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Authors
Lakew, Paulos Ashebir
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Paulos Ashebir Lakew
Yeow Chern Andre Tok

Institute of Transportation Studies,
University of California, Irvine; Irvine, CA 92697-3600, U.S.A.
plakew@uci.edu, ytok@uci.edu

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Institute of Transportation Studies
University of California, Irvine
Irvine, CA 92697-3600, U.S.A.
http://www.its.uci.edu

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Abstract

Studies on the economic impact of air cargo traffic have been gaining traction in recent years. The slowed growth of air cargo traffic at California's airports, however, has raised more pressing questions amongst airport planners and policy makers regarding the determinants of air cargo traffic. Specifically, it would be useful to know how California's air cargo traffic is affected by urban economic characteristics surrounding airports. Accordingly, this study estimates the socioeconomic determinants of air cargo traffic across cities in California. We construct a 7-year panel (2003-2009) using quarterly employment, wage, population, and traffic data for metro areas in the state. Our results reveal that the concentration of service and manufacturing employment impacts the volume of outbound air cargo. Total air cargo traffic is found to grow faster than population, while the corresponding domestic traffic grows less than proportionally to city size. Wages play a significant role in determining both total and domestic air cargo movement. We provide point estimates for the traffic diversion between cities, showing that 80 percent of air cargo traffic is diverted away from a small city located within 100 miles of a large one. Using socioeconomic and demographic forecasts prepared for California's Department of Transportation, we also forecast metro-level total and domestic air cargo tonnage for the years 2010-2040. Our forecasts for this period indicate that California's total (domestic) air cargo traffic will increase at an average rate of 5.9 percent (4.4 percent) per year.

Keywords: air cargo, air freight demand, metropolitan economy, California
JEL Codes: J21, L930, R12, R41

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*E-mail: plakew@uci.edu. *Institute of Transportation Studies, University of California, Irvine.*

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‡*Institute of Transportation Studies, University of California, Irvine.*

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, 2000; Boeing, 1998).[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 interested 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, 2010; Tsao, 2002; BAEF, 2000a, 2000b; Erie, Mckenzie, MacKenzie, & Shaler, 2005).[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, 2010). 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 (2010) report 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 (1985) 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 & Debbage (2011) attempted to find specific employment, establishment, and wage variables that explain the geographic distribution of air freight in 2003. More recently, Button & Yuan (2013) 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 (2010) report, for understanding how regional economies impact air cargo traffic in California. Hence, this paper will examine the socioeconomic determinants of outbound total and domestic air cargo traffic for a sample of 22 airports across 15 metropolitan areas in California, using seven years of quarterly data (2003Q1-2009Q4). 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.

[1] The FAA's March 2000 long-range forecasts 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 (FAA, 2000).

[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, 2014)*.

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

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 total (domestic) volume of air cargo will grow at an average rate of 5.9 percent (4.4 percent) per year.

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, 2008; Carron, 1981). 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 (2002) 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, 2000a; Hansen, Gosling, & Rice, 2002; Erie et al., 2005; SCAG, 2012). 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, 2010).

Although Tsao (2002) outlined the many research gaps in understanding the role of air cargo in California's goods movement, the authors of the TranSystems (2010) 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.

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, 2013) 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

[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.

state's $1.240 trillion export of commodities (TranSystems, 2010). 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, 2013). 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 & Zhang, 2002a). Zhang & Zhang (2002a) 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 & Zhang (2002b) 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, & Strong, 1997; Button & Taylor, 2000; Debbage & Delk, 2001; Brueckner, 2003; Alkaabi & Debbage, 2007; Green, 2007), suggesting that growth in air traffic is associated with the economic development of metro areas. Brueckner (2003), Green (2007), and Sheard (2014) 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 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*

[5]See Lakew (2014) and Alkaabi & Debbage (2011) for national-level studies of air cargo determinants.

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

Traffic T-100 Segment tables (BTS, 2014), which can be found on the Bureau of Transportation Statistics (BTS) website. Freight and mail volumes are 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*) (TranSystems, 2010). 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 with more than 50,000 people in the core, while the core-population of micro areas is between 10,000 and 50,000. 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, 2013).

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 & Debbage (2011). 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 1.

Figure 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.

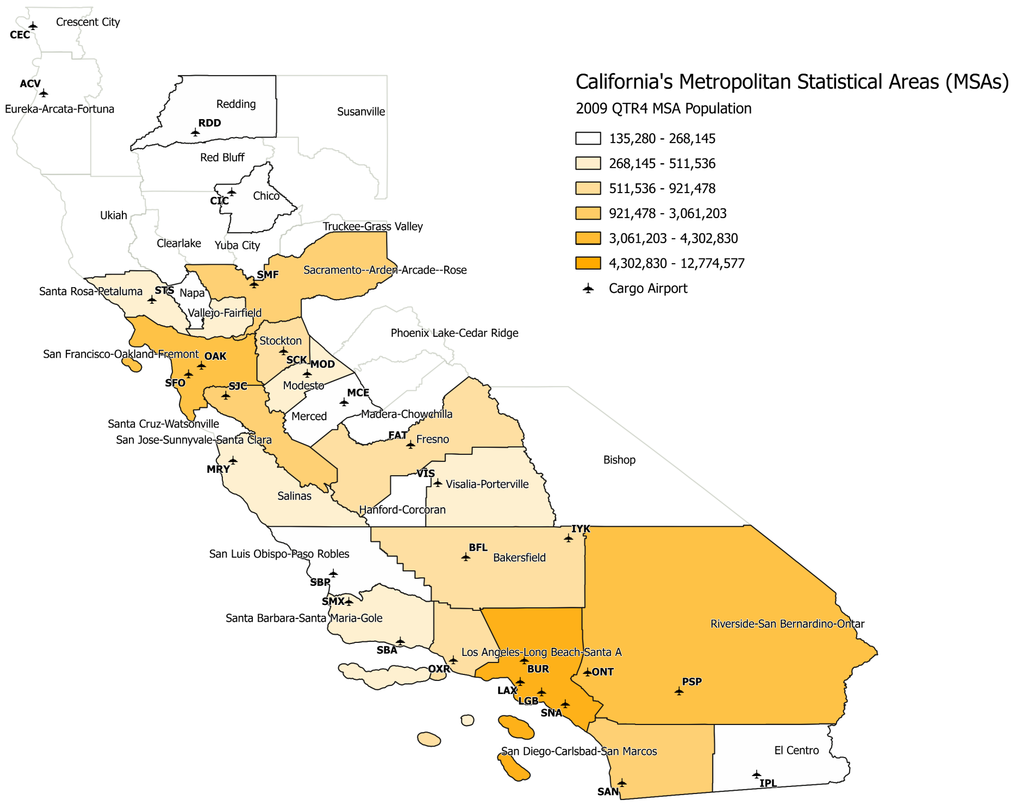
[7]The map in this figure (as well as the subsequent ones) are designed using the U.S. Census Bureau's *TIGER/Line® shapefiles* (Census, 2009). The socioeconomic, demographic, and traffic data are obtained from the BLS QCEW databank (BLS, 2010), U.S. Census Bureau *Intercensal Estimates 2000-2010* (Census, 2010), and the BTS *T-100 Segment* tables (BTS, 2014), respectively. Airport-specific coordinate and spatial information are obtained from the 2012 BTS *National Transportation Atlas Database* (*NTAD*) files (BTS, 2012).

Table 1: MSA Average Outbound Air Cargo Tonnage (U.S. 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 U.S. 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 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) (BLS, 2010), 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-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.

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 (1985) found a significant 0.95 point estimate for the elasticity of passenger travel with respect to a city's population. We

[8]2-digit North American Industry Classification System (*NACIS*) codes are shown in parentheses.

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, 2010), at the MSA level.

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, 1985):

$$T_{it} = \alpha + \beta E_{it} + \gamma X_{it} + \sum \delta_i D_i + \tau_t + \varepsilon_{it}, \tag{1}$$

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; 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);[9] 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 1.

The variables in Equation 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, 2003), 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 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.[10] To get around this challenge, we can take Brueckner's (1985) approach and restrict

[9] Lakew's (2014) 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.

[10] 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

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, 2003). 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 1/4 since *LAX*, which serves as a metro hub for *FedEx Express*,[11] 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 *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, 2010).[12] 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 & Debbage (2011) showed that traffic is diverted from small MSAs to larger ones through a *traffic shadow* effect. This issue was addressed by Brueckner (1985, 2003) 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 (2003) and Alkaabi & Debbage (2011), 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 U.S. tons of freight annually) is less than 100 miles away from the largest airport in a large MSA (an

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.

[11] 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*.

[12] *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.

MSA that generates more than 175,000 U.S. tons of freight annually).[13] The 100-mile cutoff was chosen to allow for consistent comparisons of our findings with the results of the relevant literature (Alkaabi & Debbage, 2011). 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.

4 Results and Discussion

Tables 2 and 3 provide definitions and descriptive statistics for the variables used in the regression analysis.

4.1 Estimation Results

Table 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.[14] 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.

Table 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

[13] 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.

[14] 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 4.

Table 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)

Table 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 for variables (annual measures for *POP*, *YOUNG*, and *OLD*), 2003-2009. Standard deviations are in parentheses.

Table 4: Regression results (420 obs.)

	Total (Domestic & International)		Domestic (*-DOM*)	
	(1) ACTRAFFIC	*(2) TRAFFIC*	*(3) ACTRAFFIC*	*(4) TRAFFIC*
INTERCEPT	-11.909^{a}	-15.893^{a}	-8.291^{a}	-11.781^{a}
	(3.771)	(4.812)	(2.669)	(3.671)
POP	0.979^{a}	1.169^{a}	0.709^{a}	0.880^{a}
	(10.061)	(11.761)	(7.134)	(8.897)
SERV	7.539^{a}	5.840^{a}	10.463^{a}	9.054^{a}
	(4.234)	(3.240)	(5.803)	(1.803)
MANUF	1.765^{b}	0.894	2.435^{a}	1.600^{c}
	(2.193)	(1.086)	(2.902)	(1.905)
WAGE	0.640^{a}	0.883^{a}	0.524^{b}	0.717^{a}
	(2.552)	(3.374)	(2.114)	(2.810)
YOUNG	0.939	1.018	2.039	2.237
	(0.374)	(0.697)	(0.822)	(0.875)
OLD	-19.253^{a}	-12.879^{b}	-27.750^{a}	-22.133^{a}
	(3.603)	(2.367)	(5.077)	(4.036)
CAP	1.555^{a}	1.338^{a}	1.886^{a}	1.703^{a}
	(13.884)	(11.883)	(16.585)	(15.283)
HUB	3.911^{a}	3.660^{a}	4.031^{a}	3.770^{a}
	(23.465)	(21.542)	(22.590)	(21.663)
PROXIMITY	-1.556^{a}	-1.595^{a}	-1.553^{a}	-1.589^{a}
	(19.608)	(19.424)	(20.038)	(19.991)
TREND	0.002	-0.004	0.007	0.002
	(0.706)	(0.442)	(1.554)	(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: $^{a}p < 0.01$; $^{b}p < 0.05$; $^{c}p < 0.10$.

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 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.[15]

In Table 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, 2010). 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 the southern part of the state were relatively unharmed by the end of the *dot-com bubble* (TranSystems, 2010).

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,

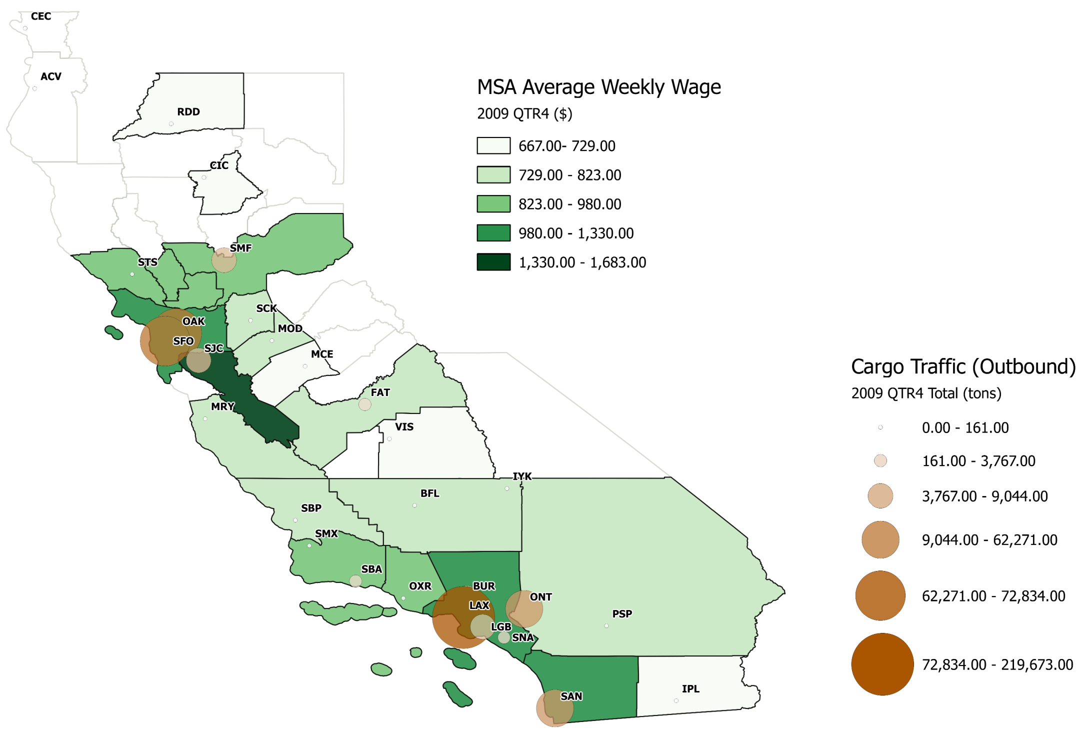
[15]We thank Jan Brueckner for his insights into the traffic impact of sectoral-employment shifts captured by our model's specification.

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, 2010). 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 & Debbage (2011) 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. Figure 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).[16] 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).

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

Figure 2: MSA Average Weekly Wages and Cargo Enplanements in California (2009Q4)



Turning to the passenger side, Brueckner (1985) was first to confirm the relationship between metro area passenger-air traffic and *white collar* employment. Finding a point estimate of 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, 2003), 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 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.[17] 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.[18]

Brueckner (2003) and Green (2007) 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 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, 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 & Yuan, 2013).[19]

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

[18] 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*) (TranSystems, 2010).

[19] Since this reverse causality may lead the employment-share variables to have some correlation with the error term in Equation 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.

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, 2013). 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 (2000) 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 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.

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) (TCEF, 2013). 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, 2013).

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[20] as inputs to the econometric model shown in Equation 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 the insignificant coefficient on *TREND*, and

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

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 and 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.[21] The corresponding domestic traffic forecasts are provided in the Appendix.

Table 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

[21]Forecast performance details can be provided by the authors upon request.

Figure 3: MSA Total *All-Cargo* and *Passenger Cargo* Forecasts (2010-2040)

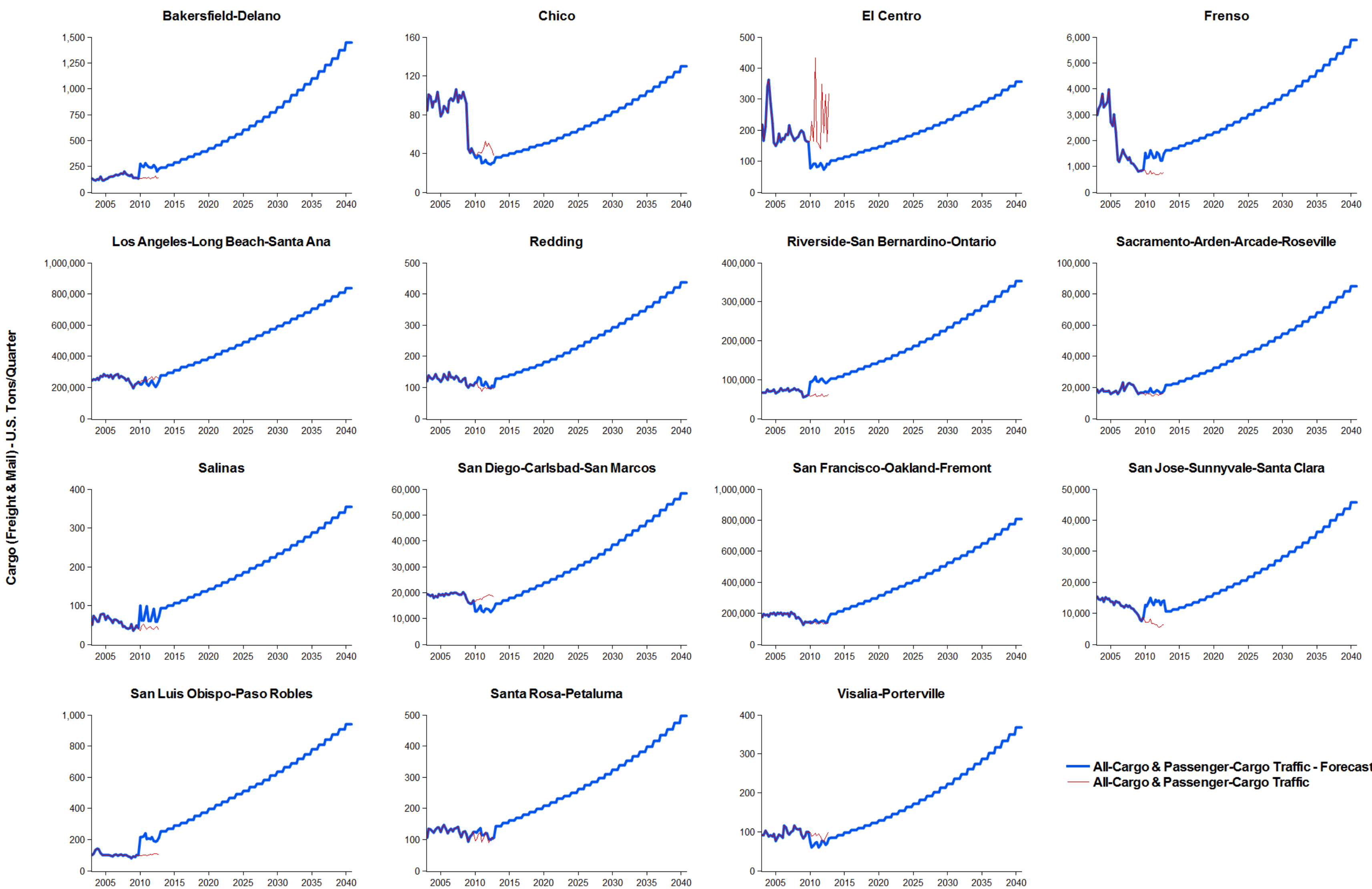
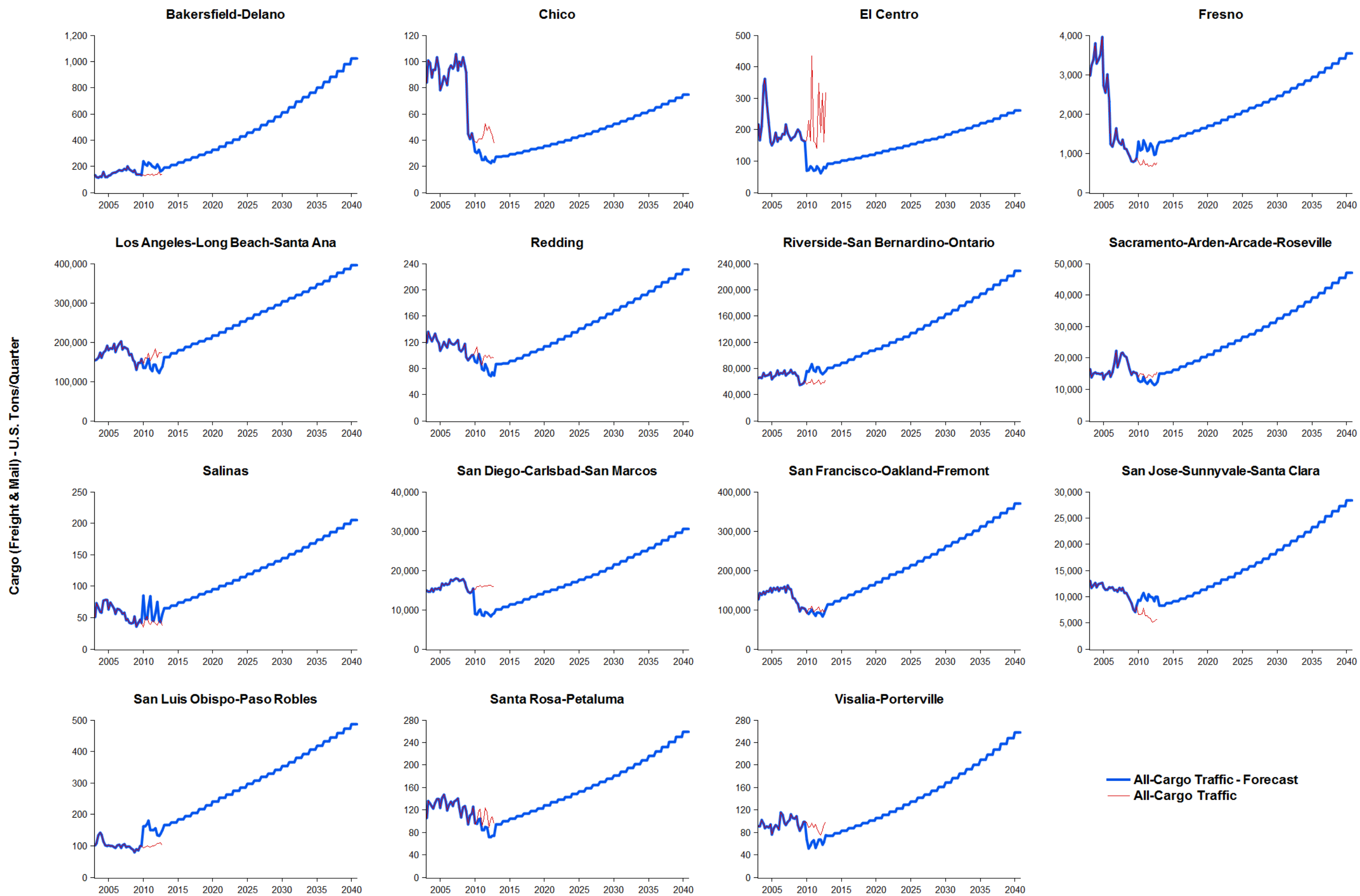


Figure 4: MSA Total *All-Cargo* Forecasts (2010-2040)



Figures 3-4 and Table 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, 2013) for Latin- and North-American markets, in the 2011-2030 period.[22] The Boeing growth rates are estimated using economic and trade indicators for air cargo markets and international trade lanes. Moreover, Table 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, 2000a, 2000b) 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, 2010), the metro 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 (2010) 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 6 shows the projections reported in the TranSystems study alongside our equivalent estimates.

[22]The corresponding annual growth rate of our forecasted traffic in the 2011-2030 period is 5.3 percent.

Table 6: Annual Traffic Forecast Comparison (in U.S. tons)

	TranSystems (2010) 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 6 to associate our forecasts to the projections of the TranSystems (2010) 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 6 reveals that our forecasts for 2015 and 2020 are similar to projections made by TranSystems.

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 (Brueckner, 1985), we let manufacturing and service-related employment represent *blue collar* and *white collar* employment, respectively. Our findings suggest that, unlike passenger 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.

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7 Appendix

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 7. 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 4).

Table 7: Regression results with time dummies (420 obs.)

	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 7) 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: $^a p < 0.01$; $^b p < 0.05$; $^c p < 0.10$.

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, 2010). 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.

Figure 5: MSA Manufacturing Employment Shares (2009Q4)

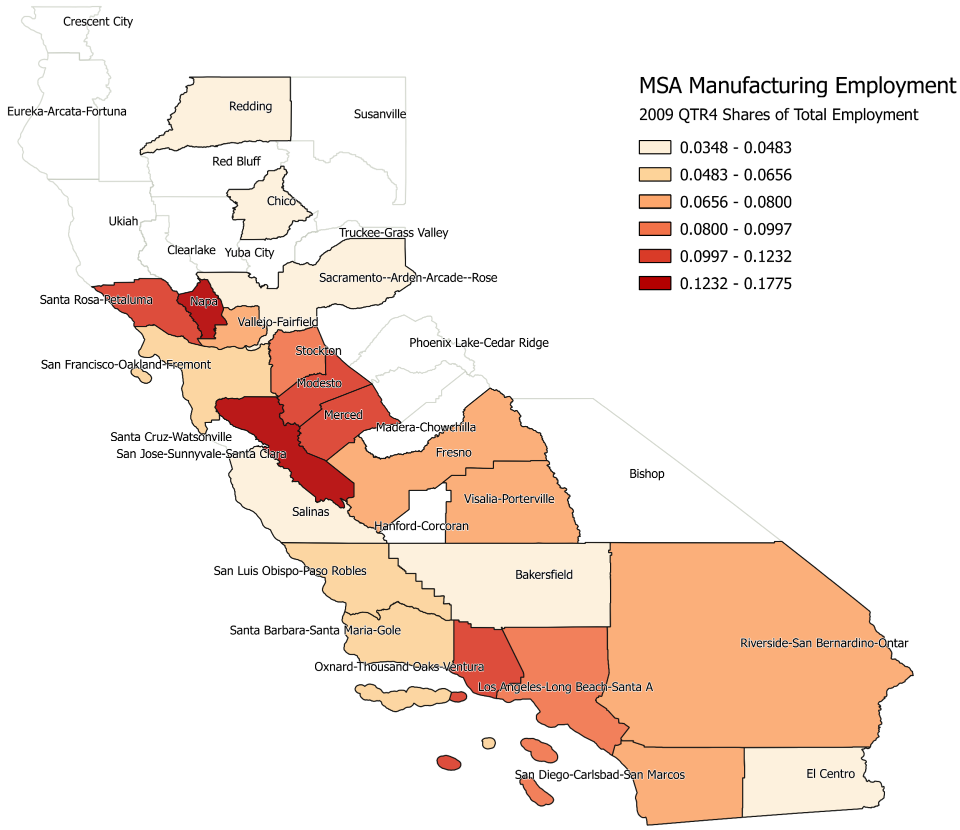

Figure 6: MSA Service Employment Shares (2009Q4)

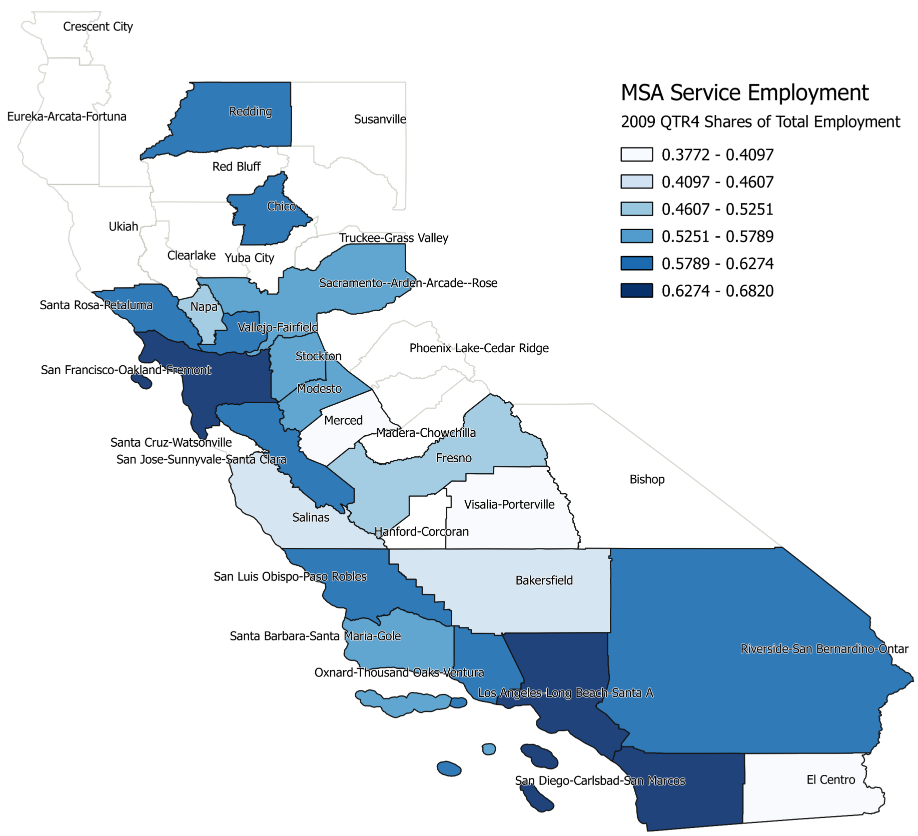

Figure 7: MSA Domestic *All-Cargo* and *Passenger Cargo* Forecasts (2010-2040)

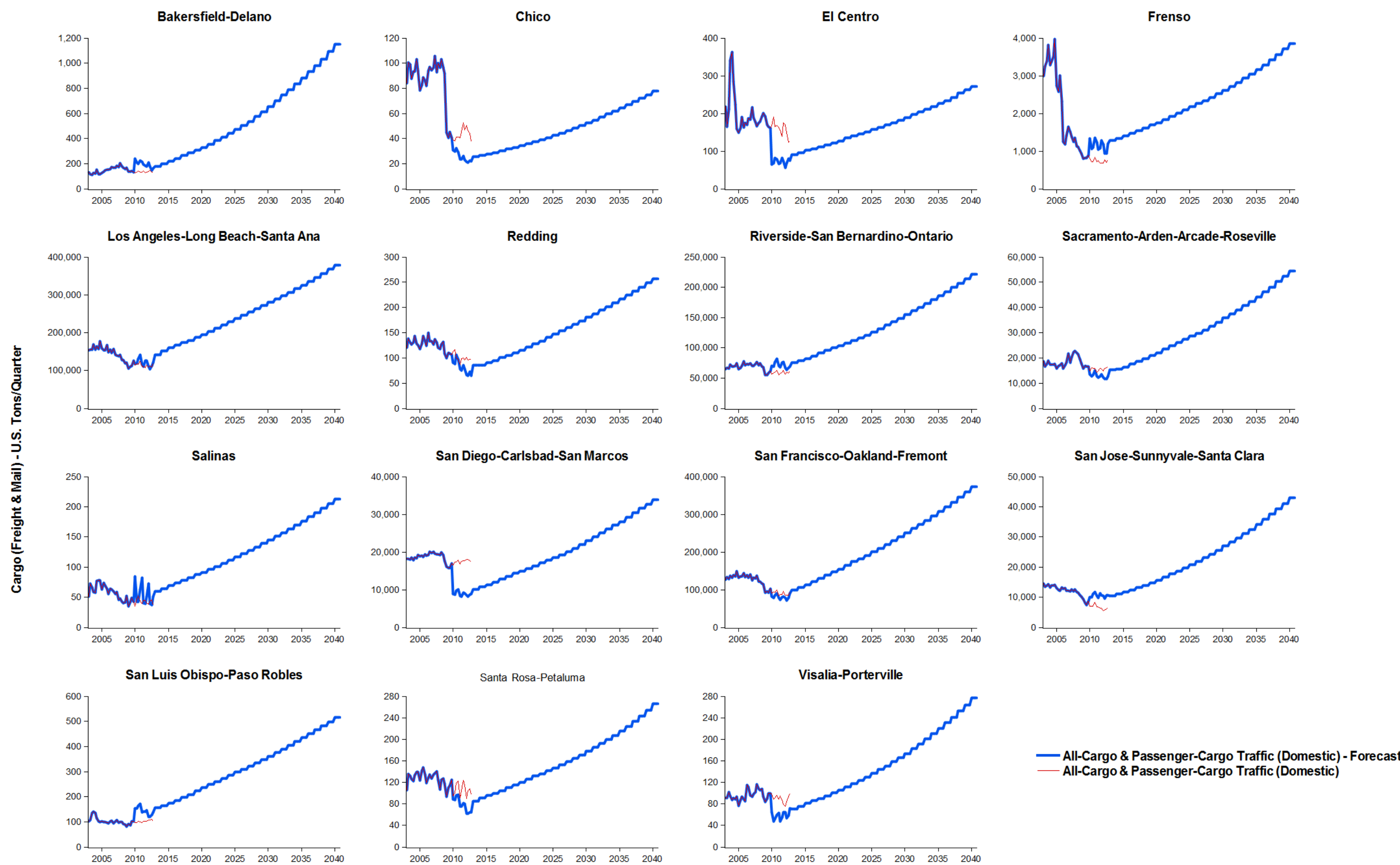

Figure 8: MSA Domestic *All-Cargo* Forecasts (2010-2040)