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Spatial analysis of the relationship between out-of-pocket expenditure and socioeconomic status in South Korea

Young Gyu Kwon,[1] Man Kyu Choi[1,2]

[1]Department of Health Policy & Management, College of Public Health Science;
[2]BK21 FOUR R&E Center for Learning Health Systems, Korea University, Seoul, Republic of Korea

Abstract

The rapid increase in the out-of-pocket expenditure for healthcare in South Korea (the share of the total cost paid by the patient) negatively affects public health and raises the issue of equity in medical access opportunities according to the level of income. Most previous studies on out-of-pocket expenditure do not consider the environmental impact at the regional level. Individual health and quality of life improve as social relationships are formed and centred on the individual residential situation when seen in the local community context. Therefore, this study investigated the potential gap with respect to out-of-pocket expenditures by examining the factors influencing co-payments by region using a geographically weighted regression (GWR) model. A spatial analysis of outpatient out-of-pocket expenditures for 237 local governments across the country, excluding islands and island regions, was conducted from 2015 to 2020. The out-of-pocket expenditure incurred was found to have regional correlations and be influenced by community factors. The GWR model showed a better fit than the ordinary least squares (OLS) one. Significant hotspots were identified and the influence of regional factors on out-patient out-of-pocket expenditure was shown to vary by region. The results showed that if social and economic resources are appropriately invested in areas identified as vulnerable, a spill-over effect in neighbouring areas can be expected. This study provides new insights on policy strategies for co-payment management to regional healthcare policymakers and it can be used as a basis for the distribution of customised healthcare resources by region.

Correspondence: Man Kyu Choi, BK21 FOUR R&E Center for Learning Health Systems, Korea University, 145, Anam-ro, Seongbuk-gu, Seoul, Republic of Korea.
Tel.: +82.2.3290.5669
E-mail: mkchoi@korea.ac.kr

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Introduction

Until 2020, the out-of-pocket expenditure for healthcare in South Korea (the share of the total cost paid by the patient) was 27.8%, which was considerably higher than the average (18.1%) among the Organisation for Economic Co-operation and Development (OECD) (OECD Health Statistics, 2022). In addition, with regard to the share of tax and public health insurance in medical expenses, most OECD countries have a high coverage rate of (≥70%), whereas South Korea's rate is only 62.6% (OECD Health Statistics, 2022).

A sharp increase in out-of-pocket expenditure can drive low- and middle-income households into poverty and disrupt living standards by limiting basic medical needs (Asante *et al*., 2016). Therefore, it is necessary to carefully review the structural aspects of the healthcare system at the local level. In a study by Kim *et al.* (2005) comparing previous studies at home and abroad, it was reported that patients with long hospitalisation stays and high household incomes strongly affect the out-of-pocket expenditure, which is commonly higher for old patients, those living in large cities and those using general, tertiary hospitals. According to An (2011), there is a statistically significant higher effect on the out-of-pocket expenditure for women than for men in South Korea. The same is true for patients aged 65 years or older; patients whose annual household gross income exceed KRW 46 million (USD 34,800); or patients admitted to hospitals or comprehensive specialised nursing institutions in the medical institution category. Chou *et al.* (2009) found that variables, such as the gross domestic product (GDP), old age, urbanisation and the number of hospital beds available had a significant impact on the health expenditure per capita. For example, in Australia, aboriginal and coastal islanders, people with chronic conditions and those living in rural and remote areas disproportionately incur high out-of-pocket expenditures (Laba *et al*., 2014), a spatial dependence on the per capita health expenditure as identified by Bose (2014).

Previous studies focused on the analysis of the relationship between independent and dependent variables in this area of research include work by Kim *et al.* (2005), Yang (2007), Kim *et al.* (2011), An (2012), Malik *et al*. (2012), Bose (2014), Zhang *et al.* (2019), Tang *et al*. (2021) and Mwale *et al.* (2022). Investigation of potential associations between independent and dependent variables is commonly carried out using the ordinary least squares (OLS) methodology. However, because OLS assumes that the dependent variables and errors are mutually independent and have equal variance, the spatial variation caused by spatial heterogeneity cannot be identified leading to loss of regional estimates and efficiency of parameter estimation (Joo *et al*., 2013). Ultimately, policy decisions on the inequality of demand and supply with regard to medical services would suffer, and public health experts and policymakers cannot make effective decisions for specific regions (Bai *et al.,* 2021).

This study used a spatial regression model to identify the influence of regional factors on outpatient out-of-pocket expenses. The specific purpose was to: i) identify the regional coefficient of out-patient out-of-pocket expenses in South Korea; ii) compare demographic/social/economic factors, urbanisation, and healthcare resources for out-patient out-of-pocket expenditures searching the most suitable statistical model; and iii) distinguish regions with high regional regression coefficients for out-patient out-of-pocket expenditures and suggesting health policies that can be applied. To this end, the regional distribution of the distribution of out-of-pocket expenditure was visualised and spatial autocorrelation investigated.

Materials and Methods

Study area

All data in this analysis were collected from 2015 to 2020 from 237 cities, counties and districts, excluding islands and island regions. These were secondary data released by the most recent Community Health Survey.

Variables

The out-of-pocket expenditure, defined as the share of the total out-patient treatment cost (excluding national health insurance fees) borne by the patient in question was the dependent variable. It was calculated by dividing each city, county and district by the number of treated out-patients there. We used three types of independent variables related to i) socioeconomy; ii) urbanisation; and iii) available health resources.

The socioeconomic variables were the average health insurance premiums (substituting for income level) and the ratio of the number of ≥65 years olds per population. The data on medical care by area were those announced by the National Health Insurance Corporation. Road pavement was selected as the urbanisation factor based on information from the National Statistical Office. The healthcare resource factors were the type of medical institutions available, number of hospital beds per 1,000 people and number of doctors per 1,000 people based on information from the National Health Insurance Corporation. Table 1 shows the summary description of variables used.

Statistical methods applied

Ordinary least squares (OLS)

This global regression model explores the association between a response variable and explanatory variables. Assuming stationary and linear relationships between out-of-pocket expenditure and socioeconomic status as used by Hutcheson *et al.* (2011), we applied the formula:

$$y_i = \beta_0 + \beta X_i + \varepsilon_i \qquad \text{(Eq. 1)}$$

where y_i represents the out-of-pocket expenditures in South Korea for region *i*; β_0 the intercept; β the estimated coefficients vector of dependent variables; and the selected dependent vector. R software (version 4.1.1) was used for the analysis. We tested the normality, homoscedasticity and spatial autocorrelation of errors, which are basic assumptions of the general regression model, using the Jarque-Bera test (1981) and the Koenker (Breusch-Pagan) statistic (Koenker and Bassett Jr., 1978) confirming the accuracy by the adjusted R^2 and the Akaikeinformation criterion (AIC) (Akaike, 1974).

Geographically weighted regression (GWR)

Since OLS assumes that dependent variables and errors are each mutually independent granting equal variance, spatial varia-

Table 1. Characteristics of the variables used in the study.

Category			Definition	
Dependent variable		Out-of-pocket expenditure	Medical cost – National Health Insurance reimbursement fee)/number of patients based on out-patients (KRW/1,000)	
Independent variables	Socioeconomy	Health insurance	Average health insurance premium (KRW/1,000)	
		Age	Ratio of population ≥65 years old (%)	
	Urbanisation	Pavement	Length of pavement (metres)	
	Health resource	Medical institution	General hospital	Hospitals with ≥100 beds (no.)
			Smallhospital	Hospitals with>100 beds(no.); normally = 30-100
			Clinic	Clinics (no.)
			Public health centre	Medical centres without beds (no.)
			Beds	Beds per 1,000 population (no.)
			Doctors	Doctors per 1,000 population (no.)

KRW=South Korean Won.

tion due to spatial heterogeneity and regional characteristics cannot be considered, the efficiency of parameter estimation decreases. To solve the heteroscedasticity problem caused by spatial heterogeneity, the GWR model estimates the change in parameters by region through kernel weight regression as shown by Fotheringham and Oshan (2016), we used the following GWR formula:

$$y_i = \beta_{i0} + \sum_{j=1}^{m} \beta_j X_{ij} + \varepsilon_i, i = 1,2, \dots, n \quad \text{(Eq. 2)}$$

where y_i denotes out-of-pocket expenditures; β_{i0} the intercept for region i; m the number of independent variables; β_j the estimated coefficient of the j^{th}, X_{ij} the j^{th} variable in region i; and ε_i the error term. Calculations were carried out using the free GWR software, version 4.0.9 (https://gwr4.software.informer.com/download/) as done by Nakaya *et al*. (2009). Goodness-of-fit were tested by the adjusted R^2 asnd AIC as decribed for OLS.

Spatial autocorrelation

Spatial data refer to interdependencies and interactions that show similar characteristics between geographic spaces.The closer they are spatially, the more similar their characteristics are and the higher the correlation (Anselin and Bera, 1998). In this study, Moran's I statistic (1950) was used as expressed below:

$$I = \frac{N \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{(\sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij}) \sum_{i=1}^{n} (Y_i - \bar{Y})^2} \quad \text{(Eq. 3)}$$

where N is the number of regional units; $\bar{Y}$ the dependent variable; Y_i the mean of region I region; and w_{ij} the spatial weighting matrix of the i and j points. Moran's I determines the statistical significance through the Z-scoreusing the basic formula:

$$Z = \frac{I - E(I)}{S_e(I)} \quad \text{(Eq. 4)}$$

where $E(I)$ and $S_e(I)$ are the mean and standard deviation of the statistics, respectively. The spatial autocorrelation as expressed by Moran's I ranges from –1 to +1, with positive correlations indicated by outcomes close to +1 and negative ones close to –1 (Roh, 2013). Geoda, version 1.20.0.1(https://gisgeography.com/geoda-software/) was used to calculate this autocorrelation.

Hotspots of each city were calculated using the Local Indicators of Spatial Association (LISA) as published by Anselin (1995). There are four major patterns: High-High (HH), which means that the dependent variable in one area has a high value and that of the surrounding areas as well; High-Low (HL), which means that the dependent variable in one area has a high value, and that of the surrounding areas are low; Low-High (LH), means that the value of the dependent variable in one area is lower than that in the surrounding areas; and Low-Low (LL), which means that the dependent value in one area is as low as in the surrounding areas.

Results

Regional variations in out-patient out-of-pocket expenditure

Table 2 shows the results for the top five and bottom five of out-of-pocket expenditure groups by city/county and district-from2015 to 2020. As can be seen in the table, the areas remained at the same level for only a few of the tree time periods investigated but otherwise varied; however, they generally stayed in the same group.

Spatial autocorrelation

Figure 1 shows the spatial autocorrelation according to Moran's I of the out-of-pocket expenditure, which gradually decreased reaching 0.255; 0.210; and 0.156 in the periods 2015-2016; 2017-2018; and 2019-2020, respectively, with all values statistically significant. Considering local autocorrelation among the 237 cities/counties and districts nationwide, several areas showed considerable clustering, both of the HH and the LL type. The former appeared in provincial areas, *e.g.*, in Chungcheongnamdo, Jeollabuk-do and Gyeongsangbuk-do, while the LL clusters were more common in metropolitan cities, such as Seoul, Gyeonggi, Incheon and Ulsan.

Table 2. Upper and lower ranking of areas in South Korea with regard to out-of-pocket expenditure.

Time & area Rank	2015-2016 City/ county, districts	Expenditure*	2017-2018 City/ county, districts	Expenditure*	2019-2020 City/ county, districts	Expenditure*
Upper level						
1	Buan-gun, Jeonbuk	259.0	Yeonggwang-gun, Jeonnam	291.1	Yeonggwang-gun, Jeonnam	318.8
2	Yeonggwang-gun, Jeonnam	256.6	Buan-gun, Jeonbuk	286.6	Buan-gun, Jeonbuk	309.4
3	Goheung-gun, Jeonnam	240.9	Goheung-gun, Jeonnam	260.6	Iksan-si, Jeonbuk	292.7
4	Sangju-si, Gyeongbuk	225.9	Iksan-si, Jeonbuk	257.5	Gangneung-si, Gangwon-do	288.0
5	Iksan-si, Jeonbuk	224.8	Sangju-si, Gyeongbuk	256.5	Sangju-si, Gyeongbuk	285.1
Lower level						
1	Gangseo-gu, Seoul	75.0	Gangseo-gu, Seoul	96.1	Gangseo-gu, Seoul	112.0
2	Uiwangsi, Gyeonggi-do	99.0	Uiwang-si, Gyeonggi-do	110.2	Gyeryong-si, Chungcheongnam-do	118.7
3	Gwacheonsi, Gyeonggi-do	100.0	Gyeryong-si, Chungcheongnam-do	114.9	Uiwang-si, Gyeonggi-do	119.6
4	Gwonseongu, Suwon	105.5	Gwacheon-si, Gyeonggi-do	115.6	Gwacheon-si, Gyeonggi-do	120.8
5	Sujigu, Yongin	106.0	Yangyang-gun, Gyeonggi-do	115.8	Yangyang-gun, Gyeonggi-do	121.4

*KRW/1,000.

Descriptive analyses

Table 3 shows the results of the descriptive statistical analyses. From 2015 to 2020, the average out-patient out-of-pocket expenditure ranged from KRW 160,000 (USD 120) to KRW 200,000 (USD 150). The average health insurance premiums ranged from KRW 85,000 (USD 64) to KRW 101,000 (USD 76), the old age percentage from 18% to 21%, and the length of road pavement from 445,1 to 475,3 meters. With respect to medical institutions per city/county, the average number of general hospitals was always one and that of small hospitals six, while it varied between 244 and 263 for clinics. The average number of public health centres stayed the same at 14 throughout the study, with the number of hospital beds at 15 and that of doctors at 3 throughout the study (Table 3).

OLS·GWR regression analysis

Table 4 compares the results of OLS and GWR for the 237 areas under study. From 2015 to 2020, the number old people, general hospitals, clinics, public health centres, and hospital beds had a positive effect on out-patient out-of-pocket expenditure, but the size of the regression coefficient varied slightly between the periods under study. Figure 2 shows the distribution of the GWR coefficients. When comparing the two models, the largest difference waswith regard to the number of clinics. It was found that the OLS coefficient between the number of clinics and level of out-of-pocket expenditure had a positive regression, while the GWR one ranged from negative to positive. During the study period, there was a difference in the coefficient of determination depending on the region, and the closer it was to the Chungcheong-do and

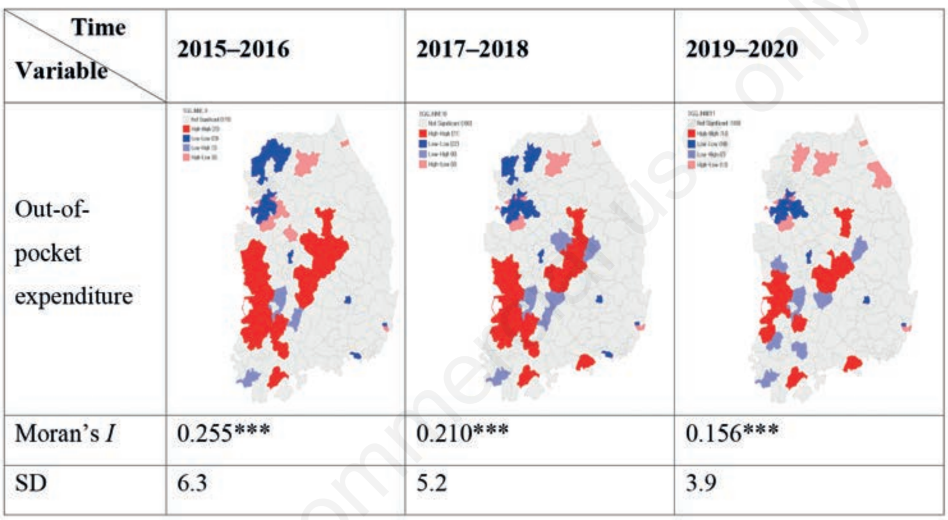

Figure 1. Spatial autocorrelation of out-patient out-of-pocket expenditure in South Korea. SD=standard deviation; *P<0.05, **P<0.01 and ***P<0.001.

Table 3. Descriptive statistics.

Time & type of data / Variable	2015-2016 Mean	SD	Min	Max	2017-2018 Mean	SD	Min	Max	2019-2020 Mean	SD	Min	Max
Out-of-pocket expenditure (KRW)	16	31	75	259	179	35	96	291	200	39	112	319
Health insurance (KRW)	85	18	55	166	91	2	58	181	101	23	65	209
Age ≥65 years (%)	18	8	7	37	19	8	7	39	21	8	8	41
Road pavement (m)	445,035	295,075	51,732	1,665,143	462,203	305,499	55,276	1,689,989	475,315	312,568	55,276	1,729,169
Medical institution												
General hospital (no.)	1	1	0	7	1	1	0	7	1	1	0	7
Small hospital (no.)	6	6	0	34	6	6	0	33	6	6	0	33
Clinic	244	253	7	2,404	254	263	6	2,489	263	273	6	2,597
Public health centre (no.)	14	12	0	44	14	12	0	44	14	12	0	44
Beds (no.)	15	9	0	63	15	10	0	69	15	9	0	68
Doctors (no.)	3	2	1	22	3	2	1	23	3	2	1	20

SD=standard deviation; KRW=South Korean Won.

Gangwon-do regions, the higher the GWR value. Figure 2 showed that the regression coefficients for each region differed depending on the variable in question.

Accuracy assessment

The suitability of the OLS and GWR models was confirmed by comparing the adjusted R^2 and the AIC. According to general practice, the latter is the preferred statistic for evaluating goodness of fit, but it requires a value greater than 4 to indicate a clear difference between readings (Cho, 2010; Jo *et al.*, 2014). The AIC indices for the OLS regression analysis from 2015 to 2016;2017 to 2018; and 2019 to 2020 were 2,158.2; 2,222.6; and 2,289.1, respectively, while those for the GWR model were 2,155.2; 2,216.9; and 2,278.1, respectively, an outcome suggesting that the GWR model was more suitable than OLS in this study (Table 4).

Discussion

In the OLS analysis, the out-patient out-of-pocket expenditure generally increased with the percentage of old age per npopulation, while the GWR regression coefficient differed by region. This outcome is consistent with a large number of previous studies that show that the burden of medical expenses grows as the population ages. According to Kim (2011), the increase of older adults in the population is the primary reason for increasing medical expenses. Through a spatial panel analysis of 48 states in the United States, Bose (2014) suggests that the higher the proportion of older adults in the population, the higher the per capita medical expenditure. Zhang *et al*. (2019), using geographic information systems (GIS) analysis of a panel of data from 31 regions in China, argue that ageing of the population is, directly and indirectly, significantly related to the out-of-pocket expenditure, and Łyszczarz *et al*. (2021), based on the association between socioeconomic factors and out-of-pocket expenditures in 16 Polish regions, found that the out-of-pocket expenditure increased by 8.5%when the proportion of the elderly in the total population increased by 1%. It is thus evident that the burden of co-payments increases when the population ages, suggesting that it is difficult to manage excessive medical expenses with the current health insurance system alone. Considering the burden of medical expenses that may arise from South Korea's unprecedented, rapidly ageing population, it is necessary to develop policies and services to reduce the burden of medical expenses at the local government level.

Second, according to the OLS analysis, the number of general hospitals, clinics, and public health centres had a significant effect on the out-patient out-of-pocket expenditure, as shown by the regression coefficients. This is similar to the results of previous studies, which found that patients' out-of-pocket expenditures increase when tertiary, general hospitals are chosen (Kim, 2011). However, the interpretation is not straightforward because this study did not use regional data for the analysis.

Third, the OLS analysis showed that the number of beds had a significant effect on the out-patient out-of-pocket expenditure. However, this is still a contended issue. In a spatial model study by Zhang *et al.* (2019), the number of hospital beds was found to increase the co-payment component, directly or indirectly, while Yang *et al.*'s (2021), based on the fixed effects model, showed that the effect of increasing the number of hospital beds in the district and district units decreased co-payment. Considering that the results of these preceding studies differed, follow-up studies at the individual and regional levels are needed for an accurate interpretation. Unlike previous studies, we found that the number of doctors did not significantly impact the per capita health expenditure. Łyszczarz *et al.* (2021), on the other hand, found that medical expenditures increased by 1.8% when the availability of doctors increased by 10%. However, in our study, the correlation between the number of doctors and out-of-pocket expenditures was not significant, indicating that the demand for incentives by medical per-

Table 4. Resulting coefficients of the influential factors measured by OLS and GWR.

Time	2015-2016					2017-2018					2019-2020				
Variable	OLS	GWR			VIF	OLS	GWR			VIF	OLS	GWR			VIF
		Min	Med	Max			Min	Med	Max			Min	Med	Max	
Intercept	108.6	80.9	99.2	140.5		124.3	77.8	112.4	150.3		145.1	97.6	127.5	179.9	
Health insurance	-0.2	-0.7	-0.1	0.2	3.2	-0.2	-0.8	-0.2	0.4	3.4	-0.2	-0.8	-0.2	0.2	3.4
Age ≥65 years	1.3***	0.7	1.7	2.3	3.6	1.3***	0.6	1.9	2.5	3.4	1.1*	0.4	1.6	2.4	3.4
Road pavement	0.00	-0.00	0.00	0.00	1.3	0.00	-0.00	0.00	0.00	1.3	0.00	-0.00	0.00	0.00	1.3
Medicalinstitution															
General hospital	8.4***	6.5	7.9	19.7	1.9	10.3***	7.3	9.5	26.3	2	11.4***	8.1	10.9	30.9	2
Small hospital	-0.5	-1.6	-0.4	0.05	3.2	-0.6	-2.1	-0.2	0.6	3.3	-0.8	-2.8	-0.3	0.7	3.4
Clinic	0.03*	-0.00	0.02	0.07	4.6	0.03*	-0.04	0.02	0.12	4.9	0.04**	-0.02	0.02	0.13	5
Public health centre	1.1***	0.5	1	1.3	2.2	1.2***	0.5	1.2	1.5	2.1	1.3***	0.7	1.4	1.8	2.1
Number of beds	0.7*	0.2	0.9	2.1	2	0.7**	0.1	0.8	2.4	2	0.8**	0.2	0.8	2.9	2
Number of doctors	-0.2	-3.7	-0.2	2.2	2.1	-0.01	-3.3	0.02	4.9	2.2	0.5	-4	0.3	6.1	2.2
Adjusted R^2	0.48		0.52			0.46		0.52			0.42	0.5			
AIC	2,158.2		2,155.20			2222.6		2,216.90			2289.1		2,278.1		
Jarque-Bera	8.5*					5					1.1				
Koenker (BP) statistic	9					13.3					19.5				

OLS=ordinary least squares; GWR=geographically weighted regression; VIF=variance inflation factor; Med=Median;Koenker(BP) Statistic=Koenker's studentized Bruesch-Pagan statistic; AIC=Akaike Information Criterion; *P<0.05, **P<0.01 and ***P<0.001.

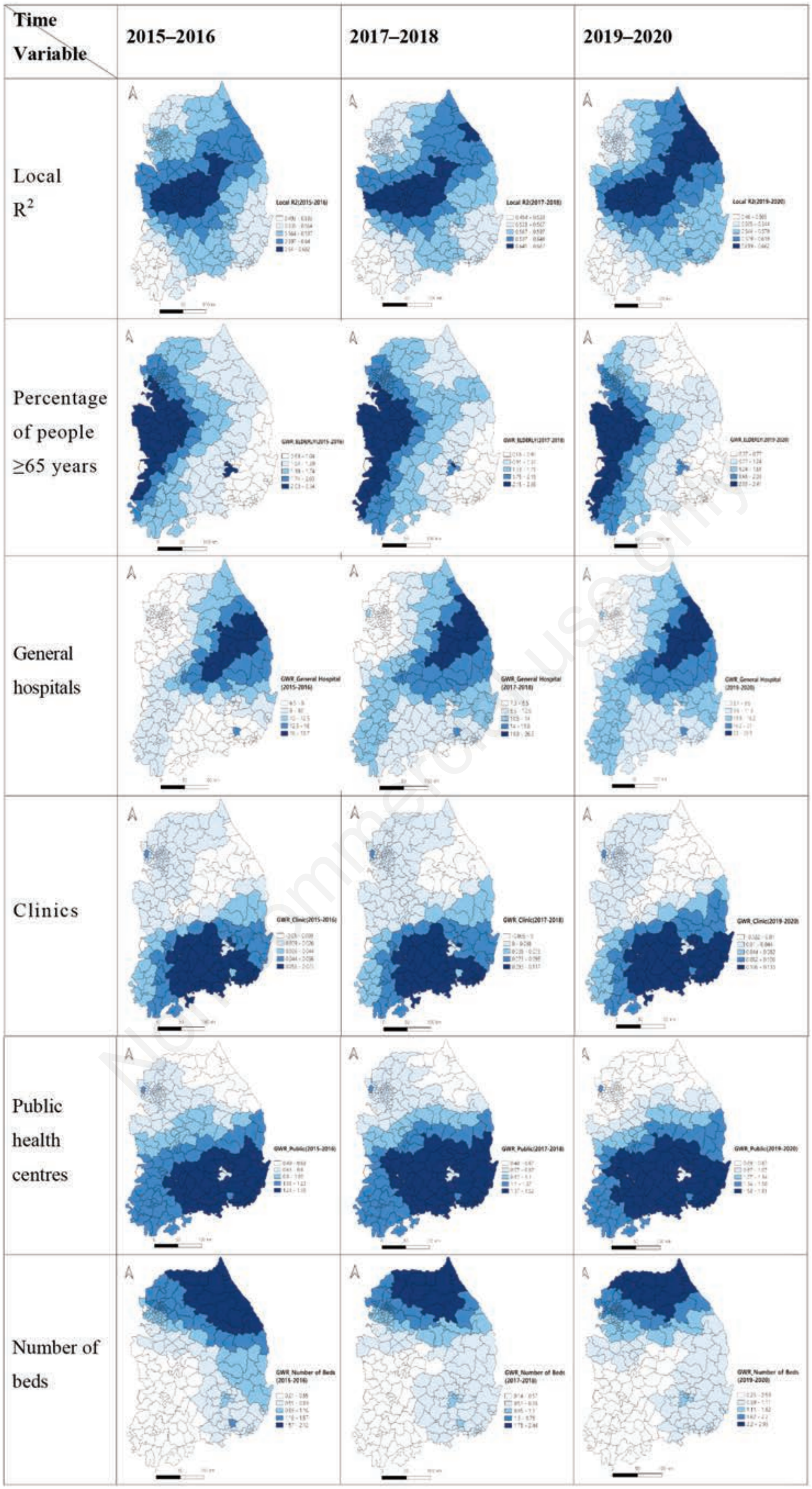

Figure 2. Regional distribution of regression coefficients.

sonnel was also not significant. Finally, Zhang *et al.* (2019) conducted a spatial analysis of 31 regions in China and found that the per capita income had direct and indirect effects on the out-of-pocket expenditure. Follow-up research by Yang *et al.* (2021) demonstrated by means of the fixed-effects model that the higher the income level, the higher the out-of-pocket expenditure in the eastern, central and western regions of China. However, we did not find a significant such association, possibly because of limitations in data collection, which only considered the average health insurance premium in the region at the individual income level.

The GWR findings reported here, can be used to support the distribution of healthcare resources by region. Therefore, if healthcare resources are invested in vulnerable areas, e.g., parts of Chungcheongnam-do, Jeollabuk-do and Gyeongsangbuk-do, a spill-over effectreducing the region's co-payment can be expected. However, this study had the following limitations. First, the ecological method used did not consider individual units because of limitations in data collection (Schwartz, 1994). For example, even if they affect each region differently, they cannot be said to have the same effect on everyone in the region. Second, the superiority of GWR, which reflects spatial characteristics over OLS, has been verified in previous studies with respect to the direction and size of regression coefficients of regional variation factors in healthcare. However, it was difficult to accurately interpret the significance of the regression coefficients by region using the GWR model, making it impossible to identify the exact cause. Third, the study area was limited. Before the analysis, islands and island regions were excluded from the spatial analysis in the study area, and some of the study regions were integrated and changed because of the uniformity of regional data. Unlike general data, the analysis units of geographic data were not independent but had spatial dependence or spatial autocorrelation, which was closely related to the Modifiable Areal Unit Problem (MAUP) (Cho, 2010). This kind of problem arises because spatial unit settings are determined by the availability of data and/or researcher judgements.

Despite these limitations, we were able to confirm the effect on the out-patient out-of-pocket expenditure. Previous studies used an estimated OLS model under the assumption that the regression coefficient was the same in all regions, while we also applied GWR analysis finding that the magnitude and direction of the regression coefficient were different for each region. This means that the GWR model explains regional characteristics better than the OLS model. Second, identifying the regression coefficient by region as a time series was meaningful in that it identified the related factors affecting the out-patient duty charge over this period, including the temporal change of magnitude and direction of the coefficient by region. Third, whereas previous studies used individual data to identify factors affecting the out-patient out-of-pocket expense, this study used community-based data. This is significant because it suggests the need for a community approach to managing the individual out-of-pocket expenditure and diverse healthcare policies by region.

This study differs from previous studies in that it used spatial analysis to identify the factors influencing co-payments in great detail (*e.g.*, Beck *et al*., 2005; An, 2011). The spatial autocorrelation showed that out-patient out-of-pocket expenditure was correlated between regions, and that the community had a clear influence. The decreasing autocorrelation over the whole time of study might have been affected by the COVID-19 pandemic and this could have affected the out-patient medical care, or will do so whether or not individual patients have private medical insurance schemes. A follow-up study is therefore needed.

Conclusions

It was confirmed that an imbalance in the distribution of healthcare resources as well as residents' socioeconomic status influence their out-of-pocket expenditure. This suggests that this can be managed by deploying healthcare resources more appropriately. If social and economic resources are invested appropriately in vulnerable areas, a spill-over effect in neighbouring areas can be expected. In terms of policy recommendations, the central government sets overall policies and standards, but the roles and functions of the local governments are needed to provide support and services for specific population groups. The results of this study provide insights for public health experts and policymakers in local governments to suggest regionally tailored policy strategies for managing co-payments for those who are vulnerable. Importantly, however, the results show that the gap with regard to what we know ofthe out-of-pocket expenditures due to socioeconomic factors persists.

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