The geography of the demand for electric logistic vehicles in the era of E-commerce: Evidence from Shanghai

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ABSTRACT

With the burgeoning activities of E-commerce, the demand for electric logistic vehicles (ELVs) have been growing tremendously in megacities. However, the empirical evidence on how electric logistic demand is distributed across neighborhoods and correlated to spatially varying factors is limited. This study used the activity data of ELVs to analyze the main factors that contribute to the demand for ELVs based on spatial econometric models. Results showed that the demand for ELVs is directly influenced by post offices, restaurants, and warehousing places in general, and retail places, while charge stations and road freight places had indirect impacts on the ELV demand regarding time periods. Spatial differences in the demand for ELVs between influential factors were illustrated by maps. The findings could help further understand the activity characteristics and regularities of ELVs and help policymakers develop effective measures for ELV management and urban planning.

Key words: electric logistic vehicles, spatial models, GPS trajectory data

1. Introduction

Over the past 10 years, the rise of E-commerce has led to rapid growth in urban demand for electric logistic vehicles (ELVs). In China, ELVs, which are small compact electric vehicles typically used to deliver light products such as food and beverage, are gradually being popular in urban terminal distribution. In addition, the exhaust from internal combustion engine (ICE) trucks has exacerbated air pollution, further bolstering the market for ELVs (Verlinde, 2015).

Although ELVs have already been operated for several years, a complete understanding of their management is still lacking. Therefore, it is necessary to analyze the spatial and temporal characteristics and regularities of the demand for ELVs. This article intends to answer the following questions:

- Where is the demand for ELVs during different periods of a day?
- How do spatial relationships affect the demand for ELVs?
- What are the implications of the demand for ELVs for urban management?

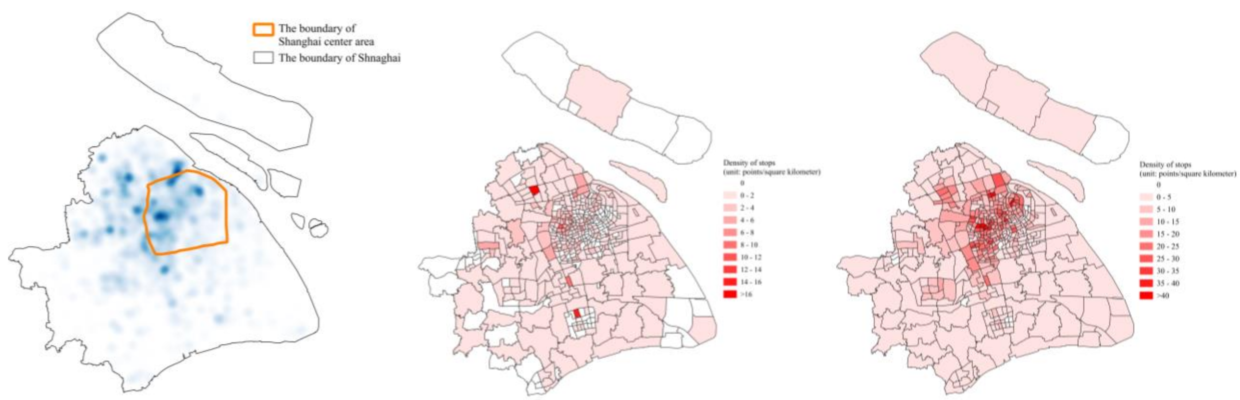
Previously, Yang et al. (2021) demonstrated that truck trips can concentrate in close vicinity of freight generators and terminals such as seaports, airports, intermodal facilities, and warehouses. However, locations of detailed industries and other built environmental factors were seldom considered to explain truck activities in previous research. As for spatial analysis methods, the geographically weighted regression model (GWRM) was used to understand the role of urban form in explaining recreational walking, and the spatial Durbin model (SDM) was previously employed in the evaluation of regional economic development and transportation accident issues (Özbil Torun et al., 2020; Tian et al., 2010; Yang et al., 2021). Therefore, the GWRM and SDM are chosen as the spatial analysis methods in this research.

2. Data and Methodologies

2.1 Data preparing and preprocessing

The data included the trajectory of 636 ELVs operating in Shanghai for a consecutive week (from October 18 to 24 in 2018). We used 10 min as the threshold of dwelling time to identify the stop points for ELVs, since it reflects a truck's stop behavior due to the operation process, and can eliminate the interference caused by external factors (Adam et al., 2021). The 636 ELVs produced 23,054 stop points within a week, Fig. 1(a). We divided the Shanghai area into 445 analytic zones according to traffic functions and collected public charging station data, 8 types of freight-related point-of-interest data, and road network data.

Based on the data above, we constructed dependent and explanatory variables to analyze the differences in the demand for ELVs in different areas and explore influential factors that affect such differences. We define the dependent variable as the density of ELV stops in each analytic zone. The explanatory variables are the density of the quantity corresponding to each indicator (as shown in Table 1) in each analytic zone. Chen et al. (2022) found that the daily travel time of traditional freight vehicles was concentrated between 7am and 7pm, and their activities are more frequent than passenger cars from night to early morning. **Therefore, we divided the whole data into two datasets with time periods of 7pm-7am (overnight) and 7am-7pm (daytime), respectively, for comparative analysis (called Overnight Data and Daytime Data).** The distributions of the dependent variables of the two datasets were shown in Fig. 1(b) and (c), and the descriptions and statistics of the explanatory variables were given in Table 1.



(a) The heat map of the spatial distribution of ELV stop points. (b) The spatial density of ELV stop points in Overnight Data. (c) The spatial density of ELV stop points in Daytime Data.

Fig. 1 The spatial distribution of ELV stop points.

Table 1 The summary of the statistics of explanatory variables for different datasets.

Variable type	Variable name	Variable description	The Overnight Data				The Daytimedata			
			Mean	St.Dev	Min.	Max.	Mean	St.Dev	Min.	Max.
Charging stations	den. charge	The density of the electric charging stations in an analytic zone. (Unit: piece/km^2)	21.66	28.35	0.00	178.61	9.15	9.60	0.01	58.12
Points of interest that related to freight activities	den. post	The density of postal places in an analytic zone. (Unit: piece/km^2)	0.49	0.88	0.00	5.95	20.77	28.10	0.00	178.61
	den. food wholesaling	The density of food wholesaling places in an analytic zone. (Unit: piece/km^2)	3.32	4.76	0.00	29.77	0.49	0.90	0.00	6.45
	den. heavy production wholesaling	The density of heavy production wholesaling places in an analytic zone. (Unit: piece/km^2)	31.89	51.03	0.00	529.22	3.14	4.53	0.00	29.77
	den. light production wholesaling	The density of light production wholesaling places in an analytic zone. (Unit: piece/km^2)	14.37	20.12	0.00	176.30	28.59	45.44	0.00	529.22
	den. general retail	The density of general retail places in an analytic zone. (Unit: piece/km^2)	3.16	4.23	0.00	30.52	13.47	19.06	0.00	176.30
	den. catering	The density of catering places in an analytic zone. (Unit: piece/km^2)	8.35	14.42	0.00	137.01	3.14	4.23	0.00	30.52
	den. road freight	The density of road freight places in an analytic zone. (Unit: piece/km^2)	0.72	2.23	0.00	28.30	0.05	0.16	0.00	1.56
	den. warehousing	The density of warehousing places in an analytic zone. (Unit: piece/km^2)	0.35	0.66	0.00	8.58	0.67	2.13	0.00	28.30
Road facilities	den. primary roads	The density of primary roads in an analytic zone. (Unit: km/km^2)	0.60	0.93	0.00	5.64	0.31	0.61	0.00	8.58
	den. secondary roads	The density of secondary roads in an analytic zone. (Unit: km/km^2)	1.09	1.05	0.00	5.71	0.57	0.93	0.00	5.64
	den. tertiary roads	The density of tertiary roads in an analytic zone. (Unit: km/km^2)	4.64	2.62	0.34	17.35	1.14	1.09	0.00	5.71

2.2 Spatial analytic methods

The ordinary least-squares (OLS) regression model, the geographically weighted regression model (GWRM), and the spatial Durbin model (SDM) were applied to analyze the influencing factors in Table 1 with regard to the demand for ELVs.

The spatial dependence of variables is called "spatial autocorrelation". In order to overcome the shortcoming that the linear regression model cannot reflect the spatial autocorrelations among analytic objects, Brunsdon et al. (1999) proposed GWRM, whose expression is as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)x_{ik} + \epsilon_i, \epsilon_i \sim N(0, \sigma^2) \quad (1)$$

where $\beta_k(u_i, v_i)$ is a spatial geographic function, which is related to geographic location and geographic spatial weight; x is an explanatory variable; and p is the number of explanatory variables.

As the value of the dependent variable will not only be affected by local explanatory variables, but also by independent variables in the neighboring analytic zones (LeSage & Pace, 2009), we introduced SDM to analyze the relationship between the demand for ELVs in a certain analytic zone and the various facilities in surrounding analytic zones. The expression of SDM is as follows:

$$\boldsymbol{y} = \rho \boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}\boldsymbol{\delta} + \boldsymbol{\epsilon}, \boldsymbol{\epsilon} \sim N(0, \sigma^2\boldsymbol{I}) \quad (2)$$

where, $\boldsymbol{y}$ represents the vector of dependent variables $(n \times 1)$; $\boldsymbol{X}$ represents the matrix of independent variables $(n \times (k+1))$, which refers to the variables shown in Table 1; $\boldsymbol{\beta}$ represents the vector of regression coefficient parameter $((k+1) \times 1)$; ρ represents the spatial lag coefficient parameter on dependent variables; $\boldsymbol{\delta}$ represents the vector of spatial lag coefficient parameters $(n \times 1)$; $\boldsymbol{W}$ represents the weighted matrix $(n \times n)$, which is the same as the spatial weighed matrix in 2.2.1; $\boldsymbol{I}$ represents the identity matrix $(n \times n)$; and n represents the number of analytic zones and k represents the number of the independent variable.

The change of an explanatory variable in the spatial econometric model will produce two effects: one is the impact on the local dependent variable, that is, the direct effect, and the other is the impact on dependent variables in surrounding areas, that is, the indirect effect (Lesage & Fischer, 2008). We calculated the direct and indirect effects of SDM, and the total effect, the sum of the direct and indirect effects, is set as the marginal effect. We can get Eq. (3) by transforming Eq. (2) and the matrix $\boldsymbol{S}$ is denoted as Eq. (4).

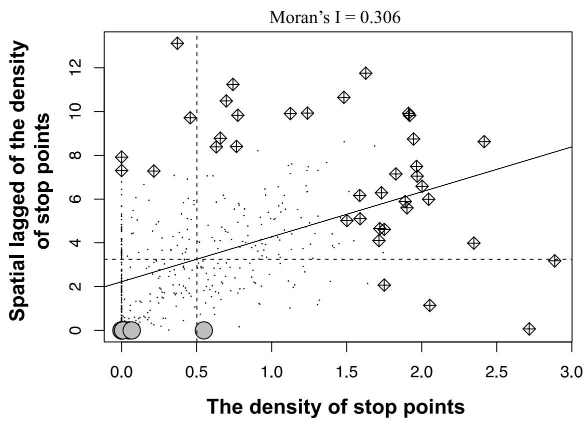
$$\boldsymbol{y} = (\boldsymbol{I} - \rho\boldsymbol{W})^{-1}(\boldsymbol{I}\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{\delta})\boldsymbol{X} + (\boldsymbol{I} - \rho\boldsymbol{W})^{-1}\boldsymbol{\epsilon}, \boldsymbol{\epsilon} \sim N(0, \sigma^2\boldsymbol{I}) \tag{3}$$

$$\boldsymbol{S} = (\boldsymbol{I} - \rho\boldsymbol{W})^{-1}(\boldsymbol{I}\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{\delta}) \tag{4}$$

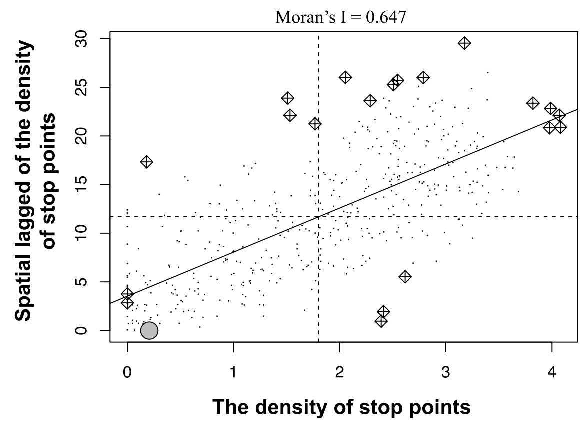
when the number of analytic zones is n, the $\boldsymbol{S}$ is a matrix by $n \times n$, and the elements on the main diagonal of $\boldsymbol{S}$ represent the direct effects while the other elements represent the indirect effects.

3. Results

We used the global Moran's I to test the spatial autocorrelation of the dependent variable in two datasets, and the Moran scatter plot and test results are shown in Fig. 2. The dependent variable in both scenarios had a certain degree of spatial autocorrelation at a significant level. Compared with the daytime period, the spatial autocorrelation of the stop point density during the overnight period is weaker.



(a) Overnight Data.



(b) Daytime Data.

Fig. 2 The scatterplot and statistics of Moran' I for different datasets.

The results of the two datasets under the OLS model were shown in Table 2, and some results under the GWRM were illustrated in Fig. 3 and 4. The density of post offices, the density of catering places, and the density of warehousing places had a positive and significant effect on the demand for ELVs regardless of the overnight and daytime periods. It can be inferred that the activities of ELVs concentrated on the urban ordinary package (e.g., the commodities that customers ordered online) delivery, food (made by restaurants) delivery, and light products (from storage centers to distribution branches) delivery. Nevertheless, the GWRM results demonstrated some spatial differences between the two periods. Taking the catering places for example, the demand for ELVs centered in the city's central area during the night, indicating that restaurants had to prepare enough food for high activity intensity the next day, but the demand for ELVs was dense in the south of Shanghai during the daylight, indicating that most food suppliers were likely located in that region. In addition, we noticed that the density of charge stations had a positive and significant effect on the demand for ELVs only in the daylight, meaning that many ELVs choose to charge between 7am to 7pm rather than during the night. We inferred that the congestion in urban roads during the daylight might restrict part of ELV activities, and thus, users chose to charge vehicles instead (probably at noon). The detailed causality needs further exploration.

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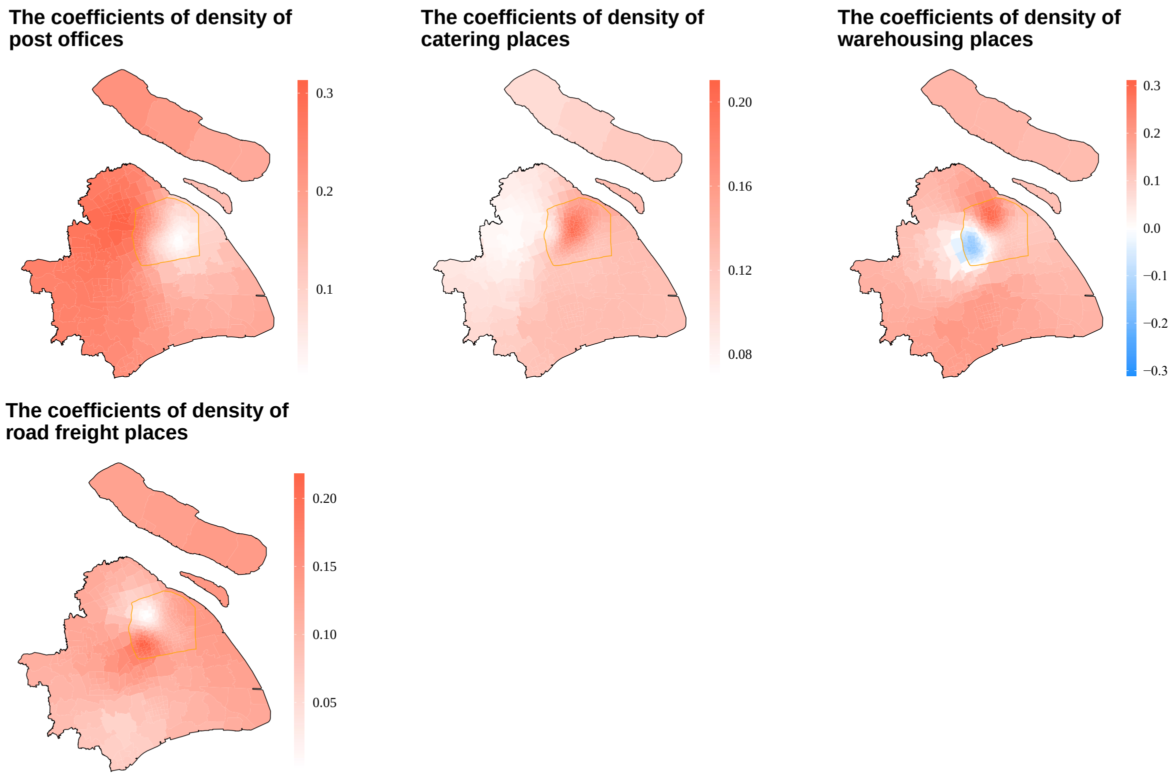

Fig.3 The spatial distribution of coefficients of independent variables in Overnight Data.

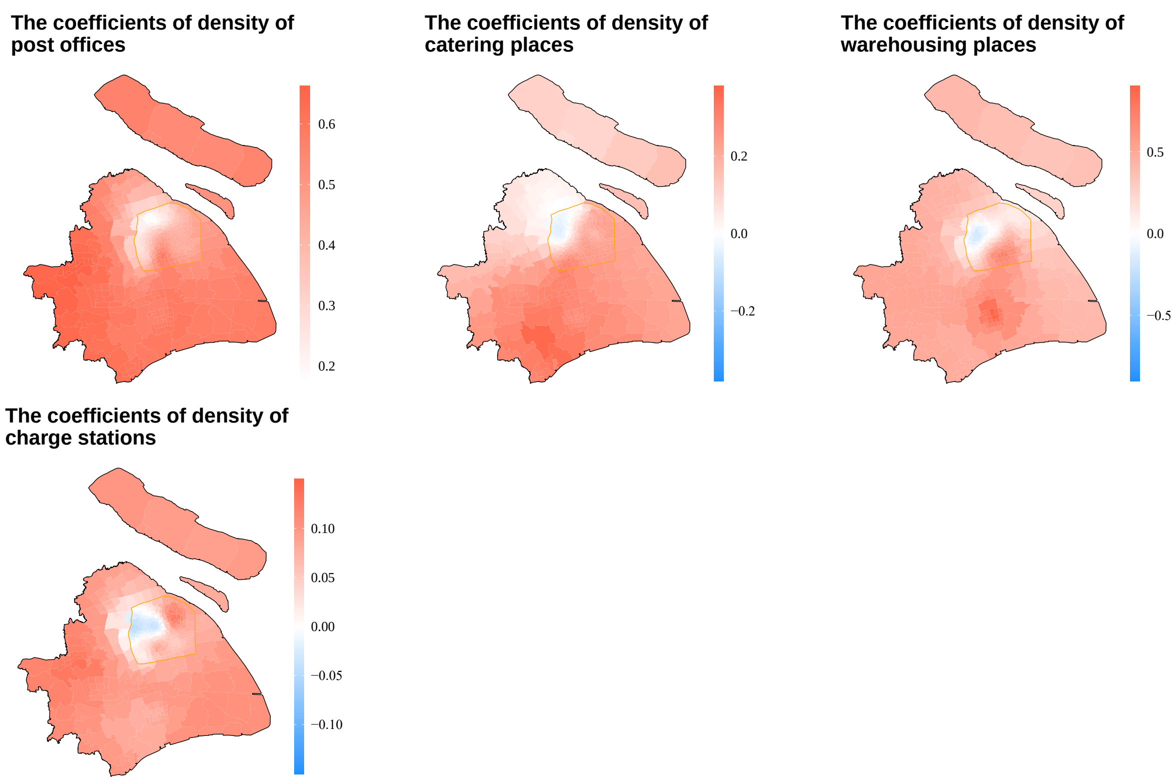

Fig.4 The spatial distribution of coefficients of independent variables in Daytime Data.

Further, we used SDM to explore the spatial interactions between dependent variables, and the results are shown in Table 2. It was tested that the SDM cannot degenerate into a spatial Autoregressive model (SAM) and a spatial error model (SEM), so it is reasonable to use SDM for analysis. At night, increasing the density of post offices and catering places could stimulate the demand for ELVs significantly within a local region. We also witnessed that there were some indirect effects: the charging stations and road freight facilities in a local area would have a positive effect on the increase of the demand for ELVs in neighborhoods, and vice versa.

Table 2 OLS and SDM estimations of different datasets.

Variable	OLS		SDM							
	Overnight	Daytime	Overnight				Daytime			
	Coefficient	Coefficient	Coefficient	Direct	Indirect	Total	Coefficient	Direct	Indirect	Total
(Intercept)	0.036	0.399 ***	0.021				0.448 **			
den. charge	0.035	0.107 ***	0.014	0.021	0.011 **	0.033 ***	0.064 **	0.075 ***	0.006	0.081 ***
den. post	0.215 ***	0.601 ***	0.151 ***	0.158 ***	0.011	0.169	0.379 ***	0.414 ***	0.019 *	0.432 ***
den. food wholesaling	0.004	0.098	0.005	-0.005	-0.015	-0.020	0.107 *	0.086	-0.012	0.074
den. heavy production wholesaling	0.002	-0.071	0.017	0.011	-0.008	0.003	-0.132 **	-0.110 *	0.012	-0.097
den. light production wholesaling	0.026	0.079	0.023	0.029	0.008	0.037	0.168 **	0.148 **	-0.011	0.138 *
den. general retail	-0.087	0.032	-0.071	-0.067	0.006	-0.060 ***	0.087	0.053	-0.019	0.034
den. catering	0.111 **	0.184 ***	0.133 ***	0.133 ***	0.000	0.133	0.149 ***	0.181 ***	0.017 *	0.198 ***
den. road freight	0.118 **	0.107	0.024	0.042	0.026 *	0.067	-0.057	-0.053	0.002	-0.051
den. warehousing	0.154 *	0.434 ***	0.097	0.090	-0.011	0.079	0.112	0.166	0.029 *	0.196 *
den. primary roads	-0.056	0.007	-0.023	-0.034	-0.017	-0.051	0.048	0.022	-0.014	0.008
den. secondary roads	-0.049	-0.170 **	0.043	0.031	-0.018 *	0.012	-0.016	-0.046	-0.016 *	-0.062
den. tertiary roads	-0.047	-0.054	0.000	-0.012	-0.018	-0.030	0.120	0.084	-0.019	0.065
W * den. charging			0.017 **				0.011			
W * den. post			0.009				0.019			
W * den. food whole-saling			-0.024				-0.039			
W * den. heavy pro-duction wholesaling			-0.014				0.042 **			
W * den. light produc-tion wholesaling			0.012				-0.041 *			
W * den. general retail			0.014				-0.056 **			
W * den. catering			-0.008				0.033			
W * den. road freight			0.040 *				0.010			
W * den. warehousing			-0.023				0.068 **			
W * den. primary roads			-0.026				-0.041 *			
W * den. secondary roads			-0.032 **				-0.041 **			
W * den. tertiary roads			-0.028				-0.060 **			
W * Y			0.055 ***				0.079 ***			

Notes: significance codes: '***' <0.01; '**' <0.05; '*' <0.1.

During the daytime, increasing the density of charge stations, post offices, food wholesaling places, light production wholesaling places, and catering places could significantly increase the demand for ELVs. It was not found that the density of warehousing places did not have a significant impact on the increase of the ELV demand in a local area, but the density of warehousing places in a local analytic zone would promote the demand for ELVs in surrounding regions. We also found that the increase in the density of heavy production wholesaling places and warehousing places in surrounding analytic zones would significantly stimulate the development of the ELV demand in a local analytic zone. We inferred that ELVs are mainly responsible for the transportation of small and light cargo locally but deliver medium or large freight only from adjacent regions rather than farther regions.

Regardless of the periods, it was shown that the peripheral ELV demand had a significant impact on the increase of the local ELV demand, which reinforces that there were strong spatial interactions in the demand for ELVs. Additionally, we found that the density of secondary roads in surrounding areas affected the local demand for ELVs negatively at a statistically significant level, which indicated that ELVs would heavily rely on secondary roads for transportation, especially overnight.

4. Discussion & Conclusion

This study answered the two questions "where are the demands for ELVs" and "how do spatial relationships affect the demand for ELVs" in megacities from a spatial view. We found that ELVs mainly served express package deliveries and served upstream and downstream enterprises related to grocery manufacturing and sales. The ELVs served different clients in the central city and the suburbs during different time periods. Additionally, although ELVs were able to transport medium and large goods, they tended to deliver to nearby regions rather than travel long distances. We inferred that ELVs are likely to deliver small packages in adjacent areas, which would help optimize the facility layout and distribution plan for short-distance express delivery in the era of E-commerce. Moreover, it was deduced that ELVs were usually charged in regions that are close to the zone where they make business and activities during the night. Thus, when installing or adjusting vehicle charging facilities, the number and types of clients that ELVs serve in surrounding areas should be fully considered.

Our conclusions will be helpful for city managers to make policies. There are obvious differences between ELVs and traditional trucks in terms of serving clients and activity intensity, so customized management measures are required. As e-logistic activities concentrate on postal and food industries, it is feasible to encourage these companies to use or rent electric vehicles to deliver goods, which will also help energy conservation and emission reduction in the city. In addition, the activity intensity and types of ELVs are different between the central city and the suburbs, thus it is plausible to optimize the layout of enterprises so that ELVs can serve short-distance cargo transportation better. Moreover, to improve the efficiency of urban logistics, city managers can give different travel access rights to ELVs with different activity purposes during the daytime and nighttime without affecting the commuting traffic.

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