Testing the 'Freight Landscape' Concept for Paris

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ABSTRACT

The concept of “Freight Landscape,” the basis for a modeling approach for urban freight traffic estimation using commonly available datasets, was proposed by Giuliano et al., 2017, applying it to the Los Angeles metropolitan area. To extend the scope of their research, we conduct another case study, using data from the Paris region, France. We estimate spatial lag models using population, employment or establishment, transportation accessibilities as explanatory variables and network-based truck traffic as the dependent variable, modifying Giuliano et al.’s approach. We identify differences in the characteristics of the variables and the models between Los Angeles and Paris cases, each having distinctively different urban structure from one another. While the models estimated for the Paris region give us beneficial insights on the relationships between Freight Landscape indicators and urban freight traffic, the complex correlation structure among indicators as well as the limitation of the models to specify the areas of very high truck traffic underlines the need for further research on modeling framework and adding more case studies.

INTRODUCTION

The scarcity of data for urban freight is a long-standing issue that hampers the analysis of urban freight flows and impacts. The complexity and heterogeneity of urban freight activities make data collection costly and challenging to implement. Only a limited number of cities implement surveys for urban freight. Even where survey data exists, scope is often limited. On the other hand, growth in population and economic activities in cities around the world results in an increase of urban freight activities. Development of policies that address various issues associated with such increase in freight activities requires urban freight traffic analysis. As such, finding robust yet easily obtainable secondary data to estimate urban freight traffic demand ~~could be~~ is an important step toward overcoming the lack of resource for data collection. ~~Therefore,~~ The methodology for using the secondary data to characterize urban freight traffic is an important research subject.

The primary focus of this research is methodological. Following the research by Giuliano et al. (1), we explore the use of available secondary data to estimate urban freight traffic. The objective of their work is to determine whether it is possible to accurately predict urban freight flows' spatial patterns "using simple measures of population, employment and transport access". (1) The authors define the concept of 'freight landscape' as "a description of freight activity imputed from population, employment and transport network characteristics," with the hypothesis that "freight flows depend systematically on the spatial organization of freight suppliers and demanders as well as on the transportation facilities within the metropolitan areas." To test the hypothesis, they analyze the relationship between the distributions of population, employment, and transportation supply, and truck flow using the data from Los Angeles. The estimation of spatial regression models indicates the ~~presence of~~ systematic relationships between those factors and truck traffic. In this line of work, ~~as suggested by Giuliano et al. (1),~~ we add another case study from Paris, which is the largest urban cluster of population and business activities in France, and one of the largest in Europe.

The rest of this paper consists of the following five sections: 1) a brief literature review that focuses on urban form - urban freight relationship is provided; 2) freight features and freight data collection in the Paris region are explained; 3) analytical framework and data sources are detailed; 4) the estimated models are discussed; and 5) the conclusion of this research is provided.

LITERATURE REVIEW: THE RELATIONSHIP BETWEEN URBAN FORMS AND URBAN FREIGHT

"Freight landscape," i.e. a systematic relationship between easily accessible socio-economic indicators and goods transport activity, is an important concept, as the relationship between freight and urban forms, a broad category which encompasses the distribution of various indicators of human activities in an area (2), is generally understudied in the literature (3-4). Past efforts of urban freight modeling developed various types of freight (or freight trip) generation methods since at least the 1970s (5). Existing papers, including Gonzalez-Feliu and Routhier (6), Taniguchi et al. (7), and Holguín-Veras et al. (8), attempt to inventory the variety of urban freight modeling efforts. Most models try to estimate freight trips generated from the economic establishments of an urban area. Even though spatial distribution plays no part in the generation of freight trips at the establishment level, other studies (9-10) emphasize the possibility that space can explain operational characteristics of deliveries/pick-ups such as the type of vehicle, type of parking, duration of parking.

The studies of the relationship between freight flows and urban forms are emerging at a theoretical level. Researchers recognize, for example, the links between density and inefficiency of deliveries. Dense urban centers bring about efficiency on goods transport activity, namely the shorter distances between delivery points and, therefore, the higher potential for consolidated urban freight tours. On the other hand, high density can lead to inefficiency because of narrow streets (11), the use of small vehicles due to local or national regulations (12), traffic congestion (13), and the lack of supply of parking spaces for freight vehicles (14-16).

FREIGHT TRANSPORTATION AND DATA COLLECTION IN THE PARIS REGION

The Paris region's Freight transportation in the Paris region

The Paris region (i.e. Ile-de-France) is by far the richest and most productive French region, concentrating about one fifth of the nation's population and employment as well as roughly 30% of its GDP in only 2% of the surface for 2012. The region is also a highly attractive tourist destination. As for freight tonnage, the Paris region displays a slight imbalance between inflows and outflows. 55% of the tons of transported goods are internal, 25% are inflows and 20% are outflows (17). 31% of the tons of goods moved in the Paris region are finished products, and 9% are food products (17). The Paris region requires a very efficient logistics network of freight terminals to provide high frequencies and variety of small deliveries. That is why, alongside its national economic prominence, the Paris region holds about 17% of the total surface of warehouses in France (18) and 26% of the French logistics sector workforce (19), while it only represents 10.5% in tonnage of the nation's transported goods (17). It is estimated that through-traffic represents about 20% of the total truck traffic in the Paris region (17), even though the Paris region is the most congested French region (20) and one of the most congested urban areas in Europe (21).

The Paris region relies mostly on trucks to transport goods (17); in total, 88.6% of the tons of goods transported within, to, or from the Paris region are transported on roads. About 6.3% of tons are transported through waterway system, 60% of which are construction materials, and about 4.5% are transported by rail that mainly carries long-distance shipments of construction materials and finished products. Despite policy attempts designed to reduce the Truck-Kilometers Traveled (TKT), road transportation has maintained its share for moving products over the last decade (17). Last mile freight movements rely highly on small vehicles: about 60% of the deliveries/pick-ups are made using light goods vehicles of 3.5 tons or less in gross vehicle weight (22).

Truck traffic data collection efforts

French local authorities have jurisdiction over large portions of the road network and conduct counts and cordon surveys frequently, although at irregular intervals. The national government has jurisdiction over the highway network (autoroutes), and produces yearly data on vehicle flows obtained through automatic counts (most of the national network are equipped with traffic sensors that can distinguish between small and large vehicles). The results of these surveys are often aggregated at the regional level. Other data collection efforts focus on freight flows to produce OD matrices, which can then be used in traffic assignment models. The national government conducts a yearly mandatory survey of heavy goods vehicles' users (vehicles over 3.5 tons in gross weight) called the TRM survey (Transport Routier de Marchandises - Freight Road Transport), which is used to produce freight flow matrices at the departmental and regional levels (23). Those data on

vehicle counts and flows allows regional agencies to produce regular reports on the state of the Paris Region's mobility and traffic conditions, including truck traffic (17, 24), which can be used for policy implementation (25). This paper relies heavily on the data from the counts (automatic or not), which are calibrated using the data from the TRM survey, to obtain the truck traffic in the Paris region.

METHODOLOGY AND DATA

Methodology

The Paris region consists of 1,300 local municipalities, consisting of 20 *arrondissements* in the City of Paris and 1280 *communes* outside of Paris, with an average size of 9.3 km². A 'municipality' is the most detailed unit for analysis for which population, employment and establishment data are fully available. This spatial unit also matches the availability of the road network and truck traffic data, which do not include the municipal road network. It is still required to exclude 262 municipalities from the analysis, which have no truck traffic data as the road network and truck traffic data do not cover those municipalities.

The purpose of this research is to test whether widely available socio-economic indicators, such as population, employment and establishments, and transportation accessibility, can describe freight traffic with the level of accuracy that warrants the use of such indicators for urban freight traffic analysis. We develop regression models for estimating TKT per square km, which represents truck traffic demand. The model development is conducted in four steps, using the following groups of indicators for independent variables: (i) population and employment ~~indicators~~, (ii) population and establishment ~~indicators~~, (iii) transportation accessibility ~~indicators~~, and (iv) population, employment or establishment, and transportation accessibility ~~indicators~~. Employment and establishment ~~indicators~~ are not used at the same time for regression analysis due to ~~the~~ high correlations between the two indicators.

As the spatial auto-correlation becomes an issue in this type of analysis in which the effects from neighboring municipality influence truck traffic demand (1, 26-29), we use a spatial lag model which formula is shown below.

$$y_m = \alpha + \sum_i \beta_i x_{m,i} + \rho \sum_{n \neq m} w_{mn} y_n + \varepsilon_m \quad (1)$$

where:

- y_m : TKT per km² (dependent variable) in municipality m
- $x_{m,i}$: an indicator (independent variable) i for municipality m
- w_{mn} : the spatial weight for the pair of municipality m and n
- ε_m : a randomly distributed unobserved component
- α, β, ρ : parameters to be estimated; ρ is the autoregressive lag coefficient

The spatial lag model requires spatial weight matrix. We tested various formulas including Radial Distance Weights, Power Distance Weights, Exponential Distance Weights, and Queen Contiguity Weights, and found that the Power Distance Weights provide the highest fits for the tested models. Weight matrix is calculated using the formula below. We tested $\gamma = 0.5, 1, 2, 3, 4$ and $\gamma = 3$ gives the best results.

$$w_{mn} = d_{mn}^{-\gamma} \quad (2)$$

where:

d_{mn} : network distance between municipality m and n

γ : a positive exponent

All variables, including independent and dependent variables, are log-transformed as it gives higher Pseudo R^2 and AIC. “Spdep” package (30) in R, the software environment for statistical computing, is used for estimating models, applying the maximum-likelihood method. The model estimations are conducted in the way to find statistically significant independent variables and minimize AIC.

Data

We use population, employment, and the number of establishments at the municipal level in the Paris region as the independent variables. To measure population density and employment density, we use the data provided by the French National Institute for Statistics (INSEE) for the year 2014. The Paris region is a monocentric metropolitan area. Population, employment and establishments (especially the latter two) are concentrated in the center of the region, the City of Paris, and the surrounding suburban municipalities (Figure 1).

The source for detailed employment and establishment patterns is the “Local Knowledge of the Productive System” (CLAP) database provided by the INSEE. This database uses the European NACE classification (Statistical Classification of Economic Activities in the European Community), which provides similar categories with the North American Industry Classification System (NAICS). The NACE classification only considers the main purpose of each building so that the other functions in the establishment may not be recognized. In this analysis, we use aggregated version of the CLAP database that groups the NACE classes into 17 categories (Table 1).

In the Paris Region, economic activities of various types are located close to one another. As for the log-transformed employment densities, all pairs of the 17 industry categories excluding AZ (agriculture, forestry and fishing), C2 (coke and refined petroleum) and C4 (manufacture of transport equipment) have strong correlations, with Pearson’s correlation coefficients of 0.58 or higher. Such strong correlations indicate high potential for the multicollinearity problem, leading to biased estimations of the effects, even showing the opposite signs from the actual ones. To avoid the problem, we consider only statistically significant variables in the final models.

The list of road infrastructures in the Paris region was provided by the French Institute for Geography (IGN). We use the Route 120® database which gave us all the roads and highways as well as road nodes and intersections to calculate the road accessibilities to logistics infrastructures, for the year of 2015. The database of logistics infrastructures is the product of our own compilation from HAROPA (Ports of Paris) and SNCF (French National Railway Company) information. Those infrastructures are widespread, with some located within the inner suburban areas, while others stretching from the north to the east, and in the southeast (Figure 2). This has led to the development of the areas close to the infrastructures and the ports of Gennevilliers and Bonneuil or the Charles de Gaulle and Orly airports. The spatial distributions of some logistics infrastructures are similar and, therefore, there are strong correlations among the associated accessibility indicators like those of employment/establishments. Pearson’s correlation coefficient of the log-transformed distances to rail-road ~~intermodal terminal~~ and river-road intermodal

terminal_s is as high as 0.96. Those two distance measures are also highly correlated with the distance to airport (log-transformed), with the coefficients of 0.82 and 0.78, respectively.

Truck traffic data were provided by the Regional bureau of infrastructures and urban planning for the Paris region (DRIEA). We use the hourly average truck traffic volume of morning rush hours on the road network in the Paris region in 2009 that were estimated based on the samples collected by each Department (comparable to county in the US) of the Paris region (Figure 3). It should be noted that the data do not contain light commercial vehicles (i.e. commercial vehicles of 3.5 tons or less in gross weight), which account for 57% of freight flows for deliveries according to the urban freight survey conducted in 2012 for the Paris region (22). The summary of the variables is shown in Table 2.

ANALYSIS AND RESULTS

In the following subsections, the results are discussed for the models with (i) population and employment variables, (ii) population and establishment variables, (iii) accessibility variables, and (iv) the combinations of population, employment/establishment, and accessibility variables. These models underline the set of indicators that contribute to the truck traffic estimation in each category or among all available variables.

Models with population and employment/establishment data

The three models that apply population and employment variables are shown in Table 3. For the first model (left in Table 3), only total population and total employment are used; the second model (center in Table 3) is estimated using total population and employment for 17 industrial categories; for the third model (right in Table 3), independent variables are reduced to population and only the statistically significant employment variables that show the p-values of less than 0.10.

“Population” is insignificant for all three models; population is highly correlated with employment (Pearson's correlation coefficient is 0.96) so that its apparent contribution for estimating truck traffic demand is limited. The second model shows the heterogeneity on the impacts of employment by industry type. Coefficients of some employment variables are negative, which are likely due to the multicollinearity problem, i.e. the correlations among independent variables result in the biased estimated coefficients.

To find the variables that are highly related to truck traffic demand, the insignificant employment variables and those with negative coefficients are removed and, thus, the third model is obtained. “Emp. IZ” and “Emp. KZ” are omitted in the process as these variables turn to be insignificant when some other variables are omitted. Among various industrial categories, GZ (trade; automobile and motorcycle repair) shows the largest effect on truck traffic demand, followed by HZ (transportation and storage), and C3 (manufacture of electrical equipment, electronic, computer; manufacturing machines). Autoregressive lag coefficients are significant for all three models and the comparison between AIC and AIC for linear regression model indicates that the spatial auto-regressive effects are non-trivial.

Similarly, three models that apply population and establishment, instead of employment, variables are shown in Table 4. Compared with the models in Table 3, Pseudo R^2 is slightly lower and AIC is higher for each step, which indicates that employment variables are likely to be better indicators for predicting truck traffic demand.

Only “Estt. GZ” (trade; automobile and motorcycle repair) is the significant establishment variable that remains in the third model, and autoregressive lag coefficient is, again, significant in all the three models.

Models with accessibility indicators

Next, the models are estimated using nine accessibility variables. All variables are used in the first model and, in the second model, non-significant variables and the variables with positive coefficients are excluded. Among all accessibility variables considered, “Dist. to autoroute” is most important for truck traffic prediction. This is likely due to the simple fact that a large volume of trucks use autoroutes. Also, the locations near autoroute’s interchanges and exits are efficient for logistics activities.

“Dist. to rail-road intermodal terminal” is also significant and its effect on truck traffic demand is strong. Two municipalities, Gennevilliers and Bonneuil, accommodate two of the region’s main rail-road intermodal terminals, as well as the two main river ports in the Paris region. The other two main intermodal terminals are in Valenton and Noisy. They are all located in the fringes of the Paris urban area. The other variable which is statistically significant is “Dist. to freight terminal”, though the effect is smaller than the two accessibility variables mentioned above.

Comparison of the models in Table 5 with Table 3 and 4 shows that accessibility indicators tend to produce more reliable models than the models with only population and employment/establishment variables. The autoregressive lag coefficient is significant, but its effects are smaller in the models with accessibility variables, which indicates that the accessibility variables could capture a part of spatial auto-correlation effect.

Models with population employment/establishment, and accessibility indicators

The first two models (1 and 2) in Table 6 are those using population, employment, and accessibility variables. We use the three accessibility variables that are statistically significant in the earlier analysis (“Dist. to autoroute”, “Dist. to freight terminal”, and “Dist. to rail-road combined terminal”) (see the second model in Table 5). The first model in Table 6 uses the total employment and the second model uses, instead, the categories of the employment that are significant in the earlier model estimation (see the third model in Table 3).

When population, employment and accessibility are included in the model, the contribution of autoregressive lag coefficient to AIC is small (i.e. the gap between AIC and AIC for linear regression model is small), although autoregressive lag coefficient is still statistically significant. Interestingly, the effect of population becomes significant with the inclusion of accessibility variables. The effect of population density is masked if accessibility variables are not adequately considered. All employment categories considered (“Emp. C3”, “Emp. GZ”, and “Emp. HZ”) remain significant in the second model. On the other hand, “Dist. to freight terminals” becomes insignificant in both models and, therefore, is removed. The second model generates the highest Pseudo R^2 and the lowest AIC, which indicates the model is superior to the other models tested in this section.

The next two models (3 and 4) in Table 6 shows the models that apply the number of establishments, instead of employment. Again, “Dist. to freight terminal” is insignificant in the models. Also, when “Estt. GZ” (trade; automobile and motorcycle repair) are included, “Dist. to rail-road terminals” is insignificant, because the two variables are negatively correlated to each other (Pearson’s correlation coefficient is -0.76).

We also test the models using income level (i.e. median income) as an independent variable; however, the income level is always insignificant, unlike the case of Los Angeles

metropolitan region (1). As discussed by De Lara (31), logistics activities may be associated with low-income neighborhoods in L.A. but that is not the case in the Paris region (32).

Further discussion

The analysis in this section highlights the socio-economic and accessibility indicators that best characterize truck traffic density in the Paris Region. Our approach also clarifies the challenging issues for estimating truck traffic using those indicators. First, for the cities where mixed land use is common, like the Paris Region, high correlations among indicators of urban forms make it difficult to accurately specify the effects of the indicators. As for accessibility indicators, the distances to rail-road intermodal terminal, river-road intermodal terminal, and airport, are highly correlated with one another and, therefore, the use of one of those three indicators returns the combined effect.

Secondly, key factors should be jointly and comprehensively considered. Our analysis shows adding accessibilities to the models with population and employment/establishment densities is essential to capture the effect of population density on truck traffic. The two suburban municipalities, Cergy-les-Meaux and Limours, exemplifies this mechanism. They have similar employment densities and truck traffic density, although population densities are different ("Pop." (log-transformed) are 7.1 and 6.1, respectively). The effect of the population density become apparent only when the distance to autoroute, which negatively associated with truck traffic, is considered; "Dist. to autoroutes" (log-transformed) are 1.5 and 2.1, respectively. In this case, the effects of population density and the distance to autoroute counteract each other. Missing accessibility indicators leads to the negation of the population density effect.

Taking one step further, we compare the actual TKT per km² (non-log transformed) and those estimated using the best model (the second model in Table 6). The root-mean-square error (RMSE) is 297 and the adjusted R² is 0.76. The correlation between actual and estimated TKT per km² is 0.64, which indicates the difficulty in differentiating the areas with very high truck traffic densities from those with moderately high truck traffic densities (and, the areas with very low traffic densities from those with moderately low traffic densities). While the modeling approach used for the L.A. and the Paris Region works for identifying the factors for truck traffic and the locations where truck traffic concentrates, the approach still has difficulty in estimating truck traffic volume with high accuracy. Incorporating the data of other dimensions, such as network-based characteristics (e.g. centrality), land use regulations, and spatial design (road width, plot size, parking capacity, etc.) is worthy of testing for both accurate specifications of indicator effects and prediction.

CONCLUSION

In this paper, we use the concept of 'freight landscape' and applied the modeling approach of Giuliano et al. (1) with some refinements for the Paris region. The concept hypothesizes that urban freight patterns can be predicted from simple indicators of population, employment, and the accessibility to transportation infrastructure, which are generally available. For the Los Angeles case, the results mostly validate the hypothesis with nuances. Giuliano et al. find that there is a systematic relationship between density and truck traffic. In L.A., truck volumes are associated with employment density, especially for services, manufacturing, and trade. Their analysis also shows that transportation supply and highway access are good indicators explaining truck traffic, although the accessibility to major freight generators (airports and seaports) is not. The intensity

of truck activity is strongly and negatively associated with population density and household income.

We develop and test models using TKT per km² on the Paris region's road network as a dependent variable for finding the approach to estimate urban freight traffic. Main results are the following:

- (i) In the Paris region, the distributions of the residential population and employment are monocentric and quite similar. Thus, the contribution of population for estimating truck traffic demand is limited when employment variables are also in the model. However, the addition of accessibility variables highlights the significant negative effect of population on truck traffic.
- (ii) Employment is a better business activity indicator for estimating truck traffic than establishments.
- (iii) The following activities: trade & automobile and motorcycle repair; transportation and storage; and manufacture of electrical equipment, electronic, computer & manufacturing machines show the largest effects on truck traffic demand.
- (iv) Among all accessibility variables, the distance to autoroute is most important for truck traffic demand prediction.
- (v) Distance to rail-road intermodal terminal is also significant and its effect on truck traffic demand is strong. The effect of this accessibility indicator is enhanced due to its high correlations with the distances to river-road terminal and airport.
- (vi) The highest fit of the model is achieved by the set of the variables including population, employment in the three industrial categories mentioned earlier, the distances to autoroute and rail-road intermodal terminal; and
- (vii) The income level is always insignificant.

We identify the relationship between population, employment and accessibilities, and truck traffic demand in the Paris region, similarly to the L.A. case, but with many differences. It is not surprising, as the urban structure of the Paris region is monocentric and different types of activities are located close to one another, while in L.A., the urban area spreads widely with a more evenly distributed road network. The analysis presented in this research has shortcomings. One of them is that we did not consider light commercial vehicles (i.e. vans), which represents more than half of the vehicles used for deliveries and pick-ups in the Paris region. The updating of the analysis using comprehensive freight traffic flow data is a future research task.

For pushing the freight landscape concept forward and making the proposed approach of use for urban freight planning, more case studies are required, especially those for cities that have similar urban structure with the Paris Region (or the L.A.) for comparison. Also, as discussed earlier, other commonly available indicators that can characterize urban truck traffic must be explored. It should be noted that rapidly emerging practices in logistics, such as night time deliveries, consolidations, and crowdsourced deliveries, may be changing the relationships between urban forms and truck traffic overtime and the validity of the concept of 'freight landscape' must be reviewed accordingly.

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Source: French National Institute for Statistics and French Institute for Geography

FIGURE 1 Density of population, employment and establishments in the Paris region: (a) population density, (b) employment density, (c) establishment density.

1 **TABLE 1 Industry Category Based on NACE Classification (17 Categories)**

Code	Industry	% of employment in the Paris region (total=100)
AZ	Agriculture, forestry and fishing	0.08
BE	Mining, energy, water, waste management and Remediation activities	1.57
C1	Manufacture of food products, beverages and tobacco products	0.88
C2	Coke and refined petroleum	0.02
C3	Manufacture of electrical equipment, electronic, computer& manufacturing machines	1.39
C4	Manufacture of transport equipment	1.43
C5	Manufacture of other industrial products	3.33
FZ	Construction	5.08
GZ	Trade & automobile and motorcycle repairs	12.90
HZ	Transportation and storage	6.80
IZ	Accommodation and food	5.17
JZ	Information and communication	6.99
KZ	Financial and insurance activities	6.14
LZ	Real estate activities	1.44
MN	Scientific and technical activities & Administrative and support services	16.76
OQ	public administration, education, human health and social work	25.44
RU	Other service activities	4.41

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Source: Regional bureau of infrastructures and urban planning for the Paris region, French Institute for Geography and others

FIGURE 2 Main logistics infrastructures in the Paris region.

FIGURE 3 Density of Truck-Kilometers Traveled (TKT) (log-transformed).

1 **TABLE 2 Summary of Variables (before Log-Transformation)**

Variables	Annotation	Mean	Median	S.D.	Min	Max
TKT per km ²	-	180.7	48.4	363.6	0.0	4089.2
Population density (/sq. km)	Pop.	2094.8	263.9	4688.6	3.6	41858.5
Employment density (/sq. km)	Emp.	1110.0	56.4	4528.4	0.2	68238.4
Establishment density (/sq. km)	Estt.	262.3	19.1	1187.4	0.5	18679.8
Distance to <i>autoroute</i> (km)	Dist. to autoroute	9.0	6.6	8.2	0.0	51.4
Distance to airport (km)	Dist. to airport	36.9	33.7	20.0	0.9	94.4
Distance to freight terminal (km)	Dist. to freight terminal	7.9	7.1	5.0	0.0	29.7
Distance to main logistics area (km)	Dist. to main logistics area	15.0	11.2	10.9	0.0	51.3
Distance to multimodal hub port (km)	Dist. to multimodal hub port	25.8	23.7	13.6	0.9	69.4
Distance to river container terminal (km)	Dist. to river container terminal	28.6	24.6	16.7	0.0	83.9
Distance to rail-road intermodal terminal (km)	Dist. to rail-road intermodal terminal	34.6	32.7	19.6	0.8	85.0
Distance to river-road intermodal terminal (km)	Dist. to river-road intermodal terminal	34.5	32.5	19.0	1.8	84.2
Distance to urban port (km)	Dist. to urban port	15.4	12.5	11.4	0.0	54.4

2 Note: The breakdowns of employment density and establishment density by industry category are omitted from the
3 table.

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1 **TABLE 3 Estimated Spatial Lag Models with Population and Employment Variables**

	1. Total pop. and total emp.			2. Total pop. and emp. by industry group			3. Total pop. and significant emp. variables.		
	Coef.	S.E.	P-value	Coef.	S.E.	P-value	Coef.	S.E.	P-value
Intercept	1.453	0.214	0.000**	1.869	0.329	0.000**	2.122	0.230	0.000**
Pop.	-0.080	0.065	0.220	0.017	0.087	0.842	-0.073	0.051	0.154
Emp.	0.386	0.051	0.000**						
Emp. AZ				-0.036	0.101	0.725			
Emp. BE				-0.036	0.043	0.402			
Emp. C1				-0.129	0.075	0.087*			
Emp. C2				-0.130	0.182	0.475			
Emp. C3				0.075	0.048	0.120	0.083	0.043	0.054*
Emp. C4				0.053	0.044	0.235			
Emp. C5				0.010	0.050	0.847			
Emp. FZ				0.036	0.065	0.584			
Emp. GZ				0.256	0.063	0.000**	0.314	0.053	0.000**
Emp. HZ				0.095	0.047	0.042**	0.117	0.044	0.007**
Emp. IZ				0.152	0.075	0.042**			
Emp. JZ				-0.092	0.055	0.094*			
Emp. KZ				0.181	0.076	0.017**			
Emp. LZ				0.043	0.081	0.599			
Emp. MN				0.054	0.057	0.345			
Emp. OQ				-0.117	0.069	0.091*			
Emp. RU				-0.136	0.083	0.102			
Autoregressive lag coefficient	0.316	0.037	0.000**	0.286	0.037	0.000**	0.288	0.037	0.000**
Pseudo R ²	0.403			0.440			0.429		
AIC	3611.2			3576.0			3568.9		
AIC for linear regression model	3678.5			3630.2			3624.9		

2 *: Significant at 90% confidence level; **: significant at 95% confidence level.

3 Note: Dependent variable is a log of TKT per sq. km; all independent variables are in log-transformed density (per sq. km); “pop.”

4 stands for population and “emp.” stands for employment; refer to Table 1 for the codes of industrial category (AZ~RU).

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1 **TABLE 4 Estimated Spatial Lag Models with Population and Establishment Variables**

	1. Total pop. and total estt.			2. Total pop. and estt. by industry group			3. Total pop. and significant estt. variables		
	Coef.	S.E.	P-value	Coef.	S.E.	P-value	Coef.	S.E.	P-value
Intercept	1.935	0.293	0.000**	1.892	0.456	0.000**	2.387	0.317	0.000**
Pop.	-0.304	0.105	0.004**	0.012	0.126	0.924	-0.182	0.077	0.017**
Estt.	0.728	0.111	0.000**						
Estt. AZ				-0.305	0.147	0.038**			
Estt. BE				-0.063	0.139	0.650			
Estt. C1				-0.522	0.236	0.027**			
Estt. C2				-0.224	0.753	0.766			
Estt. C3				0.498	0.207	0.016**			
Estt. C4				-0.204	0.374	0.586			
Estt. C5				-0.090	0.179	0.615			
Estt. FZ				-0.236	0.157	0.134			
Estt. GZ				0.699	0.176	0.000**	0.683	0.090	0.000**
Estt. HZ				0.266	0.140	0.058*			
Estt. IZ				0.344	0.202	0.089*			
Estt. JZ				-0.363	0.172	0.035**			
Estt. KZ				0.408	0.190	0.031**			
Estt. LZ				-0.122	0.202	0.546			
Estt. MN				0.418	0.185	0.024**			
Estt. OQ				-0.624	0.191	0.001**			
Estt. RU				-0.046	0.233	0.844			
Autoregressive lag coefficient	0.316	0.037	0.000**	0.286	0.038	0.000**	0.309	0.037	0.000**
Pseudo R ²	0.396			0.439			0.404		
AIC	3622.8			3578.1			3609.0		
AIC for linear regression model	3688.8			3630.8			3672.7		

2 *: Significant at 90% confidence level; **: significant at 95% confidence level.

3 Note: Dependent variable is a log of TKT per sq. km; all independent variables are in log-transformed density (per sq. km);
4 "pop." stands for population and "estt." stands for number of establishments; refer to Table 1 for the codes of industrial
5 category (AZ~RU).6
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1 **TABLE 5 Estimated Spatial Lag Models with Accessibility Variables**

	1. All accessibility variables			2. Significant accessibility variables		
	Coef.	S.E.	P-value	Coef.	S.E.	P-value
Intercept	6.481	0.480	0.000**	6.732	0.386	0.000**
Dist. to autoroute	-0.791	0.071	0.000**	-0.732	0.066	0.000**
Dist. to airport	-0.077	0.122	0.531			
Dist. to freight terminal	-0.226	0.079	0.004**	-0.193	0.073	0.008**
Dist. to main logistics area	-0.071	0.095	0.455			
Dist. to multimodal hub port	0.173	0.101	0.087*			
Dist. to river container terminal	0.146	0.089	0.103			
Dist. to rail-road intermodal terminal	-0.450	0.227	0.048**	-0.553	0.078	0.000**
Dist. to river-road intermodal terminal	-0.212	0.232	0.359			
Dist. to urban port	0.111	0.078	0.157			
Autoregressive lag coefficient	0.204	0.041	0.000**	0.214	0.041	0.000**
Pseudo R ²	0.446			0.441		
AIC	3547.7			3545.6		
AIC for linear regression model	3571.2			3572.2		

2 *: Significant at 90% confidence level; **: significant at 95% confidence level.

3 Note: Dependent variable is a log of TKT per sq. km; all independent variables are in log-transformed.

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TABLE 6 Estimated Spatial Lag Models with Total Population, Employment/Establishment and Accessibility Variables

	1. Total pop. and emp. and accessibility variables			2. Total pop. and significant emp. and accessibility variables.			3. Total pop. and estt. and accessibility variables			4. Total pop. and significant estt. and accessibility variables.		
	Coef.	S.E.	P-value	Coef.	S.E.	P-value	Coef.	S.E.	P-value	Coef.	S.E.	P-value
Intercept	5.017	0.561	0.00**	5.305	0.556	0.00**	5.714	0.577	0.00**	5.226	0.384	0.00**
Pop.	-0.169	0.065	0.01**	-0.169	0.052	0.00**	-0.491	0.099	0.00**	-0.323	0.073	0.00**
Emp.	0.320	0.049	0.00**									
Emp. C3				0.078	0.041	0.06*						
Emp. GZ				0.279	0.051	0.00**						
Emp. HZ				0.101	0.042	0.02**						
Estt.							0.758	0.105	0.00**			
Estt. GZ										0.716	0.084	0.00**
Dist. to autoroute	-0.673	0.064	0.00**	-0.670	0.063	0.00**	-0.740	0.064	0.00**	-0.749	0.063	0.00**
Dist. to rail-road intermodal terminal	-0.246	0.096	0.01**	-0.176	0.096	0.07*	-0.189	0.096	0.05**			
Autoregressive lag coefficient	0.164	0.041	0.00**	0.142	0.041	0.00**	0.146	0.041	0.00**	0.159	0.040	0.00**
Pseudo R ²	0.471			0.493			0.476			0.481		
AIC	3489.7			3448.7			3480.0			3468.6		
AIC for linear regression model	3504.5			3459.3			3491.0			3483.3		

*: Significant at 90% confidence level; **: significant at 95% confidence level.

Note: Dependent variable is a log of TKT per sq. km; all independent variables are in log-transformed; “pop.” stands for population, “emp.” stands for employment in density (per sq. km) and “estt” stands for number of establishments in density (per sq. km); refer to Table 1 for the codes of industrial category.