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Spatial Differentiation and Influencing Mechanism of Medical Care Accessibility in Beijing: A Migrant Equality Perspective

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Abstract: Spatial equality of access to basic public services, especially medical care services which are directly related to life safety, is the first step to achieve the goal of equalization of basic public services for all the people proposed by central government of China. Using the spatial analysis and the statistical analysis, this study evaluates the spatial differentiation of medical care facilities accessibility by constructing STT (Shortest Travel-Time) and SAI (Spatial Accessibility Index). And then this study explores the neighborhood effects on the medical care facilities accessibility in Beijing, with a particular focus on the effect of neighborhood migrant proportion by constructing spatial dependent regression model. The spatial accessibility analysis of medical care facilities show that the spatial distribution of medical care facilities was basically consistent with administrative regions but not with population demands. Bivariate LISA cluster maps identify that suburban areas are the overlapped clusters of high percent of migrants and limited medical care services. This is associated with the public service allocation rule in China, which stresses equality within urban areas and within rural areas but overlooks equality between urban areas and rural areas; and stresses local resident demands but overlooks migrant demands. To estimate the effects on medical care accessibility of neighborhood migrant proportion, spatial dependence models are applied due to spatial dependence of accessibility of medical care facilities. The regression results show that neighborhoods with high percent of migrants, even conditioning on neighborhood SES, are related to limited spatial accessibility of medical care services. Besides neighborhood characteristics, another important factor influencing spatial accessibility of medical care services is the process of spatial spillover effects. This indicates that the attenuate accessibility of medical care services for migrants is not only because of their own constraints but also because of their proximity to other disadvantaged neighborhoods. Therefore, it is urgently needed to increase the medical facilities in the suburban areas, to take into account migrants' demands and to reduce residential segregation between local residents and migrants for local governments to achieve the goal of equalization of medical care service.

Keywords: medical care facility; spatial accessibility; migrant equality; influencing mechanism; Beijing

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1 Introduction

Chinese cities have been undergoing a rapid transformation in the past three decades: from a homogeneous socio-spatial structure into a heterogeneous socio-spatial structure due to the economy transition and the market economy development (Feng et al., 2008). Heterogeneous urban socio-spatial structure, especially residential

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segregation, will bring in a series of social problems and challenges such as social inequality in access to public services. Numerous studies of public service provision focused on the effects of residential neighborhoods on the access to public services (Yin and Xu, 2009; Gao et al., 2010; Wang, 2014; Wang et al., 2014). As one of the most concerned issues for public, inequality in access to medical care service for disadvantaged groups has drawn much more attention.

Residential neighborhoods such as socioeconomic disadvantages and racial and ethnic isolation act as barrier to medical care provision (Kirby and Kaneda, 2005; Kirby, 2008; Small et al., 2008). Studies in western countries find that places characterized by geographical segregation of the poor and ethnic minorities, are facing a variety of healthcare problem, such as high infant mortality, poor prenatal care and physical disorder (Wilson, 1987; Sampson et al., 2002). Smaje (2000) argued that residential segregation of the poor and ethnic minorities impacted the location and spatial distribution of medical care facilities. The inverse care law proposed by Hart (1971) argued that the availability of medical care services tended to vary inversely with the need of the population. That is affluent people get many medical care services while poor people do not get any of them. Macintyre (2007) extended this law as the deprivation amplification. The deprivation amplification is that medical care services tend to be poorer in more disadvantaged areas, which is detrimental to health, the quality of life and opportunities for social mobility (Macintyre et al., 1993).

Compared to western countries, residential neighborhoods in Chinese cities exhibit not only socioeconomic differentiation, but also differentiation between local residents (the resident population with local household registration) and migrants (the resident population without local household registration). Since the 1980s, the government has started to encourage migration, which brings in a massive influx of rural migrants into cities. In 2012 urban migrants accounted for 32.87% of the urban population in China. Due to the constraints of the Hukou system (household registration), migrants are not entitled to full citizenship rights by local residents, which lead to inequality in the residential differentiation in cities (Wu, 2008; Huang and Jiang, 2009; Wang et al., 2010). They have very limited or no access to the housing-distribution system and the citywide welfare programs (Logan et al., 1999; Wu, 2002). Most of them have no access to medical insurance for urban residents but their new rural cooperative medical insurances can not cover the medical cost in non-registered residence. Moreover, China's medical care facilities are allocated according to the registered population and Hukou system, which may result in the disparity in access to medical care services by neighborhood migrant proportion.

In Chinese, a large amount of literatures study the spatial pattern of accessibility of medical care facilities in large cities, such as Beijing (Zhong et al., 2016), Guangzhou (Qi et al., 2014), Dalian (Fu et al., 2014), and in semi-urban areas, such as Rudong County in Jiangsu Province (Song and Chen, 2009), Lankao County in Henan Province (Wu et al., 2008). But there are a small number of literatures focusing on the effects of neighborhood disadvantages on access to medical care services (Gao et al., 2010; Wang et al., 2014). Gao et al. (2010) found that the medical care facilities of Guangzhou spatially concentrated in high income areas. He thought that this was cause by market economy and it was consistent to the inverse care law in western countries. However, little is known about the migrant inequality in access to medical care facility. And the relationships between neighborhood migrant proportion and medical care accessibility differentiation is still unclear.

This paper aims to analyze the spatial differentiation and the influencing mechanism of medical care accessibility in Beijing, with a particular focus on the migrant equality. Integrating the spatial analysis techniques with the statistic alanalysis techniques, the objectives of this study are to evaluate the spatial accessibility of medical care facilities measured by shortest travel-time (STT) to the nearest hospital and spatial accessibility index (SAI) of the hospitals. And then this study accesses the effects of neighborhood migrant proportion on the spatial accessibility of medical care facilities.

2 Data and Methodology

2.1 Data

Our study area is the built-up area of Beijing, mostly confined within the Sixth Ring road (Fig. 1). The built-up area of Beijing involves 12 administrative districts (Pinyin: *qu*) and 185 subdistricts (Pinyin: *jiedao*) or towns (Pinyin: *zhen*). It covers 3477 km^2 of land, and had a population of 16.14 million people with a density of 4641 people per km^2 in 2010. In our analysis, the inter-provincial migrants, who are referred to as the people who reside in Beijing city for more than six months but are registered in other provinces, are called migrants for short. We use the community or village as our unit of observation.

We use population data from the 2010 Population Census. The finest scale of population census is subdistrict or township but it is too rough to calculate the medical care accessibility. Therefore, we use population spatialization methods proposed by Eicher and Brewer (2001) and Mennis (2003) to acquire the population data on the community or village scale. This approach is to allocate population on the community or village scale using the population data on the subdistrict/township scale by incorporating the 1 : 5000 scale urban land-use data. The calculation to assign a population value to a given village level within a given township level can be expressed as:

$$POP_{vt} = \sum_{i} D_{it} \times A_{iv} \tag{1}$$

where POP_{vt} is population assigned to v village in town t, D_{it} is population density for land-use class i in town t, A_{iv} is the total area of land-use class i in v village.

The urban land-use data are classified into three classes: nonresidential land, urban residential land and rural residential land. Population density of nonresidential land is set to 0. Population density of urban residential and nonresidential land in each subdistrict/town is acquired form sampling. Due to spatial homogeneity of migrant percentage within urban residential land and within rural residential land but spatial heterogeneity of migrant percentage between urban and rural residential land, we also employ this method to obtain the migrant population data on the community or village scale. As for the female and young population, we omit the relatively small differences between urban and rural residential land. We use the areal uniform weighting approach, whereby each community or village is assigned a population value based on its percentage of residential land area in the subdistrict or township.

Medical care data are obtained from the Beijing Public Health Information Center. Medical care facilities in our analysis are limited to licensed hospitals, which are designated as primary, secondary or tertiary hospitals based on their ability on medical care, medical education and medical research. There were 595 licensed hospitals in Beijing, with 52 381 licensed physicians or physician assistants and 100 317 qualified beds in 2014. The tertiary hospitals of 31 956 licensed physicians and

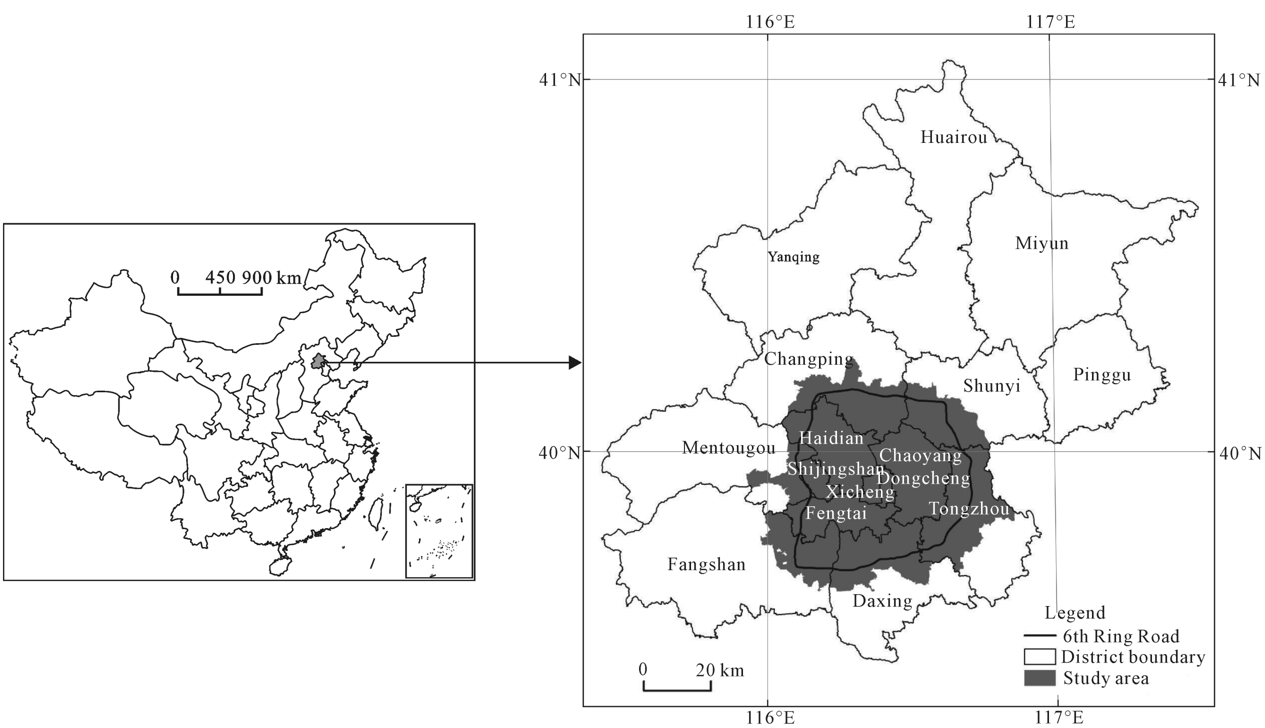

Fig. 1 Geographical location of the study area in Beijing

58 518 qualified beds accounted for more than half of the total licensed physicians and qualified beds.

2.2 Measurement of spatial accessibility of medical care facility

We use two indexes to measure the spatial accessibility of medical care facility: shortest-travel-time (STT) and spatial accessibility index (SAI). STT is the accessibility to the nearest medical care facility, which represents the spatial coupling between medical care facilities and residential areas. Whereas, SAI is the accessibility to the medical care facilities within certain threshold time and considers the supply-demand ratio of medical care facilities. SAI represents the spatial coupling between medical care supply and population demand.

STT is based on the cost distance analysis. First, the study area is divided into a grid with cells of 100 m by 100 m, assuming that each cell has equal travel speed. According to the road network and class of road, the standard speed is set at 45 km/h for expressways, 40 km/h for national roads, 30 km/h for main roads, 25 km/h for secondary roads and branches, and 5 km/h for land. Second, we calculate the time cost from each community/village centroid to the nearest hospital based on standard speed.

SAI is based on two-step floating catchment area method (2SFCA) developed by Radke and Mu (2000). Considering medical care demands of population with varied demographic characteristics, we use the adjusted population rather than total population.The adjusted population is composed of two parts: basic part and adjusted part. Basic part is the population size which is directly related to the general medical demand. Adjusted part is the weighted disadvantageous population which has significantly different medical demand from the ordinary people. The difference of medical care demands mainly involves two aspects: prevalence rate and doctor visit rate, which also can be regarded as physiological aspect and socio-economic aspect respectively. In our analysis, the physiological aspect includes two factors: gender and age; and the socio-economic aspect is represented by migration status. Hereby, the adjusted part of adjusted population is composed by three disadvantageous groups: older, female and migrant.The formula of adjusted population (AP) is as follows:

$$AP_i = POP_i + \sum_{j=1}^{J} \beta_i \times POP_{ij} \tag{2}$$

where POP is the total population size, j is the disadvantageous group (older, female, migrant), β is the weight of difference of medical care demand between the disadvantageous population and the ordinary people. Two-Week Prevalence Rate (TWPR) is an index to evaluate health conditions widely used in medical studies; the Ratio of Those Who Should Visit A Doctor But Not (RTWSVADBN) is a index to evaluate health seeking behavior. We choose these two index to determine the difference of the medical care demand. As for TWPR, the *Analysis Report of National Health Services Survey in China* (Center for Health Statistics and Information, NHFPC, 2016) stated that TWPR of older (age ≥ 65) was 1.514 times higher than the average rate, TWPR of female was 9.4 percent higher than the average rate. As for RTWSVADBN, Zhou et al. (2011) found that RTWSVADBN of floating population was as high as 42.73 percent, which was 25.7 percent higher than the average rate. According to above literatures, we put weights of 1.514, 0.094 and –0.257 on older (age ≥ 65), female and migrant respectively.

The steps of measuring spatial accessibility of medical care facility are as follows. First, for each facility location j, search all population locations (k) that are within a threshold travel time (d_0) from facility location j (i.e., catchment area j), and compute the facility capacity to population demanding ration R_j within the catchment area. Second, for each population location i, search all facility location (j) that are within the threshold travel time (d_0) from population location i (i.e., catchment area i), and sum up the facility to population ratios R_j at these locations. The formula is as follows:

$$R_j = \frac{S_j}{\sum_{k \in \{d_{kj} \le d_0\}} WP_k} \tag{3}$$

$$A_i^F = \sum_{j \in \{d_{ij} \le d_0\}} R_j \tag{4}$$

where A_i^F represents the accessibility at resident location i. R_j is the facility-to-population ratio at facility location j whose centroid falls within the catchment centered at i (i.e., $d_{ij} \le d_0$). WP_k is the weighted population of commnunity/village k whose centroid falls within the catchment. S_j refers to the number of doctors at location j. d_{kj} is the travel time between k and j, d_{ij} is the travel time between i and j. A larger value of A_i^F indicates a better accessibility at a location.

2.3 Spatial autocorrelation index

We use spatial autocorrelation index to analyze the correlativity between neighborhood migrant proportion and hospital accessibility since the existence of spatial dependence of hospital accessibility. The distribution of hospital accessibility demonstrates a significant spatial dependence across the communities/villages. The value of Moran's *I*, a statistical indicator of spatial correlation of SAI, significantly suggest the existence of such spatial dependence (the Moran's *I* is provided by Table 1). we examine the spatial correlation between hospital accessibility and percent of migrantsin surrounding areas by using bivariate local spatial autocorrelation (LISA). The bivariate LISA (*I*) can be defined as:

$$I_{ab}^{i} = \frac{(a_i - \bar{b})}{(a_i - \bar{b})^2 / n} \sum_j w_{ij} (b_j - \bar{b}) \tag{5}$$

where $\bar{b}$ is the mean value of the variable *b* with the sample number of *n*; a_i is the value of the variable *a* at location *i*; b_j is the value of the variable *b* at other locations; w_{ij} is the spatial weighting matrix between *i* and *j* (Anselin, 1995). Bivariate LISA can be categorized into four groups: two categories of positive spatial correlation (high-high and low-low) and two categories of negative spatial correlation (high-low and low-high). The Bivariate LISA map can demonstrate the spatial pattern of overlapped clusters of hospital accessibility and percent of migrants.

2.4 Spatial regression model

We construct spatial regression model to estimate the extent to which neighborhood migrant proportion affects hospital accessibility at the community/village level. As the existence of spatial dependence violates the assumption of OLS regression, we apply the spatial dependence model to deal with this problem. There are two primary types of spatial dependence model: spatial lag model and spatial error model. The spatial lag model is of the form (Anselin, 2004).

$$y = \rho \boldsymbol{W} y + \boldsymbol{X}\beta + \varepsilon \tag{6}$$

where $\boldsymbol{W}$ is the weighting matrix, $\boldsymbol{X}\beta$ is the direct effects on *y* of the attribute values, ρ is a spatial lag parameter, $\varepsilon–N(0, \sigma)$.

The spatial error model is of the form (Anselin, 2004):

$$\begin{aligned} y &= \boldsymbol{X}\beta + \mu \\ \mu &= \lambda \boldsymbol{W} \mu + +\varepsilon \end{aligned} \tag{7}$$

where λ is a coefficient on the spatially correlated errors.

In the spatial dependence model, the explanatory variable is percent of migrants. Neighborhood socio-economic characteristics (including percent of workers as manager or professional and unemployment rate), population density and road density are control variables in the spatial dependence model. Neighborhood socio-economic context impacts medical care provision, and socio-economic disadvantageous neighborhoods have limited hospital accessibility (Chen et al., 2013). Population density directly affects medical care demands and road density affects transportation accessibility. Maximum likelihood estimates are used for spatial estimation in this paper. We use multivariate Moran's I test to diagnose whether spatial dependence produces bias in the regression model, Robust LM(lag) and Robust LM(error) to determine which type of spatial dependence may be at work.

Table 1 Summary statistics for main variables

Variables	Variable description	Mean	SD	Moran's I
STT	Shortest-travel-time from each community/village centroid to the nearest hospital (min)	5.20	5.84	0.929
PCTM	Percent of inter-provincial migrants (%)	37.35	16.44	0.850
PCTMP	Percent of migrants who are managers or professionals (%)	17.80	9.73	0.752
UNEMP	Percent of total workforce who are unemployed and are looking for a paid job (%)	4.47	1.70	0.840
POPDEN	Population density (1000 people per km^2)	16.37	17.39	0.590
ROADDEN	Road Density (1 km per km^2)	10.37	8.27	0.534
Number of communities/villages		2867		

3 Spatial Accessibility of Medical Care Facility

In section 3 we analyze the spatial pattern of access to medical care facility by two indexes: shortest-travel-time (STT) and spatial accessibility index (SAI). STT represents travel time to the nearest hospital, which is expected to be lower in the areas with better transportation accessibility and higher hospital density. SAI considers complex interaction between population (supply) and physician (demand) based on distances in different regions. When calculating SAI, we use 30 min travel time as the threshold time. The 30 min is a widely used threshold in numerous spatial accessibility literatures, as it is designated for determining whether contiguous resources are excessively distant in the guidelines for HPSA designation (Wang et al., 2005). Fig. 2 shows the spatial distribution of shortest-travel-time (STT) to the nearest hospital in the built-up areas of Beijing. STT from the community/village centroids to their closest hospital is shorter in the city center than the suburban areas. We can see 5-min STT exhibits radial pattern outward from the city center, which is highly related to the road network and high-speed transport facilities. STT is less than 5 min in most areas of the city center and the district government office location. In the majority inner suburban areas, the time distance is between 5 minutes and 15 minutes. In the border of the built-up areas, the time distance is between 15 minutes and 30 minutes.

Fig. 3 shows the geographic distribution of spatial accessibility index (SAI) of hospitals in Beijing. It shows a very clear pattern of concentration of higher SAI the city center, as is similar to STT. SAI of hospitals declined as the distance from the city center increased. And SAI is higher in the western city center than the eastern city center. Besides city center, there are three clear sub-centers of high SAI of hospitals: northeastern sub-center near Shunyi district government office, northwestern sub-center near Changping district government office, and southwestern subcenter located in Liangxiang new town. This 'one-center plus multi-subcenters' spatial pattern corresponds to the public resource allocation designation of Beijing, which is highly correlated to administrative management system. Comparing the spatial distribution of STT and SAI, it is found that SAI exhibited spatial heterogeneity while STT exhibited extensive spatial homogeneity. It implied that the spatial distribution of medical care facilities was basically consistent with administrative regions. Almost all the population could get access to the nearest medical care facilities within 15–20 minutes. In contrast, the spatial consistence of medical care facilities and population demands was not very well. The SAI of city center was apparently higher than the suburban areas. Accordingly, the section 4 explores the impact factors of SAI spatial heterogeneity.

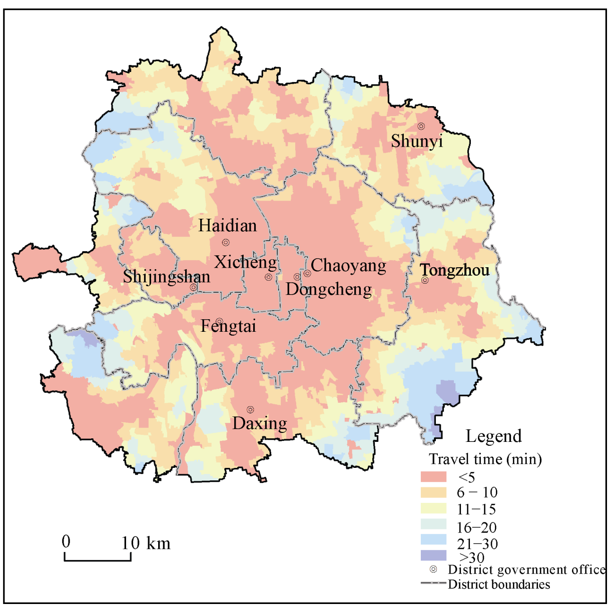

Fig. 2 The spatial distribution of travel time to the nearest hospital (STT) in Beijing

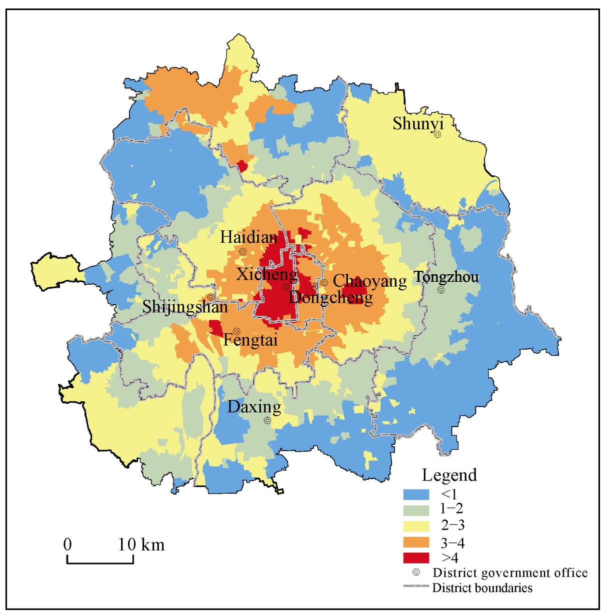

Fig. 3 The spatial distribution of spatial accessibility index of hospitals (SAI) in Beijing (d_{max}= 30 min)

4 Neighborhood Effects on Access to Medical Care Services

In this section, we examine the associations of SAI of hospitals with neighborhood migrantproportion conditioning on the neighborhood socioeconomic characteristics in the built-up area of Beijing.

4.1 Descriptive statistics

Table 1 shows summary statistics of outcome variables and covariates examined in this study. The mean SAI of hospitals is 2.67 with the standard deviation of 1.32. The mean percentage of migrants is 37.35. As for the neighborhood socioeconomic characteristics of Beijing communities/villages, the percent of managers or professionals is 17.80 and the mean unemployment rate is 4.47%. The scores of Moran's I show that SAI of hospitals tends to cluster significantly among communities/villages, as does neighborhood characteristics. Then we examine the correlations between these clusters.

4.2 Spatial correlation analysis

We use the bivariate LISA cluster map to show the local patterns of spatial correlation of hospital accessibility and percentage of migrants for its neighbors. In Fig.4 Low-High represents low SAI of hospitals, high percent of migrants; High-Low represents high SAI of hospitals, low percent of migrants; High-High or Low-Low represents high SAI, high percent of migrants or low SAI, low percent of migrants. The map is coded so as to show that communities/villages with little accessibility of hospitals and higher percent of migrants (colored by blue), as do those with more accessibility of hospitals and lower percent of migrants (red). The yellow areas in Fig. 4 represent the clusters of communities/villages with either high degree of spatial accessibility in high-percent migrant neighborhood or low degree of spatial accessibility in low-percent migrant neighborhood.

Fig. 4 illustrates the spatial patterns of clusters of hospitals accessibility and percent of migrants. Specifically, overlapped clusters of community/village with high percent of migrants and limited medical care services are mostly located in the suburban areas. In the suburban areas, there are many large residential communities, which aimed to provide economically affordable housing to low-income families, such as Huilongguan community and Tiantongyuan community. Besides

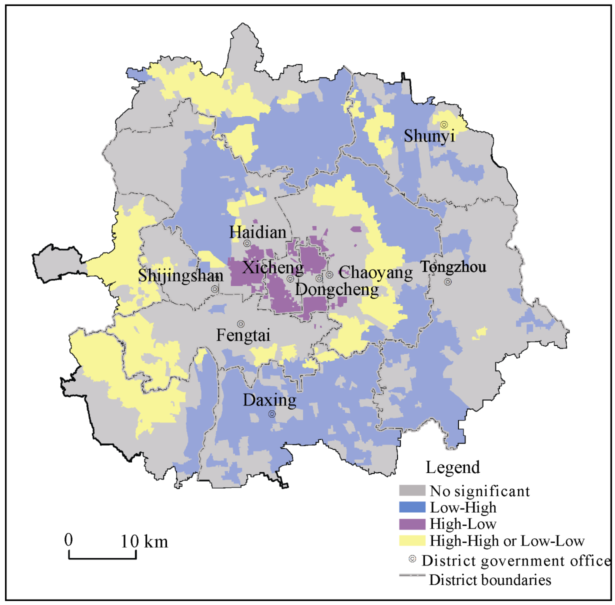

Fig. 4 Bivariate LISA clusters of SAI of hospitals and percent of migrants

this, plenty of rural housings are located in the border of built-up areas, where the rural people constructed a large number of low-cost rental housing due to the urban-rural dual land system. All above attracts a large amount of migrants, which brings up high demands for medical care services. However, the medical care facility investment and construction do not keep pace with the population growth in the suburban areas. In contrast, clusters of community/village with low percent of migrants and abundant medical care services overlaped in the city center. The city center is the administrative, culture, education and medical center of Beijing, even of the whole country. It is clustered by numerous hospitals, not only the municipal hospitals but also the national hospitals.

4.3 Spatial regression results

Table 2 presents results of spatial regression of SAI on neighborhood characteristics. Neighborhood migrant proportion is the main explanatory variable. The additional factors that may influence accessibility are controlled: percent of managers or professionals, unemployment rate, population density and road density.

Table 2 consists of two types of models: OLS and spatial lag models. Columns 1–3 of Table 2 presents OLS results of log SAI of hospitals. The results show that percent of migrants is significantly negatively related to SAI. Moreover, low neighborhood socioeconomic status (SES), which is measured by percent of managers or professionals, is linked to lower SAI. Population density and road density, which indicates the potential medical care demand and transportation accessibility, both have significantly positive effects on the hospital accessibility.

Moran's I score in the complete model of log SAT is both highly significant (Model 3, 0.781 P<0.001), indicating strong spatial autocorrelation of the residuals. Then we use Robust Lagrange-Multiplier Test (Robust LM) to determine whether spatial error or spatial lag models best fit the data. We find that both robust test of the lag and error models are significant. As the spatial lag model fits better than the spatial error model, we choose the spatial lag model to estimate the effects on the SAI. Columns 4–6 of Table 2 demonstrate regression results of log SAI with maximum likelihood approach while controlling for the spatial lag term (ρ). The weighted spatial lag term reflects the spatial autocorrelation between communities/villages, measuring the average influence on communities/villages by their neighboring communities/villages. The results show the spatial lag term has positive effect and is highly significant (Model 6, 0.913, P<0.001). This is consistent with our expectation that SAI of hospitals is social-spatial phenomenon dependent on local contexts in each community/village. The spatial lag models fit largely improved, as indicated by higher values of R-squared and Log likelihood.

In the complete spatial model of log SAI, the effects of percent of migrants, unemployment rate, population density and road density remain significant, but become smaller than OLS model. Conditioning all covariates, a 1 percent point increase in the percent of migrants corresponds to a 0.1 percent lower SAI of hospitals. Low neighborhood SES is associated with less hospital accessibility. A 1 percent point increase in the unemployment rate is related to a 0.5 percent lower SAI of hospitals.

5 Discussion and Conclusions

This paper analyses the spatial differentiation of medical care facilities accessibility and explores the neighborhood effects on the medical care facilities accessibility

Table 2 Regression results for the spatial accessibility index (SAI) of hospitals

Ln (SAI)	OLS Models			Spatial Lag Models		
	(1)	(2)	(3)	(4)	(5)	(6)
Explanatory variables						
PCTM	–0.010	–0.012	–0.006	–0.001	–0.001	–0.001
	(0.001)***	(0.001)***	(0.001)***	(0.000)***	(0.000)***	(0.000)***
PCTMP		0.007	0.003		0.001	0.000
		(0.001)***	(0.001)***		(0.001)	(0.000)
UNEMP		–0.068	–0.051		–0.006	–0.005
		(0.004)***	(0.004)***		(0.001)***	(0.001)***
POPDEN			0.005			0.001
			(0.001)***			(0.000)***
ROADDEN			0.018			0.002
			(0.001)***			(0.000)***
Rho (ρ)				0.937	0.932	0.913
				(0.006)***	(0.006)***	(0.007)***
Constant	1.591	1.845	1.321	0.107	0.142	0.116
	(0.019)***	(0.031)***	(0.034)***	(0.010)***	(0.014)***	(0.015)***
R^2	0.145	0.250	0.394	0.936	0.936	0.937
Log likelihood ratio	–1407.15	–1265.42	–920.38	1826.3	1835.71	1878.27
AIC	2818.29	2538.84	1852.76	–3646.6	–3661.43	–3742.54
Moran's I (error)	0.921	0.891	0.781			
N	2867	2867	2867	2867	2867	2867

Note: *P<0.10; **P<0.05; ***P<0.01.

in Beijing, with a particular focus on the effect of neighborhood migrant proportion. Traditional urban medical care accessibility studies usually do not take the differentiation between local residents and migrants into consideration. This work highlights a problem that is severely affecting groups in China who suffer from institutional constraints and residential segregation. It demonstrates that the planning and management of medical care facility systems must take into account migrant demands in the decision making process. The spatial distribution of accessibility of medical care facilities demonstrates a large differentiation among city center, suburban areas and urban fringe. The effect of neighborhood migrant proportion on spatial accessibility of medical care facilities are evaluated by spatial dependence model, which represents the extent to which migrants have limited spatial accessibility of medical care services.

The indexes of STT and SAI are used to evaluate the spatial accessibility of medical care facilities. STT represent the spatial coupling between medical care facilities and administrative regions, while SAI represent the spatial coupling between medical care supply and population demand. The index of SAI represents complex interaction between provision (medical care services) and demands (population), which use the measurement proposed by Radke and Mu (2000). However, given the differentiated demands of population with varied demographic characteristics, a revision is put forward to the population demands. The results show that SAI exhibits spatial heterogeneity while STT exhibits extensive spatial homogeneity. It implies that the spatial distribution of medical care facilities is basically consistent with administrative regions but not with population demands. This is associated with the public service allocation rule in China, which stresses equality within urban areas or within rural areas but overlooks equality between urban and rural areas; stresses equality among administrative regions at the same level but overlooks equality among administrative regions at the varied level. Bivariate LISA cluster maps show the suburban areas are the overlapped clusters of high percent of migrants and limited medical care services. Therefore, it is urgently needed to increase the basic public facilities in the suburb areas.

Due to spatial dependence of SAI, spatial dependence models are applied to estimate the effects on medical care accessibility of neighborhood migrant proportion. It has been demonstrated that neighborhood migrant proportion plays a role in the explanation of the spatial differentiation of accessibility of medical care services. Neighborhoods with high percent of migrants, even conditioning on neighborhood SES, are related to limited spatial accessibility of medical care services. This verifies inverse care law proposed by Hart (1971) and the deprivation amplification proposed by Macintyre (2007), which argue that medical care services tend to be less for disadvantaged groups and areas. It can be deduced that improving access to medical care services for the low income and the low social strata is not adequate to reduce the inequality in medical care service. Medical care service authorities should pay attention to migrants and propose strategies to solve these difficulties (e.g., implement new medical care facilities, services adapted for migrants, improve medical insurance of migrants).

Besides neighborhood characteristics, another important factor influencing spatial accessibility of medical care services is the process of spatial dependence. The spatial dependence models suggest that spillover between neighborhoods occurs in such a way that neighborhoods with high percent of migrants tend to cluster and experience similar limited accessibility of medical care services. This indicates that the attenuate accessibility of medical care services for migrants and disadvantaged neighborhoods is not only because of their own constraints but also because of their proximity to other disadvantaged neighborhoods. Therefore, reducing residential segregation by Houkou should be taken into account in improving equality in access to medical care services.

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