



Paper to be presented at the DRUID Academy Conference 2016 in Bordeaux,
France on January 13-15, 2016

The Role of Agglomeration Economies regarding Innovative Competence: Exploitation and Exploration

Bo Kyeong Lee
Yonsei University
Information and Industrial Engineering
move314@gmail.com

So Young Sohn
Yonsei University
Dept. of Information and Industrial engineering
sohns@yonsei.ac.kr

Abstract

The role of agglomeration economies has been unresolved with regard to regional innovative competence. We consider that it is due to neglecting the heterogeneity in innovative competence across regions. In this paper, we employ the concepts of exploitation and exploration to reflect the different types of innovative competence and relate them with agglomeration externalities using the patent data of metropolitan statistical areas (MSAs) in the United States. The empirical results indicated that, regardless of the type of externality, a region with a high level of agglomeration externalities tends to have strong exploitative innovative competence. Further, it was observed that exploratory innovative competence is likely to be promoted in a region where Jacobian externalities exist. Thus, we confirm that the type of externality is not relevant in deciding the level of exploitative innovative competence and that only Jacobian externalities are positively linked to exploratory innovative competence.

The Role of Agglomeration Economies regarding Innovative Competence: Exploitation and Exploration

Bo Kyeong Lee,¹ So Young Sohn^{2*}

¹ Department of Information and Industrial Engineering, Yonsei University,
Yonsei-ro 50, Seoul 120–749, Korea. E-mail: lee.boyong@yonsei.ac.kr

² Department of Information and Industrial Engineering, Yonsei University,
Yonsei-ro 50, Seoul 120–749, Korea. E-mail: sohns@yonsei.ac.kr

*Corresponding author

Abstract

The role of agglomeration economies has been unresolved with regard to regional innovative competence. We consider that it is due to neglecting the heterogeneity in innovative competence across regions. In this paper, we employ the concepts of exploitation and exploration to reflect the different types of innovative competence and relate them with agglomeration externalities using the patent data of metropolitan statistical areas (MSAs) in the United States. The empirical results indicated that, regardless of the type of externality, a region with a high level of agglomeration externalities tends to have strong exploitative innovative competence. Further, it was observed that exploratory innovative competence is likely to be promoted in a region where Jacobian externalities exist. Thus, we confirm that the type of externality is not relevant in deciding the level of exploitative innovative competence and that only Jacobian externalities are positively linked to exploratory innovative competence.

Keywords

Agglomeration economy, MAR externality, Jacobian externality, exploration, exploitation.

1. Background

The literature of geographic economies poses a long-established question: How do agglomeration economies contribute to regional innovation? The link between innovation activity and agglomeration economies is embedded in three formal factors: sharing, matching, and knowledge spillover (Carlino and Kerr, 2014; Duranton and Puga, 2004). The advantage of sharing in agglomeration economies is economies of scale because these enable the efficient sharing of inputs. With regard to matching, agglomeration economies guarantee labor market pooling and the quality of skilled labor forces. Finally, knowledge spillover encourages knowledge transfer among individuals who are in the same place. In other words, geographical proximity facilitates information sharing through face-to-face contact (Storper, 2013), a benefit that has been recognized for many years. For example, in the seventeenth century, Jonathan's Coffee House was crowded with stockbrokers and in 1698 became the London Stock Exchange. More recently, many young and growing firms in Silicon Valley such as Facebook, Google, and Twitter have created open workplaces to promote buzz through face-to-face contact.

Glaeser et al. (1992) suggested two types of agglomeration economy in accordance with the structure of regional economic systems: a specialized economic system with MAR (Marshall-Arrow-Romer) externalities (Arrow, 1962; Marshall, 1920; Romer, 1986) and a diversified economic system with Jacobian externalities (Jacobs, 1969). The specialized regional economic system can encourage knowledge spillover in a region through various channels, such as business interaction and the turnover of skilled labor in similar industries, at relatively low cost (Saxenian, 1994). In this context, an inbuilt type of knowledge externality in such an economic system can be explained by MAR externalities that emphasize the importance of concentrated homogeneous industries promoting regional firms' innovation.

However, Jacobian externalities stress that industry diversification within a region can promote innovation by utilizing inter-industry spillover effects, and that such externalities are involved in diversified economic systems in general. Indeed, Lin (2011) argued that regions with diverse industries have the potential to create more “new work” compared with regions that have homogeneous industries.

The concept of knowledge externalities provides an effective explanation of the benefits of agglomeration economies for regional innovation. To date, theoretical studies have used the mechanisms of sharing, spillover knowledge, and matching skilled labor forces to try to investigate how MAR externalities and Jacobian externalities encourage regional innovation. However, because the concepts of MAR externalities and Jacobian externalities contrast with each other, the mechanisms related to the way in which agglomeration economies are linked to innovation activities are still inadequately explained. Identifying the effective structure of agglomeration externalities in order to encourage innovative competence is the first step to understanding how such externalities are associated with regional innovation. Thus, many empirical regional economic studies have conducted investigations and considered specific regional, organizational, and industrial conditions that may affect the mechanisms of a regional economic system in order to aid local innovation. For example, the intensity of R&D (Forni and Paba, 2002; Greunz, 2004; Henderson et al., 2001), the types of industry (Cainelli et al., 2001), the specific regions and countries (Beaudry and Breschi, 2003; Cingano and Schivardi, 2004), and the types of externality measurement (de Lucio et al., 2002) have been considered control variables. Such control variables determine whether local innovation is embedded in either a specialized economic system with MAR externalities or a diversified economic system with Jacobian externalities. However, there has been little research from the perspective of innovation performance measures. Thus, an argument continues about the selection of proxy variables from patents, patent quality, patent renewal, and research papers

(Baten et al., 2005; Ejermo, 2005; Paci and Usai, 1999; van der Panne, 2004). In particular, although Feldman and Audretsch (1999) highlighted the limitation of considering innovation performance as homogeneous, no prior study has focused on the heterogeneity of innovation performance.

We consider that each region possesses distinctive innovative competence compared with other regions. Further, the distinct characteristics of innovative competence have been generally described in terms of exploration and exploitation (March, 1991). Explorative innovation in this context means the development of novel knowledge, while exploitative innovation involves the refinement of existing knowledge. Based on evolutionary theory (Nelson and winter, 1982), we propose a set of hypotheses about the ways in which different agglomeration economies affect different regional innovative competences.

This study also seeks to contribute to the inconclusive debate concerning the impact of agglomeration externalities on regional innovative competence. In order to explore the mechanism of how each knowledge externality can have a different impact on innovative competence, we apply the concept of heterogeneous innovative competence in terms of exploitation and exploration.

The rest of the paper is organized as follows. In Section 2, we review the related theories about knowledge externalities based on agglomeration economies and innovative competence. Using the related theories, we then present hypotheses and an empirical model. In Section 3, we discuss our data and method. The last two sections present the results and discuss the hypotheses and the practical implications.

2. Theories and Hypotheses

2.1 Agglomeration economies and innovative competence

There are two categories of knowledge: tacit knowledge and explicit knowledge. Tacit knowledge is uncodified information that can only be acquired through social interaction while explicit knowledge is codified information that can be freely distributed and used. Thus, although both tacit knowledge and explicit knowledge can be transmitted, the transmission of tacit knowledge is particularly affected by distance. Consequently, spillovers of tacit knowledge are bounded within a region through face-to-face interaction, a phenomenon that is linked to agglomeration economies.

Following Weber's (1909) concentration on location studies in the early 1900s, Hoover (1937) proposed the classification of agglomeration economies. Hoover (1937) argued that a distinction exists among regional economic systems in accordance with the structures of specialized industries and diversified industries. A specialized economy has specific industries that are associated with firms' similar activities. These activities lead to emerging spatial agglomeration with related firms. However, in diversified economies, the external economies are available to all local firms irrespective of their industries.

While Hoover's (1937) study was limited to an investigation of a static situation, Glaeser et al. (1992) extended the concept of agglomeration economies with regard to dynamic externalities over time. In essence, Glaeser et al. (1992) suggested that the structure of agglomeration economies has two knowledge externalities: MAR externalities and Jacobian externalities.

2.2 Agglomeration externalities: MAR externalities and Jacobian externalities

Marshall (1980) argued that industries cluster geographically because firms can obtain advantages from a concentrated market for skilled labor, achieve pecuniary externalities through forward and backward links, and benefit from technological spillover among firms. Marshall's (1980) idea was first formulized by Arrow (1962) and then by Romer (1986). Glaeser (1992) integrated the externality ideas of Marshall, Arrow, and Romer to emphasize the insight that the concentration of a single industry in a bounded region promotes knowledge spillover, thus promoting innovation.

The benefits of MAR externalities arise when a regional industry is relatively large (Frenken et al., 2005). The main sources of such benefits are economies of scale from shared labor and a reduction in distribution costs. Thus, from the perspective of MAR externalities, a local monopoly is beneficial to local competence because the monopoly can maximize a firm's ability to maximize economic value stacking from innovations (Koo, 2005). However, MAR externalities may ignore the knowledge externalities among industries by restricting the knowledge spillover that occurs in a single industry.

Jacobs (1969), however, argued that the source of innovation is external to an industry. In this regard, the author developed a theory that the diversity of industries in a region can promote knowledge externalities. According to Jacobian externalities, increased diversification and the complexity of the local economy can promote high and sustained levels of local firms' innovation activities. The concept of Jacobian externalities is in a similar context to Hoover's (1937) urbanization economies because the diversity of knowledge sources is abundant in cities.

A more diverse industry within a region increases the chances of imitating, sharing, and recombining ideas from various sources. The exchange of complementary knowledge among industries promotes a firm's search and experimentation activities for innovation. Further, in

Jacobian externalities, a competitive environment is considered a more desirable condition for regional development because firms can obtain much stronger incentives for innovation activities. However, as argued in Storper (2013), innovative large cities simply appear to be highly diversified and provide weak evidence to support the concept of Jacobian externalities.

To date, theoretical studies seem to be inconclusive when they explain the relationship between agglomeration economies and regional innovation (van der Panne and van Beers, 2006). For example, MAR externalities and Jacobian externalities present opposite arguments about the effective structure of regional economic systems for knowledge spillover. MAR externalities focus on specialization while Jacobian externalities stress diversity. Moreover, MAR externalities and Jacobian externalities have different positions regarding the role of local competition. MAR externalities favor a monopolistic environment while Jacobian externalities prefer a competitive environment as conducive to regional development.

2.3 Innovative competence: Exploitation and exploration

Glising and Nooteboom (2006) compared the characteristics of innovation in two contexts: competence and governance. Competence refers to organizational learning and innovation while governance means the management of relational risk. Because we focus on the interrelationship between agglomeration externalities and innovation, we apply the competence concept to current regional innovation.

Feldman and Audretsch (1999) argued that it is necessary to consider the heterogeneity of innovation. In this regard, the concepts of exploration and exploitation can be used to explain heterogeneous regional innovative competence. These concepts were introduced by March (1991) as follows.

“Exploration includes things captured by terms such as search, variation, risk taking,

experimentation, flexibility, discovery, and innovation. Exploitation includes such things as refinement, choice, production, efficiency, selection, implementation, and execution.” (March, 1991, p.71).

In terms of innovative competence, exploration covers radical innovations from completely different, previously undiscovered information. Conversely, exploitation involves incremental innovation based on existing knowledge (Bierly and Daly, 2007; Østergaard et al., 2011; Quintana-García and Benavides-Velasco, 2008).

2.4 The link between agglomeration economies and innovative competence

Having reviewed studies of agglomeration economies in the context of innovation, we now turn to considering their different roles regarding different types of innovation. Since the classical notion of exploration and exploitation describes first and foremost the behavior of individuals or organizations with regard to research and development, it is necessary to confirm that there is specific innovative competence in a region.

Barrutia and Echebarria (2010) argued that knowledge is embodied in local communities; thus, local communities are a key factor that promotes innovation. In a similar context, Boekema (2000) presented the concept of regional learning, which indicates spontaneous cooperation in terms of sharing knowledge among actors in the same region. The concepts of local communities and regional learning connections both reflect social capital that encourages innovative competence in a region.

Social capital includes common cultural backgrounds, shared values, and trust, all of which originate from interpersonal networks (Putnam et al., 1993). This definition focuses on the roles of family and culture that emerge from a long history. More recently, this concept includes regional agglomeration which refers to the collective value of all types of social

network including both private relations and public relations. Further, collective behavior that originates from social networks in a region has unique features compared with other region. Consequently, we can assume that specific innovative activities occur in a region.

In addition, Bathelt et al. (2004) argued that local buzz explains the processes of knowledge spillover and knowledge creation. Thus, innovation originates from interpersonal knowledge exchange in a region because agglomeration economies have super-additive communication processes. In the context of the theory of social capital and the concept of local buzz, one can expect that each region has its own local buzz related to collective behavior with regard to the innovation process. Indeed, Storper (2013) confirmed that all regions are not equally innovative and specialize in various fields. Moreover, the author argued that each region has a special context. Context here refers to the ‘integrated behavioral experience factor’ generated from unique social capital.

Based on prior theoretical studies, we can assume that distinct regional innovation competence exists according to local context (or social capital or local buzz). Additionally, we can infer that because the structure of a regional economic system affects the features of local context, social capital, and local buzz, innovative competence is also related to the system. Next, we discuss and hypothesize how different types of agglomeration economy are linked to innovative competence in terms of exploration and exploitation.

2.5 Hypotheses

MAR externalities arise from specialized economies with concentrated and specialized labor pools that enable more effective matching of skilled labor forces. From the perspective of innovation, MAR externalities describe the benefit of a specialized regional economic system that can encourage knowledge spillover in a region through various channels, such as business interaction and the turnover of skilled labor in similar industries, at relatively low

cost. The mechanism of MAR externalities with regard to innovative competence can be explained by evolutionary theory. This theory is based on “local search,” which demonstrates that firms tend to search for similar technologies (Sahal, 1985). These firms are able to improve their products or technologies by combining existing technologies, thereby leading to exploitative innovation. Thus, one can expect that many exploitative innovations occur in a region with strong MAR externalities. Consequently, our first hypothesis is as follows.

Hypothesis 1 (**H1**): MAR externalities from specified economies are linked to regional exploitative innovative competence.

In contrast, Jacobian externalities are associated with various technologies that are fundamental to creativity (Boshma, 2014). Jacobs (1969) argued that diversified cities would promote new ideas because a new invention is not oriented toward the resolution of efficiency problems as Adam Smith argued. Further, Patel and Pavitt (1997) stated that technological diversity is the root of revolutionary innovation rather than normal technological advancement.

Exposure to diversified industries encourages individuals and firms to find new types of solution to solve existing problems (Cardinal, 2001; Quintana-Garcia and Benavides-Velasco, 2008). Thus, we propose a relationship between exploratory innovative competence and Jacobian externalities as follows.

Hypothesis 2 (**H2**): Jacobian externalities from diversified economies are associated with regional exploratory innovative competence.

In the following section, we suggest models to examine the proposed hypotheses.

3. Methodology

3.1 Research setting

In order to formalize our models, we referred to the modified knowledge production (KPF) function proposed by Crescenzi et al. (2007). This derives from the KPF developed by Jaffe (1986). Our initial model takes the following form:

$$I_r = f(K_r, RD_r, H_r, MA_r, JC_r) \quad (1)$$

where I_r is the innovation output in region r , A is constant, K is the initial knowledge stock, RD is the amount of research and development investment, H is the human capital, MA is the level of MAR externalities, and JC is the level of Jacobian externalities.

This study employs patent data as a proxy indicator of innovative competence. Because we consider different types of innovative competence, we determine regional innovation levels in terms of exploitative competence and explorative competence. Thus, following the study of Quintana-Garcia and Benavides-Velasco (2008), we classified the patents in each region into an exploitative patent group and an explorative patent group using citation information. Further, we established proxies for function (1) as shown in Table 1.

Table 1. Proxy variables

Endogenous factors	Proxy indicators
Level of MAR externalities	Location quotient (MAR)
Level of Jacobian externalities	Herfindahl index (JC)
Initial knowledge stock	Initial number of patents granted in the region (StockedPatent)
R&D investment	R&D investment in the specific industry in the region (RnD)
Human capital	College completion rates in the region (Edu)

The goal of this study is to investigate the relationship between agglomeration economies and innovative competence. First, because each industry has a specific knowledge base and

learning process, we focused on the manufacturing sector¹ in the United States. Because our study investigates the role of agglomeration economies with regard to regional innovative competence, it is critical to select the appropriate geographic unit of analysis in order to test the hypotheses. Beaudry and Schiffauerova (2009) stated that when the geographical level is established in detail, the effects of externalities tend to be found easily. Thus, we chose metropolitan statistical areas (MSAs)² as the geographic units that focus on populated cities in detail.

Further, the manufacturing sector can appear as an homogeneous entity if we establish an industrial classification with one or two -digits, whereas the sector can present a wide diversity if we choose a six-digit industrial classification. Beaudry and Schiffauerova (2009) stated that when a researcher establishes a detailed industrial classification level, the probability of detecting Jacobian externalities becomes higher while the effect of MAR externalities are found in two-digit industrial classifications. The authors argued that the three-digit level of industrial classification is a threshold at which agglomeration economies do not lean toward either MAR externalities or Jacobian externalities.

3.2 Measures and data

3.2.1 Dependent variables: Innovative competence

The dependent variables in the analysis present innovative competences. This approach indicates the regional capacity for inventing new technologies or products (Quintana-Garcia and Benavides-Valesco, 2008). In order to estimate innovative competences, we employed

¹ The studied manufacturing industries include food (311); beverage and tobacco products (312); textiles, apparel, and leather products (313); wood products (321); paper (322); printing and related support activities (325); plastics and rubber products (326); nonmetallic mineral products (327); primary metals (331); fabricated metal products (332); machinery (333); computer and electronic products (334); electrical equipment, appliances, and components (335); transportation equipment (336); furniture and related products (337); and miscellaneous manufacturing (339) according to the North American industry classification system (NAICS).

patent data as proxy indicators.

Some researchers have argued that patent data are limited for estimating innovation. First, patent data cover only high-technology sectors from diverse industries (Mansfield, 1986). In addition, some inventions are not revealed through patent data because not every invention is patentable, or firms decide not to patent inventions for strategic reasons. However, although patent data are imperfect for estimating innovation, they provide the most accessible and detailed written information about new inventions.

Because the analysis of industries is at the level of MSAs, we used geo-linked patent data and categorized them for each industry. We geo-located each patent according to the inventor's address written in the specification. When there were more than two inventors in different MSAs, we regarded the patent as an invention applicable to all MSAs. As aforementioned, because patenting activities may differ across industries, we focused on patent data in the manufacturing sector. Using the concordance table of the United States patent classification (USPC) system and the North American industry classification system (NAICS) from the United States Patent and Trademark Office (USPTO),³ we retrieved patent data with USPC classifications that are connected to the manufacturing sector. Then, we categorized the patent data into sub-industries in the manufacturing sector using three-digit NAICS classification.

In order to classify the regional patents into exploratory innovative competence and exploitative innovative competence, we used citation data. Exploratory innovative competence covers radical innovation while exploitative innovative competence involves incremental innovation. Prior empirical studies (Ahuja and Lampert, 2001; Quintana-Garcia and Benavides-Velasco, 2008) assumed that a patent that cites few or no other patents is a

³ The USPTO provides the USPC-NAICS concordance table at http://www.uspto.gov/web/offices/ac/ido/oeip/taf/data/naics_conc/.

result of exploratory innovative competence; namely, there is no prior information to indicate that a new invention refers to the patent. Similarly, when a patent cites existing references, it is considered an outcome of exploitative innovative competence.

In this study, we have followed the definitions of exploratory and exploitative innovative competences from prior studies. We categorized granted patents in an MSA into two groups. Thus, 10% of patents with the lowest number of citation references compared with other patents in the same industry (using three-digit NAICS) are the result of exploratory innovative competence while the others are the result of exploitative innovative competence.

3.2.2 Explanatory variables: MAR externalities and Jacobian externalities

In order to determine MAR externalities, this study employed the location quotient (LQ), which shows the relationship between a region's share of a specific industry and the national share. The LQ measures the strengths and weaknesses in each MSA against the proportion of employment in a particular industry over all industries (Beaudry and Schiffauerova, 2009; Galliano et al., 2014; O'Donoghue and Gleave, 2004).

We established the total number of regions and industries in the United States as the benchmark for the LQ computations of the MSAs as follows:

$$MAR_{i,r,t} = \frac{s_{r,i,t}}{s_{i,t}} \quad (2)$$

where $s_{r,i,t}$ is the share of employment for industry i in region r in year t , and $s_{i,t}$ is the share of employment for industry i in year t in the United States. When the MAR level is estimated as more than 1 in a specific region, this region has more employment proportionately than the benchmark region in the specific industry.

However, we estimated Jacobian externalities with the inverse of the Herfindahl index as follows:

$$JC_{r,t} = 1 / \sum_{i=1}^I \left(\frac{s_{r,i,t}}{\sum_{i=1}^I s_{r,i,t}} \right)^2 \quad (3)$$

This approach has been widely used to measure the level of diversification within an occupation or firm (Galliano et al., 2014; Henderson, 1997; Usai and Paci, 2003). Because we used the inverse value of the Herfindahl index, when a region has a higher value, this indicates that the region has more diversified agglomeration economies.

3.2.3 Control variables: Initial knowledge stock, R&D investment, and human capital

There are factors besides agglomeration economies that influence innovation. For such factors, please see function (1). Thus, we included initial knowledge stock, R&D investment, and human capital in the models. Moreover, we included the gross domestic product (GDP) of MSAs during the investigation period to control economic size per unit of analysis.

First, we introduced knowledge stock using the number of accumulated patents in each region. Prior accumulated patents enable the more effective investigation of the role of regional agglomeration economies in promoting innovative competence.

Although we can obtain a firm's R&D expenditure, it is hard to determine a firm's R&D expenditure for an MSA unit when the firm has branches around the country. Thus, to ensure the robustness of the results, we employed R&D investment data for state units and assumed these represented general amounts of R&D expenditure in subregions.

Further, the educated workforce is used as a proxy for the level of human capital in each region. In particular, we used the workforce ratio of employees with higher education, namely college completion rate, because a positive relationship exists between numbers of highly educated employees and the amount of innovative outcomes (Østergaard et al., 2011).

Finally, to control the robustness of our results, we added the GDP of MSAs per capita to compensate for different economic sizes according to each MSA's economic condition.

3.3 Sample and statistical method

Because we investigated 323 MSAs in the United States, we retrieved patents granted between 2009 and 2013 from the USPTO. Prior empirical studies aligned exploratory innovative competence with patents that do not cite other patents; however, this study defines exploratory innovative competence as 10% of the patents with the lowest number of citation references in the same industry (using three-digit NAICS in the manufacturing sector).

The total number of granted patents from the manufacturing sector between 2009 and 2013 is 156,436. We allowed the duplication of patents according to the inventors' origins; thus, there were 201,090 inventions across 323 MSAs in the United States in the same period. The numbers of granted patents for each three-digit NAICS in the manufacturing sector are shown in Table 2. Because a USPC can be included in multiple NAICS, one patent can be repeatedly categorized in different industries.

Table 2. The number of patents for manufacturing industries

NAICS	Industry	No. of patents	10% of the lowest number of citation references
311	Food	4,795	3
312	Beverage and tobacco products	1,517	2
313	Textile, apparel, and leather products	24,414	4
321	Wood products	13,387	4
322-323	Paper, printing, and related support activities	13,087	4
325	Chemicals	31,311	2
326	Plastics and rubber products	42,906	4
327	Nonmetallic mineral products	30,225	3
331	Primary metals	17,905	3
332	Fabricated metal products	56,161	4
333	Machinery	74,051	3
334	Computer and electronic products	121,976	2
335	Electrical equipment, appliances, and components	58,717	3
336	Transportation equipment	51,961	4
337	Furniture and related products	5,783	5
339	Miscellaneous manufacturing	56,771	3

As shown in Table 2, the 10% of patents with the lowest number of citation references differs across industries. Using these numbers as thresholds, we categorized the patents into two groups: exploratory innovative competence and exploitative innovative competence.

Table 3 presents the statistics of the innovative competences in the MSAs. For instance, in 323 MSAs, the average numbers of exploratory innovative competence and exploitative innovative competence for the computer and electronic products (334) industry are 37.1 and 451.1 respectively.

Table 3. The statistics of innovative competence for MSAs

NAICS	Exploitative innovative competence				Exploratory innovative competence			
	Mean	Standard deviation	Max	Percentage of zero	Mean	Standard deviation	Max	Percentage of zero
311	19.9	48.9	335	26.9%	2.0	5.2	46	65.3%
312	6.5	16.0	151	47.4%	0.6	2.0	20	84.2%
313	86.2	192.8	1489	3.1%	9.0	22.9	184	35.9%
321	51.5	113.2	787	6.2%	4.0	9.5	81	47.1%
322	51.2	122.1	844	12.1%	4.9	13.3	114	52.0%
325	120.2	321.9	2362	5.6%	10.5	27.8	230	33.4%
326	159.4	361.9	2393	1.9%	15.5	40.0	290	22.6%
327	115.6	277.0	2567	2.5%	9.3	23.6	173	32.2%
331	68.1	183.7	2010	10.8%	6.2	16.1	128	44.3%
332	196.3	440.1	3015	0.9%	20.7	53.8	401	18.9%
333	267.3	638.1	5146	0.6%	23.7	65.2	599	21.1%
334	451.1	1483.5	18317	0.3%	37.1	142.6	1863	21.7%
335	211.4	570.4	6150	2.2%	20.9	69.7	839	27.2%
336	176.6	425.9	3573	1.5%	20.1	56.4	573	21.1%
337	21.0	49.1	440	18.6%	1.9	5.5	52	67.8%
339	205.7	496.0	3432	1.5%	18.6	47.4	339	22.0%
	Percentage of zero for total industries in all areas			8.9%	Percentage of zero for total industries in all areas			38.5%

The data on exploitative innovative competence and exploratory innovative competence are in the category of typical count data. With regard to count data, a Poisson regression model has been widely employed. However, because the distributions of our dependent variables present over-dispersion, we used a negative binomial model that we developed to

estimate over-dispersed parameters (Cameron and Trivedi, 1998). Moreover, as shown in Table 3, approximately 8.9% and 38.5% of two dependent variables show zero. In other words, the data of innovative competences in MSAs are essentially zero-inflated. With regard to such dependent variables, namely over-dispersed and zero-inflated, Greene (1994) argued the necessity of a zero-inflated negative binomial model. Recently, this method has been widely used in empirical studies that include patent data as their dependent variable (Faems and Subramanian, 2013; Guan and Liu, 2016; Lee et al., 2007). We employed a zero-inflated negative binomial model and a negative binomial model to reflect different shares of zero among dependent variables. In the empirical models, we corrected potential endogeneity by employing patent data from 2009 to 2013. Then, we included key explanatory variables: location quotient for the MAR externalities and Herfindahl index for the Jacobian externalities in 2009. Both indices were calculated using the employment data of the Bureau of Labor Statistics.⁴

The college completion rate, which estimates the skilled labor force in the MSAs, was taken from American Community Survey Data on Educational Attainment in 2009.⁵ The initial number of granted patents in the region (StockedPatent) is the sum of patents that were granted between 2000 and 2008. In order to determine the amount of R&D investment, we used the survey data of Business and Industrial R&D (BIRD) for 2006, 2008, and 2010⁶ so that we included an appropriate time lag in our models (Belderbos et al., 2004).

⁴ We used the annual averages of the NAICS-based data of the Quarterly Census of Employment and Wages (QCEW), available at <http://www.bls.gov/cew/datatoc.htm>.

⁵ <http://www.census.gov/hhes/socdemo/education/data/acs/index.html>.

⁶ We considered three years as the time lag during which the impact of R&D investment is revealed. Because we aggregated patent data between 2009 and 2013, we used 2006, 2008, and 2010 R&D expenditure. The survey data of 2007 and 2009 are not available.

4. Results

We categorized innovative competences into two groups: exploratory and exploitation. Table 4 and Table 5 present the results of the zero-inflated negative binomial models for exploitative innovative competence and exploratory innovative competence respectively. The first two columns in Table 4 and Table 5 show that both exploitation and exploratory innovative competences follow the traditional knowledge production function (see function (1)), which includes knowledge stock, human capital, and R&D expenditure.

The estimated results reported in Table 4 present evidence of the positive relationship between knowledge externalities based on agglomeration economies and exploitative innovative competence in MSAs between 2009 and 2013.

Using MAR externalities, we estimated the relative concentration level of manufacturing industries within a specific region compared with other regions. The results in Table 4 (see columns 2, 3, and 4) show a positive relationship between MAR externalities and exploitative innovative competence. Thus, we can confirm that MAR externalities from specified economies are linked to regional exploitative innovative competence (**H1**). The positive estimates of JC in columns 3 and 4 (Table 4) imply that not only MAR externalities but also Jacobian externalities from diversified economies have a positive impact on exploitative innovative competence.

Table 4. The results of the zero-inflated negative binomial models: Exploitative innovative competence

	Exploitative innovative competence			
	(1) Estimate (standard errors)	(2) Estimate (standard errors)	(3) Estimate (standard errors)	(4) Estimate (standard errors)
Constant	1.6919(0.0722)***	1.6415(0.0743)***	1.1087(0.0767)***	1.0006(0.0801)***
MAR		0.0939(0.0155)***	0.0659(0.014)***	0.2055(0.0352)***
JC			0.1285(0.0078)***	0.152(0.0093)***
MAR and JC				-0.0277(0.0062)***
StockedPatent	0.1026(0.0079)***	0.0976(0.0077)***	0.115(0.0075)***	0.1148(0.0074)***
RnD	0.0431(0.0051)***	0.0402(0.0049)***	0.0382(0.0048)***	0.0376(0.0047)***
GDP	0.0025(0.0004)***	0.0027(0.0004)***	0.0012(0.0003)***	0.0012(0.0003)***
Edu	0.07(0.0026)***	0.0702(0.0027)***	0.0659(0.0025)***	0.0659(0.0025)***
Observations	5696	5483	5483	5483
Criterion				
Deviance	57669.1638	56097.5198	55815.1768	55796.9820
Pearson chi-square (value/d.f.) ⁷	6290.0009(1.1054)	5940.1565(1.0848)	6374.5998(1.1643)	6369.3015(1.1636)

Notes: *** p<0.001. We allow the duplication of the MSAs that are situated in more than two states.

⁷ When dividing Pearson chi-square statistics by their degrees of freedom, a resulting value near 1.0 indicates that over-dispersion in dependent variables has been satisfactorily addressed by using the negative binomial model.

Table 5. The results of the zero-inflated negative binomial models: Exploratory innovative competence

	Exploratory innovative competence			
	(1) Estimate (standard errors)	(2) Estimate (standard errors)	(3) Estimate (standard errors)	(4) Estimate (standard errors)
Constant	-0.5004(0.0835)***	-1.0358(0.0897)***	-0.9688(0.0916)***	-1.0136(0.0965)***
MAR (t)			0.0022(0.0138)	0.0578(0.0428)
JC (t)		0.1158(0.0089)***	0.1093(0.009)***	0.1188(0.0109)***
MAR (t) and JC (t)				-0.0108(0.0073)
StockedPatent (t)	0.0942(0.0084)***	0.1059(0.008)***	0.1032(0.0079)***	0.1029(0.0079)***
RnD (t)	0.0417(0.0053)***	0.0399(0.0051)***	0.0384(0.005)***	0.0381(0.005)***
GDP (t)	0.0029(0.0004)***	0.0018(0.0004)***	0.0018(0.0004)***	0.0018(0.0004)***
Edu (t)	0.0642(0.0029)***	0.0616(0.0028)***	0.0618(0.0028)***	0.0619(0.0028)***
Observations	5696	5952	5483	5483
Criterion				
Deviance	31403.1862	31229.0500	30597.1917	30594.7420
Pearson chi-square (value/d.f.)	6631.6873(1.1655)	7531.9266(1.3239)	7124.3564(1.3013)	7140.1222(1.3044)

Notes: *** p<0.001. We allow the duplication of the MSAs that are situated in more than two states.

This finding partly contradicts the result proposed by Feldman and Audretsch (1999). The authors found that when the regression model separately includes different types of agglomeration economies, both specialization and diversity present positive relationships with innovation.⁸ However, specialization shows a negative impact while diversity shows a positive impact in the model that includes both agglomeration externalities as explanatory variables. Hence, we include the interaction variable of MAR and JC (see column 4 in Table 4). The estimate of this variable is negative. The result indicates that exploitative innovative competence can be promoted in a region where one type of externality is high while the other is low.

Moreover, columns 2, 3, and 4 in Table 5 show that the estimates of JC, which measures Jacobian externalities from diversified economies, are positively associated with regional exploratory innovative competence (**H2**). With regard to this dependent variable, specified agglomeration economies are insignificant (see columns 3 and 4 in Table 5) and the interaction effect of MAR and JC for exploratory innovative competence is insignificant. This implies that exploratory innovative competence can be promoted in a region with high Jacobian externalities.

Some prior studies considered differences in technological intensity across industries (Forni and Paba, 2002; Greunz, 2004; Henderson et al., 2001; Soloaga and Pereira, 2013). Thus, with a taxonomy drawn from Hatzichronoglou (1997), we categorized industries into three groups according to the intensity of technology (see Table 6) for additional analysis. In accordance with the technological intensities among manufacturing industries, we examined the role of MAR externalities and Jacobian externalities on two different types of innovative competence.

⁸ Feldman and Audretsch (1999) used inventions from the United States Small Business Administration's Innovation Database (SBIDB) as dependent variables. The database includes mostly incremental innovations that can be considered in terms of exploitative innovative competence.

Table 6. Industrial sector by technological intensity

Industrial sector	NAICS	Average no. of patents granted
Low-tech	311, 312, 313, 321, 322-323	11,440
Medium-tech	326, 327, 331, 332, 333, 337, 339	40,543
High-tech	325, 334, 335, 336	65,991

First, we can infer that the results of the high technology sector are similar to those for the whole industry. Both agglomeration externalities are positively associated with exploitative and exploratory innovative competence. However, regional GDP is statistically insignificant for the relationship with exploitative innovative performance. This may imply that exploitative innovative competence in high-tech industries is not associated with regional economic size, while R&D expenditure and human capital are positively associated (see Table 7).

Table 7. The results of the zero-inflated negative binomial models: High-tech sector

	Exploitation	Exploration
	(1) Estimate (standard errors)	(2) Estimate (standard errors)
Constant	1.4095(0.1219)***	-0.8311(0.1522)***
MAR (t)	0.0913(0.0211)***	0.0681(0.027)**
JC (t)	0.1267(0.0122)***	0.1019(0.0145)***
StockedPatent (t)	0.1321(0.0119)***	0.1121(0.0132)***
RnD (t)	0.012(0.0029)***	0.0173(0.0036)***
GDP (t)	0.0006(0.0005)	0.0016(0.0006)**
Edu (t)	0.0701(0.004)***	0.0694(0.0047)***
Observations	1386	1386
Criterion		
Deviance	15508.6	8981.04
Pearson chi-square (value/d.f.)	1710.42(1.2412)	1731.22(1.2563)

Notes: ** p<0.05, *** p<0.001. We allow the duplication of the MSAs that are situated in more than two states.

Next, the results for exploratory innovative competence in manufacturing industries with medium technological intensity show that MAR externalities are not significant on the

dependent variable (see column 2 in Table 8). Similarly, for low-tech industries, this type of externality has no impact on exploitative innovative competence and even has a negative impact on exploratory innovative competence (see Table 9).

Table 8. The results of the zero-inflated negative binomial models: Medium-tech sector

	Exploitation	Exploration
	(1) Estimate (standard errors)	(2) Estimate (standard errors)
Constant	1.2269(0.1026)***	-0.7981(0.1252)***
MAR (t)	0.0815(0.0211)***	-0.0116(0.0218)
JC (t)	0.1246(0.0105)***	0.1093(0.0123)***
StockedPatent (t)	0.1032(0.01)***	0.0975(0.0107)***
RnD (t)	0.2671(0.0369)***	0.2335(0.0388)***
GDP (t)	0.0018(0.0005)***	0.002(0.0005)***
Edu (t)	0.0646(0.0034)***	0.0601(0.0039)***
Observations	2457	2457
Criterion		
Deviance	25804.2	14423.6
Pearson chi-square (value/d.f.)	2752.8(1.1241)	3263.24(1.3325)

Notes: *** p<0.001. We allow the duplication of the MSAs that are situated in more than two states.

Table 9. The results of the zero-inflated negative binomial models: Low-tech sector

	Exploitation	Exploration
	(1) Estimate (standard errors)	(2) Estimate (standard errors)
Constant	0.0506(0.1561)	-1.707(0.1985)***
MAR (t)	-0.0091(0.014)	-0.0342(0.0179)**
JC (t)	0.1781(0.0156)***	0.157(0.0193)***
StockedPatent (t)	0.1193(0.0146)***	0.0965(0.0155)***
RnD (t)	-0.2243(0.1591)	-0.3654(0.2057)**
GDP (t)	0.0006(0.0007)	0.0019(0.0008)***
Edu (t)	0.0605(0.005)***	0.0487(0.0058)***
Observations	1640	1640
Criterion		
Deviance	13165.8	6422.78
Pearson chi-square (value/d.f.)	1810.59(1.1094)	2187.85(1.3406)

Notes: ** p<0.05, *** p<0.001. We allow the duplication of the MSAs that are situated in more than two states.

Interestingly, we found that only Jacobian externalities are positively associated with exploitative and exploratory innovative competences across technological intensities. These results suggest that with regard to low- and medium-technology industries, when diversified

agglomeration increases, both exploitation and exploration can be promoted, while exploitative innovative competence may experience no change and exploratory innovative competence may be reduced by increases of specified agglomeration. This finding is the opposite of arguments from prior studies. Beaudry and Schiffauerova (2009) stated that the impact of MAR externalities is slightly stronger in low-tech industries while the effect of Jacobian externalities is stronger in high-tech industries according to reviews of prior studies.

We established that Jacobian externalities are accompanied by a diversified labor market and diversified market size while MAR externalities have professional labor flow and specialized market scale. A diversified market brings with it various needs for products/services. Further, the necessities of innovation are eventually increased in a diversified region. In this situation, a highly skilled labor force is relatively less important for new inventions in low- and medium-tech industries compared with high-tech industries. Thus, we believe that advancement in regional innovative competence for low- and medium-tech industries is likely to result in a wide variety of needs.

In sum, we found that exploitative innovative competence is promoted in both specialized and diversified regions. However, exploratory innovative competence tends to be advanced in diversified regions. Further, when we categorized industries by technological intensity, both types of innovative competence in low- and medium-tech industries are promoted only in diversified regions.

5. Concluding Remarks

In this study, we verify the classical argument about the impact of knowledge externalities from agglomeration economies on innovative competence. Using the concepts of exploration

and exploitation (March, 1991), we estimate the exploitative innovative competence and exploratory innovative competence for MSAs in the United States by employing patent data. Consequently, this study presents the first research that investigates the role of knowledge externalities for two different types of regional innovative competence.

The empirical results confirm the classical belief that MAR externalities encourage exploitative innovative competence by promoting knowledge spillover among firms in the same industries (Glaeser et al., 1992). The basic assumption of prior works that emphasize the positive role of MAR externalities on innovation is that knowledge spillover occurs effectively only within the same industry. However, as we have found with our empirical results, Jacobian externalities also have a positive impact on exploitative innovative competence. This implies that not only specified agglomeration economies but also diversified economies are positively related to exploitative innovative competence. Specifically, exploitative innovative competence is promoted in a region that has a much stronger type of externality than another. Because MAR externalities and Jacobian externalities are contradictory concepts, this implies that a region with strong agglomeration economies, regardless of its structure, tends to have a high level of exploitative innovative competence.

In addition, we find that a region with Jacobian externalities that is based on various industries tends to have exploratory innovative competence while MAR externalities have no impact. It is worth noting that the impact of knowledge externalities differs depending on the type of innovative competence. More specifically, Jacobian externalities promote all types of innovative competence for all levels of technological intensity. Thus, consistent with van Oort (2002), diversification externalities are positively related to innovative performance in manufacturing industries.

Acknowledgements

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korean government(MSIP) (2013R1A2A1A09004699).

References

- Ahuja, G., & Morris Lampert, C. (2001). Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strategic Management Journal*, 22(6-7), 521-543.
- Arrow, K. J. (1962). The economic implications of learning by doing. *The review of economic studies*, 155-173.
- Beaudry, C., Breschi, S., 2003. Are firms in clusters really more innovative? *Economics of Innovation and New Technology* 12, 325–342.
- Belderbos, R., Carree, M., & Lokshin, B. (2004). Cooperative R&D and firm performance. *Research policy*, 33(10), 1477-1492.
- Bierly, P. E., & Daly, P. S. (2007). Alternative knowledge strategies, competitive environment, and organizational performance in small manufacturing firms. *Entrepreneurship Theory and Practice*, 31(4), 493-516.
- Cainelli, G., Leoncini, R., Montini, A., 2001. The evolution of industrial sectors in Europe. In: Nelson and Winter Conference, Aalborg, 12–15 June 2001.
- Cameron A.C. & Trivedi P.K. *Regression Analysis of Count Data*, Cambridge University Press, Cambridge (1998)
- Cingano, F., Schivardi, F., 2004. Identifying the sources of local productivity growth. *Journal of the European Economic Association* 2, 720–742.
- Crescenzi, R., Rodríguez-Pose, A., & Storper, M. (2007). The territorial dynamics of innovation: a Europe–United States comparative analysis. *Journal of Economic Geography*, lbm030.
- de Lucio, J., Herce, J., Goicolea, A., 2002. The effects of externalities on productivity growth in Spanish industry. *Regional Science and Urban Economics* 32, 241–258.
- Dahlin, K. B., & Behrens, D. M. (2005). When is an invention really radical?: Defining and measuring technological radicalness. *Research Policy*, 34(5), 717-737.
- Duncan, R. B. (1976). The ambidextrous organization: Designing dual structures for innovation. *The Management of Organization*, 1, 167-188.
- Faems, D., & Subramanian, A. M. (2013). R&D manpower and technological performance: The impact of demographic and task-related diversity. *Research Policy*, 42(9), 1624-1633.
- Forni, M., Paba, S., 2002. Spillovers and the growth of local industries. *The Journal of Industrial Economics* 50, 151–171.
- Galliano, D., Magrini, M. B., & Triboulet, P. (2014). Marshall's versus Jacobs' Externalities in Firm Innovation Performance: The Case of French Industry. *Regional studies*, (ahead-of-print), 1-19.
- Glaeser, E., H. Kallal, J. Scheinkman, and A. Shleifer, 1992, Growth in cities, *Journal of Political Economy* 100, 1126-1152.
- Greene W.H., Accounting for excess zeros and sample selection in poisson and negative

binomial regression models Working Paper No. 94-10, Stern School of Business, Department of Economics, New York University, New York (1994)

Greunz, L., 2004. Industrial structure and innovation: evidence from European regions. *Journal of Evolutionary Economics* 14, 563–592.

Guan, J., & Liu, N. (2016). Exploitative and exploratory innovations in knowledge network and collaboration network: A patent analysis in the technological field of nano-energy. *Research Policy*, 45(1), 97-112.

Hatzichronoglou, T. (1997). Revision of the high-technology sector and product classification.

He, Z. L., & Wong, P. K. (2004). Exploration vs. exploitation: An empirical test of the ambidexterity hypothesis. *Organization Science*, 15(4), 481-494.

Henderson, V. (1997). Externalities and industrial development. *Journal of urban economics*, 42(3), 449-470.

Henderson, V., Lee, T., Lee, Y., 2001. Scale externalities in Korea. *Journal of Urban Economics* 49, 479–504.

Jacobs, J., 1969, *The Economies of Cities*, Random House, New York

Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D: evidence from firms' patents, profits and market value.

Koo, J. (2005). Agglomeration and spillovers in a simultaneous framework. *The Annals of Regional Science*, 39(1), 35-47.

Lee, Y. G., Lee, J. D., Song, Y. I., & Lee, S. J. (2007). An in-depth empirical analysis of patent citation counts using zero-inflated count data model: The case of KIST. *Scientometrics*, 70(1), 27-39.

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, 2(1), 71-87.

Marshall, A., 1920. *Principles of economics: An introductory volumen*. Macmillan and Company.

Nelson, R. R., & Winter, S. G. (2009). *An evolutionary theory of economic change*. Harvard University Press.

Romer, P. M. (1986). Increasing returns and long-run growth. *The Journal of Political Economy*, 1002-1037.

Quintana-García, C., & Benavides-Velasco, C. A. (2008). Innovative competence, exploration and exploitation: The influence of technological diversification. *Research Policy*, 37(3), 492-507.

Schildt, H. A., Maula, M. V., & Keil, T. (2005). Explorative and exploitative learning from external corporate ventures. *Entrepreneurship Theory and Practice*, 29(4), 493-515.

Soloaga, I., & Pereira, M. (2013). Determinants of Regional Growth by Manufacturing Sector in Mexico, 1988-2008 (No. 0713).

Tushman, M. L., & O'Reilly III, C. A. (2006). Ambidextrous organizations: Managing evolutionary and revolutionary change. *Managing innovation and change*, 170. *Organization Science*, 20(4), 685-695.

Van Oort F (2002) Innovation and agglomeration economies in the Netherlands. *Journal of Economic and Social Geography* 93(3): 344–360

Weber, A. (1909), *Theory of the Location of Industries*, Chicago, IL, University of Chicago Press

Appendix

The results of the negative binomial models: Exploitative innovative competence

	Exploitative innovative competence			
	(1) Estimate	(2) Estimate	(3) Estimate	(4) Estimate
Constant	1.6884(0.0724)***	1.6438(0.0746) ***	1.1026(0.0769) ***	1.0221(0.0805)***
MAR		0.0848(0.0146) ***	0.0611(0.013)***	0.1605(0.0336)***
JC			0.1295(0.0078)***	0.1478(0.0094)***
MAR and JC				-0.0208(0.0061)***
StockedPatent	0.1037(0.008)***	0.0992(0.0078)***	0.1163(0.0075)***	0.1165(0.0075)***
RnD	0.0432(0.0051)***	0.0405(0.0049)***	0.0385(0.0048)***	0.0381(0.0048)***
GDP	0.0024(0.0004)***	0.0025(0.0004)***	0.0011(0.0003)***	0.0011(0.0003)***
Edu	0.0701(0.0026)***	0.0704(0.0027)***	0.066(0.0025)***	0.066(0.0025)***
Observations	5696	5483	5483	5483
Deviance/Degree of freedom	1.2056	1.2056	1.2015	1.2015
Pearson chi-square/Degree of freedom	1.0987	1.0734	1.1557	1.1513

Notes: Standard errors are shown in parentheses. *** p<0.001. We allow the duplication of the MSAs that are situated in more than two states.

The results of the negative binomial models: Exploratory innovative competence>

	Exploratory innovative competence			
	(1) Estimate	(2) Estimate	(3) Estimate	(4) Estimate
Constant	-0.5521(0.0832)***	-1.1004(0.0895) ***	-1.0382(0.0916) ***	-1.0763(0.0955)***
MAR (t)			0.0007(0.0138)	0.0459(0.0359)
JC (t)		0.1175(0.009) ***	0.111(0.0091)***	0.1193(0.0107)***
MAR(t) and JC(t)				-0.0092(0.0064)
StockedPatent (t)	0.0991(0.0086)***	0.1105(0.0082)***	0.1081(0.0082)***	0.108(0.0081)***
RnD (t)	0.0429(0.0055)***	0.0411(0.0053)***	0.0397(0.0052)***	0.0395(0.0052)***
GDP (t)	0.0025(0.0004)***	0.0015(0.0004)***	0.0014(0.0004)***	0.0014(0.0004)***
Edu (t)	0.0652(0.003)***	0.0627(0.0029)***	0.0629(0.0029)***	0.0629(0.0029)***
Observations	5696	5952	5483	5483
Deviance/Degree of freedom	1.0525	1.0524	1.0605	1.0607
Pearson chi-square/Degree of freedom	1.1308	1.2829	1.2559	1.2575

Notes: Standard errors are shown in parentheses. *** p<0.001. We allow the duplication of the MSAs that are situated in more than two states.