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Illusions of Clustering: A Systematic Evaluation on the Effects of Clusters on Regional Economic Performance in Korea

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Abstract

Korea has pursued a cluster-based policy to increase industrial competitiveness and to alleviate development gaps between the regions. However, local governments have often oversupplied clusters without an objective examination of the demands and conditions in the regions. Based on these concerns, this study analyses effects and interdependencies of factors related to regional innovation and growth in Korea. Employing a PCA method and a GLS regression models on panel data, we generated three composite factors, social, capacity, and clustering, and estimated their effects on regional economic performance. The results show that it is important to have a favorable socio-economic setting to foster growth by clusters. In addition, cluster-based policies may have weaker effects than expected, because the effect of R&D capacity on regional growth was stronger and longer lasting. Finally, some specific elements that most affected economic growth in Korea's regions are identified. The overall results indicate favorable environments should be established beforehand to foster regional growth with clusters, which confirms "jobs follow people."

Keywords

cluster, policy evaluation, regional growth, regional innovation system

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Introduction

Clusters, defined as "geographic concentrations of interconnected companies, specialized suppliers, service providers, firms in related industries, and associated institutions" (Porter 2000, 15), create a capacity advantage that promotes greater innovation and economic development (Dohse 2007; Johansen et al. 2020). A number of studies have supported the argument that co-operation between regional actors based on spatial proximity facilitates knowledge spillovers by interactions and networks, resulting in increased market competitiveness (Amisse, Leroux, and Muller 2012; Fritsch and Franke 2004; Porter 1998). Consequently, there has been a lot of qualitative studies stressing the important role of clusters in the process of innovation (Cheshire and Malecki 2004; Wolman and Hincapie 2015).

However, it does not mean that constructing clusters always leads to the creation of regional networks and growth. For example, Saxenian (1994) compared the case of Silicon Valley and Route 128, both the electronics innovation leaders of the US in the 1970s, to discern why the former succeeded in experiencing dynamic growth while the latter failed. In spite of their comparable origins, their divergent outcomes demonstrated that local factors, such as social and institutional settings, played an important role. The case provided insights into the structures and dynamics of the regional conditions that surround clusters.

Meanwhile, South Korea has pursued a cluster-based policy since the 1970s in order to increase its industrial competitiveness and to alleviate development gaps among regions. At first, it was a part of government-led initiatives, building some successful clusters in sectors including electronics and shipbuilding (Park, Amano, and Moon 2012; Shin and Hassink 2011). However, local governments have often oversupplied clusters for political purposes without an objective examination of the demands and conditions in each region, incurring limited success (Kwon and Choi 2014; S. Y. Lee, Noh, and Seul 2017; Ryu, Kim, and Kim 2018).

Based on these concerns, this study aims to analyze cluster effects on regional growth from the regional innovation system (RIS) perspective. It should be noted that cluster operates best when it incorporates other actors that favor innovation (Kosfeld and Titze 2017; Saxenian 1994) such as socio-institutional environment and technological congruence (Doloreux and Parto 2005; Fagerberg 1994; Rodríguez-Pose 1999). Accordingly, Rodríguez-Pose and Comptour (2012) investigated the interaction of clusters, social capability, and research and development (R&D) capacity and its effect on economic growth in European countries.

Building on Rodríguez-Pose and Comptour (2012)'s method, this study examines the effects of clusters with customized socio-economic and R&D capacity factors for Korean regions from 2010 to 2016. First, we examine the clustering effect and the importance of favorable social settings on regional economic performance. Second, we compare the effects of clusters and R&D capabilities. Lastly, we investigate which specific elements are crucial for regional growth. Geographical scope is limited to intermediate regions to evaluate cluster-based regional development policy. In sum, this article aims to add to a line of a systematic and quantitative study on clusters, which not only provides a novel approach on Korean regional studies but also supports universalizing the idea by pooling distinguished geographic scope of data.

Literature Review

Regional Innovation System and Cluster-based Policy

Traditionally, neoclassical growth models regarded technology as an exogenous variable, however, empirical studies discovered that those models could not explain a sizable share of divergent economic growth, leading to the introduction of technological change and innovation as explanatory factors (Fagerberg 1994; Romer 1986; Trajtenberg 1990). Consequently, R&D investment became a significant issue in endogenous growth models, since more investment in R&D led to greater technological progress, innovation, and, ultimately, economic growth. Studies on this linear perception—the more the R&D input, the more the economic growth—has preserved its reputation because of its simplicity and power at the firm, sector, or country level (Rodríguez-Pose and Crescenzi 2008). However, this approach tends to ignore other key factors and contextual conditions that affect innovation (Morgan 2007).

On one hand, systematic nature of innovation became widely accepted, the idea that innovation is embedded within socio-economic systems. Edquist (1997) defined (national) systems of innovation (NSI) as "all important economic, social, political, organizational, institutional, and other factors that influence the development, diffusion, and use of innovation" (p. 14). Especially, territorially embedded elements such as networks, education and training systems, research infrastructures, financial and legal institutions, and policies are significant because they explain the conditions of innovation. Further, accepting the holistic and evolutionary perspective highlighted the interdependence between the factors in the process of innovation (Lundvall 1992).

Then RIS was derived from NSI as "localized networks of actors and institutions in the public and private sectors whose activities and interactions generate, import, modify, and diffuse new technologies within and outside the region" (Iammarino 2005, 4). This subnational level approach is preferable to the national level because, first, it enables us to explain territorially- and socially-embedded contexts in a heterogeneous way, since regions differ in their innovation capacities and potentials due to variations in their locations, knowledge bases, and institutional structures (Tödtling and Trippl 2005). Furthermore, a spatially bound region facilitates knowledge spillovers and collective learning mechanisms due to geographical proximity, which provides favorable conditions for innovation (Fritsch and Franke 2004;

Storper and Venables 2004). Lastly, industrial specialization patterns and high technological density and diversity are characteristics of regions rather than nations (Morgan 2007).

Based on the advantages, literature has focused on the essential elements that favor or hinder the emergence and development of RIS. Several studies have proven that geographic proximity generates interactions and forms firm networks that lead to innovations via collective learning mechanisms (Cooke 2002; Storper and Venables 2004), and those networks are associated with industrial agglomerations and enhance the region's innovative capacity (Lawson and Lorenz 1999; Scott 1988). As a result, geographical clusters have gained attention as key players in economic growth in terms of productivity and innovative networks (Dohse 2007; Krugman 1999; Porter 1998; Titze, Brachert, and Kubis 2011).

Clusters are the "geographic concentrations of interconnected companies, specialized suppliers, service providers, firms in related industries, and associated institutions" (Porter 2000, 15). They have transaction cost and knowledge diffusion benefits within their localized networks and local institutional environment (Amisse, Leroux, and Muller 2012; Johansen et al. 2020; Lawson and Lorenz 1999; Saxenian 1994). In addition, clusters reinforce regional competitiveness, making it easier to find new partners for further innovations and new businesses (Slaper, Harmon, and Rubin 2018).

To evaluate the effects of clusters on regional growth quantitatively, some studies attempted to develop measurements for clusters. For example, Slaper, Harmon, and Rubin (2018) developed three cluster measures to assess regional industrial clusters in the US—the Shannon Evenness Index (SEI) for diversity, location quotients (LQ) for strength, and the percentage of employment growth for growth. Then, several county-based growth indices were regressed on the cluster measures, which indicated that cluster measures explained 40–60 percent of the variation in the dependent variables. Moreover, Borghi, Del Bo, and Florio (2010) and Rodríguez-Pose and Comptour (2012) included cluster characteristics variables such as size, focus, specialization, and diversification to evaluate clusters and growth in Europe. The studies concluded that the presence of clusters was relevant to fostering innovation and regional employment. Specific results are shown in Table 1.

The benefits and positive externalities from clusters led policy makers to implement cluster-based policies, which is to boost productivity of firms and economic growth by building clusters (OECD 1999; Porter 1998). Cluster-based policy should be distinguished from sectoral policy, because it should not depend on favored economic activities or picking winners from other countries or regions. Instead, the policy should assemble firms and interrelated regional capacity including technology, skills, information, and inputs with an effort to determine which clusters are

Table 1. Studies on Clusters and Regional Growth.

	Dependent Variable	Cluster Variable (Definition)	Results
Borghi, Del Bo, and Florio (2010)	Regional employment	Size (cluster employment / total EU cluster employment)	+
		Focus (cluster employment / regional employment)	−
		Number (number of clusters)	+
Rodríguez-Pose and Comptour (2012)	Growth of GRDP	Specialisation ([industry employment in a region / regional employment] / [industry employment / EU employment])	+
		Focus (cluster employment / regional employment)	+
		Diversification (number of clusters)	(+)
Slaper, Harmon, and Rubin (2018)	Growth of GRDP	Diversity (SEI)	(+)
		Specialisation (LQ)	−
		Growth (Δcluster employment / Δregional employment)	+

(+) = not significant.

more likely to survive and sustain in the region (Titze, Brachert, and Kubis 2011; Wolman and Hincapie 2015). Moreover, from the RIS perspective, cluster works best when it is harmonized with socio-economic environment and technological congruence (Doloreux and Parto 2005; Fagerberg 1994; Rodríguez-Pose 1999). In practice, however, it is frequently neglected by picking-a-winner strategy or political purposes, and many governments make mistakes by instigating firms to locate in regions without adequate infrastructure (Porter 1996; Sternberg and Litzenberger 2004).

Therefore, it is essential to identify clusters with a comprehensive approach that investigates the spatial dynamics of clusters and their effects on regional growth among socio-economic context and R&D capabilities (Rodríguez-Pose and Crescenzi 2008; Titze, Brachert, and Kubis 2011). However, there have been only few systematic approaches with quantitative analysis because of their complexity (Rodríguez-Pose and Comptour 2012). Crescenzi, Rodríguez-Pose, and Storper (2007) and Fritsch and Franke (2004) measured agglomeration effects and regional spillovers by utilizing social and R&D factors. Furthermore, they not only estimated the effects individually, but also in combination with other factors and their interdependencies. In addition, Rodríguez-Pose and Comptour (2012) analyzed the effect of clusters among R&D filter and social filter on GDP growth, proposing that socio-economic factors were prerequisites for clusters to have effective regional economic performances.

Cluster-based Policies in Korea

In the 1970s, Korea first built government-led clusters in sectors such as electronics and shipbuilding under intensive industrial policy with the emphasis on machinery and heavy industries. It was the central government and some major companies that strategically pushed forward to create the industrial clusters in specific regions, and the government also provided technology-targeting support programs (Park, Amano, and Moon 2012; Ryu, Kim, and Kim 2018; Shin and Hassink 2011). As Korea experienced shifts to knowledge-based economy from the 1990s, the government actively promoted cluster-based policies as best practices, and at the same time, as the concept of RIS was introduced, Korean government started to focus on regional economies and inequality problems between them (S. Y. Lee, Noh, and Seul 2017; Y. S. Lee, Tee, and Kim 2009). Thus, unlike the policies carried out by the government in the past, strategies for building industrial clusters through spatial integration and networks led by local governments have prevailed in alignment with regional development policies (Kwon and Choi 2014; H. H. Lee, Lee, and Park 2012; Park 2005).

Despite the efforts to achieve the twin goals of industrialization and balanced regional development by cluster-based policy, however, many of the clusters failed to show a full occupation of firms and to attract residents (Ryu, Kim, and Kim 2018). Kwon and Choi (2014) pointed out that the local governments are oversupplying clusters for political purposes without objective and thorough examinations of their contextual conditions and regional demands, and S. Y. Lee, Noh, and Seul (2017) indicated that it is because of the lack of existence of proper regional institutions. Sternberg and Litzenberger (2004) has also pointed out that clusters are often built for political purposes in common, and so robust assessments are necessary to avoid an oversupply of clusters in too many regions.

In addition, the primary focus of academics on clusters in Korea has been limited to measuring cluster performance individually. For instance, Kwon and Choi (2014) investigated the impact of various industrial complex types on regional economic growth and the performance of clusters in terms of production size, employment, and export value. Further, Park (2005) estimated the impact of clusters on firms' production and employment levels, and H. H. Lee, Lee, and Park (2012) included dummy variables for the presence of clusters in order to evaluate their impact on regional economies. Some studies attempted to examine cluster's effects among socio-economic or R&D factors, however, mostly by qualitative approach in a specific sector (S. Y. Lee, Noh, and Seul 2017; Y. S. Lee, Tee, and Kim 2009; Park, Amano, and Moon 2012; Shin and Hassink 2011).

Methodology

Variables

This study seeks to comprehend the effect of cluster-based policy, or the strategies to promote regional development by building clusters, on regional economies in Korea by analyzing the complementary or contrasting effects of three factors: socio-economic context, R&D capacity, and clustering effects. To do so, the overall analytical framework follows the methodology of Rodríguez-Pose and Comptour (2012) for measuring clustering effects, but in a way that suits the particular Korean context.

To begin with, the overall process of innovation is established as a process in which inputs lead to processes and then to outputs (input → process → output). Then five dimensions are derived in order to structure the components of the analytical model for a comprehensive approach (Ahn 2019). The input stage constitutes resource and environmental dimensions that represent the region's socio-economic context factor. The capacity and clustering dimensions belong to the process stage, which are the region's R&D capacity and clustering factors, respectively. The last output stage is the economic performance (Figure 1).

Firstly, social factors represent the contextual socio-economic conditions of a region that make it favorable to innovation including proxies for education levels, productive employment, and the demographic structure of a region (Crescenzi, Rodríguez-Pose, and Storper 2007; Rodríguez-Pose and Crescenzi 2008). For instance, education achievements are measured as the percentage of the population with higher education, and the population participating in lifelong learning accounts for local skill levels (Lundvall 1992; Slaper, Harmon, and Rubin 2018). Also, productivity of employment is reflected by long-term unemployment or agricultural employment, which indicate the rigidity of the local market and the presence of individuals excluded from the labor market (Fagerberg 1994; Gordon 2003). The demographic structure, which is a proxy for the size of the potential labor pool, skills, knowledge, and economic potential of that region, is represented by the percentage of young people in a region (Rodríguez-Pose 1999; Rodríguez-Pose and Crescenzi 2008) or human resources in the science and technology field (Rodríguez-Pose and Comptour 2012).

This study constitutes social factors with territorially-embedded variables relevant to building regional capacity in the Korean context, which include the variables of region's resource and environment (Ahn 2019). The percentage of the population in working age (age 15–64) (D. Lee et al. 2017; H. H. Lee, Lee, and Park 2012), the percentage who are youths (age 15–24), and the number of university students (Crescenzi, Rodríguez-Pose, and Storper 2007; D. Lee et al. 2017; H. H. Lee, Lee, and Park 2012; Rodríguez-Pose and Comptour 2012; Rodríguez-Pose and Crescenzi 2008) are contained as measurements of resource, labor pool and demographic characteristics.

For environment, this study utilizes the unemployment rate to measure the rigidity of local labor markets and the size of the labor force with inadequate skills (Crescenzi, Rodríguez-Pose, and Storper 2007). Also, population density accounts for physical infrastructure (H. H. Lee, Lee, and Park 2012; Slaper, Harmon, and Rubin 2018), and the number of private education institutions per thousand people and the number of students per teacher serve as proxies for the educational environment in each region (D. Lee et al. 2017).

Second, as measure of innovative capacity, R&D expenditure and R&D intensity are among the most popular indicators (Fritsch and Franke 2004). However, this study utilizes substitute variables due to the availability of R&D expenditure data at si·gun·gu level regions. The substitute variables are: the number of university faculty members (Kwon and Choi 2014; D. Lee et al. 2017), the number of Science Citation Index (SCI) journals per university faculty member (Mathews and Hu 2007), and the number of science, technology, and innovation (STI) businesses (Riddel and Schwer 2003) in the region. These variables reflect the capacity of innovative actors or technological levels.

Third, clustering factor is a composite index that reflects various clusterization effects. The European Cluster Observatory provides assessment of clusters through various criteria: specialization, focus, and diversification, and these indexes are widely accepted in European studies (Crawley and Pickernell 2012; Rodríguez-Pose and Comptour 2012; Slaper, Harmon, and Rubin 2018). The number of clusters is also utilized as an index (Borghi, Del Bo, and Florio 2010). Due to the data availability, this study adopts the focus and diversification indexes, which are the ratio of a specific cluster's employment to the region's total employment and the number of clusters in the region, respectively. In addition, this study includes cluster size (Park 2005) in the analysis in order to determine whether cluster size affected regional growth, as some assume it relates to firm performance (McCann and Folta 2011).

Data

To evaluate cluster-based regional development strategy, this study focuses on less advanced regions in Korea. Since Korean local governments are building clusters in the aim of alleviating inequality gaps, it makes more sense to exclude metropolitan cities or advanced regions which differ greatly in capacities and gain economic profits from diverse sources other than industrial clusters (H. H. Lee, Lee, and Park 2012). Accordingly, this study conducts an analysis of the "si·gun" regions of eight provinces in Korea, excluding metropolitan cities and special administrative districts.

Korea divides its administrative districts into three levels: special metropolitan cities and provinces (si·do), cities and counties (si·gun), and towns (eup·myeon·dong). The si·gun regions, the second-level, are the smallest units that have their own independent local governments with the capacity to develop policies and organizations, which satisfies conditions of regions described in Cooke, Uranga, and Etxebarria (1997): "territories smaller than their state possessing significant supralocal governance capacity and cohesiveness differentiating them from their state and other regions" (p. 480). The capacity to develop policies and organizations

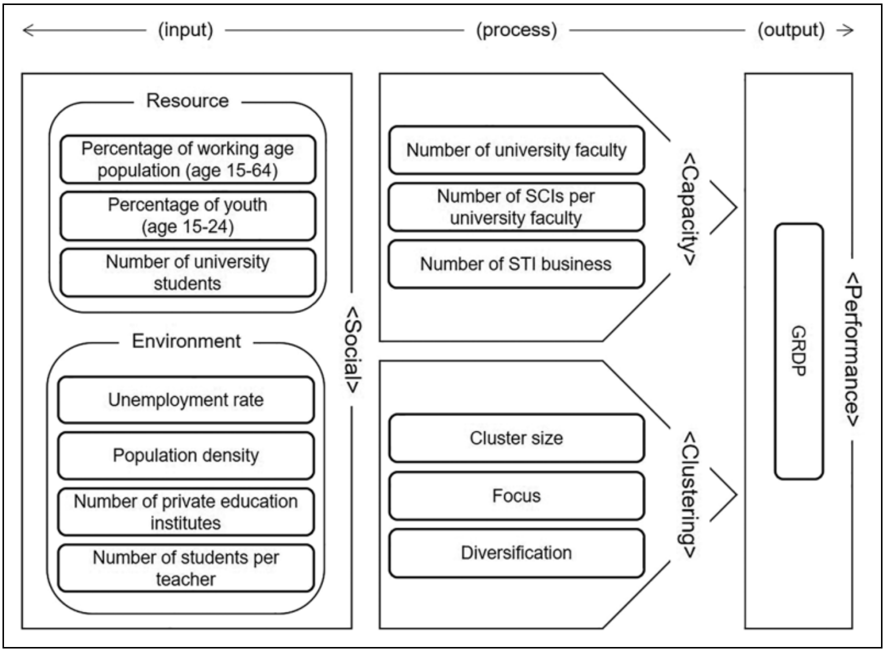

Figure 1. Structure of the variables.

that support innovation is one of the most important governance powers such regions have.

We collected data from regions where clusters existed as of 2016. Data on the social and capacity factors are retrieved from the statistical database of the Korean Statistical Information Service (KOSIS) and Higher Education in Korea. Further, data on the clustering factor variables are gathered from the Korea Industrial Complex Corporation (KICOX). KOSIS is Korea's official national statistical database, and provides one-stop service for a full range of domestic statistics on 417 agencies and 1,089 types of data and international statistics from organizations such as the OECD, World Bank, and IMF. Moreover, Higher Education in Korea is an official organization which delivers information services regarding universities. In addition, KICOX provides complete and enumerated quarterly data on every cluster in Korea, including name, location, size, number of employers and firms, rate of operation, and other information. The authors aggregated the data from each cluster into the regional level by own calculations. Table 2 shows the definitions and data sources.

After omitting missing data, the final dataset contains data from fifty-nine si·gun regions (see Figure 2) for the years between 2010 and 2016, resulting in 413 balanced observations in total.

Table 2. Definitions and Data Sources of Variables.

Variable	Definition	Source of Data
Dependent variable		
GRDP(log) (*lnGRDP*)	Logarithm of GRDP	KOSIS
Social		
Percentage of working age population (*wapop*)	Percentage of population aged 15–64	KOSIS
Percentage of young (*youth*)*	Percentage of population aged 15–24	KOSIS
Number of university students (*univstu*)	Number of university students	KOSIS
Unemployment rate (*unemp*)	Percentage of unemployment	KOSIS
Population density (*popdens*)	Total population/size	KOSIS
Number of private education institutions (*priedu*)	Number of private education institutions per thousand people	KOSIS
Number of students per teacher (*stupt*)	Number of students per teacher	KOSIS
Capacity		
Number of university faculty (*numf*)	Number of university faculty	KOSIS
Number of SCIs per university faculty (*scipf*)*	Number of SCI journal publications per university faculty	Higher Education in Korea, KOSIS
Number of STI business (*bussti*)	Number of STI business	KOSIS
Cluster		
Cluster size (*size*)*	Aggregate area of cluster(s)	KICOX
Focus (*focus*)*	Number of employees of cluster(s)/total number of employees in the region	KICOX
Diversification (*div*)*	Number of cluster(s)	KICOX
Total population (*tpop*)	Total population	KOSIS

* Based on author's calculation from the source of data.

Model

This study performs a balanced panel regression with the model:

$$\ln\mathrm{GRDP}_{\mathrm{it}} = \beta_1 + \beta_2 Social_{it} + \beta_3 Capacity_{it} + \beta_4 Clustering_{it} + \beta_5 Control_{it} + e_{it} \tag{1}$$

The logarithm of regional gross domestic product (GRDP) of region i in year t ($lnGRDP_{it}$) is the dependent variable, and the three crucial explanatory variables are: $Social_{it}$, for socially and territorially embedded variables; $Capacity_{it}$, for internal

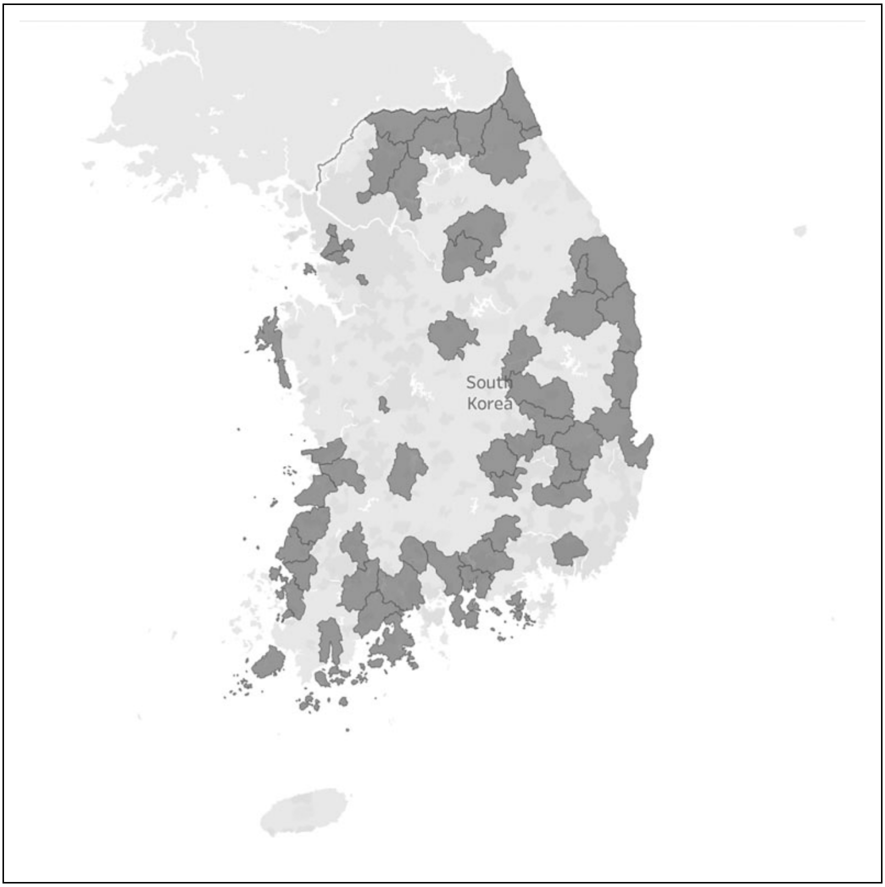

Figure 2. Identification of regions for the analysis.

innovative capacity variables; and $Clustering_{it}$, for spatially bound clustering variables, all of region i in year t. Total population serves as the control variable.

In this model, the social, capacity, and clustering factors are composite indexes that combine a bundle of related individual variables. Utilizing this model enabled us to adopt a comprehensive approach for examining clustering effects, along with social contexts and R&D capacity, quantitatively. In detail, this allows us to examine the interdependency of clusters and social factors and to compare clustering effects and R&D capability effects. This approach is distinct from the existing literature on the relationship between clusters and growth because most existing models focus on cluster's solitary effect (Borghi, Del Bo, and Florio 2010; Kwon and Choi 2014; H. H. Lee, Lee, and Park 2012; Park 2005; Slaper, Harmon, and Rubin 2018; Titze, Brachert, and Kubis 2011).

The three explanatory factors are generated by principal component analysis (PCA). PCA is a statistical procedure for reducing dimensions by utilizing an orthogonal transformation to extract the dominant patterns from a data matrix of observations of possibly correlated variables. For variables with strong correlations, this method calculates the percentage of variance explained by each component, which are eigenvalues, and then removes any components with eigenvalues below 1, according to Kaiser's criterion (Abdi and Williams 2010). Thus, PCA helps to avoid problems of multicollinearity that are inevitable when simultaneously including and merging many, possibly inter-correlated, variables by creating composite variables (Crescenzi, Rodríguez-Pose, and Storper 2007; Rodríguez-Pose and Crecsenzi 2008; Rodríguez-Pose and Comptour 2012).

Appendix A presents the results of the three PCAs. The Kaise-Meyer-Olkin (KMO) index measures the sampling adequacy of a PCA, and there is confidence in the result if the index is over 0.5. According to the results, all of the PCA variables satisfied the index for sampling adequacy (social factor KMO = 0.8246, capacity factor KMO = 0.6952, clustering factor KMO = 0.5148). However, one limitation of PCA is that it cannot explain a composite variable's effect in detail. To overcome this limitation, we add individual variables one by one and analyze them in separate regression models (Rodríguez-Pose and Comptour 2012).

We conducted several tests on the panel regression model. The results of model test statistics are as follows: No multicollinearity was detected (vif $= 2.98 < 10$; there is confidence in the result if the vif (variance inflation factor) index is under 10), and the Breusch-Pagan test for heteroscedasticity did not reject the null hypothesis H_0: *constant variance* (Prob > chi2 = 0.6634). However, the Wooldridge test for autocorrelation in the panel data rejected the null hypothesis H_0: *no first order autocorrelation* (Prob > F = 0.0000). Thus, to control for this autocorrelation problem, the regression utilized a GLS estimation method with a common AR(1) coefficient across all panels.

In addition, before estimating the model, we also checked the stationarity of the panel by employing the Levin-Lin-Chu (LLC) unit root test, given that the period includes only seven years. The LLC test has null hypothesis that the panels contain unit roots. The test results for the dependent and independent variables in Equation (1) determined that the panel generally satisfied stationarity, which means that the panel was statistically stable: all variables except the capacity variable reject the null hypothesis (p-value = 0.0000).

The analysis procedure starts with a static analysis that include eight regression models to capture aggregate interactions between the three composite factors, particularly the social and clustering factors, and any individual correlations between the variables in the social factor. The procedure continues with another static analysis that include six regression models that compare the composite capacity and clustering factors' effects on regional growth. Again, we estimate individual correlations between each of the variables within the two factors. Finally, we conduct a dynamic analysis by regressing GRDP on lagged factor variables, $n \in [1,3]$, to

Table 3. Summary Statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
lnGRDP	413	14.46733	1.00612	12.84632	17.02322
wapop	413	.6615275	.052533	.5497665	.7590121
youth	413	.1154503	.0208661	.0710186	.1628781
univstu	413	8,570.964	18,113.28	0	119,943
unemp	413	1.766586	1.097259	.1	4.7
popdens	413	1,020.639	2,721.882	19.6	16,671
priedu	413	1.146465	.5282772	.1	4.22
stupt	413	13.49441	5.292781	5.8	34.68
numf	413	201.0169	431.047	0	3,051
scipf	413	.0689988	.1511873	0	.9371392
bussti	413	171.5981	296.6767	6	1,757
size	413	5,656.903	21,418.44	0	173,335
focus	413	.0592252	.1289496	0	1.352197
div	413	2.929782	2.280651	0	12
tpop	413	146,143.7	188,881.7	21,843	890,875

estimate long-term effects. According to Kim, Altmann, and Kim (2019), it is reasonable to assume the existence of time lags within the process of innovation diffusion itself and within networks. Thus, it is worth examining the effect of composite variables with time lags.

Results

Descriptive Analysis

Tables 3 and 4 report summary statistics and correlations of the variables, respectively. According to the correlation matrix, individual variables of R&D capacity factor, especially the number of SCIs per faculty (*scipf*) and the number of STI business (*bussti*), are highly correlated with the level of GRDP, and variables of social factor also shows fairly high correlations. On the other hand, clustering variables exhibits lower correlations than the other variables.

Number of clusters and GRDP in 2016 are plotted in Figure 3. We can roughly assume a positive correlation between the existence of clusters and regional economic performance.

Regression Analysis

The results of panel model to determine the innovation sources of regional growth in Korea are reported in Tables 5–7. To begin with, the Model 1 in Table 5 reveals the results of the relationship between three explanatory factors for innovation and regional growth. As identified from the literature review, the territorially embedded

Table 4. Correlation Matrix.

Variable		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	*lnGRDP*	1.0000														
2	*wapop*	.6532	1.0000													
3	*youth*	.5392	.8411	1.0000												
4	*univstu*	.5433	.5251	.4325	1.0000											
5	*unemp*	.5627	.5643	.4800	.4620	1.0000										
6	*popdens*	.6361	.4953	.3818	.3582	.4954	1.0000									
7	*priedu*	.5125	.6984	.6427	.3789	.4656	.3117	1.0000								
8	*stupt*	.5788	.7642	.6712	.7749	.6518	.4084	.6222	1.0000							
9	*numf*	.5175	.5033	.4157	.9865	.4313	.2724	.3802	.7491	1.0000						
10	*scipf*	.7224	.4742	.4478	.4900	.3331	.1585	.3486	.5082	.5288	1.0000					
11	*bussti*	.9041	.6351	.5239	.5438	.5643	.7821	.4919	.5444	.4932	.5230	1.0000				
12	*size*	.3952	.2483	.2081	.1323	.2085	.0950	.2375	.2524	.1352	.2793	.2181	1.0000			
13	*focus*	.3314	.2379	.1215	.1271	.2664	.0589	.2128	.2045	.1287	.1693	.1966	.5996	1.0000		
14	*div*	.2447	1596	.0791	.1607	.0756	−.2083	.3500	.1275	.2217	.3494	.1069	.1003	.1115	1.0000	
15	*tpop*	.9483	.6791	.5696	.5692	.6047	.7868	.5489	.6255	.5282	.6074	.9296	.3300	.2570	.1682	1.0000

social factor, R&D capability factor, and clusters all had statistically significant effects on economic growth.

In Model 2–Model 8, the analysis excluded the composite social factor, and each individual variable within the social factor was regressed one by one. In these models, the clustering factor becomes insignificant (Models 2, 3, 4, 6, 8). This indicates that clustering is only effective when combined with social factors. This result is consistent with Rodríguez-Pose and Comptour (2012) which argued that the existence of clusters had positive effects on regional economic growth only within an adequate social context, revealing the interdependence of the presence of clusters and an adequate social context.

Specifically, the variables for the percentage of the population of working age (*wapop*), the population density (*popdens*), and the education levels (*priedu, stupt*) of the region had statistically significant effects on economic growth. While population density (*popdens*) has a relatively small influence, the pool of the labor force (*wapop*) exhibits a huge impact on regional economic growth. In addition, higher numbers of private education institutions (*priedu)* and fewer students per teacher in schools *(stupt*), the proxies for good education environments, have significant influences. However, the percentage of population aged 15–24 (*youth*) and the number of university students (*univstu*) did not have significant effects, implying that the presence of young people is not very essential. It seems that people who actually participate in production activities affect the region's economies to a much greater degree.

Furthermore, when it comes to the comparison of the R&D capacity and clustering factors (Model 1 from Table 5 and Models 9–14 from Table 6), the capacity factor demonstrates a greater influence on growth than the presence of clusters. In other words, regions in Korea with more innovative capacity, in terms of their R&D capabilities, tend to have higher incomes. Fritsch and Franke (2004) also observed that R&D investment had a greater influence on growth than knowledge spillover impacts did.

Among the variables in the capacity factor, human resources for R&D (*numf*) and the number of SCI journal publications per faculty member (*scipf*) in the region had positive and statistically significant effects, while the number of SCIs (*scipf*) had a much bigger effect than the number of faculty members (*numf*). In other words, instead of how big universities are, or how many faculty members they have, the qualitative level of R&D, as measured by SCI performance, has a strong association with growth.

Lastly, when examining the clustering indexes, *size*, *focus*, and *div* were positively related to economic growth. In particular, a region's cluster density (*focus*) turned out to be the most significant element, then diversification (*div*). That is, higher employment intensity facilitates knowledge diffusion between firms, which in turn promotes economic growth (Rodríguez-Pose and Comptour 2012). The impact of *size* was also positive and statistically significant, however, its effect was so small that it was barely recognizable.

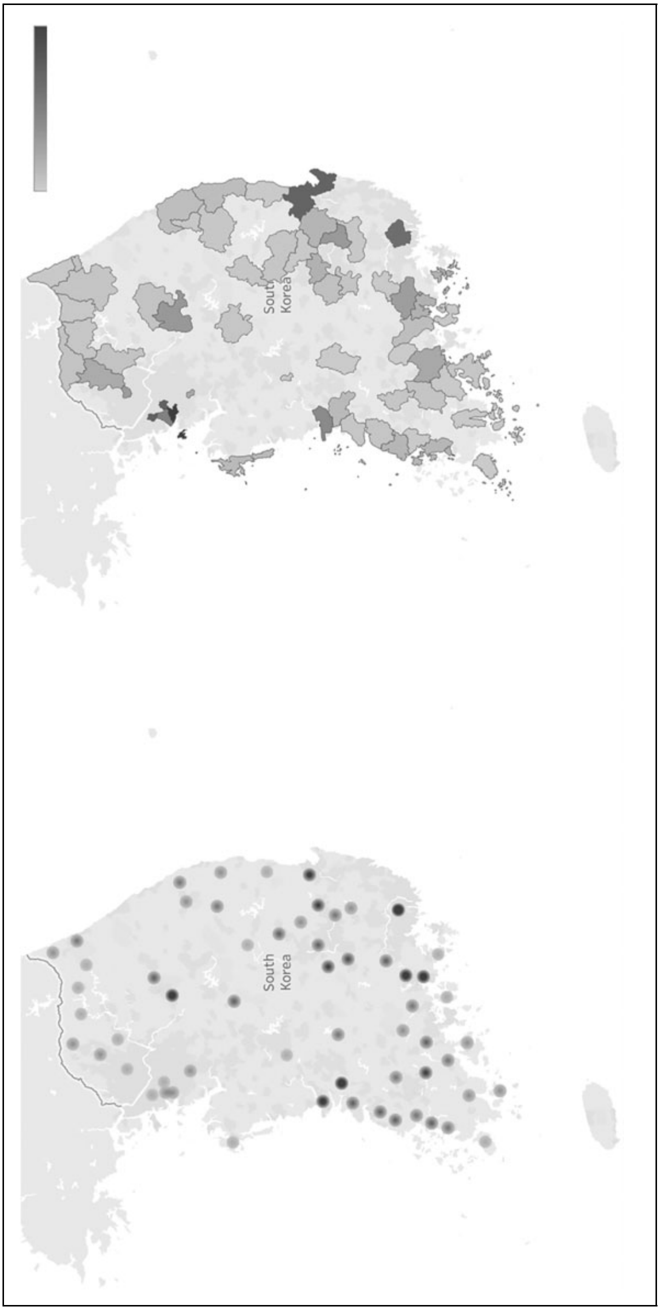

Figure 3. Number of clusters and GRDP in 2016.

Table 5. Results of Static Analysis 1.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Constant	13.994***	13.86***	13.907***	13.938***	13.966***	13.845***	13.921***	14.142***
Social	.03*							
Capacity	.179***	.167***	.032***	.162***	.198***	.127***	.197***	.131***
Clustering	.02*	.005	.008	.01	.033***	.005	.033***	.004
wapop		2.686***						
youth			1.35					
univstu				1.26e-06				
unemp					.009			
popdens						−.0001***		
priedu							.063***	
stupt								−.021***
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 6. Results of Static Analysis 2.

	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
Constant	13.815***	13.858***	13.87***	13.91***	13.836***	13.615**
Social	.024	.051***	.052***	.071***	.07***	.054**
Capacity				.179***	.114***	.132***
Clustering	.022*	.024**	.028**			
numf	.0004***					
scipf		.871***				
bussti			.0002			
size				2.57e-06***		
focus					.259***	
div						.081***
Control	Yes	Yes	Yes	Yes	Yes	Yes

**p* < 0.1, ***p* < 0.05, ****p* < 0.01.

Table 7. Results of Dynamic Analysis.

	Lag 0	Lag 1	Lag 2	Lag 3
Constant	13.994***	14.043***	14.065***	14.084***
Social	.03*	.04***	.042**	.041*
Capacity	.179***	.184***	.182***	.182***
Clustering	.02*	.03***	.03***	.017
Control	Yes	Yes	Yes	Yes

**p* < 0.1, ***p* < 0.05, ****p* < 0.01.

Finally, in order to capture long-term effects, we conducted dynamic analyses with time lags of up to three years. Table 7 displays the regressions with lagged variables for the three factors. Especially, the composite capacity factor produced the highest and continuous significant effects, and the gaps between the capacity coefficient and others were quite high. The social factor also demonstrates the importance of creating a favorable and supportive environment; its impact grows slightly in the long term. However, the clustering factor had the least and the shortest influence on regional growth. At the three-year time lag, the clustering factor no longer affected regional growth while other factors were still significant. This result shows that we might have over-expected the effect of clusters.

Robustness Check

This study considers a variety of variables that has the possibility of affecting regional growth. Among the variables, this study utilized the number of university faculty members, number of SCIs, and number of business in STI as proxies for the R&D capacity. Usually, however, R&D expenditure is used to measure the capabilities (Fritsch and Franke 2004). We had to use the substitute variables instead, because of the absence of R&D expenditure data at the si·gun level (only national and si·do level data are provided). Thus, in order to check robustness of the regression models and the substitutes, the study conducted an additional analysis that includes a variable of patent applications data, which is also a popular measure for R&D capacity, from Korean Intellectual Property Office (KIPO). Due to data availability, the time period is shortened to 2011–2016. Here, the new capacity factor includes the number of KIPO patent applications (*patent*) and number of SCIs per faculty member (*scipf*). Table 8 provides the supplementary results that confirm the robustness, which in general demonstrate no differences with the original results.

Discussion and Conclusion

To evaluate the impact of cluster-based regional development policy in intermediate regions, this paper sought to discover the effects and interdependencies between the factors related to regional innovation and growth in Korea. Employing a PCA method and GLS regression models for both static and dynamic analyses, we generated three composite factors, social, capacity, and clustering, and estimated their effects on regional economic performance of fifty-nine regions from 2010 to 2016.

Revisiting this study's research questions, the answer to the first is that clustering effect is conditional. In other words, the presence of clusters itself does not guarantee regional growth, and they are only effective when accompanied by a favorable socio-economic environment. As to the second question, this study identifies that the R&D capacity is more effective than promoting clusters, as it had stronger and longer-lasting effects in Korean regions. The answer to the third and final question is that the individual elements that significantly facilitate regional growth in Korea are the region's pool of laborers, education level, quality of R&D activities, and the employment density and diversity of its clusters.

These findings have important implications for the regional development policies of local governments in Korea. Currently, local governments are attempting to create industrial clusters competitively, without examining the regions thoroughly, under the belief that clusters will create new jobs, increase the population, and thus promote regional growth (Kwon and Choi 2014; H. H. Lee, Lee, and Park 2012; Park 2005).

What they intend to do, to attract people by building clusters, brings a longstanding discussion of causality between people and employment change in regional development process in mind. Regional scientists have empirically investigated the causality direction in the process of suburbs development: "Jobs follow people" or "people follow jobs" (Hoogstra, van Dijk, and Florax 2017). When jobs follow people, regional growth is driven by the community population or labor supply, and when people follow jobs, the growth originate from the community employment or labor demand. Consequently, the direction of regional development policy would change depending on which comes first (Østbye et al. 2018). Studies have used

Table 8. Robustness Check.

	1	2	3	4	5	6	7	8	9	10	11	12	13
Constant	13.989***	12.425**	13.808***	13.885***	13.905***	13.799***	13.875***	14.197***	13.914***	13.888***	13.997**	13.924***	13.788***
Social	.057***								.062***	.053***	.07***	.112***	.08***
Capacity	.123***	.101***	.028***	.091***	.122***	.063*	.116***	.076***			.126***	.134***	.092***
Clustering	.034**	.018	.012	.009	.05***	.008	.035**	.002	.04***	.036***			
wapop		2.323***											
youth			.858										
univstu				3.99e-06									
unemp					.015								
popdens						-.0001***							
priedu							.043*						
stupt								−.03***					
patent									.0001*				
scipf										.872***			
size											2.44e-06*		
focus												.424***	
div													073***
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

partial adjustment model in the regional text by including a (lagged) people variable and a (lagged) jobs variable simultaneously to figure out the causal relationship (Lambert, Xu, and Florax 2014). While a lot of studies verify "jobs follow people" in rural development process (Henry, Schmitt, and Piguet 2001), cluster-based policy led by Korean local governments indicates "people follow jobs."

Although in a different context, the findings of this study also demonstrate "jobs follow people." Clusters have significant effects only when supported by an adequate social context encompassing them. Specifically, regions in which there are rich labor pools and favorable education systems tend to be more successful at deriving positive results from clustering. This means that jobs can be created and sustained where there are people with adequate skills. Therefore, a preliminary investigation into regional demands and conditions is necessary to acquire successful outcomes from establishing clusters. Further, regions should seek to develop favorable residential and educational environments to attract inhabitants or make employees settle in their regions.

In addition, local governments should also focus on developing consistent and stable R&D investment strategies instead of sticking to only cluster-based policies, since R&D capacity has much more impact on regional growth. As seen from both the static and dynamic analysis, the importance of clusters in regional innovation may have been overestimated. Rather, R&D capabilities had stronger and longer effects on regional growth. Thus, while striving to establish favorable socio-economic conditions, regions should strengthen their R&D investment in order to enhance the capacities of their individual economic actors. Substantial and effective synergies would ensue when local governments are able to create innovative networks between cluster of firms, universities, and research agencies within their regions.

Lastly, this study also proposes some practical implications on individual elements that effectively facilitate regional growth. First, we found that the effect of working age population is statistically significant and strong, while the effect of young people had no effect. These results indicate that regions should invest in employee training and develop long-life educational systems that provide people with adequate vocational skills. In addition, the number of SCIs per university faculty member had a significant effect, while the number of university students and the number of university faculty members had little or no effect. This means the quality of university education matters, and the quantity, such as the size and number of universities, is irrelevant to regional economic performance.

This study contributes, first, by conducting a RIS perspective study targeting intermediate regions to evaluate the effect of current cluster-based regional development strategy in Korea. It adds to a line to the systematic and quantitative literature on clusters by widening its universality via distinguished dataset. Also, this research has constructed a regional level aggregated dataset of socio-economic structures, R&D capacity, and clustering information in Korea. Currently, several datasets including university faculty, SCI outputs, and cluster information are only provided at individual institutional level. Finally, the results suggest important policy implications, as discussed above, by revealing that regional development policy in Korea is going counter to the truth of regional growth patterns.

However, this study has some limitations. This study employed substitute variables for R&D capacity, however, we corroborated the robustness of the model and variables through an additional analysis with patent data. For the future research, investigating the role of intermediate organization in interconnecting the factors would provide local governments with more fruitful implications. In addition, the methodology can be applied in diverse area such as innovation cities or special economic zones.

Appendix A

Table A1. Eigen Analysis of the Correlation Matrix: Social Factor.

Component	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7
Eigenvalue	0.468535	0.734097	0.121837	4.35528	0.810648	0.375073	0.134527
Proportion	0.0669	0.1049	0.0174	0.6222	0.1158	0.0536	0.0192
Cumulative	0.0669	0.1718	0.1892	0.8114	0.9272	0.9808	1.0000

Table A2. Coefficient of the Principal Components Analysis: Social Factor.

Variable	*wapop*	*youth*	*univstu*	*unemp*	*popdens*	*priedu*	*stupt*
Comp1	0.4399	0.3951	0.3414	0.3658	0.2866	0.3631	0.4313

*Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy = 0.8246.

Table A3. Eigen Analysis of the Correlation Matrix: Capacity Factor.

Component	Comp1	Comp2	Comp3
Eigenvalue	2.03016	0.507061	0.462775
Proportion	0.6767	0.1690	0.1543
Cumulative	0.6767	0.8457	1.000

Table A4. Coefficients of the Principal Components Analysis: Capacity Factor.

Variable	*numf*	*scipf*	*bussti*
Comp1	0.5744	0.5854	0.5722

*Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy = 0.6952.

Table A5. Eigen Analysis of the Correlation Matrix: Clustering Factor.

Component	Comp1	Comp2	Comp3
Eigenvalue	1.63495	0.964772	0.400278
Proportion	0.5450	0.3216	0.1334
Cumulative	0.5450	0.8666	1.000

Table A6. Coefficients of the Principal Components Analysis: Clustering Factor.

Variable	*size*	*focus*	*div*
Comp1	0.6872	0.6893	0.2296

* Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy = 0.5148.

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