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Spatial Patterns of Car Sales and Their Socio-economic Attributes in China

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Abstract: Using data from the Economic Advisory Center of the State Information Center (SIC), we examined the spatial patterns of car sales in China at the prefectural level in 2012. We first analyzed the spatial distributions of car sales of different kinds of automakers (foreign automakers, Sino-foreign joint automakers, and Chinese automakers), and then identified spatial clusters using the local Moran's indexes. Location quotient analysis was applied to examine the relative advantage of each type of automaker in the local markets. To explain the variations of car sales across cities, we collected several socioeconomic variables and conducted regression analyses. Further, factor analysis was used to extract independent variables to avoid the problem of multicollinearity. By incorporating a spatial lag or spatial error in the models, we calibrated our spatial regression models to address the spatial dependence problem. The analytical results show that car sales varied significantly across cities in China, and most of the cities with higher car sales were the developed cities. Different automakers exhibit diverse spatial patterns in terms of car sales volume, spatial clusters, and location quotients. The scale and incomes factor were extracted and verified as the two most significant and positive factors that shape the spatial distributions of car sales, and together with the spatial effect, explained most of the variations of car sales across cities.

Keywords: car sales; spatial clusters; Location Quotient; socio-economic attributes; China

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1 Introduction

International experiences suggest that the proliferation of automotive sales typically occurs after the economy of a nation or a region reaches certain levels (Dargay and Gately, 1999). As incomes increase, the propensity to purchase auto vehicles increases as they become more affordable. It is therefore no surprises that, China, one of the world's largest and fastest developing economies, is experiencing a rapid expansion of automobile ownership and has become one of the largest markets for car sales. In particular, after the entry to WTO, Chinese automobile markets are becoming more open and competitive. Car manufacturers from all over the world are increasing their car production and car sales in China. According to the statistics from the China Association of Automobile Manufacturers (CAAM), China's automobile sales in 2015 reached 2.46×10^7, extending the country's lead as the world's largest car market by sales. It is foreseeable that, as China's economy continues to grow, the number of high-income urban households will expand greatly, and the infrastructure such as high quality roads will be improved significantly in the next decades. Therefore, the market for car sales is expected to maintain strong growth momentum (Huo and Wang, 2012).

Such rapid growth of car sales has created many

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challenges. In addition to problems associated with traffic jams, car use also has implications on local and global environmental issues such as air pollution, energy security, energy scarcity, and climate change (Lo, 2014; Wang *et al*., 2014). Hence, the phenomenon and its policy implication need to be analyzed in more details. Since China has a vast territory with significant regional heterogeneity, car sales are likely to vary across cities due to the diverse economic capacities. It is also interesting and meaningful to explore the spatial differences of car sales across cities because car consumption, as a common and important consumer durable, is to a certain degree indicative of the consumption capacity of the cities.

Nowadays, as the market economy develops, nearly all the markets of the cities are full of competition from different car manufacturers, after which various market structures are shaped across cities. What is the spatial pattern of the car sales across the nation? What are the differences with respect to spatial patterns of cars sales of different manufacturers, such as foreign automakers, Sino-foreign joint automakers and Chinese automakers? What about the differences regarding the market shares of different kinds of manufacturers? What factors could exert impacts on car sales across cities? The answers to these questions would provide helpful insights into understanding the car consumption process, and would be valuable for relevant policymakers to formulate industrial policies for the automotive sector. This study aims to address these questions using the data of actual car sales at the prefectural level, obtained from the Economic Advisory Center of the State Information Center (SIC). The data were analyzed using location quotient, spatial cluster analysis, factor analysis as well as regression analysis to illuminate the spatial patterns and socioeconomic associations of car sales among Chinese cities.

2 Literature Review

Many subjects regarding to the production and manufacturing of automobile, such as the automobile purchasing, car ownership, and automobile industry, have been studied extensively over the years in the developed countries, such as the United States, Great Britain, Spain, Japan and South Korea (Bandeen, 1957; Rubenstein, 1986; Pallares-Barbera, 1998; Giuliano and Dargay, 2006; Clark and Finley, 2010; Lee, 2011). As their economy grows, more and more developing countries, especially China, are consuming an increasing number of automobiles. Thus, researchers are focusing more on car consumption, automobile industry, and socioeconomic attributes of car ownership in China. There is a burgeoning literature concerning car consumption in China (Rits *et al.*, 2004; Qian and Soopramanien, 2014; 2015; Wan *et al.*, 2015). However, most of these studies focus on the overall characteristics or prediction of sales of cars (or some particular type of cars, such as green car), with few focusing on the spatial distribution of car sale across Chinese cities and the spatial pattern of car markets shared by different car manufacturers. The studies on car sales or car markets in China from a spatial perspective are limited, and are mostly conducted at a macro level, such as national, regional or provincial dimensions (Xiao, 2010; Xie and Liu, 2014). Geographical researchers in China are mainly interested in the production and manufacturing of automobiles, as opposed to their consumption. Therefore, they focus on the development of automotive industry in the country, such as the spatial pattern of car manufacturers or auto industrial cluster (Liu and Yeung, 2008; Wang and He, 2009; Liu and He, 2011; Zhao *et al.*, 2014), areal division of auto industrial chain (Li and Gu, 2010) and spatial evolution of auto industry (Huang and Zhang, 2014). The reason why studies on spatial pattern of car sales are scarce is likely that the data of car sales at such a middle or micro level are usually not accessible in China. Nevertheless, as argued previously, it is interesting and meaningful to explore the spatial differences across cities in terms of car sales.

The purchase of a car is an important indicator of car use and changes to travel behavior (Clark *et al.*, 2015). Existing studies have identified several factors affecting car ownership and purchases. The factors that affect car ownership and sales include individual and household income, employment status, ethnic background, household location, demographic change, car price, access to and quality of public transportation, parking supply, population density, parking price, specific life cycle events (such as employment change and childbirth), and financing availability (Cullinane, 2002; Guo, 2013; Ritter and Vance, 2013; Oakil *et al.*, 2014; Clark *et al.*, 2015; Ling *et al.*, 2015; Oakil *et al.*, 2016; Seya *et al.*, 2016; Wu *et al.*, 2016; Yagi and Managi, 2016). Considerable discrepancies exist on the relative importance of these factors that appear to be spatially differentiated and are dependent on local contexts. For example, Ling *et al.* (2015) found that China's car ownership is closely related to household characteristics such as household income and household size vis-à-vis environmental factors. In contrast, using a household survey in the New York City region, Guo (2013) argued that the influence of parking supply on household car ownership outperforms household income and demographic characteristics. These differences suggest that it is important to understand the spatial patterns by conducting city-level comparison studies of car sales data, as opposed to studies that are focused on a single city using household-level data or using aggregated data at the regional or national levels (Cao and Huang, 2013). This research is conducted based on the actual car sales data at the prefectural cities level, which can be deemed as a valuable empirical reference for further recognitions towards the spatial distribution of car sales across China.

3 Data and Method

3.1 Data and research area

This study focuses on passenger cars, which can be classified into three types: sedans, multi-purpose vehicles (MPV), and sport-utility vehicles (SUV). Car sales data used in our research are from the Economic Advisory Center of the SIC. It is composed of the actual amount of car sales of each manufacturer in each prefectural city in China (excluding Taiwan, Hong Kong, and Macao) in 2012. This study includes 337 prefectural cities as the basic analytical units. Other data used in our research, such as GDP, population, and other socioeconomic indicators, are from the China Statistical Yearbook for Regional Economy 2012. The data contain 107 manufacturers that sold cars in China in 2012, comprising 47 foreign-owned automakers, 24 Sino-foreign joint automakers, and 36 Chinese automakers.

3.2 Spatial cluster analysis

To capture the local city clusters with higher car sales, we employed local Moran's *I* to detect the hotspots of car sales of different manufacturers. As one of the most common local indicators of spatial association (LISA), local Moran's *I* has been applied to identify statistically significant local clustering of specific phenomena in many fields of research. In this study, local Moran's *I* efficiently measures the geographical concentration of car sales clusters by detecting spatial autocorrelation among cities in China. The local Moran's *I* statistic was derived for each city area and defined as:

$$I_i = \frac{x_i - \overline{X}}{S_i^2} \sum_{j=1, j\neq i}^{n} \omega_{i,j}(x_j - \overline{X}) \quad (1)$$

where x_i is the car sales in city i, $\overline{X}$ is mean of the car sales, $\omega_{i,j}$ is the spatial weight between city i and j, and

$$S_i^2 = \frac{\sum_{j=1, j\neq i}^{n} (x_j - \overline{X})}{n-1} - \overline{X}^2 \quad (2)$$

where n equals the total number of cities in China (Anselin, 1995). The significance of the local Moran's *I* statistic is often tested by a normal *Z* index (Anselin, 1995; Wang, 2006). When the local Moran's *I* statistics are positive and significant ($Z > 1.96$), we can label the corresponding areas as 'hotspots' (clustering of high values/High-High) or 'coldspots' (clustering of low values/Low-Low). When the Local Moran's *I* statistics are negative and significant ($Z < -1.96$), we can label the corresponding areas as outlier spots that can be further divided into two types: convex spots (high values surrounded by low values neighbors/High-Low) and concave spots (low values surrounded by high values neighbors/Low-High). This study focused on all these spatial relations. Hotspots refer to the cities with higher car sales values surrounded by neighbors whose car sales are also above the average, and coldspots refer to the cities with lower car sales values surrounded by neighbors whose car sales are below the average. Convex spots refer to the cities with higher car sales surrounded by neighbors whose car sales are below the average, and concave spots refer to cities with lower car sales values surrounded by higher car sales values above the average. We applied cluster and outlier analysis-(Anselin Local Moran's *I*) tool in ArcGIS 9.3, which is built upon the above equations, to compute local Moran's *I* statistics for all the cities. The spatial weights matrix that we used to define the spatial relationships is calculated based on the inverse distance.

3.3 Location quotient

In addition to the general spatial pattern of car sales across cities in China, we are also interested about the relative advantage of a manufacturer in each city's market. After long and intensive competition, a city's market is usually shared by many automakers. If a manufacturer obtains a larger market share in a city than the average market share it has across the cities in the whole country, this automaker has obtained a relative advantage in this city. To measure the relative advantage, we computed the location quotient as follows:

$$LQ_{i,j}=\frac{Q_{i,j}/T_j}{Q_i/T} \tag{3}$$

where $LQ_{i,j}$ is the location quotient of manufacturer i in city j and $Q_{i,j}$ is the amount of car sales of manufacturer i in city j. T_j represents the total amount of car sales in city j. Q_i is the total amount of car sales of manufacturer i, and T is the total car sales of all the manufacturers in the country.

3.4 Factor and regression analyses

To interpret the spatial patterns of car sales, the multivariate linear regression was conducted to explore the socioeconomic factors that may be associated with the spatial variation. Based on the data from the China Statistical Yearbook for Regional Economy 2012, a set of explanatory variables were selected assuming that they were related to car sales in cities. Theoretically, the car sales could be related with many factors, such as population size, GDP, residents' income, comprehensive consumption capacity, investment on infrastructure, *etc*. Because these variables are usually highly correlated, we used the factor analysis to arrive at fewer and more manageable independent factors from these variables. The factor extraction method that we used was the default principal component solution to estimate the coefficients. To simplify the interpretation of factors, the orthogonal rotation was made to achieve a simple structure that each factor had large loadings in absolute value for only some of the variables. The factor analysis was conducted using the software SPSS 16.0, through which factor scores for each city could be obtained simultaneously. Thus, several regression models could be calibrated using fewer but uncorrelated components as independent variables, and car sales from different kinds of manufacturers as dependent variables. The regression model can be described as follows:

$$y_i = \alpha_0 + \sum_k \beta_k x_{ik} + \varepsilon_i \ (i=1,\ 2,\ \ldots,\ n) \tag{4}$$

where y_i is the dependent variable, α_0 is the constant, β_k is the regression coefficient for the independent variable k, ε_i is the random error or residuals, n is the number of cases, and k is the number of independent variables.

Since the car sales data had spatial attributes, the spatial dependence problem may exist when we conduct regression analysis, especially when hotspots and coldspots were identified in the process of spatial cluster analysis. To address this issue, we used GeoDa 1.8.8 to evaluate spatial dependency in the regression (Anselin, 2005). The first-order queen's contiguity was used to specify the spatial weights matrix for car sales and the Moran's *I* (error) as well as Lagrange multiplier statistics (*LM lag* and *LM error*) were calculated. The multivariate models were estimated using the maximum likelihood method. The models and spatial regression process can be referred to the work of Wang (2006).

4 Results

4.1 Spatial distribution of car sales

According to the data we collected, the total amount of car sales in China in 2012 is 1.31×10^7, with 1.04×10^6 cars produced and imported by foreign-owned automakers (7.88%), 8.85×10^6 by Sino-foreign joint ventures (67.71%), and 3.19×10^6 by Chinese automakers (24.41%). From the descriptive statistics shown in Table 1, there is a great variation of car sales across cities in China for each type of manufacturer. The maps in Figs. 1(a–d) capture the spatial characteristics of these variations; we can clearly see the significant heterogeneity in the spatial pattern of car sales.

Table 1 Descriptive statistics of car sales among different automakers across cities

Variables	Maximum	Minimum	Average	SD
Total car sales amount	539494	353	38798	57402.72
Foreign-owned automakers	77356	14	3072	6952.34
Sino-foreign joint automakers	394192	200	26256	40628.94
Chinese automakers	89125	103	9469	11531.60

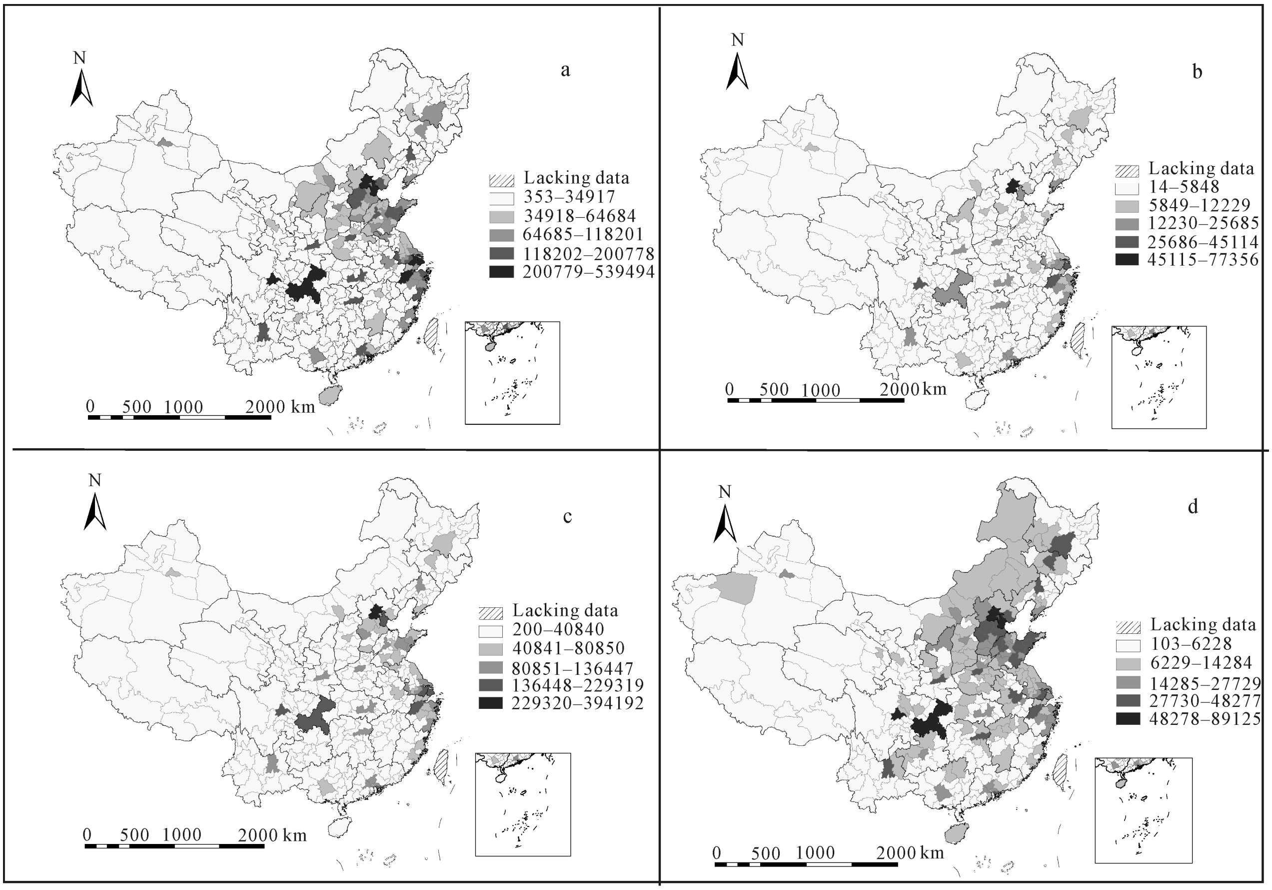

Fig. 1 Car sales for total automakers (a), foreign automakers (b), Sino-foreign joint automakers (c), and Chinese automakers (d)

In Fig. 1a, the minimum number of car sales is only 353 in Shennongjia forestry district, but the maximum reaches 539 494 in Beijing City. The huge gap in terms of car sales among cities was definitely attributed to the diverse consumption capacities. The distribution of total car sales is consistent with China's economic map to a large extent: car sales are higher in more developed cities, such as in the Yangtze Delta Region, Beijing-Tianjin-Hebei (Jing-Jin-Ji) Region, Pearl River Delta Region, and capital cities in each province. Figs. 1b and 1c show the spatial distributions of car sales for foreign-owned and Sino-foreign joint automakers, respectively. Car sales of the imported foreign cars, which were more expensive, were highly concentrated in the most developed core cities, such as the capital cities and the largest cities in each province. These cities play a central role in the economic development of each province and represent the highest consumption capacities in China. The car sales of Sino-foreign joint automakers were also more concentrated in the developed cities, but some differences in the spatial pattern were also notable, such as the relatively higher car sales in Shandong Peninsula. In contrast, the car sales of Chinese automakers show a very different and more scattered pattern, as shown in Fig. 1d. The second- and third-tier cities, especially in the North and Northeast China, were very important target markets for Chinese automakers, although the first-tier cities still recorded relatively higher car sales. This implies that the Chinese automakers focused more on the middle and small cities where they faced less competition because the residents in those cities had less capacity to consume expensive cars that were produced by the foreign automakers and Sino-foreign joint automakers.

4.2 Spatial clusters

The global Moran's I values for the distribution of car sales of total automakers, foreign automakers, Sino-foreign joint automakers, and Chinese automakers were 0.15, 0.08, 0.15, and 0.22 with a standard normal z-value of 10.67, 6.45, 10.99, and 15.66, respectively. These show that the car sales of all kinds of automakers were distributed non-randomly and displayed positive spatial autocorrelations. There were clusters of cities with higher or lower car sales, meaning the cities that had high car sales were typically surrounded by cities with high car sales, whereas cities with low car sales were typically surrounded by cities with low car sales. To detect these local clusters, the z-score of each city's local Moran's I was computed and reported in Fig. 2. Since we focused on all the four types of car sale spots in Chinese prefectural cities (High-High, Low-Low, High-Low, and Low-High), cities with a z-score more than 1.96 or less than –1.96 (more than 95% significance) were highlighted using different colors, as shown in Figs. 2(a–d).

Fig. 2a shows the spatial clusters of the total car sales. We use red and blue colors to represent the areas whose indexes of local Moran's I are positive and negative, respectively, with a statistical significance at the 0.05 level. All the cities with positive indexes of local Moran's I were hotspots (High-High), and were mostly located in the Jing-Jin-Ji region, Shandong Province, Yangtze Delta Region, and Pearl River Delta Region, indicating that these areas had significantly higher car sales and were surrounded by cities with similar higher values. These clusters were the major places for car sales in China. Most of these cities were economically developed and densely populated. While cities with negative indexes of Moran's I can be classified into two types: the convex spots (High-Low) and concave spots (Low-High). Almost all the clusters were convex spots, except Zhoushan City in Zhejiang Province, which was a concave spot. Zhoushan City was a small island city and located in the Yangtze Delta Region. The demand for cars in Zhoushan City was relatively small because of the isolated and orographic conditions as well as the relatively smaller population. However, Zhoushan's neighbors were mostly developed cities with higher car sales; therefore, the same pattern of Low-High was generated, as illustrated in Figs. 2(b–d). Other cities with negative local Moran's I were convex spots (high car

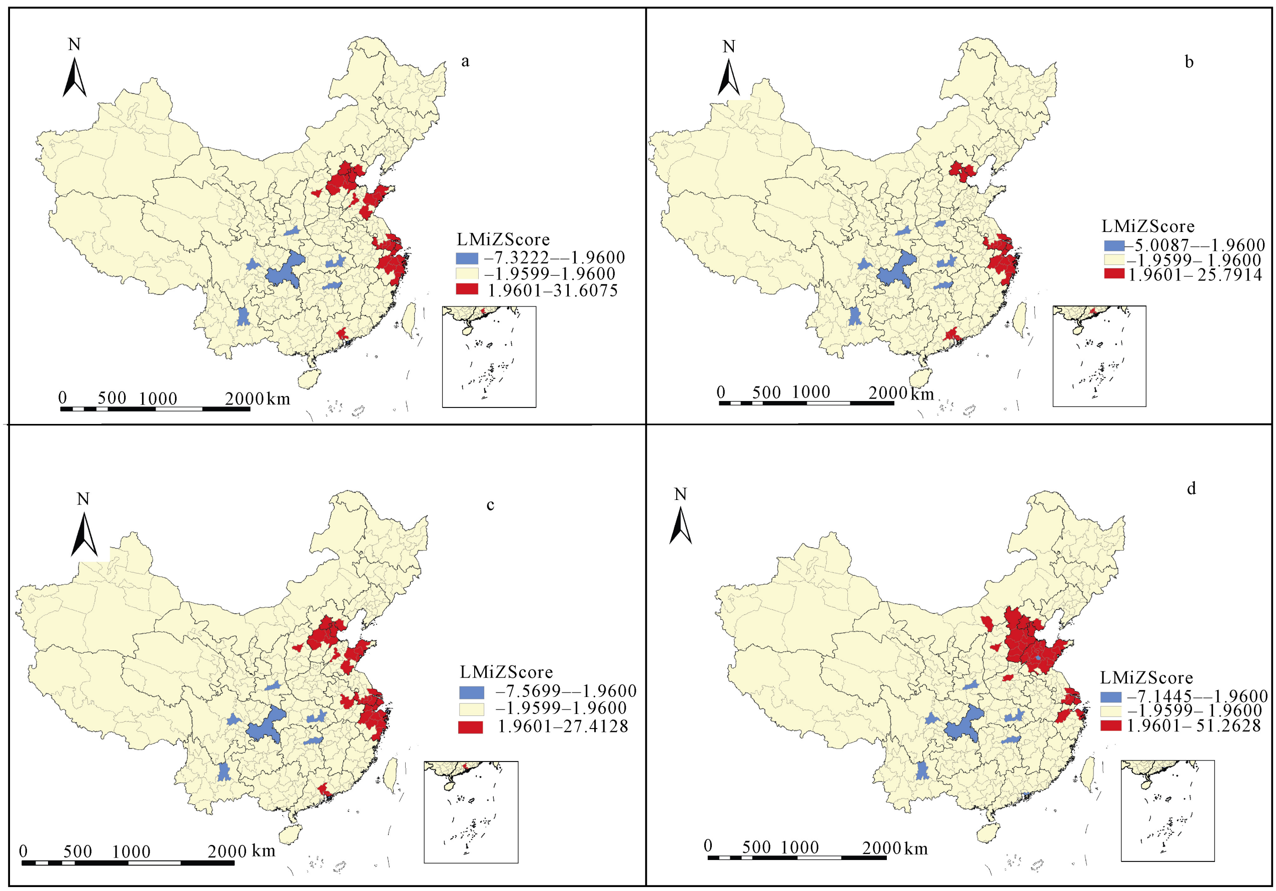

Fig. 2 Spatial clusters of car sales for total automakers (a), foreign automakers (b), Sino-foreign joint automakers (c), and Chinese automakers (d)

sales but neighbors had low car sales), including the cities of Xi'an, Chongqing, Wuhan, Changsha, Chengdu, and Kunming. These cities were all capital cities of their provinces, which played a central role in leading economic development and urbanization in the hinterland provinces they were located. Thus, a High-Low pattern of car sales was generated.

Fig. 2b shows the spatial clusters of car sales by foreign-owned automakers, in which we can see fewer but more concentrated hotspots, especially in the Jing-Jin-Ji Region. Only Beijing and Tianjin were identified as car sale hotspots for the foreign-owned automakers, which is understandable as only the most developed cities had enough capacity to consume these relatively expensive cars. However, the convex spots of car sales for foreign-owned automakers were nearly the same as the ones for total car sales, with only one more city (Zhengzhou, the capital city of Henan Province) identified.

Fig. 2c illustrates the spatial clusters of car sales for Sino-foreign joint venture automakers, which is almost identical to the pattern of the total car sales. It may be because more than 70% of the total car sales in 2012 were produced by this type of automakers. Therefore, the car sales by joint ventures are largely consistent with the total sales.

In contrast, the car sales for Chinese automakers present a distinguishing spatial clustering pattern. As shown in Fig. 2d, numerous hotspots were located in North China, particularly in the Jing-Jin-Ji Region and Shandong Province. Only a few hotspots were located in the Yangtze Delta Region, and none was located in South China. This shows that car sales by Chinese automakers were concentrated in North China and East China rather than South China. The convex spots of car sales by Chinese automakers were identical to the other types of automakers, with Shenzhen as an exception, another city with a large population and developed economy. Note also that in Fig. 2d, besides Zhoushan, another city named Laiwu was identified as a concave spot. It is because Laiwu was the smallest prefectural city in Shandong Province with a population of 1.30×10^6, while all its neighboring cities had a population of over 5×10^6. Hence, the car sales of Chinese automakers in Laiwu were significantly lower than its surrounding neighbors, which in turn make Laiwu City a concave spot.

4.3 Location quotient of car sales

Location quotient (LQ) is a useful indicator to measure the comparative advantage of an automaker in a city. It focuses on the relative share of car markets that a manufacturer commands, as opposed to the absolute value of car sales. It is also a valuable way of quantifying the level of importance of a manufacturer in a city's market, which further reveals local differences in comparison to the national average. If a city has a LQ by a particular type of automaker higher than 1, it means that this type of manufacturer managed to achieve more market share in this city than the average level in the country.

As illustrated in Fig. 3a, high LQ for foreign automakers appeared mostly in the more developed cities in each province, such as cities in the southeast coastal provinces and capital cities in the inner provinces. This is not surprising because people in these cities can afford more imported cars due to the relatively higher income level. What is surprising is that some inland cities that were not commonly considered developed, such as Yulin, Ordos, Da Hinggan Ling Prefecture, and some cities in Tibet, nevertheless recorded high LQ. There are several possible reasons for this phenomenon. First, some types of cars produced by foreign-owned automakers are popular in the western China, especially the SUV produced by manufacturers such as Toyota, Mitsubishi, and Hyundai. Second, these cities have relatively higher average income level compared to ordinary inland cities. For example, residents in Yulin and Ordos were relatively richer because these two cities had abundant coal resources.

Fig. 3b shows a different pattern of LQ distribution for Sino-foreign joint venture automakers. The variances of LQ for joint ventures were not as large as the other two types, with the highest values of LQ no more than 1.3. This indicates that the joint ventures had a more even market shares across China. As shown in Fig. 3b, cities with higher LQ were concentrated in the eastern and southeastern China. The LQ for Chinese automakers exhibits almost an opposite pattern to the other two types. Most cities in the middle, western, and northeastern part of China had a high LQ. Cities in the western China, including provinces of Tibet, Xinjiang, and Inner Mongolia, had LQ values higher than 1.5, which means that the Chinese automakers obtain above average market shares in these cities. Note also that most of these cities were underdeveloped.

As illustrated in Fig. 3c, the more underdeveloped the city is, the higher LQ values for Chinese automakers tend to be. This may be because residents in these underdeveloped cities had lower car consumption than those in developed cities, and price factor was still the primary consideration for consumers in these cities; therefore, cheaper cars produced by domestic automakers were more popular. It also shows that the domestic automakers invested more effort on grabbing the markets in these developing cities where they face less competition from joint ventures and foreign-owned companies. To meet the consumer demand in the western China, the Chinese automakers have designed cheaper but prevailing car models, such SUV and MPV. In a certain sense, these cities contributed significantly to the development of domestic automakers, although the amount of car sales might not be large compared to those in developed cities. In some cities in the western China, domestic automakers have acquired an absolute dominant position in the market. Without doubt, these underdeveloped cities will play increasingly important roles in the market strategies of Chinese automakers.

4.4 Factor analysis and regression analysis

Several variables capturing the socioeconomic and demographic characteristics in cities were selected to examine the factors that may have affected car sales. As shown in Table 2, these variables exhibit large variations across cities. For example, the average income of residents (including both urban and rural) in the city is an important indicator that may determine the people's consumption capacity. The GDP of a city is a basic indicator that may directly reflect the economic development level. The resident population variable is usually positively associated with the car sales because more people mean more demand for goods. Meanwhile, the fixed assets investment, the RMB deposits in financial institutions, and the local fiscal revenue can reflect the consumption power in the society and the investment capability of the government and people.

Because these variables may correlate with each other, it is useful to identify a small number of easily interpretable factors that were responsible for the observed

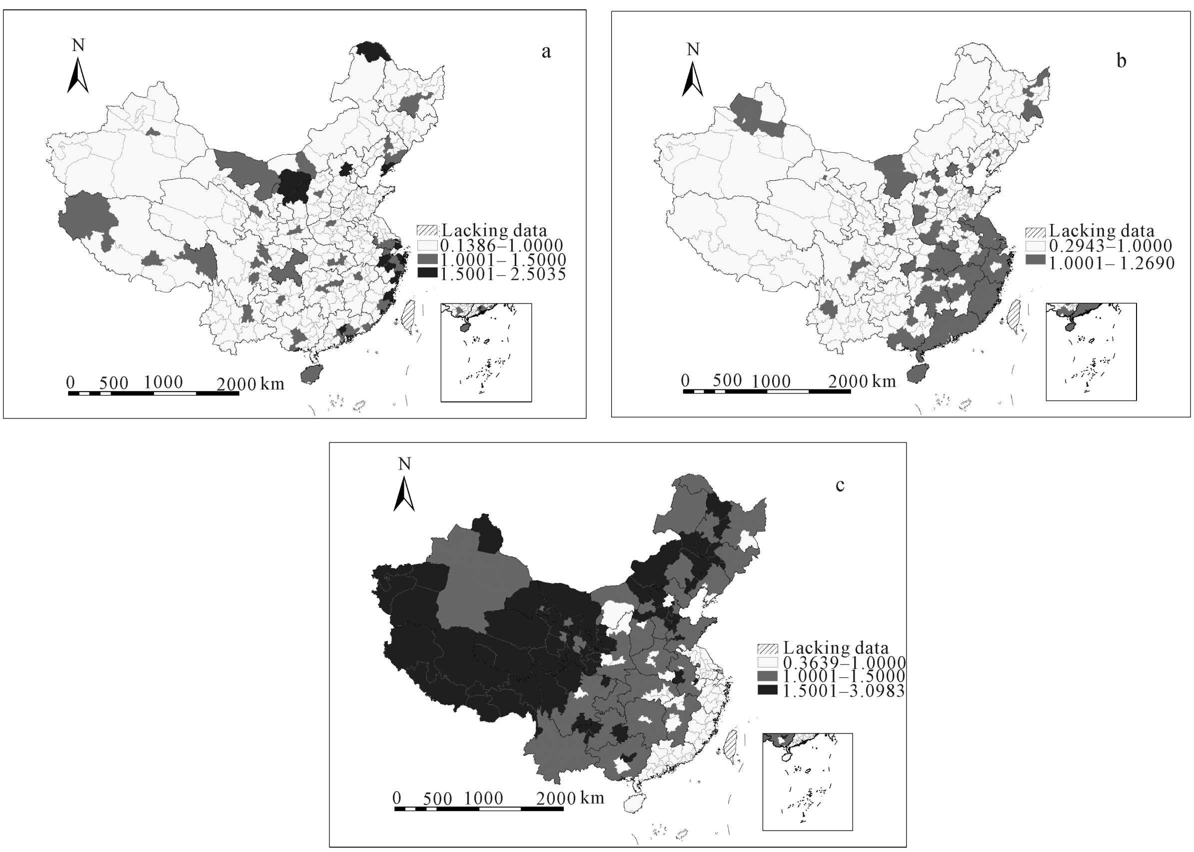

Fig. 3 Location quotient of car sales for foreign-owned automakers (a), Sino-foreign joint automakers (b), and Chinese automakers (c)

Table 2 Descriptive statistics of the variables

Variables	*N*	Minimum	Maximum	Mean	SD
Population (10^4 persons)	337	7.60	2919	396.07	324.92
GDP (10^8 yuan (RMB))	337	14.53	19195.69	1574.60	2213.22
Fixed assets investment (10^8 yuan (RMB))	337	15.37	7579.45	886.33	1034.53
Local fiscal revenue (10^8 yuan (RMB))	337	1.26	3429.83	134.51	305.59
Per-capita net income of rural residents (yuan (RMB))	337	2362	22842	7548.25	2960.45
Per-capita disposable income of urban residents (yuan (RMB))	337	9759	39513	19181.40	4879.53
Total volume of retail sales of consumer goods (10^8 yuan (RMB))	337	3.16	6900.32	545.64	828.80
RMB deposits in financial institutions (10^8 yuan (RMB))	337	41.30	69883.87	2313.03	5728.23

correlations among variables. We conducted a factor analysis to obtain the underlying constructs. The principal component analysis (PCA) is used to extract factors from the correlation matrix. Table 3 illustrates the results of total variance explained, which shows the percentage of the total variance attributable to each factor. According to the extraction sums of squared loadings, more than 89% of the total variance is explained by the first two factors and their eigenvalues are more than 1. Therefore, the first two factors are chosen as the final factors to represent the variables.

To interpret the two factors, we used the varimax orthogonal rotation method. Table 4 shows the rotated component matrix. The first factor is highly correlated with population, GDP, fixed assets investment, local fiscal revenue, total volume of retail sales of consumer goods, and the RMB deposits in financial institutions. Thus, we labeled it the scale factor. The second factor had large loadings on the per-capita disposable income of urban residents and the per-capita net income of rural residents, so we labeled it the income factor. Based on the scores for each factor, two new independent variables are generated, and regression models are calibrated to evaluate the impacts of these factors on car sales by different manufacturers.

OLS regressions are conducted initially in GeoDa 1.8.8; Table 5 shows the results. To diagnose the spatial dependence problem, the Moran's *I* (error) and Lagrange multiplier statistics are also computed and shown. As observed in Table 5, the spatial dependence problem existed in all the models. To address this problem, we incorporated a spatial lag or spatial error variable into the models following Wang (2006). By comparing the results of Lagrange multiplier tests for different models, we chose either a spatial lag model or a spatial error model to calibrate the spatial regression models based on whose significances were higher; Table 6 shows the results.

Table 3 Total variance explained

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative (%)	Total	% of variance	Cumulative (%)	Total	% of variance	Cumulative (%)
1	6.089	76.117	76.117	6.089	76.117	76.117	4.838	60.481	60.481
2	1.068	13.345	89.461	1.068	13.345	89.461	2.318	28.980	89.461
3	0.410	5.125	94.586						
4	0.170	2.120	96.706						
5	0.158	1.974	98.680						
6	0.059	0.743	99.423						
7	0.036	0.449	99.872						
8	0.010	0.128	100.000						

Table 4 Rotated Component Matrix[a]

Variables	Component	
	1	2
Population	0.888	0.111
GDP	0.883	0.441
Fixed assets investment	0.835	0.366
Local fiscal revenue	0.903	0.294
Per-capita net income of rural residents	0.233	0.930
Per-capita disposable income of urban residents	0.332	0.892
Total volume of retail sales of consumer goods	0.902	0.391
RMB deposits in financial institutions	0.883	0.280

As shown in Table 6, the spatial regression models for car sales by all automakers, foreign-owned automakers, and Sino-foreign joint automakers were better by incorporating a structure of spatial dependence (spatial error) in the error term. The spatial regression model for car sales by Chinese automakers was better by including a spatial lag of the dependent variable as an additional explanatory variable. Compared to the OLS regression, all the goodness of fit measures, such as the log likelihood, Akaike's Information Criterion (AIC), and Schwartz's Criterion (SC), demonstrated that all the spatial regression models show a better model fit. This demonstrates that the car sales in one city were related to the car sales of the city's neighbors. The reasons may derive from different aspects. People from neighboring cities tend to have similar socioeconomic status, cultural background, and hence similar purchasing capability and consumption habit. Thus, they are inclined to purchase the same brand of cars. Furthermore, if some automakers have won wide acceptance in a city, they are also likely to be preferred in the neighboring cities.

Table 5 Results of ordinary least squares regression models

Variables	Car sales of all automakers	Car sales of foreign-owned automakers	Car sales of Sino-foreign joint automakers	Car sales of Chinese automakers
Constant	38455.2***	3045.03***	26024.7***	9385.44***
Factor_1(scale)	48850.3***	5816.74***	34459.9***	8573.67***
Factor_ 2(income)	23106.6***	2698.15***	17112.8***	3295.68***
Adjusted R^2	0.8794	0.8466	0.8902	0.6266
F value	1236.56	930.16	1375.13	285.479
Log likelihood	–3846.73	–3170.41	–3713.18	–3493.42
AIC	7699.46	6346.83	7432.35	6992.84
SC	7710.95	6358.31	7443.84	7004.32
Moran's *I* (error)	3.3819***	3.6935***	2.6729***	6.6378***
LM lag	5.4092**	3.0655*	2.0317	52.4932***
Robust LM (lag)	0.9429	17.4212***	0.1314	14.3239***
LM error	10.4253***	12.5162***	6.3794**	41.7014***
Robust LM (error)	5.9590***	26.8719***	4.4791**	3.5321*

Notes: * statistical significance at 10% level; **statistical significance at 5% level; ***statistical significance at 1% level

Table 6 Results of spatial regression models

Variables	Car sales of all automakers	Car sales of foreign-owned automakers	Car sales of Sino-foreign joint automakers	Car sales of Chinese automakers
Constant	38012***	3061.82***	25859.1***	6638.79***
Factor_1(scale)	48720.8***	5942.93***	34475.6***	8157.77***
Factor_ 2 (income)	23150.3***	2782.69***	17077.9***	2738.59***
R^2	0.8855	0.8536	0.8938	0.6794
Log likelihood	–3841.37	–3164.77	–3709.93	–3472.21
AIC	7688.74	6335.53	7425.87	6952.43***
SC	7700.23	6347.02	7437.36	6967.74***
Spatial lag	–	–	–	0.293119***
Spatial error	0.244387***	0.23487***	0.190741***	–

Notes: * statistical significance at 10% level; **statistical significance at 5% level; ***statistical significance at 1% level

Generally, the models present good prediction ability, especially for car sales of the total automakers, foreign-owned automakers, and Sino-foreign joint automakers, which could explain more than 80% of the variation of the car sales. Although the R^2 is not very high, the model for car sales for Chinese automakers can still explain nearly 68% of the variation. Moreover, as expected, the coefficients of the independent variables reveal that car sales are positively and significantly related with the scale factor, income factor, and car sales in neighboring cities. The coefficients of the scale factor were the highest in all the models, which means the scale factor makes the largest contribution to the variations of car sales. The models also confirm that car sales in a city are affected by the income level of the urban and rural residents. In other words, the higher car sales are more likely to appear in cities with higher income level. As the previous studies we mentioned revealed, the car ownership for a household largely depends on the income level. This research provides another example illustrating the importance of income level in affecting the car sales in a city.

By comparing the results of the four different models, we can further distinguish the differences among the models in terms of their explanatory power. The regression model for the car sales of the Sino-foreign joint automakers has the highest R^2 of 0.8938, which indicates the strongest association between the car sales of Sino-foreign joint automakers and the exploratory factors. The possible reason may be that the consumers in cities with larger proportion of population and with higher income level place more importance on the quality of cars (produced by the Sino-foreign joint automakers) despite higher prices. Probably due to the same reason, the car sales of the foreign-owned automakers are also highly related with the two factors. However, the R^2 for car sales of Chinese automakers is 0.6794, which is obviously lower than that of the others. The relative lower explaining capability of this model may be because more Chinese cars are sold in undeveloped cities, which exerts a reverse impact on the coefficients of the model.

5 Discussion and Conclusions

Although the nature of car sales is one of the most enduring topics among researchers, the understanding of their spatial distribution across cities in China was limited due to the lack of reliable data. By mapping spatial distributions of car sales, we were able to examine the differences in spatial patterns among types of automakers. In particular, by identifying the different spatial clusters, we obtained a clearer pattern of spatial agglomeration or heterogeneity. Through calculating and visualizing the location quotients of different manufacturers regarding car sales, we could further examine and understand the various roles that different types of automakers play in the car markets in cities across China. Finally, by conducting the regression analysis, we further explored the factors that were related to the car sales volume. Three conclusions emerged from the findings.

First, car sales varied greatly across cities in China, and different types of automakers exhibited different spatial patterns. Generally, the more developed the city was, the more cars were sold there, although there are some significant exceptions in car sales by domestic automakers. Cities with high car sales were usually located in the Yangtze Delta Region, Jing-Jin-Ji Region, Pearl River Delta Region, or were capital cities in inland provinces. The spatial pattern became clearer after the identification of hotspots, convex spots, and concave spots. The developed cities were the most important markets for all the manufacturers.

Second, different kinds of automakers obtain diverse advantages in the markets across cities in China. The foreign-owned automakers obtain more market shares in the most developed cities, such as cities in the Yangtze Delta Region and the capital cities of inland provinces. The Sino-foreign joint automakers had relatively even market shares in most cities, although people in the eastern and southeastern part of China tended to buy more cars produced by the joint ventures. The Chinese automakers commanded more market shares in most parts of middle and western China. The more underdeveloped the city was, the higher proportion of market share the domestic automakers tended to obtain.

Third, the scale and the income factors, together with the spatial effects, were strong factors for determining the amount of car sales. All the coefficients in the models were positive and statistically significant. The models for car sales of the Sino-foreign joint automakers exhibited the highest explanatory power, indicating that the scale and income factors were key indicators to predict the amount of car sales of the Sino-foreign joint automakers. However, the association between car sales of the Chinese automakers and the contextual factors was a little weaker than that of the others, which may be because Chinese automakers obtain more market share in the underdeveloped cities.

This study could provide some valuable insights into the process of car purchasing across cities. Different types of auto manufactures had different marketing orientations and strategies, and hence diverse market shares across cities. Further, this study also demonstrated that car sales could be related with the scale factor, income factor, and the car sales in neighboring cities, which is helpful for predicting the car sales in cities. In the future, it will be interesting and necessary to further explore the dynamic characteristics of spatial patterns regarding car sales if more data that are accurate in terms of car sales in different years are available.

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