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The importance of spatial agglomeration in product innovation: A microgeography perspective

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ABSTRACT

This study focuses on how innovation in general and product innovation in particular are influenced by firms' agglomeration in smaller local districts, the so-called microgeography of product innovation. Using spatial analytic methods on the mobile gaming industry in the Seoul Metropolitan Area, this study finds that mobile gaming firms co-locate to form sub-clusters for specializing in specific product innovation activities such as visual complexity, product price, and product upgrade. Furthermore, results show that the relationships between product innovation and sales performance differ across individual firms and sub-clusters. The findings confirm that microgeographic location plays a key role in promoting different product innovation activities within a city-level cluster. One key implication is that regional and district policy makers should consider product innovation policies based on each sub-cluster's specific product innovation potential, due to the heterogeneous agglomeration effects in product innovation activities.

1. Introduction

Product innovation is central for firms in developing and maintaining their competitive advantage (Chen, 2007), and increasing competition and accelerating product life cycles mean that product innovation becomes even more important (Slater, Mohr, & Sengupta, 2014). A firm's choice where to geographically locate its product innovation efforts is based on specific circumstances and other contributing factors (Demirbag & Glaister, 2010). Although information and communication technologies improve interaction among people, especially in virtual teams of global firms (Sole & Edmondson, 2002), geographic distance as well as geopolitical borders restrict the flow of knowledge between firms (Singh & Marx, 2013) and deteriorate both quality and quantity of knowledge transfer (Boschma, 2005; Malmberg & Maskell, 2006). Therefore, substantial research has focused on how innovation in general is influenced by the spatial positioning of firms and industries from a macro perspective (e.g., at the country-, state-, or metropolitan-level).

However, less attention has been paid to how innovation generally and product innovation in particular, is configured and effective in smaller local districts within a cluster, from a micro perspective (e.g., at the district- or firm-level within a city), the so-called "microgeography of innovation." The microgeography of innovation deals with detailing the spatial delimitation of clusters based on firm-based micro-data (Boix, Hervás-Oliver, & Miguel-Molina, 2015). This view can be extended to the spatial distribution of firm-level product innovation within a single cluster. Local presence enables firms to participate in and benefit from localized and highly specialized knowledge exchanges that occur only in face-to-face interactions and unanticipated encounters (Storper & Venables, 2004). Although a firm's internal factors are important for its innovation efforts, a firm's external environment, its collaboration network and internal capabilities to exploit the network externalities, also influence its innovation performance (Chiu & Lee, 2012).

Furthermore, agglomeration benefits are not always equally distributed. Specifically, firms do not benefit symmetrically from agglomeration because of unique characteristics that enable them to obtain greater benefits from specialized inputs (McCann & Folta, 2011) or because some clusters have different labor market structures from other clusters (Agrawal, Cockburn, Galasso, & Oettl, 2014). Recently, Boix et al. (2015) found that creative industries are highly clustered and co-locate to form smaller clusters that are predominantly metropolitan, cross-border, and heterogeneous. Despite a growing literature in asymmetric agglomeration effects, researchers have mainly focused on 'macro-heterogeneity' across locations but with less attention to 'micro-heterogeneity' across people and firms (Ottaviano, 2011).

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The objectives of this study are to explore empirically (1) if individual firms co-locate to form smaller local clusters, henceforth referred to as sub-clusters and (2) if they asymmetrically benefit from product innovation agglomerations individually and in sub-clusters, based on geospatial data of firm-level product innovation and the related sales performance. Specifically, we aim to explore how micro-geographic proximity shapes firms' product innovation behaviors ("spatial dependence") and to what extent relationships between product innovation and sales performance vary across firms and sub-clusters ("spatial heterogeneity"). If such microgeographic effects exist, both incumbent and newly-entering firms will be interested in allocating their limited R & D budgets more efficiently and policy makers may facilitate firms and their product innovation activities more effectively. Thus, by focusing on the role of the microgeography of product innovation, this paper contributes to the study of geography of innovation under simultaneous consideration of spatial dependence and spatial heterogeneity.

This paper continues with a literature review and the development of research hypotheses. Spatial effects on the effectiveness of product innovation are tested and discussed using a data set of 72 mobile game developers, with 355 commercialized mobile gaming products, across 30 local districts in the Seoul Metropolitan Area in South Korea. This paper concludes with implications for academic research and management practice.

2. Literature review and research hypotheses

2.1. Knowledge externalities in product innovation

Agglomeration theory argues that innovation depends on the nature of local knowledge (Tallman, Jenkins, Henry, & Pinch, 2004) and the variety of knowledge in the region (Frenken, Van, & Verburg, 2007). Such variety of knowledge consists of related variety and unrelated variety. The related variety denotes the balance between cognitive proximity and distance across sectors in a region and provides a basis for knowledge spillovers among sectors (Nooteboom, 2000), causing specialization externalities (Audretsch & Feldman, 2004). The unrelated variety denotes that the higher number of technologically related sectors in a region results in the higher inter-sectorial knowledge spillovers between those related sectors (Frenken et al., 2007), eventually enhancing diversification of regional innovation.

According to Audretsch and Feldman (2004), a firm's innovation activity should take place in those locations where the direct knowledge-generating inputs are the greatest and where knowledge spillovers are the most prevalent. The related variety enhances innovation as related technologies are more easily recombined into new technology both at the firm level (Breschi, Lissoni, & Malerba, 2003) and the regional level (Castaldi, Frenken, & Los, 2015). Although both types of knowledge variety are beneficial for innovation, related variety seems to be more important than unrelated variety in regional innovation (Castaldi et al., 2015). Applying the agglomeration theory to the product innovation context, firms benefit from specialized knowledge of product innovation spilled over in local sub-clusters. Location-specific advantages provide firms with opportunities to optimize activities along the value chain across different metropolitan areas (McCann & Folta, 2011). But due to firm-specific and site-specific factors, not all innovating firms benefit equally from their participation within micro- or macro-level clusters. Specifically, asymmetry in the learning capability of firms leads to asymmetric benefits of knowledge spillovers in clusters (McCann & Folta, 2011).

Recent research on the geography of innovation has begun to address micro-level locations of firms and sub-clusters in an industrial cluster (Arbia, Cella, Espa, & Giuliani, 2015). Using a geo-statistical algorithm and firm-based micro-data, Boix et al. (2015), identified clusters in creative industries in Europe. Taking a micro-level view on the geography of knowledge dynamics, Strambach and Klement (2012) found that space and place shape cumulative and combinatorial knowledge dynamics by proximity economies and the institutional embeddedness of actors. Arbia et al. (2015) analyzed the demographic dynamics of Italian retail food stores (i.e., their birth, growth, and survival) based on micro-geographic data and uncovered the relative importance of competitive and cooperative interactions in determining the spatial distribution of economic activities. But while these studies explore the spatial distribution or clustering of micro-level firms or economic activities, they pay little attention to the analysis of asymmetric sales performances of product innovations across individual firms or sub-clusters.

These considerations give rise to two types of microgeographic effects in product innovation and sales performance: spatial dependence and spatial heterogeneity. The concept of spatial dependence is determined both "by similarities in position, and by similarities in attributes" (Longley, Goodchild, Maguire, & Rhind, 2005, p. 517), representing the extent to which neighboring firms specialize in certain aspects of product innovation. In contrast, spatial heterogeneity refers to the tendency for the relationships among variables to vary across locations, or the unevenness of a trait, event or relationship across a region (Anselin, 2001). As these effects are likely to be strong even for firms in close proximity, the product innovation activities of a firm and its sales performance are likely to be associated with other firms and/or sub-clusters heterogeneously.

2.2. Spatial dependence in product innovation

According to the knowledge production function model (Griliches, 1979), incumbent firms engage in the pursuit of new economic knowledge as an input into the process of innovation. By shifting the unit of observation from a firm to geography, Feldman and Florida (1994) confirmed that the knowledge production function was robust at the geographic level of analysis: the output of innovation is a function of the innovative inputs in that location. The importance of geographic proximity for knowledge spillovers is dependent on the propensity of similar industrial activity to agglomerate geographically (Autant-Bernard, 2001). While long distances require more complementary proximities to achieve closeness, short distances favor interaction, networking, collaboration and innovation (Boschma, 2005). Lazzeretti and Capone (2016) found that whereas the influence of social proximity diminishes as the cluster evolves and matures, geographical proximity continues to play a significant role along the cluster evolution.

Therefore, firms choose the location of their product innovation efforts based on specific local circumstances (Demirbag & Glaister, 2010). The collocation of related innovating firms generates knowledge spillovers and facilitates product innovation (Malmberg, Sölvell, & Zander, 1996). According to Malmberg and Power (2006), true clusters have a spatial agglomeration of similar and related economic activity, and the activities are interlinked by relations and interactions of local collaboration and competition. Darchen (2016) found that video game developers located in the Central Business District in Melbourne mainly specialize in complex games which require more face-to-face meetings and collaborative work than less complex games. As such, if the tenets of microgeography hold up for innovation, we should also expect product innovation activities to be spatially dependent upon neighboring innovating firms in smaller local

districts. In other words, firms specializing in specific product innovation activities may co-locate to form sub-clusters because sub-clustered firms capitalize on local knowledge spillovers and/or specialized resources. Consequently, we hypothesize:

H1. Firms specializing in specific product innovation activities tend to co-locate to form sub-clusters within an industrial cluster.

2.3. Spatial heterogeneity in product innovation

Geographical agglomeration performance may vary considerably across different industries and different regions (McCann & Folta, 2011). Feldman and Florida (1994) detected a relationship between product innovation and the locally underlying technological infrastructure, such as firms in related manufacturing industries, industrial R & D, university R & D, and business-service firms. Subsequent empirical research at the firm level suggests a strong positive association between firm innovativeness and regional location (Beaudry & Breschi, 2003). From a labor market perspective, innovation output is higher in regions where both a sizable population of small firms and large R & D labs are present (Agrawal et al., 2014). Large firms have an advantage in the production of ideas when their R & D labs can spread R & D fixed costs over a larger number of innovations (Cohen & Klepper, 1996). In addition, the presence of small firms can develop a culture of entrepreneurship that induces employees of large firms to start their own firms (Glaeser & Kerr, 2009). Thus, large and small firms are complementary and regional innovation may be enhanced when they coexist.

However, regional and urban studies have illustrated the existence of spatially varying agglomeration effects. Cheng and Li (2011) examined spatially varying relationships between new firm formation and its macroeconomic determinants across U.S. counties. Kang and Dall'erba (2016) explored the spatially varying innovation capacity across U.S. MSA (metropolitan statistical area) and non-MSA counties. In addition, Shearmur (2012) analyzed how innovation of knowledge-intensive business services vary within the Montreal metropolitan area. It is assumed that the nation- and province-level innovation heterogeneity can be applied to the micro-heterogeneity at firm-level product innovation. Therefore, the effectiveness of a firm's product innovation should be spatially dependent upon neighboring innovating firms within a single cluster. We argue that sales performance deriving from a firm's product innovation activities has local disparities and consequently hypothesize:

H2a. The relationships between specific product innovation activities and sales performance vary across individual firms within an industrial cluster.

Context matters in innovation because the quality of the innovation system in which a firm operates (besides a firm's internal factors) influences a firm's innovation performance (Srholec, 2010). This has been recognized in various contextual perspectives on geography of innovation, including technology districts (Storper, 1992) and learning regions (Morgan, 1997) in regional innovation systems. When firms co-locate to benefit from local resources, capabilities and knowledge spillovers, the flow of information and ideas about product and market knowledge can be shared easily (Gordon & McCann, 2000).

Such contextual perspectives can be applied to the microgeography of product innovation. Because inter-firm knowledge spillovers in a sub-cluster can include different qualities of product innovation knowledge, asymmetric agglomeration benefits in product innovation can also vary across different sub-clusters. Although neighboring firms benefit from the transfer of knowledge on innovation, the effectiveness of a sub-cluster may depend on the nature of knowledge (Tallman et al., 2004) and the quality of knowledge (Frenken et al., 2007) in a sub-cluster. For example, whereas analytic knowledge (e.g., in the pharmaceutical industry) and synthetic knowledge (e.g., in the mechanical engineering industry) are less sensitive to distance-decay, symbolic knowledge (e.g., in the creative industries) tends to be extremely local and consequently highly clustered (Boix et al., 2015).

If some firms are more effective in specializing in a certain product innovation and securing higher sales performance, they may be in a better position to transmit their knowledge and strengthen the positive feedback emanating from the sub-cluster. Alternatively, local firms that struggle to increase sales performance, may not contribute as much to the local sub-cluster and they and their neighbors may jointly underperform. Given these considerations, we expect heterogeneous relationships between product innovation and sales performance across different sub-clusters. Consequently, we hypothesize:

H2b. The relationships between specific product innovation activities and sales performance vary across sub-clusters within an industrial cluster.

3. Methodology

3.1. Data collection and sample

We collected secondary data related to product innovation and sales performance of the mobile game developers (MGDs) that commercialized their products from February 2010 to June 2011 in the Seoul Metropolitan Area (henceforth referred to as Seoul) in South Korea. The mobile gaming industry is a reliable choice as an industry to focus on, for several reasons. First, the gaming software industry is characterized by different incremental and technological complexity (Storz, 2008) and requires combinative creativity—the recombination of existing ideas from different sources—for product innovation (Tschang, 2007). Second, gaming software developers tend to agglomerate due to the collaborative nature of complex game development, easy access to transportation and affordable rent (Darchen, 2016). Finally, knowledge exchange among video game developers in agglomerations tend to be benevolent (i.e., improving confidentiality) rather than malicious (i.e., undermining confidentiality); spatial concentration of gaming software developers thus tends to enhance levels of confidentiality performance (Massimino, Gray, & Boyer, 2017).

Finally, we chose Seoul as the study area because capital cities develop a unique regional innovation system and position themselves in the national urban hierarchy through a set of locational policies formulated in local policy regimes (Mayer, Sager, Kaufmann, & Warland, 2016). Locational policies should aim at enhancing the economic competitiveness of the targeted district by identifying, developing and exploiting its place-specific assets in order to bring economic gains in a specific spatial area (van der Heiden, 2010), likely leading to multiple sub-clusters of MGDs within the Seoul regional cluster.

Initially, we obtained the data set of 1215 mobile games launched by 159 MGDs from the leading mobile app market in South Korea and extracted the final sample to meet three requirements: (1) corporate-type MGDs to provide their location information while excluding individual-type MGDs with no location information; (2) MGDs whose mobile games launched between February 2010 to June 2011 had already reached the end-of-life stage, in order to measure lifetime sales

performance of new products more accurately; and (3) MGDs located in Seoul, with MGDs located sparsely outside Seoul excluded, in order to assess microgeography of product innovation within the Seoul boundary. The final sample consists of product innovation activities and sales performance from 355 mobile games launched by 72 MGDs across 30 government districts in Seoul (Appendix A).

3.2. Operationalization of variables

In our application, we used sales performance as the dependent variable. The objectives of product innovations are primarily related to performance (e.g., improving product quality, increasing market share, entering new markets) (OECD & Eurostat, 2005). Firms can transform innovative inputs (e.g., knowledge and R & D) into innovation outputs (e.g., number or share of product innovations) (Geroski, 1994). Innovation outcomes, as a consequence of R & D and product development, have economic effects for the focal firms (Janger, Schubert, Andries, Rammerd, & Hoskens, 2017). In the case of product innovation, the number of products sold in a market is one measure of firm-level innovation outcome. Furthermore, product life cycle sales are a highly relevant measure of the focal firm's sales performance derived from product innovation activities because the focal firm devotes attention to product innovation not only during the product development period but also after commercialization (Jang & Chung, 2015; Mallick, Ritzman, & Sinha, 2013). Therefore, we measure sales performance (*SALES*) by the average sales unit of mobile games developed by an MGD and sold over the product life cycle.

In order to build the explanatory variables for product innovation, we employed concepts from innovation diffusion literature (Rogers, 1962) specifically developed for the purpose of understanding how perceptions of product innovation characteristics influence people's likelihood of innovation adoption. Talke and O'Connor (2011) proposed three content elements of product-related information during innovation adoption: technical (technical details and technical consequences), financial (profitability and financial viability), and usability (relative product advantage and product compatibility). As such, we operationalized three aspects of product innovation that influence consumer innovation adoption and product sales.

First we considered the technical aspects of product innovation in mobile games, starting with a product's design features and functions but also including other technical properties of the product. Researchers argue that visually complex products can be favored when consumers pay more attention to product function and quality (Creusen, Veryzer, & Schoormans, 2010). Furthermore, a visually complex product appearance can improve consumer comprehension of the product innovation in comparison to a visually simple product (Cheng & Mugge, 2015). In mobile game software, larger software size often represents higher visual complexity and is associated with the number of lines of code, the richness of content and the complexity of individual graphic objects (Tschang, 2007). Therefore, we use visual complexity (*COMPLEXITY*) as the proxy variable for product innovation input and measure software size by the average number of megabytes of mobile games developed by an MGD.

Second, we identified product price as the financial aspect of product innovation, because pricing is a process that is strongly related to new product development, as resources are deployed not only to develop beneficial product innovations but also to determine prices (Day, 1994). Prior innovation literature has viewed pricing as one of several decisions to be made when launching a new product (Langerak, Hultink, & Robben, 2004). The pricing of new products not only directly affects the innovation's market performance but also indirectly affects

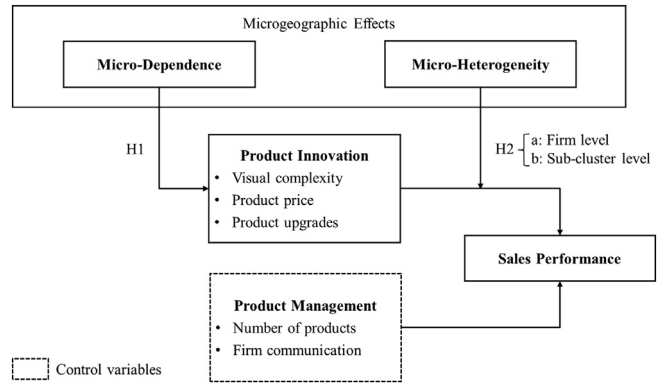


Fig. 1. The empirical model of microgeography of product innovation.

this performance through its influence on the perceived relative product advantage (Ingenbleek, Frambach, & Verhallen, 2010). As such, price level can imply the level of product innovation input, so we measure product price (*PRICE*) as the average price of mobile games set by an MGD.

Finally, we considered product upgrades as the usability aspect of product innovation. Product upgrades designate modifications of the design of a product after the start of its production and release into the market (Mallick et al., 2013) and involve the experimentation, learning and creation of new knowledge or combining new with old knowledge after the start of production of a product and its release into the market. Product upgrades can be initiated by market-related and manufacturing-related considerations (Balakrishnan & Chakravarty, 1996), increase quality capability and in turn, have an impact on business performance (Jang & Chung, 2015). Hence, we consider product upgrades (*UPGRADE*) as product innovation input and measure product upgrades as the average number of product upgrades of mobile game(s) during the product life cycle conducted by an MGD (Jang & Chung, 2015).

We controlled for two factors related to product management strategies that might affect sales performance. We first controlled for the total number of products developed and commercialized by an MGD during the study period (*NUMBER*), which represents an MGD's R & D capability. The second variable we sought to control was a firm's online communication input associated with the commercialized product, which is measured by the average number of firm-generated e-mails sent to customers for the focal mobile game (*COMMUNICATION*).

The empirical model (Fig. 1) proposes that firms tend to co-locate in sub-clusters to efficiently specialize in product innovation activities (i.e., visual complexity, product price, product upgrades) and product management strategies (i.e., number of products, firm communication) within an industrial cluster (i.e., micro-dependence) (H1) and that the relationships between product innovation and sales performance vary across individual firms (H2a) and sub-clusters (H2b) within an industrial cluster (i.e., micro-heterogeneity).

3.3. Models

First, in order to assess the existence of spatial dependence among the product innovation activities of two firms (H1), we apply global Moran's I as a measure of spatial autocorrelation (Li, Calder, & Cressie, 2007):

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} w_{ij} (x_i - \mu)(x_j - \mu)}{\sum_i (x_i - \mu)^2} \quad (1)$$

where w_{ij} is the matrix of weights such that $w_{ij} = 1$ if firm i and firm j are adjacent and otherwise, $w_{ij} = 0$; x_i is the attribute value of a specific product innovation at firm i; x_j is the attribute value of a specific product innovation at firm j; μ is the average attribute value of a specific product innovation; and N is the total number of firms. Furthermore, in order to identify the location and type of spatial clusters, the local indicator of spatial association (LISA) is applied to identify the location and type of spatial clusters. LISA is calculated as:

$$I_i = \frac{(x_i - \mu)}{m_2} \sum_i w_{ij}(x_j - \mu) \quad (2)$$

where m_2 is calculated by $\sum_i (x_i - \mu)^2 / N$. The results of LISA analysis can be presented in the form of Moran's scatter plot or LISA cluster map with information regarding type of spatial clusters (Anselin, 1995). Results from a LISA cluster map are typically classified into five categories: (1) HH: spatial clusters with high values, indicating positive spatial autocorrelation, also called hot spots; (2) HL: spatial clusters with high values adjacent to low values, indicating negative spatial autocorrelation, also called spatial outliers; (3) LH: spatial clusters with low values adjacent to high values, indicating negative spatial autocorrelation, also called spatial outliers; (4) LL: spatial clusters with low values, indicating positive spatial autocorrelation, also called cold spots; and (5) not significant: no spatial clusters between locations.

Second, in order to investigate spatially varying relationships between product innovation and sales performance (H2a and H2b), we use a spatial statistical technique called geographically weighed regression (GWR) (Fotheringham, Brunsdon, & Charlton, 2002). GWR produces a set of local regression coefficients for exploring spatially varying relationships between variables. In each area's individual regression, characteristics of each area in the subsample are weighted by the spatial proximity of that area. The GWR model can be modified as:

$$\begin{aligned} SALES_i &= \beta_{i0}(u_i, v_i) + \sum_{j=1}^{k} \beta_{ik}(u_i, v_i) x_{ik} + \varepsilon_i \\ &= \beta_{i0}(u_i, v_i) + \beta_{i1}(u_i, v_i) VISUAL + \beta_{i2}(u_i, v_i) PRICE + \beta_{i3}(u_i, v_i) UPGRADE \\ &+ \beta_{i4}(u_i, v_i) NUMBER + \beta_{i5}(u_i, v_i) COMMUNICATION + \varepsilon_i. \end{aligned} \quad (3)$$

where (u_i, v_i) is the location in geographic space of the ith observation (Fotheringham et al., 2002); $\beta_{i0}(u_i, v_i)$ is the intercept parameter at point i; $\beta_{ik}(u_i, v_i)$ is the local regression coefficient for the kth independent variable at point i; and $\beta_{ik}$is the value of the kth independent variable at point i.

When employing GWR, observations closer to the regression points are weighted more than those located farther away. One of the most commonly employed weighting methods is the bi-square kernel function that is utilized when the observed data points are not regularly distributed across the study area. As for the bi-square kernel function, the weight w_{ij} is calculated as:

$$w_{ij} = [1 - (d_{ij}/b^2)] \text{ when } d_{ij} \le b,\ w_{ij} = 0 \text{ when } d_{ij} > b \quad (4)$$

where d_{ij} is the Euclidean distance between the regression point i and the data point j and b is the bandwidth. At the regression point i, the weight of the data point is unity and falls to zero when the distance between i and j equals the bandwidth. The optimal bandwidth distance or neighboring units used in each observation's regression is determined by minimizing the corrected Akaike Information Criterion (AIC_c) estimated as:

$$AIC_c = 2k - 2\ln(L) + \frac{2k(k+1)}{n-k-1} \quad (5)$$

where L denotes the maximum value of the likelihood function for the model, k denotes the number of estimated parameters in the model and n denotes the sample size.

3.4. Data analysis

We first used global Moran's I statistic and LISA to analyze the existence of spatial dependence in MGDs' product innovation activities. Second, we ran the OLS multivariate regression analysis to investigate the global relationship between product innovation activities and sales performance. Third, we used GWR to explore spatial variations among variables using the same independent and dependent variables by applying a bi-square kernel function due to varying density of MGDs in Seoul. In order to minimize AIC_c, the optimal kernel size was determined through an iterative statistical optimization process. Fourth, spatial autocorrelation analyses were also employed to investigate the existence of spatial dependence of local coefficients produced by GWR. Finally, statistical diagnostics such as local coefficients and local R^2 from GWR were mapped to examine spatially varying relationships among variables.

4. Results

4.1. Spatial dependence in product innovation

Table 1 reports that firm-level global Moran's I values for three independent variables (i.e., visual complexity, product price, and product upgrade) and two control variables (i.e., product number and firm communication) are all positive, consisting of 0.05, 0.14, 0.18, 0.10, and 0.07, respectively. Among them, MGDs that conduct high-level product upgrades tend to co-locate more than other product innovation activities. The results are similar to the findings of Kolympiris, Kalaitzandonakes, and Miller (2011) for biotechnology firms in the U.S., showing that the spatial dependence (global Moran's I) among neighboring biotechnology firms located < 30 miles from the origin biotechnology firm, is 0.06.

Furthermore, corresponding maps (Appendix B) also provide visual evidence of spatial dependence by identifying the location and type of spatial clusters of local coefficients for those variables. Interestingly, Gangnam or Seoul's east area (with red dots) shows the HH (high-high) cluster for product price and product number, meaning that MGDs in the Gangnam area tend to set high prices for their products while commercializing a high number of products in the given study period. Thus, both the global Moran's I values and the maps of product innovations confirm the existence of spatial dependence in specializing in a certain aspect of product innovation in the mobile gaming industry, thus supporting H1.

4.2. Spatial heterogeneity in product innovation

Table 2 presents the summary statistics and correlation matrix of variables used for analysis. The correlation coefficients between the dependent variable and independent variables are positive and relatively high and indicate a good selection of variables. Potential multicollinearity was ruled out by computing the variance inflation factors (VIFs) and all were within an acceptable range with a mean VIF value of 1.25 (Table 1).

Table 1
Results of OLS regression and GWR models.

Variables	Global Moran's I		OLS coefficients	GWR coefficients (H2a)			VIF
	Individual firm (H1)	Sub-cluster (H2b)		Minimum	Mean	Maximum	
Visual complexity	0.05	0.56	118.97	33.73	92.34	274.34	1.25
Product price	0.14	0.69	272.58	–1243.68	− 118.19	2862.94	1.15
Product upgrade	0.18	0.78	896.80*	− 7.21	1391.43	3379.30	1.37
Number of products	0.10	0.53	− 126.75	− 1141.73	− 207.24	6.77	1.13
Firm communication	0.07	0.66	111.74*	13.98	87.24	172.89	1.36
Intercept			− 2174.80	− 8565.16	− 2344.43	650.36	
R^2			0.63	0.44	0.68	0.97	
Adjusted R^2			0.62	0.43	0.67	0.96	
Condition index				5.71	6.89	12.91	
Number of observations			72	72			
Number of neighbors				25			
Corrected AIC			1390.26	1335.43			
Moran's I of standard residual			0.48	0.23			

Notes: Condition index and number of neighbors are only applied to coefficients of GWR. The values for corrected AIC and Moran's I are applied for the overall GWR model.
* $p < 0.05$.

Table 2
Descriptive statistics and correlation matrix.

Variable	Mean	S.D.	1	2	3	4	5	6
1. Product sales	7749.29	18,278.70	1					
2. Visual complexity	11.24	11.45	0.077	1				
3. Product price	1.98	1.07	0.159	0.268	1			
4. Product upgrade	4.42	4.13	0.549	− 0.047	0.120	1		
5. Number of products	4.93	10.22	0.003	0.333	0.114	0.035	1	
6. Firm communication	40.14	111.04	0.778	0.044	0.162	0.502	0.063	1

The results in Table 1 show that two of the five coefficients of independent variables were statistically significant at the 0.05 significance level, suggesting that more product upgrades and firm-to-customer communications positively influence sales performance of MGDs. Although the OLS model indicates that visual complexity, product price and product number have no relationship with the performance, the GWR model arrives at a range for the local coefficients. This variability in the local coefficients suggests that the relationships between MGDs' product innovation and sales performance vary across individual firms. For example, the impact of product upgrade on sales performance can be negative for a certain firm ($\beta = -7.21$) or extremely positive for a certain firm ($\beta = 3279.30$), while the average coefficient in the OLS regression is positive ($\beta = 896.80$). These results strongly support H2a. Furthermore, the local adjusted R^2 varies from 0.43 to 0.96 whereas the average value is 0.62. The local condition indexes range from 5.71 to 12.91, indicating the absence of local collinearity among the independent variables.

As supplementary analysis, the maps reveal how spatial heterogeneity in the relationships between product innovation activities and sales performance vary across individual firms in Seoul (Appendix C). Specifically, the effectiveness of a firm's product innovation activity varies across the firm's specific location (see the first five maps) and furthermore, the econometric model performance (i.e., adjusted R^2) differs across firms (see the final map). Dark-colored firms have more positive relationships between the focal aspect of product innovation and sales performance whereas light-colored firms have less positive or more negative relationships.

Finally, Table 1 also reveals that global Moran's I values in the sub-cluster level are all positive and close to 1 (visual complexity: 0.56; product price: 0.69; and product upgrade: 0.78). It means that agglomeration benefits of product innovation significantly exist across sub-clusters. In other words, the relationships between product innovation activities and sales performance vary across sub-clusters, i.e., spatial dependence of heterogeneous agglomeration benefits. As shown in the maps (Appendix D), MGDs with high level of visual complexity or high price policy that are located in Seoul's east area tend to outperform but MGDs in Seoul's west area tend to underperform. Interestingly, the opposite is the case for product upgrades; Seoul's east area belongs to a low-performing cluster whereas Seoul's west area belongs to a high-performing cluster. Thus, both Moran's I values and maps confirm the existence of heterogeneous agglomeration benefits in product innovation across sub-clusters, thus supporting H2b.

5. Discussion and conclusion

This study contributes to the understanding of the microgeography of product innovation in terms of (1) how firms specializing in product innovation co-locate in sub-clusters ("micro-dependence") and (2) how the relationships between product innovation and sales performance vary across firms and sub-clusters ("micro-heterogeneity") in the mobile gaming industry. As demonstrated empirically, firms with a similar specialization of product innovation are micro-clustered and they benefit asymmetrically across individual firms and sub-clusters. Therefore, this study develops a bridge between the geography of innovation and the product innovation literatures. Moreover, this paper applies three methodologies–statistical, spatial and visual–to the microgeography of product innovation. The empirical results show that the GWR model not only outperforms the traditional OLS model but also

supports the development of place-based product innovation strategies when combined with maps. It is important for innovation researchers and practitioners alike to utilize geospatial data and analytic techniques to examine how the effectiveness of product innovation can vary across locations where firms operate.

Consistent with the broader finding on geographical agglomeration of similar industrial activity (Autant-Bernard, 2001), our findings demonstrate the existence of micro-dependence of product innovation. Some researchers argue that leading firms may prefer to avoid clusters, resulting in adverse selection in agglomeration because their relative advantage may suffer (Shaver & Flyer, 2000). However, our conjecture is that firms specializing in similar aspects of product innovation agglomerate geographically within a single cluster, possibly because sub-clustered firms perform more efficiently by capitalizing on local knowledge spillovers associated with new product development (Rosenkopf & Almeida, 2003). This study extends the literature on agglomeration externalities by tapping into the microgeography of product innovation within a city-level industrial cluster. Our results, derived from a leading regional cluster, support the view that micro-spatial proximity has a hugely important role as a knowledge production source for specializing product innovation and improving its sales performance.

This research further shows that agglomeration effects accrue asymmetrically to individual and clustered firms in terms of a different aspect of product innovation. The results of the GWR model and the maps indicate that the influence of local variations between product innovation and sales performance variables were explained by micro-heterogeneity. In our study, MGDs located in the Gangnam district were more likely to improve sales performance by specializing in visual complexity and/or product price, whereas MGDs that located in industry parks (e.g., Geumcheon and Guro districts) expected a better outcome by specializing in product upgrades. These results provide meaningful implications to both existing and newly-entering firms in city clusters. In our case, if an MGD pursues radical innovations through fundamental changes in new products (e.g., high visual complexity), they would benefit from collocating in the Gangnam district, possibly because of the recruitment of creative product designers and knowledge spillovers. However, if an MGD considered incremental innovations through continuous product upgrades as a key product innovation goal, they should co-locate in the Geumcheon and Guro districts where relevant industry parks are located. As such, exploring the spatially varying effects of product innovation on sales performance can help guide location decision-making for new start-ups with a different strategic focus on product innovation and finally result in a high success rate for new product launches.

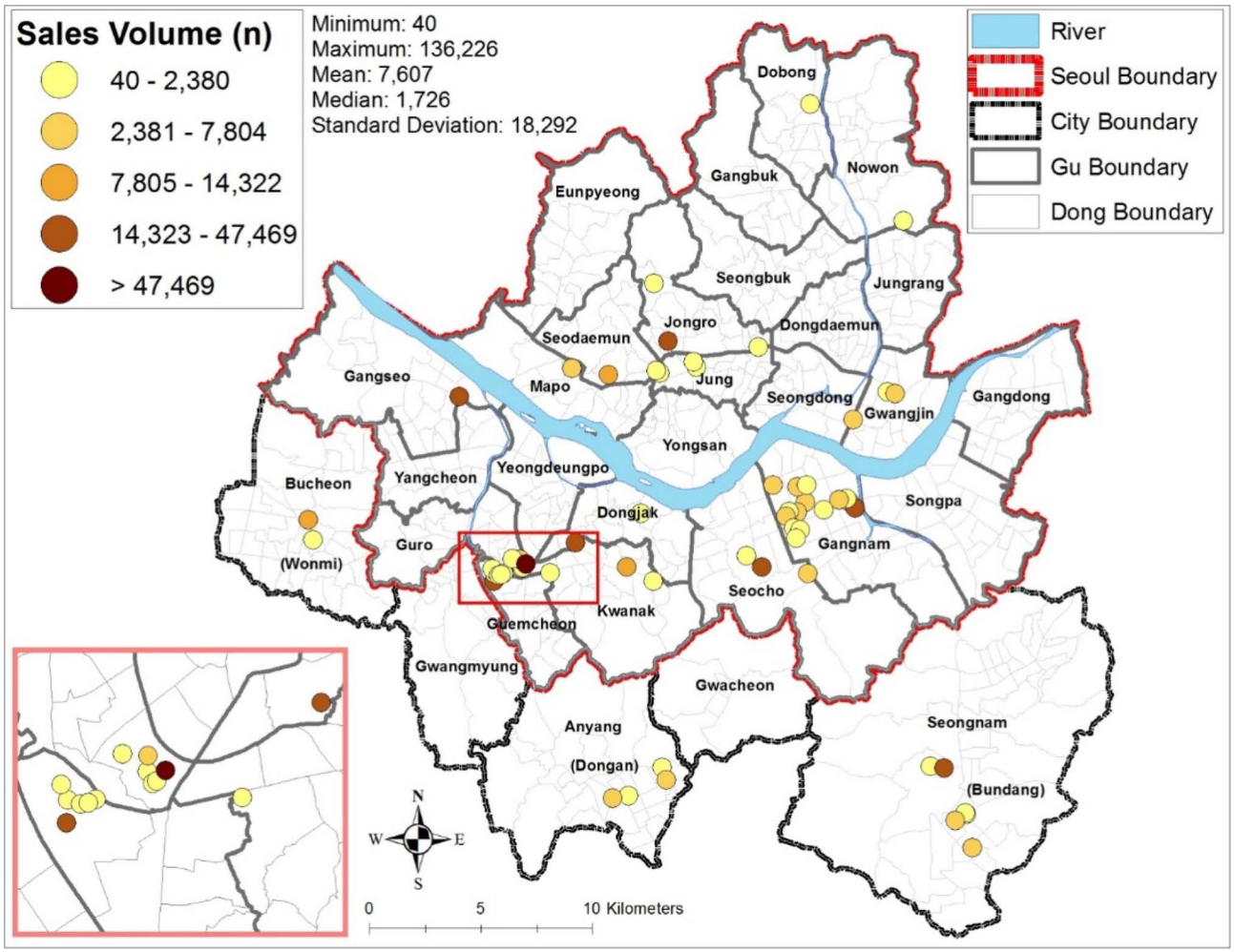
Our findings also represent a starting point for future quantitative or qualitative investigations into the location-specific factors associated with performance differentials. Porter (2000) noted that the geographic scope of a cluster relates to the distance over which informational, transactional and other efficiencies occur. Examples are land prices (informational factor) and industry varying recruitments (transactional factor) in a certain district. According to Seoul Metropolitan Government, the lowest land prices (with which office rent is generally aligned) are shown in the districts of Geumcheon ($1933 per square meter) and Guro ($2246 per square meter), respectively, while the average land price in Seoul is $3291 per square meter. Due to the low-cost benefit, quite a few small high tech firms, including MGDs, have started in or moved to these areas, resulting in the sub-clustering of MGDs in two industry parks. Although the Gangnam district showed one of the highest land prices ($5761 per square meter), it recruited the largest number of employees in the fields of science and technology services (25%), mainly driven by multinational high-tech firms such as Samsung Electronics and Google, while the average ratio of the other 25 districts was just 4%. Thus, the interrelationships between recruitment of specialized workers and transfer of tacit knowledge should be investigated to understand why the performance results for product innovation differ across districts within a regional cluster.

What conclusions can be drawn with respect to policy? Our analysis yields two broader areas for policy makers to consider. First, our research emphasizes that microgeographic location tends to play a key role in promoting different aspects of product innovation in the creative industries such as mobile gaming. The knowledge base in the mobile gaming industry is highly embedded, tacit and context-specific (i.e., symbolic knowledge is important), thus knowledge spillovers are highly local (Boix et al., 2015). We thus shed light on the important role of mircrogeographic proximity and sub-clustering in disseminating product innovation-related knowledge spillovers. District authorities in a city need to attract and promote different aspects of product innovation as much as to facilitate the formulation of locally appropriate product innovation and R & D solutions. Policy makers should engage in building a specialized local innovation community to encourage greater knowledge sharing and spillovers from indigenous product innovation efforts. For example, local government agencies can provide special funds for a collaborative R & D to spatially proximate firms and should guide the neighboring firms to specialize in a certain R & D area.

Second, regional and district policy makers should consider leveraging heterogeneous agglomeration of product innovation to maximize sales performance. The effectiveness of a local sub-cluster depends on the quality of the local firms and the specialization of product innovation. If some firms are more effective in specializing in a certain aspect of innovation (e.g., technical excellence) and increasing sales performance, their knowledge sharing and spillovers can strengthen the sub-cluster's comparative advantage in that aspect of product innovation. This research can help local industry promotion agencies to allocate limited budgets more efficiently by accurately pinpointing the right aspect of product innovation at the most competitive sub-cluster within a city-level cluster. Moreover, our study facilitates a more advanced policy decision making because information regarding micro-geographic heterogeneity of product innovation contributes to a place-based decision support system by comparing across administrative boundaries.

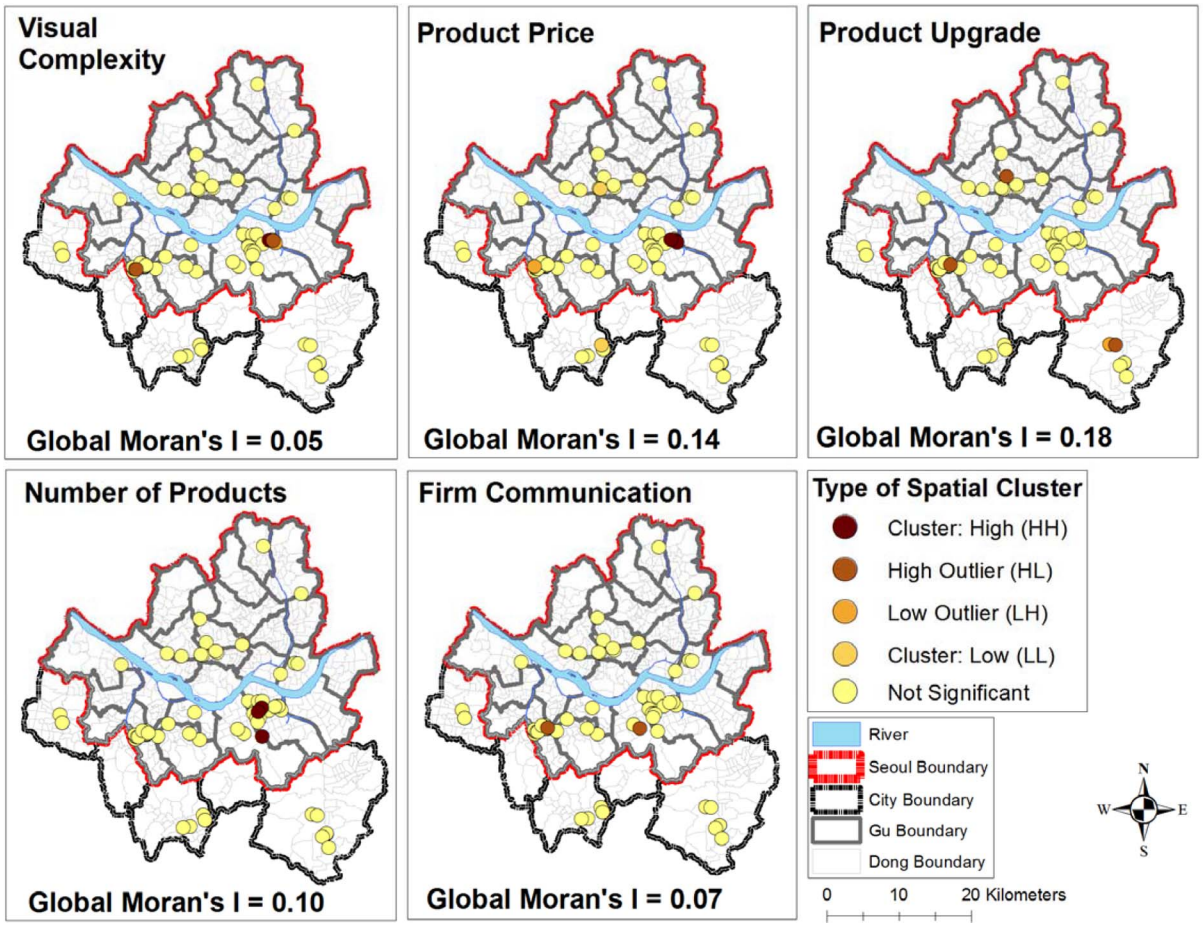
While the present research offers important theoretical and managerial implications, we recognize some limitations. First, the measurement for product innovation output was restricted to product sales. Due to limitations in data collection, the relationship between product innovation and customer satisfaction and/or financial-based performance could not be studied. Future research should also include data related to firm R & D expenditures and the degree to which customers are satisfied with the products they purchase. Second, the findings are based on the study of one industry (mobile gaming) and in the geography of one regional cluster (Seoul in South Korea). In order to increase confidence in the microgeography of product innovation, additional studies need to be conducted in other regional clusters and high-tech industries. Finally, although this study explored spatially varying sales performance of firms across one regional cluster, this study did not prove a causality of firm-level microgeographic location and product innovation on sales performance. Future studies need to examine the causal relationship among micro-level spatial agglomeration, product innovations and their sales performance.

Appendix A. The study area

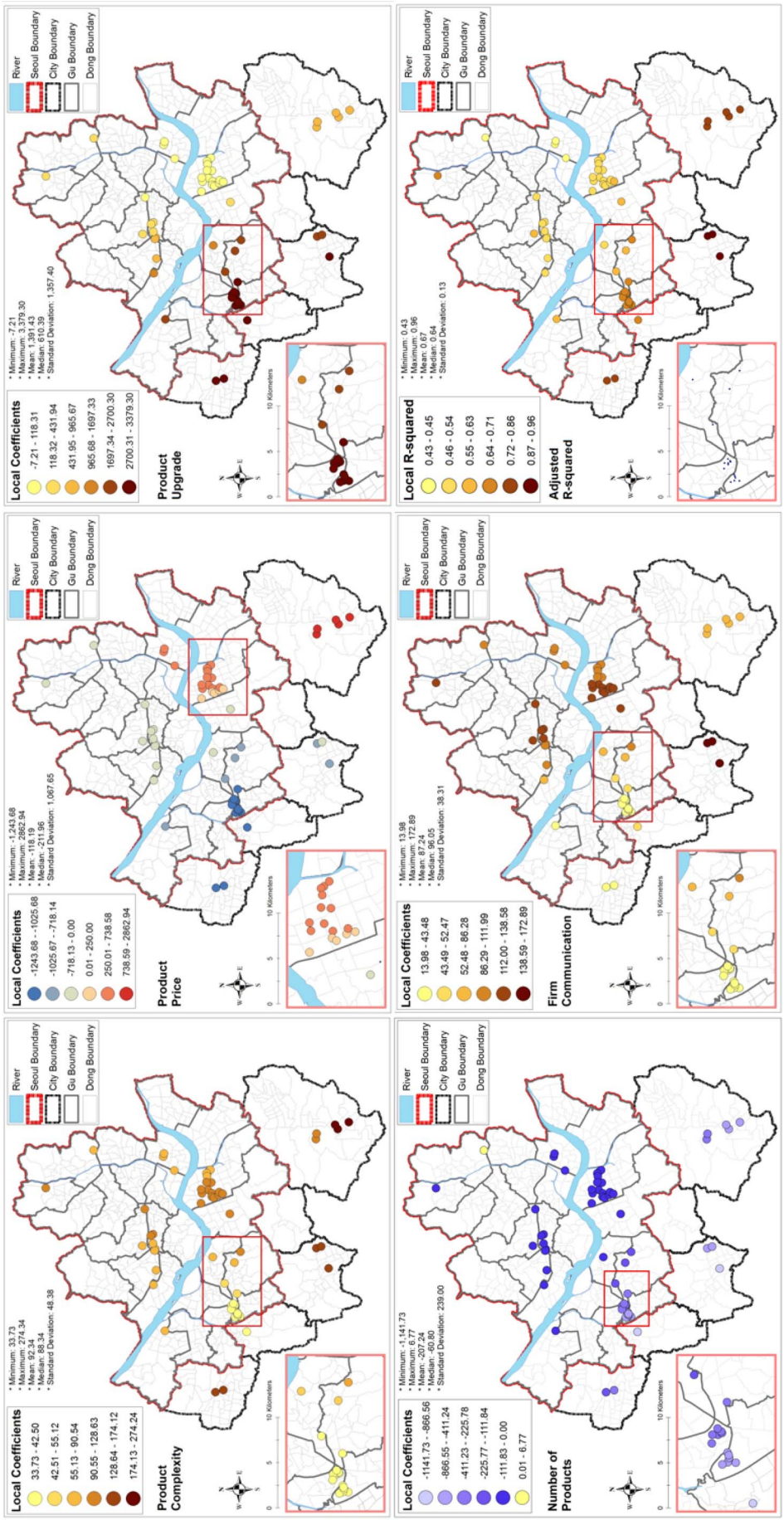


Notes: The unit of analysis is individual firm and the spatial scale of the study is kilometer, which is the common metric of distance in South Korea

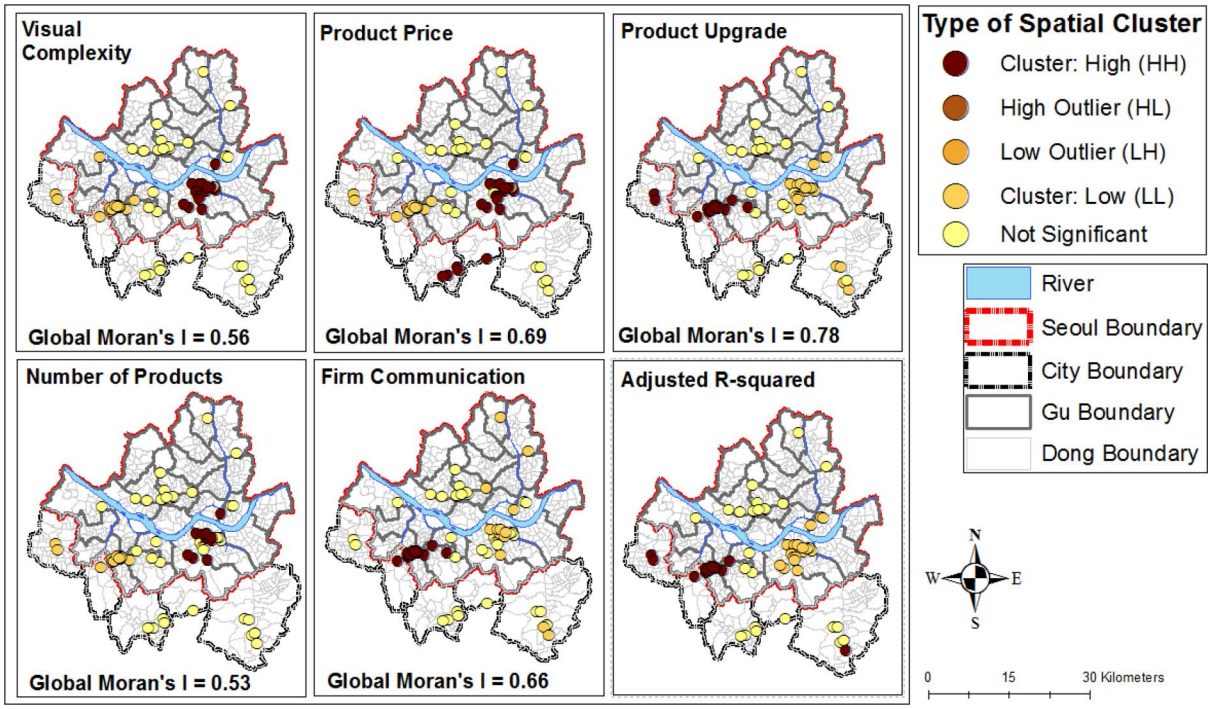
Appendix B. Maps of spatial dependence in product innovation



Appendix C. Maps of spatial heterogeneity in product innovation across firms


Local Coefficients
33.73 - 42.50
42.51 - 55.12
55.13 - 90.54
90.55 - 128.63
128.64 - 174.12
174.13 - 274.24
• Minimum: 33.73
• Maximum: 274.34
• Mean: 92.34
• Median: 86.34
• Standard Deviation: 48.38
Product Complexity
Local Coefficients
-1243.68 - -1025.68
-1025.67 - -718.14
-718.13 - 0.00
0.01 - 250.00
250.01 - 738.58
738.59 - 2862.94
• Minimum: -1,243.68
• Maximum: 2862.94
• Mean: -118.19
• Median: -211.96
• Standard Deviation: 1,067.65
Product Price
Local Coefficients
-7.21 - 118.31
118.32 - 431.94
431.95 - 965.67
965.68 - 1697.33
1697.34 - 2700.30
2700.31 - 3379.30
• Minimum: -7.21
• Maximum: 3,379.30
• Mean: 1,391.43
• Median: 610.39
• Standard Deviation: 1,357.40
Product Upgrade
Local Coefficients
-1141.73 - -866.56
-866.55 - -411.24
-411.23 - -225.78
-225.77 - -111.84
-111.83 - 0.00
0.01 - 6.77
• Minimum: -1,141.73
• Maximum: 6.77
• Mean: -207.24
• Median: -60.80
• Standard Deviation: 239.00
Number of Products
Local Coefficients
13.98 - 43.48
43.49 - 52.47
52.48 - 86.28
86.29 - 111.99
112.00 - 138.58
138.59 - 172.89
• Minimum: 13.98
• Maximum: 172.89
• Mean: 87.24
• Median: 96.05
• Standard Deviation: 38.31
Firm Communication
Local R-squared
0.43 - 0.45
0.46 - 0.54
0.55 - 0.63
0.64 - 0.71
0.72 - 0.86
0.87 - 0.96
• Minimum: 0.43
• Maximum: 0.96
• Mean: 0.67
• Median: 0.64
• Standard Deviation: 0.13
Adjusted R-squared
River
Seoul Boundary
City Boundary
Gu Boundary
Dong Boundary
10 Kilometers

Appendix D. Maps of spatial heterogeneity in product innovation across sub-clusters



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