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The spatial dimension of human capital segregation: An empirical investigation for Seoul, Korea

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Abstract

This research note examines changes in the spatial patterns of human capital segregation in Seoul, Korea from 1995 to 2005, and investigates whether spatial clusters of human capital can be isolated across neighborhoods in the metropolitan area. The major finding is that the proportion of college-educated individuals in the population aged 25 years and over increased significantly over the 1995–2005 period, and human capital segregation declined. However, the spatial distribution of human capital is by nature clustered and tends to be more clustered over the period. The neighborhoods with relatively high level of human capital tend to be localized close to other neighboring areas with high level of human capital. Most of these neighborhoods are located in the southern parts of Seoul, and these spatial clusters, which can be considered as *hot spots* of human capital, persist throughout the period. These results may have important implications for how the spatial dimension of human capital segregation contributes to the manner through which neighborhood effects of human capital impact metropolitan socioeconomic outcomes.

1. Introduction

Over the last decades, there has been increasing concern in many areas of social sciences over the importance of human capital accumulation. While existing research strongly suggests that the aggregate accumulation of human capital has a positive impact on metropolitan outcomes (Benabou, 1993; Durlauf, 2004; Lucas, 1988), it ignores preexisting spatial segregation of human capital and residential enclaves that fix in space and reinforce patterns of spatial inequality that shape and reshape the location of residents. It is possible that the spatial dimen-

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sion of human capital segregation might influence economic performance through residential neighborhood effects. Given that social interactions tend to be more intense between individuals located near one another than between individuals separated by long distances, people tend to be influenced by the composition of their neighborhoods (Moretti, 2004; Quercia & Galster, 2000).

Although a substantial body of empirical research on racial and ethnic segregation and occupational segregation (e.g., Cutler, Glaeser, & Vigdor, 1999; Farley & Frey, 1994; Glaeser & Vigdor, 2001; Iceland, 2004; Queneau, 2005) exists, few works have uncovered how human capital is spatially distributed across metropolitan neighborhoods. Given the aforementioned concerns over the importance of the spatial dimension of human capital segregation, we must investigate whether residential enclaves of human capital can be identified by a segregated landscape across neighborhoods in a metropolitan area. By using human capital data of Seoul metropolitan area, Korea from 1995 to 2005, this study explores changes in the spatial patterns of human capital segregation, and examines whether the level of human capital in a neighborhood is spatially correlated with the level of human capital in neighboring areas within the metropolitan area. This study also investigates whether spatial clusters of human capital can be isolated across neighborhoods in the metropolitan area.

2. Data and methods

In keeping with most other quantitative studies that involve analysis of neighborhood segregation, this study uses 518 *dong* areas within Seoul metropolitan area. The human capital embodied in an individual is calculated using data on educational attainment for the population aged 25 years and over, from the *Population and Housing Census* 1995, 2000, and 2005, published by the Korea National Statistical Office. This study focuses upon college-educated individuals as our population of high human capital individuals because the empirical literature on human capital externalities has found the greatest support for spillovers emanating from this group (Iranzo & Peri, 2006).

The index of dissimilarity, which is the most widely used measure of segregation, measures the fraction of college-graduate population that would have to change residence for each neighborhood to have the same fraction of that group as the metropolitan area overall (Cutler et al., 1999; Duncan & Duncan, 1955). Formally, it is defined as

$$D = \frac{1}{2}\sum_{i}\left|\frac{college_i}{college_{total}} - \frac{noncollege_i}{noncollege_{total}}\right|, \tag{1}$$

where $college_i$ is the number of college-educated individuals in geographic unit i, $college_{total}$ is the total number of college-educated individuals in the metropolitan area as a whole, $noncollege_i$ is the number of individuals without a college degree in geographic unit i, and $noncollege_{total}$ is the total number of individuals without a college degree in the metropolitan area. This index ranges from 0 to 1, indicating no segregation to perfect segregation, respectively. By adjusting the index of dissimilarity, this study tries to capture the interaction information indirectly by using the concept of composite population counts, which treat different population groups in neighboring areas as if they are in the same area (Wong, 2005). The composite population count of college-educated individuals in geographic unit i is defined as

$$c\_college_i = \sum_j d(college_j), \tag{2}$$

where $d(\cdot)$ is a function defining the neighborhood of i, and j can be i. The traditional approach to specifying the function of neighborhood relies on the spatial arrangement of the geographic units, designating geographic units as neighbors when they share a common border, i.e., $d(college_j) = 1$ if geographic units i and j share a common border, 0 otherwise. Based upon these composite population counts, the index of generalized spatial segregation, proposed by Wong (2005), can be defined as

$$GD = \frac{1}{2}\sum_i \left| \frac{c\_college_i}{\sum_i c\_college_i} - \frac{c\_noncollege_i}{\sum_i c\_noncollege_i} \right|. \tag{3}$$

The GD index ranges between 0 and 1, indicating no spatial segregation and perfect spatial segregation, respectively.

This study also applies recently developed methods of exploratory spatial data analysis (ESDA) to examine whether the concentration of college-graduate population in a geographic area is spatially correlated with the concentration of neighboring areas' college-graduate population, and thereby further investigate if spatial clusters of college-graduate population can be isolated across neighborhoods in the metropolitan area. We first consider global spatial autocorrelation, the measurement of which is usually based upon the Moran's I statistic (Cliff & Ord, 1981; Upton & Fingleton, 1985):

$$I = \left(\frac{n}{s_0}\right) \frac{\mathbf{x}'\mathbf{W}\mathbf{x}}{\mathbf{x}'\mathbf{x}}, \tag{4}$$

where $\mathbf{x}$ is the vector of the $n = 518$ observations (proportion of college-educated individuals in the population aged 25 years and over) in deviation from the mean, $\mathbf{W}$ is the spatial weights matrix, designating geographic units as neighbors when they share a common border (i.e., the elements w_{ij} is 1 if geographic units i and j share a common border and 0 otherwise), and s_0 is a normalizing factor equal to the sum of the elements of the spatial weights matrix (i.e., $s_0 = \Sigma_i \Sigma_j w_{ij}$) (Anselin, 1995). The value of the Moran's I statistic ranges from -1 for negative spatial autocorrelation to 1 for positive spatial autocorrelation. Over the entire geographic units, if similar values are more likely than dissimilar values between neighbors, the Moran's I statistic tends to be positive, and vice versa.

Since the elements in the vector $\mathbf{x}$ in Eq. (4) are in deviations from the mean, the Moran's I statistic is formally equivalent to the slope coefficient in the linear regression of the spatial lag $\mathbf{Wx}$ on $\mathbf{x}$. The Moran scatterplot decomposes global spatial association into the four different quadrants, which correspond to the four types of local spatial association between a geographic area and its neighbors: (i) HH: high–high association (high values surrounded by high values, quadrant I); (ii) LH: low–high association (low values surrounded by high values, quadrant II); (iii) LL: low–low association (low values surrounded by low values, quadrant III); (iv) HL: high–low association (high values surrounded by low values, quadrant IV). The Moran's I statistic is a global statistic and does not allow us to assess the local structure of spatial autocorrelation. In order to identify local spatial clusters, or *hot spots*, of human capital, we use a local indicator of spatial association (LISA). LISA, the local version of the Moran's I statistic, for each geographic area i can be defined as

$$I_i = \left(\frac{x_i}{m_0}\right) \sum_j w_{ij} x_j, \tag{5}$$

where $m_0 = \sum_i x_i^2/n$ and the summation over j is such that only neighboring values of j are included. A positive value for I_i indicates spatial clustering of similar values, whereas a negative value indicates spatial clustering of dissimilar values between a geographic area and its neighboring areas.

3. Empirical findings

Table 1 provides some basic segregation statistics for neighborhoods in the metropolitan area from 1995 to 2005. It indicates that the proportion of college-educated individuals in the population aged 25 years and over increased significantly over the 1995–2005 period. The dissimilarity index for human capital segregation declined by 0.0275 from 0.2921 in 1995 to 0.2646 in 2005. However, people in neighboring geographic units can interact and are not perfectly segregated by administrative boundaries if there are no effective physical or administrative barriers stopping people from interacting. By using the concept of composite population count, the results for the generalized dissimilarity measure show that the values of *GD* are lower than the a-spatial *D*, because the potential interaction between the two human capital groups is accounted for by *GD*.

Table 1
Summary measures of human capital segregation, 1995–2005.

	1995	2000	2005
(a) Segregation indexes			
Proportion of college-educated individuals	0.2613	0.2527	0.3294
Dissimilarity index (*D*)	0.2921	0.2733	0.2646
Generalized dissimilarity index (*GD*)	0.2249	0.2117	0.2063
Moran's *I* statistic	0.5225 (19.8231)	0.5451 (20.6718)	0.5724 (21.6919)

	Moran scatterplots		LISA statistics	
	1995	2005	1995	2005
(b) Changes in the Moran scatterplots and LISA statistics (percentages)				
HH	28.4	32.8	80.0	51.3
LL	50.4	47.5	18.8	47.0
HL	9.3	8.7	1.2	0.9
LH	12.0	11.0	0.0	0.9
Total	100.0	100.0	100.0	100.0

Note: The expected value for the Moran's I statistic is −0.002 for each year and z-values are in parentheses. All statistics are significant at the 1% level.

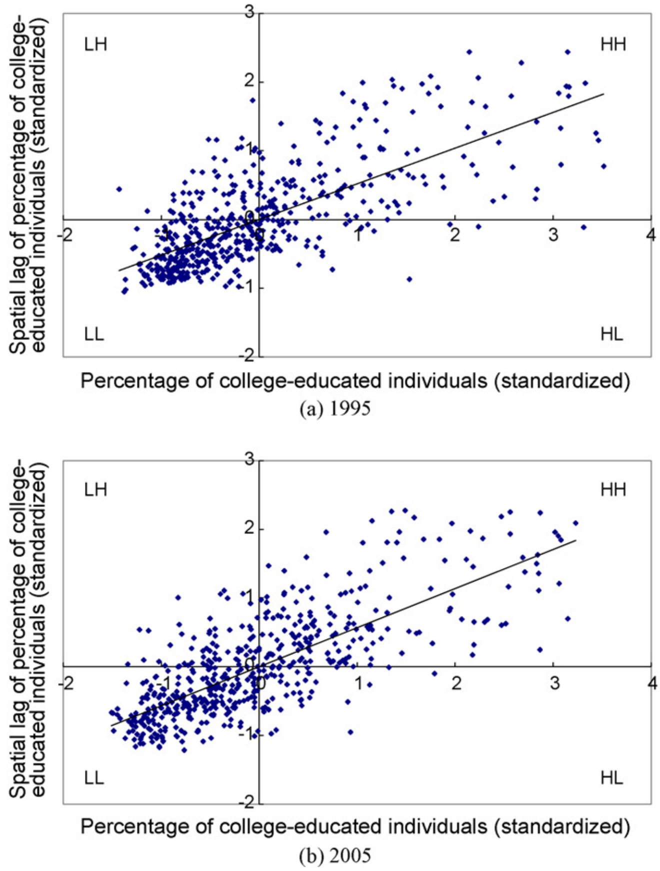

Fig. 1. Moran scatterplot for human capital: (a) 1995 and (b) 2005.

If it is the case that spatial clustering patterns, which spread out over the neighborhood borders, still matters for human capital segregation, we would expect to find significant spatial clustering, which is indicated by the presence of significant spatial autocorrelation. The result of spatial autocorrelation for the proportion of college-educated individuals in the population aged 25 years and over for the period 1995–2005. The analysis of the spatial patterns of human capital by means of the Moran's *I* statistic provides strong evidence of positive spatial autocorrelation with $p < 0.001$. The result shows that the spatial distribution of human capital is by nature clustered and tends to be more clustered over the period. The neighborhoods with relatively high level of human capital tend to be localized close to other neighboring areas with high level of human capital more often than if their localizations were purely random. Table 1 also presents the changing distribution of neighborhoods in the quadrants of the Moran scatterplot expressed in percentages of the total number of neighborhoods between 1995 and 2005. Fig. 1 displays the associated Moran scatterplots for 1995 and 2005. For 1995, it appears that most of neighborhoods were characterized by positive spatial association, while only a small proportion of the other neighborhoods are characterized by a negative spatial association. For 2005, most of the observations are still characterized by positive spatial association, while the other neighborhoods are characterized by a negative spatial association. Another interesting finding is the trend in spatial clustering of human capital during the period. A positive value for the LISA statistic indicates spatial clustering of similar values, whereas a negative value indicates spatial clustering of dissimilar values between a geographic area and its neighboring areas. A set of significant HH quadrants indicates a local spatial cluster covering several neighborhoods, while significant HL neighborhoods represent isolated poles of human capital. For 1995, most of the significant neighborhoods are characterized by positive spatial association, while only a small proportion of the other neighborhoods are characterized

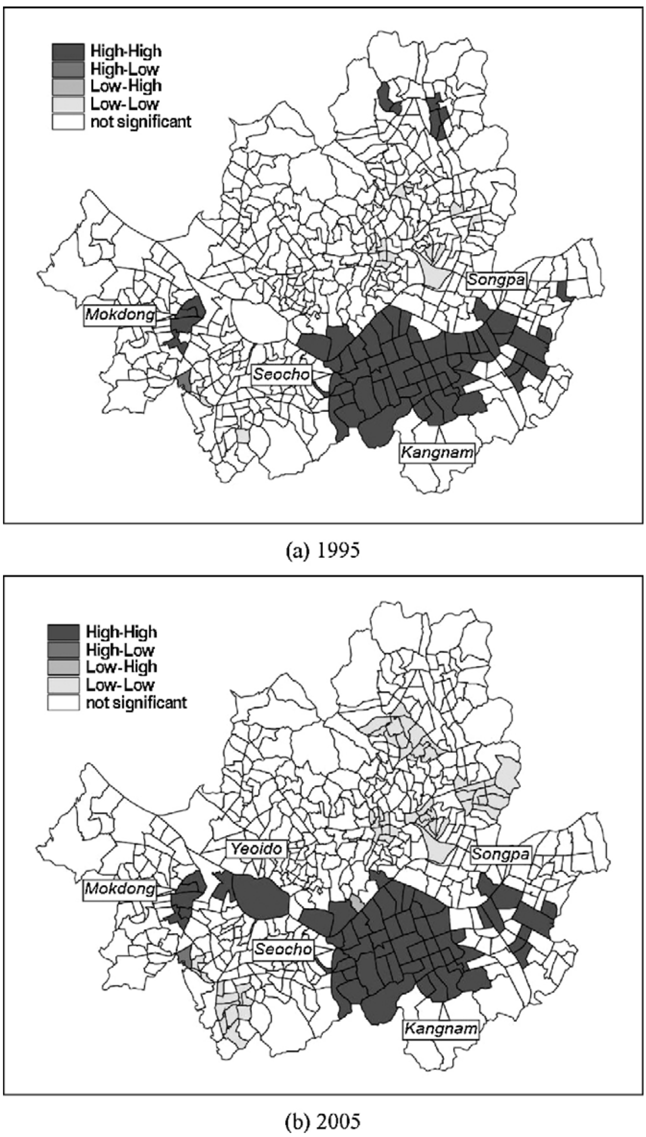

Fig. 2. Moran significance map for human capital: (a) 1995 and (b) 2005.

by a negative spatial association. For 2005, most of the observations are still characterized by positive spatial association, while the other neighborhoods are characterized by a negative spatial association.

The associated Moran significance maps for years 1995 and 2005 are presented in Fig. 2. The map combines the information in a Moran scatterplot and the significance of LISA by showing the neighborhoods with significant LISA and indicating the quadrants in the Moran scatterplot to which these neighborhoods belong. Most of the significant observations are characterized by positive spatial association and concentrate in the areas of *Kangnam*, *Seocho*, and *Songpa*. The sets of significant HH neighborhoods in the area of *Mokdong* can also be considered as *hot spots* of human capital. These spatial clusters of significant HH neighborhoods persist over time. Furthermore, *Yeoido*, which is a hub for finance, banking, and insurance industries in Seoul, has emerged as a significant HH neighborhood in the area of *Yeongdeungpo*, while some significant LL neighborhoods form spatial clusters in *Kangbook* and *Jungrang* areas over the decade.

The spatial segregation of human capital seems systematically linked to other dimensions of socioeconomic isolation and residential separation, and these patterns of spatial segregation may also be associated with uneven urban development policies for the southern parts of Seoul metropolitan area, especially in *Kangnam*, *Seocho*, and *Songpa*. Highly educated people with socioeconomic resources are attracted to the most desirable metropolitan environments where new investment takes place, and those with financial and social resources tend to aggregate in newly developed areas, such as *Kangnam*, *Seocho*, and *Songpa*, thereby reinforcing the spatial segregation of human capital. This uneven urban development is considered a major cause of the social stratification and group differentiation of urban spaces and is thus a fundamental contributor to the segregated landscape (Smith, 1991).

4. Conclusions

This research note examines changes in the spatial patterns of human capital segregation in Seoul, Korea from 1995 to 2005, and investigates whether spatial clusters of human capital can be isolated across neighborhoods in the metropolitan area. The major finding is that the proportion of college-educated individuals in the population aged 25 years and over increased significantly over the 1995–2005 period, and human capital segregation declined by 0.0275 from 0.2921 in 1995 to 0.2646 in 2005. However, the spatial distribution of human capital is by nature clustered and tends to be more clustered over the period. Another important finding is that most HH neighborhoods are located in the southern parts of Seoul metropolitan area, such as *Kangnam*, *Seocho*, *Songpa*, and *Mokdong*, and these spatial clusters of HH neighborhoods, which can be considered as *hot spots* of human capital, persist throughout the period.

Although most of the previous empirical research on residential segregation in the United States has been on trends in racial/ethnic and economic segregation (among others, Glaeser & Vigdor, 2001; Iceland, 2004; Jargowsky, 1996), those works have suggested that racial/ethnic segregation is systematically linked to various dimensions of residential separation, including income and educational attainment. Together, the empirical findings of this study remind us that contemporary circumstances reflect urban development that is context-specific and therefore dependent upon larger social spatial processes.

Even though we have not attempted to explain, in more depth, specific results for socioeconomic outcomes through neighborhood effects, the empirical findings of this study may have important implications for how the spatial dimension of human capital segregation can contribute to the manner through which human capital impacts metropolitan socioeconomic outcomes. These findings should be considered as an exploratory step before suggesting factors that affect metropolitan socioeconomic performance through neighborhood effects.

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