METROFREIGHT
Volvo Center of Excellence

Title: Using proxies to describe the metropolitan freight landscape

Project Number: 15-1C

FINAL REPORT
June 2015

Principal Investigator
Genevieve Giuliano

Researchers
Sanggyun Kang
Quan Yuan

MetroFreight Center of Excellence
USC Sol Price School of Public Policy, University of Southern California
Los Angeles, California, USA

Title: Using proxies to describe the metropolitan freight landscape

Abstract

Metropolitan areas around the world are seeking to better manage freight flows and reduce negative impacts on local populations. A major challenge to better urban freight management is the lack of data; little is known about freight movements at the intra-metropolitan level. We develop the concept of a freight landscape: spatial patterns of freight activity. We hypothesize that the freight landscape can be described using data on population, employment and transport system supply. We test the concept using network model data for the Los Angeles region. We find that our simple proxies have significant explanatory value, and hence may provide an effective means for approximating spatial patterns of freight activity.

INTRODUCTION

Countries and cities around the world are closely connected by economic interactions and goods movement. Large gateway cities function as logistics hubs in the global freight network, while the concentration of population and production in these cities also generate substantial demand for goods movement. The volume of freight moving within and across metropolitan areas is increasing due to more complex supply chains, changing consumer and business preferences, and the rise of e-commerce (Dablanc and Rodrigue, 2014). Freight movements are a problem in cities around the world. Though essential for the functioning of metropolitan areas, freight generates negative externalities such as air pollution, noise, and GHG emissions, and contributes to congestion (Giuliano et al, 2013).

Efforts to better manage freight are constrained by lack of data and methodological tools. Basic data such as the number of trucks operating in a metropolitan area, number of deliveries taking place in commercial districts, or of truck volumes on major streets is virtually unknown and typically not available except via costly one-time surveys. Urban freight modeling research has developed various types of freight trip generation methods, but freight generation does not provide a sufficient portrayal of the overall impacts of freight across various locations. In addition, little research has been conducted on the relationship between spatial structure and freight flows, in contrast to the extensive literature on spatial structure and passenger flows. A better understanding of these relationships would improve our ability to understand the dynamics of urban freight distribution and to design more effective solutions to freight problems.

PROJECT OBJECTIVE

We seek to contribute to the understanding of spatial structure and freight flows by developing and testing the concept of a "freight landscape." Our main hypothesis is that freight flows generated by economic activities depend on the spatial organization of freight supply and demand, as well as on the transportation facilities within the metropolitan area. Manufacturing zones generate specific types of freight activity, downtown centers others. In downtown centers, transport capacity is limited for both freight and passengers. High land prices in the urban core push warehouses and distribution centers to more distant locations, increasing delivery distance. Suburban shopping centers typically have plenty of transport access and freight loading capacity. The freight landscape seeks to differentiate such zones. If freight flows are explained by the distribution of population and economic activity, and the structure of the transport network, it follows that these factors may serve as good proxies for describing intra-metropolitan freight flows.

This paper presents some preliminary evidence that simple measures of freight supply, demand, and transport capacity are associated with observed freight flows on the transport network. The remainder of the paper is organized as follows. We discuss the relevant literature in Section 2, present our research approach and methodology in Section 3, data in Section 4, and results in Section 5. Conclusions are presented in the final section.

PROJECT DESCRIPTION

Freight activity in metropolitan areas can be roughly described as two main types: freight related to local supply or demand, and freight related to national or international trade. Globalization has increased as a result of transport and communications technology as well as trade liberalization policies (Dicken, 2007). Production supply chains have become more complex as producers seek out comparative advantage opportunities around the world. Goods production processes – spatially fragmented but temporally integrated -- connect countries and cities into 'global production networks' demanding cost-efficient and timely flow of goods (Leinbach and Capineri, 2007). The outcome is consistent growth in cross-border trade for the last several decades. In the US, total foreign merchandise trade increased by nearly one third from 2000 to 2012 (FHWA 2014).

Background: Global and local flows

Large metropolitan areas are the major nodes of the global production network, containing the largest ports, airports and intermodal facilities. For example, the total value of merchandise foreign trade for the US in 2011 was $3688 billion. The top 25 import/export facilities are located in 15 metro areas; they account for 44% of total trade. The top 5 (Los Angeles, New York, Detroit, Houston, and Laredo) account for 27% of the total (FHWA, 2014).These metro areas serve as transshipment nodes, consolidating exports or distributing imports, as well as major centers of production and consumption. Rodrigue (2004) notes that these gateway cities are usually located in 'mega-urban regions' through which logistics functions are geographically and functionally integrated at the local, regional, and global levels. These large urban regions developed historically as points of trade. With large and concentrated population and economic activity, they generate much of the trade demand and provide the array of expertise for managing global supply chains. Large US metropolitan areas – those with population of 1 million or more – account for over 90% of freight shipment origins and destinations by value.[1] The concentration

[1] Calculated from 2007 Commodity Flow Survey data, http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/commodity_flow_survey/index.html

of trade in large metro areas means concentrated demand on the rail and highway systems. Eleven of the top 25 highway bottlenecks are located in Los Angeles and Chicago (Cambridge Systematics, 2005). In a ranking of corridors (highway segments) by Inrix for 2014, Los Angeles and New York have 13 of the worst 25 corridors.[2]

The second type of freight activity is associated with the supply and demand of the local population: the "last mile" delivery or pickup of imports/exports, and the intra-metropolitan trade of commodities (local production and consumption). Freight related to local supply and demand is also increasing due to longer and more complex supply chains, increasing velocity within supply chains (e.g. just-in-time practices), the rise of e-commerce, and overall per capita income, population and employment growth. Increased freight activity at the metropolitan level means increased truck trips and vehicle miles traveled. Unfortunately, there is no data source for metropolitan truck traffic in the US. European data suggests that truck traffic accounts for 10-15 percent of total urban vehicle traffic (BESTUFS, 2006). From Laboratory of Transport Economics (Lyon, France) surveys, Dablanc (2011) estimates one delivery or pickup per week for every job, and 300 to 400 truck trips per 1000 residents per day. These numbers are likely to be much higher in major gateways such as New York or Los Angeles.

Research Review: Freight and urban form

Freight activities have substantial effects on the urban landscape. The growth in trade has led to growth and development of large terminal facilities (ports, airport, intermodal yards), and scale economies have focused this growth on major metropolitan areas (Dablanc and Rodrigue, 2014). The rise in trade is associated with an increase in warehouse and distribution facilities; one example is the tripling in the number of freight and logistics facilities from 1998 to 2008 in Atlanta (Dablanc and Ross, 2012).

There is little research on how freight dynamics may influence or be associated with land use patterns at the intra-metropolitan scale. It is generally observed that urban freight is inefficient due to 1) restrictions on routes and delivery time windows; 2) parking and loading limitations, 3) a larger share of small deliveries (including home deliveries), and 4) inventory and replenishment practices of urban retailers (Holguin-Veras, et al, 2005; Giuliano et al, 2013; Xing et al, 2010; Bomar, Becker and Stollof, 2009). Dablanc and colleagues have examined the growth and spatial distribution of warehousing in several metropolitan areas (Cidell, 2010; Dablanc, 2014; Dablanc and Ross, 2012; Dablanc, Ogilvie and Goodchild, 2014). In all cases except Seattle warehouses have decentralized, likely due to rising land prices and demand for larger scale facilities. Warehouse and distribution has decentralized more rapidly than population and employment, and thus may generate more truck VMT.

There is evidence that freight activity and congestion is associated with density. Studies of New York City show very high rates of deliveries to restaurants in Manhattan (Holguin-Veras et al., 2005), as well as higher rates of illegal truck parking in Manhattan than other parts of the city (Bomar, Becker and Stollof, 2009). Less direct evidence is provided by the observation that the focus of most urban freight mitigation programs is on the city core (Giuliano et al, 2013).

[2] http://www.inrix.com/worst-corridors/, accessed February 6, 2015.

Finally, the urban freight modeling literature offers some evidence. Freight generation rates are based on land use characteristics, e.g. type and intensity of economic activities (Ambrosini, Patier, and Routhier, 2010; Holguin-Veras et al, 2012). Therefore the spatial distribution of economic activity should reflect the spatial distribution of freight supply and demand. The freight impact, however, is not just from the location of origins and destinations, but also from the flows on the network that result. Our approach explores the relationship between spatial structure and freight flows.

RESEARCH APPROACH

We noted in our introduction that our understanding of urban freight is limited by the lack of data. In the US, the USDOT generates freight data in the form of the Freight Analysis Framework (FAF) from the Commodity Flow Survey, the Economic Census, and other data sources. FAF produces interstate (and limited intra-state) shipments by commodity, transport mode, and source (FHWA, 2014). The level of geographic aggregation of FAF does not allow intra-metropolitan level analysis. Ideally one would like the same type of data at a much finer geographic scale. In the absence of such data, urban freight analysis relies on proxies (e.g. employment, highway volume counts) and one-off surveys. The lack of data has been a particular challenge for developing metropolitan level freight planning models (Chase et al, 2013). It is also a challenge for examining the more general question of freight activity and urban form.

As summarized in the previous section prior research has shown that urban spatial structure influences freight flows, but little is known about systematic relationships. We hypothesize that freight flows generated by economic activities depend systematically on the spatial organization of freight suppliers and demanders, as well as on the transportation facilities within the metropolitan areas.

Conceptual framework

There are many different types of freight flows in metropolitan areas. For example, Dablanc and Rodrigue (2014) identify consumer and producer flows. Consumer flows include independent and chain retailing, food deliveries, and parcel and home deliveries. Producer flows include industrial production, warehousing and distribution, construction materials, and waste. Each is associated with a unique supply chain, and hence unique flow characteristics. We use the example of retailing to illustrate, and consider how development density – the combined effects of population and employment density – might affect retail deliveries. We illustrate in Figure 1.

In rural areas with dispersed population and economic activity, delivery costs are relatively high due to smaller loads and long delivery distances, even though there is plenty of road capacity. In suburban areas there is still adequate transport supply, and the greater density of demand makes deliveries more efficient. Trips are generally shorter due to proximity to warehouse/distribution centers. When we approach higher levels of density, delivery costs increase at an increasing rate. Higher density is associated with higher land values, and higher land values lead to more intense use of the space available. For retailers, this means more sales per square foot, more turnover of product, and less space devoted to storage, compared to retail activities in lower density environments. A similar dynamic is at work for commercial businesses and residences.

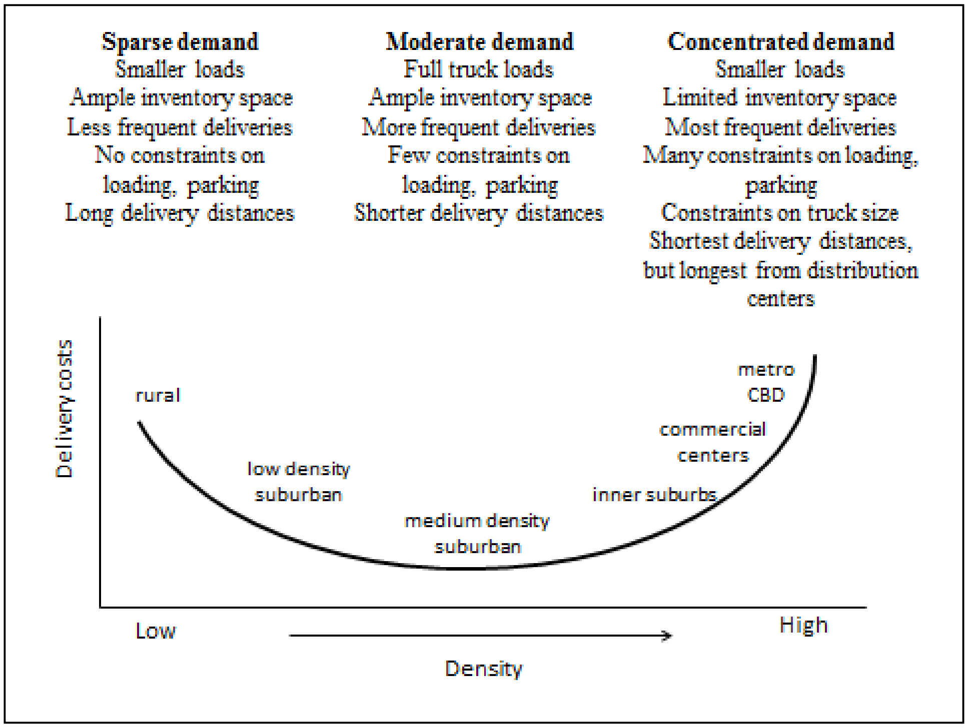

Figure 1: Development density and delivery costs for retailing activities

Higher density is also associated with more product and consumption diversity, especially in areas with higher income populations. This diversity is exhibited by greater prevalence of independent retailers (restaurants, specialty clothing, etc.) who together offer a broad spectrum of consumer goods and services and hence use a wide variety of suppliers for relatively small volume orders. These relationships imply more and smaller shipments. Finally higher density implies more frequent basic services (trash pickup, maintenance services, etc.). These more intense truck activities take place in an environment of limited parking and loading facilities and competition for scarce road, curb and sidewalk space (Dablanc et al, 2013). At the highest density, truck size may be limited, again increasing trip frequency and cost. We therefore expect the attributes of freight flows (frequency, volume, vehicle mix, etc.) to vary with development density.

Development density, transport demand, and transport infrastructure capacity are interdependent. The high price of land promotes more intense utilization (and hence transport demand), while also making the provision of transport capacity ever more costly. Thus we observe congested roads, subways, and sidewalks in the densest parts of cities.

Models

Our purpose is to test whether basic land use characteristics are useful proxies for describing the spatial pattern of freight flows in a metropolitan area. If the relationships described above hold, then we should observe more truck activity on the road network in higher density locations. Further, population and employment density may have different effects: areas with concentrated population but little employment may have a high level of general traffic, but lower truck traffic. Conversely, areas with concentrated employment but little population (e.g. industrial zones) may have lower general traffic but more truck traffic. Also, relative location should matter: areas with major links to the intercity system (e.g. major highway corridors) should experience more "through" traffic than more peripheral locations.

We use data from the Los Angeles region to estimate the intensity of truck activity as a function of land use characteristics. The general model is,

$$Y_i = f\,(S_i,\ D_i) \qquad (1)$$

where Y = density measure of truck activity intensity in zone *i*, S = vector of transport supply and relative location measures, and D = vector of transport demand measures for zone *i*. We expect flow density to be related both to transport system supply and demand. In addition, we want to control for relative location – access to airports, seaports, or intermodal facilities – since, all else equal, we expect more truck traffic closer to such facilities. We estimate two models. For Model 1 we generate a series of combined population and employment density categories that provide a grid of spatial characteristics, each reflective of a particular freight landscape. We use dummy variables to test their effects. This model tests whether each given combination of population and employment is significantly related to truck activity intensity.
Model 1 assumes that population and employment are homogeneous. Since consumption is related to income and other household characteristics, it is possible that truck activity intensity varies with neighborhood characteristics. Similarly it is well known that some industry sectors are more freight intensive than others, for example warehousing compared to financial services. In Model 2 we consider the effects of population and employment characteristics. The model is

$$Y_i = f\,(S_i,\ P_i,\ E_i) \qquad (2)$$

where Y and S are defined as in (1); P = vector of population characteristics; E = vector of employment characteristics. We discuss appropriate measures in the next section.

DATA

We use the Los Angeles region as our case study area. The Los Angeles region is the second largest US metropolitan area, with 2010 population of about 18 million and employment of about 7million. The region includes five counties in 88,048 square kilometers. It is a US Census Combined Statistical Area (CSA) comprised of three Metropolitan Statistical Areas (MSAs) and five counties.[3]The Los Angeles-Long Beach-Anaheim, CA MSA has the highest average population density in the US, 1,037 persons per square kilometer.[4] The region is also noted for its polycentric urban form: it is characterized by a corridor of high employment density that extends from the downtown to the coastline, and numerous employment clusters around the region (Giuliano et al, 2007). The Los Angeles region is also a major global trade hub. The Los Angeles/Long Beach port complex is the largest container port in the US, with trade in 2011 of $382 billion. The Los Angeles airport is the 5th largest air freight center in the US. The region's size, diversity, and trade intensity make it an appropriate case for testing freight and urban form relationships.

Data sources

Our data includes population, employment and transport system characteristics. Population characteristics are drawn from the 2010 US Census. Employment is from the 2010 Longitudinal Employer-Household Dynamics (LEHD) which provides employment counts in two-digit NAICS industry sectors at the census tract level. According to the LEHD data description, all employment but uniformed military, self-employed workers, and informally employed workers are counted.[5] Its data sources are Unemployment Insurance wage data, the Quarterly Census of Employment in Wages, and the Office of Personnel Management data. All data were converted to Transportation Analysis Zones (TAZs), spatial units that are approximately the same size as census tracts. We use TAZs rather than census tracts, because tract boundaries often follow major roadways, making it difficult to assign traffic to spatial units. The conversion from census tracts to TAZs was conducted by aerial apportioning. In the case of median household income, we assigned the value of the census tract that had the greatest coverage of the TAZ. There are 3,999 TAZs in the five county region; after cleaning for missing data and sparsely populated areas, we have 3,736 TAZs for analysis.

Transport system data includes a complete mapping of highways, major arterials, freight rail, airports, ports, and intermodal facilities. The highway network was obtained from the Southern California Association of Governments (SCAG). SCAG also provided output from its 2008 baseline regional model, which includes link flows by time of day and vehicle type (personal vehicles and trucks in 3 weight categories). The SCAG model includes 68,389 links. The link flows are used for calculating the dependent variable.

Data description

In this section we describe the population, employment, and transport system data used in the regression models.

---

[3] Los Angeles-Long Beach-Anaheim MSA, Riverside-San Bernardino-Ontario MSA, and Oxnard-Thousand Oaks-Ventura MSA

[4]This density figure uses the entire region area including 2010 census-defined land and water except islands.

[5]http://lehd.ces.census.gov/applications/help/onthemap.html#!faqs#7

Population and employment

Designation of metropolitan areas as collections of contiguous counties is not perfect. The Los Angeles CSA includes desert, national forests and other sparsely populated areas. In order to focus our analysis on the urban portions of the CSA, we eliminated all zones with population and employment density below the one-tailed 1.65 standard deviation of the mean of the natural log form of the variables. The cutoff values are 52 persons/km^2 and 14jobs/km^2. We also eliminated zones for which traffic flow data were not available. For the remaining zones (3,736), the 2010 population and employment are 17.54 million and 6.76million respectively.

Descriptive statistics for population and employment density are given in Table 1.It can be seen that the employment distribution is notably more skewed than population. Average population density is higher than average employment density (this must be the case for the region as a whole, because total population is more than twice as large as total employment). For most zones, employment is sparser than population; a large proportion of employment is concentrated in relatively few zones. For example, using 2005 employment data, more than 40% of all employment is located in less than 1% of the land area (Giuliano et al., 2013). Thus the range of employment density is much greater: whereas the greatest population density is about 35,000 per square km, the highest employment density is about 7 times as high.

Table 1: Population and employment density descriptive statistics

	Mean	Median	Min[6]	Max
Population	3,622	2,825	0.0	35,021
Employment	1,564	562	0.0	247,629

We generated quartiles of population and employment density, and then combined them to estimate Model 1. Descriptive data for the quartiles are given in Tables 2 and 3. Because of the differences in the spatial distribution of population and employment, the highest quartile for employment has a much greater range than the highest quartile for population, and the mean values for each quartile are higher for population than for employment.

Table 2: Population density quartiles

Quartile	N of zones	Mean	Min	Max
P1	909	546.2	0.0	1,275.1
P2	942	2,051.3	1,275.4	2,806.1
P3	946	3,647.4	2,807.7	4,726.4
P4	939	8,149.2	4,727.7	35,020.9

[6] Minimum of zero is possible because elimination of a zone requires both population and employment to fall below the minimum value.

Table 3: Employment density quartiles

Quartile	N of zones	Mean	Min	Max
E1	933	93.3	0.0	206.7
E2	942	372.6	207.2	564.7
E3	933	883.9	565.6	1,307.4
E4	928	4,937.1	1,307.8	247,629.2

The population and employment quartiles are combined to generate a 4x4 grid (16 categories of population and density combinations). Figure 2 shows the spatial distribution of the 16 combinations. The zones with both the highest population and employment density (P4|E4) mainly concentrate in the Los Angeles downtown area, westward towards the coast and northward. Zones with low population density and high employment density, (P1|E4), are major industrial areas, and these tend to follow the major highway corridors. Medium population and employment density areas tend to be located in the inner suburbs, while the lowest population and employment density are located in the outer suburbs and at the periphery of the urban area. This simple map illustrates substantial spatial variation in the mix of population and employment density.

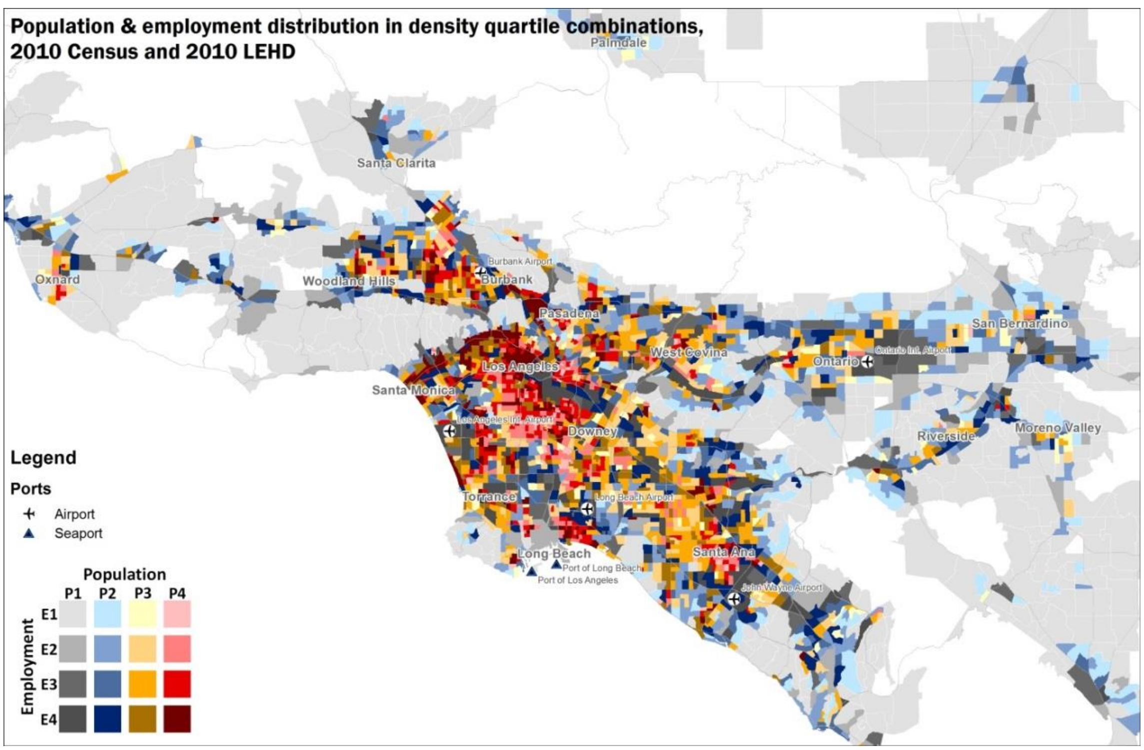

Figure 2 Population and employment distribution in density quartile combinations (data source: 2010 Census and 2010 LEHD)

Table 4 gives the share of TAZs in each combination. The zones with both the lowest population and employment density take up the largest share of all the 3,736 TAZs. The most job-rich and populous zones are the second biggest group. Only 1.4% of the total zones belong to the combination with the highest population density quartile but the lowest employment density quartile, and 4.5% of the total has the lowest population density and highest employment density.

There is a general correlation of population and employment density, with the diagonal percentages being the largest for each column. About a third of the zones are in various combinations of middle categories (second or third quartiles of both population and employment density). These patterns make sense; a large portion of employment is population serving, so should be distributed with the population. Also, access to employment is a major factor in residence location, hence, all else equal, employment concentrations should attract more population.

Table 4: Distribution of zones across population and employment combinations (% share of total)

	P Q1	P Q2	P Q3	P Q4
E Q1	14.75%	5.81%	2.94%	1.47%
E Q2	3.21%	8.06%	8.11%	5.84%
E Q3	2.36%	5.51%	8.57%	8.54%
E Q4	4.01%	5.84%	5.70%	9.29%

For model 2, we use data on population and employment characteristics. We use median household income as a measure of consumption demand, and population density as a measure of consumer demand concentration. We explored different measures for employment. We conducted a factor analysis on the 2 digit NAICS LEHD employment data, and then clustered TAZ employment by the resulting factors. The factor analysis generated four factors with five industry sectors (agriculture, mining, utility, information and education) left out. Since agriculture, mining and utility employments accounts for just 1.9% of total employment, we combined them and treated them as one omitted sector. Information (5.5% of total employment) and education (10.0% of total employment) sectors are treated individually. Based on the factor analysis, we aggregate employment into seven aggregated industry sectors and calculate density measures. The aggregated sector designation is as follows:

- Sector 1: finance, real estate, professional, management, administrative & accommodation
- Sector 2: construction, transportation, arts & public
- Sector 3: manufacturing, wholesale & retail trade
- Sector 4: health & other
- Sector 5: agriculture, mining & utility
- Sector 6: information
- Sector 7: education

We also used more simple measures of employment: employment density, and relative diversity. . The relative diversity index is defined as the inverse of the sum of the absolute difference of industry j's share in location i (S_{ij}) from the regional employment share of industry j. A higher diversity index represents more similar industry composition of location i to the industry composition of the entire region (Duranton, G. and Puga, D., 2000, Equation (3)).

$$RDI_i = 1/\sum_j |s_{ij} - s_j| \quad (3)$$

Transport system and access data

The region's freight transport system is extensive. Figure 3 shows the highway and rail networks, as well as ports, major airports, and intermodal facilities. Intermodal facilities are located at the major junctions of the rail system. The main "freight corridors" are from the ports to central Los Angeles, from central Los Angeles eastward to San Bernardino, north towards Burbank and beyond, and south towards Orange County.

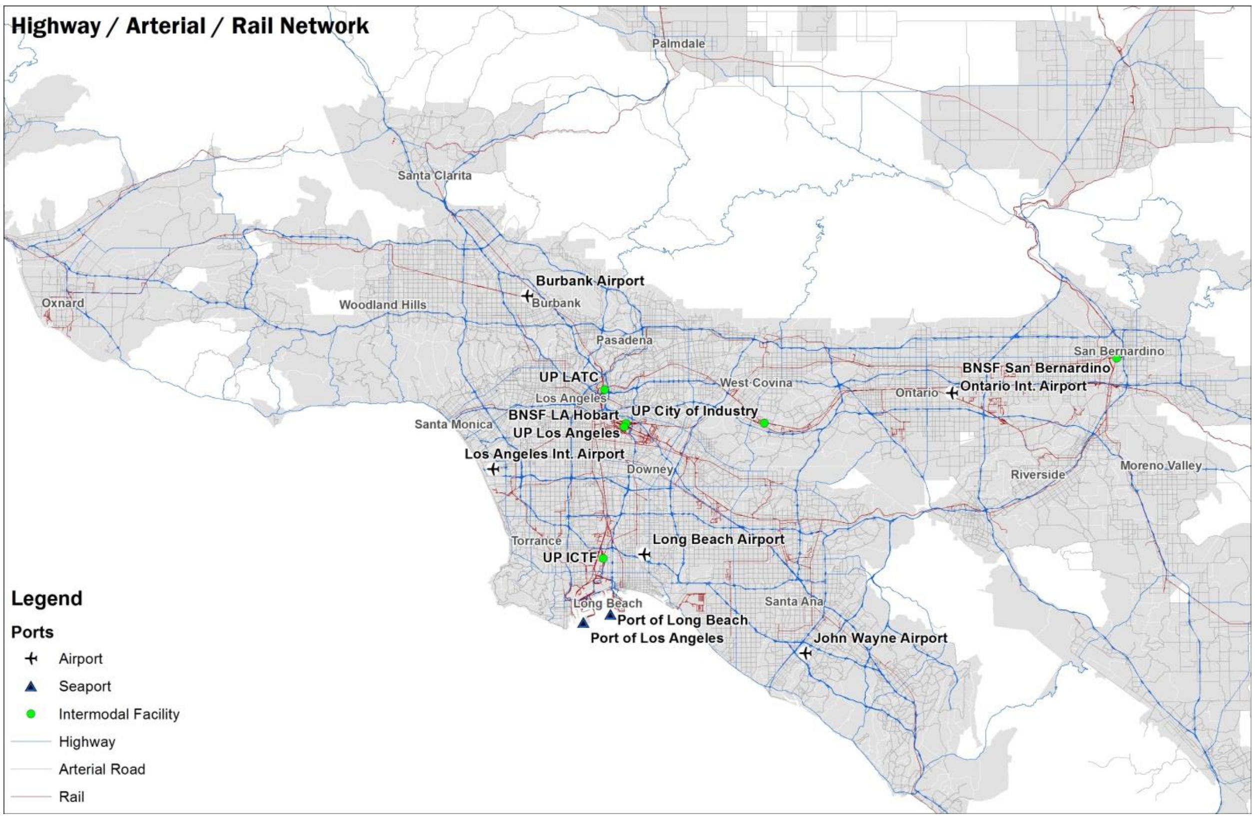

Figure 3 Highway, arterial and rail network; airport, seaport, and intermodal facilities

Because there is no source for truck flows on the metropolitan network, we use the baseline calibration of the regional transportation model provided by SCAG. Our dependent variables are daily truck vehicle kilometer traveled (VKT) per square kilometer and daily total vehicle kilometer traveled (VKT) per square kilometer. Trucks are defined as all heavy-duty vehicles (e.g. more than 8,500 pounds gross weight).These variables are calculated as the total VKT (link volume times link length) for all links within the zone, divided by the area of the zone (in square kilometers). Transport network links do not match up with TAZ boundaries. Links that cross TAZ boundaries are split at the boundary, and only the length of the link within the given TAZ is used in the VKT calculation.

Figure 4 shows truck VKT intensity on the road network, again in quartiles. In general, truck activity intensity is concentrated on the region's major freeways, particularly those connecting major intermodal facilities or inter-regional destinations. The highest concentrations are found around the ports, the old industrial zone in the center of the region, in industrial zones around Ontario airport, and on the major inter-regional highways.

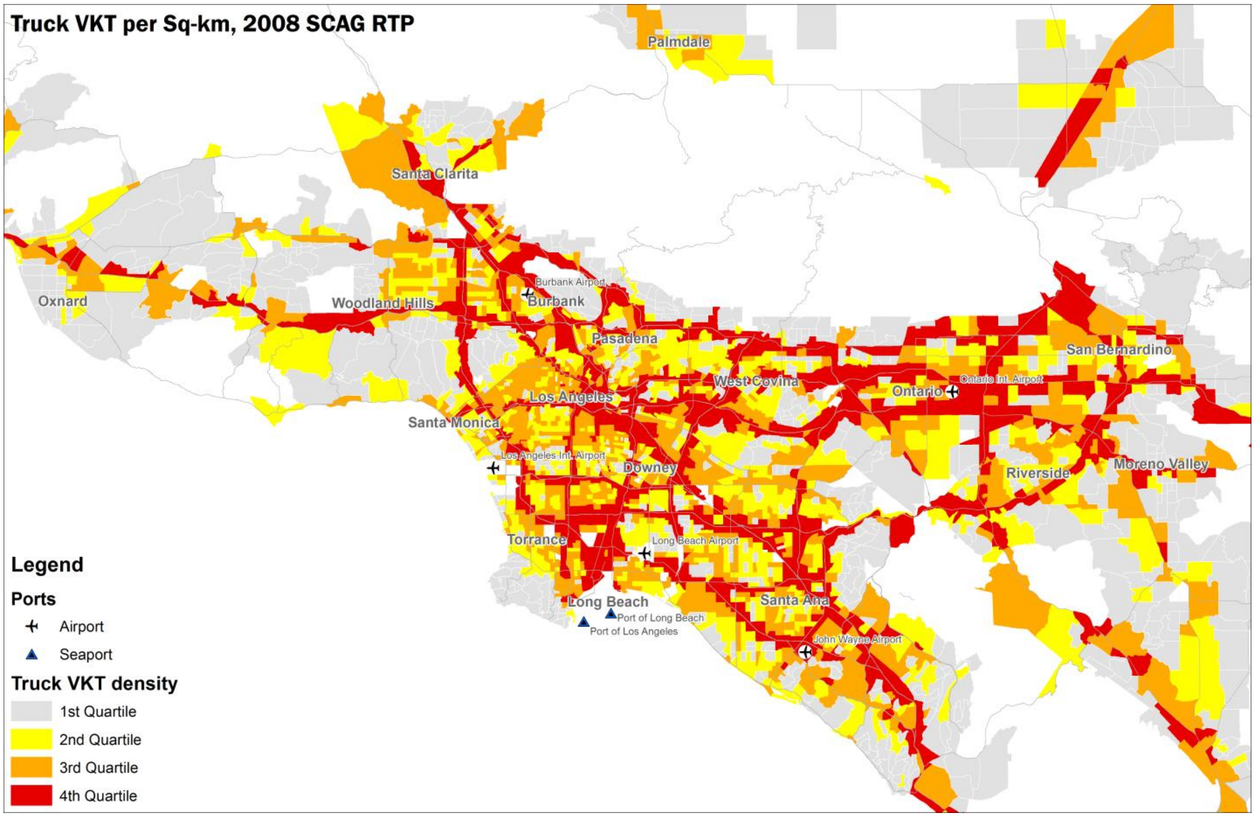

Figure 4 Truck link volume density on the highway and arterial network.

Our independent variables include various access measures. In addition to the effects of the overall spatial distribution of economic activity, we expect that major generators attract more traffic, all else equal. Access measures include distance to the nearest highway access point, to major airports, ports, and intermodal facilities. Intermodal facilities include the various freight rail yards in the region. All distances are measured as Euclidean distance from the zone centroid.

Table 5: Transport and access variables descriptive statistics

Variable	Mean	Median	S.D.	Min	Max
Total truck VMT per sq-km	4,432.0	1,198.4	7,578.0	0.0	90,544.0
Total vehicle VMT per sq-km	91,512.8	50,850.5	116,260.6	20.7	952,379.8
Distance to highway exit (km)	2.2	1.4	2.8	0.0	50.4
Distance to airports (km)	24.9	17.0	24.9	0.5	283.9
Distance to seaports (km)	54.3	43.3	35.6	2.3	336.5
Distance to intermodal (km)	26.4	18.5	24.3	0.5	258.4

N = 3736

Descriptive statistics for dependent and independent variables are given in Table 5. The vehicle flow intensity numbers suggest a lot of variation in the utilization of the system, but on average for all vehicles a relatively heavy utilization, consistent with the well-known heavy congestion of the LA region. On average, most zones are quite close to a highway access/egress point. Because there are 5 major airports in the region, most zones are within 17 miles of the nearest airport. In contrast, the two seaports are collocated at the coast, and hence most zones are quite distant from the port. The major intermodal rail yards, like airports, are distributed around the region.

ANALYSIS AND RESULTS

We turn now to model results. Due to the shape of the variable distributions, we use the natural log form for all dependent and independent variables except the categorical variables (density dummies) and the relative diversity variable. For each model we estimate two regressions, one for total vehicles and one for trucks. Total vehicles provide a means for comparing the extent to which truck volume patterns may be different from the general pattern of vehicle traffic.

We hypothesize that access to major trip generators, whether passenger or freight, is associated with more volume density. We have no a priori expectations for the relationship between total traffic and distance to seaports and intermodal. These large facilities generate substantial externalities and may repel passenger traffic, or as part of major industrial zones may attract passenger traffic. Access to highways should have a positive effect: we expect more development density (and hence more travel demand) in more accessible locations. However, the roles of population and employment density should differ between truck and total vehicle volume, as discussed in Section 3.2.

Another consideration is spatial autocorrelation. Zones in close proximity to one another have similar accessibility characteristics, and traffic volume in one zone must be correlated with that of nearby zones. We therefore estimated simple regressions for each model and tested for spatial autocorrelation using Moran's I. All tests were significant (results not shown). We therefore estimate spatial lag models (see Boarnet, 1994; Wouldsma et al, 2008).
We create Queen Contiguity Weights matrices for the dependent variables and calculate the spatially lagged terms based on the matrices.

Model 1

Results for Model 1 are given in Tables 6a and 6b for total vehicles and trucks respectively. We present stepwise results, with just the control variables in the first step, and with all variables in the second step. The spatial lag term coefficient is significant and positive, as expected. For total vehicles VKT (Table 6a), all control variable coefficients have the expected sign, with all but distance to airport statistically significant. Results are more mixed for total truck VKT: the coefficient for distance to highway is significant and of the expected sign, coefficients for the other access measures are not. For highway access, the magnitude of the coefficient is substantially greater for trucks than for all vehicles, as would be expected (total vehicle traffic should be more dispersed, and large trucks must observe route restrictions).

When we add the population/employment measures, the explanatory power of both estimations increases, but not by much. The magnitude of some of the access variable coefficients goes down for total vehicles, but not for trucks. All coefficients are relative to the base, P1/E1. For the total vehicles regression, all of the coefficients are significant and positive, as expected. We observe a general relationship: for each population category, the coefficient value tends to increase with increasing employment density. Also, the P4/E4 category has the largest coefficient.

Relationships for total truck VKT are similar but more complex. Eleven of the 15 coefficients are statistically significant and have the expected positive signs. Similar to the total vehicle model, for each population category, the coefficient value tends to increase with increasing employment density. But for each employment category, the coefficient value generally decreases with increasing population density, which does not occur in the total vehicle model. The results may imply that the intensity of freight activities is influenced by both employment and population density, but in opposite directions. Finally, both models have a reasonable level of explanatory power.

Table 6a: Regression analysis result of model 1 (Dependent variable: VKT for Total Vehicles)

	Vehicle Kilometer Traveled (VKT) for Total Vehicles					
	Step 1			Step 2		
	Coefficient	S.E	Sig.	Coefficient	S.E	Sig.
Spatial lagged term	0.394	(0.019)	***	0.290	(0.019)	***
Distance to Hwy	-0.560	(0.018)	***	-0.515	(0.017)	***
Distance to Airport	-0.062	(0.024)	***	-0.010	(0.023)	
Distance to Seaports	-0.131	(0.032)	***	-0.069	(0.031)	***
Distance to Intermodal	-0.067	(0.020)	***	-0.040	(0.020)	***
Pop Q1 Emp Q2				0.669	(0.084)	***
Pop Q1 Emp Q3				0.820	(0.094)	***
Pop Q1 Emp Q4				0.994	(0.080)	***
Pop Q2 Emp Q1				0.322	(0.067)	***
Pop Q2 Emp Q2				0.744	(0.062)	***
Pop Q2 Emp Q3				0.927	(0.071)	***
Pop Q2 Emp Q4				0.931	(0.072)	***
Pop Q3 Emp Q1				0.540	(0.089)	***
Pop Q3 Emp Q2				0.856	(0.065)	***
Pop Q3 Emp Q3				0.833	(0.064)	***
Pop Q3 Emp Q4				1.018	(0.074)	***
Pop Q4 Emp Q1				0.697	(0.121)	***
Pop Q4 Emp Q2				0.656	(0.074)	***
Pop Q4 Emp Q3				0.869	(0.067)	***
Pop Q4 Emp Q4				1.036	(0.066)	***
Constant	7.513	(0.254)	***	7.432	(0.254)	***
Pseudo R-squared	0.562			0.598		
Sample Size	3774			3774		

Table 6b: Regression analysis result of model 1 (Dependent variable: VKT for Total Trucks)

	Vehicle Kilometer Traveled (VKT) for Total Trucks					
	Step 1			Step 2		
	Coefficient	S.E	Sig.	Coefficient	S.E	Sig.
Spatial lagged term	0.400	(0.019)	***	0.375	(0.019)	***
Distance to Hwy	-0.810	(0.024)	***	-0.764	(0.025)	***
Distance to Airport	-0.008	(0.032)		0.025	(0.032)	
Distance to Seaports	-0.043	(0.043)		-0.031	(0.043)	
Distance to Intermodal	-0.031	(0.027)		-0.036	(0.027)	***
Pop Q1 Emp Q2				0.688	(0.117)	***
Pop Q1 Emp Q3				0.786	(0.131)	***
Pop Q1 Emp Q4				0.791	(0.110)	***
Pop Q2 Emp Q1				-0.122	(0.094)	
Pop Q2 Emp Q2				0.427	(0.086)	***
Pop Q2 Emp Q3				0.639	(0.099)	***
Pop Q2 Emp Q4				0.508	(0.099)	***
Pop Q3 Emp Q1				-0.015	(0.124)	
Pop Q3 Emp Q2				0.453	(0.089)	***
Pop Q3 Emp Q3				0.305	(0.088)	***
Pop Q3 Emp Q4				0.532	(0.102)	***
Pop Q4 Emp Q1				-0.029	(0.168)	
Pop Q4 Emp Q2				0.064	(0.102)	
Pop Q4 Emp Q3				0.276	(0.092)	***
Pop Q4 Emp Q4				0.378	(0.090)	***
Constant	2.795	(0.186)	***	4.499	(0.221)	***
Pseudo R-squared	0.525			0.544		
Sample Size	3774			3774		

Model 2

In Model 2 we test whether more detailed measures of employment and population are more effective in explaining traffic activity. We estimate two forms of the model. Model 2a uses total employment density and relative diversity; Model 2b uses the factor analysis generated industry sectors.

Results for Model 2a are given in Tables 7a and 7b, again for total vehicles and trucks respectively. We present stepwise results; step 1 includes the spatial lag and control variables, step 2 adds the population variables, and step 3 adds the employment variables. As with Model 1, the step 1 coefficient of access to highway is significant and of the expected sign, but the distance to other freight generators coefficients are not statistically significant in the truck model. When we add population characteristics in step 2, both median income and population density coefficients are significant. Signs are expected – traffic activity is higher in high-density areas, and higher income households typically locate further from major traffic generators. For truck volume, both coefficients are significant and negative as expected.

Results change with step 3. Both employment variable coefficients are significant, and as in Model 1, explanatory value also increases. This suggests that employment characteristics do a better job of explaining total vehicle traffic than population characteristics. In contrast, for truck volume, adding the employment variables does not affect the coefficients of the other variables. Both are significant and have the expected sign.

Table 7a: Regression analysis result of Model 2a (Dependent variable: VKT for Total Vehicles)

	Vehicle Kilometer Traveled for Total Vehicles (Using total employment density and diversity)								
	Step 1			Step 2			Step 3		
	Coef.	S.E	Sig	Coef.	S.E	Sig	Coef.	S.E	Sig
Spatial lagged term	0.397	(0.019)	***	0.374	(0.019)	***	0.277	(0.019)	***
Distance to Hwy	-0.558	(0.017)	***	-0.549	(0.017)	***	-0.511	(0.017)	***
Distance to Airport	-0.066	(0.024)	***	-0.080	(0.024)	***	-0.029	(0.023)	
Distance to Seaports	-0.136	(0.032)	***	-0.137	(0.033)	***	-0.098	(0.031)	***
Distance to Intermodal	-0.066	(0.020)	***	-0.015	(0.021)		-0.033	(0.020)	*
Population Density				0.055	(0.011)	***	0.031	(0.010)	***
Median HH Income				-0.184	(0.034)	***	-0.075	(0.034)	**
Employment Density							0.201	(0.011)	***
Relative Diversity							0.172	(0.056)	**
Constant	7.519	(0.254)	***	9.267	(0.504)	***	7.619	(0.494)	***
Pseudo R-squared	0.569			0.576			0.608		
Sample Size	3736			3736			3736		

Table 7b: Regression analysis result of Model 2a (Dependent variable: VKT for Total Truck)

	Vehicle Kilometer Traveled for Total Trucks (Using total employment density and diversity)								
	Step 1			Step 2			Step 3		
	Coef.	S.E	Sig	Coef.	S.E	Sig	Coef.	S.E	Sig
Spatial lagged term	0.405	(0.019)	***	0.390	(0.019)	***	0.360	(0.019)	***
Distance to Hwy	-0.805	(0.024)	***	-0.809	(0.024)	***	-0.767	(0.024)	***
Distance to Airport	-0.020	(0.032)		-0.051	(0.032)		-0.001	(0.032)	
Distance to Seaports	-0.027	(0.043)		-0.098	(0.044)	**	-0.058	(0.044)	
Distance to Intermodal	-0.034	(0.027)		0.000	(0.028)		-0.013	(0.028)	
Population Density				-0.080	(0.015)	***	-0.109	(0.015)	***
Median HH Income				-0.272	(0.047)	***	-0.212	(0.048)	***
Employment Density							0.145	(0.016)	***
Relative Diversity							0.362	(0.078)	***
Constant	4.730	(0.197)	***	8.693	(0.619)	***	6.925	(0.641)	***
Pseudo R-squared	0.530			0.535			0.549		
Sample Size	3736			3736			3736		

Results for Model 2b are given in Tables 8a and 8b. The Step 1 and 2 estimations are the same as Model 2a, as the only difference between the two models is how we measure employment activity. We observe the same result for total vehicle VKT density (Table 13a) as for Model 2a; the coefficient for population density loses significance. In this case five of the seven sector variable coefficients and the diversity variable coefficient are significant. For truck VKT density, results are also similar to those of Model 2a; when employment variables are added, the population and control variable coefficients are not affected. Just three of the employment variables coefficients are significant, though the two that should have the greatest effect on truck traffic (services; manufacturing and trade) are positive and significant, as expected. How to interpret the results of the sector variables is unclear.

We examined the employment sector data to try to understand why the more sector specific measures did not perform as well as the simple employment measures. First, the sector level measures are correlated with each other (correlations range from .5 to .7). As noted earlier, employment is more concentrated than population. Although clearly employment mix varies spatially, the spatial variation of these large aggregations of sectors tends toward the spatial variation of total employment. Second, the effects of some industries (say transportation) may be captured by the access variables which are the main generators of such traffic.

Both versions of Model 2 are generally consistent. The access measure coefficients have the expected sign, though in several cases are not significant. Population and employment measures are generally consistent across the models, and differences between total vehicles and trucks are as expected.

Table 8a: Regression analysis result of model 2b (Dependent variable: VKT for Total Vehicles)

	Vehicle Kilometer Traveled for Total Vehicles (Using seven industry sector employment densities and diversity)								
	Step 1			Step 2			Step 3		
	Coefficient	S.E	Sig.	Coefficient	S.E	Sig.	Coefficient	S.E	Sig.
Spatial lagged term	0.397	(0.019)	***	0.374	(0.019)	***	0.282	(0.019)	***
Distance to Hwy	-0.558	(0.017)	***	-0.549	(0.017)	***	-0.511	(0.017)	***
Distance to Airport	-0.066	(0.024)	***	-0.080	(0.024)	***	-0.033	(0.023)	
Distance to Seaports	-0.136	(0.032)	***	-0.137	(0.033)	***	-0.080	(0.032)	***
Distance to Intermodal	-0.066	(0.020)	***	-0.015	(0.021)		-0.039	(0.020)	*
Population Density				0.055	(0.011)	***	0.018	(0.012)	
Median HH Income				-0.184	(0.034)	***	-0.087	(0.034)	**
Emp S1 (services)							0.113	(0.015)	***
Emp S2 (const, transp)							-0.005	(0.013)	
Emp S3 (manuf, trade)							0.070	(0.012)	***
Emp S4 (health, other)							0.043	(0.015)	***
Emp S5 (agri, util)							-0.017	(0.013)	
Emp S6 (info)							-0.028	(0.012)	**
Emp S7 (educ)							0.015	(0.007)	**
Constant	7.519	(0.254)	***	9.267	(0.504)	***	8.181	(0.496)	***
Pseudo R-squared	0.569			0.576			0.613		
Sample Size	3736			3736			3736		

Table 8b: Regression analysis result of Model 2b (Dependent variable: VKT for Total Trucks)

	Vehicle Kilometer Traveled for Total Trucks (Using seven industry sector employment densities and diversity)								
	Step 1			Step 2			Step 3		
	Coefficient	S.E	Sig.	Coefficient	S.E	Sig.	Coefficient	S.E	Sig.
Spatial lagged term	0.405	(0.019)	***	0.390	(0.019)	***	0.349	(0.019)	***
Distance to Hwy	-0.805	(0.024)	***	-0.809	(0.024)	***	-0.769	(0.024)	***
Distance to Airport	-0.020	(0.032)		-0.051	(0.032)		-0.005	(0.032)	
Distance to Seaports	-0.027	(0.043)		-0.098	(0.044)	**	-0.027	(0.044)	
Distance to Intermodal	-0.034	(0.027)		0.000	(0.028)		-0.024	(0.028)	
Population Density				-0.080	(0.015)	***	-0.081	(0.017)	***
Median HH Income				-0.272	(0.047)	***	-0.207	(0.048)	***
Emp S1 (services)							0.109	(0.021)	***
Emp S2 (const, transp)							0.005	(0.018)	
Emp S3 (manuf, trade)							0.123	(0.016)	***
Emp S4 (health, other)							-0.072	(0.021)	***
Emp S5 (agri, util)							-0.025	(0.018)	
Emp S6 (info)							-0.027	(0.016)	
Emp S7 (educ)							0.012	(0.010)	
Constant	4.730	(0.197)	***	8.693	(0.619)	***	7.240	(0.639)	***
Pseudo R-squared	0.530			0.535			0.557		
Sample Size	3736			3736			3736		

CONCLUSIONS

We have presented the concept of a freight landscape and tested the hypothesis that these patterns are related to population, employment and access to transport infrastructure. We used network model data for the Los Angeles region and estimated two sets of models, one using simple categories of combined population and employment density, and the other using separate measures of population and employment characteristics. We estimated models for both total vehicles and heavy trucks.

In most cases, we find that transport supply and highway access are significant factors, with the effects of greater magnitude for trucks than for total vehicles. Access to major generators (airports, seaports, intermodal facilities) is generally significant for total vehicles, but not for trucks, suggesting that even in a hub region like Los Angeles, truck traffic is related to more general economic activity. Using the simple categories of combined population and employment in Model 1, results for total vehicles are consistent and as expected: traffic increases systematically with increasing population and employment density. However, results for truck activities are mixed. There is a generally systematic relationship with density, but it is more complicated. For each population category, the coefficient value tends to increase with increasing employment density. But for each employment category, the coefficient value generally decreases with increasing population density.

In Model 2 we separate the effects of population and employment. Using employment density and relative diversity, there is a clear positive relationship of total vehicles with employment density. The relationship for truck volume is as expected, negative for population density and positive for employment density. When we replace a single employment density measure with sector level measures, not all the sector measure coefficients are significant, but the coefficients for services and manufacturing and trade – the sector groups with the largest number of jobs – are significant.

Overall, population, employment and transport access have different effects on total vehicle and truck volume densities. For total vehicle volume, employment variables and transport supply and access measures contribute much more than population variables to the variations of dependent variable. Truck volume is not always significantly related to transport access to major generators; we suspect that since areas around airports and seaports tend to be industrial zones, the employment variables capture some of their effect. Truck activity intensity is strongly and negatively associated with population density and household income. This makes sense: higher income households are likely to live further away from freight intensive activities, and although high population density creates demand for freight, locations with high population density – an indicator of high land price – would crowd out truck (and land) intensive activities such as warehousing and distribution.

Our results are encouraging. Our analysis provides some preliminary evidence that population, employment, and transport supply and access measures explain truck flows. The freight landscape concept may be a promising approach to describe spatial patterns of freight flows with generally available proxies. However, more research is needed. Much of the spatial variation in truck traffic remains unexplained, and our analysis was conducted with model generated data. We have conducted a study of one metropolitan area; studies of other metro areas would help to determine the extent to which the freight landscape concept may contributing to a better understanding of urban freight dynamics.

Acknowledgment

This research is supported by the Volvo Research and Education Foundation through the MetroFreight Center of Excellence, METRANS Transportation Center, University of Southern California. Data was provided by the Southern California Association of Governments. Comments by Laetitia Dablanc, and Jean-Paul Rodrigue, and Sangyup Chung on an earlier drafts are gratefully acknowledged. All errors and omissions are the responsibility of the authors.

REFERENCES

Ambrosini, C, D. Patier, and J. Routhier (2010) Urban freight establishment and tour-based surveys for policy oriented modelling, *Procedia – Social and Behavioral Sciences, 2(3), 6013-6026.*

BESTUFS. (2006). Quantification of Urban Freight Transport Effects I. Deliverable, October 10, 2006. Retrieved November 16, 2012 from http://www.bestufs.net/download/BESTUFS_II/ key_issuesII/BESTUF_Quantification_of_effects.pdf.

Boarnet, M. G. (1994). An empirical model of intrametropolitan population and employment growth. Papers in Regional Science, 73(2), 135-152.

Bomar, M.A., Becker, E.P. and Stollof, E.R. (2009). *Urban Freight Cases Studies: New York City*. Report No. FHWA-HOP-10-019. Washington D.C.: USDOT, Federal Highway Administration, Office of Freight Management and Operations.

Cambridge Systematics (2005). *An initial assessment of freight bottlenecks on highways*. Washington, D.C.: Federal Highway Administration.

Chase, K. M., Anater, P., & Phelan, T. J. (2013). *Freight Demand Modeling and Data Improvement*. Transportation Research Board.

Cidell, J. (2010). Concentration and decentralization: The new geography of freight distribution in US metropolitan areas.*Journal of Transport Geography, 18,* 363-371.

Dablanc, L., Giuliano, G., Holliday, K., & O'Brien, T. (2013). Best Practices in Urban Freight Management. *Transportation Research Record: Journal of the Transportation Research Board*, 2379(1), 29-38.

Dablanc, L. & Ross, C. (2012). Atlanta: A mega logistics center in the Piedmont Atlantic Megaregion (PAM). *Journal of Transport Geography, 24*, 432-442.

Dablanc, L. (2011). City distribution, a key element of the urban economy: guidelines for practitioners, in C. Macharis and S. Melo (Eds.), *City distribution and urban freight transport: multiples perspectives* (pp. 13-36). Cheltenhan, UK: Edward Elgar Publishing Limited.

Dablanc, L. (2014). Logistics sprawl and urban freight planning issues in a major gateway city: The Case of Los Angeles, in J. Gonzalez-Feliu, F. Semet & J.L. Routhier (Eds.), *Sustainable Urban Logistics: Concepts, Methods and Information Systems* (pp. 49-69). Berlin-Heidelberg: Springer-Verlag.

Dablanc, L. and Rodrigue, J-P (2014) Urban Freight Distribution: A Global Typology, in G. Giuliano and S. Hanson (Eds.) *The Geography of Urban Transportation*, 4th Edition, New York: The Guilfold Press. in press.

Dablanc, L., Ogilvie, S., and Goodchild, A. (2014). Logistics Sprawl: Differential Warehousing Development Patterns in Los Angeles, California, and Seattle, Washington. *Transportation Research Record:Freight Systems 2014*, *1*, 105-112.

Dicken, P. (2007) *Global Shift: Mapping the Changing Contours of the World Economy*, 5th edition. London: Sage Publications.

Duranton, G. and Puga, D. (2000). Diversity and specialization in cities: Why, where and when does it matter? *Urban Studies*, 37:533.

Federal Highway Administration (2014) *Freight Facts and Figures 2013.* Report FHWA-HOP-14-004. Washington, DC: FHWA Office of Freight Management and Bureau of Transportation Statistics Office of Transportation Analysis.

Giuliano, G., Redfearn, C., Agarwal, A., Li, C., & Zhuang, D. (2007). Employment concentrations in Los Angeles, 1980–2000. *Environment and Planning A, 39*(12), 2935-2957.

Giuliano, G., O'Brient, T., DaBlanc, L., and Holliday, K. (2013) Synthesis of Freight Research in Urban Transportation Planning, NCFRP Report 23. Washington D.C.: National Cooperative Freight Research Program.

Giuliano, G., Hou, Y., Kang, S., and Shin, E. (2013) Accessibility, Location and Employment Center Growth. Metrans Project 11-06, Final Report, University of Southern California, Los Angeles.

Holguin-Veras, J., Polimeni, J., Cruz, B., Xu, N., List, G., Nordstrom, J., & Haddock, J. (2005). Off-peak freight deliveries: Challenges and stakeholders' perceptions. *Transportation Research Record: Journal of the Transportation Research Board*, *1906*(1), 42-48.

Holguín-Veras, José, Miguel Jaller, Iván Sánchez-Díaz, Jeffrey Wojtowicz, Shama Campbell, Herbert S. Levinson (2012) Freight Trip Generation and Land Use. NCHRP Project No. 08-80.Transportation Research Record.

Leinbach, T. and Capineri, C. (2007), *Globalized Freight Transport*. Northampton, MA: Edward Elgar Publishing.

Rodrigue, J. P. (2004). Freight, Gateways and Mega-Urban Regions : The Logistical Integration of the Bostwash Corridor. *Tijdschrift voor economische en sociale geografie*, *95*(2), 147-161.

Woudsma, C., Jensen, J. F., Kanaroglou, P., & Maoh, H. (2008). Logistics land use and the city: A spatial–temporal modeling approach. Transportation Research Part E: Logistics and Transportation Review, 44(2), 277-297.

Xing, Y., Grant, D. B., McKinnon, A. C., & Fernie, J. (2010). Physical distribution service quality in online retailing. *International Journal of Physical Distribution & Logistics Management*, *40*(5), 415-432.