Using spatial analysis to understand the spatial heterogeneity of disability employment in China

Yilan Liao,* Jinfeng Wang,* Wei Du,[†] Bingbo Gao,* Xin Liu,[‡] Gong Chen,[†] Xinming Song[†] and Xiaoying Zheng[†]

Chinese Academy of Sciences, Beijing
[†]*Peking University, Beijing*
[‡]*Curtin University, Bentley, WA, Australia*

Abstract

During the formulation of employment disability policy, policymakers are often interested in regional variations of disability employment. Decision-makers are required to distinguish between various geographical factors. However, few previous studies take spatial heterogeneity into account and most of them conducted only a qualitative analysis. Geographical detectors based on spatial variation analyses of identified factors were applied in the study to establish connections between regional features and the disability employment rate, and to identify the city groups with significantly higher and lower percentage rates of disability employment. It is the first application of spatial statistics in studying the employment problem of the disabled. The findings can help the government formulate reasonable adjustments to both job opportunities for, and work roles of, disabled people.

1 Introduction

There are more than 600 million disabled people worldwide. Most of them are marginalized and socially excluded. Disability and poverty are intricately linked (Beresford 1996; Elwan 1999; DFID 2000; Yeo and Moore 2003; Mitra 2006; Braithwaite and Mont 2009). Existing studies prove that employment contributes to a reduction of poverty, an improvement of health, and an increased participation in society (Borg et al. 2009). However, disabled people face discrimination in every aspect of employment, particularly in access to job opportunities. In the US, 15.6 million disabled people of working age participate in the workforce. But the disability employment rate is less than half of the non-disabled working age persons (US Bureau of Census 1993). In China, the employment rate of working age people with disabilities is half that of the non-disabled. Approximately 42% of people living in absolute poverty are disabled (Lai et al. 2008).

Existing studies have identified two major sources of discrimination against disabled people in employment (Lai et al. 2008; Kidd et al. 2000; Findley and Sambamoorthi 2004; Mondéjar-Jimenéz et al. 2009; Bell and Heitmueller 2009; Campolieti and Riddel 2012): (1) individual factors (i.e. nature of the disability, self-limiting behavior, education, and gender); and (2) organizational factors (i.e. perceptions of limited job-fit, and the impact of some

policies or actions). In addition, the geographic context or built environment has an impact on the quality of life of disabled people. Botticello et al. (2014) applied multivariate logistic regression to model the influence of residential density, land use mix, destination counts, and open space on four groups of participation for physically impaired adults at the neighborhood and community scales. They found that living in communities with greater land use mix and more destinations was associated with a decreased likelihood of reporting optimum social and physical activity. Greek experts used a shift-share method to evaluate the industry- and region-related impacts on the increasing/decreasing employment flexibility and the emerging patterns of temporary employment in Greece. The findings contest assertions that lower employment protection and greater flexibility accomplish labor market adaptation to demand fluctuations and thus greater employability (Gialis and Tsampra 2015). In China, researchers explored the employment structure features and the spatial distribution of 139 counties in Shandong province by principal component analysis and cluster analysis. Five factors, including natural conditions, core city, transportation and the relation between cities, were studied to understand the local employment structure and its spatial distribution in Shandong, China (Wang et al. 2007). However, these methods rarely considered the interactions between variables.

Beside the traditional methods, Geographic Information Systems (GIS) have also been used to qualitatively and quantitatively analyze the region-specific influence on disability employment and to develop a plan for ameliorating the life of disabilities. In the last decade, extensive literature focused on the measurements of spatial autocorrelation, such as Moran's I, Geary's C, Getis-Ord General G to assess the spatial autocorrelation of the study objects and to identify the regions with significantly higher/lower values than the surrounding areas (Lu 2000; Wang et al. 2010). The spatial autocorrelation index r-value, which quantifies the spatial autocorrelation among spatial units of the study area, has been widely used in spatial statistics to revise the traditional estimator (Ripley 1981; Haining 1988; Griffith et al. 1994). However, as described above, employment rate of disabled people is affected by a number of factors, such as individual condition, built environment and environmental context. Generally, the values of the regional factors appear to be spatially autocorrelated, but with some extent of spatial heterogeneity. Therefore, beside the spatial autocorrelation, the spatial heterogeneity is another important feature of the distribution of the employment rate of disabled people. To understand the various characteristics of disability employment among different regions and to examine the effectiveness of the existing policy on disability employment, spatial heterogeneity needs to be measured. We defined spatial heterogeneity as the differences in disability employment rates among different cities. When the spatial heterogeneity is more pronounced than autocorrelation, the spatial variance analysis (SVA) method which analyses the variance of the disability employment rate of different regional factor strata should be more appropriate to measure the spatial heterogeneity.

In this study, we compared the spatial autocorrelation r-value with the spatial stratification q-value in order to choose between spatial variance analysis (SVA) (Wang et al. 2010) and spatial clustering analysis methods. The spatial stratification q-value measures the stratified heterogeneity by comparing the global variance and variance of strata after stratification. It has been successfully used by previous studies to analyze the spatial heterogeneity of neural tube defects, under-five mortality, etc. (Wang et al. 2010; Hu et at. 2011). Based on calculation results, we applied a method of geographical detection proposed by Wang et al. (2010) to identify city groups with significantly higher or lower disability employment rates based on data from the Second China National Sample Survey on Disability. In addition to spatial variation analysis, this method also aims to establish connections between regional features and the employment rate of disabled people in different cities. It takes into account the spatial consistency of various

regional features and the employment rate of disabled people, which are traditionally difficult to model. Furthermore, the individual circumstances of all respondents in the cities with significantly higher or lower disability employment rates were included in the analysis of the local employment situation. Our findings may help to raise the awareness of the employment situation of disabled people among policymakers and the general public, and facilitate the initiatives to improve working conditions for disabled people.

2 Material and Methods

2.1 Data Sources

In this study, the employment data of disabled people were derived from the Second China National Sample Survey on Disability. In 2006, with the approval of the State Council, the Leading Group of China National Sample Survey on Disability and the National Bureau of Statistics conducted the Second China National Sample Survey on Disability in all province-level administrative regions of mainland China (Zheng et al. 2011). There are four levels of administrative units in China: the province including autonomous regions and municipalities directly under the Central Government, city, county and town. In this survey a total of 734 counties and 2,980 towns from the 31 provinces, autonomous regions, and municipalities directly under the Central Government were sampled. Interviews were conducted with 2,526,145 people in 771,797 households, and the sampling ratio was 1.93 per 1,000 people (Office of the Second China National Sample Survey on Disability 2007). All survey respondents provided consent to the Chinese government. Strict quality control measures were undertaken at every step of the survey: drafting the sampling frame, field sampling, filling out questionnaires, checking returned forms, inputting data, and checking data quality (Lu 2000).

In the Second China National Sample Survey on Disability, "disability" was defined as having one or more abnormalities in anatomical structure or the loss of an organ or function (either psychological or physiological) that affects a person's ability to perform normal activities. "Employed" meant that the respondent had the ability to earn, or was earning, a salary, or had a family income during the week (25 March, 2006 - 31 March, 2006) prior to the survey. If working time was less than one hour per week the respondent was regarded as being unemployed. Peasant manual labor and family members being employed in shops, retail departments or factories run by their own family were regarded as having jobs with income. Those who were not working because of a holiday or job training, and those who had stopped working temporarily or were seasonally employed were regarded as being employed at the time of the survey (Zheng et al. 2011).

As a result of previous studies (Lai et al. 2008; Kidd et al. 2000; Findlay and Sambamoorthi 2004; Mondéjar-Jiménez et al. 2009; Bell and Heitmueller 200) we included some elements, including regional and individual features, in the study. All regional data came from the 2006 Local Statistical Yearbook for each city, and individual data came from the Second China National Sample Survey on Disability. The regional features included urbanization (the proportion of non-agricultural population in cities), industrial structure, gross domestic product (GDP) per capita, total passenger traffic (total number of passengers transported by all the means of transportation), average worker's wage, proportion of local expenditure which social welfare and social security account for, number of hospital doctors per 10,000 people, medical insurance rate, unemployment insurance rate, and population density. It was noted that industrial structure was determined by Ward's minimum variance method (Ward 1963) according to the proportions of individuals employed in the main industries and the tourism index.

Industrial categories refer to the manufacturing, production and supply of electric power, gas, and water; mining and quarrying; geological prospecting; construction; transport, storage, post, and telecommunications; wholesale and retail trade and catering services; banking and insurance; governments, parties, and social organizations; and other industries. The tourism index was applied to handle the problem of data on employment in tourism cities being sparse. It is a function of the government-authorized tourism ranking and the city's non-farmer population (Wang et al. 2012). The number of cities with the same industrial structure in each classification of cities' industrial structure was determined by selecting the solution with the smallest possible increase in the error sum of squares, a measure of the total sum of squared deviations of each case from the mean for a cluster (Ward 1963). During every classification, the industrial structure of various cities were identified by Nelson's (1955) city classification method. In the Nelson method, the mean of various factors is considered as a "standard" of functional structure and the standard deviation was used to measure functional importance. The individual features included race, education level, and whether the respondent had received a minimum living subsidy, or periodic or temporary relief funding, medical services and assistance, vocational training, or accessible information. Continuous regional data were discretized using Ward's minimum variance method, a statistical criterion, before being applied to spatial analysis.

2.2 Data Analysis

2.2.1 Calculation of the employment rate of disabled people

The survey used methods of probabilistic proportional sampling as multiple tiers, multiple phases and group sampling, in which the whole nation was considered as a general unit and provinces, autonomous regions and municipalities were taken as secondary general units. In accordance with the principle of stratification set, different provinces, autonomous regions and municipalities, according to their own specific conditions, employed a four-stage sampling strategy involving four public purpose corporations (i.e. county, town, village and community). That is, all the provinces, autonomous regions and municipalities first selected 20% of counties as first-level samples according to their population, socio-economic, and terrain conditions. Then four towns were chosen as second-level samples from the selected counties. In the same way, two villages were chosen from each of the selected towns. Finally, only one community with about 400 persons was chosen from every selected village.

Therefore, the unbiased estimator $\overline{\overline{\hat{Y}_u}}$ and the unbiased variance estimator $v\left(\overline{\overline{\hat{Y}_u}}\right)$ representing the initial employment rate of disabled people in each city with sampling counties were computed by multiple-stage sampling equations:

$$\overline{\overline{\hat{Y}_u}} = \frac{R \times \sum_i^r \left(\sum_j^{l_i} \sum_s^{k_{ij}} N_{ijs}\right) \times \overline{y}_i}{r \times N},$$

$$\overline{y}_{ijs} = \frac{\sum_v^{n_{ijs}} y_{ijsv}}{n_{ijs}}, \overline{y}_{ij} = \frac{\sum_s^{k_{ij}} N_{ijs}\overline{y}_{ijs}}{k_{ij}\overline{N}_{ij}}, \overline{y}_i = \frac{\sum_j^{l_i} \left(\sum_s^{k_{ij}} N_{ijs}\right)\overline{y}_{ij}}{l_i\overline{N}_i} \tag{1}$$

$$v\left(\overline{\overline{\hat{Y}_u}}\right) = \frac{1}{N^2}\frac{R^2}{r}(1-f_1)S_1^2 + \frac{R}{r}\sum_i^r \frac{L_i^2}{l_i}(1-f_{2i})S_{2i}^2 + \frac{R}{r}\sum_i^r \frac{L_i}{l_i}\sum_j^{l_i}\frac{K_{ij}^2}{k_{ij}}(1-f_{3ij})S_{3ij}^2$$

$$+ \frac{R}{r}\sum_i^r \frac{L_i}{l_i}\sum_j^{l_i}\frac{K_{ij}^2}{K_{ij}}\sum_s^{k_{ij}}\frac{N_{ijs}^2}{n_{ijs}}(1-f_{4ijs})S_{4ijs}^2, \; f_1 = \frac{r}{R}, \; f_{2i} = \frac{l_i}{L_i}, \; f_{3ij} = \frac{k_{ij}}{K_{ij}}, f_{4ijs} = \frac{n_{ijs}}{N_{ijs}},$$

$$S_1^2 = \frac{1}{r-1}\sum_i^r \left(\left(\sum_j^{l_i}\sum_s^{k_{ij}}N_{ijs}\right)\times \overline{y}_i - \frac{\sum_i^r\left(\sum_j^{l_i}\sum_s^{k_{ij}}N_{ijs}\right)\times\overline{y}_i}{r}\right)^2,$$

$$S_{2i}^2 = \frac{1}{L_i-1}\sum_j^{l_i}\left(\sum_s^{k_{ij}}N_{ijs}\times\overline{y}_{ij} - \frac{\sum_j^{l_i}\left(\sum_s^{k_{ij}}N_{ijs}\right)\times\overline{y}_{ij}}{l_i}\right)^2,$$

$$S_{3ij}^2 = \frac{1}{K_{ij}-1}\sum_s^{k_{ij}}\left(N_{ijs}\times\overline{y}_{ijs} - \frac{\sum_s^{k_{ij}}N_{ijs}\times\overline{y}_{ijs}}{l_{ij}}\right)^2,$$

$$S_{4ijs}^2 = \frac{1}{N_{ijs}-1}\sum_v^{n_{ijs}}\left(y_{ijsv} - \overline{y}_{ijs}\right)^2 \tag{2}$$

where N was the number of sampling cities: R and r were the total number of all counties and sampling counties belonging to a sampling city, respectively; L_i and l_i were the number of all towns and sampling towns belonging to the sampling county i, respectively; K_{ij} and k_{ij} indicated the number of all villages and sampling villages belonging to the sampling town ij, respectively. Similarly, N_{ijs} and n_{ijs} indicated the number of all communities and sampling communities belonging to the sampling village, respectively ijs. y_{ijsv} indicated the employment rate of disabled people in the sampling community v, village s, town j belonging to the sampling county i. The conservative confidence intervals for $\overline{\overline{\hat{Y}_u}}$ were calculated as $\overline{\overline{\hat{Y}_u}} \pm t\left(v\left(\overline{\overline{\hat{Y}_u}}\right)\right)$, where $t()$ was the upper $^{\alpha/2}$ critical value from the $t(n-1)$ distribution.

To provide a single summary measurement, the initial employment rate of disabled people in each city with sampling counties was adjusted to take account of the population structure.

2.2.2 Spatial autocorrelated and heterogeneous estimator

Spatial autocorrelation and spatial heterogeneity are two major features of all spatial objects, and r- and q-values are their corresponding quantitative indices, respectively. The larger the quantitative index, the more obvious the corresponding feature is. If the spatial autocorrelation is dominant, the spatial autocorrelated estimator can be more suitable. Otherwise, if spatial heterogeneity is dominant, the heterogeneous estimator is more suitable. In order to determine an appropriate method for estimating the disability employment rate in the cities with sampling

counties, we calculated the r- and q-values to evaluate its characteristics. The spatial autocorrelation r-value was measured by a semivariogram. It was used to estimate the spatial autocorrelation of the household income census data in Syracuse, New York (Griffith et al. 1994). In this study, the autocorrelation r-value is represented as:

$$r = \frac{1}{NC \times NC \times S^2} \sum_{a,b} \text{cov}\left(y_a^c, y_b^c\right) = \frac{c(h)}{c(0)} \tag{3}$$

$$S^2 = \frac{1}{NC} \sum_{a=1}^{NC} \left(y_a^c - \overline{Y^c}\right)^2 \tag{4}$$

where NC was the total number of cities with sampling counties, and S^2 was the dispersion variance of disability employment rate in all cities with sampling counties. $\text{cov}\left(y_a^c, y_b^c\right)$ is the covariance between y_a^c and y_b^c in two cities a and b. $C(h)$ was the estimated autocovariance at distance h and $C(0)$ was the estimated variance. h was the distance between a random pair of cities with sampling counties.

The quantity (h) was calculated by a constant (K) multiplied by the square root of the area of the entire sampling region in China. The value of the constant K is determined by the shape of the entire sampling region in China (Office of the Second China National Sample Survey on Disability 2007).

The spatial heterogeneity q-value was defined as (Wang et al. 2010):

$$q = 1 - \frac{1}{m \times S_{dis}^2} \sum_{i=1}^{n} m_{geo,i} \times S_{disgeo,i}^2 \tag{5}$$

where vectors $Geo_i(i=1,2,\ldots,n)$ were the attribute values associated with the geographical stratum of a regional feature denoted as $Geo = \{Geo_i\}$; $m_{geo,i}$ was the number of cities with sampling counties in the sub-region i of regional feature attributes Geo_i; and $m = \sum_{i=1}^{n} m_{geo,i}$ was the total number of cities with sampling counties over the entire sampling region A. Moreover, S_{dis}^2 and $S_{disgeo,i}^2$ corresponded, respectively, to the global variance of the employment rate of disabled people in region A, and the dispersion variance of the employment rate of disabled people in the sub-regions of Geo_i. The more differentiated between S_{dis}^2 and $S_{disgeo,i}^2$, the larger the q-value of spatial heterogeneity, while $q \in [0, 1]$.

2.2.3 Spatial statistics

In the study, we used four geographical detectors (risk, factor, ecological and interaction) based on SVA to estimate the relationship between the selected regional features and the distribution of employment, and to detect city groups with significantly higher and lower levels of disability employment rate. SVA is applied to compare the spatial consistency of a specified event distribution (e.g. employment rate) with the geographical strata in which potential features exist. There are many advantages of using geographical detectors to analyze the spatial heterogeneity of disability employment in China:

1. Geographical detectors support both nominal and continuous data. They provide great flexibility in their capacity of accepting input and providing output.
2. Geographical detectors have insight into quantifying connections between regional features and the employment rate of disabled people in different cities due to their spatial variance. This method is particularly suitable for a situation where there is no spatial autocorrelation.

3. Geographical detectors can quantify the interactive effect of two regional features. It can determine whether the combination of two regional features gives a stronger or weaker representation of disability employment rate than the features independently. Moreover, in order to better understand the employment situation of disabled people, the individual circumstances of all respondents in certain areas were included in the subsequent analysis of the local employment situation.

First, we assumed that a grid stratum *grid* covering the study area A at a resolution of approximately 1.5 km, which is the shortest distance between the centers of all cities with sampling counties, was created. Then the employment rate distribution of disabled people *Dis* was overlaid with the grid stratum *grid* and the regional feature stratum $Geo=\{Geo_i\}$. The "even spatial discretization" strategy (Ward 1963) was used to downscale the employment rate of disabled people from *Dis* to $Geo=\{Geo_i\}$. The estimated employment rate of disabled people RA_{geo} in every polygon of the regional feature stratum $Geo=\{Geo_i\}$ can be calculated with the following equations:

$$RA_{geo} = \sum_{dis=1}^{N_{geo,dis}} \frac{Area_{geo,dis}}{Area_{geo}} RA_{geo,dis} \tag{6}$$

$$RA_{geo,dis} = \frac{Area_{geo,dis}}{Area_{dis}} RA_{dis} \tag{7}$$

where $N_{geo,dis}$ is the number of grids which lie within the target polygon of $Geo=\{Geo_i\}$; $Area_{geo,dis}$ and $RA_{geo,dis}$ are the area and employment rate of disabled people, respectively, for each grid mentioned above. Similarly, $Area_{dis}$ and RA_{dis} are the area and employment rate of disabled people, respectively, for the polygon in *Dis* which coincides with those grids.

The factor detector used Equation (5) to calculate the representativeness $R_{geo,dis}$ (equal to *q*) of the regional feature stratum $Geo=\{Geo_i\}$ to the distribution of employment rate of disabled people *Dis*. Note here that $R_{geo,dis}=1$ implies that the distribution of regional features is equivalent to the distribution characteristics of disability employment. The ecological detector was used to explore the most representative regional features. It compared global variances calculated from each sub-region according to one regional feature with that according to another regional feature. If the dispersion variance of a regional feature was significantly larger than that of another feature, this feature was regarded as more representative. The interaction detector quantified the interactive effect of two regional features. For this detector, two regional feature stratums were overlaid and their attributes were combined to form a new attribute. The representativeness of both the original and the new regional feature stratums on the disability employment rate were calculated using Equation (5). The risk detector was applied to detect city groups with significantly higher and lower levels of disability employment rates. According to the central limit theorem, the mean employment rates of disabled people are supposed to be normally distributed. From the super-population perspective (i.e. realizations from a theoretical population), the mean is a single realization of an underlying process (Griffith et al. 1994). Therefore the risk detector used Student's t-distribution to compare the different average values between sub-regions. The greater the difference, the more obvious the employment cluster of disabled people.

The tools applied in this study to evaluate the geographic detectors are available at http://www.sssampling.org/GeoDetector.
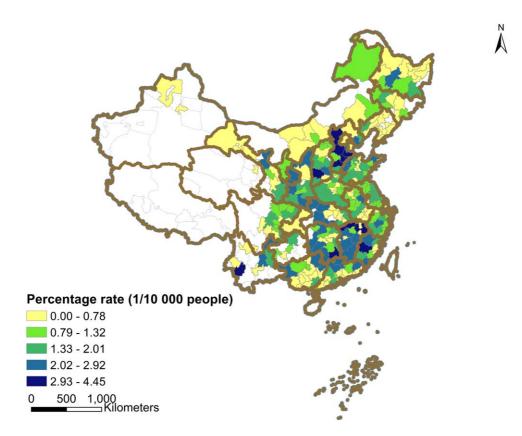
Figure 1 Estimated employment percentage rate of people with disabilities in sampling cities, China

3 Results

Figures 1 and 2 illustrates the spatial distribution of the employment rate of disabled people in cities in the sampling counties of China.

   According to Equations (1) and (2), we also calculated the employment rate of disabled people in all sampled counties and provinces. The results in Table 1 indicate that there are no significant differences among the rates of disability employment at county, city, and province levels. It was identified that spatial scale seems to have very little impact on the trend and distribution of disability employment.

   In the entire sampling range, distance h equals to 1883.39 km. The sill, nugget, and range value of the variogram used in this study are respectively 0.41, 0.0, and 102.07 km. The distance is obviously beyond the range, and spatial autocorrelation r-value is 0. Therefore, the disability employment rates of all cities with sampling counties are not spatially correlated. However, spatial heterogeneity q-values of selected regional feature stratums are all more than 0. It means that spatial heterogeneity exists in the sampling targets. So we chose geographical detection, a spatial variance method, to evaluate the connections between regional features and the disability employment rate and to identify city groups with significantly higher or lower disability employment rates.

   The factor detector shows that regional feature stratums are ranked by their representative-ness ($R_{geo,dis}$) as follows: the number of hospital doctors per 10,000 people (18.38%) > total
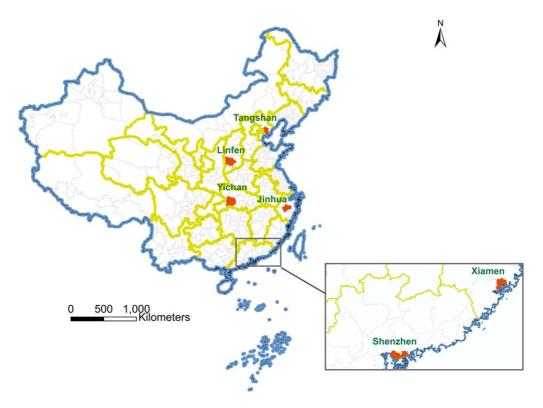
Figure 2 Cities with significantly higher or lower employment percentage rate of people with disabilities in China

Table 1 Descriptive statistics for disability employment rates at different spatial scales (unit: 1/10 000 people)

Spatial scales	Minimum value	Maximum value	Mean value	Std. Deviation value
County	2	89	16	11
City	2	102	4	7
Province	1	21	8	4

passenger traffic (13.42%) > urbanization rate (12.58%) > industrial structure (10.41%) > GDP (per capita) (9.97%) > medical insurance rate (9.39%) > unemployment insurance rate (8.61%) > average worker's wage (8.45%) > population density (7.41%) > the proportion of local fiscal expenditure which social welfare accounts for (6.32%) > the proportion of local fiscal expenditure which social security accounts for (3.57%).

The ecological detector (Table 2) shows that differences of the representativeness $R_{geo,dis}$ between number of hospital doctors per 10,000 people and other features are statistically significant. Additionally, the differences between: industrial structure and GDP per capita; industrial structure and total passenger traffic; average worker's wage and the proportion social welfare accounts for; and average worker's wage and the proportion with social security accounts, are also statistically significant. Differences between the other features included in

Table 2 Statistical significance of the risk difference between various factors

	Doctors	Passenger traffic	Urbanization rate	Industrial structure	GDP	Medical insurance rate	unemployment insurance rate	Work's age	Population density	Social welfare	Social security
Doctors											
Passenger traffic	Y										
Urbanization rate	Y	N									
Industrial structure	Y	Y	N								
GDP	Y	N	N	Y							
Population Density	Y	N	N	N	N						
Medical insurance rate	Y	N	N	N	N						
unemployment insurance rate	Y	N	N	N	N	N					
Work's age	Y	N	N	N	N	N	N				
Population density	Y	N	N	N	N	N	N	N			
Social welfare	Y	N	N	N	N	N	N	Y	N		
Social security	Y	N	N	N	N	N	N	Y	N	N	

Note: Y means the risk difference between the factors is significant with the confidence of 95%, and N means it is not significant.

the survey are not statistically significant. Results from the factor and ecological detectors show that the number of hospital doctors per 10,000 people has strong regional representativeness for disability employment, whereas the other features have weak local representativeness.

The findings from interaction analysis between the different detectors are shown below. All features were found to enhance the others' impacts and thus increased their individual representativeness in the distribution of disability employment. The results of interactive effects are: hospital doctors per 10,000 people and average worker's wage (31.78%); urbanization rates and average worker's wage (31.42%); urbanization rates and total passenger traffic (30.58%); hospital doctors per 10,000 people and GDP per capita (29.45%); hospital doctors per 10,000 people and total passenger traffic (29.31%); and unemployment insurance rate and average worker's wage (28.64%), are all larger than the single effect of number of hospital doctors per 10,000 people (18.38%), which has the strongest sole representativeness in the disability employment cluster. This shows that interactions between features play an important role in the distribution of disability employment.

We also estimated the interactive effects of some multiple (two or more) regional features on the representativeness of disability employment. The most significant interactive impact was identified among the factors: number of hospital doctors per 10,000 people, total passenger traffic, average worker's wage, and urbanization rates, and this achieves 42.80%.

The result from risk detector analysis shows that the employment rates of disabled people in cities such as Tangshan, Linfen, Jinhua and Yichang, having relatively scarce medical resources, a low urbanization rate and low employee salaries, are significantly higher than those in other cities. Furthermore, the employment rate of disabled people in Shenzhen and Xiamen, having plentiful medical resources, a high urbanization rate, frequent people movement and high employee salaries, are significantly lower than other cities with sampling counties (see Figure 3).

4 Discussion and Conclusions

The problem of disability employment is complicated. In comparison with other studies, this study first attempted to identify the regional representativeness of areas of interests, then analyzed the reasons behind the spatial heterogeneity of disability employment on a sub-regional
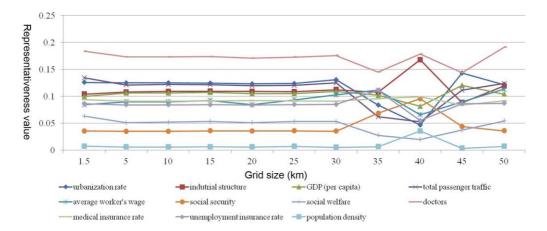

Figure 3 Representativeness of various regional features for different values of grid size

scale. This study identified that the geographical heterogeneity level of disabled employment identified at sub-regions was close to the heterogeneity level of the entire study region. The local representativeness of the features studied was weak. However, the interactive effects of features on disability employment increased when the number of hospital doctors per 10,000 people interacted with total passenger traffic, average worker's wage, and urbanization rates. This suggests that the employment clusters of disabled people are influenced by local features. This finding is consistent with previous Chinese studies (Lai et al. 2008).

This study also revealed that some high levels of disabled employment appeared in the cities with relatively poor economic and medical conditions and, similarly, low employment levels were found in some relatively developed cities. These findings are different from the initial understanding of disabled employment, which were caused by a number of factors, including both organizational and individual factors.

In areas of low employment, the major source of income for 65.49% of unemployed disabled people of 15 years or older, is the basic living premium provided by the local government. A previous study concluded that non-participation in the labor market is often associated with take-up of welfare benefits (Wilkins 2003). This may be a reason for the low disabled employment rates. Therefore, the government should conduct economic and administrative measures to encourage disabled people to find jobs, while the corresponding assistance from governmental agents or the society will also be appreciated. Low employment areas identified in this study are normally in industry-oriented commercial cities with more sophisticated technology and knowledge-based systems of production and services. Firms in such cities are more likely to look for a work force that is not only technically trained, but also skilled in managing rapidly changing businesses (Reich 1991). However, 55.75% of unemployed disabled people of 15 years or older only attained a junior middle school diploma, or never attended school. Furthermore, 99.12% of unemployed disabled people have not received any vocational training. It is difficult for the disabled with low education and skill levels to find a job in these competitive cities. It is also noted that the ethnic minorities with disabilities account for 87.17% of unemployed disabled people, and 87.22% of the disabled population in these cities. Therefore, additional work opportunities should be provided to those among ethnic minorities with disabilities.

In the cities with significantly higher disability employment rates, 61.16% of unemployed disabled people of 15 years or older were supported by other family members. However, according to the survey data, the 2005 total household income in 91.51% of unemployed disabled people's families was less than 6,000 RMB. Living under difficult circumstances induces people with disabilities to find jobs. Moreover, cities with high levels of disability employment share these features: medium-sized, integrated cities or mining cities. The primary engine of economic development in these cities is based on mass-production industries and low-skill service jobs. A low employment threshold makes it easier for persons with disabilities to find employment. However, the employment rate of disabled males in these cities is approximately double that of disabled females, i.e. 35.52% vs. 18.03%. The overall unemployment rate of disabled females is 81.79%. Based on this fact, the government should not only provide support to those disabled people who cannot work, but should also be encouraged to minimize or eliminate gender discrimination, by either law or social media.

In this study, information about the disability employment rates and regional features was extracted from the location of the grids when we applied the geographical detectors to explore the geographical heterogeneity of disabled employment across various cities with sampling counties, and to estimate the representativeness of selected regional features on the distribution of employment. A proper grid size is important to improve the accuracy of the results of

geographical detectors. Therefore, this article also evaluates the grid size in the statistical experiment. Constant values for representativeness ($R_{geo,dis}$) of various regional features for different values of grid size were applied to analyze their impact on the stability of the results. Figure 3 shows that there are few differences between the representativeness values of all regional features if the grid size changes from 1.5 to 50 km.

This study has several limitations and has identified a number of points that require further analysis. One limitation of this article is that the geographical detectors measure association rather than causation. An examination of why disability employment rates are low or high in specific places should be undertaken to identify relevant factors and/or policy targets. Furthermore, it is possible that the distribution of employment rates of a particular population does not follow specific spatial patterns and hence a further field sampling survey is necessary (Wang et al. 2010). The choice of regional features and the development of the grid stratum require further investigation. Discretization of quantitative factors will result in a loss of information, and thus actual relationship between features and the prevalence of injury-related disability might be hidden.

However, based on the literature review, this is first application of spatial statistics to examine the employment of disabled people in China. It provides a number of insights into the effects of the complex interactions between various regional features on disability employment. The geographical detectors used in this study are derived from the spatial variance analysis of the spatial consistency of employment rate distribution with regional feature strata. The validation of the results is provided by statistical significance tests. These detectors are easy to implement, and are suitable for both continuous and categorical variables (Wang et al. 2010). They provide an innovative and systematical method to address the difficulties in disability employment problems.

References

Bell D and Heitmueller A 2009 The Disability Discrimination Act in the UK: Helping or hindering employment among the disabled? *Journal of Health Economics* 28: 465–80

Beresford P 1996 Poverty and disabled people: Challenging dominant debates and policy. *Disability and Society* 11: 553–67

Borg J, Linfström A, and Larsson S 2009 Assistive technology in developing countries: National and international responsibilities to implement the convention on implement the convention on the rights of persons with disabilities. *Lancet* 374: 1863–65

Botticello A L, Rohrbach T, Cobbold N 2014 Disability and the built environment: An investigation of community and neighborhood land uses and participation for physically impaired adults. *Annals of Epidemiology* 24: 545–50

Braithwaite J and Mont D 2009 Disability and poverty: A survey of World Bank poverty assessments and implications. *European Journal of Disability Research* 3: 219–32

Campolieti M and Riddell C 2012 Disability policy and the labor market: Evidence from a natural experiment in Canada, 1998-2006. *Journal of Health Economics* 96: 306–16

DFID (Department for International Development) 2000 Disability, Poverty and Development. WWW document, http://www.miusa.org/idd/resources/dispolicies/disabilitypoverty/view.html

Elwan A 1999 *Poverty and Disability: A Survey of the Literature*. New York, World Bank Social Protection Discussion Paper Series No. 9932

Findley P A and Sambamoorthi U 2004 Employment and disability: evidence from the 1996 medical expenditures panel survey. *Journal of Occupational Rehabilitation* 14: 1–11

Gialis S and Tsampra M 2015 The diverse regional patterns of atypical employment in Greece: Production restructuring, re/deregulation and flexicurity under crisis. *Geoforum* 62:175–187

Griffith D A, Haining R, and Arbia G 1994 Heterogeneity of attribute sampling error in spatial data sets. *Geographical Analysis* 26: 300–20

Haining R 1988 Estimating spatial means with an application to remotely sensed data. *Communications in Statistics: Theory and Methods* 17: 573–79

Hu Y, Wang J F, Li X, Ren D, and Zhu J 2011 Geographical detector-based risk assessment of the under-five mortality in the 2008 Wenchuan earthquake, China. *PloS ONE* 6: 2592–99

Kidd M P, Sloane P J, and Ferko I 2000 Disability and the labour market: An analysis of British males. *Journal of Health Economics* 19: 961–81

Lai D S, Liao J, and Liu W 2008 Employment of the disabled and its determinants in China. *Journal of Renmin University of China* 1: 10–5 (in Chinese)

Lu Y 2000 Spatial cluster analysis for point data: Location quotients versus kernel density. In *Proceedings of the Information Science Summer Assembly*, Portland, Oregon

Mitra S 2006 The capability approach and disability. *Journal of Disability and Policy Studies* 16: 236–47

Mondéjar-Jiménez J, Vargas-Vargas M, Meseguer-Santamaría M L, Mondéjar-Jiménez J A 2009 Impact of social factors on labour discrimination of disabled women. *Research in Development Disabilities* 30: 1115–23

Ripley B 1981 *Spatial Statistics*. New York, John Wiley and Sons

Nelson H J 1955 A service classification of American cities. *Economic Geography* 31: 189–210

Office of the Second China National Sample Survey on Disability 2007 *Documentation of the Second China National Sample Survey on Disability*. Beijing, China, China Statistics Press

Reich R B 1991 The real economy. *Atlantic Monthly* 267(2): 35–52

US. Bureau of the Census. (1993). Current Population Reports, Series P60-185, Poverty in the United States. Washington, DC, US. Government Printing Office.

Wang J F, Haining R, and Cao Z D 2010 Sample surveying to estimate the mean of a heterogeneous surface: reducing the error variance through zoning. *International Journal of Geographical Information Science* 24: 523–43

Wang J F, Liu X H, Christakos G, Liao Y L, Zhang T, Gu X, and Zheng X Y 2010 Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region, China. *International Journal of Geographical Information Science* 24: 107–27

Wang J F, Liu X H, Peng L, Chen H Y, Driskell L, and Zheng X Y 2012 Cities evolution tree and applications to predicting urban growth. *Population and Environment* 33: 186–201

Ward J H Jr 1963 Hierarchical grouping to optimize an objective function. *Journal of the American Statistical Association* 58: 236–44

Wang Z B, Zhu C G, and Sun F H 2007 Employment spatial models and mechanism of Shandong Province. *China Population, Resources and Environment* 17(2): 131–35

Wilkins R 2003 *Labor Market Outcomes and Welfare Dependence of Persons with Disabilities in Australia*. Melbourne, Victoria, Melbourne Institute of Applied Economic and Social Research

Yeo R and Moore K 2003 Including disabled people in poverty reduction work: Nothing about us, without us. *World Development* 31: 571–90

Zheng X Y, Chen G, Song X M, Liu J F, Yan L J, Du W, Pang L H, Zhang L, Wu J L, Zhang B Z, and Zhang J 2011 Twenty-year trends in the prevalence of disability in China. *Bulletin of the World Health Organization* 89: 788–97