AIRPORT TRAFFIC AND METROPOLITAN ECONOMIES: DETERMINANTS OF PASSENGER AND CARGO TRAFFIC

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ABSTRACT

The present paper assesses the impacts of urban size, employment, and income on air traffic, while controlling for the unique and unobserved characteristics of cities. Previous studies have established links between the socioeconomic characteristics of cities and the volume of passenger and cargo traffic enplaned at their airports. Using the variation of population, employment, and income across urban areas, researchers have found that passenger enplanements are proportional to city size and that they increase with income and service-sector employment. However, most of these earlier works rely on cross-section methods that ignore city-specific differences, which may influence the drivers of air traffic. This paper is based on a 10-year quarterly panel of city-level economic and traffic measures, from which a city fixed effects model is estimated. Thus, the results presented in this study shed light on the within-city effects that population, employment composition, and the average wage have on traffic, providing new insights into the determinants of air travel and goods movement. Controlling for the unobserved features of a metro area, this paper confirms that passenger and cargo enplanements are proportional to population. Service-sector employment and higher wages, indicating *white collar* jobs, continue to induce both passenger and cargo transport, while a city's share of employment in manufacturing (*blue collar*) jobs mostly affects cargo traffic. Additionally, the fixed effects results show that 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.

Keywords: airport traffic, air travel demand, air cargo, urban employment

JEL Codes: *J21, L930, R12, R41*

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 impacts of airport traffic, while also examining the effectiveness of investments in transportation infrastructures (*1*; *2*; *3*; *4*). In parallel, empirical studies have addressed urban-agglomeration economies, which are facilitated by airline services that connect commercial activities between metropolitan areas (*5*). Drawing connections between air transport and employment in metro areas, numerous papers established a positive relationship between airport traffic and economic development (*6*; *7*; *8*; *9*; *10*; *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 (*8*; *10*), only a small body of empirical work has addressed how a city's size and economic features induce passenger and cargo traffic at airports (*12*; *13*; *14*). Moreover, most of these studies employ cross-section methods that do not control for city-specific unobserved features that may 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 using the same industry groups defined by a recent empirical study regarding industry mix and airline traffic (*3*).

Seeing that planners and policy makers commonly use economic indicators 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. The effects of region-specific differences in national models, however, have not been explored sufficiently (*15*). Thus, this paper exploits the empirical benefits of panel data to control for the unique and unobserved features of different cities, while providing a countrywide analysis of urban-socioeconomic impacts on air traffic.

A quarterly panel dataset (2003Q1 - 2012Q4) 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, in the passenger regressions, the dependent variable is the total passenger enplanements at airports in a metro area. In the cargo regressions, the dependent variable is a metro area's total departed air cargo (freight and mail) tons. The variation of demographic and sector-specific socioeconomic characteristics, both across and within metropolitan areas, is used to assess the impacts 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 the 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 between counties within each urban area (*16*).

Controlling for unobserved and city-specific differences, this 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 affected 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.

Literature Highlights

Brueckner (*12*) examined metro-area size, employment, and income factors that affect U.S. air-passenger transport using 1970 data (pre-deregulation). He found 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* jobs. Noting that the airline industry has reorganized considerably since deregulation (1978), and that advances in technology may have changed the relationship between airport traffic and local economies, Discazeaux and Polese (*13*) 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 relationships between air traffic and urban economic characteristics established by Brueckner (*12*) remained unchanged.

Air cargo 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. Like passenger traffic, hub-cargo traffic is also not primarily driven by the hub airport's local demand, but rather by the market demand of the cities it connects. Growth in air cargo traffic may introduce new transport-related jobs in the vicinity of airports, and thereby alter the surrounding metro area's employment composition through spillover effects. Therefore, understanding causation between air cargo and the urban economy is pertinent. Kasarda and Green (*17*) drew some preliminary connections between global air cargo traffic and national economic indicators, while Chang and Chang (*18*) addressed the causal link between economic development and air cargo growth in Taiwan. Using *Granger causality* tests, Chang and Chang demonstrated that the long-term relationship between economic development and air cargo expansion is bidirectional. Button and Yuan (*19*) also used this methodology to investigate the causal relations between air freight transportation and regional economic development in the U.S. Their findings suggest that air freight induces local-economic development.

While *Granger causality* tests are useful for determining short-term causal links, Chi and Baek (*20*) posited that such tests do not sufficiently capture the long-term equilibria in the relationship between air traffic and economic development. Hence, the authors used an *autoregressive distributed lag* model to examine 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 showed minimal effects on air freight traffic, Chi and Baek found air-passenger traffic to be sensitive to some market shocks and both short- and long-term economic development. However, both passenger *and* freight traffic demonstrated growth with economic development in the long-run, implying that the urban-economic influence on freight traffic is also not a transient effect. More pertinently, Alkaabi and Debbage (*14*) analyzed socioeconomic variables that they deemed to be the most influential predictors of the distribution of outbound air freight. The authors found that there is a strong traffic-diversion effect between small and largo metro areas while income, medical establishments, and transportation-related jobs exhibit considerable impacts on freight traffic.

Still, the inherent problem of identifying causation in the airport-traffic and urban-employment relationship remains, especially for passenger travel. 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 (*8*), 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. (*21*) 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 (*15*; *22*; *23*). Mukkala and Tervo (*22*) 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 suggested 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* (*24*), 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 that investigate the influence of air transport on urban employment, it is not examined in the present analysis.

EMPIRICAL SPECIFICATION AND DATA

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

$$T_{ist} = \alpha_i + \beta E_{ist} + \gamma X_{ist} + \theta_s Q_s + \delta_t Y_t + \varepsilon_{ist}, \qquad (1)$$

where α_i is the MSA-specific intercept; E_{ist} denotes the shares of sectoral employment; X_{ist} is a vector of exogenous control variables; Q_s and Y_t respectively represent quarter and year dummies; and ε_{ist} is the error term. The parameter estimates corresponding to the explanatory variables are represented by β, γ, θ_s, and δ_t. Hence, the empirical point estimates will indicate how much a shift in sector-specific employment shares will impact airport traffic, while controlling for other city and operational characteristics that also affect traffic. The controlled features in X_{ist} are population, age distribution, average weekly wage, unemployment rate, hub status, air temperature, airport-to-airport distance, and fuel price. 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 (*12*).

A key contribution of this paper is the treatment of unobserved city-specific heterogeneity that may influence the determinants of air traffic. Given the panel structure of the data, a fixed effects or random effects model can be used to control for time-invariant and unmodeled city differences, which would otherwise end up in the error term. A fixed effects model is appropriate if the omitted features that are unique to a city are correlated with the regressors. Thus, the city-specific intercept (α_i) would control for observation similarities within cities as well as differences across cities. On the other hand, the random effects estimator assumes that α_i is not correlated with the independent variables. Hence, a test for *redundant fixed effects* is first used to confirm the existence of unobserved heterogeneity in the sample MSAs. Then, the choice between fixed effects and random effects is based on the *Hausman* test. This test's null hypothesis (positing unobserved errors are uncorrelated with regressors) is rejected, implying that random effects would give inconsistent coefficient estimates (*25*). Therefore, in this case, a fixed effects model is chosen for the estimations.

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 *Form 41 Traffic T-100 Segment* tables, provided by the Bureau of Transportation Statistics (BTS) (*26*). 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 (*27*). 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 *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 (*28*, p.77), examining freight and mail outputs separately would be ideal. However, mail transported by some integrated carriers (e.g., FedEx Express), albeit relatively small, cannot be distinguished from freight (*29*, p.28). Therefore, although the separate analysis of freight and mail is preferred, it is precluded by the available data.

Employment and Wages

The employment characteristics 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) (*30*). Wage and sectoral-employment data are also included at the MSA level, using numbers from the BLS Quarterly Census on Employment and Wages (QCEW) (*31*). 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) *Goods Producing* and (2) *Service Providing*. Further disaggregation of the data provides *subsector* employment information (NAICS codes are in brackets):

1. *Goods Producing*
    a. *Manufacturing* [31-33]
    b. *Construction* [23]
    c. *Natural resources and mining* [11, 21]
2. *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]
    g. *Other services* [81] excluding *Public administration* [92]

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

i. Service (*SERV*): Share of total employment in *Education and health service, Financial activities, Information*, *Leisure and hospitality, Professional and business services,* and *Trade, transport and utilities* jobs.
ii. Manufacturing (*MANUF*): Share of total employment in *Manufacturing* jobs.

In view of the employment diversity in the service sector, especially as it pertains to air transportation, Sheard's (*3*) classification of *tradable* and *non-tradable* services is adopted in this paper. *Tradable* services include employment groups where the provided services can be "consumed" in a different geographical location. As such, employees in the *tradable* service industries may benefit from the networking and face-to-face contact advantages afforded by air travel more than employees in service occupations that are *non-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 classification of employment categories as *tradable* or *non-tradable* is not based on strictly objective grounds, the justification that these two service groups have unique air-travel demand characteristics is reasonable (*3*).

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 variation in the economic health of MSAs. Figure 1 shows the broad range of passenger-enplanement volumes and average weekly wages across the sample MSAs in the country (2012Q4 data).

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 Bureau's county-level annual demographic measures (*32*). Further, since the population data are also provided in 5-year age groups, they are organized by age-group shares (*YOUNG* and *OLD*) to control for the labor-force characteristics of cities in the sample. Figure 2 illustrates MSA-level tonnage of departed cargo in 2012Q4, overlaying the corresponding area's population estimates for that year.

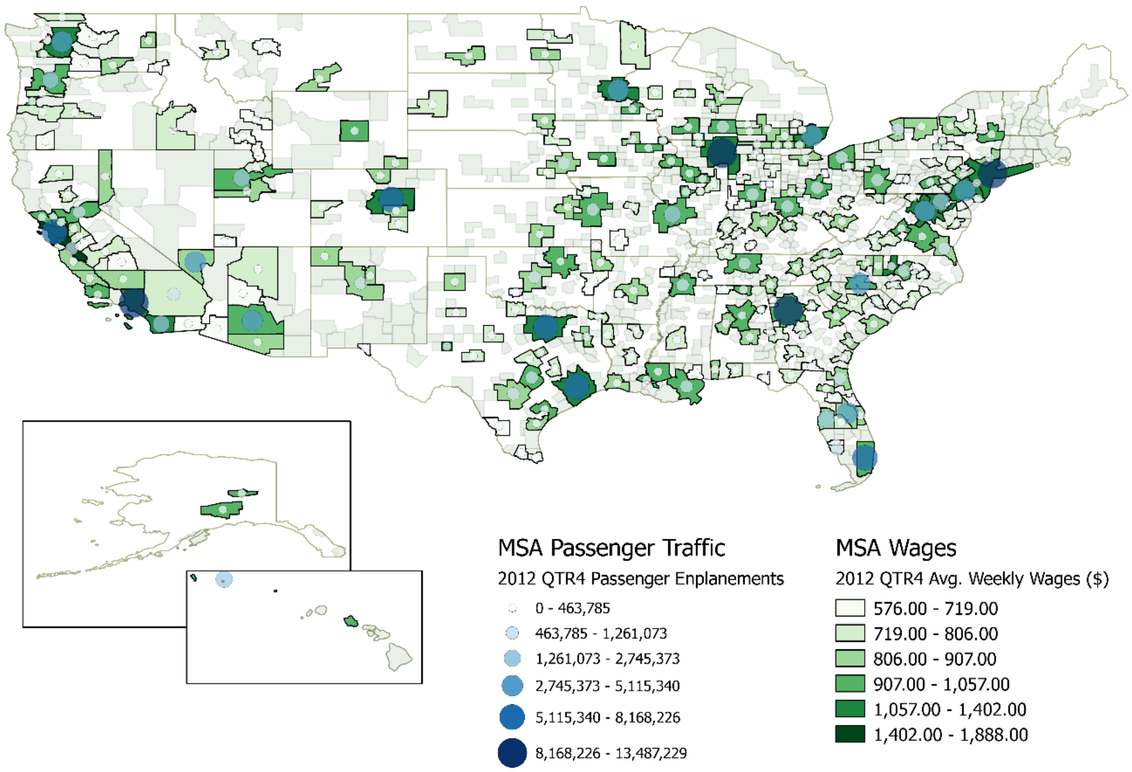

FIGURE 1 MSA Average Weekly Wages (nominal) and Passenger Enplanements in 2012Q4.

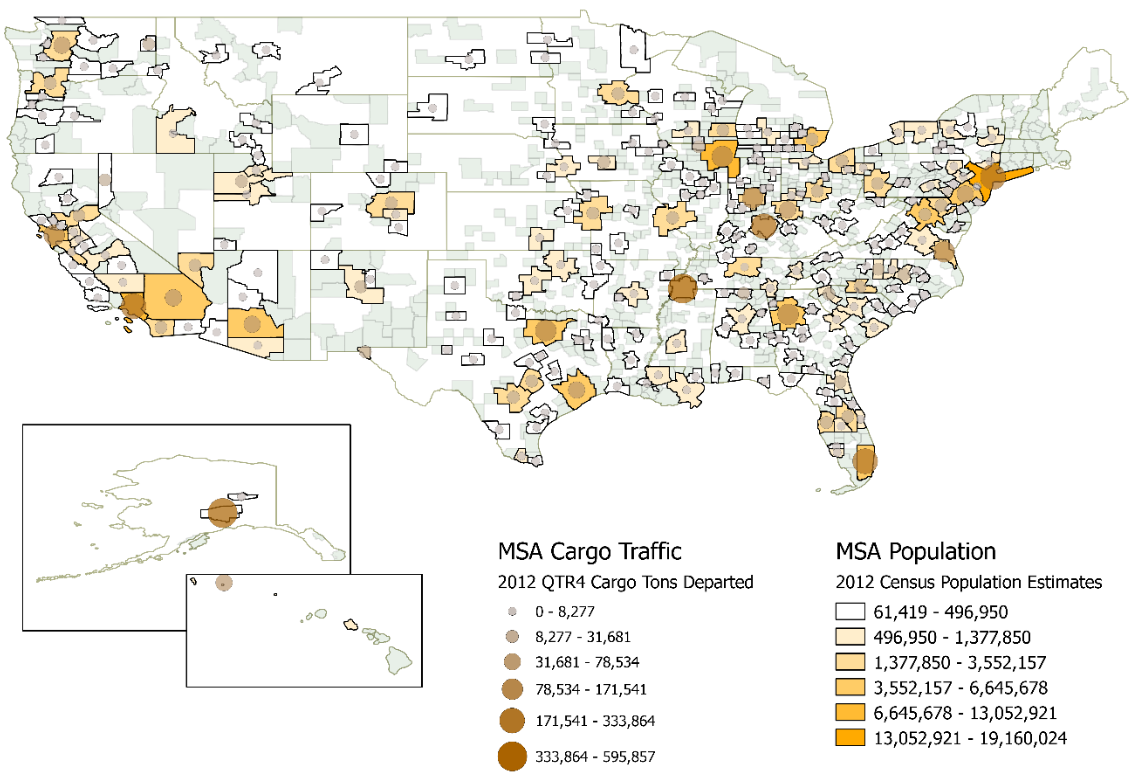

FIGURE 2 MSA Populations in 2012 and Departed Cargo Tonnage in 2012Q4.

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 (*33*). The new hub features of certain cities could potentially alter the airport traffic and urban-growth relationships established in the literature. Hub airports, which handle the highest levels of passenger or cargo traffic in the nation, are not necessarily in metro areas that are affluent or have strong concentrations of service-sector jobs (consider Atlanta, GA and Memphis, TN as examples of passenger and cargo cities that fit this scenario) (*13*). 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 *true* origin (or destination) volumes of passengers and freight to be identified. Hence, since local originations cannot be distinguished from all enplanements (which also include *transit* and *intermediate-stop* traffic), 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. One solution to capture *true* originations would be to drop all hub airports (cities) for passenger and cargo operations from the sample (*12*). A problem with this approach is that some cities 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 the point-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 *focus cities* of passenger carriers, 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. While the FAA provides hierarchical passenger-hub definitions based on an airport's annual share of passenger enplanements in the U.S., researchers have employed other metrics to determine the hub status of airports more accurately (see Ryerson and Kim, *34*). On the cargo side, FedEx Express and UPS Airlines operate the first and second largest cargo hubs (*Memphis Intl.* and *Louisville Intl.*) in the country. 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 structures of the cities heavily depends on the hub operations, the corresponding MSAs are dropped from the cargo samples.

Traffic Diversion
The relevant literature suggests 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 (*12*; *14*). In view of the transportation amenities availed by big cities, passengers (freight forwarders) will forego travelling (shipping products) from the closest airport, using surface-transportation modes to reach larger airports that are farther away and possibly in another metro area. This traffic-diversion effect, also called a *traffic-shadow effect*, consequently 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). The small- and large-MSA classifications were 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 1 lists the sample MSAs that face traffic diversion (*PROXIMITY* is equal to 1).

TABLE 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 air temperature are also included at the city level. Weather data are downloaded from the National Oceanic and Atmospheric Administration's *Global Historical Climatology Network* (GHCN) (*35*). The average daily maximum temperature in January (*JANTEMP*), measured at airport GHCN stations, is collapsed to the MSA level, and used to identify cities that are attractive to leisure travel. Given that warmer locations usually draw 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 (1.43.2) percent for passenger (cargo) carriers (*36*; *37; 38*). 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 effect of this exogenously-determined variable.

Data on fuel expenditures, for both passenger and cargo carriers, are obtained from the DOT's *Air Carrier Financial Reports* (*Schedule P-5.2*) (*39*). 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 3 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 influence 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 (*25*; *40*). Therefore, MSA fixed effects estimations are employed to control for the latter factors that are otherwise unobserved.

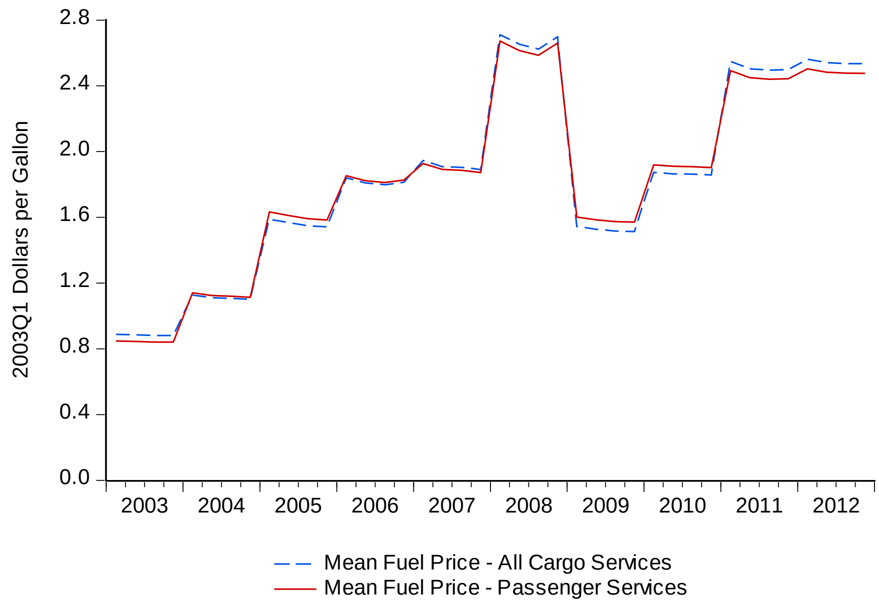

FIGURE 3 Fuel Price (2003Q1 Dollars per Gallon).

Panel

The start and end dates of this study's panel are mainly restricted 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 for the two biggest integrated carriers, FedEx Express and UPS Airlines, starting from 2002 Quarter 1 and Quarter 4, respectively. Morrell (*28*, 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 result from the traffic-reporting changes that took place.

The panel is constructed with metro area (MSA) cross-sections of quarterly data over the 2003Q1 - 2012Q4 period. Airport-level traffic data are consolidated to their respective MSAs, and the samples for this study are restricted to primary MSAs 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 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 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-sections in the cargo sample vary between the cross-sectional and fixed effects specifications, as well as the total and domestic samples. Table 2 provides definitions of variables used in this study, and Table 3 shows the corresponding summary statistics for the MSAs in the samples.

TABLE 2 Variable Definitions

Variables	**Description**
PASSENGERS†	Number of passengers enplaned at MSA
CARGO(*-AC*)	Freight & mail tons enplaned at MSA (-*All Cargo* services only)
POP	Total MSA population (annual)
YOUNG	Share of MSA population of age 19 and under
OLD	Share of MSA population of age 60 and over
TOTEMP	Total MSA employment
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 empl. share of *TOTEMP*
WAGE	Average weekly wages for MSA (in 2003Q1 dollars)
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 daily maximum temperature in January (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). *PASSENGERS*, *CARGO*, *POP*, *WAGE*, and *FUELPRICE* are logged in the regressions.
† *Total* (international & domestic) passenger and cargo traffic are analyzed separately from *Domestic*-only passenger and cargo traffic.

TABLE 3 Summary Statistics

	PASSENGER SAMPLE (4,149 obs.)			CARGO SAMPLE (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 (tons)	–	–	–	28,248	57	851,576
DOMESTIC	–	–	–	16,576	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	0.2081	0.3853	0.2774	0.2131	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	0.3978	0.8923	0.6104	0.3874	0.7852
PIF (***Tradable***)	0.1902	0.0605	0.3310	0.1931	0.0773	0.3310
Professional-Business	0.1175	0.0367	0.2433	0.1182	0.0409	0.2433
Information	0.0195	0.0057	0.0605	0.0200	0.0070	0.0605
Financial	0.0532	0.0175	0.1728	0.0550	0.0228	0.1728
TLE (***Non-tradable***)	0.4168	0.2680	0.7770	0.4172	0.2680	0.6645
Trade-Transport-Util.	0.1835	0.1177	0.2945	0.1856	0.1177	0.2608
Leisure-Hospitality	0.1048	0.0636	0.4900	0.0995	0.0577	0.3205
Education-Health	0.1285	0.0645	0.2236	0.1322	0.0500	0.4144
MANUF	0.0857	0.0100	0.2261	0.0882	0.0104	0.2399
WAGE	675.98	435.62	1,611.82	686.87	435.62	1,611.82
UR (%)	6.54	2.27	17.43	6.42	2.26	17.26
FUELPRICE ($/gal.)	1.83	0.84	2.67	1.81	0.88	2.71
HUB	0.11	0.00	1.00	0.06	0.00	1.00
AIRPORTS	1.24	1.00	6.00	1.46	1.00	5.00
PROXIMITY	0.13	0.00	1.00	0.26	0.00	1.00
JANTEMP (*degrees C*)	8.61	-27.89	27.35	7.87	-27.89	27.35

Notes: Quarterly MSA statistics shown here (except for *POP*, *YOUNG*, *OLD*, *HUB, and JANTEMP*, which are measured annually). *PASSENGERS*, *CARGO*, *POP*, *WAGE*, and *FUELPRICE* are logged in the regressions.
† 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 & domestic) sample.

The summary statistics in Table 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 substantial 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 work force of most cities, particularly in the area of trade, transport, and utilities (*Trade-Transport-Util.*). Some cities also exhibit considerably-high 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.* Observations that have unreported data for employment in any of the chosen sectoral categories are dropped from the sample to maintain consistent measures of employment across cities. Consequently, 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 in most quarters. To ensure the robustness of the estimation results without such large cities, all regressions are re-estimated with these MSAs included in the samples for all quarters. The qualitative results and significance levels for both passenger and cargo traffic (exhibited in the following section) remain the same, with relatively small differences in the estimated coefficient magnitudes.

RESULTS

Passenger Traffic Results – A

The first regression in Table 4 essentially replicates the work of Brueckner (*12*), using a quarterly panel dataset. Contrary to Brueckner's (*12*) expectation, and consistent with the results of Discazeaux and Polese (*13*), 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*, *WAGE*, and *PROXIMITY* are comparable to the results found in Brueckner's study. Treating *SERV* and higher wages as proxies for *white collar* jobs, 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 is actually negatively correlated with 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. While this difference is statistically significant, it does not indicate that there is an economically-meaningful difference. However, assuming that a city's outbound enplanements are commensurate to inbound traffic, this finding lends some support to the expectation that larger cities are self-sufficient (*12*).

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* indicate the degree to which service 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 that around 47 percent of small-city passengers may be 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 impacts of the volatile oil prices in the sample period. Recall that *FUELPRICE* is based on time series data, with no cross-sectional variation. Therefore, while time on its own may not drive the observed within variation of the price of fuel, *FUELPRICE* is inherently correlated with the period dummies. 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 effects estimates (in columns 2, 3, 5, and 6) account for unobserved, 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 (*8*). While the effects of a city's centrality are possibly accounted for by the *HUB* dummy, other uncaptured regional characteristics, such as airport policies, facilities, transportation infrastructure, fuel supply, and proximity to national boundaries (*13*), can impact air transport considerably. Also, airfare levels (endogenously determined in the specified model) may be 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 (*12*). 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 and land ports, truck and rail terminals), warehouse facilities, and customs brokerage services, are unobserved regional differences that affect goods movement. The fixed effects 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 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 (1) holds (*12*). Consistent with Brueckner's (*12*) 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 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 are consistent with the possibility that the *OLD* age group (mostly retired) has a higher demand for air travel, potentially reflecting the group's 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. The cross-sectional results, however, exhibit the expected negative signs on the *YOUNG* and *OLD* coefficients, in line 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 main findings that hold in all total and domestic regressions of Table 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 impacts of service-sector employment and wages.

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 (*3*). The traditional 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 (*3*; *5*; *8*). The cross-sectional results for total and domestic passenger traffic in Table 5 confirm this expectation, exhibiting a positive and significant coefficient for *PIF* that is larger than the coefficient for *TLE* (difference is 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 relative 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 compared to the impact of an equivalent increase in a city's share of *tradable* service jobs (statistically-significant difference: standard error = 0.395). The coefficient estimates corresponding to *non-tradable* service employment, 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 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, some services provided in these industries (e.g., retail, dining, lodging, entertainment, etc.) have distinctive and potentially substantial impacts on leisure travel and tourism (*3*). 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 and strong relationships with tourism and air transport.

The traffic impacts 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.

TABLE 4 Passenger Traffic – A

	Total (Domestic & International)			*Domestic*		
PASSENGERS	*(1) Pooled OLS*	*(2) Fixed Effects (FE)*	*(3) FE, Clustered SE*	*(4) Pooled OLS*	*(5) Fixed Effects (FE)*	*(6) FE, Clustered SE*
CONSTANT	-7.3030***	-6.2987***	-6.2987	-6.7057***	-6.5538***	-6.5538
	(11.653)	(4.840)	(1.560)	(10.846)	(5.045)	(1.617)
POP	0.9689***	1.1660***	1.1660***	0.9420***	1.1694***	1.1694***
	(93.645)	(12.416)	(3.988)	(93.010)	(12.496)	(3.979)
SERV	2.4924***	2.0218***	2.0218***	2.4394***	2.0315***	2.0315***
	(16.572)	(11.126)	(3.392)	(16.669)	(11.158)	(3.416)
MANUF	-5.6215***	0.5228*	0.5228	-5.2944***	0.4588	0.4588
	(26.624)	(1.717)	(0.600)	(25.942)	(1.507)	(0.527)
WAGE	1.2010***	0.3210***	0.3210**	1.1519***	0.3366***	0.3366**
	(17.358)	(4.940)	(2.297)	(16.911)	(5.198)	(2.426)
UR	-0.0093*	-0.0039*	-0.0039	-0.0095*	-0.0054**	-0.0054
	(1.755)	(1.668)	(0.662)	(1.828)	(2.311)	(0.922)
YOUNG	-4.5123***	-1.3526	-1.3526	-4.2647***	-1.2195	-1.2195
	(8.319)	(1.355)	(0.445)	(7.935)	(1.234)	(0.401)
OLD	-4.6511***	1.2975*	1.2975	-4.5498***	1.6754**	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)	(0.780)	(1.242)
HUB	0.8017***	–	–	0.8100***	–	–
	(26.971)			(28.021)		
PROXIMITY	-0.6427***	–	–	-0.6506***	–	–
	(25.926)			(26.830)		
JANTEMP	0.0051***	–	–	0.0044***	–	–
	(4.598)			(4.197)		
Adj. R^2	0.8944	0.9940	0.9940	0.8943	0.9937	0.9937
F-STAT	1,402.19	4,245.73	4,245.73	1,401.43	4,050.41	4,050.41
(Prob.)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Obs.	3,807	3,955	3,955	3,807	3,955	3,955

1. *PASSENGERS*, *POP*, *WAGE*, and *FUELPRICE* are in natural logs.
2. Sample is restricted to MSAs enplaning more than 200,000 passengers per year.
3. Quarter and year dummies are suppressed.
4. Absolute t-statistics in parenthesis: *(1), (2)* based on robust standard errors; *(3) based on* clustered standard errors.
5. ***$p<0.01$; **$p<0.05$; *$p<0.1$.

TABLE 5 Passenger Traffic – B (Service Disaggregated)

	Total (Domestic & International)			***Domestic***		
PASSENGERS	*(1) Pooled OLS*	*(2) Fixed Effects (FE)*	*(3) FE, Clustered SE*	*(4) Pooled OLS*	*(5) Fixed Effects (FE)*	*(6) FE, Clustered SE*
CONSTANT	-6.4598***	-6.4720***	-6.4720	-5.7450***	-6.7092***	-6.7092
	(10.043)	(4.926)	(1.555)	(9.120)	(5.114)	(1.608)
POP	0.9554***	1.1662***	1.1662***	0.9267***	1.1696***	1.1696***
	(88.621)	(12.371)	(3.898)	(87.360)	(12.453)	(3.900)
PIF	3.5640***	1.3784***	1.3784*	3.6607***	1.4545***	1.4545*
	(11.337)	(4.932)	(1.826)	(11.875)	(5.200)	(1.927)
TLE	2.1401***	2.3372***	2.3372***	2.0380***	2.3143***	2.3143***
	(11.918)	(9.398)	(2.875)	(11.699)	(9.258)	(2.824)
MANUF	-5.8569***	0.4513	0.4513	-5.5625***	0.3946	0.3946
	(26.628)	(1.487)	(0.518)	(25.955)	(1.300)	(0.454)
WAGE	1.0711***	0.3423***	0.3423***	1.0038***	0.3558***	0.3558***
	(14.205)	(5.266)	(2.376)	(13.669)	(5.487)	(2.477)
UR	-0.0025	-0.0050**	-0.0050	-0.0018	-0.0064***	-0.0064
	(0.471)	(2.116)	(0.801)	(0.339)	(2.696)	(1.022)
YOUNG	-4.2438***	-1.2687	-1.2687	-3.9588***	-1.1443	-1.1443
	(7.605)	(1.269)	(0.416)	(7.148)	(1.156)	(0.375)
OLD	-4.3225***	1.3564*	1.3564	-4.1754***	1.7282**	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***	–	–	0.7876***	–	–
	(26.808)			(27.899)		
PROXIMITY	-0.6276***	–	–	-0.6334***	–	–
	(25.076)			(25.917)		
JANTEMP	0.0043***	–	–	0.0035***	–	–
	(3.724)			(3.193)		
Adj. R^2	0.8949	0.9940	0.9940	0.8951	0.9937	0.9937
F-STAT	1,351.77	4,225.52	4,225.52	1,354.06	4,029.60	4,029.60
(Prob.)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Obs.	3,807	3,955	3,955	3,807	3,955	3,955

1. *PASSENGERS*, *POP*, *WAGE*, and *FUELPRICE* are in natural logs.
2. Sample is restricted to MSAs enplaning more than 200,000 passengers per year.
3. Quarter and year dummies are suppressed.
4. Absolute t-statistics in parenthesis: *(1)*, *(2)* based on robust standard errors; *(3) based on* clustered standard errors.
5. ****p<0.01*; ***p<0.05*; **p<0.1*.

Cargo Traffic Results – A

Despite the difficulties in tracing the movement of air cargo goods, due to data limitations, Table 6 and 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 noted by Kiesling and Hansen (*39*), 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, *14*), 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 typically 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* reveals that air cargo traffic is actually proportional to population. Therefore, for a given city, a commensurate 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 estimate 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 impacts on cargo traffic lack statistical significance when unobserved city features are controlled in the fixed effects estimations. The negative and significant *UR* coefficient, however, implies 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 impacts 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 variable coefficients in the fixed effects estimations mostly exhibit the expected signs, but prevent any conclusions from being drawn due to their statistical insignificance.

Cargo Traffic Results – B (Service Disaggregated)

Table 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 *Trade, transport, and utilities*), the results suggest that air cargo enplanements are sensitive to the concentration of establishments and jobs that provide the needed transportation infrastructure and labor capacity to support goods movement. The fixed effects estimations in Table 7 show similar patterns observed in Table 6, where the shares of service employment are insignificant, but manufacturing employment emerges as an important driver of air cargo traffic.

The poor performance of the fixed effects estimations in the results summarized in Tables 6 and 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) suggest that the data gaps may be too wide, precluding robust estimations of the impacts of key socioeconomic variables.

The suppressed quarter- and year-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, indicating 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 6 Cargo Traffic (All-Cargo and Passenger-Cargo Services) – A

	Total (Domestic & International)			***Domestic***		
CARGO	*(1) Pooled OLS*	*(2) Fixed Effects (FE)*	*(3) FE, Clustered SE*	*(4) Pooled OLS*	*(5) Fixed Effects (FE)*	*(6) FE, Clustered SE*
CONSTANT	-1.1635***	-6.9841	-6.9841	-3.2895***	-9.2589**	-9.2589
	(17.220)	(1.561)	(0.547)	(2.779)	(2.407)	(0.783)
POP	0.8500***	0.9996***	0.9996	0.8470***	1.2937***	1.2937
	(40.328)	(2.748)	(0.884)	(46.635)	(4.455)	(1.349)
SERV	3.2279***	0.4411	0.4411	3.9007***	-0.0381	-0.0381
	(13.746)	(0.794)	(0.271)	(19.207)	(0.081)	(0.025)
MANUF	-2.6701***	4.8727***	4.8727	-2.8804***	8.2559***	8.2559*
	(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**	-0.0197***	-0.0197
	(1.326)	(1.304)	(0.544)	(2.322)	(3.281)	(1.420)
YOUNG	-5.0586***	6.6734*	6.6734	-0.6773	-0.2228	-0.2228
	(4.170)	(1.712)	(0.496)	(0.606)	(0.079)	(0.023)
OLD	-8.6354***	-11.9114***	-11.9114	-5.2752***	-4.5171**	-4.5171
	(9.504)	(4.967)	(1.395)	(6.534)	(2.139)	(0.589)
FUELPRICE	0.7610	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***	–	–	2.2485***	–	–
	(26.948)			(30.741)		
PROXIMITY	-1.1068***	–	–	-0.8339***	–	–
	(25.565)			(22.929)		
JANTEMP	-0.0097***	–	–	-0.0164***	–	–
	(4.217)			(8.633)		
Adj. R^2	0.7134	0.9541	0.9541	0.7473	0.9535	0.9535
F-STAT	369.57	516.90	516.90	434.71	511.46	511.46
(Prob.)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Obs.	3,407	3,623	3,623	3,375	3,558	3,558

1. *CARGO*, *POP*, *WAGE*, and *FUELPRICE* are in natural logs.
2. Sample is restricted to MSAs departing more than 1,000 tons of freight per year.
3. Quarter and year dummies are suppressed.
4. Absolute t-statistics in parenthesis: *(1)*, *(2)* based on robust standard errors; *(3) based on* clustered standard errors.
5. $^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$.

TABLE 7 Cargo Traffic – B (Service Disaggregated)

	Total (Domestic & International)			*Domestic*		
CARGO	*(1) Pooled OLS*	*(2) Fixed Effects (FE)*	*(3) FE, Clustered SE*	*(4) Pooled OLS*	*(5) Fixed Effects (FE)*	*(6) FE, Clustered SE*
CONSTANT	-2.5955*	-6.4910	-6.4910	-5.3583***	-10.0938***	-10.0938
	(1.850)	(1.453)	(0.527)	(4.280)	(2.758)	(0.900)
POP	0.8824***	0.9832***	0.9832	0.8938***	1.3738***	1.3738
	(39.982)	(2.700)	(0.885)	(48.729)	(4.944)	(1.490)
PIF	1.4425***	1.3736	1.3736	1.3082***	-0.1388	-0.1388
	(3.189)	(1.374)	(0.463)	(3.111)	(0.154)	(0.048)
TLE	3.9698***	0.0487	0.0487	4.9713***	0.3066	0.3066
	(11.086)	(0.069)	(0.030)	(15.199)	(0.524)	(0.200)
MANUF	-2.4601***	5.0194***	5.0194	-2.5759***	8.1948***	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*	-0.0068	-0.0068	-0.0299***	-0.0210***	-0.0210
	(1.917)	(0.934)	(0.387)	(3.296)	(3.209)	(1.326)
YOUNG	-5.5432***	6.6401*	6.6401	-0.0166	-0.4613	-0.4613
	(4.601)	(1.703)	(0.494)	(0.015)	(0.164)	(0.048)
OLD	-9.2891***	-12.3669***	-12.3669	-6.2249***	-5.2912**	-5.2912
	(9.989)	(5.121)	(1.445)	(7.516)	(2.502)	(0.685)
FUELPRICE	0.6193	0.3456	0.3456	1.3167	0.7380	0.7380
	(0.190)	(0.249)	(0.385)	(0.468)	(0.543)	(0.731)
HUB	2.3398***	–	–	2.1708***	–	–
	(26.622)			(29.472)		
PROXIMITY	-1.0394***	–	–	-0.8669***	–	–
	(26.479)			(24.171)		
JANTEMP	-0.0080***	–	–	-0.0139***	–	–
	(3.473)			(7.234)		
Adj. R^2	0.7149	0.9543	0.9543	0.7513	0.9536	0.9536
F-STAT	356.91	517.37	517.37	425.68	510.62	510.62
(Prob.)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Obs.	3,407	3,633	3,633	3,375	3,568	3,568

1. *CARGO*, *POP*, *WAGE*, and *FUELPRICE* are in natural logs.
2. Sample is restricted to MSAs departing more than 1,000 tons of freight per year.
3. Quarter and year dummies are suppressed.
4. Absolute t-statistics in parenthesis: *(1)*, *(2)* based on robust standard errors; *(3) based on* clustered standard errors.
5. $^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$.

Multicollinearity

Total passenger traffic appears to increase less than proportionally to *POP* in the cross-sectional analysis (column 1 of Table 4), possibly due to the correlation between *SERV* and *POP*. Unlike *SERV*, the share of manufacturing employment (*MANUF*) is not correlated with *POP*. When *SERV* is removed from the specification, traffic exhibits a proportional relationship with *POP*. Therefore, a *multicollinearity* problem may explain why the *POP* coefficient is less than unity in the original regression results. This finding only holds for total passenger traffic, however. The remaining traffic measures (Domestic Passenger, Total Cargo, and Domestic Cargo) in the cross-sectional analysis all increase less than proportionally to *POP*, even when *SERV* is removed from their respective specifications. The proportional relationship that is found between total passenger traffic and population, however, is consistent with equivalent fixed effects estimation results (where the identifying variation comes from within-city changes over time). Keeping the possible influence of multicollinearity in mind, *SERV* is included in all of the specifications to avoid conflating the impacts of a *POP* and *SERV* on traffic.

Multicollinearity is also 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 4, 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, and 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.

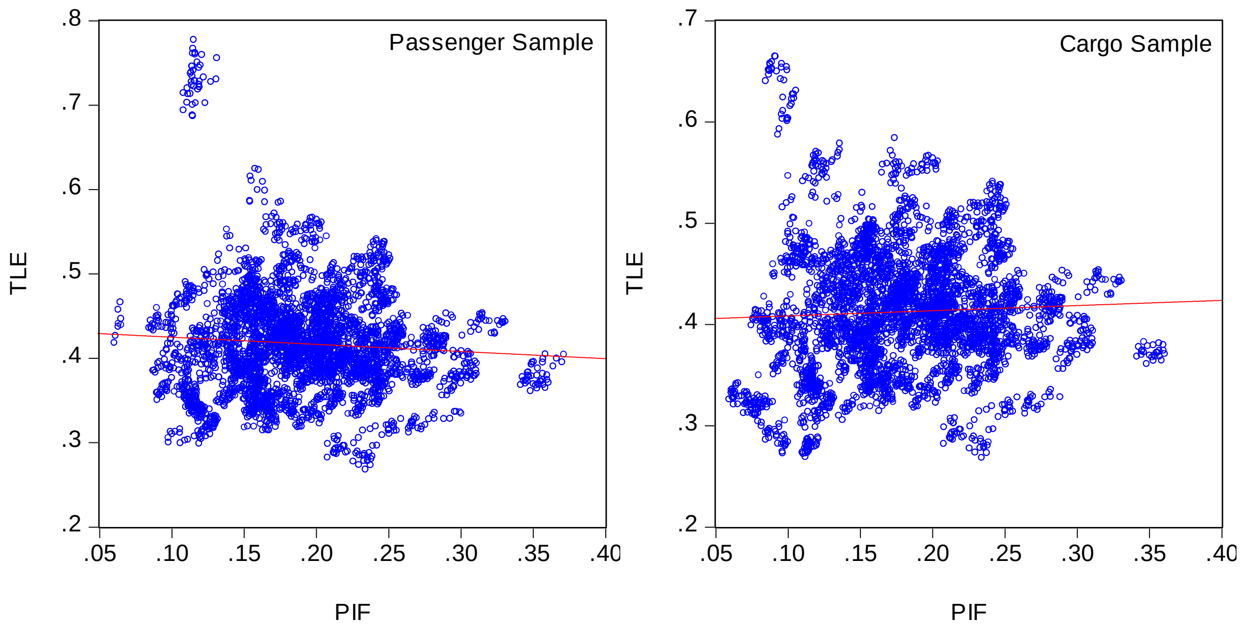

FIGURE 4 Tradable (*PIF*) versus Non-tradable (*TLE*) Employment Shares.

CONCLUSION

While the variation of socioeconomic factors *across* U.S. cities has been used by previous studies to understand demand for passenger and cargo air traffic, this study specifies a fixed effects empirical model to show how changes in a city's population, employment structure, and income affect airport traffic. Despite the considerable restructuring that the airline industry has endured since deregulation, the impacts of metro-area population and employment-structure on airport passenger enplanements mostly remain unchanged.

Consistent with past findings, city size is found to have a nearly proportional relationship with air traffic. While *white collar* employment continues to be 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 stronger impact on passenger traffic, compared to an equivalent growth in *tradable* services. These findings are reversed for air cargo traffic, where *non-tradable* (*tradable*) services exhibit a stronger influence on demand in the cross-sectional (fixed effects) analysis. However, the qualitative results showing the impacts 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 impacts 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 shows 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.

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