structure to address the issues of returns to traffic density and returns to scale. Domestic costs for FedEx are more than three times as high as they were in the Kiesling and Hansen [54] sample period. The price of fuel has doubled, while the costs of labor, materials and services have also increased considerably. Likewise, output and capacity have grown substantially in the current time period. It is also clear that technology has changed, as newer airplanes are able to achieve higher load factors and to provide a larger carrying capacity per departure (evidenced by higher load factors and available line haul measures). Drawing parallels to the implications of Figure 1.2, the means and standard deviations of the two points-served measures indicate that the network size of the carriers are comparable when focusing on their core hub-and-spoke airports.

In light of the considerable growth of FedEx since Kiesling and Hansen's [54] study, it is important to check if their characterization of the FedEx cost structure still holds. The same analysis will also be carried out for UPS, to draw comparisons between the two industry leaders.

1.4 Estimates of the total cost model

The first specification in Table 1.3 assumes that the two carriers have a similar cost structure. The firms have the same intercept: $u_i = u$ holds in equation (3) for both firms. This assumption might not be acceptable considering that the two integrators serve different markets and customer bases and that they also have stark differences in their operations and logistics, but it serves as a benchmark.

Table 1.2: Summary of Domestic Quarterly Statistics, 1986 - 1992 and 2003 - 2011

		FedEx				UPS
	1986Q1-1992Q3		2003Q1-2011Q4		2003Q1-2011Q4	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
2003Q1 U.S. \$ — Cost (000)						
Total Cost			2,346,834	242,149	1,588,239	129,014
Total Cost (K & H, 1993)	618,101	196,803	2,359,332	215,841	1,550,266	153,448
Fuel Cost	40,430	18,248	313,835	103,228	188,134	71,338
Labor Cost	134,014	44,718	512,331	47,913	160,194	15,471
Materials-Service Cost	106,887	27,266	160,636	23,227	57,542	22,274
Input Price						
Fuel Price (\$ per gallon)	0.63	0.12	1.67	0.57	1.92	0.65
Labor Price (\$ per employee)[a]	2,531	410	39,703	4,732	39,274	6,230
Materials Price (\$)			115	12	115	12
Traffic						
Output (freight & mail RTM) (000)	396,080	160,879	1,516,054	86,746	849,519	79,080
Available Line Haul[b]	14,657	2,705	35,363	2,089	54,665	5,549
Average Stage Length			1,010	10	1,034	35
Load Factor	0.57	0.03	0.61	0.02	0.58	0.03
Points Served (hub-related)			136	3	93	3
Points Served Total [c]	212	20	294	12	108	3

Notes: First column (1986Q1 - 1992Q3) statistics are from Kiesling and Hansen [54]
[a] Labor Price measures the average wage of pilots and maintenance employees in the 2003Q1 - 2011Q4 period
[b] Available ton-miles per departure
[c] Number of airports served at least 12 times per quarter (no hub-connection requirement) in the 2003Q1 - 2011Q4 period

1.4.1 Pooled Results

In the first set of regression results (*Pooled 1* and *Pooled 2*) for the panel dataset shown in Table 1.3, the coefficients on output and the input-price variables all have the expected positive signs and are significant at the 1-percent significance level. The labor-price coefficients indicate an elasticity of 0.08, so that a 10-percent increase in wages is associated with a 0.8-percent rise in costs for the carriers. The coefficients on fuel price imply that costs are more sensitive to the price of fuel than to the price of labor, with an elasticity of 0.14. Likewise, the price of materials exhibits a strong positive effect on total cost in all of the specifications. As expected, the coefficients on the payload-weighted average stage length and load-factor variables are negative and significant.

In *Pooled 1*, the positive coefficient on output (0.22) indicates that, holding everything else constant, a 1-percent increase in the carriers' output increases their total cost by 0.22 percent. The inverse of this coefficient, 4.52, indicates that the carriers' operations exhibit substantial economies of density. This finding is statistically significant in the sense that the output coefficient is significantly different from 1. The elasticity of total cost with respect to equiproportional increases in output and points served is equal to the sum of the coefficients on output and points served (0.91). The inverse of this sum, 1.10, implies that there are increasing returns to scale. However, the null hypothesis of constant returns to scale cannot be rejected.[6] *Pooled 2* includes a dummy variable for UPS to control for carrier-specific heterogeneity. While most results do not change, this specification reveals that, controlling for unmodeled cost differences, economies of density still hold but the carriers now exhibit decreasing returns to scale. The null hypothesis of constant returns to scale, however, still cannot be rejected at the 5-percent significance level (0.167 standard error). Moreover, the coefficient on the UPS dummy variable indicates that, all else equal, UPS is less cost-efficient

[6] Linear-restrictions hypothesis tests of the coefficient values reject the null that the output coefficient is unity (standard error = 0.071) and fail to reject the null that the sum of the output and the points-served coefficients is equal to one (standard error = 0.049), at the 5-percent significance level.

Table 1.3: Pooled Results for FedEx and UPS (Balanced Panel: 72 observations)

Regressor	*Pooled 1*	*Pooled 2*	*Pooled 3*	*Pooled 4*
Intercept	17.330	15.185	18.779	19.806
	(1.102)	(1.084)	(1.765)	(1.581)
Output	0.221	0.341	0.642	0.456
	(0.071)	(0.073)	(0.018)	(0.087)
Points Served	0.685	0.953		
	(0.117)	(0.167)		
Labor Price	0.077	0.079	0.056^{b}	0.060^{b}
	(0.023)	(0.019)	(0.036)	(0.034)
Fuel Price	0.144	0.102	0.118	0.153
	(0.014)	(0.021)	(0.016)	(0.021)
Materials Price	0.193	0.317	0.423	0.284^{a}
	(0.073)	(0.081)	(0.086)	(0.122)
Stage Length	-0.845	-1.176	-1.983	-1.478
	(0.232)	(0.247)	(0.276)	(0.412)
Load Factor	-0.500	-0.466	-0.574	-0.577
	(0.079)	(0.072)	(0.117)	(0.113)
UPS Dummy		0.192		-0.125^{a}
		(0.072)		(0.056)
Adj. R^2	0.988	0.989	0.980	0.981
D-W Statistic	1.07	1.20	0.72	0.71
Degree of Returns to Scale	1.10	0.77		
Degree of Returns to Density	4.52	2.93		
Degree of Returns to Size			1.56	2.19
F-statistic for $\beta_Q = 1$	119.036	81.592	393.33	39.412
	(0.071)	(0.073)	(0.018)	(0.087)
F-statistic for $\beta_Q + \beta_P = 1$	3.624	3.108		
	(0.049)	(0.167)		

Notes: Specifications use natural logarithms for all variables, except for dummy variables and intercepts. Robust standard errors in parentheses to account for unconditional heteroscedasticity and contemporaneous correlation: ^{a} $p \nless 0.01$; ^{b} $p \nless 0.05$.

than FedEx. Exponentiation of the coefficient on the UPS dummy implies that UPS is 21 percent less cost efficient than FedEx, *ceteris paribus*.

The *Pooled 3* and *4* specifications allow measurement of economies of size since the effect of network size (previously captured by points served) is absorbed into output. The coefficients on output (0.642 and 0.456) are now higher than in the previous two regressions since the output variable now measures both traffic and points served. The inverse of the output coefficients, 1.56 and 2.19, show that the carriers exhibit increasing returns to size (constant returns is rejected at the 5-percent level in both specifications). The results thus indicate economies of size, showing that growth in output accompanied by an appropriate adjustment in network size increases efficiency, raising costs less than in proportion. However, the inclusion of the UPS dummy variable in the *Pooled 4* regression reveals that, without controlling for network-size differences, UPS is more (not less) cost efficient than FedEx (13 percent more cost efficient).

Overall, the industry clearly exhibits economies of density and economies of size, while constant returns to scale cannot be ruled out. This finding is investigated further in the next section by looking at the cost structures of the carriers individually.

1.4.2 Individual Carrier Results (FedEx and UPS)

This section examines the total cost model for the carriers separately, to determine whether they individually exhibit economies of density, scale, and size. Table 1.4 shows the results for FedEx and UPS separately. Payload-weighted average stage length and load factor are again included as controls in addition to output, points served, and the prices of input factors.

The results for FedEx reveal that the carrier operates under economies of density, decreasing returns to scale and modest economies of size. The coefficient on output in *FedEx 1* is

Table 1.4: Individual-Carrier Results (Time series: 36 observations)

Regressor	*FedEx 1*	*FedEx 2*	*UPS 1*	*UPS 2*
Intercept	9.572	12.631	15.090	17.661
	(1.933)	(2.363)	(1.680)	(2.024)
Output	0.626	0.701	0.331	0.433
	(0.108)	(0.125)	(0.086)	(0.112)
Points Served	0.521[a]		0.901	
	(0.195)		(0.290)	
Labor Price	0.078	0.075[a]	0.059[a]	0.039[b]
	(0.027)	(0.034)	(0.024)	(0.036)
Fuel Price	0.073	0.077	0.107[a]	0.201
	(0.018)	(0.019)	(0.047)	(0.034)
Materials Price	0.521	0.623	0.172[b]	-0.165[b]
	(0.113)	(0.099)	(0.171)	(0.134)
Stage Length	-1.085[a]	-1.450[a]	-0.932	-0.774[a]
	(0.45)	(0.559)	(0.227)	(0.282)
Load Factor	-0.742	-0.728	-0.321	-0.445
	(0.139)	(0.149)	(0.077)	(0.123)
Adj. R^2	0.977	0.972	0.940	0.905
D-W Statistic	1.59	1.40	1.20	1.25
Degree of Returns to Scale	0.87		0.81	
Degree of Returns to Density	1.60		3.02	
Degree of Returns to Size		1.43		2.31
F-statistic for β_Q =1	12.004	5.759	60.784	25.479
	(0.108)	(0.125)	(0.086)	(0.112)
F-statistic for $\beta_Q + \beta_P = 1$	0.526		0.647	
	(0.203)		(0.289)	

Notes: Specifications use natural logarithms for all variables, except for dummy variables and intercepts. Robust standard errors in parentheses to account for unconditional heteroscedasticity and contemporaneous correlation: [a] p $\nless$ 0.01; [b] p $\nless$ 0.05.

significantly different from unity (0.11 standard error) and the inverse of this coefficient indicates that FedEx exhibits economies of density. The inverse of the sum of the output and points served coefficients in *FedEx 1* (0.87) implies that decreasing returns to scale hold for FedEx. However, constant returns to scale cannot be rejected at the 5-percent level (0.20 standard error). Considering that decisions on the number of airports to serve are made concurrently with output decisions, the FedEx cost structure is examined for economies of size in *FedEx 2*. The inverse of the output elasticity in *FedEx 2* (1.43) indicates that increasing returns to size hold for FedEx. The output coefficient itself (0.701) is significantly different from 1 at the 5-percent level, which confirms the finding of increasing returns to size.

These results show that some of Kiesling and Hansen's [54] conclusions no longer hold for FedEx. Kiesling and Hansen found decreasing returns to scale for FedEx (of degrees ranging from 0.54 to 0.62) and much stronger economies of density than in the present results (degrees of returns to density ranging from 2.36 to 4.07). The authors then showed that an approximately constant degree of returns to size (1.04) held for FedEx. Clearly, the cost structure of FedEx has changed significantly in the decade after their study. The current results suggest that FedEx can enjoy unit cost savings by increasing output on its existing network of airports. The degree of returns size (1.43) also implies that FedEx will enjoy some cost savings per unit of output by expanding its services.

On the other hand, the results for UPS show that the carrier exhibits strong economies of density, decreasing returns to scale, and strong economies of size. Specifically, the inverse of the output elasticity in *UPS 1* (3.02) indicates substantial returns to density hold for the carrier (an effect that is statistically significant). The inverse of the sum of the output elasticity and the coefficient on points served is 0.81, which implies diseconomies of scale. The hypothesis of constant returns to scale, however, cannot be rejected (0.29 standard error). In the last specification of Table 1.4 (*UPS 2*), the inverse of the coefficient on output (2.31) indicates the strong returns to size for UPS. The output coefficient in the last specification is also significantly different from unity. The results altogether imply that UPS could be substantially more cost efficient by increasing its output either on a fixed network or on one that is growing with output.

The coefficients on labor price exhibit the expected positive relationship with cost, and are of comparable magnitudes for FedEx and UPS. The coefficient estimates for this variable imply that a 10-percent rise in average pilot and maintenance-worker wages would increase total costs by around 0.78 percent for FedEx and by 0.59 percent for UPS. The slightly higher labor-price impact on FedEx's costs is not expected considering the underlying federal-labor rules that the companies are governed by.[7]

The fuel price appears to affect carrier costs in all specifications. This finding is not surprising in view of the important role that fuel costs play in determining the profitability of air cargo firms. Even though carriers may pass on the impact of fuel-price increases partially to their customers (through fuel surcharges, for example), there is not much else that carriers can do to improve efficiency in the short run (Morrell [61], pp. 212-213).

Figure 1.3 shows the fluctuation in fuel prices during the sample period of this analysis. The dramatic increase in fuel prices in July 2008, when the price of oil reached its record peak, is evident in Figure 1.3, as is the subsequent fall in December 2008. Such volatility in the fuel prices explains why some carriers find it advantageous to purchase their fuel through hedge contracts. The consistently lower price observed for FedEx in the figure may reveal the underlying differences in how the carriers purchase fuel. As Kiesling and Hansen [54] pointed out, most of FedEx's aircraft fuel is purchased through contracts with suppliers or is included in wet-lease agreements, which allows the company to be temporarily safe from

[7]UPS, having started out as a ground-shipping company, and still having strong trucking ties, only transports a small fraction (around 15 percent) of the company's daily volume of North American shipments by air (TranSystems [87], p. 47). UPS is consequently governed by the 1935 National Labor Relations Act (NLRA) while FedEx, founded as an air cargo company, has always been subject to airline regulations. Consequently, UPS has stronger labor unions in comparison to FedEx.

unprecedented cost impacts of short-term price increases. Fuel prices may also vary across the carriers depending on fleet mix and the regional variation in fuel supply (Greene [48]). The matter of fuel-price fluctuations needs to be addressed further while also looking into how the carriers buy their fuel.

Figure 1.3: Domestic Fuel Price (2003Q1 Dollars)

1.5 Conclusion

In view of the continued expansion of FedEx's integrated services and the emergence of UPS as a prominent air cargo carrier, this paper reexamines the cost structure of the integrated air cargo industry. The estimated total cost model for the domestic region of FedEx and UPS reveals that the carriers, and arguably the rest of the integrated air cargo industry, have a cost structure that is characterized by increasing returns to density and constant returns scale. Different specifications of the cost model also provide comparative results of the carriers' cost efficiencies. Specifically, if network-size differences between the two carriers are controlled, FedEx is found to be more cost-efficient than UPS. This finding implies that FedEx is able to achieve a given level of output over a set of points with relatively less cost than UPS. However, allowing for network-size differences between the two carriers, UPS emerges as the more cost-efficient carrier.

To better understand these cost-efficiency differences between the two carriers, the individual cost structures of the carriers were examined. Looking at the carriers individually, the results show that FedEx operates under weak economies of density and diseconomies of scale. In contrast, while UPS also operates under diseconomies of scale, the carrier exhibits strong economies of density. The null hypothesis positing constant returns to density was rejected at the 5-percent significance level in all specifications. However, the null hypothesis of constant returns to scale cannot be rejected for either carrier, individually, and for the carriers pooled together (see pooled-carrier results). Therefore, strong evidence suggesting that constant returns to scale hold for integrated air cargo carriers is found.

Economies of size, which captures the combined effect of economies of density and economies of scale, is also investigated. The pooled results show that the integrated industry's cost structure is characterized by increasing returns to size, suggesting that carriers can maintain cost efficiency if they adjust their network size in step with output growth. The carrier-specific results also show that both FedEx and UPS individually exhibit increasing returns to size. The null hypothesis of constant returns to size is rejected at the 5-percent significance level in the pooled- and individual-carrier results. The statistically-significant findings of economies of size for both carriers imply that FedEx and UPS can be more cost efficient by exploiting economies of density. UPS, however, is able to make relatively more unit cost savings through economies of density and economies of size, as evidenced by the carrier-specific point estimates.

Noting that a given set of points is most efficiently served by one carrier, Kiesling and Hansen [54] concluded that FedEx falls just short of monopolizing the air cargo industry. Clearly, as shown by some of the evidence in this study, this characterization of the industry may be outdated. In addition to competing with FedEx and other integrators in areas that are part of a broader service mix, UPS presents itself as a strong competitor in air cargo services. This paper finds that UPS has substantial potential for growth, enabled by strong economies of density and economies of size.

Chapter 2

Airport Traffic and Metropolitan Economies

2.1 Introduction

Airports serve as gateways and hubs for intercity-airline passengers and cargo, playing a key role in the economic development of urban areas. Although the airport-city relationship has been examined extensively in the literature, researchers have mainly focused on the economic impact of airport traffic, while also examining the effectiveness of investments in transportation infrastructures (Oster, Rubin, and Strong [71]; Pereira and Flores de Frutos [3]; Sheard [82]). In parallel, empirical studies have addressed urban-agglomeration economies, which are facilitated by airline services that connect commercial activities between metropolitan areas (see Rosenthal [76]). Drawing connections between air transport and employment in metro areas, numerous papers established a positive relationship between airport traffic and economic development (Button, Lall, Stough, and Trice [27]; Debbage and Delk [39]; Brueckner [19]; Alkaabi and Debbage [1]; Green [47]; Blonigen and Cristea [11]). However, a metro area's provision of air-transport services is itself also determined by local economic and demographic characteristics. Even though this bidirectional-causality relationship between airport traffic and urban-economic characteristics has been acknowledged in the relevant literature (Brueckner [19]; Green [47]), only a small body of empirical work has addressed how a city's size and economic features induce passenger and cargo traffic at airports (Brueckner [18]; Discazeaux and Polese [40]; Alkaabi and Debbage [2]). Moreover, these studies employ cross-section methods that do not control for city-specific unobserved features that affect the determinants of air traffic. This paper aims to fill these gaps by examining how air traffic in a city is impacted by the variation of socioeconomic and demographic features in that city, over time. The implications of an urban area's sectoral-employment composition are also addressed in line with the most recent empirical findings regarding industry mix and airline traffic (Sheard [82]).

Seeing that planners and policy makers commonly use economic predictors to forecast air traffic volumes, this paper revisits the question of what urban characteristics determine airport traffic. Traffic forecasts are instrumental benchmarks for decisions regarding airport capacity and spending on transportation infrastructures. Private businesses that depend on air transport services (manufacturers, retail vendors, hotels, etc.) also benefit from air traffic projections, and presumably base their strategic decisions on such information. While regional studies may be more suitable for understanding how local economic factors affect air traffic, national-scale models are also needed to gain generalizable insights into the role of air transport in the urban economy. However, region-specific differences in national models have not been sufficiently treated in the literature (Cidell [38]). Thus, exploiting the empirical benefits of panel data, the present paper aims to provide a national empirical model that shows how urban socioeconomic factors determine air traffic, while controlling for the unique and unobserved features of the sample cities.

A quarterly panel dataset (2003-2012) is first constructed from demographic, socioeconomic, and airport-traffic measures of metro areas in the United States (U.S., hereafter). Based on urban economic theory, an econometric model is specified to provide point estimates of the elasticities of air passenger and cargo traffic with respect to metropolitan-size and employment features. Accordingly, the dependent variable in this study is the total passenger enplanements and cargo (freight and mail) tons that depart from airports in chosen metro areas. The variation of demographic and sector-specific socioeconomic characteristics, both across and within metropolitan areas, is used to assess the impact of selected metro-level factors on air traffic, while controlling for exogenous city features. Given the panel structure of the data, metropolitan fixed effects are employed to capture remaining city-related idiosyncrasies. Metro-areas correspond to the U.S. Office of Management and Budget's (OMB) 2009 definitions of Metropolitan Statistical Areas (MSA), a subset of the Core Based Statistical Areas (CBSA). The OMB defines MSAs by consolidating contiguous counties that hold urban-core area populations of more than 50,000 people, and that also maintain a substantial level of socioeconomic integration within urban areas, across county lines (Census [34]).

In view of Brueckner's [18] findings that pertain to the regulated U.S. airline industry, this study reveals that the local-economic determinants of a city's air services have mostly remained the same since the deregulation of the airline industry. Controlling for unobserved and city-specific differences, the paper shows that passenger traffic grows proportionally to city size, while wages and the share of service-sector employment increase demand for air travel. Moreover, contrary to traditional expectations, an MSA's share of *tradable* service jobs appears to have a weaker impact on passenger enplanements, compared to the share of jobs providing *non-tradable* services. Even though the cross-sectional analyses for air cargo and passenger traffic produce comparable results, the fixed effects estimations reveal that air cargo enplanements are impacted by employment-composition shifts that increase a city's share of workers in manufacturing jobs. Data limitations that preclude robust estimations of cargo-traffic elasticities are also discussed.

2.1.1 Literature Highlights

Brueckner [18] examined metro-area size, employment, and income factors that affect U.S. air-passenger transport using data for 1970 (while the airline industry was still regulated). Brueckner revealed that there is a proportionate relationship between a city's population and passenger enplanements, and also gave the first empirical insight into the positive relationship between air traffic and white collar employment. Noting that the airline industry has reorganized considerably since deregulation, and that advances in technology may have changed the relationship between airport traffic and local economies, Discazeaux and Polese [40] used data from 2000 to re-examine the effects of urban employment and size characteristics on airport traffic in the U.S. and Canada. The authors identified new geography and market features that affect passenger traffic, but found that the core relationship between air traffic and urban economic characteristics established by Brueckner [18] remains unchanged. A more recent study by Chi and Baek [37], estimated the short- and long-term impacts of economic development on passenger and freight air traffic, while controlling for disruptions in market equilibria caused by exogenous events. Even though market shocks and short-run economic growth have minimal effect on air freight traffic, air-passenger traffic was found to be sensitive to some market shocks and both short- and long-term economic growth. Dobruszkes et al. [41] provided an analysis of the metropolitan determinants of air traffic in Europe.

Air cargo (freight) has received less attention in the relevant literature, even though much of the *a priori* expectations for the urban economic determinants of cargo transportation parallel those for passenger transportation. Growth in air cargo traffic may also introduce new airport-related jobs in the short term, and thereby alter the surrounding metro area's employment composition through spillover effects. Like passenger traffic, hub-cargo traffic is also not driven by the hub airport's local demand, but rather by the market demand of the cities it connects. Kasarda and Green [53] drew some preliminary connections between global air cargo traffic and national economic indicators while Chang and Chang [36] addressed the causal relationship between economic development and air cargo growth. Although their results mostly pertain to Taiwan, Chang and Chang used *Granger causality* tests to demonstrate that the long-term causal link between economic development and air cargo expansion is bidirectional. Button and Yuan [29] also used this methodology to understand the causal link between air freight transportation and regional economic development in the U.S. Their findings suggest that air freight induces local-economic development. More pertinently, recognizing the lack of research on the spatial distribution of air freight, Alkaabi and Debbage [2] analyzed socioeconomic variables that they deemed to be the most influential predictors of the distribution of outbound air freight.

Brueckner [19] and Green [47] addressed the inherent problem of identifying causation in the airport-traffic and urban-employment relationship. While growth in a city's workforce or change in a city's industry mix is expected to induce enplanements at airports, the aggregate-passenger traffic at airports could also affect the employment structure of that city. Higher passenger volumes indicate increased travel between cities, which can improve the access and connectivity of small metro areas, and thereby change a city's commercial and employment structure. Brueckner [19], for example, showed that a city's service-sector employment grows by 1 percent if the airline-passenger traffic in that city increases by 10 percent. Button et al. [27] also found evidence indicating that higher levels of airport traffic increase employment in areas related to *high-tech* technology industries.

A growing body of literature, however, suggests that the causal relationship between airports and urban development is sensitive to empirical specifications of the spatial region, urban size, and time period being analyzed (Cidell [38]; Mukkala and Tervo [63]; Neal [64]). Mukkala and Tervo [63] examined the causal link between air traffic and regional growth in Europe, using *Granger non-causality* tests on panel data (region heterogeneity was controlled using fixed effects). Based on their findings, the authors posited that while airline services stimulate regional growth in remote areas, economic development in *core* regions drives airport traffic. Considering that the present study is based on metro areas (MSAs) that contain a sizable core-urban population, and that demand for transportation is mostly *derived* (Ortúzar and Willumsen [70]), the causal effect running from urban employment to air traffic is assumed to be much stronger than the effect running from air traffic to employment. Therefore, while treatment of reverse causation would be important in empirical studies examining the impact of air transport on urban employment, it is precluded from the present analysis.

2.2 Empirical Specification and Data

The following specification is used to estimate the impact of urban features on air passenger and cargo (freight and mail) traffic. The dependent variable is the volume of total or domestic passengers (cargo tons) that are enplaned at an MSA i in quarter t:

$$T_{it} = \alpha_i + \beta E_{it} + \gamma X_{it} + \sum \theta_t Q_t + \varepsilon_{it}, \tag{2.1}$$

where α_i is the MSA-specific intercept; E_{it} denotes the shares of sectoral employment; X_{it} is a vector of exogenous control variables; Q_t represents time dummies (year and quarter); and ε_{it} is the error term. Hence, the empirical point estimates will indicate how much a change in sector-specific employment shares will impact airport traffic, while controlling for other city characteristics that also affect traffic (population, wages, unemployment, age distribution, hub operations, and airport location). Considering that the price of an airline ticket (shipping rate) is jointly determined with the volume of passenger (cargo) traffic, the specified equation assumes a reduced-form relationship that treats price as an endogenous variable (Brueckner [18]).

A test for *redundant fixed effects* supports the existence of unobserved heterogeneity in the sample MSAs. The choice of fixed effects over random effects is based on the *Hausman* test. The null hypothesis positing unobserved errors are not correlated with the regressors is rejected, implying that random effects would give inconsistent coefficient estimates.

Traffic

The passenger volumes and cargo tons carried by aircraft operating at the airports in the sample are obtained from the U.S. Department of Transportation's (DOT) *Form 41 Traffic T-100 Segment* tables, provided by the Bureau of Transportation Statistics (BTS). The *T-100 Segment* tables show monthly passenger and cargo traffic data reported by large certificated carriers at the *carrier-origin-destination-service type-aircraft type* level. Although the data are reported by both U.S. and foreign carriers for domestic (U.S. and Canada) and international operations, international data are only reported when at least one point of service is a domestic origin or destination (BTS [21]). This paper focuses on U.S. airports and MSAs (excluding Canada) to maintain compatibility with the socioeconomic data, and to stay within the scope of the study.

Passenger, freight, and mail volumes are aggregated to the airport level, by *carrier-service type* (Passenger-only, All-cargo, and Passenger-Cargo combination). Further, these data are tracked by the carrier's *region of operation* to analyze domestic operations separately from total operations, which include international services. Therefore, this study captures all U.S.-airport passenger and cargo enplanements, regardless of whether the traffic is moved by U.S. or foreign carriers. Considering that 70 percent of intra-U.S. mail is flown by passenger carriers (Morrell [61], p. 77), examining freight and mail outputs separately is preferred. However it has also been reported that mail transported by some integrated carriers (e.g. FedEx Express), albeit relatively small, cannot be distinguished from freight (TranSystems [87], p.28). Therefore, although the separate analysis of freight and mail is ideal, it is precluded by the available data.

Employment and Wages

The socioeconomic features of metro areas in this study are captured by quarterly measures of total employment and the unemployment rate, obtained from the U.S. Bureau of Labor Statistics (BLS) Current Population Survey (CPS). Income and sectoral-employment information is also included at the MSA level, using data from the BLS *Quarterly Census on Employment and Wages* (*QCEW*). The BLS recoded these survey and employer-reported data (initially organized according to the 2002 *National American Industry Classification System NAICS*) to two high-level domains: (1) *Service Providing* and (2) *Goods Producing.* Further disaggregation of the data provides subsector employment information (*NAICS* codes in parenthesis):[1]

1. *Service Providing*
    (a) Education and health service (61, 62)
    (b) Financial activities (52, 53)
    (c) Information (51)
    (d) Leisure and hospitality (71, 72)
    (e) Professional and business services (54-56)
    (f) Trade, transport and utilities (22, 42, 44, 45, 48, 49)

[1] A more disaggregated list of the high-level domains is provided in the Appendix.

(g) Other services (81) excluding Public administration (92)

2. *Goods Producing*

    (a) Manufacturing (31-33)

    (b) Construction (23)

    (c) Natural resources and mining (11, 21)

This study analyzes the following employment shares of the two high-level domains:

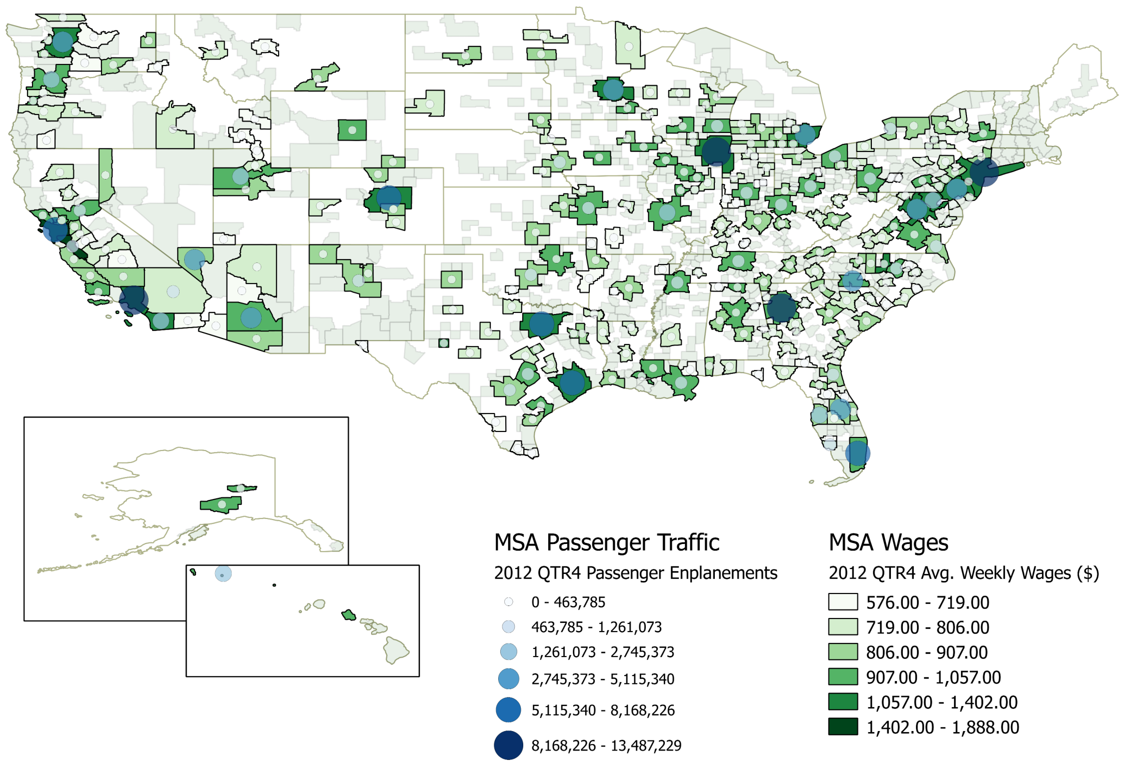
1. Service (*SERV*): Total employment share of Education and health services, Financial activities, Information, Leisure and hospitality, Professional and business services, and Trade, transport and utilities employment.

2. Manufacturing (*MANUF*): Total employment share of Manufacturing employment.

In view of the employment diversity in the service sector, especially as it pertains to air transportation, Sheard's [82] classification of tradable and non-tradable services is adopted in this paper. *Tradable* services include employment groups where the services that are provided by the employees can be consumed in a different geographical location. As such, employees in the *tradable*-service industries benefit from the networking and face-to-face contact advantages afforded by air travel more than employees in service occupations that are not *tradable*. Accordingly, *Professional-Business*, *Information*, and *Finance* employment are classified as *tradable* services, while *Trade-transport-utilities*, *Leisure-hospitality*, and *Education-health* employment are classified as *non-tradable*. Even though the classifications of employment categories as tradable or non-tradable is not based on an objective approach, the justification that tradable and non-tradable services have unique air-travel demand characteristics for air travel is reasonable (Sheard [82]).

Average weekly wages, across all sectors, are used to proxy for average personal income in an MSA. Data on the unemployment rate are also used to account for the wealth variation and economic health of MSAs. Figure 2.1 shows the broad range of passenger-enplanement volumes and average weekly wages across the sample MSAs in the country (2012Q4 data).[2]

Figure 2.1: MSA Average Weekly Wages and Passenger Enplanements (2012Q4)



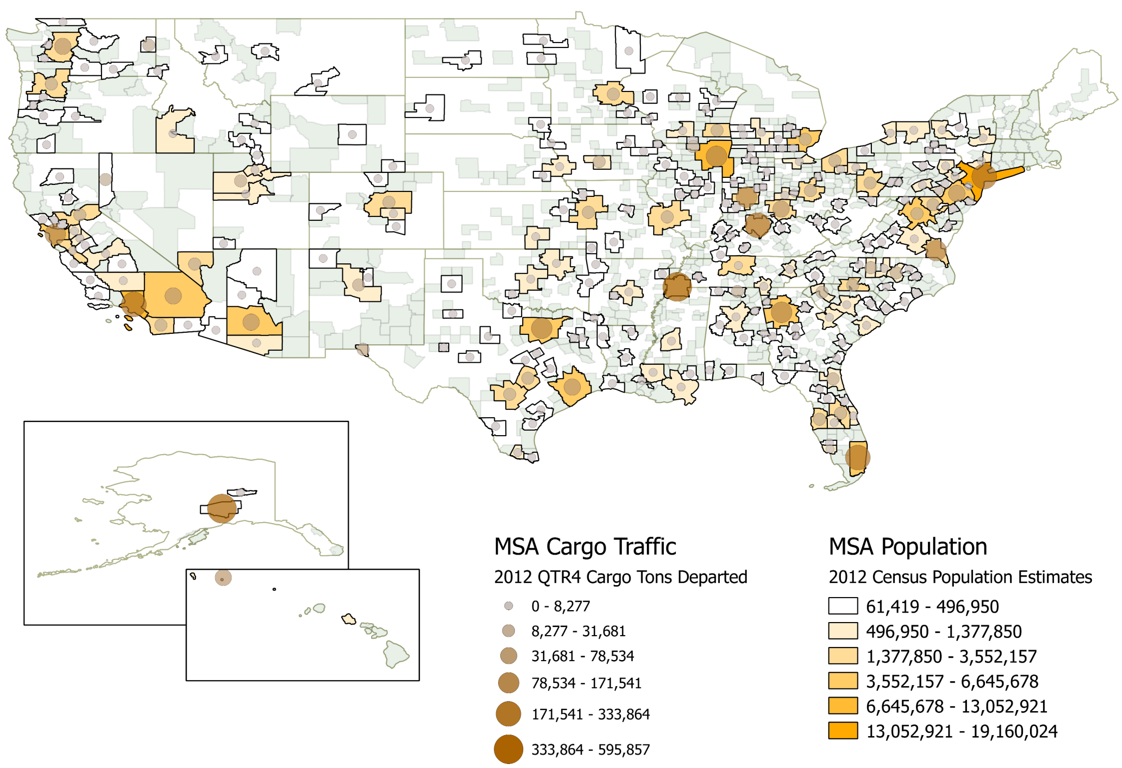
Population

In view of the substantial role that city size plays in determining air-service demand (mainly through scale effects), data on MSA population are included by aggregating the U.S. Census

[2]The map in this figure (as well as the subsequent ones) are designed using the U.S. Census Bureau's *TIGER/Line® shapefiles* [32]. The socioeconomic, demographic, and traffic data are obtained from the BLS *QCEW* databank [12], U.S. Census Bureau *Intercensal Estimates (2000-2010)* [33], and the BTS *T-100 Segment* tables [24], respectively. Airport-specific coordinate and spatial information are obtained from the 2012 BTS *National Transportation Atlas Database* (*NTAD*) files [22].

Bureau's county-level annual demographic measures. Further, since the population data is also provided in 5-year age groups, the data are organized by age-group shares (*YOUNG* and *OLD*) to control for the labor-force characteristics of cities in the sample. Figure 2.2 illustrates the U.S. Census Bureau's population estimates and the corresponding MSA-level tonnage of departed cargo.

Figure 2.2: MSA Population and Departed Cargo Tonnage (2012Q4)



Hub Cities

Deregulation of airline passenger and cargo services in the late 1970's brought about major structural changes in the industry. As carriers were given the freedom to choose the markets they serve and how frequently they fly between airports, their operations and network structures naturally conformed to a more efficient hub-and-spoke configuration (Borenstein

[16]). The new hub features of certain cities could potentially alter the airport traffic and urban growth relationships established in the literature. For example, hub cities that handle the highest levels of passenger or cargo traffic in the nation are not necessarily cities that have high-wage earners or strong concentrations of service-sector jobs (consider Atlanta, GA and Memphis, TN as examples of passenger and cargo metro areas that fit this scenario) (Discazeaux and Polese [40]). Therefore, hub cities potentially undermine the empirical links drawn between employment and airport-traffic characteristics.

The route-level traffic data provided in the BTS *T-100 Segment* tables do not allow identification of *true* origin (destination) volumes of passengers and freight; that is, local originations cannot be distinguished from all enplanements (which include *transit* and *intermediate-stop* traffic). Therefore any measurement of locally-generated traffic at major airports is precluded. Such differentiation is especially important at hubs, where unusually high levels of traffic that cannot be explained by the features of the hub city are observed. The BTS *T-100 Market* data would be a likely solution to this problem, since the data are claimed to show true origins and destinations of enplaned passengers and freight. However, in the event that a carrier's flight number changes at a connecting airport, the data will show that transported passengers (cargo) terminated their trip at that connection. Therefore, the data associated with flight-number changes may be misreported. Even though the frequency of such flight-number changes is not entirely clear, it presents a problem in the usage of the *T-100 Market* data.

One solution to capture true originations would be to drop all hub airports (cities) for passenger and cargo operations from the sample (Brueckner [18]). A problem with this approach is that a city may contain both hub and non-hub airports. Therefore, selecting only non-hub cities could weaken the representativeness of the sample. Another solution, which is employed in this study, is to use a binary variable to indicate whether a city contains at least one hub airport (HUB). If there are other non-hub airports in this city, HUB is scaled down to be a fraction of the city's airports. Therefore, *HUB* will control for the connecting passenger and cargo traffic at hub cities, which would otherwise not be explained by that city's characteristics.

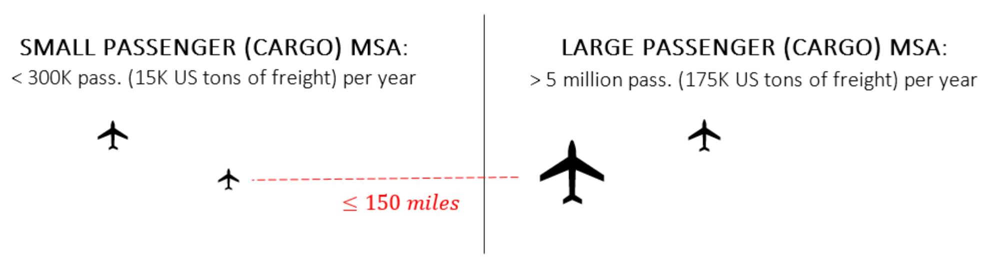
The hub status of an airport is determined by the number of carrier-specific domestic points it serves. Initially, an airport is considered a passenger (cargo) hub if an airline operating at the airport flies to at least 25 (20) destinations in a given quarter. A *k-means clustering* methodology is used to determine these points-served cutoffs, where 2 groups (hubs and non-hubs) are chosen such that airport-carrier pairs are assigned to the group with the closest mean number of destinations served. The methodology essentially assigns airport-carrier pairs to the hub or non-group such that the within-group sum of squares is minimized. Other considerations, such as established carrier *focus cities*, are taken to eliminate non-hub cities that meet the initial hub-selection criteria. The chosen hubs are also cross-checked for consistency with a sparse record of the airlines' declared hub airports. FedEx Express and UPS Airlines operate the first and second largest cargo hub airports (*Memphis Intl.* and *Louisville Intl.*) in the country, respectively. As such, the two carriers are among the top employers in their respective hub cities, Memphis, TN and Louisville, KY. Seeing that the vast majority of the traffic departing from these hubs is *through* traffic, and that the employment structure of the cities heavily depends on the hub operations, the corresponding MSAs are dropped from the cargo samples.

Traffic Diversion

The literature presents evidence suggesting that passengers and shippers are attracted to the enhanced services, network connections, facilities and lower prices that are provided by airports in large metropolitan areas (Brueckner [18]; Alkaabi and Debbage [2]). In view of the transportation amenities availed by big cities, passengers (freight forwarders) will forego travelling (shipping products) from the closest airport, using surface modes of transportation to reach larger airports that are farther away and possibly in another metro area. This traffic-diversion effect, also called a *traffic-shadow effect*, depresses the volume of passenger and cargo traffic generated by a small metro area.

Therefore, to capture the degree to which passenger and cargo traffic are diverted from small-to-large metro areas, a dummy variable (*PROXIMITY*) is constructed. *PROXIMITY* is equal to 1 if the smallest airport in a small MSA (an MSA that departs less than 300,000 passengers or 15,000 tons of freight annually) is within 150 miles of the largest airport in a large MSA (an MSA that departs more than 5 million passengers or 175,000 tons of freight annually). Figure 2.3 illustrates how the smallest airport in a small MSA may be within 150 miles of the largest airport in a large MSA, and potentially faces the traffic-diversion effect sought to be captured by *PROXIMITY*.

Figure 2.3: Traffic Diversion from small-to-large metro areas



The small- and large-MSA classifications were also determined using *k-means clustering* of the MSA-level traffic data. After creating 4 clusters (groups) based on departed-traffic volumes, the mean and maximum values of the smallest cluster were used to define the small and large MSA categories, respectively. Table 2.1 lists the sample MSAs that face traffic diversion (*PROXIMITY* equal to 1). Cargo MSAs that are also facing passenger-traffic diversion are shown in bold typeface.

Table 2.1: List of MSAs Facing Traffic Diversion ($PROXIMITY$ =1)

Passenger MSAs	Cargo MSAs
Appleton, WI	Albany-Schenectady-Troy, NY
Asheville, NC	Allentown-Bethlehem-Easton, PA-NJ
Augusta-Richmond County, GA-SC	Baton Rouge, LA
Bellingham, WA	Birmingham-Hoover, AL
Bend, OR	Brownsville-Harlingen, TX
Bloomington-Normal, IL	Burlington-South Burlington, VT
Charleston, WV	Cape Coral-Fort Myers, FL
Charlottesville, VA	Cedar Rapids, IA
Chattanooga, TN-GA	Charleston-N. Charleston-Summerville, SC
Deltona-Daytona -Ormond Beach, FL	Dayton, OH
Evansville, IN-KY	Decatur, IL
Fargo, ND-MN	Dover, DE
Fayetteville, NC	El Centro, CA
Flagstaff, AZ	Flint, MI
Fort Wayne, IN	Fresno, CA
Kalamazoo-Portage, MI	Grand Forks, ND-MN
Killeen-Temple-Fort Hood, TX	Huntington-Ashland, WV-KY-OH
Lafayette, LA	Jackson, MS
Lansing-East Lansing, MI	Kingsport-Bristol-Bristol, TN-VA
Lincoln, NE	Lexington-Fayette, KY
McAllen-Edinburg-Mission, TX	Madison, WI
Medford, OR	Ocala, FL
Mobile, AL	Pensacola-Ferry Pass-Brent, FL
Palm Bay-Melbourne-Titusville, FL	Providence-New Bedford-Fall River, RI-MA
Peoria, IL	Santa Barbara-Santa Maria-Goleta, CA
Poughkeepsie-Newburgh-Middletown, NY	Savannah, GA
Rapid City, SD	Springfield, MO
Saginaw-Saginaw Township North, MI	Stockton, CA
Salinas, CA	Tallahassee, FL
Scranton–Wilkes-Barre, PA	Vallejo-Fairfield, CA
Shreveport-Bossier City, LA	Wausau, WI
Sioux Falls, SD	Wichita, KS
Toledo, OH	
Wilmington, NC	

Notes: Table shows sample MSAs that enplane less than 300,000 passengers (15,000 tons of freight) per year, and are within 150 miles of a large MSA that enplanes more than 5 million passengers (175,000 tons of freight) per year. MSAs facing both passenger- and cargo-traffic diversion are shown in bold typeface.

Weather

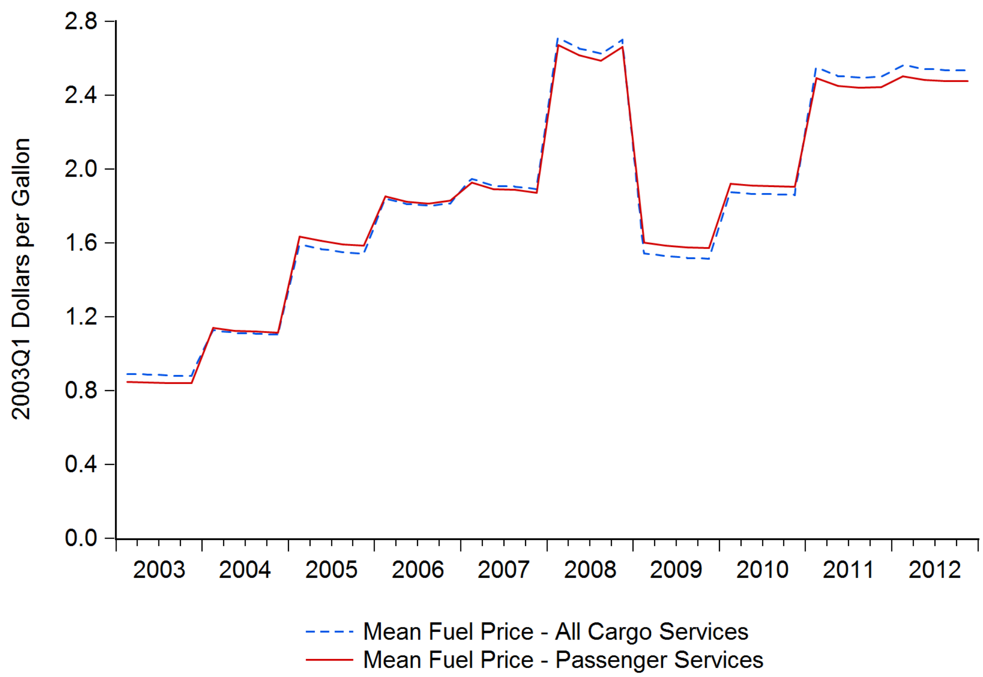
In view of climate and weather preferences for industrial establishments, travel destinations, and the location of transport facilities, controls for temperature are also included at the city level. Weather data are downloaded from the National Oceanic and Atmospheric Administration's (NOAA) *Global Historical Climatology Network* (*GHCN*) [66]. The maximum January temperature (*JANTEMP*), measured at airport *GHCN* stations, is collapsed to the MSA level, and used to identify cities that are attractive to employment or leisure travel. Given that warmer locations generally attract leisure travel, a positive sign is expected for the *JANTEMP* coefficient in the passenger-traffic regressions. However, for air cargo traffic, the sign on *JANTEMP* is ambiguous.

Fuel Price

The price of fuel is an important input cost for both passenger and cargo airlines; traditional cost-structure studies have shown that a 10-percent increase in fuel price can raise total costs by 1.6 (1.4) percent for passenger (cargo) carriers (Caves, Christensen, and Tretheway [31]; Lakew [57]); Onghena, Meersman, and Van de Voorde [69]). Thus, the price of fuel is naturally expected to have a direct impact on airline operations, while also having an indirect impact on the economy of a metro area by changing its production capacity and demand characteristics. While the data show the volatile oil prices observed over this studies time period, it is important to directly capture the impact of this exogenously-determined variable.

Data on fuel expenditures, for both passenger and cargo carriers, are obtained from the DOT's *Form 41 Financial Schedule* tables (*P5.2*) (BTS [25]). A quarterly varying fuel price (*FUELPRICE*) is calculated by dividing carrier expenses on fuel (for flying operations) by the total gallons of air-fuels issued to the airlines. Figure 2.4 shows the fluctuation in fuel price over the sample period in this study. The peak-oil prices of July 2008 can be seen in the figure, as well as the fall in oil prices that shortly followed. While the proposed fuel-price measures may capture the aggregate impact of fluctuations in the price of oil, note that there are carrier-specific differences in fuel-acquisition (including contracts that allow them to avoid short-term price shocks), as well as differences in regional-fuel supply (Kiesling and Hansen [54]; Greene [48]). Therefore, MSA fixed effect estimations are employed to control for the latter factors that are otherwise unobserved.

Figure 2.4: Fuel Price (2003Q1 Dollars)



Panel

The choice for the start and end dates of this study's panel is mainly driven by the availability of the cargo-traffic data from the *T-100 Segment* tables. Due to a major BTS reporting-requirement change that took place in 2001-2002, the *T-100 Segment* tables contain complete operations data (scheduled and non-scheduled) for the two biggest integrated carriers, FedEx Express and UPS Airlines, starting from 2002 Quarter 1 and Quarter 4, respectively. Morrell ([61], p.2) noted that carriers have been required to report non-scheduled freight traffic as scheduled traffic since 2003. Therefore, Quarter 1 of 2003 is chosen as the start date for this study to prevent discrepancies that might exist during the traffic-reporting changes that took place.

The panel is constructed with MSA cross-sections of quarterly data over the quarters 2003Q1 to 2012Q4. The airport-level traffic data are consolidated to their respective metro-areas (MSA). The samples for this study are restricted to primary metro areas that enplane more than 200,000 passengers (1,000 U.S. tons of freight) per year. Non-primary cities are excluded from this study since they account for insubstantial amounts of passenger or freight traffic, and could potentially bias estimation results if included. 200,000 enplanements, which is less than 0.05 percent of total annual enplanements in the U.S., falls within the upper range of the FAA's primary airport classification. While the distribution of freight traffic is different from passenger traffic, the 1,000-annual MSA tonnage cutoff is used to drop cities that account for insignificant levels of goods enplanements. Note, however, that cities with relatively low levels of passenger or freight traffic are still included in the sample, usually falling in the group of MSAs that experience traffic diversion (summarized in Table 2.1). After collapsing the airport-level data to MSAs and applying the above-mentioned restrictions to the data, the passenger total and domestic samples are both comprised of 136 MSAs (cross-sections) while the cargo total and domestic samples include 119-127 and 116-124 MSAs, respectively. Note, due to missing data for some of the cargo MSAs, the number of cross-section in the cargo sample vary between the cross-sectional and fixed effects specifications, as well as the total and domestic samples. Table 2.2 provides definitions of variables in this study, and Table 2.3 shows summary statistics for MSAs in the sample that meet these criteria.

Table 2.2: Variable Definitions

Variables	**Description**
PASSENGERS †	Total number of passengers enplaned at MSA
CARGO(-AC)	Total freight & mail tons enplaned at MSA (-*All Cargo* services only)
POP	Total MSA population
YOUNG	Share of MSA population of age 19 and under
OLD	Share of MSA population of age 60 and over
TOTEMP	Total MSA employment (non-farm)
SERV	Service-related employment share of MSA total employment (*TOTEMP*)
PIF	Professional-Business, Information, and Financial empl. share of *TOTEMP* (**Tradable**)
TLE	Trade-transport-utilities, Leisure-hospitality, Education-health empl. share of *TOTEMP* (**Non-tradable**)
MANUF	Manufacturing employment share of *TOTEMP*
WAGE	Average weekly wages (in 2003Q1 dollars) for MSA
UR	Unemployment Rate (%) in MSA
HUB	MSA hub indicator, scaled by number of airports in MSA
PROXIMITY	Dummy = 1 if smallest airport in a small MSA is within 150 miles of largest airport in a large MSA
JANTEMP	Average maximum January temperature (in degrees Celsius) recorded at MSA airports
FUELPRICE	Average price of fuel for Passenger- and Cargo-service carriers (in 2003Q1 dollars per gallon)

Notes: Variables represent quarterly measures (except for *POP*, *YOUNG*, *OLD*, *HUB*, and *JANTEMP*, which are measured annually).
† Domestic passenger and cargo traffic are analyzed separately.

Table 2.3: Variable Summary Statistics

Sample:	PASSENGER (4,149 obs.)			CARGO (3,831 obs.)		
Variables	***Mean***	***Min.***	***Max.***	***Mean***	***Min.***	***Max.***
PASSENGERS	1,058,896	31,147	14,354,804			
DOMESTIC †	961,647	31,147	10,617,402			
CARGO				28,248	57	851,576
DOMESTIC				16,57	107	232,984
CARGO-AC				24,219	0	844,278
DOMESTIC				14,244	0	227,607
POP	1,247,045	79,984	18,597,872	1,332,338	68,246	18,597,872
YOUNG	0.2751	0.2080	0.3853	0.2774	0.2130	0.3853
OLD	0.1743	0.0800	0.3226	0.1708	0.0800	0.3226
TOTEMP	585,821	36,738	8,862,150	626,400	35,954	8,862,150
SERV	0.6071	0.3980	0.8923	0.6104	0.3870	0.7852
PIF (Tradable)	0.1902	0.0605	0.3310	0.1931	0.0770	0.3310
Prof.-Business	0.1175	0.0370	0.2433	0.1182	0.0410	0.2433
Information	0.0195	0.0060	0.0605	0.0200	0.0070	0.0605
Financial	0.0532	0.0180	0.1728	0.0550	0.0230	0.1728
TLE (Non-Tradable)	0.4168	0.2680	0.7770	0.4172	0.2680	0.6645
Trade-Transp.-Util.	0.1835	0.1180	0.2945	0.1856	0.1180	0.2608
Leisure-Hospitality	0.1048	0.0640	0.4900	0.0995	0.0580	0.3205
Education-Health	0.1285	0.0650	0.2236	0.1322	0.0500	0.4144
MANUF	0.0857	0.0100	0.2261	0.0882	0.0100	0.2399
WAGE	675.98	435.60	1,611.82	686.87	435.60	1,611.82
UR	6.54	2.27	17.43	6.42	2.26	17.26
FUELPRICE	1.83	0.84	2.67	1.81	0.88	2.71
HUB	0.11	0	1	0.06	0	1
AIRPORTS	1.24	1	6	1.46	1	5
PROXIMITY	0.13	0	1	0.26	0	1
JANTEMP	8.61	-27.89	27.35	7.87	-27.89	27.35

Notes: Quarterly MSA summary statistics shown here (except for *POP*, *YOUNG*, *OLD*, *HUB*, and *JANTEMP*, which are measured annually).
† Summary statistics of non-traffic variables in the domestic sample are not shown separately since the values are very close to those of the total (international and domestic) sample.

The summary statistics in Table 2.3 show the wide distribution of both passenger and cargo traffic across cities in the U.S. A smaller gap between total- and domestic-passenger traffic is also evident, in comparison to the large disparity between total- and domestic-air cargo traffic. This difference suggests that a considerable portion of the air cargo traffic in the U.S. is borne by international services (operated by U.S. or foreign carriers). Given the differing passenger and cargo samples, the corresponding city-level socioeconomic measures also vary slightly. While the city-size and employment levels of the cargo sample are larger than the passenger sample, the sector-level employment concentrations of the samples are similar.

The non-tradable sector appears to dominate the workforce of most cities, particularly in the area of trade, transport, and utilities (*Trade-Transport-Util.*). Some cities also exhibit anomalous employment concentrations in leisure and hospitality (*Leisure-Hospitality*). Most notably, leisure-and-hospitality employment accounts for 43 percent of *Atlantic City-Hammonton, NJ's workforce.* Other cities where the leisure and hospitality industry is disproportionately represented include *Las Vegas-Paradise, NV*; *Myrtle Beach-North Myrtle Beach-Conway, SC*; *Gulfport-Biloxi, MS*; and *Orlando-Kissimmee-Sanford, FL*. While excluding cities with outlier-employment structures may be prudent, they are left in the study in view of the MSA fixed effects that will be used to account for such city-specific differences. Cities that have unreported data for employment in any of the chosen sectoral categories are dropped from the sample. From the cities initially classified as hubs, *Cincinnati-Middletown, OH-KY-IN*; *Chicago-Joliet-Naperville, IL-IN-WI*; *Dallas-Fort Worth-Arlington, TX*; and *St. Louis, MO-IL* are excluded for not meeting this full-employment data requirement.

2.3 Results

2.3.1 Passenger Traffic Results — A

The first regression in Table 2.4 essentially replicates the work of Brueckner [18] , using a quarterly panel dataset. Following up with Brueckner's suggestion, the period analyzed in this paper (2003-2012) allows sufficient time for the restructuring of the deregulated industry to have taken place (*The Airline Deregulation Act* was passed by the U.S. Congress in 1978). Contrary to Brueckner's expectation, however, and consistent with the results of Discazeaux and Polese [40], the cross-sectional results of this study (columns 1 and 4) indicate that the demand characteristics of air travel have not changed significantly after deregulation. The point estimates for *POP*, *SERV* and *WAGE*, and *PROXIMITY* are comparable to the results found in Brueckner's study. Treating *SERV* and higher wages as proxies for *white collar* employment, Brueckner's conclusion that the demand for air travel increases with the concentration of *white collar* employment still holds. While Brueckner found manufacturing employment (representing *blue collar* jobs) to have a statistically insignificant effect on passenger traffic, this study finds that increasing an MSA's share of manufacturing employment actually depresses passenger travel (a statistically-significant result). Also, unlike the strictly proportional relationship between city size and traffic that Brueckner found in a cross-sectional analysis, the 0.9689 (0.9420) coefficients estimated for *POP* are significantly different from 1 in this study (0.010 standard error), implying that passenger traffic does not rise equally as fast as city population.

Since total employment in a city is proportional to population, the model shows how compositional shifts in sectoral employment affect passenger and cargo volumes at the corresponding metro areas. For example, the coefficient on *SERV* reveals the extent to which an increase in a city's share of service employment, for an equivalent reduction in the excluded-employment groups (non-service and non-manufacturing), would generate passenger or cargo traffic. Since the excluded-employment sectors generate traffic themselves, a positive (negative) coefficient for *SERV* indicates that any decline in traffic is more than (less than) offset by a gain in traffic from a higher service share. Therefore, the coefficient estimates for *SERV* (*MANUF*) indicate the degree to which service (manufacturing) employment can generate traffic, relative to the non-service and non-manufacturing employment groups.

Turning to the control variables, the exponentiated *HUB* and *PROXIMITY* coefficients indicate that around 2.2 times as much traffic is flown through hub cities relative to their non-hub counterparts, and around 47 percent of small-city passengers are diverted to large airports in neighboring cities. As an important cost driver for airlines, *FUELPRICE* exhibits the expected negative coefficient in all of the specifications. However, the coefficients on *FUELPRICE* are insignificant, possibly due to the year dummies absorbing the impact of the volatile oil prices in the sample period. Finally, the positive and significant coefficient on *JANTEMP* is not surprising, as it implies that temperate-climate cities attract more air passengers.

Given the panel structure of the data, this study provides new insights into air-travel demand characteristics by controlling for the unique unobservable features of cities. Specifically, the fixed effect estimates (in columns 2, 3, 5, and 6) account for unobserved and time-invariant city features that may influence the determinants of air traffic. For example, a city's distance from the center of the U.S. population (*Texas County, Missouri* according to the 2010 Census) affects the volume of air traffic since urban areas located closer to the population centroid are preferred for airline-hub operations (Brueckner [19]). While the effect of a city's centrality is possibly accounted for by the *HUB* dummy, other uncaptured regional characteristics, such as airport policies, facilities and transportation infrastructure, fuel supply, and proximity to national boundaries (Discazeaux and Polese [40]), can impact air transport considerably. Airfare levels (endogenously determined in the specified model) are affected by the proximity of small sample cities to important business and leisure destinations. Small urban areas that are close to major destinations are expected to face lower airfares on average, which in turn stimulates traffic (Brueckner [18]). Therefore, in a cross-sectional analysis, the distance between certain city-pair markets is an unmodeled city feature that could potentially bias coefficient estimates through its effect on fares. More pertinently to air cargo transportation, access to transshipment nodes (sea ports, rail and truck terminals), warehouse facilities, and customs brokerage services, are unobserved regional differences that affect goods movement. The fixed effect estimations are instrumental in controlling for these characteristics that are unique to urban areas, while capturing the variation of socioeconomic factors within cities to explain changes in the volume of air traffic. Hence, city-specific variables that are *mostly* constant over time (HUB, $PROXIMITY$, and $JANTEMP$) are dropped in the fixed effects specifications, preventing singularity issues in the estimations.

Even though the POP coefficient is greater than unity in the fixed effects regressions (columns 2, 3, 5, and 6 in Table 2.4), suggesting that traffic rises faster than city size, linear-restrictions tests show that the coefficient (approximately 1.17) is actually not significantly different from 1. The $SERV$ coefficient indicates that a 10 percentage-point increase in the share of service-sector employment would increase total and domestic passenger enplanements by around 0.20 percent, while the coefficient on $WAGE$ shows that a 1-percent rise in a city's average weekly wages increases total (domestic) passenger by 0.32 (0.34) percent. In view of air transport as a luxury good, an income-elasticity that is greater than 1 would be expected from a demand relationship. However, the coefficient on $WAGE$, which is well below unity, suggests that the predicted reduced-form relationship status of Equation 2.1 holds (Brueckner [18]). Consistent with Brueckner's [18] conclusions, unobserved supply-side factors (such as higher fares in markets that connect wealthy cities) may weaken the income-elasticity that is measured by the model. Still, the predicted impact of $WAGE$ in this study is considerably weaker than the unitary income-elasticity that Brueckner estimated. The results for $SERV$ and $WAGE$, together, suggest that urban affluence induces air traffic, and are consistent with the implications of the negative sign of the unemployment-rate coefficient (UR). Interestingly, a higher rate of unemployment (UR) appears to have a stronger dampening effect on domestic traffic, compared to its effect on total traffic.

The sign on $MANUF$ becomes positive in the fixed effects regressions, implying that a given city's total and domestic air traffic increase as more workers in that city join the manufacturing workforce (coming from non-service occupations). However, the marginal effect size of this result suggests that a 10 percentage-point increase in *MANUF* results in a mere 0.05 percent gain in total passenger traffic. Lastly, age-group shares (*YOUNG* and *OLD*) are included to account for differences in the labor-force size of cities, as well as changes in the labor-force structure within cities over time. The results suggest that the *OLD* age group (mostly retired) has a higher demand for air travel, possibly reflecting the group's high propensity for leisure travel. Elderly travelers (known as *Snowbirds*) that seasonally migrate between colder and warmer regions may account for considerable increases in air travel, especially in cities where a high concentration of retirees reside.[3] The cross-sectional results, however, exhibit the expected negative signs on the *YOUNG* and *OLD* coefficients, consistent with hypothesis that MSAs with a larger share of their population in the labor force (20-59 age group) require more air-travel services.

Columns 3 and 6 also provide the coefficients for the fixed effects estimations, but with standard errors (*SE*) that are clustered around the cross-section MSAs. The clustered standard errors account for heteroscedasticity across cities, while controlling for potential correlation in the residuals within cities over time. Evidently, the significance of the coefficients on *POP*, *SERV*, and *WAGE* are robust to the strict requirements of the clustered standard errors. Therefore, the findings that hold in the robust total- and domestic-regressions of Table 2.4 are as follows: (1) traffic is proportional to city size, and (2) service-sector employment, along with higher wages (*white collar* jobs), increases demand for passenger air travel. The fixed effects results also confirm that the unobserved effects marginally discount the effect of city size (*POP*), and inflate the impact of service-sector employment and wages.

2.3.2 Passenger Traffic Results — B (Service Disaggregated)

Bearing in mind the diversity of industry groups within the service sector, *tradable services* (*PIF*) are separated from *non-tradable* services (*TLE*), following Sheard [82]. The traditional

[3]The author thanks Nicholas Sheard for this insight.

expectation is that employees in *tradable-service* establishments demand higher air-transport services while also benefiting the most from agglomeration economies that are harnessed from a city's improved air services (Sheard [82]; Rosenthal [76]; Brueckner [19]). The cross-sectional results for total and domestic passenger traffic in Table 2.5 confirm this expectation, exhibiting a positive and significant coefficient for PIF that is larger than the coefficient for TLE (statistically significant: standard error = 0.385). A 10-percentage point increase in the share of *tradable* (*non-tradable*) employment services increases total passenger enplanements by 0.36 (0.21) percent.

It is interesting to note, however, that the effect sizes are reversed when MSA fixed effects are applied. Now, an increase in a city's employment share of *non-tradable* services has a stronger impact on passenger traffic than the same increase in a city's employment share of *tradable* services (statistically significant difference: standard error = 0.395). The corresponding coefficient estimates, which are also statistically significant in the clustered standard-error specifications, may indicate that an increase in a city's provision of leisure, hospitality, trade, and transport services are reasonably important determinants of tourism and commerce-related air travel. Considering that jobs in the *Leisure and hospitality* industries are generally confined to a particular location, they are strictly defined as *non-tradable* in this analysis. However, services (e.g., retail, dining, lodging, entertainment, etc.) provided in these industries have a distinctive and potentially substantial impact on leisure travel and tourism ([82]). The *Trade, transport, and utilities* industries also include employment in transportation-related services, which conceivably have a considerable correlation with business and trade-related air transport. Therefore, the relatively stronger impact of non-tradable services on passenger traffic (compared to tradable services) may largely be driven by location-specific jobs that share unique relationships with tourism and air transport.

The traffic impact of the remaining variables in the fixed effects analysis do not change. The domestic-only traffic results (columns 4-6) also continue to exhibit comparable results to the total traffic. The domestic-only traffic results (columns 4-6) also continue to exhibit comparable results to the total traffic.

Table 2.4: Passenger Traffic — A

PASSENGERS	Total (Domestic & International)			Domestic		
	(1) Pooled OLS	(2) Fixed Effects (FE)	(3) FE, Clust. SE	(4) Pooled OLS	(5) Fixed Effects (FE)	(6) FE, Clust. SE
INTERCEPT	-7.3030^a	-6.2987^a	-6.2987	-6.7057^a	-6.5538^a	-6.5538
	(11.653)	(4.840)	(1.560)	(10.846)	(5.045)	(1.617)
POP	0.9689^a	1.1660^a	1.1660^a	0.9420^a	1.1694^a	1.1694^a
	(93.645)	(12.416)	(3.988)	(93.010)	(12.496)	(3.979)
SERV	2.4924^a	2.0218^a	2.0218^a	2.4394^a	2.0315^a	2.0315^a
	(16.572)	(11.126)	(3.392)	(16.669)	(11.158)	(3.416)
MANUF	-5.6215^a	0.5228^c	0.5228	-5.2944^a	0.4588	0.4588
	(26.624)	(1.717)	(0.600)	(25.942)	(1.507)	(0.527)
WAGE	1.2010^a	0.3210^a	0.3210^b	1.1519^a	0.3366^a	0.3366^b
	(17.358)	(4.940)	(2.297)	(16.911)	(5.198)	(2.426)
UR	-0.0093^c	-0.0039^c	-0.0039	-0.0095^c	-0.0054^b	-0.0054
	(1.755)	(1.668)	(0.662)	(1.828)	(2.311)	(0.922)
YOUNG	-4.5123^a	-1.3526	-1.3526	-4.2647^a	-1.2195	-1.2195
	(8.319)	(1.355)	(0.445)	(7.935)	(1.234)	(0.401)
OLD	-4.6511^a	1.2975^c	1.2975	-4.5498^a	1.6754^b	1.6754
	(8.001)	(1.648)	(0.545)	(7.854)	(2.128)	(0.705)
FUELPRICE	-1.2178	-0.3519	-0.3519	-1.0738	-0.3108	-0.3108
	(0.718)	(0.879)	(1.404)	(0.648)	(0.779)	(1.242)
HUB	0.8017^a			0.8100^a		
	(26.971)			(28.021)		
PROXIMITY	-0.6427^a			-0.6506^a		
	(25.926)			(26.830)		
JANTEMP	0.0051^a			0.0044^a		
	(4.598)			(4.197)		
Adj. R^2	0.8944	0.9940	0.9940	0.8943	0.9937	0.9937
Observations	3807	3955	3955	3807	3955	3955

Notes: *PASSENGERS*, *POP*, *WAGE*, and *FUELPRICE* are in natural logs.
Sample is restricted to MSAs enplaning more than 200,000 passengers per year.
Dummies for years and quarters are suppressed.
Absolute t-statistics in parenthesis: (1), (2) based on robust standard errors; (3) based on clustered standard errors: $^a p < 0.01$; $^b p < 0.05$; $^c p < 0.10$.

Table 2.5: Passenger Traffic — B (Service Disaggregated)

PASSENGERS	Total (Domestic & International)			Domestic		
	(1) Pooled OLS	(2) Fixed Effects (FE)	(3) FE, Clust. SE	(4) Pooled OLS	(5) Fixed Effects (FE)	(6) FE, Clust. SE
INTERCEPT	-6.4598^a	-6.4720^a	-6.4720	-5.7450^a	-6.7092^a	-6.7092
	(10.043)	(4.926)	(1.555)	(9.120)	(5.114)	(1.608)
POP	0.9554^a	1.1662^a	1.1662^a	0.9267^a	1.1696^a	1.1696^a
	(88.621)	(12.371)	(3.898)	(87.360)	(12.453)	(3.900)
PIF	3.5640^a	1.3784^a	1.3784^c	3.6607^a	1.4545^a	1.4545^c
	(11.337)	(4.932)	(1.826)	(11.875)	(5.200)	(1.927)
TLE	2.1401^a	2.3372^a	2.3372^a	2.0380^a	2.3143^a	2.3143^a
	(11.918)	(9.398)	(2.875)	(11.699)	(9.258)	(2.824)
MANUF	-5.8569^a	0.4513	0.4513	-5.5625^a	0.3946	0.3946
	(26.628)	(1.487)	(0.518)	(25.955)	(1.300)	(0.454)
WAGE	1.0711^a	0.3423^a	0.3423^a	1.0038^a	0.3558^a	0.3558^a
	(14.205)	(5.266)	(2.376)	(13.669)	(5.487)	(2.477)
UR	-0.0025	-0.0050^b	-0.0050	-0.0018	-0.0064^a	-0.0064
	(0.471)	(2.116)	(0.801)	(0.339)	(2.696)	(1.022)
YOUNG	-4.2438^a	-1.2687	-1.2687	-3.9588^a	-1.1443	-1.1443
	(7.605)	(1.269)	(0.416)	(7.148)	(1.156)	(0.375)
OLD	-4.3225^a	1.3564^c	1.3564	-4.1754^a	1.7282^b	1.7282
	(7.257)	(1.733)	(0.570)	(7.037)	(2.207)	(0.728)
FUELPRICE	-1.0960	-0.3934	-0.3934	-0.9350	-0.3480	-0.3480
	(0.648)	(0.986)	(1.570)	(0.566)	(0.875)	(1.384)
HUB	0.7820^a			0.7876^a		
	(26.808)			(27.899)		
PROXIMITY	-0.6276^a			-0.6334^a		
	(25.076)			(25.917)		
JANTEMP	0.0043^a			0.0035^a		
	(3.724)			(3.193)		
Adj. R^2	0.8949	0.9940	0.9940	0.8951	0.9937	0.9937
Observations	3807	3955	3955	3807	3955	3955

Notes: *PASSENGERS*, *POP*, *WAGE*, and *FUELPRICE* are in natural logs.
Sample is restricted to MSAs enplaning more than 200,000 passengers per year.
Dummies for years and quarters are suppressed.
Absolute t-statistics in parenthesis: (1), (2) based on robust standard errors; (3) based on clustered standard errors: $^a p < 0.01$; $^b p < 0.05$; $^c p < 0.10$.

2.3.3 Cargo Traffic Results — A

Despite the difficulties in tracing the movement of air cargo goods, due to data limitations, Table 2.6 and Table 2.7 show some clear patterns of how a city's socioeconomic factors affect demand for air cargo traffic.

Starting with the cross-sectional results, total (domestic) traffic appears to grow less than proportionally with city size, as shown by the 0.850 (0.847) coefficient on *POP*, which is significantly different from unity. In comparison to the corresponding results for passenger traffic, the large coefficient on *HUB* implies that air cargo operators funnel a substantial share of their traffic through hub cities (around 11 times as much compared to non-hubs). As per Kiesling and Hansen's [54] claim, air freighters typically employ a relatively small number of hub airports in their network, but consolidate, sort, and transfer a larger proportion of their traffic through those hubs compared to passenger carriers. Thus, it is also unsurprising to see a stronger traffic shadow effect for air cargo traffic (consistent with Alkaabi and Debbage [2]), indicating that around 66 percent of cargo traffic is diverted from small to large MSAs. This finding is reasonable in view of the limited and inflexible set of transport-facility choices available for shippers and freight forwarders, in comparison to alternative-airport choices that passengers usually have. Unlike passenger traffic, the negative and significant coefficient on *JANTEMP* indicates that warmer regions enplane less cargo traffic. The spatial distribution of the manufacturing-employment concentration supports this finding, since the highest shares of manufacturing employment are found in regions that experience colder winter seasons.

In the fixed effects estimations, the coefficient on *POP* indicates that air cargo traffic is actually proportional to population. Therefore, for a given city, a 1-to-1 relationship is expected between its population growth and enplaned cargo traffic. The results also show that a 10 percentage-point increase in *MANUF* leads to a 0.48 (0.83) percent growth in total (domestic) cargo traffic. The coefficient estimates for *MANUF* in the domestic sample is also significant (although only marginally) for the regressions using clustered standard errors (column 6). While shifting a city's labor force towards service jobs induces passenger traffic, the corresponding impact on cargo traffic lacks statistical significance when unobserved city features are controlled in the fixed effects estimations. The negative and significant *UR* coefficient, however, suggests that growth in the unemployment rate of a city reduces its domestic cargo enplanements. Although this finding only holds for domestic-cargo traffic, it is consistent with the passenger-traffic findings, and supports the notion that economically-stable urban areas generate more traffic. Further, although statistically insignificant, the sign of the coefficient on *WAGE* implies that the demand for cargo services is elastic with respect to income.

The *YOUNG* and *OLD* age-group shares also exhibit the expected negative impact on cargo traffic in the cross-sectional results. However, the positive and significant coefficient on *YOUNG* in the fixed effects estimations was not anticipated. The remaining fixed effects variable coefficients mostly exhibit the expected signs, but prevent any conclusions from being drawn due to their statistical insignificance.

2.3.4 Cargo Traffic Results — B (Service Disaggregated)

Table 2.7's cross-sectional results show that the employment share of *non-tradable* services has a stronger impact on total and domestic cargo traffic, compared to the share of *tradable* services. In contrast, recall that passenger traffic is more elastic with respect to the share of *tradable*-service employment. Thus, in view of the industries that make up the *non-tradable* service categories (particularly the trade, transport, and utilities category), the results possibly imply that air cargo enplanements are sensitive to the concentration of establishments that provide the needed transportation infrastructure and labor capacity to support goods movement. The fixed effects estimations in Table 2.7 show similar patterns observed in Table 2.6, where the shares of service employment are insignificant, and manufacturing employment emerges as an important driver of air cargo traffic.

The poor performance of the fixed effect estimations in the results summarized in Tables 2.6 and 2.7 might be explained by the underlying cargo-data problems. While the issue of unknown true originations is also shared by the data for passenger traffic, the circuitous nature of air-goods movement makes it more difficult to associate cargo traffic with geographical areas. Thus, drawing a link between metro-area socioeconomic characteristics and air cargo traffic is clearly a challenge with the segment-level traffic data that are available. The insignificant coefficient estimates obtained by using clustered standard errors for cargo traffic (in columns 3 and 6) indicate that the data gaps may be too wide, precluding robust estimations of the impact of key socioeconomic variables.

The suppressed year- and quarter-dummy coefficients are insignificant in all of the regressions related to cargo traffic. However, in the passenger-traffic regressions, the coefficients on the second and third quarter dummies are positive and significant in all of the specifications, suggesting that higher traffic levels are observed in those quarters compared to the first (excluded) quarter. The year dummies are all insignificant in the passenger-traffic regressions.

Table 2.6: Cargo Traffic (All-Cargo and Passenger-Cargo Services) — A

CARGO	Total (Domestic & International)			Domestic		
	(1) Pooled OLS	(2) Fixed Effects (FE)	(3) FE, Clust. SE	(4) Pooled OLS	(5) Fixed Effects (FE)	(6) FE, Clust. SE
INTERCEPT	-1.1635^a	-6.9841	-6.9841	-3.2895^a	-9.2589^b	-9.2589
	(17.220)	(1.561)	(0.547)	(2.779)	(2.407)	(0.783)
POP	0.8500^a	0.9996^a	0.9996	0.8470^a	1.2937^a	1.2937
	(40.328)	(2.748)	(0.884)	(46.635)	(4.455)	(1.349)
SERV	3.2279^a	0.4411	0.4411	3.9007^a	-0.0381	-0.0381
	(13.746)	(0.794)	(0.271)	(19.207)	(0.081)	(0.025)
MANUF	-2.6701^a	4.8727^a	4.8727	-2.880^a	8.2559^a	8.2559^c
	(4.963)	(3.723)	(0.926)	(6.974)	(6.535)	(1.649)
WAGE	0.0025	0.2696	0.2696	-0.0550	0.1239	0.1239
	(0.015)	(1.367)	(0.726)	(0.403)	(0.684)	(0.358)
UR	-0.0140	-0.0089	-0.0089	-0.0209^b	-0.0197^a	-0.0197
	(1.326)	(1.304)	(0.544)	(2.322)	(3.281)	(1.420)
YOUNG	-5.0586^a	6.6734^c	6.6734	-0.6773	-0.2228	-0.2228
	(4.170)	(1.712)	(0.496)	(0.606)	(0.079)	(0.023)
OLD	-8.6354^a	-11.9114^a	-11.9114	-5.2752^a	-4.5171^b	-4.5171
	(9.504)	(4.967)	(1.395)	(6.534)	(2.139)	(0.589)
FUELPRICE	0.761	0.3158	0.3158	1.5159	0.7474	0.7474
	(0.233)	(0.227)	(0.348)	(0.536)	(0.548)	(0.724)
HUB	2.3931^a			2.2485^a		
	(26.948)			(30.741)		
PROXIMITY	-1.1068^a			-0.8339^a		
	(25.565)			(22.929)		
JANTEMP	-0.0097^a			-0.0164^a		
	(4.217)			(8.633)		
Adj. R^2	0.7134	0.9541	0.9541	0.7473	0.9535	0.9535
Observations	3407	3623	3623	3375	3558	3558

Notes: *CARGO*, *POP*, *WAGE*, and *FUELPRICE* are in natural logs.
Sample is restricted to MSAs enplaning more than 1,000 tons of freight per year.
Dummies for years and quarters are suppressed.
Absolute t-statistics in parenthesis: (1), (2) based on robust standard errors; (3) based on clustered standard errors: $^a p < 0.01$; $^b p < 0.05$; $^c p < 0.10$.

Table 2.7: Cargo Traffic — B (Service Disaggregated)

CARGO	Total (Domestic & International)			Domestic		
	(1) Pooled OLS	(2) Fixed Effects (FE)	(3) FE, Clust. SE	(4) Pooled OLS	(5) Fixed Effects (FE)	(6) FE, Clust. SE
INTERCEPT	-2.5955^c	-6.491	-6.491	-5.3583^a	-10.0938^a	-10.0938
	(1.850)	(1.453)	(0.527)	(4.280)	(2.758)	(0.900)
POP	0.8824^a	0.9832^a	0.9832	0.8938^a	1.3738^a	1.3738
	(39.982)	(2.700)	(0.885)	(48.729)	(4.944)	(1.490)
PIF	1.4425^a	1.3736	1.3736	1.3082^a	-0.1388	-0.1388
	(3.189)	(1.374)	(0.463)	(3.111)	(0.154)	(0.048)
TLE	3.9698^a	0.0487	0.0487	4.9713^a	0.3066	0.3066
	(11.086)	(0.069)	(0.030)	(15.199)	(0.524)	(0.200)
MANUF	-2.4601^a	5.0194^a	5.0194	-2.5759^a	8.1948^a	8.1948
	(4.612)	(3.741)	(0.935)	(6.265)	(6.360)	(1.596)
WAGE	0.1992	0.2325	0.2325	0.2293	0.0983	0.0983
	(1.164)	(1.181)	(0.625)	(1.560)	(0.545)	(0.284)
UR	-0.0203^c	-0.0068	-0.0068	-0.0299^a	-0.0210^a	-0.021
	(1.917)	(0.934)	(0.387)	(3.296)	(3.209)	(1.326)
YOUNG	-5.5432^a	6.6401^c	6.6401	-0.0166	-0.4613	-0.4613
	(4.601)	(1.703)	(0.494)	(0.015)	(0.164)	(0.048)
OLD	-9.2891^a	-12.3669^a	-12.3669	-6.2249^a	-5.2912^b	-5.2912
	(9.989)	(5.121)	(1.445)	(7.516)	(2.502)	(0.685)
FUELPRICE	0.6193	0.3456	0.3456	1.3167	0.738	0.738
	(0.190)	(0.249)	(0.385)	(0.468)	(0.543)	(0.731)
HUB	2.3398^a			2.1708^a		
	(26.622)			(29.472)		
PROXIMITY	-1.0394^a			-0.8669^a		
	(26.479)			(24.171)		
JANTEMP	-0.0080^a			-0.0139^a		
	(3.473)			(7.234)		
Adj. R^2	0.7149	0.9543	0.9543	0.7513	0.9536	0.9536
Observations	3407	3633	3633	3375	3568	3568

Notes: *CARGO*, *POP*, *WAGE*, and *FUELPRICE* are in natural logs.
Sample is restricted to MSAs enplaning more than 1,000 tons of freight per year.
Dummies for years and quarters are suppressed.
Absolute t-statistics in parenthesis: (1), (2) based on robust standard errors; (3) based on clustered standard errors: $^a p < 0.01$; $^b p < 0.05$; $^c p < 0.10$.

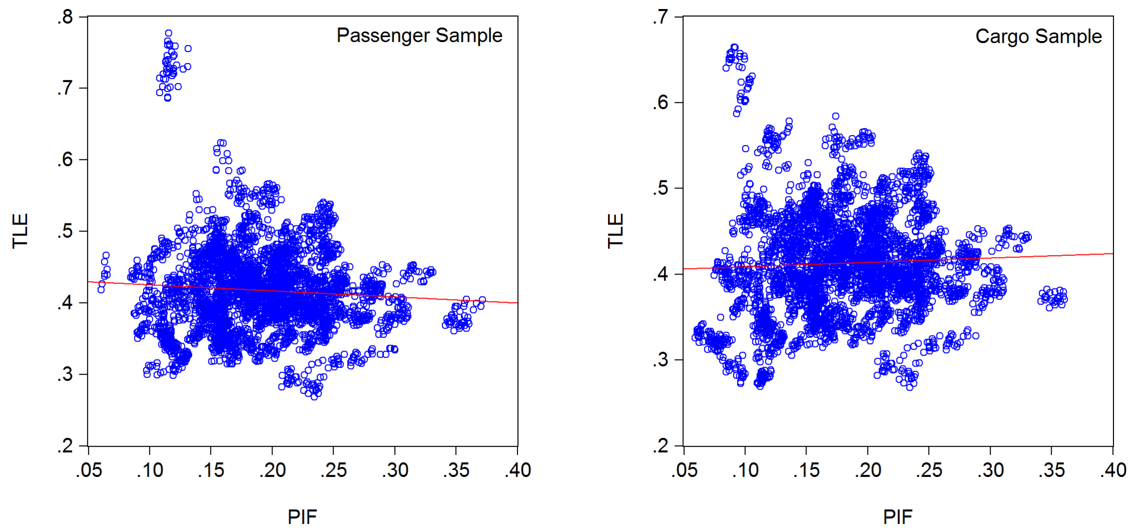
2.3.5 Multicollinearity

Total passenger traffic appears to increase less than proportionally to *POP* in the cross sectional analysis (column 1 of 2.4), but only because *SERV* also increases with *POP*; when *SERV* is removed from the specification, traffic is actually proportional to *POP*.[4] Therefore, the *POP* coefficient is less than unity in the cross sectional results due to *multicollinearity* with the *SERV* measure. This finding only holds for total passenger traffic, however. In the cross sectional analysis, the remaining traffic measures (Domestic Passenger, Total Cargo, and Domestic Cargo) all increase less than proportionally to *POP*, even when *SERV* is removed from their respective specifications. Therefore, when multicollinearity is controlled, most of the cross sectional analysis results remain unchanged. The proportional relationship that is found between total passenger traffic and population, however, is consistent with equivalent fixed effects estimation result (where the identifying variation comes from within-city changes over time).

Multicollinearity is concerning in the disaggregated service specifications, where a correlation between tradable (*PIF*) and non-tradable (*TLE*) service employment shares may be suspected. The plots shown in Figure 2.5, however, demonstrate that the correlation between these two groups is minimal in both passenger and cargo samples. Even so, the disaggregated service regressions were run with only one of these service measures, as well as with *MANUF* removed. The results in these test regressions indicate that the estimated coefficients for *PIF* and *TLE* are robust to varying specifications, abating the multicollinearity concerns.

[4] *MANUF* exhibits no correlation with *POP*. See Appendix for scatter plots showing the relationship between *POP*, *SERV*, and *MANUF*.

Figure 2.5: Tradable (PIF) versus Non-tradable (TLE) Employment Shares



2.4 Conclusion

While the variation of socioeconomic factors across U.S. cities has been used to understand demand for passenger and cargo air traffic, this study, using a fixed effects specification, provides the first evidence showing how changes in population, employment structure, and income affect airport traffic. Despite the considerable restructuring that the airline industry has endured since deregulation, including significant advancements in technology and the events of September 11, 2001, the impact of metro-area population and employment-structure on airport passenger enplanements mostly remain unchanged.

Consistent with past findings on the regulated industry, city size is found to have a nearly proportional relationship with air traffic. While *white collar* employment remains an important determinant of the demand for air travel, the income-elasticity of passenger traffic appears to be attenuated. Contrary to cross-sectional findings, as well as traditional views, the city fixed effects estimations of this study show that employment growth in *non-tradable services* has a larger impact on passenger traffic, compared to growth in *tradable* services. These findings are reversed for air cargo traffic, where *tradable* (*non-tradable*) services exhibit a stronger influence on demand in the cross-sectional (fixed effects) analysis. However, the qualitative results showing the impact of sectoral employment on air cargo traffic render statistical significance only in the cross-sectional analyses, where city-specific differences are not controlled. Taken together, the results suggest that employment concentration in *non-tradable* service jobs (presumably those related to leisure, hospitality, trade, transport, and utilities) have substantial impact on airport traffic.

In summary, both passenger and cargo traffic are found to grow proportionally with metro-area population, while a shift that increases the share of service (manufacturing) employment in a city has considerable impact on passenger (cargo) traffic. The statistical significance of the results show that city-level socioeconomic effects on passenger traffic are robust to specifications that allow for heteroscedasticity and autocorrelation in the error structure. However, most of the corresponding results for air cargo traffic do not pass the error-structure robustness checks. A worthy challenge for future research is to repeat the present exercise with more accurate data on cargo movement.

Chapter 3

Determinants of Air Cargo Traffic in California

3.1 Introduction

The air cargo industry is seldom brought up in the literature without mention of its remarkable growth and its importance to global trade and commerce. The rapid maturation of air cargo markets in the 1990's led industry analysts to project an average 5-percent annual growth in domestic air cargo traffic between 1998 and 2017 (FAA [43]; Boeing [14]).[1] This pace of growth also instilled great concern in California's policy makers and airport planners, seeing that four of California's international hubs, Los Angeles (LAX); Metropolitan Oakland (OAK); San Francisco (SFO); Ontario (ONT), rank amongst the country's top sixteen airports in handling cargo tonnage.[2] Regional and state-wide studies have mostly been inter-

[1]The FAA's March 2000 long-range forecasts [43] anticipated air-freight *revenue ton miles* to increase from 26.6 million to 36.5 million by 2005, and to 48.4 million by 2010.

[2]Ranks are based on our calculation of airport shares of all outbound cargo from airports in the United States. For the years 2003-2009, national ranks of the four airports are as follows: (4) LAX; (12) SFO; (13) OAK; (16) ONT. Data source: *Bureau of Transportation Statistic (BTS), T-100 Segment tables.*

ested in assessing the impacts of increased air cargo traffic on the state's economy and, more immediately, on the capacity constraints faced by airports that already handle high volumes of cargo (TranSystems [87]; Tsao [88]; BAEF [5]; BAEF [6]; Erie, Mckenzie, MacKenzie, and Shaler [42]).[3] While the expansion of air cargo transportation initiated numerous studies on the role of goods movement by air, current numbers show that the growth of air cargo traffic in California has slowed down markedly over the 2000-2009 period (TranSystems [87]). The slowing of both outbound and inbound air cargo traffic is especially revealed at California's major airports.

California's air cargo demand was comprehensively explored by a TranSystems report [87] prepared for the state's Department of Transportation (*Caltrans*). The report underscored the industrial, demographic, and geographical diversity of California's economic zones, advising transportation planners to attune their air cargo demand forecasts to changes in the unique economies of the regions served by the state's airports. Therefore, a valuable aggregative question that arises is how the total air cargo traffic at airports in California is affected by the characteristics of the corresponding metropolitan economies.

At the national scale, Brueckner [18] examined the effect of metro-level socioeconomic and demographic factors on air-passenger transport, using data for 1970 (eight years prior to the deregulation of the airline industry). Alkaabi and Debbage [2] attempted to find specific employment, establishment, and wage variables that explain the geographic distribution of air freight in 2003. More recently, Button and Yuan [29] addressed the issue of causality between air freight transportation and regional economic development. Our research aims to extend the foundational work of these studies while addressing the research needs, as highlighted by the TranSystems [87] report, for understanding how regional economies impact air cargo traffic in California. Hence, this paper will examine the socioeconomic determinants of out-

[3] Economic reports published in 2000 by the Bay Area Economic Forum (*Air Transport and the Bay Area Economy-Phase 1 and 2*) [6, 42] expected air cargo volume at *SFO*, *OAK*, and *SJC* to grow an annual average of 6 percent, between 2000 and 2020.

bound total and domestic air cargo traffic for a sample of 22 airports across 15 metropolitan areas in California, using seven years of quarterly data (2003-2009). Based on the key-traffic determinants identified in this study, and using county-level economic forecasts prepared for *Caltrans* as input data, we give insights into the expected short- and long-term growth in the state's cargo tonnage.

Consistent with the past literature, we find empirical evidence confirming a direct relationship between metropolitan socioeconomic factors and air transport. Specifically, we show manufacturing and service-related employment have a considerable impact on air cargo traffic. Despite the sharp fall of high-technology manufacturing employment, subsequent to the collapse of the *internet bubble* in 2000, California's manufacturing firms are believed to still be important drivers of traffic. The role that other employment areas play in determining air cargo demand is also expected to be nontrivial, although not as clear *a priori*. Our results demonstrate that, analogous to the passenger-air travel literature, metropolitan characteristics such as city size, income, age distribution, and hub operations have a sizeable impact on air cargo traffic. These findings can be used to inform policies related to airport expansion, and to gain some understanding of the demand and spatial distribution of air cargo in California. We also provide metro-level traffic forecasts for the 2010-2040 period, which indicate that California's volume of total (domestic) air cargo will grow at an average rate of 5.9 percent (4.4 percent) per year.

3.2 Background

The air cargo industry has markedly expanded since its deregulation in 1977.[4] Although the regulatory reforms affecting air freighters set a precedent for the imminent deregulation of passenger airlines, the air cargo industry has not received its deserved attention in the literature (Bailey [7]; Carron [30]). The relatively small modal share of cargo tons that are flown by airlines and the sparse nature of the data on air cargo operations have left the economic impact of air cargo transportation mostly overlooked in earlier studies. Shortly after Tsao's [88] report on California's air-goods movement brought attention to the paucity of air cargo studies for the state, several research reports unequivocally corroborated the value of air cargo to California's economy and international trade (BAEF [5]; Hansen, Gosling, and Rice [49]; Erie et al. [42]; SCAG [79]). These reports have drawn more attention to the importance of air cargo transportation in California as researchers also consider the value-to-weight ratio of transported goods to capture the economic impact of air cargo operations (TranSystems [87]).

Although Tsao [88] outlined the many research gaps in understanding the role of air cargo in California's goods movement, the authors of the TranSystems [87] report point to the fact that the existing literature, albeit thin, has addressed the effects of air freight on California's economy. The TranSystems report cited works as early as the 1988 *California State World Trade Commission* study, which was first to note that more than half of the state's export-trade goods, measured by value, are transported by air. Therefore, it has long been recognized that air cargo plays a key role in California's export economy.

[4] The difference between *air cargo* and *air freight* should be distinguished as they are sometimes used interchangeably in the literature. According to the *Airport Council International* (*ACI*), air cargo is defined as the sum of freight, mail, and passenger baggage revenue tons. This definition is consistent with the *U.S. Department of Transportation*'s and *Government Printing Office*'s description of air freight as only being property (excluding express, mail and passenger baggage) that is transported by air.

By transporting high-value goods, air cargo accounts for a significant share of the value of California's commodity exports. *The Boeing Company's World Air Cargo Forecast 2012-2013* (Boeing [15]) estimates that goods transported by air are generally worth more than $7.26 per pound ($16 per kilogram). According to the *Foreign Trade Division* of the U.S. Census Bureau statistics prepared by *WISER*Trade, goods flown by air between 1998 and 2008 accounted for just over half of the state's $1.240 trillion export of commodities (TranSystems [87]). Commodities transported by air, depending on city-pair markets, include express shipments, small packages, electronics (computers, telecommunication equipment, and machinery), pharmaceutical products, specialized equipment, and perishables (Boeing [15]). Therefore, California's international airports are pivotal in connecting the state's manufacturing and service-related businesses to markets overseas, particularly those in the *Pacific Rim* countries.

International trade and air cargo operations are facilitated by multilateral agreements, which relax constraints on route designations, service frequencies, and pricing. These arrangements came about during the air cargo liberalization period of the 1990's, which enhanced bilateral treaties through agreements such as *Open skies* (Zhang and Zhang [89]). Zhang and Zhang [89] addressed matters related to liberalization of air cargo services by giving a general overview of approaches to liberalization and by outlining the U.S. *Open skies* initiatives with their resulting liberalization movements in bilateral and multilateral air-service agreements. The authors also discussed the underlying issues of jointly liberalizing agreements for passenger and cargo services. Zhang and Zhang [90] developed a multi-market oligopoly model for air cargo liberalization to understand how *all-cargo* and mixed *passenger-cargo* carriers compete.

The aforementioned studies on the impact of air traffic on California's economy mirror the inclination of the national-level research, especially with regard to passenger airlines. Studies have drawn connections between passenger-airline service and employment in metropolitan areas (Oster, Rubin, and Strong [71]; Button and Taylor [28]; Debbage and Delk [39]; Brueckner [19]; Alkaabi and Debbage [1]; Green [47]), suggesting that growth in air traffic is associated with the economic development of metro areas. Brueckner [19], Green [47], and Sheard [82] show that growing passenger numbers at an airport stimulate service-related employment in the corresponding metropolitan area. Their findings can be used to evaluate the effects of airport expansion on urban economic development.

The purpose of the present study is to measure the effect of a city's socioeconomic variables on aggregate air cargo traffic at metropolitan areas in California. In addition to identifying the baseline-socioeconomic features of cities that influence air cargo volume, this study will also address the traffic impact of city-level employment composition. While a similar examination of all U.S. cities would be useful, and more generalizable, the size and unique economic characteristics of California suggest that a state-level analysis is also appropriate.[5] Further, successful air cargo operations must maintain a balance between outbound and inbound loads, even while the transported products are significantly different. California provides a sufficiently-large market for carriers to comfortably meet this condition.[6]

3.3 Data and Empirical Framework

By associating airports to their corresponding metro areas, we can assess the impact of urban-socioeconomic factors on outbound air cargo traffic (total and domestic) across cities in California. Hence, the dependent variable for our model is the total cargo tons (freight and mail) that is flown from airports in chosen metro areas. The cargo tons carried by aircraft operating at the airports in our sample are obtained from the U.S. Department of Transportation's (DOT) *Form 41 Traffic T-100 Segment* tables [24], which can be found on the Bureau of Transportation Statistics (BTS) website. Freight and mail volumes are

[5]See Lakew [56] and Alkaabi and Debbage [2] for national-level studies of air cargo traffic determinants.

[6]We thank an unnamed conference proceeding referee for this insight.

aggregated to the metro-area level by carrier-service type (*all-cargo and passenger-cargo*). Using these data, we constructed a panel that has metropolitan-area cross-sections and quarter periods, over 7 years (2003 to 2009). Since the largest integrator, FedEx Express, did not report complete data on its freight volumes to the DOT until Quarter 4 of 2002, our sample begins in Quarter 1 of 2003. FedEx Express also does not sufficiently differentiate between freight, express freight, and mail in the data (*Form 41 Traffic*) [87]. Accordingly, we analyze the two outputs of the industry (freight and mail) together as *cargo*.

Our metro-area definitions are based on the 2009 metropolitan and micropolitan statistical area (MSA) delineations created by the U.S. Office of Management and Budget (OMB). Under the umbrella of Core Based Statistical Areas (CBSA), metro areas correspond to urban regions containing more than 50,000 people, while micro areas contain between 10,000 and 50,000 people. This level of aggregation is chosen for our study's socioeconomic variables, as well as most of the aforementioned studies, since the inherent geographical definition of the areas is based on a consolidation of counties that contain the core-urban population and maintain high levels of socioeconomic interactions (Census [34]).

We then classified the cargo-airport cities in our base sample analogously to the Federal Aviation Administration's (FAA) passenger primary-airport classification. The FAA maintains a 10,000-passenger enplanement cutoff for separating primary airports from the smaller non-primary airports. Similarly, we restricted our sample to cities that depart more than 50 U.S. tons (100,000 lbs.) of freight annually (consistent with cutoff used by Alkaabi and Debbage [2]). This cutoff eliminates noisy data that may arise from including cities that account for insubstantial amounts of freight traffic. Hence, our sample is restricted to approximately 22 primary airports, contained in 15 MSAs across California. The exact number of MSAs in our sample varies over the periods and regression specifications of our study. The airports and MSAs represented in our study are summarized in Table 3.1.

Table 3.1: MSA Average Outbound Air Cargo Tonnage (US Tons/Year)

MSA	*Total Cargo*	*Domestic Cargo*	*Airport Name*	*Airport Code*
Los Angeles-Long Beach-Santa Ana	1,026,196 (77,281)	577,232 (71,793)	Los Angeles Intl.	*LAX**
			Long Beach	*LGB*
			Burbank Bob Hope	*BUR*
			John Wayne	*SNA*
San Francisco-Oakland-Fremont	729,539 (84,322)	507,246 (58,179)	Oakland Intl.	*OAK**
			San Francisco Intl.	*SFO*
Riverside-San Bernardino-Ontario	279,512 (21,253)	276,180 (20,009)	LA/Ontario Intl.	*ONT**
			Palm Springs Intl.	*PSP*
San Diego-Carlsbad-San Marcos	75,187 (4,589)	74,302 (4,439)	San Diego Intl.	*SAN*
Sacramento-Arden-Arcade-Roseville	73,748 (6,249)	73,199 (6,221)	Sacramento Mather	*MHR*
			Sacramento Intl.	*SMF*
San Jose-Sunnyvale-Santa Clara	50,091 (8,410)	48,537 (7,258)	San Jose Intl.	*SJC*
Fresno	8,097 (4,271)	8,097 (4,271)	Fresno Yosemite Intl.	*FAT*
Stockton†	3,788 (3,524)	3,788 (3,524)	Stockton Mtp.	*SCK*
Santa Barbara-Santa Maria-Goleta†	2,239 (160)	2,226 (161)	Santa Barbara	*SBA*
			Santa Maria Pub.	*SMX*
El Centro	790 (130)	790 (130)	Imperial County	*IPL*
Bakersfield	594 (85)	594 (85)	Meadows Field	*BFL*
			Inyokern	*IYK*
Santa Rosa-Petaluma	507 (35)	507 (35)	Sonoma County	*STS*
Redding	504 (37)	504 (37)	Redding Mun.	*RDD*
San Luis Obispo-Paso Robles	412 (41)	412 (41)	San Luis Obispo County Reg.	*SBP*
Visalia-Porterville	385 (25)	385 (25)	Visalia Mun.	*VIS*
Chico	345 (75)	345 (75)	Chico Mun.	*CIC*
Salinas	230 (44)	230 (44)	Monterey Reg.	*MRY*

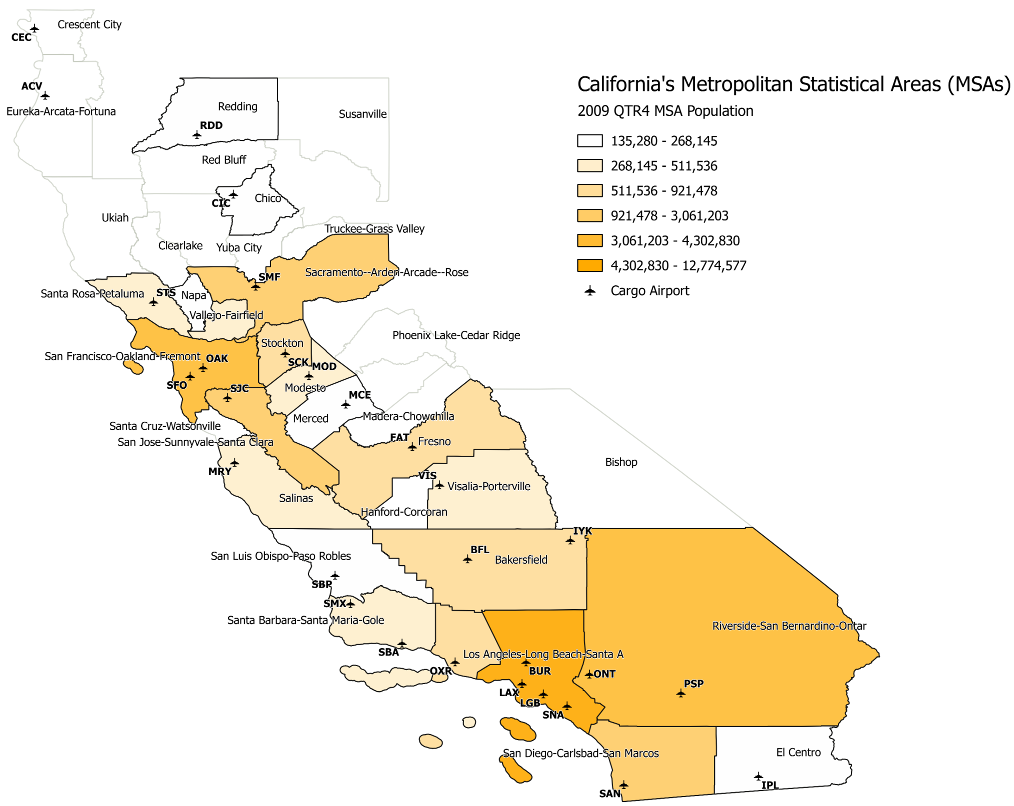
Notes: Annual mean values for total outbound cargo (freight and mail) tons (2003-2009). Standard deviations are shown in parentheses. Only data for MSAs handling over 50 US tons of freight/year are used in our calculations.

† MSA dropped from sample due to lack of complete data.

* Cargo hubs for the integrators, FedEx Express and UPS Airlines.

Figure 3.1 illustrates the geographical distribution of California's population (in 2009) and cargo airports.[7] 15 of the 26 California MSAs are included in our sample.

Figure 3.1: Cargo airports and MSA Population of California (2009)



Industry-specific socioeconomic variables on employment, number of establishments, and average weekly wages are collected from the U.S. Department of Labor's Bureau of Labor Statistics (BLS) *Quarterly Census of Employment and Wages* (*QCEW*) [12], at the MSA level. The data were organized into high-level groups, *Goods-producing* and *Service-providing*, from which we select the following employment categories to calculate industry-

[7]The map in this figure (as well as the subsequent ones) are designed using the U.S. Census Bureau's *TIGER/Line® shapefiles* [32]. The socioeconomic, demographic, and traffic data are obtained from the BLS *QCEW* databank [12], U.S. Census Bureau *Intercensal Estimates 2000-2010* [33], and the BTS *T-100 Segment* tables [24], respectively. Airport-specific coordinate and spatial information are obtained from the 2012 BTS *National Transportation Atlas Database* (*NTAD*) files [22].

sector level shares:[8] Manufacturing (31-33) and Service-related. The Service-related category used for this study comprises of Professional and Business (54-56), Information (51), Financial activities (52, 53), Education and Health (61, 62), Leisure and Hospitality (71, 72), and Trade-Transportation-Utilities (22, 42, 44, 45, 48, 49) employment. The remaining (excluded) employment categories are Natural Resources and Mining (11, 21) and Construction (23), Public Administration (92), Other services (81), and Unclassified (99). We supplemented this data with *QCEW*'s statistics on average weekly wages (for all industries) to control for income variation across MSAs.[9]

Population has been used to capture city-market size in previous studies, and has exhibited an important role in determining both cargo and passenger traffic. Brueckner [18] found a significant 0.95 point estimate for the elasticity of passenger travel with respect to a city's population. We expect a similar, if not stronger, relationship to hold between MSA population and air cargo traffic. Thus, we also included population data, provided by the U.S. Census Bureau's *Intercensal Estimates 2000-2010* (Census [33]), at the MSA level.

3.3.1 Empirical Model

In view of shipping rates (price) being jointly determined with the level of air cargo traffic, we specify a reduced-form equation that treats price endogenously (Brueckner [18]):

$$T_{it} = \alpha + \beta E_{it} + \gamma X_{it} + \sum \delta_i D_i + \tau_t + \varepsilon_{it}, \tag{3.1}$$

where T_{it} represents the total (domestic) outbound-cargo traffic for a metro area i in quarter t; α is the intercept; E_{it} denotes the shares of manufacturing and service employment;

[8] 2-digit North American Industry Classification System (*NACIS*) codes are shown in parentheses.
[9] See Appendix for more dissagregated industry groups.

X_{it} is a vector of exogenous-control variables (population, average weekly wage, and population shares by age); D_i indicates MSA dummy variables that affect cargo traffic (to be discussed);[10] τ_t denotes the quarterly-time trend variable, and ε_{it} is the error term. The time-trend variable is included to control for unobserved features that vary quarterly but are constant across MSAs. A separate model is specified, using quarter and year dummy variables, to better identify the time effects in the sample period. The results, which are shown in the Appendix, can be compared to the model specified in Equation 3.1.

The variables in Equation 3.1 were chosen bearing in mind that the demand for goods being transported between cities depends on the nature of active industries at both the origin and destination MSAs. Cities with a high share of businesses that manufacture goods will likely favor using air cargo services more than cities that are not driven by production activities. Air transport generally facilitates the movement of time-sensitive finished products to wholesale markets, retail vendors, and the end-users; however, manufacturers may also use air cargo services in their supply chain to transport inputs for products they are developing. On the consumption side, service-providing industries (financial and legal firms, medical establishments, information technology, and pharmaceutical companies, etc.) are expected to rely heavily on the expedited and door-to-door delivery services guaranteed by express forwarders and integrators to maintain their competitiveness.

Considering that the age distribution of an MSA's population will determine the city's labor structure (Brueckner [19]), and ultimately demand for cargo traffic, variables that measure the share of the population that is not in the work force are included in X_{it}. *YOUNG* measures the population share of the 19-and-younger age group, while *OLD* measure the population share of the 60-and-older age group. By selecting these population share variables, we effectively excluded the age group of the MSA's population that is predominantly in the

[10] Lakew's [56] national-scale study includes an MSA-specific intercept (fixed effects) in a similar reduced-form specification. The study's fixed effects estimations control for unobserved city-specific differences that are constant over time.

work force (ages 20-59). Hence, we expect larger shares of *YOUNG* and *OLD* to have a depressing effect on air cargo traffic. The remaining control variables in our study are explained in the following paragraphs.

The *T-100 Segment* data on freight and mail volumes is reported at the segment level, precluding us from using the data to discern cargo volumes that are truly originating from (destined to) airports.[11] To get around this challenge, we can take Brueckner's [18] approach and restrict our sample to airports that do not serve as hubs in California. However, such airports can also be found within the same MSA as the hub airports themselves, and excluding them would seriously restrict our sample and ability to generate robust point estimates. Therefore, rather than dropping the hub airports, we created hub-dummy variables that are scaled by the number of airports in the hub city (Brueckner [19]). If a city has at least one hub airport, the indicator equals 1. If this city has other non-hub airports (in addition to at least one hub airport), the variable is set equal to the fraction of non-hub airports that are in that city. Specifically, for the Los Angeles-Long Beach-Santa Ana MSA, the hub variable is set equal to 1/2 since *LAX*, which serves as a metro hub for FedEx Express,[12] is amongst three other important cargo airports in the MSA (*BUR*, *LGB*, and *SNA*). For the San Francisco-Oakland-Fremont MSA, the hub variable is set equal to 1/2 since the MSA is served by *SFO* and *OAK* (a regional hub for FedEx Express). Even though *SFO* is not an integrated carrier's sorting hub, it serves as a transfer point for connecting traffic between international and domestic flights. Lastly, we set the hub dummy equal to 1/2 for the Riverside-San Bernardino-Ontario MSA to account for UPS Airlines' hub operations at

[11] The *BTS T-100 Market* data are structured to indicate the true origin and destination of transported cargo (freight and mail) between market cities. Although these market-level data would be preferred, the data are flight-number driven, and may be erroneous when flight numbers change at connecting airports. A flight-number change will show that transferring cargo, for example, is destined to (then originating from) the connecting airport. Therefore, we decided to use the more consistently reported volumes of departed (landed) cargo data that the *T-100 Segment* tables provide.

[12] Our calculations show that FedEx Express accounted for around 21 percent of all departed cargo at *LAX* while also accounting for nearly 17 percent of all landed cargo at the airport, between 2003 and 2009. FedEx Express maintains a large presence in Los Angeles, operating the *Metroplex* sorting and warehouse facilities at *LAX*.

ONT. Although the traffic levels are not substantial, this MSA is also served seasonally by *PSP*. *ONT* serves as a pure hub for regional traffic; parcels coming from (going to) beyond the region are sorted at *ONT* and ultimately flown through UPS Airlines' main hub (*SDF*) in Louisville, Kentucky (TranSystems [87]).[13] Therefore, the hub variable is designed to account for the fact that the majority of the observed traffic at a hub city is connecting, such that the total cargo is much larger than can be explained by the characteristics of that city. In all areas with multiple airports, cargo tons are summed across the relevant airports.

Alkaabi and Debbage [2] showed that traffic is diverted from small MSAs to larger ones through a *traffic shadow* effect. This issue was addressed by Brueckner [18, 19] for passenger traffic, hypothesizing that travelers located in small metro areas would prefer driving or taking a bus to a large airport nearby. By providing better network services, frequent flights, and lower fares, large airports are generally attractive to passengers. We can expect that air cargo forwarders would also prefer to transport goods from large airports for similar reasons. Because the connectivity and specialized cargo services offered by large airports are desirable for goods movement, air cargo traffic may be depressed at smaller airports nearby. To address this traffic-diversion effect, we took a similar approach to Brueckner [19] and Alkaabi and Debbage [2], using a dummy variable to indicate that a small metro area is in the vicinity of a large one. Our *PROXIMITY* dummy variable is set equal to 1 if the smallest airport in a small MSA (an MSA that generates less than 15,000 US tons of freight annually) is less than 100 miles away from the largest airport in a large MSA (an MSA that generates more than 175,000 US tons of freight annually).[14] The 100-mile cutoff was chosen to allow for consistent comparisons of our findings with the results of the

[13] FedEx Express and UPS Airlines are integrators that provide all-inclusive transportation of cargo from origin to destination, taking on the role of a shipper, forwarder, and carrier. To provide such *door-to-door* services, under very stringent time constraints, integrators also operate a large fleet of trucks and vans.

[14] The small- and large-MSA cutoffs were determined by using a *k-means clustering* methodology. This methodology separates the MSAs into a chosen number of cluster groups (4) by locating a significant break in their outbound-freight volume. Small and large MSAs were separated by choosing the mean and maximum values of the smallest cluster group (out of 4 groups), respectively. The smallest (largest) airport in an MSA was then chosen as the airport that enplanes the lowest (highest) levels of that MSA's annual-freight traffic.

relevant literature (Alkaabi and Debbage [2]). By including the *PROXIMITY* indicator variable, we can capture the tendency for cargo traffic to understate locally-generated traffic at small MSAs that are located near large ones. Given that the traffic levels change at airports over time, the proximity indicator may also change values accordingly. We expect that *PROXIMITY* will be inversely related to the cargo generated by a small MSA.

3.4 Results and Discussion

Tables 3.2 and 3.3 provide definitions and descriptive statistics for the variables used in the regression analysis.

3.4.1 Estimation Results

Table 3.4 exhibits the estimation results for the linear-regression analysis we used to assess the impact of socioeconomic characteristics on air cargo traffic in California.[15] The dependent variables for the regressions are *ACTRAFFIC* (MSA cargo tons transported by *all-cargo* services) and *TRAFFIC* (MSA cargo tons transported by *all-cargo* and *passenger-cargo* services). Although passenger carriers transport a smaller fraction of the total air cargo tons in most markets, they still play a considerable role at gateway markets in California. Based on our calculations, passenger carriers that transport cargo in their belly holds (or as *Combi* aircraft), accounted for around 7 percent of all departed cargo tons in our sample MSAs, over the 2003-2009 period. Therefore, we considered the cargo tons carried by passenger airlines as part of the total traffic departing from (landing at) MSA airports in our sample.

[15] See Appendix for the corresponding results with year and quarter dummy variables. The results in the Appendix closely resemble the results with a trend variable, shown in Table 3.4.

Table 3.2: Variable Definitions

Variable	Definition
TRAFFIC (- DOM)	Total (Domestic) MSA outbound cargo tons departed by *all-cargo* and *passenger-cargo* services
ACTRAFFIC (- DOM)	Total (Domestic) MSA outbound cargo tons departed by *all-cargo* services only
POP	Total MSA population
WAGE	Average weekly wages (real) across all industries at MSA (2003Q1 dollars)
Employment Shares	
SERV	Share of service-related employment at MSA
MANUF	Share of manufacturing-related employment at MSA
Population Shares	
YOUNG	Share of MSA population of age 19 and younger
OLD	Share of MSA population of age 60 and older
Dummy Variables	
CAP	Dummy variable equal to 1 for capital-city MSA (Sacramento-Arden-Arcade-Roseville, CA)
HUB	Scaled dummy equal to 1/2, 1/2, 1/4 for hub cities of *ONT*, *OAK*, and *LAX*, respectively
PROXIMITY (*PRXM*)	Dummy variable equal to 1 for small MSA within 100 miles of a large MSA
TREND	Linear-time trend from 2003Q1 to 2009Q4
QTR 2,3,4	Dummy variable equal to 1 for corresponding quarter of the calendar year (2,3, or 4)
YEAR	Dummy variable equal to 1 for corresponding calendar year (2004-2009)

Notes: Quarterly measures used for variables (annual measures for *POP*, *YOUNG*, *OLD*, and *HUB*).

Table 3.3: Variable Summary Statistics

MSA	*POP*	*WAGE*	*SERV*	*MANUF*	*YOUNG*	*OLD*	*HUB*	*PRXM*
Los Angeles-Long	12,703,921	841.72	0.663	0.114	0.288	0.143	0.25	0.00
Beach-Santa Ana	(43,806)	(46.40)	(0.010)	(0.008)	(0.007)	(0.006)	(0.00)	(0.00)
San Francisco-	4,185,192	1,058.78	0.680	0.069	0.242	0.168	0.50	0.00
Oakland-Fremont	(60,959)	(63.10)	(0.008)	(0.003)	(0.002)	(0.007)	(0.00)	(0.00)
Riverside-San	3,939,582	635.56	0.591	0.092	0.332	0.138	0.50	0.00
Bernardino-Ontario	(188,220)	(17.12)	(0.021)	(0.010)	(0.004)	(0.004)	(0.00)	(0.00)
San Diego-Carlsbad-	2,969,919	795.88	0.639	0.080	0.274	0.151	0.00	0.00
San Marcos	(50,538)	(31.57)	(0.009)	(0.003)	(0.004)	(0.005)	(0.00)	(0.00)
Sacramento-Arden-	2,056,446	778.19	0.563	0.048	0.288	0.157	0.00	0.00
Arcade-Roseville	(53,463)	(24.96)	(0.011)	(0.006)	(0.004)	(0.007)	(0.00)	(0.00)
San Jose-Sunnyvale-	1,756,136	1,312.06	0.623	0.191	0.270	0.145	0.00	0.00
Santa Clara	(37,124)	(74.15)	(0.016)	(0.009)	(0.001)	(0.006)	(0.00)	(0.00)
Fresno	884,514	587.58	0.494	0.078	0.340	0.134	0.00	0.00
	(24,955)	(26.31)	(0.015)	(0.003)	(0.003)	(0.004)	(0.00)	(0.00)
El Centro	160,340	542.61	0.379	0.045	0.332	0.138	0.00	0.00
	(7,924)	(18.74)	(0.014)	(0.003)	(0.003)	(0.003)	(0.00)	(0.00)
Bakersfield	778,221	634.71	0.452	0.048	0.341	0.126	0.00	1.00
	(40,597)	(25.66)	(0.010)	(0.002)	(0.002)	(0.002)	(0.00)	(0.00)
Santa Rosa-	469,193	718.08	0.595	0.122	0.258	0.182	0.00	1.00
Petaluma	(4,929)	(25.72)	(0.012)	(0.009)	(0.004)	(0.012)	(0.00)	(0.00)
Redding	175,846	581.88	0.626	0.043	0.266	0.216	0.00	0.00
	(1,367)	(21.54)	(0.011)	(0.002)	(0.007)	(0.009)	(0.00)	(0.00)
San Luis Obispo-	261,129	616.65	0.593	0.060	0.245	0.196	0.00	0.00
Paso Robles	(4,651)	(26.76)	(0.009)	(0.004)	(0.006)	(0.009)	(0.00)	(0.00)
Visalia-Porterville	414,039	520.16	0.401	0.081	0.363	0.130	0.00	0.70
	(16,111)	(19.26)	(0.014)	(0.003)	(0.001)	(0.002)	(0.00)	(0.46)
Chico	216,057	552.4	0.603	0.053	0.263	0.201	0.00	1.00
	(2,903)	(22.81)	(0.006)	(0.006)	(0.005)	(0.007)	(0.00)	(0.00)
Salinas	406,298	656.62	0.460	0.038	0.304	0.142	0.00	1.00
	(3,224)	(28.19)	(0.029)	(0.005)	(0.003)	(0.006)	(0.00)	(0.00)

Notes: Quarterly means reported (annual means for *POP*, *YOUNG*, *OLD*, and *HUB*), 2003-2009. Standard deviations are in parentheses.

Table 3.4: Regression results (420 obs.)

	Total (Domestic & International)		Domestic (*—DOM*)	
	(1) ACTRAFFIC	*(2) TRAFFIC*	*(3) ACTRAFFIC*	*(4) TRAFFIC*
INTERCEPT	-11.909^a (3.771)	-15.893^a (4.812)	-8.291^a (2.669)	-11.781^a (3.671)
POP	0.979^a (10.061)	1.169^a (11.761)	0.709^a (7.134)	0.880^a (8.897)
SERV	7.539^a (4.234)	5.840^a (3.240)	10.463^a (5.803)	9.054^a (1.803)
MANUF	1.765^b (2.193)	0.894 (1.086)	2.435^a (2.902)	1.600^c (1.905)
WAGE	0.640^a (2.552)	0.883^a (3.374)	0.524^b (2.114)	0.717^a (2.810)
YOUNG	0.939 (0.374)	1.018 (0.697)	2.039 (0.822)	2.237 (0.875)
OLD	-19.253^a (3.603)	-12.879^b (2.367)	-27.750^a (5.077)	-22.133^a (4.036)
CAP	1.555^a (13.884)	1.338^a (11.883)	1.886^a (16.585)	1.703^a (15.283)
HUB	3.911^a (23.465)	3.660^a (21.542)	4.031^a (22.590)	3.770^a (21.663)
PROXIMITY	-1.556^a (19.608)	-1.595^a (19.424)	-1.553^a (20.038)	-1.589^a (19.991)
TREND	0.002 (0.706)	-0.004 (0.442)	0.007 (1.554)	0.002 (0.494)
Adj. R^2	0.967	0.968	0.965	0.966

Notes: The dependent variables, *POP*, and *WAGE* are in natural logs.
Absolute t-statistics in parentheses, based on robust standard errors: $^a p < 0.01$; $^b p < 0.05$; $^c p < 0.10$.

Table 3.4 shows the coefficient estimates for total (domestic and international) and domestic cargo traffic, separately. The coefficients on *POP* in *(1)* and *(2)* indicate that a nearly proportional relationship between population and total air cargo traffic holds. Linear-restrictions hypothesis tests confirm that the coefficients are not significantly different from 1 (standard errors = 0.097 and 0.099, for *(1)* and *(2)*, respectively). Specifically, the point estimates for *POP* suggest that a 1-percent increase in city size raises *all-cargo* traffic (*passenger-belly* and *all-cargo* traffic) by around 0.98 percent (1.2 percent). The higher elasticities for total traffic may be indicative of city size having substantial influence on international traffic, where a considerable amount of the traffic is borne by passenger carriers (*passenger-cargo*). This finding is unsurprising considering that California's largest cities (Los Angeles and San Francisco) are gateways to both national and state traffic coming from (going to) *Pacific Rim* countries. Therefore, the corresponding *POP* coefficients potentially reflect the inherent attractiveness of large metropolitan areas for international cargo operations. Large cities offer access to larger and specialized cargo facilities (customs brokerage services, for example), wider network connections, and more intermodal-transportation options. At the state level, we can also expect that large cities have higher demand for air cargo services to satisfy the supply-chain needs of their numerous manufacturing and service establishments. Meanwhile, the coefficients on *POP* in *(3)* and *(4)* are less than unity, showing that domestic traffic rises less than proportionally to metro population. However, this finding holds with statistical significance only for *ACTRAFFIC—DOM*.

Considering that a city's employment and total-population levels are proportional, our specification in Equation 3.1 essentially captures the effect of employment-composition changes on traffic. Therefore, for example, the estimated *MANUF* coefficient shows what happens when employment shifts into manufacturing from the excluded (non-manufacturing and non-service) sectors, holding the share of service employment (*SERV*) constant. To the extent that the excluded sectors themselves generate cargo traffic, there is a reduction in traffic that is in turn more than counterbalanced by a gain in traffic as the share of manufacturing employment increases. Thus, the magnitude of the *MANUF* coefficient reveals the extent to which manufacturing employment can generate cargo, relative to the excluded sectors. Likewise, the coefficient on *SERV* shows the cargo-generating ability of employment in the service sector, *relative* to the excluded sectors.[16]

In Table 3.4, the shares of manufacturing and service employment both exhibit the expected positive and significant signs. The 1.77 (2.44) *MANUF* coefficient indicates that a 10 percentage-point increase in the share of manufacturing employment, increases total (domestic) all-cargo traffic by 0.18 percent (0.24 percent). Columns (3) and (4) show that a rise in the share of manufacturing employment has a stronger impact on domestic traffic in comparison to its impact on total traffic. Moreover, the *MANUF* coefficient mostly exhibits significance in the *all-cargo* specifications, which is consistent with the expectation that manufacturers rely on the time-definite and *just-in-time* delivery services provided by integrators (such as FedEx Express and UPS Airlines), combination carriers (operate a combination of freighter and passenger fleet), and non-asset based logistics providers that employ the *all-cargo* services of integrators, combination carriers, and *ACMI* (aircraft, crew, maintenance, insurance) carriers.

California's manufacturing sector has gone through substantial restructuring since the 2000 *dot-com bubble* collapse. Computer parts, electronics, and other high-tech products produced by firms across the state were presumably the main drivers of the surging air cargo traffic levels of the late 1990's. Shortly after March 2000, however, manufacturing employment in California fell by 27 percent over three years (TranSystems [87]). The semiconductor industry in Northern California provides some insight into how high-tech firms have rearranged their focus from production to other specialized roles in the industry. The impact of this significant drop was mostly concentrated in the Bay Area, while high-tech manufacturing firms in

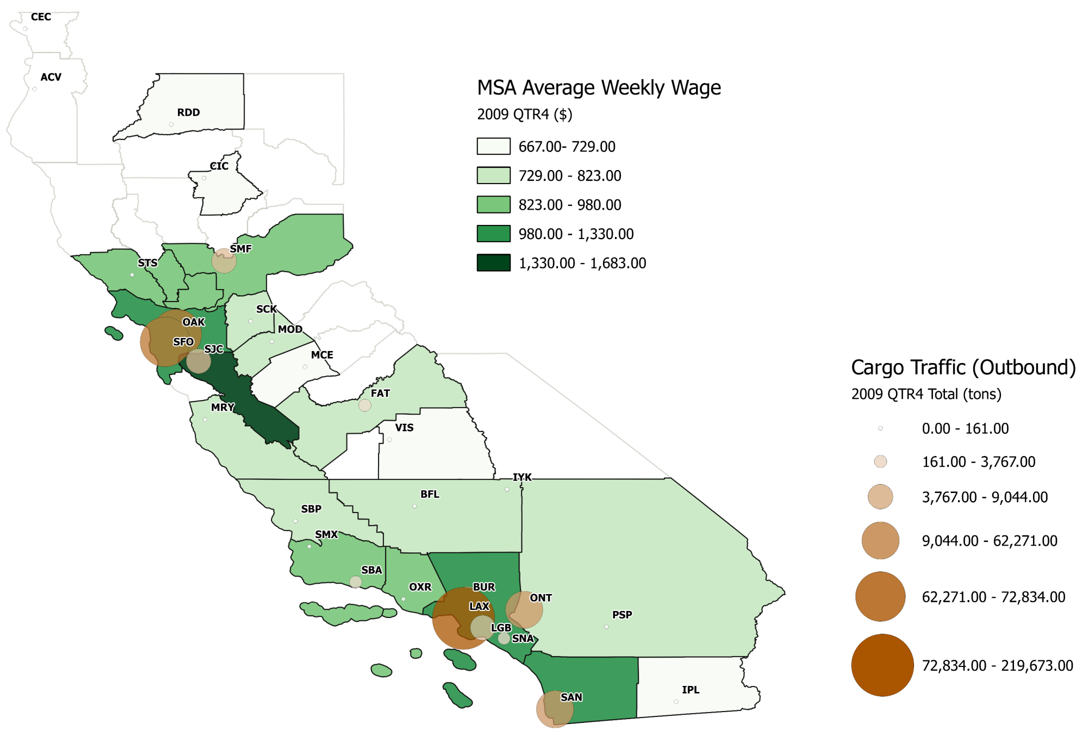
[16] We thank Jan Brueckner for his insights into the traffic impact of sectoral-employment shifts captured by our model's specification.

the southern part of the state were relatively unharmed by the end of the *dot-com bubble* (TranSystems [87]).

Considering the vast service-related businesses in California that rely heavily on expedited goods transportation, the relatively-strong influence of *SERV* on total and domestic cargo is unsurprising. MSAs with a high concentration of service-related businesses also appear to have a higher domestic demand for transporting goods by air. Specifically, the point estimates on *SERV* indicate that a 10 percentage-point increase in the share of service-related occupations results in a 0.58-percent (0.91-percent) rise in the total (domestic) cargo traffic, while the same growth yields a 0.75-percent (1.05-percent) increase in cargo tons carried on total (domestic) all-cargo services. Like manufacturing, the service-sector appears to also rely heavily on all-cargo services in comparison to passenger-cargo services. Overall, the results mostly reflect the capability of large integrators (mainly FedEx Express and UPS Airlines) to facilitate the supply chain of businesses that require next-day and specialized transportation of small packages (TranSystems [87]). These large integrators maintain a dominant presence at key airports in California, catering to the highly elastic demand of the service industry.

The significant coefficient on *WAGE* indicates that average MSA wages (representing income) play an important role in determining the level of both total and domestic cargo traffic. A 10-percent increase in average weekly wages raises total cargo tons at an MSA by 8.8 percent while also raising domestic cargo tons by 7.2 percent. The larger coefficient for total cargo possibly indicates the propensity of wealthier cities to be involved in export businesses and international trade. These point estimates are consistent with the strong correlation found by Alkaabi and Debbage [2] between per capita personal income, average high-tech wages, and the spatial distribution of national air freight. The highest average wages are mostly concentrated in Northern California, as can be seen in Table 3.3. Figure 3.2 also highlights the other high-wage earning metro areas in California, and the associated large volumes of total cargo traffic for the most recent quarter in our sample (2009Q4).[17] The concentration of highly skilled jobs at high-tech establishments in the southern region of the San Francisco Bay explains why average wages of the metro area are well above the state's average. The significant income elasticities we observe can also be explained by the reliance of high-tech firms on air cargo for transporting inputs (electronic components) and other manufactured products (computers, mobile phones, and other high-value goods).

Figure 3.2: MSA Average Weekly Wages and Cargo Enplanements in California (2009Q4)



Turning to the passenger side, Brueckner [18] was first to confirm the relationship between metro area passenger-air traffic and *white collar* employment. Finding a point estimate of

[17]Maps displaying the spatial distribution of the MSA-employment concentrations in the manufacturing and service sectors are provided in the Appendix.

2.4 for the elasticity of air travel with respect to *white collar* employment, Brueckner also demonstrated that *blue collar* employment (measured by manufacturing employment) has no effect on passenger traffic. Our model allows for a similar inference, whereby *MANUF* continues to measure *blue collar* employment and *SERV* can proxy for *white collar* jobs (measuring high-skill, professional, business, legal, information technology, and financial sector employment). Therefore, our industry-share results indicate that both *white collar* and *blue collar* employment increase outbound air cargo traffic in California. In view of the relatively higher wages earned by employees in the service sector, particularly in tradable services, the implications of *white collar* employment are consistent with the results found for *WAGE*.

The coefficients on the *OLD* population-share variables exhibit the expected negative signs in all specification, and are significant. Analogous to passenger-traffic findings (Brueckner [19]), however, the coefficients on the *YOUNG* variable are insignificant for total and domestic cargo. *OLD* and *YOUNG* were included in the specifications to control for the variation in labor structure (relative work-force size) across MSAs in our sample. Consistent with our expectations, the results indicate that a high concentration of residents in the retirement age (60 and over) significantly depresses demand for cargo traffic. Although we also anticipated a similar effect from a high share of young residents (19 and under), who are presumably also not in the city's labor force, both the sign and significance of the variable do not support our expectation.

The dummy variables all exhibit the expected signs in Table 3.4. First, by including the *CAP* dummy, we control for the unique labor structure that a state's capital city may have. The *CAP* dummy captures the high concentration of state-government employment in the capital, for example. The positive and significant *CAP* dummies indicates that the Sacramento-Arden-Arcade-Roseville MSA exhibits high cargo-traffic demand (particularly for domestic traffic), facilitated by the freight-handling facilities at *MHR* and *SAC*. The exponentiated coefficients for CAP show that the capital city generates 3.8 (5.5) times as much cargo traffic as an equivalent non-capital city in California. Taking government-employment as a *white collar* occupation, the positive coefficient also supports our finding that a higher concentration of *white collar* jobs increases cargo traffic.

The HUB dummy coefficient is positive and significant, signaling the higher levels of through-traffic that are captured by the variable. Specifically, exponentiating the hub coefficients informs us that hub cities enplane 39 (43) times as much total (domestic) air cargo traffic as their non-hub counterparts in the sample. This figure is expectedly higher for *all-cargo* services, which operate a purer form of hub-and-spoke services (around 50 times more cargo is handled through hubs by *all-cargo* services). $PROXIMITY$ also confirms our *a priori* belief that a small airport, in the 100-mile vicinity of a large airport, will experience traffic diversion.[18] The results imply that freight shippers and forwarders greatly prefer large metro areas to small ones. This finding is largely determined by integrators, which provide all-inclusive services for transporting goods from the shippers (consignors) to the customers at the destination (consignees). The exponentiated coefficients on $PROXIMITY$ indicate that approximately 80 percent of total and all-cargo traffic is diverted away from small airports to large airports that are within 100 miles. The observed traffic-diversion effects may also indicate the need for carriers to access customs facilities at large (international) airports.[19]

Brueckner [19] and Green [47] treated the contemporaneous and lagged effects of passenger-airport traffic on economic development, respectively. The authors' concern that employment is co-determined with traffic in a relationship like Equation 3.1 is reasonable for passenger traffic. More passenger traffic indicates increased travel between cities, which can improve the connectivity of small metro areas, changing the city's commercial and employment structure. Although the same relationship cannot be as clearly drawn with air cargo transportation,

[18] Recall that multiple airports are consolidated within an MSA.

[19] However, it is interesting to note that inbound international flights to OAK and ONT (hubs of FedEx Express and UPS Airlines) clear customs in Anchorage, Alaska (ANC) [87].

one could still argue that increased cargo traffic can introduce more jobs in the locality of an airport and change the city's labor specialization through spillover effects (Button and Yuan [29]).[20]

3.5 Forecasts: 2010-2040

The socioeconomic variables used in this study are variables of interest to transportation planning and policy-oriented government entities. As such, *The California Economic Forecast's* (TCEF, hereafter) 2013 report provides long-term population and socioeconomic forecasts of sectoral employment, income (wages), and industrial production for all 58 counties in California (TCEF [86]). The employment categories for which we obtained county-level forecasts directly correspond to the industry groups of the BLS *QCEW* data we used in our analysis (both are based on *NAICS*). Therefore, we aggregated the county-level personal income and employment data that match our service- and manufacturing-employment categories to the MSA level, and we evaluated the forecasted trends in a city's labor characteristics. The employment and wage forecasts obtained from TCEF were developed using county-specific econometric models that simultaneously determine employment, income, wages, population, and demand for housing. These econometric models use exogenously-determined national, state-level, and regional forecasts of economic characteristics as inputs see the forecast-methodology report by Schniepp [80] for details).

The 2013-2040 socioeconomic and population forecasts indicate increasing trends in all MSAs of our sample. Therefore, considering the positive and significant coefficient estimates for most variables in the regression results, we expected that the corresponding air cargo traffic

[20] Since this reverse causality may lead the employment-share variables to have some correlation with the error term in Equation 3.1, we also specify and estimate a two-stage least-squares (*2SLS*) model. The *2SLS* equations use 1-year (4 quarters) lagged employment shares for the chosen employment categories as instruments. While the exact point estimates are different (marginally in most cases), the results of the *2SLS* estimation are consistent with the findings presented in this paper. The *2SLS*-model results can be made available by the authors upon request.

at our sample MSAs will also exhibit rising volumes in the forecast period. We filled the 3-year gap between the end date of our panel (2009) and the beginning of the forecasts (2013) with *actual* quarterly data obtained from our original data sources.

3.5.1 Economic Forecast Highlights

Consistent with the strengthening of the national economy and growing cities, California's county-level economic indicators for 2013 are optimistic. The short-term U.S. GDP forecasts exhibit rising figures, with declining unemployment due to new jobs (unemployment rate in California is forecasted to drop to 6.9 percent by 2015) [86]. The 2013 TCEF report views falling unemployment rates and rising housing prices as positive signs of the state's recovery from the 2008-2009 financial crisis. Five of California's counties (San Francisco, Sacramento, San Jose, Orange, and San Joaquin) are projected to be leading urban areas in the growth of the national housing sector. California's export economy is also expected to remain strong, mainly driven by the job creation of port cities in the state (Los Angeles, Long Beach, Port Hueneme, and Oakland) (TCEF [86]).

To forecast metro-level total and domestic air cargo tonnage, we used the TCEF forecasted annual values for metro-level population, service-sector employment (*Professional and Business*, *Information*, *Financial Activities*, *Educational and Health*, *Leisure and Hospitality, and Trade-transport-utilities*), *Manufacturing* employment, and income[21] as inputs to the econometric model shown in Equation 3.1. Our forecasts use the TCEF economic forecasts for the 2013-2040 period, and our original quarterly data sources for the 2010Q1-2012Q4 period, as inputs. Due to the lack of compatible population-projection data, age-group shares after 2012 are assumed to be constant at 2012 shares. We also assumed that the dummy variables (*CAP*, *HUB*, and *PROXIMITY*) will remain unchanged in the forecast period. In view of

[21] We approximated an equivalent measure to the BLS *QCEW* average weekly wages from the forecasted personal-income data.

the insignificant coefficient on *TREND*, and the potential specification issues it may raise in a long-term forecast, we dropped the trend variable in the forecasts.

Based on the estimated coefficient values (slopes) for the variables in our model, Figures 3.3 and 3.4 show total air cargo forecasts for the 2010-2040 period. The thin line in the figures, which ends in 2012Q4, shows the *actual* (observed) air cargo tonnage in the sample MSAs. Starting in 2010Q1, the overlapping thick line represents the forecasted air cargo tonnage for the same MSAs. Therefore, the 2010Q1-2012Q4 period can be used to evaluate the accuracy of the forecasted data.[22] The corresponding domestic traffic forecasts are provided in the Appendix.

Figures 3.3-3.4 and Table 3.5 reveal the optimistic outlook for air cargo traffic in California over the next 30 years. The 5.9-percent annual growth rate for total cargo (*all-cargo* and *passenger-cargo* services) at all metro areas is comparable to the 5.6-percent annual growth (in RTKs) forecasted by Boeing's *World Air Cargo Forecast 2012-2013* (Boeing [15]) for Latin- and North-American markets, in the 2011-2030 period.[23] The Boeing growth rates are estimated using economic and trade indicators for air cargo markets and international trade lanes. Moreover, Table 3.5 shows that the *Bay Area* airports are expected to sustain the 6-percent annual traffic growth that was projected by the *Bay Area Economic Forum* (BAEF [5, 6]) for the years 2000-2020.

Evidently, growth rates in the combined cargo tonnage of *all-cargo* and *passenger-cargo* services are higher than the growth rates of *all-cargo* services alone. This finding may indicate shippers' increasing use of belly-cargo space on passenger jets. Domestic cargo traffic is also not expected to grow as fast as total cargo in all metro areas, while showing a faster rate of growth for total tonnage compared to *all-cargo* tonnage. Although *SFO*'s traffic levels are not expected to reach 2000 levels until 2020 (TranSystems [87]), the metro

[22]Forecast performance details can be provided by the authors upon request.
[23]The corresponding annual growth rate of our forecasted traffic in the 2011-2030 period is 5.3 percent.

Figure 3.3: MSA Total *All-Cargo* and *Passenger Cargo* Forecasts (2010-2040)

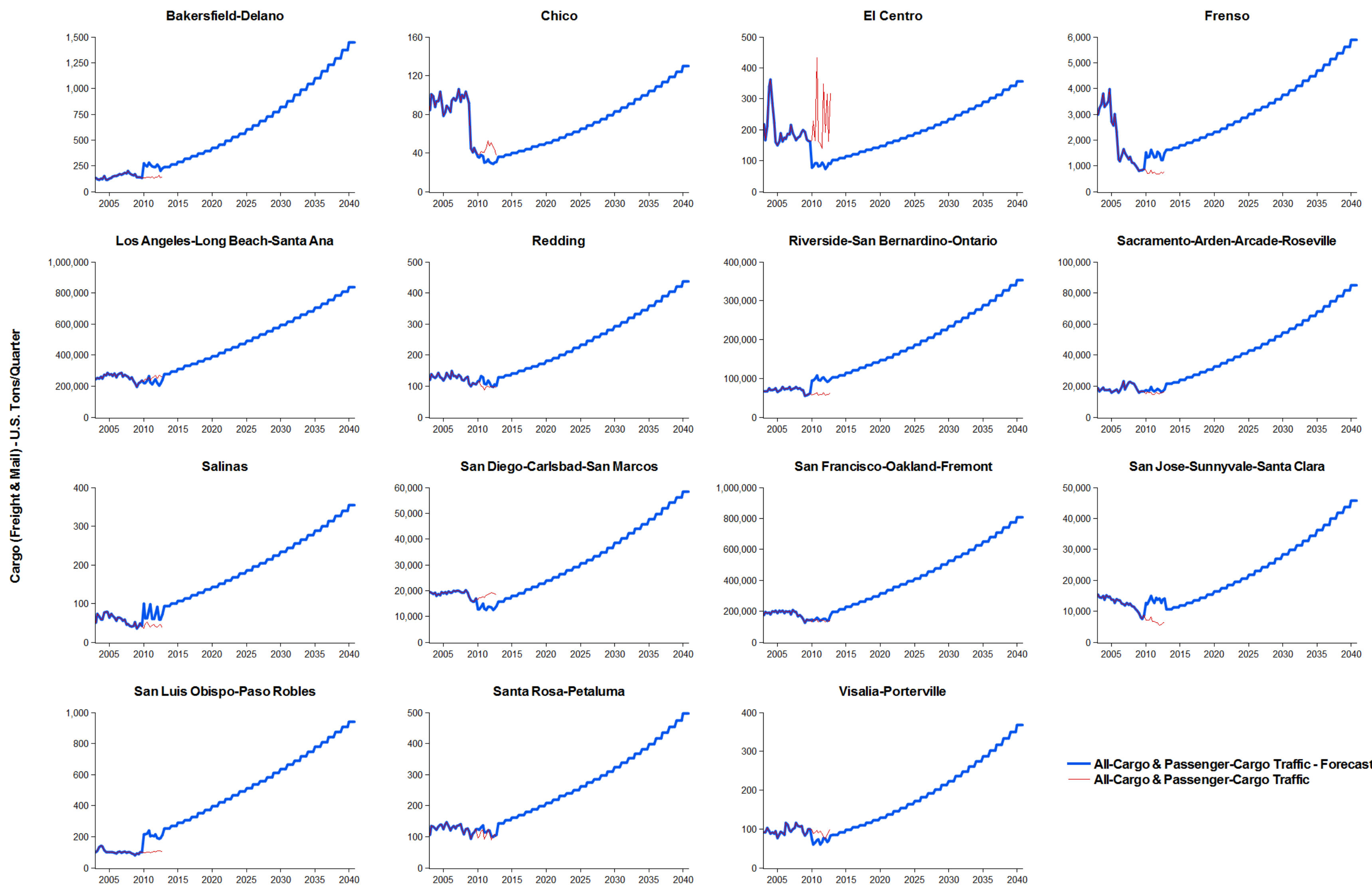


Figure 3.4: MSA Total *All-Cargo* Forecasts (2010-2040)

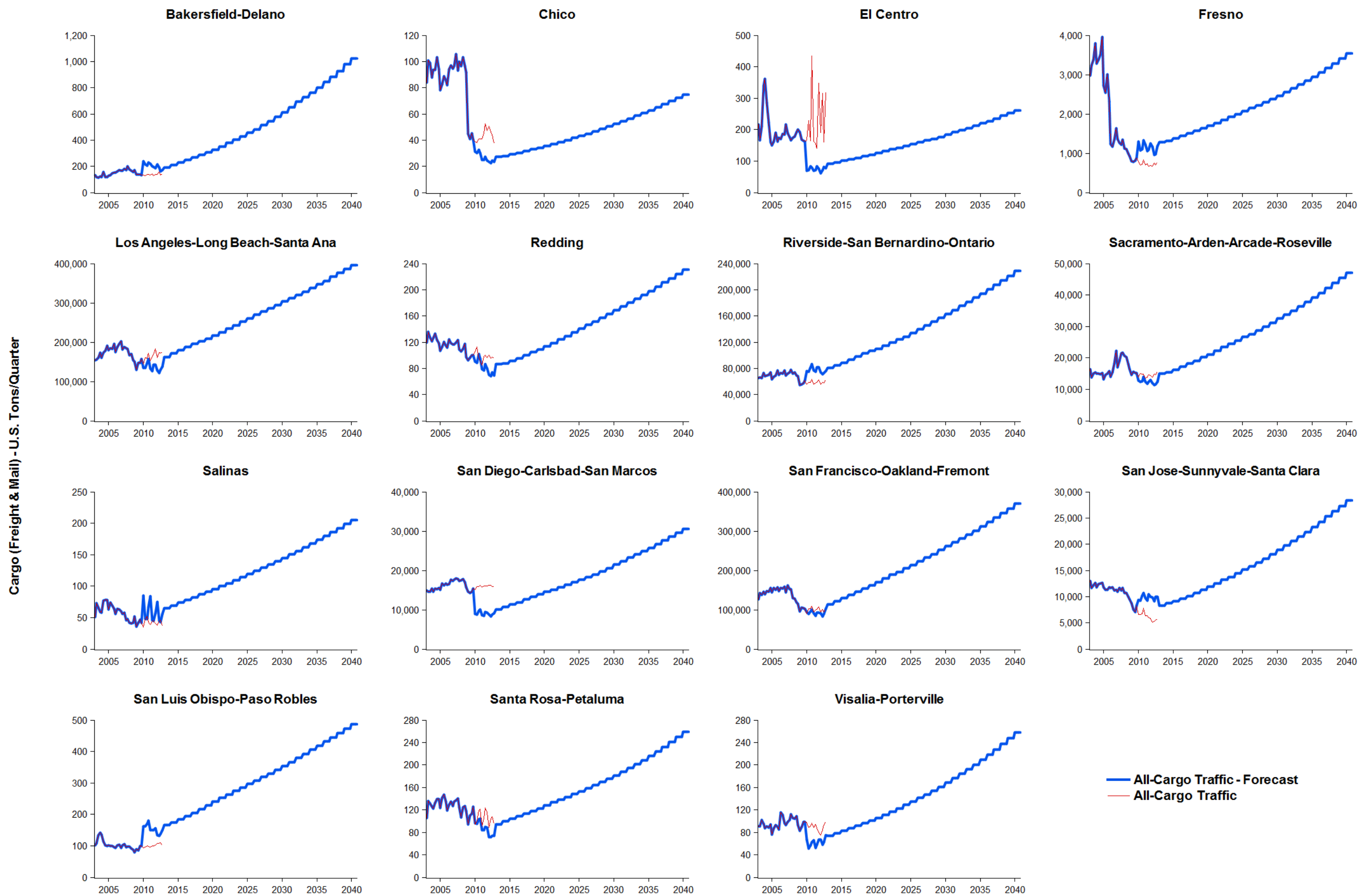


Table 3.5: Annual Average Traffic Growth Rate (2010-2040)

	Total (Domestic & International)		Domestic (—*DOM*)	
MSA	*(1) ACTRAFFIC*	*(2) TRAFFIC*	*(3) ACTRAFFIC*	*(4) TRAFFIC*
Los Angeles-Long Beach-Santa Ana	0.0340	0.0451	0.0311	0.0409
San Francisco-Oakland-Fremont	0.0436	0.0597	0.0335	0.0465
Riverside-San Bernardino-Ontario	0.0477	0.0651	0.0329	0.0457
San Diego-Carlsbad-San Marcos	0.0276	0.0436	0.0177	0.0295
Sacramento-Arden-Arcade-Roseville	0.0389	0.0553	0.0290	0.0413
San Jose-Sunnyvale-Santa Clara	0.0437	0.0616	0.0409	0.0553
Fresno	0.0516	0.0712	0.0386	0.0542
El Centro	0.0241	0.0318	0.0205	0.0265
Bakersfield-Delano	0.0721	0.0869	0.0644	0.0757
Santa Rosa-Petaluma	0.0305	0.0523	0.0165	0.0324
Redding	0.0300	0.0486	0.0175	0.0316
San Luis Obispo-Paso Robles	0.0620	0.0922	0.0404	0.0620
Visalia-Porterville	0.0375	0.0481	0.0324	0.0409
Chico	0.0212	0.0384	0.0098	0.0233
Salinas	0.0598	0.0819	0.0448	0.0609
All Metro Areas	0.0416	0.0588	0.0313	0.0444

area's total cargo tonnage (including traffic from *OAK*) appears to be approaching the traffic levels of the Los Angeles metro area, particularly for domestic traffic.

In the 2010Q1-2012Q4 period, with the exception of the San Diego MSA, the predicted data appear to perform well for large metro areas (those departing more than 10,000 tons per quarter, for example), and especially for total traffic. The latter finding is not surprising in view of the stochastic nature in the usage of passenger-cargo services for transporting freight. The quarterly traffic variations are also captured in both the total and domestic traffic forecasts until 2012Q4.

The TranSystems [87] study applied Boeing's 2015-2020 cargo growth-rate estimates to California's 2008 airport-level cargo traffic, by trade lanes, and came up with 2015 and 2020 traffic projections. We aggregated their airport-level projections to match our metro areas, and compared it to forecasts made by our model for those years. Table 3.6 shows the projections reported in the TranSystems study alongside our equivalent estimates.

Table 3.6: Annual Traffic Forecast Comparison (in U.S. tons)

	TranSystems [87] Forecasts				*Forecasts*	
Metro Area	*2000*	*2008*	*2015*	*2020*	*2015*	*2020*
Los Angeles	2,247,613	1,884,952	2,542,000	3,176,000	2,501,768	3,152,072
Ontario	511,472	501,552	606,000	696,000	911,768	1,176,320
San Diego	153,221	136,687	161,000	181,000	143,904	191,472
San Francisco-Oak.	1,714,094	1,124,358	1,436,000	1,724,000	1,823,088	2,514,504
San Jose	163,142	84,878	100,000	112,000	95,784	130,752
Sacramento-Mather	251,327	145,505	172,000	193,000	191,416	261,096
Fresno	-	9,921	12,000	13,000	14,304	18,592
Total	5,040,870	3,887,852	5,029,000	6,095,000	5,682,032	7,444,808

Notes: TranSystems' reported metric tons are converted to US (short) tons. The TranSystems Los Angeles traffic is adjusted to include traffic from *LGB*, *BUR*, and *SNA* airports. The San Francisco-Oakland metro area is also adjusted to include traffic from *SFO* and *OAK*. Lastly, for comparison purposes, our quarterly traffic measures are first multiplied by 4 (to approximate annual traffic), and then by 2 (to account for inbound traffic).

Although rough approximations were made in Table 3.6 to associate our forecasts to the projections of the TranSystems [87] report, the table illustrates that estimations using different models and methodologies arrive at somewhat comparable traffic projections for large cities. The more optimistic forecasts shown by our results indicate that traffic at some metro areas, most notably San Francisco-Oakland, will return to the peak 2000 levels earlier than the 2020-date predicted by the TranSystems. However, since our aggregation level precludes us from seeing the airport-level driver of this outcome, we cannot specifically state that *SFO*'s air cargo tonnage will reach 2000 levels before 2020. Also, while our forecasts for the San Diego MSA in the 2010-2012 period severely underestimate traffic levels, Table 3.6 reveals that our forecasts for 2015 and 2020 are similar to projections made by TranSystems.

3.6 Conclusion

We investigated the impact of metropolitan socioeconomic characteristics on air cargo traffic in California. Using publicly-available data on airline operations, employment, and demographics of metropolitan areas, we constructed a panel dataset from which point estimates showing the impact that metropolitan characteristics have on air cargo traffic were generated. The socioeconomic variables studied in this paper exhibited their expected positive effect on air cargo traffic, and the corresponding forecasts indicate rising volumes of air cargo in cities throughout California.

By drawing analogies to passenger-travel studies (namely, Brueckner [18]), we let manufacturing and service-related employment represent *blue collar* and *white collar* employment, respectively. Our findings suggest that, unlike passengers enplanements, air cargo traffic increases with both *blue* and *white collar* employment in California. Although the effect of *blue collar* employment is not as high as the effect of *white collar* service-sector jobs, we found that a 10 percentage-point increase in the share of manufacturing employment still raises domestic cargo traffic by 0.24 percent.

Our results showed that a proportionate relationship between total outbound air cargo and city size holds (similar to passenger-travel findings), while domestic traffic appeared to rise less than proportionally with city population. Average wages (income) showed the expected strong and positive relationship, with both domestic and total cargo traffic, reinforcing the expected strong relationship with *white collar* employment and demand for air cargo services.

Another key finding is that the cargo traffic diversion to large-nearby airports is substantial, as evidenced by the highly significant and negative point estimates of our *PROXIMITY* coefficient. Recall that this dummy variable indicates whether a small freight airport is within 100 miles of a large airport. Our results show that such small airports would have 80 percent of their outbound traffic diverted to larger airports.

We also provide air cargo traffic forecasts based on forecasted employment, wage and demographic features of counties in California. Our forecasts indicate that total (domestic) air cargo traffic will rise at an average rate of 5.9 percent (4.4 percent) per year, over the next three decades (2010-2040). Further research can be done to capture the determinants of air cargo traffic within metro areas. But, considering the recent airport-capacity concerns expressed by the aviation community in California, we hope to have identified some key determinants and trends of air cargo traffic in the state.

Chapter 4

Airport Delays and Metropolitan Employment

4.1 Introduction

Recent studies have examined how air travel affects urban development while tackling modeling issues that inherently arise from the endogeneity of the airport-traffic and metropolitan-employment relationship. However, growing passenger volume can lead to increased airport congestion and delays, which in turn can also affect airport traffic and urban-employment characteristics. On the one hand, delays can serve to inhibit the otherwise positive effect of air traffic on regional economic development (an effect documented for road congestion by Hymel [50]). On the other hand, congestion brings about the need for services to manage its negative effects (hotels, restaurants, and retail shops to accommodate stranded passengers, additional manpower to rebook travelers on missed connections, etc.). In this important respect, air traffic delays are rather different from surface-road congestion and, thus, require further investigation.

Not accounting for any potential change in urban employment due to airport delays effectively overestimates or underestimates the impact of air traffic on regional development. Measuring the effect of delays on local employment, therefore, is an interesting question that has not been explored yet. This paper starts filling the above-identified gap in the literature by examining the impact of airport delays on the economic development of cities, and by re-evaluating studies that measure the impact of air travel on regional development (now including air traffic delays as a control variable in the analysis). We take advantage of a 9-year panel of quarterly observations, covering metropolitan-area-level observations for U.S. airports that account for a considerable portion of the nation's scheduled-commercial passenger services. We use data for both total and industry-specific employment, as well as various measures of air traffic delays.

In addition to contributing to the literature on the effects of air travel on regional development, our study adds to the discussion of the cost of air travel delays. Published estimates in this area are mostly aggregate. Most recently, Peterson, Neels, Barczi, and Graham [73] determined that a 10-percent reduction in airline delays would raise net welfare in the U.S. economy by almost $17.6 billion, while a 30-percent drop in the number of delayed flights would result in a $38.5 billion increase in welfare. These estimates stem from a black-box aggregated model, whereas our study provides evidence at the regional level, focusing on what Peterson et al. would consider indirect effects of delays (those not directly borne by the airlines and passengers).

Results of our data analysis demonstrate the following. First, controlling for unobserved city-specific characteristics, we confirm the positive effects of passenger air traffic on employment. Our estimates for total employment are similar to those reported from cross-sectional studies. However, we find that the service-sector employment is less sensitive to changes in passenger air travel than previously reported by Brueckner [19]. Contrary to recent evidence provided by Sheard [82], we also determine that air traffic impacts employment in non-tradable services jobs, but does not affect industries that provide tradable services. At the same time, however, if we decide not to account for MSA-specific heterogeneity, our results confirm the traffic and sectoral-employment relationships found by Sheard.

A robust relationship between delays and employment levels is found, indicating that a 10-percent increase in the number of flights delayed leads to about a 0.2 percent decrease in total and service sector employment, a 0.7-percent decline in employment in the leisure and hospitality sector, and a 1.1-percent reduction in employment related to goods production.[1]

The rest of the paper is organized as follows. The next section reviews the relevant literature, followed by a description of the data, methodology, and results. The last section concludes the paper, and some of the auxiliary results of our analysis are exhibited in the Appendix.

4.2 Literature

This study contributes to the following strains of literature. In broad terms, we are adding to our understanding of the effects of congestion on regional development. The existing literature here has focused on road congestion, and includes only a handful of studies. Relevant works include Boarnet [13], Fernald [44], Hymel [50], and Sweet [84, 85]. Our study extends this literature by examining the effects of airport congestion.

While air travel delays have been studied quite extensively, most of the pertinent work deals with their causes rather than their effects. Examining the effect of route- and airport-level competition, Mazzeo [60] demonstrated that both the length and frequency of flight delays decrease with competition. Lee and Rupp [58] revealed how significant pilot-wage reductions affect their effort level, and thereby an airline's on-time performance. More recently, Prince

[1]Note that we use the terms *sector* and *industry* interchangeably in this paper.

and Simon [75] showed that as multimarket contact between carriers increases, delays also increase.

The existing literature on the effect of air traffic delays consists of macro-level studies attempting to put a dollar figure on the impact of delays on the economy, and micro-level work examining the relationship between delays and airfares. Among the former, the following studies are of note. Analyzing U.S. Department of Transportation's (DOT) data of scheduled flights in 2007, a report by the majority staff of the Joint Economic Committee [51] detailed the costs associated with airline delays to carriers, to travelers, and to the U.S. economy. The report's estimates showed that the indirect costs of delays incurred by industries to be around \$10 billion [51]. Even though this is a fractional share of their estimated total burden to the economy (\$40.7 billion), the report claimed that the service (lodging, food, and retail) and public transportation industries were particularly affected by the delays.[2] Commissioned by the Federal Aviation Administration (FAA), a National Center of Excellence for Aviation Operations Research (NEXTOR) study estimated direct and indirect costs associated with airline delays in 2007 [65]. NEXTOR's comprehensive report projected \$28.9 billion in direct costs to airline delays, accounting for lost demand in air travel and costs incurred by both carriers and passengers.[3] The estimated indirect costs, calculated as a reduction to the 2007 U.S. GDP, amounted to \$4 billion. NEXTOR's estimated total cost to the economy (\$32.9 billion) is around \$8.1 billion short of the JEC measure, shedding light on the challenges of estimating the cost-impacts of airline delays.

Peterson et al. [73] addressed the discrepancies in the indirect-cost estimates of the aforementioned delay-impact works, noting that the studies attribute the transferred costs of

[2]At the regional scale, a study by the Partnership for New York City [74] on the congestion-caused delays of New York's major airports (JFK International, Newark Liberty International, and LaGuardia) suggested that this externality accounted for more than a \$2.6 billion reduction in the region's economy in 2008.

[3]Morrison and Winston [62] considered the value of time of passengers to calculate the minute-level median cost of delays for passenger (\$55.42), which they found to be higher than minute-level operating cost of delays for airlines, \$40.16 (reported in 2000 dollars). Pels et al. [72], using a 1995 air-travel survey for Bay Area airports, found that the mode-choice trends of business passengers reveal their higher value of time in comparison to leisure travelers.

users to the aggregate loss of welfare in the economy, entirely. The authors also pointed to the delay-induced reduction in the labor productivity of business travelers, and in outputs (inputs) of goods and services in industries that are dependent on air transport. Noting that these delay costs are not confined to industries affiliated with airlines, the study emphasized the importance of incorporating the indirect impacts of delays that are felt in other sectors of the economy (those specializing in the provision of leisure, hospitality, and tourism services, for example). Using a commodity- and industry-based model that accounts for the ancillary costs of flight delays, Peterson et al. found that a 10-percent reduction in airline delays would raise net welfare in the U.S. economy by almost \$17.6 billion, while a 30-percent drop in the number of delayed flights would result in a \$38.5 billion increase in welfare.

Studies of the price effects of delays include Forbes [45], Bilotkach and Pai [10], and Bilotkach and Lakew [9]. Forbes [45] examined the impact of competition at New York's LaGuardia airport. Finding that the fare-impact of delays are stronger on competitive routes, Forbes demonstrated that an additional minute of delays decreases airfares by \$1.42. Bilotkach and Pai [10] found a comparable reduction in ticket prices due to delays, using a sample of one-stop itineraries. Focusing on the cause of delays, Bilotkach and Pai also showed that weather delays (out of carrier's control) have a stronger impact on fares than delays caused by the carrier. More recently, Bilotkach and Lakew [9] examined the price effects of delays using aggregated airport-level data. They confirmed the expected price-delays relationship, and concluded that weather and late aircraft delays have the most robust effect on airfares.

Research on the relationship between air traffic and regional development has seen some resurgence recently. Most of the papers in this line of literature, however, use cross-sectional data analysis. These studies have shown that increased airport traffic is associated with higher service-sector employment and lower employment in manufacturing industries (Brueckner [19], Blonigen and Cristea [11], Sheard [82]). Similar works have also measured the effect of air cargo traffic on urban development (Oster, Rubin, and Strong [71], Kasarda and

Green [53], Green [47], Button and Yuan [29]). A dynamic-panel data analysis employed by Bilotkach [8] demonstrated that the number of destinations served from an airport appears to have a stronger impact on regional development than the level of passenger air traffic. Bilotkach's work, however, uses aggregated data on employment, without breaking it down by industry sectors as we do in the present paper.

4.3 Data

In the following empirical analysis, we use data on metropolitan employment, city-level controls, air traffic, and air travel delays. Additionally, we include data on weather and characteristics of airline networks and airport locations to construct instruments for potentially endogenous explanatory variables (traffic and delays). Descriptions of the variables used in this study are provided in Table 4.1. Table 4.2 presents the corresponding descriptive statistics for the variables. All of the data used in our analysis are aggregated to the Core Based Statistical Area (CBSA), a geographic area defined by the U.S. Office of Management of Budget (OMB).[4] Our study focuses on the Metropolitan Statistical Area (MSA) subset of the CBSA (where the urban core contains at least 50,000 people).

Using metro-level socioeconomic data from the Bureau of Labor Statistics (BLS) [12] and airport-level traffic and delay data provided by the DOT's Bureau of Transportation Statistics (BTS) [24], we construct a 9-year quarterly panel (2004Q1-2012Q4) for airline operations in U.S. airports. Our panel also includes metro-level demographic data from the U.S. Census Bureau and weather data from the National Oceanic and Atmospheric Administration (NOAA) [66]. We calculate traffic and delay variables at the quarter level to match the BLS socioeconomic data. The three-month length of a quarter is expected to be short enough to

[4]The OMB constructs CBSA geographic delineations by joining adjacent counties whose urban-core area populations demonstrate substantial levels of socioeconomic interaction (Census [34]).

allow important variation in our traffic and delay variables within a given year, while also being long enough to capture sufficient changes in urban employment levels.

Airport-passenger volumes and delays are collapsed to their corresponding MSAs. While the MSA serves as an appropriate physical and economic area to analyze airport-traffic and delay impacts, the economic data used in our analysis precludes any examination of airport-specific effects of traffic within a city. This limitation in the data can be severe in cases where airports with sizeable traffic and unique characteristics are located within the same MSA. To account for this issue, we specify models with city fixed-effects, which capture the urban-growth impacts through traffic and delay variations within cities.

We focus our analysis on metropolitan areas where at least one airport in that city enplanes more than 10,000 passengers a year (classified as a primary airport by the FAA) and departs more than 100 flights per quarter. MSAs that are missing employment data in any of the selected industries are also dropped. The resulting number of MSAs in our sample range from 175 to 190 (for specifications without delay measures). Details on the data and variables prepared for our analysis are discussed below.

Socioeconomic and demographic data

Industry-level data for metro-area employment are obtained from the Bureau of Labor Statistics' (BLS) *Quarterly Census of Employment and Wages* (*QCEW*) [12].[5] At the most aggregate level of this quarterly data, we have selected the following *QCEW* high-level employment domains (shown here with their corresponding industry *NAICS* codes):[6]

1. *Service Providing*

[5]Data are based on the National American Industry Classification System (*NAICS*).

[6]See Appendix for a complete (more disaggregated) list of industries under these high-level employment domains.

(a) Education and health service (61, 62)

(b) Financial activities (52, 53)

(c) Information (51)

(d) Leisure and hospitality (71, 72)

(e) Professional and business services (54 - 56)

(f) Trade, transport and utilities (22, 42, 44, 45, 48, 49)

(g) Other non-Public Administration services (81)

2. *Goods Producing*

(a) Manufacturing (31 - 33)

(b) Construction (23)

(c) Natural resources and mining (11, 21)

We also analyze subsets of the *QCEW*'s super-sector groups, *Service Providing* and *Goods Producing*. Consistent with Sheard's [82] classification of industries, we delineate sectors that provide tradable services and commodities from those that do not. An industry sector is considered to be tradable if the goods or services that are produced by its employees can readily be acquired or consumed in a different geographical location (Sheard [82]). Hence, *Professional and business services*, *Information*, and *Financial Activities* (*EMPPBIF*) are classified as sectors providing *tradable* services from the *Service-Providing* group (*SERV*), while *Manufacturing* is naturally selected as the *tradable* sector from the *Goods-Producing* group (*EMPGDS*). Industries involved in the provision of such tradable goods and services benefit greatly from the face-to-face contact facilitated by airline services (Brueckner [19]). Therefore, consistent with Sheard's findings, we expect that air traffic will have a noticeable impact only on the employment levels of industry sectors with tradable goods and services. The employment sectors that are not considered tradable are *Trade-transport-utilities*, *Leisure and hospitality*, and *Education and health services.* These employment areas, denoted *EMPTLE*, consist of jobs that mostly cater to the local urban area, and presumably do not heavily depend on the direct-personal contact enabled by air transport.

Lastly, we also examine the employment characteristics of the *Leisure and hospitality* sector, in view of the delay-impact implications that we invoked in the introductory section of this paper. We believe that the spillover effects of airport delays may actually stimulate employment in the local accommodation, entertainment, dining and recreational service-sectors. Therefore, the impact that both air traffic and delays have on this sector's employment levels will be studied separately.

We supplement our socioeconomic data with annual-county population figures (collapsed to their corresponding MSAs) provided by the U.S. Census Bureau. Further, in line with the existing literature, we use the population data to construct population-share variables based on two main age groups, *YOUNG* (15 and younger) and *OLD* (65 and older). The baseline group (16 to 64) is assumed to be representative of a city's population in the labor force.

Traffic and Airport data

Our key passenger-traffic measure is the number of passenger enplanements (*PAX*) from all primary airports in the MSA. This information is aggregated at the quarterly level from the BTS *Form 41 Traffic T-100 Segment* tables [24]. This dataset provides disaggregated passenger and freight traffic data for all flights where at least one point of operation is domestic (in the U.S. or Canada).

Other airport-related information that we include in our data analysis are as follows. We use detailed airport location data from the BTS *National Transportation Atlas Database 2012* (*NTAD*) [22] to link U.S. airports to their corresponding MSAs through county-MSA associations. Since the current (2013) OMB definitions of CBSAs do not correspond to the CBSA definitions that the BLS socioeconomic data are aggregated to, the OMB's 2009 CBSA county delineations were used to complete this crosswalk. The *NTAD* airport-location data also specify the latitude and longitude coordinates of the airports, which allowed us to measure great-circle distances between airports. The inter-airport distances are then used to construct variables that capture the diversion of passenger traffic between cities in our sample. This traffic-diversion effect (also known as a traffic shadow effect) is proxied by a binary variable (*PROXIM.*) that equals 1 when the smallest airport in a small MSA is within a 150-mile radius of the largest airport in a large MSA (equals 0, otherwise).[7]

One of the main instruments we use for passenger traffic is *HUB*. This variable is equal to 1 if an MSA has one airport and it happens to be a passenger hub. If there are multiple airports in that hub city, the hub variable is equal to the fraction of airports in that MSA (to discount the hub's share of enplanements). At the most basic level, an airport is classified as a passenger hub if at least one carrier at that airport serves at least 25 destinations per quarter.[8]

The following justification for the suitability of the HUB instrument is adapted from Brueckner [19]. Since hub airports facilitate sizable levels of *connecting* and *intermediate-stop* traffic, in addition to local enplanements, we can say that *HUB* (as a driver of traffic) satisfies the *relevance* requirement of an appropriate instrument. However, fulfilling the *exclusion* requirement of an instrument (no correlation with the error term) with *HUB*, is less palpable. Given that populous cities provide a strong base for local enplanements, hubs are likely to

[7] Small MSAs enplane less than 300,000 passengers a year, while large MSAs enplane more than 5,000,000 passengers annually. These cutoffs were chosen using *k-means clustering* of enplaned passengers at the sample airports; the mean and maximum values of the smallest cluster (out of 4 clusters) were used to delineate small and large MSAs, respectively. The smallest and largest airports in a given MSA respectively enplane the least and most passengers, relative to other airports in that MSA.

[8] A *k-means clustering* analysis of the number of carrier-specific domestic destinations served (in 2003) from the sample airports was used to select the 25 points-served cutoff for hubs. Some airports were removed from the resulting list of airports since they were deemed to be non-hubs or focus cities. We thank Ethan S. Singer for his insights into determining the hub status of airports.

locate in larger metropolitan areas to benefit from this natural scale advantage. And considering the strong proportionality between city size and employment levels, it follows that the hub status of airports and city employment may be correlated. Note, however, that the *exclusion* requirement for a suitable instrument necessitates that unobserved determinants of employment are not correlated with the instrument (*HUB*). Therefore, since *POP* controls for city size in our specifications, it is reasonable to assume that the remaining unobserved features in the error term (which may raise a city's employment to levels higher than a city of comparable size) have negligible relations to the classification of an airport as a hub.

A variable that measures how close a city's airports are to the center of the U.S. population is also calculated, and is used as an alternative instrument for traffic.[9] This instrument, denoted *CENTR.*, is expected to be correlated with traffic since cities located farther away from the population center of the country are less likely to be used by airlines as traffic-consolidation hubs. Given that there is no association expected between the distance of a city to the country's population centroid and that city's employment characteristics (all else equal), correlation between *CENTR.* and the error term in our key specifications is unlikely, or sufficiently small. While certain coastal hub airports are obvious exceptions to the location assumptions of this instrument, the efficiency gains of a central location in hub-and-spoke networks are likely to have a considerable impact on traffic levels.

Other instruments we have constructed for traffic are *LEISURE* and *SLOT*. *LEISURE* is a dummy variable equal to 1 for vacation cities (*Orlando*, *FL*; *Las Vegas*, *NV*; *Atlantic City*, *NJ*; *Myrtle Beach*, *SC*; *Gulfport*, *MS*), where the air travel demand is expected to be considerably unique. Correlation between *LEISURE* and employment specialization (namely in the services sector) is likely, but not necessarily with employment levels. Hence, *LEISURE*

[9]The population center of the U.S. is estimated by the U.S. Census Bureau, and is reported to be Texas Cnty, Missouri (in 2010). The corresponding decimal coordinates of the center are 37.517534 °N, 92.173096 °W. Great-circle distances are calculated from the city airports in our sample to the center of population. For a city with multiple airports, the average distance of the MSA's airports to the population centroid is measured.

is expected to meet the exclusion requirement of a proper instrument by lacking correlation with error term. MSAs of slot-controlled airports operating at capacity (*DCA*, *EWR*, *JFK*, and *LGA*) are captured by the *SLOT* variable. *SLOT* is equal 1 if an MSA has at least one airport that is slot controlled. If that MSA has multiple airports, *SLOT* is equal to the fraction of non-slot controlled airports in that MSA (to discount the slot-controlled airport's share of enplanements). Even though traffic may play an important role in airport congestion, capacity constraints are considered to be the major determinants of an airport's *SLOT* status. *CENTR.*, *LEISURE*, and *SLOT* are time-invariant variables in our sample. While *HUB* and *PROXIM.* may vary slightly over time for some cities (due to hub-status changes or traffic re-allocation), their within-city disturbances are inconsequential to our estimations.

Delays

The delay data are obtained from the BTS *On-Time Performance* databank, which gives detailed information on airline delays, flight schedules, gate-to-gate travel times and other flight-level measures for non-stop operations of certified U.S. major carriers (airlines that account for 1 percent or more of the domestic revenues of scheduled passenger operations) [26]. Our delay statistics are based on the complete data provided by BTS over the 9-year period of this study (over 5 million flights observations per year).

In this dataset, departure (arrival) delays are calculated as the difference between scheduled the *scheduled* departure (arrival) time and the *actual* departure (arrival) time. We refer to this measure as the *schedule delay*, which is often reported as the *on-time performance* statistics of airlines. Noting that carriers are able to manipulate scheduled times to improve their overall on-time performance statistics (known as schedule padding), several studies (e.g., Mayer and Sinai [59]; NEXTOR [65]; Rupp [77]; Ater [4]) have chosen to measure delays as the difference between the actual travel time and the minimum travel time (or some percentile level of fastest time) recorded for a particular segment (*excess time*). While some of these studies have controlled for carrier-specific differences in fleet-mix that might bias the measure of minimum-flight time, Rupp [77] emphasized the potential for *excess time* to be affected by anomalous fast flight times (potentially caused by strong tail winds, for example). Moreover, as argued by Rupp, passengers are attuned to the *schedule delays*, rather than *excess time*. Time-sensitive travelers (e.g., business passengers) plan their trips according to the scheduled time, not the unimpeded time. Considering the potential for erroneous measurements of *excess time* and our desire to focus on passenger-perceived delays, we have chosen to use *schedule delays* for the delay metric of this paper.[10]

The following measures of delays are constructed:

Departure delay are defined as the difference between a flight's scheduled and actual gate-departure time. We calculated the quarterly frequency (*COUNTDEL*) and sum (*SUMDEL*), of departures delayed for at least 15 minutes at the departure/origin MSA. When computing these measures, we are using the FAA's 15-minute cutoff for delayed flights. We then computed the minute-level mean delays (*MEANDEL*) of all flights in the sample (including early and on-time departures).

Arrival delay is defined as the total delay of a flight arriving at its destination gate, including its departure and en-route delays. We calculated the quarterly frequency of arrival delays (*COUNTDEL*), as well as the sum of arrival delays (*SUMDEL*) for flights delayed for 15 minutes or ore at the arrival/destination MSA. Parallel to the depature delays, we also calculated the minute-level mean delays (*MEANDEL*) of all arrivals in the sample MSAs.

The mean-delay-minutes measure is computed for all flights. On-time flights are recorded at zero minutes of delay, and flights departing (arriving) ahead of schedule are assigned

[10] *Excess time* is potentially affected by within-carrier differences in fleet mix (varying speeds based on aircraft type), changes in navigation procedures/routes, and flights operating during off-peak hours.

negative delay numbers. Measuring delay averages only for flights that are delayed would be problematic since a city with 100,000 flights out of which only 2 are delayed for an hour each will look the same as a city with 1,000 flights, each delayed for an hour. This issue does not apply to the other delay variables (*COUNTDEL* and *SUMDEL*) since they measure aggregates and appear along with passenger volume in the regressions.[11]

We also aggregated counts of canceled flights by origin and destination MSAs (*canceled*). For the latter measure, note that *canceled* (collapsed to a *destination*) still counts the number of flights that are canceled at various *origin* MSAs. Thus, this measure captures the impact that origin-city cancellations have on a particular destination city.

Observations with outlier measures for delays are dropped from outbound and inbound samples used for this paper. Specifically, observations with mean departure delays ≥ 120 minutes (2 hours) and mean arrival delays ≥ 90 minutes (1.5 hours) are excluded from the outbound and inbound samples, respectively. This restriction results in 22 (2) observations being dropped from the outbound (inbound) samples.

Descriptive statistics for the calculated delay measures are reported in Table 4.2. The table shows that, on average, arrival delays are shorter than departure delays. This finding indicates that the airlines tend to make up some time en route — evidence of either schedule padding or operational differences between on-time and delayed flights (possibly due to, for example, higher speed for flights delayed on departure, at the expense of fuel economy).

Weather

Our weather data are downloaded from the NOAA's *Global Historical Climatology Network* (*GHCN*) stations [66]. Weather stations that are located within the premises (or vicinity) of airports in our sample were then selected for our panel. We calculated the MSA averages

[11] We thank Jan Brueckner for this insight.

of the highest January temperatures (*JANTEMP*) recorded at the corresponding airport *GHCN* stations (in degrees Celsius). *JANTEMP* is included as a control for traffic, seeing that warmer regions (*Sunbelt* locations) attract leisure travelers. Similarly, we calculated the quarterly averages of recorded precipitation (*PRCP*) and snow (*SNOW*) levels (in mm). However, *PRCP* and *SNOW* are used to instrument for delays. The summary statistics for these weather measures are shown in Table 4.2.

Table 4.1: Variable Definitions

Variables	***Definition***
TRAFFIC	
PAX	Enplaned (landed) passengers at MSA
DEMOGRAPHIC AND SOCIOECONOMIC	
POP	Total MSA population (annual)
YOUNG	Share of MSA population of age 14 and under
OLD	Share of MSA population of age 65 and over
EMPTOT	Total MSA non-farm employment
EMPSERV	Service-related empl.
EMPPBIF	Professional, Business, Information, and Finance empl. (**Tradable**)
EMPTLE	Trade-transp.-util., Leisure-hospitality, and Educ.-health services empl. (**Non-tradable**)
EMPLH	Leisure-hospitality empl.
EMPGDS	Goods-producing empl.
EMPMNF	Manufacturing empl.
DELAY	
CANCEL	Number of departure cancellations at departure airports in MSA
COUNTDEL	Number of flights delayed ($\geq$ *15 mins.*) at departure/arrival airports in MSA
MEANDEL	Mean-delay-mins. of *all* flights at departure/arrival airports in MSA (*all flights*)
SUMDEL	Sum-delay-mins. of flights delayed ($\geq$ *15 mins.*) at departure/arrival airports in MSA
WEATHER	
JANTEMP	Average maximum January temperature recorded at airports in MSA (degrees C)
PRCP	Average precipitation (rain & melted snow) levels recorded at airports in MSA (mm)
SNOW	Average snowfall levels recorded at airports in MSA (mm)
DUMMIES	
HUB	MSA hub indicator, scaled by number of airports in MSA
CENTR.	MSA's average airport distance to population centroid of U.S. in 2010 (Texas Cnty, MO)
LEISURE	Dummy = 1 for Orl., FL; L. Vegas, NV; Atl. City, NJ; Myr. Beach, SC; Gulfp., MS
SLOT	Dummy = 1 for MSAs with Slot-controlled airports (*DCA*, *EWR*, *JFK*, *LGA*)
PROXIM.	Dummy = 1 if small MSA airport is within 150 miles of large MSA airport

Notes: Variables represent quarterly measures (except for *POP*, *YOUNG*, *OLD*, *JANTEMP*, and *HUB*, which are measured yearly). *CENTR.*, *LEISURE*, and *SLOT* do not vary over time.

Table 4.2: Variable Summary Statistics

	OUTBOUND TRAFFIC (DEPARTURE) SAMPLE				*INBOUND TRAFFIC (ARRIVAL) SAMPLE*			
Variables	***Mean***	***Min.***	***Max.***	***Stdev.***	***Mean***	***Min.***	***Max.***	***Stdev.***
PAX	745,058	1,383	14,354,804	1,636,048	751,427	1,438	14,564,590	1,643,638
CANCEL	100	1	3,720	211	99	1	4,010	220
COUNTDEL	1,077	1	24,798	2,269	1,139	1	24,386	2,175
MEANDEL	7.23	-6.11	37.99	4.41	7.04	-9.56	44.32	5.07
SUMDEL	61,467	21	1,655,624	125,670	63,093	33	1,670,404	124,667
POP	946,563	58,979	18,597,871	1,553,567	953,616	58,979	18,597,871	1,558,843
YOUNG	0.2013	0.1306	0.3082	0.0256	0.2011	0.1306	0.3082	0.0254
OLD	0.1271	0.0527	0.2495	0.0270	0.1269	0.0527	0.2495	0.0267
EMPTOT	417,366	24,662	8,180,412	679,058	420,669	24,662	8,180,412	681,266
EMPSERV	290,538	15,703	6,110,483	494,118	292,856	15,703	6,110,483	495,768
EMPPBIF	94,439	3,358	2,276,016	177,922	95,228	3,360	2,276,016	178,540
EMPTLE	180,769	11,587	3,499,976	286,600	182,179	11,587	3,499,976	287,521
EMPLH	44,190	2,362	644,918	70,350	44,539	2,362	644,918	70,580
EMPGOODS	62,992	2,580	931,903	97,033	63,501	2,580	931,903	97,331
EMPMNF	37,472	476	667,146	64,909	37,808	476	667,146	65,115
JANTEMP	6.39	-27.89	27.21	8.92	6.37	-27.89	27.21	8.93
PRCP	2.31	0.00	10.34	1.51	2.31	0.00	10.34	1.51
SNOW	2.23	0.00	92.50	5.23	2.25	0.00	92.50	5.73
HUB	0.0922	0.0000	1.0000	0.2549	0.0931	0.0000	1.0000	0.2560
CENTR.	1,000	22	4,554	790	993	22	4,554	791
LEISURE	0.0298	0.0000	1.0000	0.1700	0.0300	0.0000	1.0000	0.1708
SLOT	0.0009	0.0000	0.5000	0.0193	0.0009	0.0000	0.5000	0.0194
PROXIM.	0.2669	0.0000	1.0000	0.4424	0.2636	0.0000	1.0000	0.4406

Notes: Table shows quarterly MSA summary statistics for variables in the outbound and inbound samples (2004-2012). *POP*, *YOUNG*, *OLD*, *JANTEMP*, and *HUB* represent annual measures. *CENTR.*, *LEISURE*, and *SLOT* do not vary over time.

4.4 Empirical Framework

Our analysis quantifies the impact of traffic and various airline-delay measures on industry-level employment variables, while controlling for the relevant socioeconomic, demographic, and other exogenous city features. Overall, our data-analysis technique of choice is a MSA-level fixed effects model that accounts for endogeneity of both traffic and delay measures through a conventional *two-stage least squares* (*2SLS*) instrumental-variable methodology. Note that the null of the *redundant fixed effects* test, which states that the fixed effects are equal to each other, is rejected. Hence, the test results suggest that unobserved heterogeneity exists in our sample MSAs.[12]

We specify an empirical model that invokes the following reduced-form relationship between an MSA i's employment E, outbound (inbound) traffic T, departure (arrival) delays D, and exogenous city features X, in quarter t:

$$E_{it} = \alpha_i + \beta T_{it} + \delta D_{it} + \gamma X_{it} + \sum \theta_t Q_t + \varepsilon_{it}, \tag{4.1}$$

where α_i denotes the MSA-specific intercept, Q_t represents time (year and quarter) dummies, and ε_{it} is the error term. The variables included in X_{it} are total population, population shares by young- and old-age groups, and the maximum January temperature. In line with prior research (Brueckner [19]), Equation 4.1 treats the relationship between air traffic, delays, and economic development as a contemporaneous one (i.e., the three variables of interest are determined simultaneously). It is unclear how much the observed traffic and delay levels are themselves a consequence of (or codetermined with) the corresponding city's employment characteristics. Therefore, to address the potential endogeneity of both airline

[12] The reported standard errors are robust to heteroscedasticity across MSAs and autocorrelation within MSAs.

traffic and delays in this relationship, a *2SLS* estimation is used. To remain consistent with the literature and enable interpretation of our coefficient estimates as elasticities, the employment, traffic, and delay measures are included into all specifications in logarithmic form.

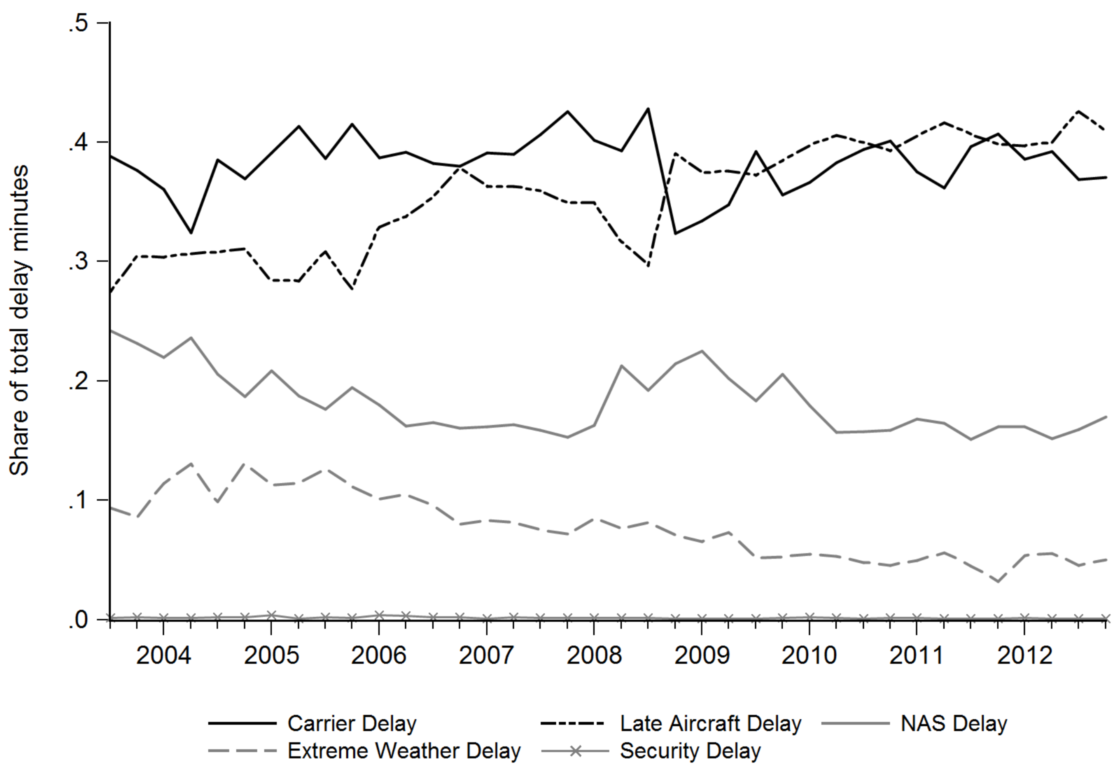
Note that relying on panel data represents a departure from the cross-sectional analysis, which remains more popular in the literature on air traffic-development relationships (Brueckner [19], Blonigen and Cristea [11], Sheard [82]). For comparison purposes, we have also conducted all of our empirical analysis without MSA fixed effects. The corresponding results, which are tangentially referred to in this paper, are available from the authors upon request. We should also note that potential co-determination issues of city population (POP) and urban-employment size ($EMPTOT$) are avoided by lagging the POP 4 quarters. Therefore, while our empirical sample begins in 2004Q1, measures for POP begin as early as 2003Q1.[13]

Instruments are chosen to fulfill the following identification and exclusion criteria: strong correlation with traffic (delays) and weak (or no) correlation with the error term in Equation 4.1. *HUB*, *CENTR.*, *PROXIM.*, *LEISURE*, and $SLOT$ are variables that fulfill this criteria, and are constructed analogous to the corresponding variables used in Brueckner [19]. Likewise, to instrument for delays, we use the average precipitation ($PRCP$) and snow levels ($SNOW$) of MSAs. Figure 4.1 shows the shares of various the delay sources identified by BTS. Even though Extreme Weather delays usually account for less than 10 percent of all sources, BTS' detailed definitions reveal that the complete spectrum of weather-related sources actually account for a sizable portion of the delays categorized as NAS delays. The weather delays included in the National Air System (NAS) category, like other sources in that category (Air Traffic Control, traffic, and airport operations), are delays whose effects can be reduced through remedial measures of the FAA. The Extreme Weather delays category,

[13]Brueckner [19] lags population 6 years to avoid this potential endogeneity problem.

on its own, represents flights delayed due to weather incidents — such as high winds, tornadoes, hurricanes and blizzards — that prohibit flight operations altogether (BTS [23]).[14] This information supports our choice of *weather* as a good instrument for delays (combined, NAS and Extreme Weather account for a substantial portion of delays).

Figure 4.1: Share of Delays by Cause



Delay shares calculated for sample airports. Data source: BTS *On-time Performance* [26].

[14] Rupp and Holmes [78] also found that weather factors are important determinants of flight cancellations.

4.5 Results

The estimation results are presented in Tables 4.3-4.14. In all of the specifications we report, delays are instrumented for with the weather variables *PRCP* and *SNOW*. Also, instruments *PROXIM.*, *LEISURE*, and *SLOT*, are used in all of these specifications to account for the endogeneity of the traffic levels. Tables 4.3 through 4.8 include the *HUB* instrument in addition to the aforementioned instruments. Then, analogous to the *HUB* instrument, results using *CENTR.* as a traffic instrument are reported in Tables 4.9-4.14. We separately report results for departure and arrival delay measures (Tables 4.3-4.5, 4.9-4.11 and Tables 4.6-4.8, 4.12-4.14, respectively). The dependent variables we use are Total Employment (Tables 4.3, 4.6, 4.9 and 4.12); Service Employment (Tables 4.4, 4.7, 4.10 and 4.13); and Goods Employment (Tables 4.5, 4.8, 4.11 and 4.14).[15]

Each table includes five specifications: baseline regression (without delay measures), and four specifications that include a different delay metric (number of canceled flights, number of delayed flights, mean delay in minutes, and total minutes of flights delayed). All specifications control for MSA-specific heterogeneity via the corresponding fixed effects, include the same set of control variables (suppressed from some of the tables to save space), and also contain year and quarter indicator variables (suppressed from all tables) to control for time-specific effects.

Tables 4.3, 4.6, 4.9 and 4.12 also report results of the *Sargan-Hansen* test. We have four over-identifying restrictions in all the specifications, meaning that, under the null hypothesis of no correlation between residuals and instruments in the *2SLS* model, the test statistic follows a chi-square distribution with four degrees of freedom. In every case we report,

[15] We have investigated all of the cross sectional and fixed effects regressions without instruments as well. Seeing that the qualitative results are similar to the results of the estimations using instruments, and in view of the serious endogeneity concerns in our empirical specification, we have decided to only exhibit the instrumented results in this paper. Results of estimations that do not use instruments are available upon request.

the null hypothesis is not rejected, suggesting that our instruments are valid. The same is observed in all other regressions, for which the *Sargan-Hansen* statistics are not directly reported.

In our interpretation of the results, we will focus on the following issues, in addition to evaluating the traffic-employment and delays-employment relationships for all the delay and employment metrics we have used here. First, we will examine whether the outcome is sensitive to our choice of delay measures (arrival versus departure delays) and instruments (*HUB* versus *CENTR.*). Second, by comparing specifications with delays to the baseline regressions, we will be able to see how the inclusion of delays alters the corresponding employment elasticities with respect to passenger air traffic. Finally, we can directly compare our elasticities to those reported in Brueckner [19]. Note that Brueckner's study uses a cross-sectional data set, whereas we are relying on a panel. Thus, our identifying variation comes from *within* MSAs over time, rather than across the metropolitan areas, as in Brueckner's work.

4.5.1 HUB Instrument results

Table 4.3: Departure Delays (*HUB* Instrument for Traffic) — Total Employment

	EMPTOT				
	(1)	(2)	(3)	(4)	(5)
INTERCEPT	6.7510^{a}	5.7984^{a}	5.6148^{a}	5.8946^{a}	5.7061^{a}
	(0.9412)	(0.9830)	(1.0044)	(0.9859)	(0.9934)
POP	0.3807^{a}	0.4685^{a}	0.4711^{a}	0.4666^{a}	0.4774^{a}
	(0.0840)	(0.0933)	(0.0941)	(0.0933)	(0.0950)
PAX	0.0627^{b}	0.0509	0.0686^{b}	0.0461	0.0595^{c}
	(0.0298)	(0.0328)	(0.0305)	(0.0335)	(0.0319)
YOUNG	1.6238^{c}	1.7458^{b}	1.9354^{b}	1.7112^{b}	1.9045^{b}
	(0.8997)	(0.7543)	(0.7709)	(0.7485)	(0.7628)
OLD	-4.2107^{a}	-4.2352^{a}	-4.2462^{a}	-4.0576^{a}	-4.2003^{a}
	(0.7955)	(1.0523)	(1.0435)	(1.0621)	(1.0481)
JANTEMP	-0.0007	-0.0009^{b}	-0.0009^{b}	-0.00079^{c}	-0.0008^{b}
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
CANCEL		-0.0080^{b}			
		(0.0041)			
COUNTDEL			-0.0232^{c}		
			(0.0119)		
MEANDEL				-0.0240^{c}	
				(0.0134)	
SUMDEL					-0.0201^{c}
					(0.0103)
Observations	4874	3603	3603	3603	3603
Adj. R^2	0.9994	0.9995	0.9995	0.9995	0.9995
Sargan-Hansen	0.2486	3.0914	2.3888	4.0930	2.3888
(p-value)	(0.9694)	(0.5427)	(0.6647)	(0.3936)	(0.6647)

Notes: *EMPTOT*, *POP*, *PAX*, *CANCEL*, *COUNTDEL*, *MEANDEL*, and *SUMDEL* are in natural logs.
Dummies for Years and Quarters are suppressed.
Robust clustered standard errors in parentheses: $^{a}p < 0.01$; $^{b}p < 0.05$; $^{c}p < 0.10$.

Table 4.4: Departure Delays (*HUB* Instrument for Traffic) — Service Employment

	(1)	(2)	(3)	(4)	(5)
			EMPSERV		
PAX	0.0474^b	0.0415	0.0574^b	0.0333	0.0492^b
	(0.0222)	(0.0264)	(0.0233)	(0.0270)	(0.0246)
CANCEL		-0.0069^b			
		(0.0034)			
COUNTDEL			-0.0192^c		
			(0.0102)		
MEANDEL				-0.0263^b	
				(0.0120)	
SUMDEL					-0.0147^c
					(0.0083)
			EMPPBIF (Tradable Services)		
PAX	0.0620	0.0581	0.0661	0.0528	0.0625
	(0.0587)	(0.0659)	(0.0563)	(0.0688)	(0.0606)
CANCEL		-0.0039			
		(0.0068)			
COUNTDEL			-0.0093		
			(0.0185)		
MEANDEL				-0.0160	
				(0.0224)	
SUMDEL					-0.0079
					(0.0160)
			EMPTLE (Non-Tradable Services)		
PAX	0.0331^b	0.0314	0.0508^b	0.0213	0.0417^c
	(0.0148)	(0.0215)	(0.0226)	(0.0223)	(0.0223)
CANCEL		-0.0092^a			
		(0.0034)			
COUNTDEL			-0.0235^b		
			(0.0101)		
MEANDEL				-0.0341^a	
				(0.0126)	
SUMDEL					-0.0201^b
					(0.0087)
			EMPLH		
PAX	0.0844	0.0849	0.1460^b	0.0460	0.1186^c
	(0.0521)	(0.0685)	(0.0719)	(0.0704)	(0.0716)
CANCEL		-0.0295^a			
		(0.0089)			
COUNTDEL			-0.0703^a		
			(0.0271)		
MEANDEL				-0.1186^a	
				(0.0343)	
SUMDEL					-0.0599^a
					(0.0231)

Notes: All variables reported here are in natural logs.
Dummies for Years and Quarters are suppressed.
Robust clustered standard errors in parentheses: $^a p < 0.01$; $^b p < 0.05$; $^c p < 0.10$.

Table 4.5: Departure Delays (*HUB* Instrument for Traffic) — Goods Employment

	EMPGDS				
	(1)	(2)	(3)	(4)	(5)
PAX	0.1480	0.0982	0.1855	0.0691	0.1412
	(0.1166)	(0.1365)	(0.1368)	(0.1361)	(0.1438)
CANCEL		-0.0400^a			
		(0.0129)			
COUNTDEL			-0.1131^a		
			(0.0406)		
MEANDEL				-0.1268^a	
				(0.0428)	
SUMDEL					-0.0976^a
					(0.0351)
	EMPMNF				
PAX	0.1586	0.1273	0.1434	0.1232	0.1344
	(0.1579)	(0.2134)	(0.1900)	(0.2216)	(0.2033)
CANCEL		-0.0070			
		(0.0164)			
COUNTDEL			-0.0231		
			(0.0456)		
MEANDEL				-0.0208	
				(0.0526)	
SUMDEL					-0.0198
					(0.0392)

Notes: All variables reported here are in natural logs.
Dummies for Years and Quarters are suppressed.
Robust clustered standard errors in parentheses: $^a p < 0.01$; $^b p < 0.05$; $^c p < 0.10$.

Table 4.6: Arrival Delays (*HUB* Instrument for Traffic) — Total Employment

	EMPTOT				
	(1)	(2)	(3)	(4)	(5)
INTERCEPT	6.7958^{a}	5.8340^{a}	5.5175^{a}	5.8483^{a}	5.6153^{a}
	(0.9398)	(0.9898)	(1.0445)	(1.0125)	(1.0239)
POP	0.3795^{a}	0.4700^{a}	0.4909^{a}	0.4773^{a}	0.4898^{a}
	(0.0833)	(0.0928)	(0.0984)	(0.0955)	(0.0979)
PAX	0.0594^{b}	0.0464	0.0592^{b}	0.0412	0.0559^{c}
	(0.0280)	(0.0311)	(0.0502)	(0.0315)	(0.0292)
YOUNG	1.7000^{c}	1.7308^{b}	1.8006^{b}	1.6786^{b}	1.7936^{b}
	(0.8758)	(0.7597)	(0.7677)	(0.7521)	(0.7626)
OLD	-4.1894^{a}	-4.2380^{a}	-4.3648^{a}	-4.2067^{a}	-4.2907^{a}
	(0.8041)	(1.0668)	(1.0497)	(1.0687)	(1.0502)
JANTEMP	-0.0007^{c}	-0.0009^{b}	-0.0010^{b}	-0.0008^{b}	-0.0009^{b}
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
CANCEL		-0.0067^{c}			
		(0.0040)			
COUNTDEL			-0.0228^{c}		
			(0.0133)		
MEANDEL				-0.0248^{c}	
				(0.0151)	
SUMDEL					-0.0189^{c}
					(0.0113)
Observations	4816	3594	3594	3594	3594
Adj. R^2	0.9994	0.9995	0.9995	0.9996	0.9995
Sargan-Hansen	0.2601	3.8887	3.4359	4.8591	3.6228
(p-value)	(0.9674)	(0.4113)	(0.4877)	(0.3021)	(0.4595)

Notes: *EMPTOT*, *POP*, *PAX*, *CANCEL*, *COUNTDEL*, *MEANDEL*, and *SUMDEL* are in natural logs.
Dummies for Years and Quarters are suppressed.
Robust clustered standard errors in parentheses: $^{a}p < 0.01$; $^{b}p < 0.05$; $^{c}p < 0.10$.

Table 4.7: Arrival Delays (*HUB* Instrument for Traffic) — Service Employment

	(1)	(2)	(3)	(4)	(5)
			EMPSERV		
PAX	0.0460^{b}	0.0460^{c}	0.0558^{b}	0.0381	0.0534^{b}
	(0.0218)	(0.0256)	(0.0218)	(0.0253)	(0.0227)
CANCEL		-0.0051			
		(0.0034)			
COUNTDEL			-0.0157		
			(0.0105)		
MEANDEL				-0.02449^{c}	
				(0.0131)	
SUMDEL					-0.0135
					(0.0090)
			EMPPBIF (Tradable Services)		
PAX	0.0604	0.0586	0.0634	0.0552	0.0623
	(0.0575)	(0.0642)	(0.0542)	(0.0680)	(0.0565)
CANCEL		-0.0024			
		(0.0069)			
COUNTDEL			-0.0072		
			(0.0219)		
MEANDEL				-0.0112	
				(0.0269)	
SUMDEL					-0.0063
					(0.0187)
			EMPTLE (Non-Tradable Services)		
PAX	0.0328^{b}	0.0372^{c}	0.0512^{b}	0.0272	0.0478^{b}
	(0.0149)	(0.0204)	(0.0205)	(0.0208)	(0.0206)
CANCEL		-0.0072^{b}			
		(0.0032)			
COUNTDEL			-0.0226^{b}		
			(0.0107)		
MEANDEL				-0.0331^{b}	
				(0.0133)	
SUMDEL					-0.0194^{b}
					(0.0091)
			EMPLH		
PAX	0.0845	0.1150^{c}	0.1590^{b}	0.0814	0.1486^{b}
	(0.0526)	(0.0647)	(0.0683)	(0.0717)	(0.0674)
CANCEL		-0.0228^{b}			
		(0.0083)			
COUNTDEL			-0.0669^{b}		
			(0.0294)		
MEANDEL				-0.1070^{a}	
				(0.0357)	
SUMDEL					-0.0588^{b}
					(0.0246)

Notes: All variables reported here are in natural logs.
Dummies for Years and Quarters are suppressed.
Robust clustered standard errors in parentheses: ${}^{a}p < 0.01$; ${}^{b}p < 0.05$; ${}^{c}p < 0.10$.

Table 4.8: Arrival Delays (*HUB* Instrument for Traffic) — Goods Employment

	EMPGDS				
	(1)	(2)	(3)	(4)	(5)
PAX	0.1311	0.0857	0.1548	0.0567	0.1372
	(0.1094)	(0.1304)	(0.1362)	(0.1374)	(0.1372)
CANCEL		-0.0358^{a}			
		(0.0132)			
COUNTDEL			-0.1186^{b}		
			(0.0483)		
MEANDEL				-0.1354^{a}	
				(0.0515)	
SUMDEL					-0.0995^{b}
					(0.0405)
	EMPMNF				
PAX	0.1586	0.1217	0.1319	0.1161	0.1290
	(0.1582)	(0.2106)	(0.1860)	(0.2237)	(0.1919)
CANCEL		-0.0053			
		(0.0179)			
COUNTDEL			-0.0208		
			(0.0581)		
MEANDEL				-0.0219	
				(0.0688)	
SUMDEL					-0.0163
					(0.0494)

Notes: All variables reported here are in natural logs.
Dummies for Years and Quarters are suppressed.
Robust clustered standard errors in parentheses: $^{a}p < 0.01$; $^{b}p < 0.05$; $^{c}p < 0.10$.

4.5.2 CENTRALITY (CENTR.) Instrument results

Table 4.9: Departure Delays (*CENTR.* Instrument for Traffic) — Total Employment

	EMPTOT				
	(1)	(2)	(3)	(4)	(5)
INTERCEPT	6.7488^a	5.7922^a	5.5995^a	5.8942^a	5.6955^a
	(0.9413)	(0.9824)	(1.0036)	(0.9862)	(0.9932)
POP	0.3814^a	0.4696^a	0.4724^a	0.4676^a	0.4790^a
	(0.0840)	(0.0933)	(0.0941)	(0.0933)	(0.0950)
PAX	0.0621^b	0.0503	0.0689^b	0.0453	0.0594^c
	(0.0298)	(0.0328)	(0.0307)	(0.0334)	(0.0320)
YOUNG	1.6257^c	1.7514^b	1.9506^b	1.7144^b	1.9182^b
	(0.90000)	(0.7558)	(0.7729)	(0.7497)	(0.7645)
OLD	-4.2116^a	-4.2428^a	-4.2538^a	-4.0553^a	-4.2055^a
	(0.7951)	(1.0529)	(1.0441)	(1.0617)	(1.0486)
JANTEMP	-0.0007	-0.0009^b	-0.0009^b	-0.0007	-0.0008^b
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
CANCEL		-0.0085^b			
		(0.0040)			
COUNTDEL			-0.0244^b		
			(0.0118)		
MEANDEL				-0.0252^c	
				(0.0134)	
SUMDEL					-0.0212^b
					(0.0103)
Observations	4872	3603	3603	3603	3603
Adj. R^2	0.9994	0.9995	0.9995	0.9995	0.9995
Sargan-Hansen	0.000387	2.8284	2.0393	4.0209	2.0249
(p-value)	(0.999998)	(0.5859)	(0.7285)	(0.4032)	(0.7312)

Notes: *EMPTOT*, *POP*, *PAX*, *CANCEL*, *COUNTDEL*, *MEANDEL*, and *SUMDEL* are in natural logs.
Dummies for Years and Quarters are suppressed.
Robust clustered standard errors in parentheses: $^a p < 0.01$; $^b p < 0.05$; $^c p < 0.10$.

Table 4.10: Departure Delays (*CENTR*. Instrument for Traffic) — Service Employment

	EMPSERV				
	(1)	(2)	(3)	(4)	(5)
PAX	0.0469^b	0.0410	0.0576^b	0.0327	0.0491^b
	(0.0222)	(0.0264)	(0.0233)	(0.0270)	(0.0246)
CANCEL		-0.0073^b			
		(0.0034)			
COUNTDEL			-0.0198^c		
			(0.0102)		
MEANDEL				-0.0272^b	
				(0.0120)	
SUMDEL					-0.0155^c
					(0.0083)
	EMPPBIF (Tradable Services)				
PAX	0.0622	0.0581	0.0661	0.0528	0.0625
	(0.0588)	(0.0659)	(0.0563)	(0.0689)	(0.0606)
CANCEL		-0.0039			
		(0.0068)			
COUNTDEL			-0.0092		
			(0.0185)		
MEANDEL				-0.0519	
				(0.0225)	
SUMDEL					-0.0079
					(0.0160)
	EMPTLE (Non-Tradable Services)				
PAX	0.0326^b	0.0309	0.0512^b	0.0206	0.0416^c
	(0.0148)	(0.0216)	(0.0229)	(0.0223	(0.0225)
CANCEL		-0.0096			
		(0.0035)			
COUNTDEL			-0.0245^b		
			(0.0102)		
MEANDEL				-0.0352^a	
				(0.0127)	
SUMDEL					-0.0201^b
					(0.0088)
	EMPLH				
PAX	0.0845	0.0848	0.1460^b	0.0459	0.1186^c
	(0.0521)	(0.0686)	(0.0718)	(0.0705)	(0.0717)
CANCEL		-0.0295^a			
		(0.0089)			
COUNTDEL			-0.0704^a		
			(0.0273)		
MEANDEL				-0.1187^a	
				(0.0344)	
SUMDEL					-0.0600^a
					(0.0232)

Notes: All variables reported here are in natural logs.
Dummies for Years and Quarters are suppressed.
Robust clustered standard errors in parentheses: ${}^a p < 0.01$; ${}^b p < 0.05$; ${}^c p < 0.10$.

Table 4.11: Departure Delays (*CENTR.* Instrument for Traffic) — Goods Employment

			EMPGDS		
	(1)	(2)	(3)	(4)	(5)
PAX	0.1465	0.0965	-0.3339	0.0670	0.1408
	(0.1166)	(0.1367)	(0.3555)	(0.1361)	(0.1446)
CANCEL		-0.0412^{a}			
		(0.0129)			
COUNTDEL			-0.1164^{a}		
			(0.0407)		
MEANDEL				-0.1300^{b}	
				(0.0427)	
SUMDEL					-0.1005^{a}
					(0.0352)
			EMPMNF		
PAX	0.1571	0.1258	0.1443	0.1212	0.1341
	(0.1579)	(0.2139)	(0.1908)	(0.2218)	(0.2042)
CANCEL		-0.0081			
		(0.0164)			
COUNTDEL			-0.0261		
			(0.0458)		
MEANDEL				-0.0238	
				(0.0526)	
SUMDEL					-0.0224
					(0.0394)

Notes: All variables reported here are in natural logs.
Dummies for Years and Quarters are suppressed.
Robust clustered standard errors in parentheses: $^{a}p < 0.01$; $^{b}p < 0.05$; $^{c}p < 0.10$.

Table 4.12: Arrival Delays (*CENTR.* Instrument for Traffic) — Total Employment

	EMPTOT				
	(1)	(2)	(3)	(4)	(5)
INTERCEPT	6.7935^a	5.8266^a	5.4943^a	5.8522^a	5.5949^a
	(0.9399)	(0.9892)	(1.0436)	(1.0119)	(1.0231)
POP	0.3802^a	0.4715^a	0.4932^a	0.4761^a	0.4923^a
	(0.0833)	(0.0928)	(0.0984)	(0.0955)	(0.0980)
PAX	0.0588^b	0.0454	0.0593^b	0.0420	0.0557^c
	(0.0280)	(0.0311)	(0.0287)	(0.0316)	(0.0294)
YOUNG	1.7020^c	1.7389^b	1.8105^b	1.6771^b	1.8044^b
	(0.8760)	(0.7615)	(0.7695)	(0.7511)	(0.7642)
OLD	-4.1904^a	-4.2427^a	-4.3754^a	-4.2054^a	-4.2980^a
	(0.8036)	(1.0671)	(1.0504)	(1.0687)	(1.0504)
JANTEMP	-0.0007^c	-0.0009^b	-0.0010^b	-0.0008^b	-0.0009^b
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
CANCEL		-0.0072^c			
		(0.0040)			
COUNTDEL			-0.0241^c		
			(0.0132)		
MEANDEL				-0.0239	
				(0.0150)	
SUMDEL					-0.0201^c
					(0.0112)
Observations	4815	3594	3594	3594	3594
Adj. R^2	0.9994	0.9995	0.9995	0.9995	0.9995
Sargan-Hansen	0.000384	3.6551	3.1448	4.8483	3.3460
(p-value)	(0.999998)	(0.4547)	(0.5339)	(0.3032)	(0.5017)

Notes: *EMPTOT*, *POP*, *PAX*, *CANCEL*, *COUNTDEL*, *MEANDEL*, and *SUMDEL* are in natural logs.
Dummies for Years and Quarters are suppressed.
Robust clustered standard errors in parentheses: $^a p < 0.01$; $^b p < 0.05$; $^c p < 0.10$.

Table 4.13: Arrival Delays (*CENTR.* Instrument for Traffic) — Service Employment

	(1)	(2)	(3)	(4)	(5)
			EMPSERV		
PAX	0.0455^{b}	0.0453^{c}	0.0558^{b}	0.0387	0.0533^{b}
	(0.0218)	(0.0256)	(0.0219)	(0.0254)	(0.0227)
CANCEL		-0.0055^{c}			
		(0.0033)			
COUNTDEL			-0.0167		
			(0.0104)		
MEANDEL				-0.0237^{c}	
				(0.0130)	
SUMDEL					-0.0144
					(0.0089)
			EMPPBIF (Tradable Services)		
PAX	0.0606	0.0588	0.0634	0.0552	0.0623
	(0.0576)	(0.0644)	(0.0542)	(0.0679)	(0.0565)
CANCEL		-0.0024			
		(0.0070)			
COUNTDEL			-0.0071		
			(0.0219)		
MEANDEL				-0.0113	
				(0.0267)	
SUMDEL					-0.0063
					(0.0188)
			EMPTLE (Non-Tradable Services)		
PAX	0.0322^{b}	0.0364^{c}	0.0513^{b}	0.0278	0.0477^{b}
	(0.0149)	(0.0204)	(0.0207)	(0.0208)	(0.0208)
CANCEL		-0.0077^{b}			
		(0.0032)			
COUNTDEL			-0.0237^{b}		
			(0.0107)		
MEANDEL				-0.0323^{b}	
				(0.0132)	
SUMDEL					-0.0204^{b}
					(0.0091)
			EMPLH		
PAX	0.0847	0.1149^{c}	0.1590^{b}	0.0812	0.1486^{b}
	(0.0526)	(0.0648)	(0.0683)	(0.0717)	(0.0674)
CANCEL		-0.0228^{a}			
		(0.0083)			
COUNTDEL			-0.0669^{b}		
			(0.0295)		
MEANDEL				-0.1072^{a}	
				(0.0357)	
SUMDEL					-0.0588^{b}
					(0.0247)

Notes: All variables reported here are in natural logs.
Dummies for Years and Quarters are suppressed.
Robust clustered standard errors in parentheses: ${}^{a}p < 0.01$; ${}^{b}p < 0.05$; ${}^{c}p < 0.10$.

Table 4.14: Arrival Delays (*CENTR.* Instrument for Traffic) — Goods Employment

	EMPGDS				
	(1)	(2)	(3)	(4)	(5)
PAX	0.1294	0.0831	0.1549	0.0584	0.1367
	(0.1095)	(0.1308)	(0.1372)	(0.1373)	(0.1382)
CANCEL		-0.0372^{a}			
		(0.0132)			
COUNTDEL			-0.1221^{b}		
			(0.0485)		
MEANDEL				-0.1331^{a}	
				(0.0515)	
SUMDEL					-0.1028^{b}
					(0.0406)
	EMPMNF				
PAX	0.1570	0.1194	0.1320	0.1179	0.1286
	(0.1583)	(0.2112)	(0.1870)	(0.2235)	(0.1930)
CANCEL		-0.0066			
		(0.0180)			
COUNTDEL			-0.0240		
			(0.0585)		
MEANDEL				-0.0195	
				(0.0688)	
SUMDEL					-0.0193
					(0.0497)

Notes: All variables reported here are in natural logs.
Dummies for Years and Quarters are suppressed.
Robust clustered standard errors in parentheses: $^{a}p < 0.01$; $^{b}p < 0.05$; $^{c}p < 0.10$.

Beginning with the sensitivity of our results to the choice of instruments and departure versus arrival delay, we can see that the estimation results do not change much if we use *HUB* rather than the *CENTR.* instrument, or departure instead of the arrival sample. The former point largely mirrors Brueckner's findings, even though *CENTR.* performs more successfully in our analysis. We should note that, despite their stability across the choice of instruments and departure versus arrival delay analyses, the estimation results noticeably depend on the measures of delay we use. Specifically, while the frequency of delayed flights (*COUNTDEL*) and total minutes delayed (*SUMDEL*) exhibit rather similar results, only marginally changing the estimate of the impact of traffic as compared to the baseline specification, the length of delays (*MEANDEL*) and the count of canceled flights (*CANCEL*) render the baseline estimates of the impact of traffic statistically insignificant.

In light of the above points, we will base our discussion predominantly on Tables 4.3-4.5. As a reminder, Table 4.3 includes regressions measuring the impact of traffic and delays on total employment at the MSA level. Tables 4.4 and 4.5 present results for the impact on service and goods employment, respectively. We employ four measures of service employment and two measures of goods employment in our analysis. Of those, total service employment and total goods employment have also been used in Brueckner [19], allowing for direct comparison to our point estimates.

The baseline estimation for the effect of passenger air traffic on total employment implies that a 10-percent increase in passenger enplanements would yield a 0.59-0.63 percent growth in city-level employment. Despite being lower, this estimate is reasonably close to the 0.72-0.88 percent effect reported by Brueckner in his cross-sectional analysis. At the sample mean, an increase of 75,000- passenger enplanements (a 10-percent increase) per quarter will yield 2,500 new jobs. To put this into context, 75,000 passengers is equivalent to about 1.5 additional daily Boeing-737 services. These elasticity estimates are not affected much by adding *COUNTDEL* and *SUMDEL* to the specifications.

Estimates of the elasticity of total employment with respect to these two delay measures suggest that a 10-percent increase in the number of delayed flights (around 100 additional delayed departures per quarter for the mean observation) or an equivalent increase in the total minutes of delay (over 6,000 extra delay minutes per quarter at the sample mean) would decrease employment by 0.2 percent (around 835 jobs at the sample mean). Further, a 10-percent increase in the number of canceled flights costs around 334 jobs. A similar delay elasticity of total employment is observed for the mean-delay metric (*MEANDEL*), where a 10-percent increase in delays implies a 0.24-percent decline in employment. Then, an additional 100 delayed departures at the sample mean will have about the same effect on employment as delaying every flight at the MSA by an extra 40 seconds.

Our estimates of the elasticity of service-sector employment with respect to the air passenger traffic imply that a 10-percent increase in traffic increases this employment measure by around 0.47 percent. Note that this is significantly less than the corresponding estimates reported by Brueckner (according to his results, an equivalent increase in traffic yields 1.1 - 1.27 percent more employment in service jobs). Thus, at the sample mean, an increase of 75,000 of passengers per quarter will yield around 1,366 additional service-sector jobs.

Turning to the disaggregated employment categories in Tables 4.4 and 4.5, it appears that the relationship between air traffic and service-sector employment is only significant for the non-tradable services sector, where a 10-percent increase in traffic yields nearly 598 jobs in non-tradable services at the sample mean. The results showing the effect of traffic on tradable versus non-tradable sector employment are fundamentally different from those reported by Sheard [82]. However, Sheard's work relies on cross-sectional data, and our estimates without MSA fixed effects also exhibit positive relationships between traffic and tradable-sector employment. Moreover Sheard used departures (not passenger volume) as the measure of air traffic, and his dependent variables are the sectoral *shares* of employment. Thus, his results are essentially reflecting how traffic influences shifts in sectoral employment (non-service to service, for example). We, on the other hand, are measuring the impact of air traffic on sectoral-employment *levels*.

Delays robustly decrease service-sector employment, with the exception of tradable services, where the coefficients have the expected sign but lack statistical significance at conventional levels. Interestingly, estimates of the service-sector employment elasticity with respect to the count of delayed flights (as well as the elasticities of both tradable and non-tradable services) are of the same order of magnitude as those found for total employment. The same observation holds true for these elasticities with respect to the number of canceled flights and mean delay.

Results showing the impact of delays on leisure and hospitality employment (*EMPLH*) contrast our initial expectations. We had previously discussed a potential channel for increased delays to positively affect employment in these sectors (through the need for infrastructure and services that accommodate stranded travelers). Yet, the outcome is quite the opposite, suggesting that delays in fact reduce employment in the leisure and hospitality sectors. Further, when *COUNTDEL* or *SUMDEL* are included in the regressions, the impact of air traffic on employment in these sectors becomes positive and significant, with the estimated elasticity similar to that reported by Brueckner for the entire service-sector employment. Moreover, employment in the leisure and hospitality sector is about three times as sensitive to delays compared to the non-tradable sector. It thus appears that as delays harm business and employment in general, the corresponding spillover effect to the leisure and hospitality establishments far outweighs any potential positive impact of delays that create service jobs aimed at accommodating stranded passengers. Notably, our results here are in line with the particularly harmful impacts of delays on lodging, food, and retail services reported by the JEC [51] and PFNYC [74] studies. Based on firm-survey results in New York City, PFNYC [74] suggested that delays lead business to hold less meetings in New York, and to choosing alternative meeting methods that do not require in-person contact (e.g., teleconferencing).

These firm decisions would in turn lower occupancy in hotels and restaurants, while also reducing other business-related retail purchases.

As reported in previous studies, there appears to be no clear statistically significant connection between passenger air traffic and employment in the goods-producing sector (*EMPGDS*). Delays, however, do have a negative impact on this employment category, where a 10-percent increase in the *COUNTDEL* (*SUMDEL*) costs around 712 (615) jobs in these sectors, at the sample mean. At the same time, we find no statistically-significant relationship between our delay measures and employment in the manufacturing sector. Note, however, that all the relevant point estimates are quite similar to those reported for total employment.[16] Additionally, the results render some support to the possibility of delay-induced reduction in productivity of goods-producing businesses that rely on air services (Peterson et al. [73]).

Overall, air travel delays show the expected negative effect on employment. There are also clear differences in the estimates of this effect across sectors. Interestingly, the goods-producing sector employment exhibits the highest sensitivity to delays, followed by the leisure and hospitality sector. Manufacturing and tradable services, on the other hand, are not affected by delays. The latter conclusion is in contrast to what is reported in the recent studies [82]. The higher sensitivity of the goods producing sector employment as compared to leisure and hospitality is unexpected.

4.6 Conclusion

This paper provides the first attempt to analyze the impact of air travel delays on city-level employment, both total and sectoral. Previous studies suggested that road congestion can

[16]Bearing in mind that *construction* employment is also included in the *EMPGDS* category, we isolated and regressed construction employment (logged analogously to *EMPGDS*) on traffic, delays, and the remaining control variables in our baseline specification. The results indicate that delays have a negative and significant impact on construction employment, suggesting that this employment category is potentially driving the delay-impact outcome of *EMPGDS*.

inhibit urban development Hymel [50]. Given the importance of air travel for business in the modern world, one would be right to hypothesize a similar effect for the airport congestion. Yet, this hypothesis has not yet been analyzed.

Our work takes advantage of a 9-year quarterly panel data, covering major airports across the U.S. We use detailed data on passenger air traffic, delays, and employment, aggregated to the MSA level. Our data analysis strategy is rather conventional, with the exception that, unlike most previous studies, we rely on within-MSA (rather than across-MSA) variation to identify the key relationships. We use the same instruments for passenger air travel volumes as those employed by Brueckner [19], and delineate service sectors into those providing tradable and non-tradable services, as suggested by Sheard [82]. Considering the services that are used to accommodate delayed and stranded passengers, we also pay specific attention to the leisure and hospitality industry, as we postulate that this sector might be positively affected by air travel delays.

Our data analysis results confirm some of the findings in the literature, while also detecting surprising relationships. We confirm the positive effects of passenger air traffic on employment, and our estimates of this effect are similar to those reported in cross-sectional studies. However, we find that the service-sector employment is less sensitive to changes in passenger air travel than previously reported by Brueckner [19]. We also determine that air traffic does have an impact on employment in non-tradable service jobs, but not in industries providing tradable services. This finding contrasts results reported by Sheard [82]. At the same time, however, our analysis that does not account for MSA-specific heterogeneity confirms relationships found by Sheard.

We find a rather robust relationship between delays and employment levels. A 10-percent increase in the number of flights delayed leads to about a 0.2-percent decrease in total and service sector employment, a 0.7-percent decline in employment in the leisure and hospitality sector, and a 1.1-percent reduction in employment in goods producing industries. The higher sensitivity of goods-producing sector employment as compared to leisure and hospitality comes out as a surprise to us.

Overall, this study provides the first evidence on what we consider to be an important relationship between air traffic, delays, and employment. As both the volume and importance of air travel in the globalizing world is expected to increase, understanding its effects on the local economy also becomes an increasingly important issue.

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Appendix

.1 Airport Traffic and Metropolitan Economies

.1.1 BLS *QCEW* Industry List

List of Industries (with corresponding *NAICS* codes) provided by the U.S. Bureau of Labor Statistics (BLS) *Quarterly Census of Employment and Wages* (*QCEW*)

Source: `http://www.bls.gov/bls/naics_aggregation.htm`

1. Goods-Producing
   - (a) Natural resources and mining
     - i. Sector 11 (Agriculture, forestry, fishing and hunting)
     - ii. Sector 21 (Mining)
   - (b) Construction
     - i. Sector 23 (Construction)
   - (c) Manufacturing
     - i. Sector 31-33 (Manufacturing)
2. Service-Providing
   - (a) Trade, transportation, and utilities
     - i. Sector 42 (Wholesale trade)
     - ii. Sector 44-45 (Retail trade)
     - iii. Sector 48-49 (Transportation and warehousing)

iv. Sector 22 (Utilities)

(b) Information

i. Sector 51 (Information)

(c) Financial activities

i. Sector 52 (Finance and insurance)

ii. Sector 53 (Real estate and rental and leasing)

(d) Professional and business services

i. Sector 54 (Professional, scientific, and technical services)

ii. Sector 55 (Management of companies and enterprises)

iii. Sector 56 (Administrative and support and waste management and remediation services)

(e) Education and health services

i. Sector 61 (Education services)

ii. Sector 62 (Health care and social assistance)

(f) Leisure and hospitality

i. Sector 71 (Arts, entertainment, and recreation)

ii. Sector 72 (Accommodation and food services)

(g) Other services

i. Sector 81 (Other services, except public administration)

(h) Public administration

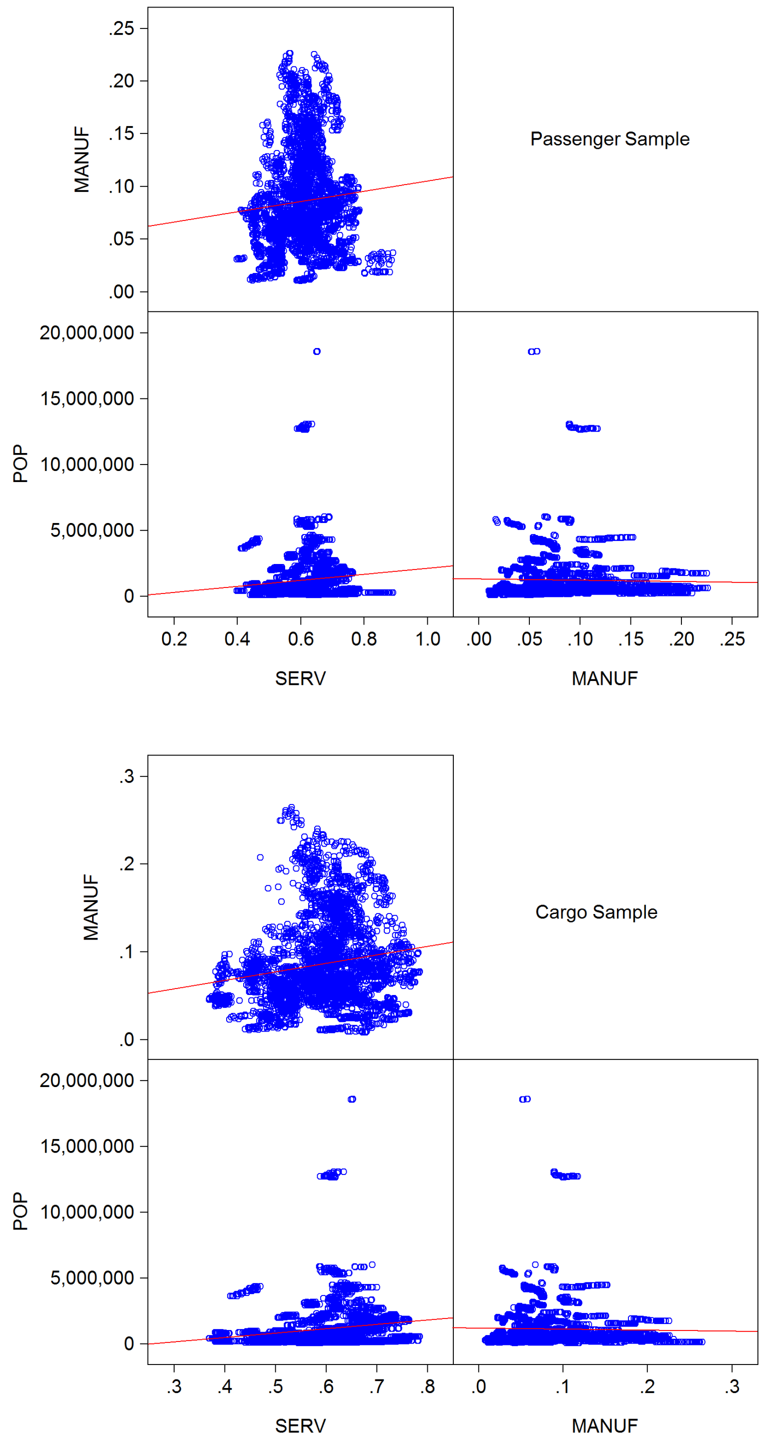
i. Sector 92 (Public administration)

(i) Unclassified

i. Sector 99 (Unclassified)

.1.2 Population and Employment Share

Figure 2: *POP*, *SERV*, and *MANUF* Scatter Plots



.2 Determinants of Air Cargo Traffic in California

To examine period-specific (seasonality) effects in our sample more closely, we have specified the following variation of our base model:

$$T_{it} = \alpha + \beta E_{it} + \gamma X_{it} + \sum \delta_i D_i + \sum \theta_t Q_t + \varepsilon_{it}, \tag{2}$$

where Q_t now represents year and quarter dummies (all other letters denote the same variables in the base model). The corresponding coefficient estimates for the model based on Equation 2 are shown in Table 15. With the exception of the time variables, the results shown here can be compared side-by-side with the output for the base model (found in Table 3.4).

Without much significance, the coefficients of the year dummies show signs that cargo traffic decreased after the 2007-peak year for national passenger and cargo traffic. The fall in traffic, captured by the 2008 and 2009 dummies, possibly reflects the shock of high oil prices observed in July of 2008, as well as the economic effects of the recession that shortly ensued. The quarter dummies do not reveal the seasonal variation that is traditionally expected for air cargo traffic, with higher demand anticipated during the holiday season (*QTR 4*). This finding is inconsistent with the claim that *FedEx Express* sees around a 50-percent rise in the daily packages it handles at *OAK* as early as September (TranSystems [87]). However, the insignificant coefficient on *QTR 4* precludes us from quantifying the effect of peak-commercial activities during the holiday season on air cargo traffic levels.

Table 15: Regression results with time dummies (420 Observations)

	Total (Domestic & International)		Domestic (*-DOM*)	
	(1) ACTRAFFIC	*(2) TRAFFIC*	*(3) ACTRAFFIC*	*(4) TRAFFIC*
INTERCEPT	-13.525^{a}	-17.911^{a}	-9.437^{a}	-13.250^{a}
	(4.095)	(5.201)	(2.899)	(3.949)
POP	0.976^{a}	1.174^{a}	0.680^{a}	0.859^{a}
	(9.756)	(11.558)	(6.566)	(8.374)
SERV	7.636^{a}	5.816^{a}	10.968^{a}	9.432^{a}
	(4.130)	(3.121)	(5.802)	(5.008)
MANUF	1.389^{c}	0.469	2.019^{b}	1.158
	(1.704)	(0.562)	(2.371)	(1.358)
WAGE	0.799^{a}	1.071^{a}	0.667^{a}	0.880^{a}
	(3.073)	(3.948)	(2.597)	(3.333)
YOUNG	2.179	2.441	3.261	3.583
	(0.830)	(0.894)	(1.261)	(1.344)
OLD	-18.139^{a}	-11.192^{b}	-27.910^{a}	-21.764^{a}
	(3.296)	(1.599)	(4.893)	(3.829)
CAP	1.533^{a}	1.306^{a}	1.889^{a}	1.695^{a}
	(13.589)	(11.494)	(16.433)	(15.032)
HUB	3.884^{a}	3.621^{a}	4.029^{a}	3.757^{a}
	(23.214)	(21.290)	(22.390)	(21.414)
PROXIMITY	-1.553^{a}	-1.592^{a}	-1.549^{a}	-1.585^{a}
	(19.429)	(19.216)	(19.898)	(19.821)

Results continued on the next page...

Regression results continued (Table 15) with time dummies (420 obs.)

	Total (Domestic & International)		Domestic (*-DOM*)	
	(1) ACTRAFFIC	*(2) TRAFFIC*	*(3) ACTRAFFIC*	*(4) TRAFFIC*
YR 2004	0.021	0.002	0.035	0.018
	(0.859)	(0.021)	(0.291)	(0.153)
YR 2005	-0.030	-0.061	-0.005	-0.0326
	(0.266)	(0.535)	(0.048)	(0.289)
YR 2006	0.051	0.005	0.077	0.0367
	(0.507)	(0.050)	(0.762)	(0.360)
YR 2007	0.095	0.010	0.157	0.083
	(0.882)	(0.093)	(1.462)	(0.761)
YR 2008	0.087	-0.020	0.202^c	0.105
	(0.738)	(0.166)	(1.717)	(0.880)
YR 2009	-0.047	-0.186	1.108	-0.018
	(0.369)	(1.435)	(0.846)	(0.141)
QTR 2	0.148^c	0.142^c	0.173^b	0.166^b
	(1.943)	(1.830)	(2.262)	(2.156)
QTR 3	0.092	0.092	0.096	0.093
	(1.225)	(1.199)	(1.269)	(1.219)
QTR 4	0.022	0.002	0.033	0.016
	(0.290)	(0.025)	(0.423)	(0.206)
Adj. R^2	0.967	0.968	0.965	0.966

Notes: The dependent variables, *POP*, and *WAGE* are in natural logs.
Absolute t-statistics in parentheses, based on robust standard errors: $^a p < 0.01$; $^b p < 0.05$; $^c p < 0.10$.

Figure 3: MSA Manufacturing Employment Shares (2009Q4)

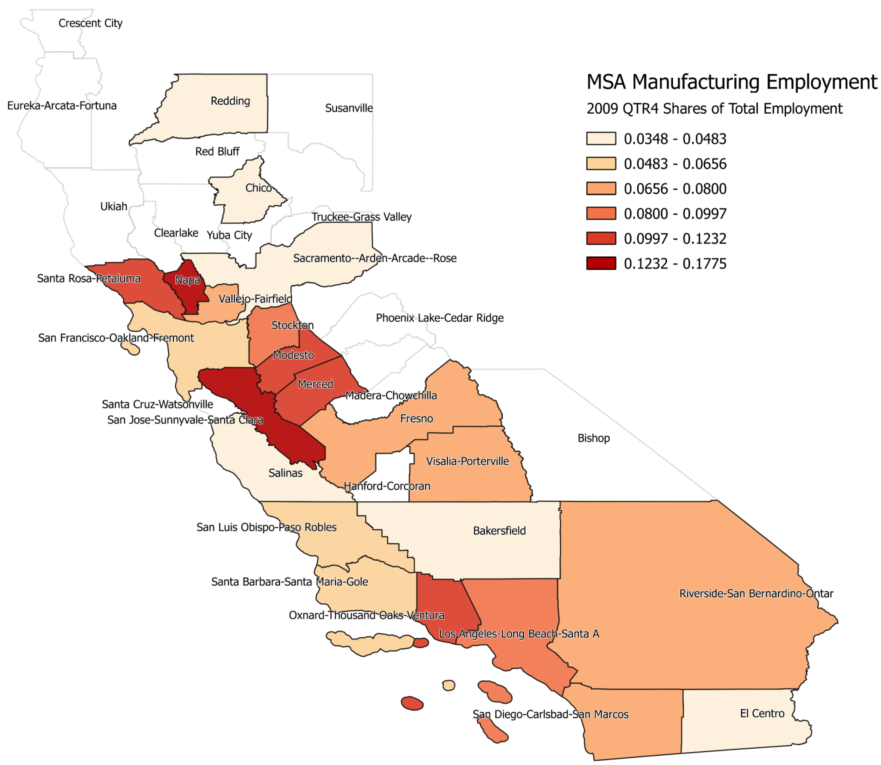


Figure 4: MSA Service Employment Shares (2009Q4)

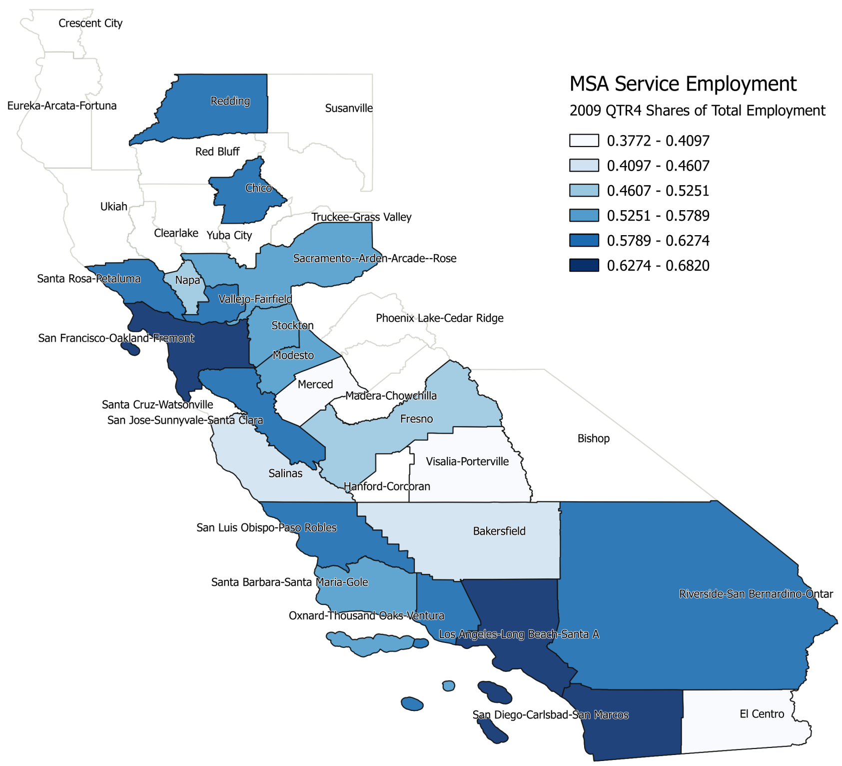


Figure 5: MSA Domestic *All-Cargo* and *Passenger Cargo* Forecasts (2010-2040)

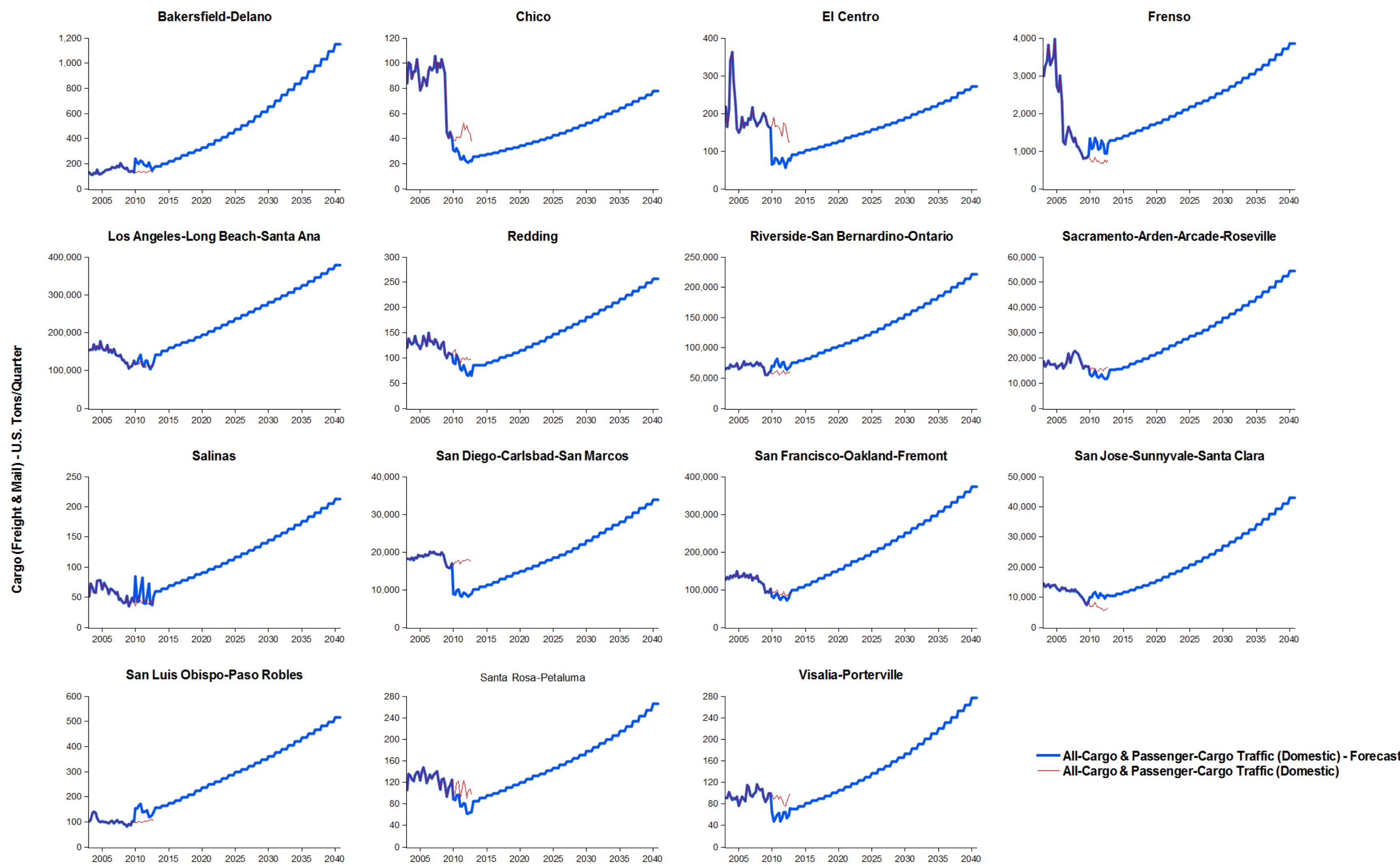
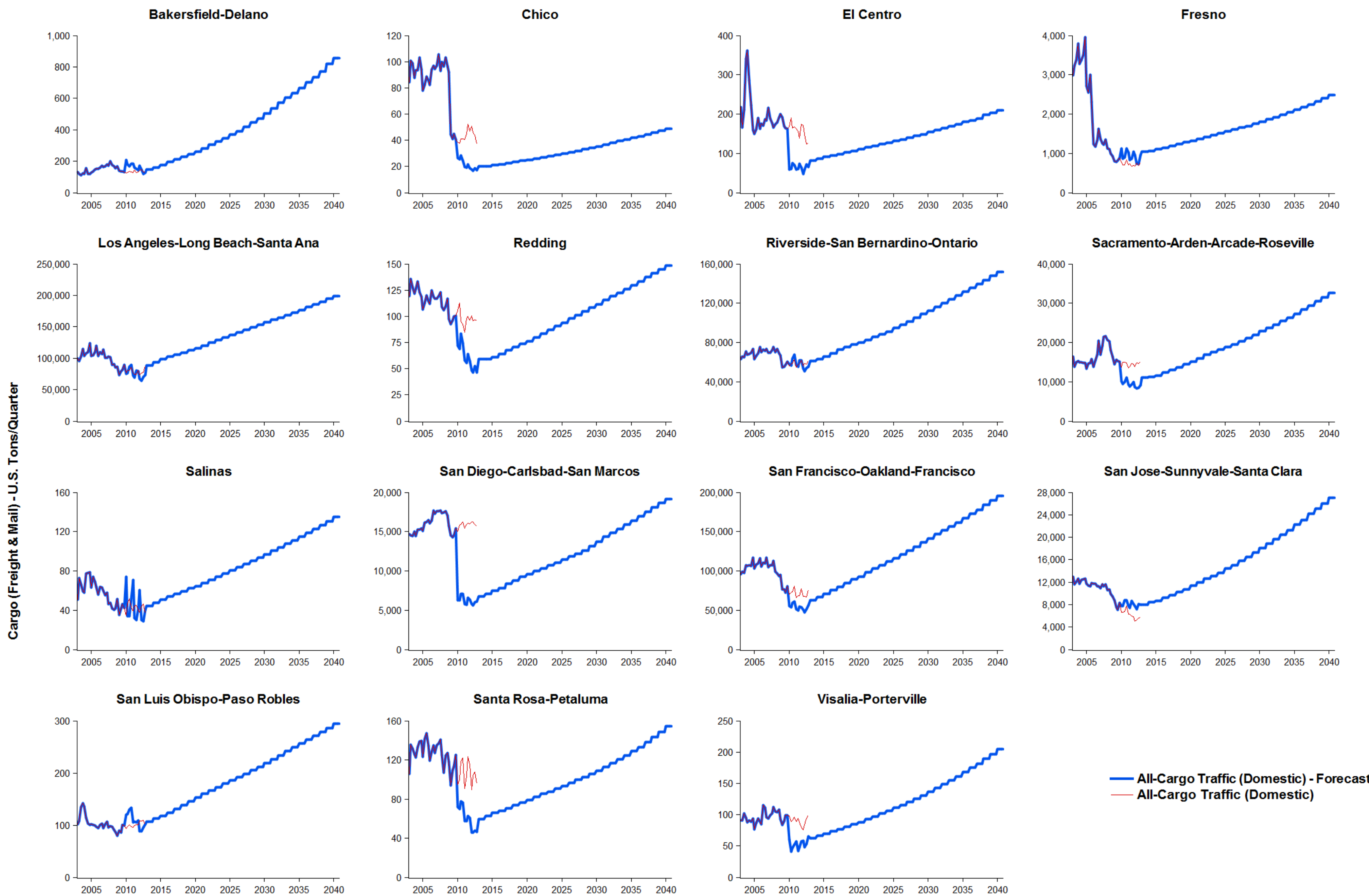


Figure 6: MSA Domestic *All-Cargo* Forecasts (2010-2040)



.3 Airport Delays and Metropolitan Employment

Table 16: First Stage Regressions — *HUB* Instrument, Departure Delay

	PAX	*CANCEL*	*COUNTDEL*	*MEANDEL*	*SUMDEL*
	(1)	(2)	(3)	(4)	(5)
INTERCEPT	2.7925^a	-4.2619^a	-3.7608^a	1.5736^a	0.4825
	(1.0751)	(1.1030)	(1.0182)	(0.3662)	(1.0372)
POP	0.9631^a	0.7436^a	0.8678^a	0.0827^a	0.8585^a
	(0.0509)	(0.0571)	(0.0554)	(0.0208)	(0.0562)
YOUNG	-8.4988^a	-1.0199	-2.3087	-0.9111	-2.9629
	(3.0880)	(3.010)	(2.6566)	(0.9323)	(2.6487)
OLD	-11.1174^a	-10.5530^a	-10.2624^a	0.1290	-9.8871^a
	(2.2946)	(2.3675)	(2.1565)	(0.8867)	(2.1846)
HUB	1.1588^a	0.8428^a	1.2055^a	-0.0265	1.0777^a
	(0.1949)	(0.1631)	(0.1677)	(0.0409)	(0.1614)
LEISURE	0.8169^a	-0.2286	0.0584	-0.0057	0.0405
	(0.2526)	(0.5164)	(0.6522)	(0.0888)	(0.6305)
SLOT	0.2612	1.8105^a	0.3724	0.1074	0.6197
	(0.4695)	(0.6528)	(0.5362)	(0.1358)	(0.5284)
PROXIM.	-1.2512^a	-0.5650^a	-1.0228^a	-0.0449	-0.9970^a
	(0.1198)	(0.1181)	(0.1218)	(0.0455)	(0.1240)
PRCP	-0.0720^a	0.0997^a	-0.0050	0.0483^a	0.0206
	(0.0206)	(0.0229)	(0.0242)	(0.0068)	(0.0241)
SNOW	0.0071^b	0.0188^a	0.0072^b	0.0053^a	0.0080^b
	(0.0031)	(0.0050)	(0.0035)	(0.0017)	(0.0035)
JANTEMP	-0.0002	0.0011	0.0132^b	0.0038^b	0.0119^b
	(0.0056)	(0.0055)	(0.0052)	(0.0018)	(0.0052)
Observations	3603	3603	3603	3603	3603
Adj. R^2	0.8853	0.7077	0.8369	0.2452	0.8205

Notes: Dependent variables and *POP* are in natural logs.
Dummies for Years and Quarters are suppressed.
Robust clustered standard errors in parentheses: $^a p < 0.01$; $^b p < 0.05$; $^c p < 0.10$.

Table 17: First Stage Regressions — *CENTR.* Instrument, Departure Delay

	PAX	*CANCEL*	*COUNTDEL*	*MEANDEL*	*SUMDEL*
	(1)	(2)	(3)	(4)	(5)
INTERCEPT	0.3140	-5.2691^a	-5.8324^a	1.7283^a	-1.2717
	(1.2590)	(1.0536)	(1.1148)	(0.3443)	(1.0815)
POP	1.1232^a	0.8623^a	1.0358^a	0.0793^a	1.0090^a
	(0.0513)	(0.0505)	(0.0548)	(0.0178)	(0.0534)
YOUNG	-7.6285^b	-1.9856	-2.4219	-1.1277	-3.2605
	(3.7986)	(3.1996)	(3.2921)	(0.9226)	(3.1559)
OLD	-9.7019^a	-11.1088^a	-9.7999^a	-0.0985	-9.6683^a
	(2.4456)	(2.5775)	(2.4400)	(0.9461)	(2.4548)
CENTR.	0.000143^c	-0.000150^a	-0.000013	-0.000035	-0.000043
	(0.000073)	(0.000056)	(0.000059)	(0.000024)	(0.000059)
LEISURE	0.9931^a	-0.0812	0.2539	-0.0074	0.2177
	(0.2962)	(0.5246)	(0.6856)	(0.0870)	(0.6578)
SLOT	0.0754	1.7141^a	0.2038	0.1164	0.4738
	(0.3583)	(0.4967)	(0.3626)	(0.1140)	(0.3578)
PROXIM.	-1.2010^a	-0.5930^a	-1.0117^a	-0.0540	-0.9950^a
	(0.1387)	(0.1202)	(0.1323)	(0.0446)	(0.1313)
PRCP	-0.0638^a	0.0624^a	-0.0241	0.0428^a	-0.0017
	(0.0201)	(0.0223)	(0.0262)	(0.0063)	(0.0253)
SNOW	0.0042	0.0188^a	0.0054	0.0056^a	0.0067^c
	(0.0035)	(0.0051)	(0.0038)	(0.0017)	(0.0038)
JANTEMP	-0.0007	-0.0029	0.0070	0.0040^b	0.0064
	(0.0057)	(0.0054)	(0.0057)	(0.0018)	(0.0056)
Observations	3603	3603	3603	3603	3603
Adj. R^2	0.8664	0.6955	0.8106	0.2497	0.7988

Notes: Dependent variables and *POP* are in natural logs.
Dummies for Years and Quarters are suppressed.
Robust clustered standard errors in parentheses: $^a p < 0.01$; $^b p < 0.05$; $^c p < 0.10$.

Table 18: First Stage Regressions — *HUB* Instrument, Arrival Delay

	PAX	*CANCEL*	*COUNTDEL*	*MEANDEL*	*SUMDEL*
	(1)	(2)	(3)	(4)	(5)
INTERCEPT	2.8462^{a}	-4.9073^{a}	-2.9382^{a}	2.2121^{a}	0.7687
	(1.0909)	(1.2973)	(0.9905)	(0.3002)	(1.0152)
POP	0.9619^{a}	0.7664^{a}	0.8162^{a}	0.0241	0.8395^{a}
	(0.0520)	(0.0625)	(0.0524)	(0.0147)	(0.0541)
YOUNG	-8.5677^{a}	-0.2653	-1.7318	0.5513	-2.4802
	(3.1242)	(3.4220)	(2.6205)	(0.7843)	(2.6343)
OLD	-11.3721^{a}	-10.5134^{a}	-9.3134^{a}	1.0512	-9.3131^{a}
	(2.3217)	(2.5402)	(2.0335)	(0.7421)	(2.0151)
HUB	1.1653^{a}	0.9880^{a}	1.0226^{a}	-0.1743^{a}	0.9969^{a}
	(0.1954)	(0.1964)	(0.1576)	(0.0355)	(0.1582)
LEISURE	0.8200^{a}	-0.2523	-0.0392	-0.0520^{b}	-0.0641
	(0.2527)	(0.5012)	(0.6055)	(0.0232)	(0.6061)
SLOT	0.2777	1.8016^{a}	0.5425	0.2369^{b}	0.6963
	(0.4738)	(0.6623)	(0.6090)	(0.1012)	(0.6635)
PROXIM.	-1.2678^{a}	-0.5681^{a}	-1.0686^{a}	-0.0410	-1.0611^{a}
	(0.1223)	(0.1264)	(0.1176)	(0.0308)	(0.1205)
PRCP	-0.0721^{a}	0.1153^{a}	-0.0100	0.0382^{a}	0.0064
	(0.0207)	(0.0244)	(0.0219)	(0.0044)	(0.0222)
SNOW	0.0065^{b}	0.0208^{a}	0.0066^{b}	0.0047^{b}	0.0080^{b}
	(0.0032)	(0.0059)	(0.0033)	(0.0019)	(0.0032)
JANTEMP	-0.0003	0.0018	0.0109^{b}	-0.0002	0.0104
	(0.0056)	(0.0059)	(0.0050)	(0.0014)	(0.0050)
Observations	3594	3594	3594	3594	3594
Adj. R^2	0.8848	0.7018	0.8426	0.2856	0.8345

Notes: Dependent variables and *POP* are in natural logs.
Dummies for Years and Quarters are suppressed.
Robust clustered standard errors in parentheses: $^{a}p < 0.01$; $^{b}p < 0.05$; $^{c}p < 0.10$.

Table 19: First Stage Regressions — *CENTR.* Instrument, Arrival Delay

	PAX	*CANCEL*	*COUNTDEL*	*MEANDEL*	*SUMDEL*
	(1)	(2)	(3)	(4)	(5)
INTERCEPT	0.3388	-6.1544^a	-4.7140^a	2.6196^a	-0.9263
	(1.2783)	(1.2434)	(1.0611)	(0.2991)	(1.0674)
POP	1.1233^a	0.9070^a	0.9596^a	0.0002	0.9795^a
	(0.0522)	(0.0554)	(0.0503)	(0.0130)	(0.0517)
YOUNG	-7.6702^b	-1.3070	-1.8151	0.3473	-2.6355
	(3.8552)	(3.6738)	(3.1759)	(0.7904)	(3.1469)
OLD	-9.9172^a	-11.1130^a	-8.9223^a	0.7630	-9.0071^a
	(2.4947)	(2.7476)	(2.2642)	(0.7906)	(2.2469)
CENTR.	0.000144^c	-0.000157^b	-0.000008	-0.000032^b	0.000020
	(0.000074)	(0.000063)	(0.000055)	(0.000016)	(0.000057)
LEISURE	0.9975^a	-0.0805	0.1269	-0.0775^a	0.0987
	(0.2968)	(0.5118)	(0.6360)	(0.0246)	(0.6349)
SLOT	0.0895	1.6761^a	0.3938	0.2662	0.5527
	(0.3630)	(0.4843)	(0.3735)	(0.1646)	(0.4211)
PROXIM.	-1.2152^a	-0.5946^a	-1.0568^a	-0.0517	-1.0525^a
	(0.1416)	(0.1294)	(0.1280)	(0.0314)	(0.1299)
PRCP	-0.0638^a	0.0754^a	-0.0254	0.0351^a	-0.0106
	(0.0202)	(0.0236)	(0.0233)	(0.0044)	(0.0234)
SNOW	0.0035	0.0206^a	0.0051	0.0052^a	0.0067^c
	(0.0036)	(0.0053)	(0.0035)	(0.0019)	(0.0035)
JANTEMP	-0.0007	-0.0029	0.0057	-0.0008	0.0053
	(0.0057)	(0.0059)	(0.0053)	(0.0014)	(0.0054)
Observations	3594	3594	3594	3594	3594
Adj. R^2	0.8659	0.6852	0.8214	0.2743	0.8150

Notes: Dependent variables and *POP* are in natural logs.
Dummies for Years and Quarters are suppressed.
Robust clustered standard errors in parentheses: $^a p < 0.01$; $^b p < 0.05$; $^c p < 0.10$.