경제학박사 학위논문

Varieties of Regional Innovation Systems (RIS) and Catch-up by Latecomers

지역혁신체제의 다양성과 후발 지역의 경제 추격

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김 진 희

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이 논문을 경제학박사 학위논문으로 제출함

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Abstract

Innovation plays a critical role in economic growth and economic catch-up. As Asian countries have witnessed, innovation is more important than price or cost when economies overcome the middle-income trap and sustain their economic growth. National innovation systems (NIS), a key concept for Schumpeterian economies, was introduced to represent the innovation capacity or efficiency of countries. However, given that NIS focuses on national-level analysis, the regional heterogeneities within a nation cannot be easily explained by this concept. To address this problem, a new framework called regional innovation systems (RIS) emerged in the 1990s. This dissertation examines the different innovation-related characteristics of cities/regions around the world using the concept of RIS and reveals the differences between catching-up and advanced regions.

This study uses seven variables to numerically measure RIS, namely, knowledge localization, nationalization, internationalization, local ownership of knowledge, technological diversification, knowledge decentralization, and technological cycle time. In NIS analysis, knowledge citation is divided into two dimensions, namely, citing locally invented patents and citing foreign patents, whereas in RIS analysis, three dimensions are employed, namely, local patent citation, national patent citation, and international patent citation. In this way, the new concept of nationalization is added in this RIS research. This study also uses local ownership of knowledge to measure the level of indigenous knowledge in a city/region.

The first chapter presents a comparative analysis of the RISs of Taipei in Taiwan, Shenzhen in China, and Penang in Malaysia to understand why Shenzhen is catching up with Taipei much faster than Penang in terms of RIS. In NIS analysis, latecomer economies need to specialize in short cycle technologies. However, this study only focuses on the divergence between per capita GRDP and economic growth rate even if the three aforementioned regions all specialize in the same short-cycle technologies because the levels of internationalization in Taipei and Shenzhen are

lower than that of Penang, that is, Taipei and Shenzhen have a lower dependence on foreign knowledge compared with Penang, whereas the local ownership of knowledge for Taipei and Shenzhen is higher than that for Penang. Through this comparative analysis, this study highlights the importance of increasing indigenous knowledge and decreasing reliance on foreign knowledge in regional economic catch-up.

The second chapter explores the RIS characteristics of 30 regions over the world to derive a typology of RIS via cluster analysis. On the basis of the cluster analysis results, four groups of RISs are classified depending on whether a region specializes in short- or long-cycle technologies and whether indigenous knowledge is large or small. The first group is the mature RIS group, which has a low level of internationalization (reliance on foreign knowledge) and high levels of local ownership of knowledge, diversification, and decentralization, whereas the second group is the catching-up RIS group, which is further divided into two types. First, cities/countries with more advanced catching-up RIS, such as South Korea and Taiwan, have low reliance on foreign knowledge and high indigenous knowledge. Second, cities/countries with less advanced catching-up RIS, including Penang and Bangalore, have low level of indigenous knowledge and high dependence on foreign knowledge.

The third chapter empirically investigates the linkage between the RIS groups resulting from cluster analysis, and economic growth. The catching-up RIS cities/countries that specialize in short-cycle technologies show a faster growth rate compared with others, and catch up with advanced region fast with specialization in long cycle technologies and high indigenous knowledge.

By considering the three aforementioned regions, the characteristics of catching-up RIS for latecomer regions as reported in the RIS and NIS analyses are the same. Improving local ownership of knowledge and decreasing reliance on foreign knowledge are prerequisites for regional economic catch-up in regions with different catching-up performances even if the latecomer regions specialize in similar short-cycle technologies.

Keywords: Regional innovation system; Regional development; Economic catch-up; Innovation; Cluster analysis; Regional economic growth; Regional economic catch-up

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I. Introduction

Innovation is a key driver of economic growth and catching up. As experienced by some East Asian economies, innovation is more binding than prices or costs as an economy moves to a later or middle-income stage of development (Lee, 2013; Mazzoleni & Nelson, 2007). National innovation systems (NIS) is a key concept in Schumpeterian economics (Freeman, 1987; Lundvall, 1992; Nelson, 1993), and Schumpeterian scholars insist that countries with different NISs demonstrate different degrees of innovation, which lead to differences in their economic growth. This concept was proposed by Freeman (1987) in the late 1980s and was later expanded by Lundvall (1992) and Nelson (1993). Lundvall (1992) defined NIS as "elements and relationships which interact in the production, diffusion and use of knowledge rooted inside the borders of a nation state" and added that this concept measures the efficiency in the acquisition, creation, diffusion, and utilization of knowledge. In this sense, NIS analysis can be useful in analyzing national-level economic activities.

This thesis explores whether NIS analysis can be applied to the regional level given the uneven distribution of innovations in the same economy (Asheim et al., 2019). For example, some regions may have a higher level of innovation than others, whereas other regions may have a lower level of innovation. In this case, NIS cannot represent the innovational capacity of each region. This problem has resulted in the emergence of a new concept called regional innovation systems (RIS) to explain the heterogeneous distribution of innovation within a territory and to formulate policies for enhancing the innovation capability of regional economies (Isaksen et al., 2018).

Cooke et al. (1998:1581) defined RIS as a "regional level system in which firms and other organizations are systematically engaged in interactive learning through an institutional milieu characterized by local embeddedness." Various RIS studies have explained the typology and dynamic change of RIS and reported a variety of criteria and perspectives toward this concept (Asheim et al., 2019; Asheim & Gertler, 2006; Asheim, 1998; Cooke, 2001, 1998, 2005). Following previous studies on theoretical underpinning, quantitative approaches have been used to assess the efficiency of different kinds of RIS (Fritsch & Slavtchev, 2011; Zabala-Iturriagagoitia et al., 2007). However, these studies have mostly focused on regions in advanced countries and have rarely considered latecomer regions. To fill this gap, this study conducts an RIS analysis by using patent citations as a measurement to identify those elements or dimensions of innovation that are binding at the regional level development for latecomers that are already beyond the middle-income stage of development where innovation is more binding than prices or costs (Mazzoleni & Nelson, 2007).

Chapter 2 reviews the literature on NIS and RIS and introduces the RIS variables. Chapter 3 compares three Asian regions that are overcoming the middle-income trap, namely, Taipei in Taiwan, Shenzhen in China, and Penang in Malaysia, in terms of their RIS and identifies the characteristics of catching-up RIS. Chapter 4 generalizes the identified characteristics of RIS for catching-up regions to more than 30 cities around the world via cluster analysis. Chapter 5 links different RIS groups to regional economic groups via regression analysis.

II. Literature Review and Research Questions

1. National Innovation Systems

Various dimensions of NIS have been introduced to analyze its relationship with economic growth (Archibugi & Coco, 2004; Castellacci, 2008, 2011; Edquist, 1997; Fagerberg & Srholec, 2018; Fagerberg & Verspagen, 2002). Although advantageous, the broad scope of such measurements may blur the boundaries between innovation and other economic aspects. Further studies, such as Lee et al. (2021a), have used a narrowly focused patent-driven measure of NIS that is close to its original definition, which highlights the mechanisms to generate, diffusion, and utilize knowledge (Lundvall, 1992).

Lee (2013) utilized a single dataset comprising patents filed in the US to measure and analyze NIS worldwide using five variables, namely, knowledge localization representing knowledge diffusion, technological diversification, knowledge decentralization, originality, and cycle time of technologies representing technology specialization. Lee et al. (2021a) introduced several varieties of NIS and proposed two alternative pathways to growth beyond the middle-income trap by using the above component variables.

Lee et al. (2021a) further categorized NIS into balanced, balanced and medium-cycle, imbalanced and short-cycle, and imbalanced and long-cycle NIS. Members of the balanced NIS group, mainly high-income or advanced economies, have evenly high NIS variables. Meanwhile, members of balanced and medium-cycle and imbalanced and short-cycle NIS groups are catching-up economies, with the latter outpacing the former in terms of catching up by specializing in short-cycle technologies. Moreover, members of the balanced and medium-cycle NIS group have modest NIS variables, whereas members of the imbalanced and short-cycle NIS group have localized knowledge creation and diversified technologies. Meanwhile, the imbalanced and long-cycle NIS group includes countries that are stuck in the middle-income trap who have low localization and diversification and are specializing in long-cycle technologies.

2. Regional Innovation Systems and Research Questions

Various RIS studies explain the typology and dynamic change of RIS and propose a variety of criteria and perspectives toward this concept (Asheim et al., 2019; Asheim & Gertler, 2006; Asheim, 1998; Cooke, 2001, 1998, 2005). Following previous studies on theoretical underpinning, quantitative approaches have been used to examine the efficiency of different RISs (Fritsch & Slavtchev, 2011; Zabala-Iturriagagoitia et al., 2007).

Asheim (1998) proposed three types of RIS, namely, territorially embedded RIS, territorially networked RIS, and regionalized NIS, whereas Cooke (2001) divided RIS into entrepreneurial and institutional RIS. Other researchers have proposed their own classifications for RIS using a place-based leadership approach (Beer & Clower, 2014; Benneworth et al., 2017).

However, an RIS typology for emerging economies and a generalized typology that covers all regions of the world are lacking. To address this gap, this study proposes a new RIS typology that uses not only RIS variables that are similar to the NIS variables used in Lee (2013), Lee et al. (2021a), and Lee and Lee (2019) but also new variables that are suitable for regional analysis, especially for catching-up economies.

The NIS literature has observed differences in the NIS characteristics of advanced and catching-up countries (Lee, 2013; Lee et al., 2021a). For instance, advanced countries tend to have equally high values for all NIS variables, whereas catching-up economies have an increasing localization that stays below that of advanced economies, increasing yet still low technological diversification, and lower decentralization compared with their advanced counterparts. Therefore, this dissertation assumes that advanced and catching-up economies show different NIS characteristics and identifies the distinct features of RIS in catching-up economies.

Some studies have highlighted the importance of indigenous knowledge for latecomer economies (Asheim et al., 2019; Hassink, 2001; Park & Markusen, 1995; Rodríguez et al., 2014). Economies with peripheral or immature RIS greatly depend on foreign knowledge because of their lack of indigenous knowledge and their low level of regional embeddedness (Asheim et al., 2019; Hassink, 2001; Park & Markusen, 1995; Rodríguez et al., 2014). The reliance of these latecomers on foreign knowledge makes sense given that typical latecomer economies tend to achieve economic growth by relying on FDI and by learning from foreign multinational corporations (MNCs) (Amsden & Chu, 2003; Bernardes & Albuquerque, 2003; Lebdioui et al., 2021). This pattern indicates that latecomer regions show a low level of patenting and localization at the early stages and have more foreign patents than indigenously owned patents even after they start to conduct their own R&D and file patents. This research then highlights the differences in the characteristics of catching-up economies from those of advanced and developing regions by focusing on their indigenously owned patents.

3. Definition of RIS Variables

This research adopts the NIS variables introduced in Lee (2013) and Lee et al. (2021a), transforms them into regional-level variables, and further develops a new RIS variable that is suitable for identifying the specific characteristics of region or city-level economic catch-up. In the NIS analysis, five NIS variables are introduced, namely, localization, technological diversification, knowledge decentralization, technological specialization, and originality. A total of seven RIS variables are proposed, namely, localization, nationalization, local ownership of knowledge, internationalization (i.e., inverse of localization in NIS), technological diversification, knowledge decentralization, and technology specialization. Lee and Lee (2019) and Lee et al. (2021a) explained the relationship between the composite indices of the five NIS variables and economic growth and measured the link among NIS groups with different income and economic growth levels. Lee and Lee (2019) built an NIS index using 3 to 5 NIS variables to explain national economic growth and obtained the most stable results when using five NIS variables. Therefore, the aforementioned RIS variables can also explain regional economic growth.

Unlike NIS studies, the RIS literature does not use the originality variable that measures the degree of knowledge convergence and combination (Lee, 2013; Lee et al., 2021a; Lee & Lee, 2019) and instead uses the local ownership of knowledge to indicate the degree that an indigenous knowledge is newly added. Lee (2013: ch.3) and Lee et al. (2021a) proved that despite having a low level of originality, catching-up countries have achieved a great economic catch-up, which implies that originality may not have a significant effect on economic growth at least at the catching-up stage. Local ownership of knowledge is introduced as a variable given the importance of acquiring indigenous technological capabilities (Mazzoleni & Nelson, 2007). In other words, indigenous ownership of knowledge is one of the key variables that can differentiate catching-up from non-catching-up economies.

RIS studies also add one more dimension of patent citations compared with the NIS literature, which only considers citations within or outside a nation. Specifically, RIS studies consider the citations between regions of the same country. Each RIS variable is explained as follows.

1) Localization, nationalization, and internationalization (Lee, 2013; Lee, Lee, et al., 2021; K. Lee & Lee, 2019)

Localization, nationalization, and internationalization are citation-based variables that indicate whether an economy utilizes local, within-nation, or international knowledge. Localization denotes the ratio of patents invented in x region that cites its own invented patents, nationalization denotes the ratio of citations from patents invented in x region to those invented in other regions within the same country (x+x$'= c$), and internationalization denotes the ratio of citations made by x region to those made by other countries (d).

$$Localization_{xt} = \frac{n_{xxt}}{n_{xt}}$$

$$Nationalization_{\ xt} = \frac{n_{xx't}}{n_{xt}}$$

$$Internationlaization_{\ xt} = \frac{n_{xdt}}{n_{xt}}$$

where n_{xxt} is the number of citations made to region x's patents by region x granted in year *t*, and n_{xt} is the number of all citations made by region x's patents granted in year *t*. $n_{xx\prime t}$ represents the number of citations made from patents invented in region x granted in year t to patents invented in region x' granted in year *t*, where region x' represents those regions other than region x but is located into the same country. n_{xdt} presents the number of citations made to country *d* by region x's patents granted in year *t*, where country *d* differs from the country where region x is located.

2) Local ownership of knowledge

Local ownership of knowledge measures how much a region has indigenous knowledge among the whole knowledge invented in the region.

$$Local\ ownership_{xt} = \frac{N_{cxt}}{N_{xt}}$$

where N_{cxt} denotes the number of patents invented in region x and assigned to a firm that is headquartered in host country c, N_{xt} represents the total number of patents assigned to any firm in region x where the first inventor lives and granted at time t, and $\frac{N_{cxt}}{N_{xt}}$ denotes the ratio of patents invented by domestic firms among the patents invented in region x.

3) Technological diversification

Technological diversification denotes how many technological fields are covered by the patents filed by a region/nation (Lee, 2013; Lee et al., 2021a). As of 2019, the US patent classification system has 473 classes at the 3-digit level. Unless when a fixed value is used for the denominator, whether the technologies are diversified or not cannot be easily confirmed as the number of classes and criteria varies from time to time.

$$Diversification_i = \frac{N_i}{total\ number\ of\ classes}$$

where N_i denotes the classification number of the technological classes of patent i. After calculating for the technological classes of individual patents, the average values for each region and time are computed.

4) Technology specialization (Jaffe & Trajtenberg, 2002; Lee, 2013; Lee et al., 2021a; Lee & Lee, 2019)

Technology specialization denotes whether a region specializes in sectors with rapid or slow obsolescence of knowledge.

$$Cycle\ time\ of\ technologies_i$$
$$= (Grant\ year\ of\ patent\ i) - (grant\ year\ of\ patent\ cited\ in\ patent\ i)$$

Given that this absolute value of cycle time of technologies keeps increasing over time, one cannot easily confirm whether the technology is changing rapidly or slowly. Therefore, this value is normalized at around 1 to denote the relative (or normalized) cycle time of technologies.

$$Relative\ cycle\ time\ of\ technologies = \frac{CTT_i}{Average\ value\ of\ CTT\ in\ year\ t}$$

If the relative CTT is smaller than 1, then the region specializes in short-cycle technologies; otherwise, the region specializes in long-cycle technologies.

5) Knowledge decentralization (Hall et al., 2001; Trajtenberg et al., 1997)

Knowledge decentralization or concentration measures the degree of even or uneven distribution of innovators, patent assignees, and legal patent owners to determine whether the patents are created by a large number of firms or dominated by only a few large firms. The Hirschman–Herfindahl index (HHI) is used to measure the concentration value.

$$HHI_{xt} = \sum_{i \in I_x} \left(\frac{N_{it}}{N_{xt}^*}\right)^2$$

where I_x is the set of assignees, N_{it} is the number of patents filed by assignee i in year t, and N_{xt}^* is the total number of patents filed by region x in year t, excluding the unassigned patents. Decentralization is computed as the inverse value of HHI, that is, $(1 - HHI_{xt})$.

Table 1 Definition of RIS variables

Variables	Definition
Localization	Degree of knowledge creation from local knowledge invented in the same region.
Nationalization	Degree of knowledge creation from national knowledge invented in other regions within the same nation.
Internationalization	Degree of knowledge creation from international (foreign) knowledge.
Technological diversification	Degree of a region creating diverse or narrow fields of knowledge.
Knowledge decentralization	Degree of knowledge creation by diverse firms or a few firms.
Relative cycle time	Denotes whether a region specializes in short- or long-cycle technologies.
Local ownership of knowledge	Degree of a region creating indigenous knowledge.

III. Case Study of RIS in Asia: Comparing the Regions of Penang, Shenzhen, and Taipei

1. Economic Backgrounds of the Three Regions

Taipei, Shenzhen, and Penang are part of three dynamic economies in Asia, namely, Taiwan, China, and Malaysia, respectively. They can also be regarded as the fastest-growing regions in their respective economies.

As the central city, Taipei largely contributes to the overall economic growth of Taiwan. Taipei not only serves as the center of enterprises in the country but also hosts the headquarters of many MNCs (Huang, 2008). While most of these MNCs have been established way back in the late 1950s, the vast majority of export-based manufacturing headquarters in Taipei arrived in the 1960s to take advantage of the administrative and policy support from the central government as Taiwan started to aggressively adopt an export-oriented mode of industrialization (Chou, 2005; Hsu, 2005; Li et al., 2016). However, the weight of foreign firms steadily decreased as some indigenous firms transformed into giants, such as Acer (Alice H Amsden & Chu, 2003; Hsu, 2005). In this study, the term "Taipei City" covers the former Taipei County (New Taipei) and the former Taipei City proper following their formal merging and recognition in 2010.[1] Table 2 shows that the population of Taipei City grew slowly from 2.2 million in 2000 to 2.6 million in 2017.

Shenzhen is one of the first four special economic zones that represent the open-door policy of China initiated by Deng Xiaoping. A former home of labor-intensive manufacturing firms that utilize and supply low-cost labor to Hong Kong, Shenzhen has eventually transformed into a high-tech region (Chen & Kenney, 2007; Yang, 2015).

Penang is one of the earliest manufacturing hubs in Asia to attract foreign MNCs

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[1] As Taipei City and Taipei County were confoundingly used in patent data, we use "Taipei City" to refer to these two regions in our analysis.

because of its low labor costs and low taxes in areas involving diverse electronic parts and components (Ariffin & Figueiredo, 2004; Rasiah, 1988; Revilla Diez & Kiese, 2006). MNCs started to operate in Penang in 1972 after the Bayan Lepas free trade zone was launched. This region initially hosted seven MNCs.

Table 2 Basic profile of Taipei, Shenzhen, and Penang, 2017

	Taipei	Shenzhen	Penang
Population	6,669,946 (2017) 6,214,370 (2000)	12,528,300 (2017) 7,012,400 (2000)	1,746,700 (2017) 1,332,700 (2000)
Area (km^2)	1,380.53	1,997.47	1,049
Per capita GDP USD (PPP)	53,013.78	39,244.69	27,569.08
Per capita GDP relative to that of the US (%)	96.75	71.62	50.31
Number of US patents filed in 2017	3785	2491	112
Number of patents per million population	5670.03	1988.30	641.21
Cumulated number of patents (1994-2017)	57714	17085	1235

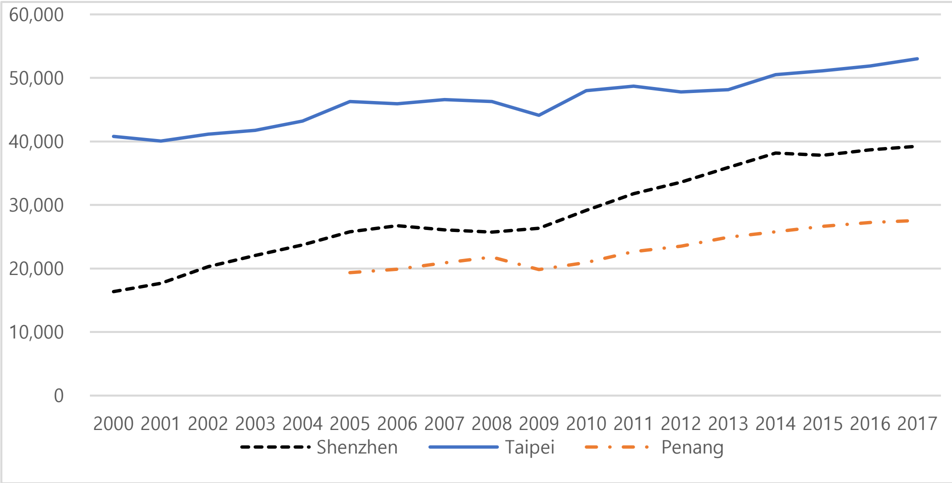
Source: Shenzhen Statistical Yearbook, Department of Statistics Malaysia Official Portal, Taipei City Statistical Yearbook, Statistical Yearbook of New Taipei City, Taiwan National Statistics, Penn World Table 9.1, China Statistical Yearbook, Department of Statistics in Malaysia, and author's calculations

One of the common features of the above three regions is that they initially invited and promoted FDI through MNCs by setting industrial parks, such as the Free Industrial Zone in Penang in 1972 and the Special Economic Zones in Shenzhen in 1980 (Hsu, 2005; UNDP, 2006). Although starting later than Penang, Shenzhen has witnessed a faster long-term growth in its income and number of patents (Table

1 and Figure 1), hence offering an interesting case to examine in this study.

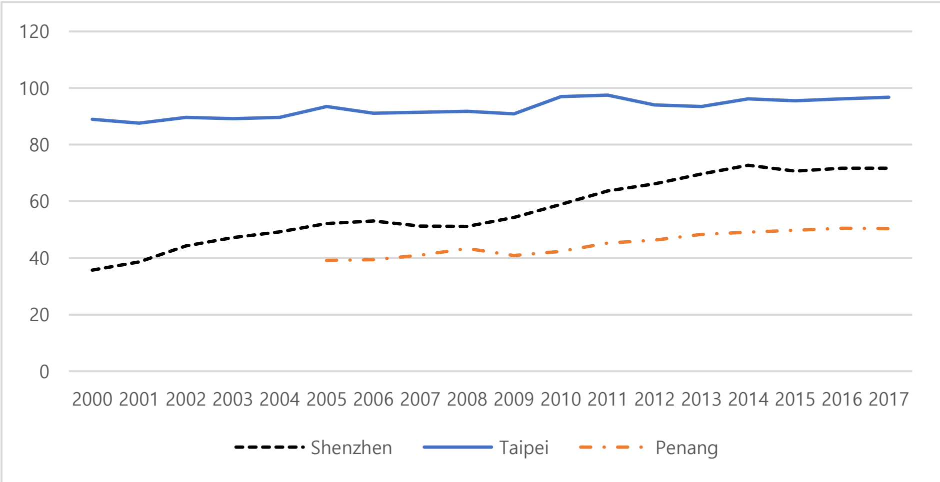
Figure 1 Per capita GRDP and its relative ratio to the US

Figure 1A Per capita GRDP (PPP, US$)



Source: Shenzhen Statistical Yearbook, Department of Statistics Malaysia Official Portal, Taipei City Statistical Yearbook, Statistical Yearbook of New Taipei City, Taiwan National Statistics, Penn World Table 9.1, China Statistical Yearbook, Department of Statistics in Malaysia, and author's calculations

Figure 1B Per capita GRDP relative to that of the US



Source: Shenzhen Statistical Yearbook, Department of Statistics Malaysia Official Portal, Taipei City Statistical Yearbook, Statistical Yearbook of New Taipei City, Taiwan National Statistics, Penn World Table 9.1, China Statistical Yearbook, Department of Statistics in Malaysia, and author's calculations

Figures 1A and 1B show the trends of per capita GRDP in each region and their per capita GRDP relative to that of the US. These three regions have a decent record of economic growth and catching up with the US. Among them, Taipei has the highest level, whereas Penang has the lowest. Since 2000, Taipei has successfully caught up after its per capita GRDP reached over 80% of that of the US. Specifically, the per capita GRDP of Taiwan exceeded $50,000 in PPP terms and reached almost 97% of that of the US in 2017. During the same year, the per capita GRDP of Shenzhen reached $39,245 in PPP terms, which was approximately 72% of that of the US, whereas the per capita GRDP of Penang reached $27,569, which was only more than 50% of that of the US (less than 40% before 2000). In other words, while these regions have shown a strong record of catching up, they differ in terms of catching-up speed (e.g., Shenzhen has a faster catching-up than Penang).

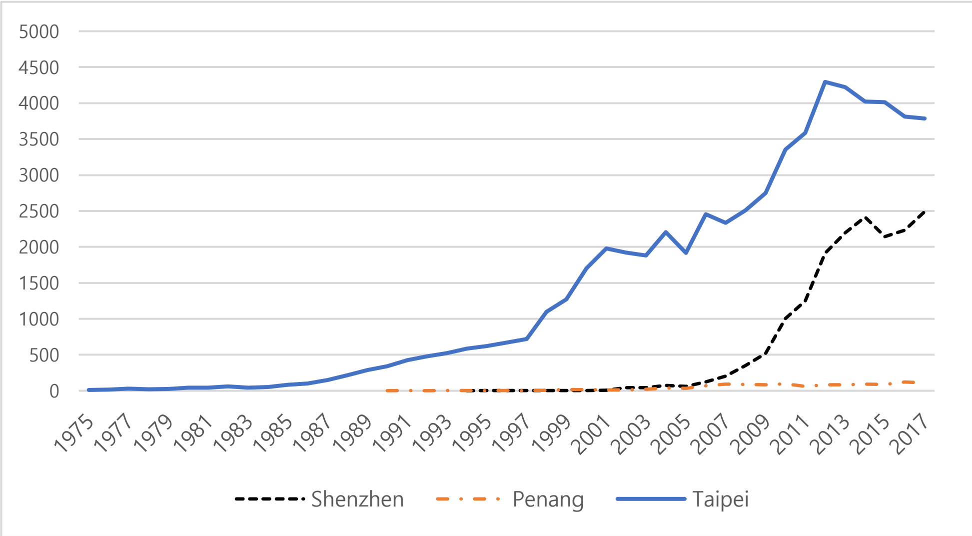
A country/region is stuck in the middle-income trap when its per capita GRDP relative to that of the US rests between 20% and 40% for several decades (World Bank, 2012). Following this definition, all the three regions escaped the middle-income trap since 2006. However, some differences were observed. For instance, Shenzhen caught up with Taipei faster than Penang. The gap of Shenzhen with Penang was about 10% of its gap with the US in the early 2000s yet increased to about 20% by the mid-2010s. Therefore, Shenzhen has reached about 70% of the US level, whereas Penang has reached just above 50%.

This study compares the three regions by using number of patents, especially those registered in the US, for the sake of fairness. Figure 2A shows that the number of the US patents registered with the inventor's address in Taipei has dramatically increased since the late 1990s. In 2017, this number reached 3,780. Shenzhen also witnessed a remarkable growth in these patents since the late 2000s, from 0 in the 1990s to about 2,500 in 2017. However, such rapid catching up was not realized in Penang, which only had 100 patents registered in the US. This comparison remains valid in terms of patent count per person (Figure 2B).

The above discussion raises the interesting question, "why does Shenzhen catch up with Taipei faster than Penang?" This study aims to explain this performance gap by analyzing the RIS of these regions. Specifically, we explore the possibility for different development trajectories to emerge among these regions due to different local–global interfaces or the roles of indigenous firms and their contributions to innovation.

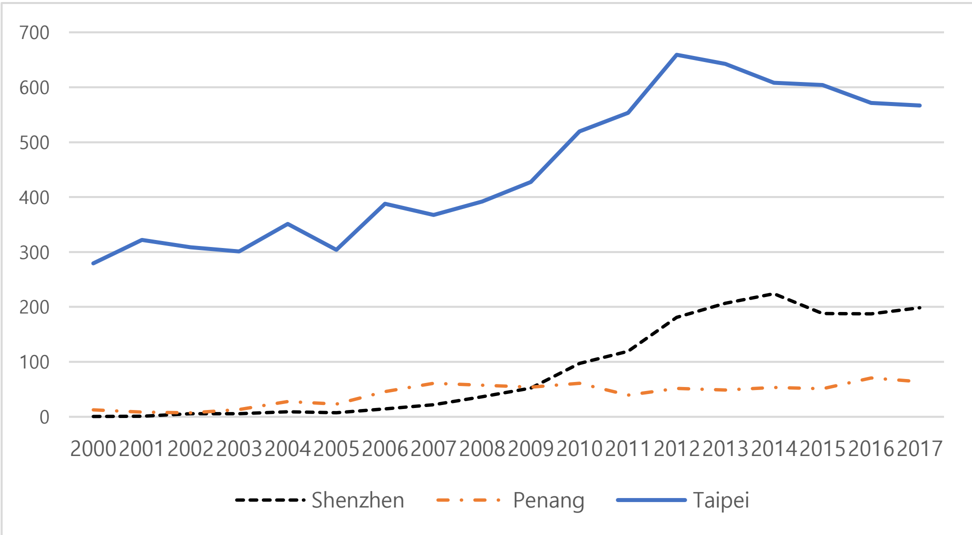
Figure 2 Patent counts

(A) Number of patents



Source: USPTO & Author's calculation

(B) Number of patents per million population



Source: USPTO and author's calculations

2. Key Aspects of Catch-Up and Hypothesis

A peripheral or immature RIS tend to heavily rely on external knowledge given its lack of an indigenous knowledge base and its low level of regional embeddedness

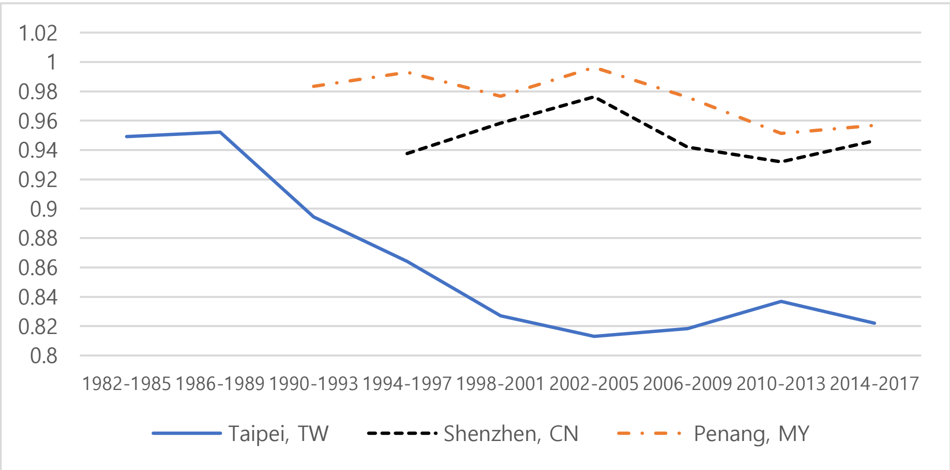
(Asheim et al., 2019: 73; Hassink, 2001; Park & Markusen, 1995; Rodríguez et al., 2014). Typical latecomer economies tend to achieve economic growth by relying on FDI and learning from foreign MNCs (Amsden & Chu, 2003; Bernardes & Albuquerque, 2003; Lebdioui et al., 2021). Such characterization of RIS in emerging economies is consistent with that of national-level studies thar use the NIS concept of emerging or catching-up economies (Lee, 2013; Lee et al., 2021a). Successfully catching-up countries have a low level of knowledge localization at the early stage before showing an increasing trend. In other words, at a low level of economic development, emerging economies tend to rely on knowledge from foreign or more advanced economies instead of creating and diffusing their indigenous knowledge. Acquiring indigenous technological capabilities or knowledge ownership is particularly important during the catching up or at the later stages of development (Lebdioui et al., 2021; Mazzoleni & Nelson, 2007).

The hypothesis of this work concerns the role of foreign knowledge and local ownership of knowledge. With their low dependence on foreign knowledge, highly advanced economies are characterized as having high localization and low internationalization. As mentioned in the previous chapter, Taipei had the highest level of per capita GRDP (2015 PPP-based USD), followed by Shenzhen and Penang. Therefore, Taipei has a high and increasing level of localization as well as a low and decreasing internationalization, whereas Shenzhen, as a rapidly catching-up region, has increasing localization and decreasing internationalization. A more advanced or catching-up region typically shows a high or increasing level of inter-regionalization, which reflects a high or increasing number of patent citations by other regions. Meanwhile, successfully catching-up countries, such as Taiwan and South Korea, can catch up with advanced economies by increasing their number of locally owned firms and indigenous technological capability (Amsden & Chu, 2003; Mazzoleni & Nelson, 2007). Relying on foreign-owned knowledge (patents) is not enough to sustain the catch-up at the later stage because foreign firms become increasingly reluctant to transfer or sell their technologies to latecomers who are catching up and approaching the frontier (Lebdioui et al., 2021; K. Lee, 2005). Therefore, Taipei needs to have a high local ownership of knowledge, whereas Shenzhen needs to have an increasing local ownership of knowledge.

3. Results

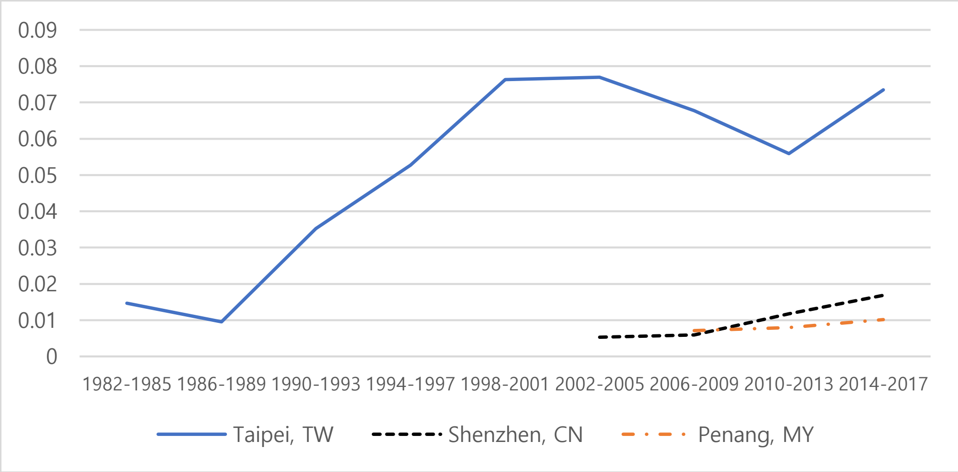
Figure 5 shows the extent and trends of the localization index of the three regions. As expected,, the level of localization in Taipei is much higher than those in Shenzhen and Penang. However, the localization in both Shenzhen and Penang shows an increasing pattern, which is consistent with the increasing per capita income of these regions that is steadily catching up with that of the US over time (Figure 1). The degree of localization in Taipei increased from 4% in the 1980s to more than 10% in the 2000s, which may reflect a self-citation rate of about 10% at the regional level. By contrast, the level of local self-citation in Shenzhen or Penang was only half of the level in Taipei (6% for Shenzhen and 4% for Penang) in the 2010s. These figures indicate that the majority of citations by Shenzhen and Penang are attributed to foreign patents. Given that this result is expected for regions in EEs, internationalization is also measured in this study.

Figure 3 Internationalization



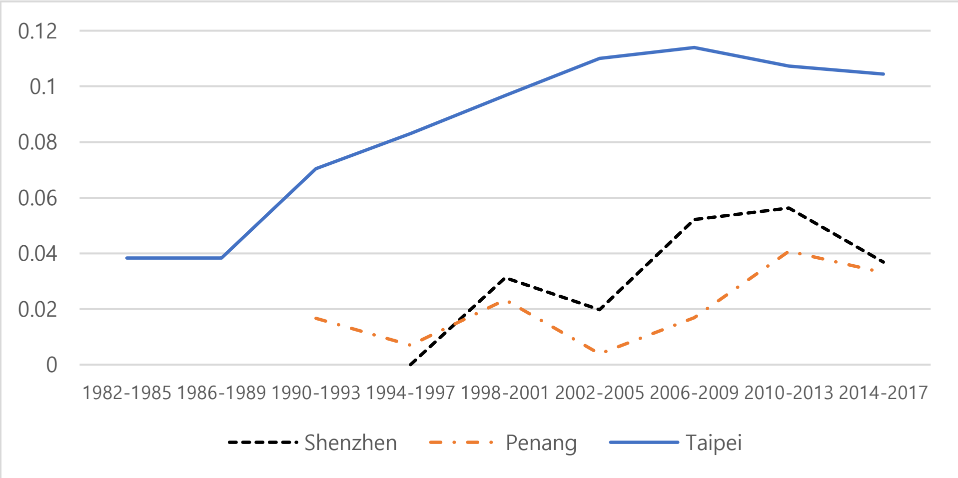
Source: Author's calculations

Figure 4 Nationalization



Source: Author's calculations

Figure 5 Localization



Source: Author's calculations

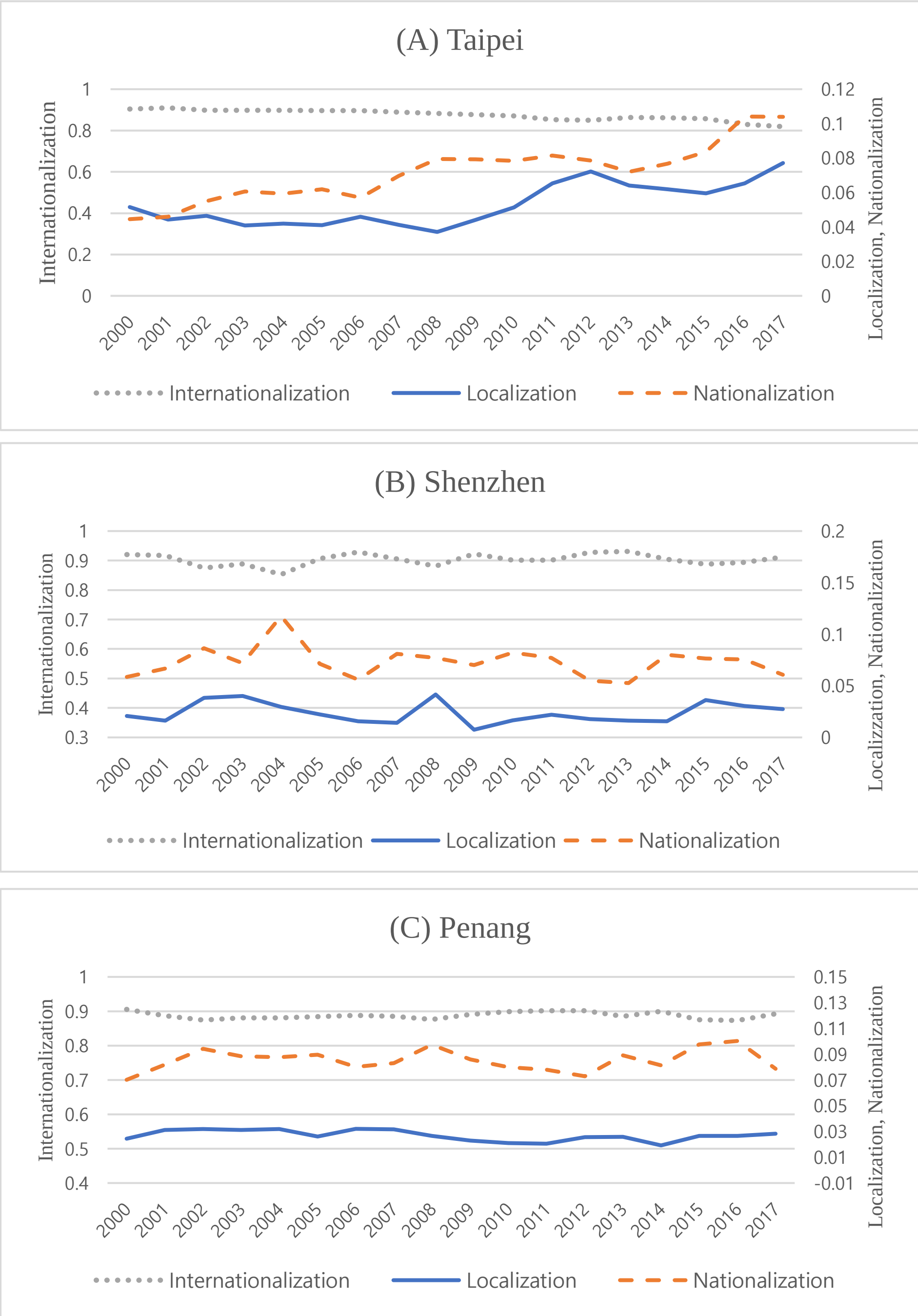
Figure 3 illustrates the extent and trends of internationalization, that is, the degree that the patents filed by inventors in a region tend to cite foreign patents or those patents whose inventors' addresses are located in foreign nations. In line with our expectations, Taipei demonstrated a decreasing internationalization or reliance on foreign patents, which reflects an increase in its own indigenous technological capabilities and RIS. Specifically, Taipei's absolute degree of internationalization decreased from 95% in the early 1980s to less than 82% in the early 2000s but slightly increased again in the 2010s. By contrast, the level of internationalization of Shenzhen or Penang both exceeded 90%, with Penang reporting a higher level than

Shenzhen. This result echoes the previous argument that Shenzhen has a higher level of development or catching-up compared with Penang.

Around the mid-2000s, the localization of Taipei stopped increasing yet slightly decreased since then, whereas its internationalization stopped decreasing yet slightly increased afterward (Figure 3 and 5). This inter-connected pattern is consistent with the hypothesis of “In-Again” with GVC after the stage of “Out” from the GVC or recoupling with GPN after the stage of decoupling (Lee et al., 2018). In other words, local firms want to open up again and globalize after reaching a certain level of indigenous capabilities, domestic value-added, and chains during the preceding stage of “out” from GVC or decoupling from GPN. Moreover, while a certain high level of localization is desirable, the degree of localization cannot increase unlimitedly. The opposite is true of internationalization. Figure 4 shows the extent and trend of nationalization, that is, the degree that a region’s innovation relies on knowledge from other regions in the same nation. The extent of nationalization of Taipei is higher than that of Shenzhen and Penang and even rapidly increased over time despite experiencing some changes in the 2000s. In the 2010s, Taipei’s degree of nationalization exceeded 6%, which was less than 2% of that of Shenzhen or Penang. However, at low levels, both Shenzhen and Penang reported an increasing trend, with Shenzhen consistently reporting a higher degree of nationalization than Penang. These patterns support the hypothesis stated in the previous section.

Figure 6 Composition of localization, nationalization, and internatiFigure 6 presents the composition of localization, nationalization, and internationalization for the three regions. These composition graphs show that all three regions rely on foreign knowledge. While the dependence of Taipei on foreign knowledge showed a decreasing trend, the region remained highly dependent on such knowledge.

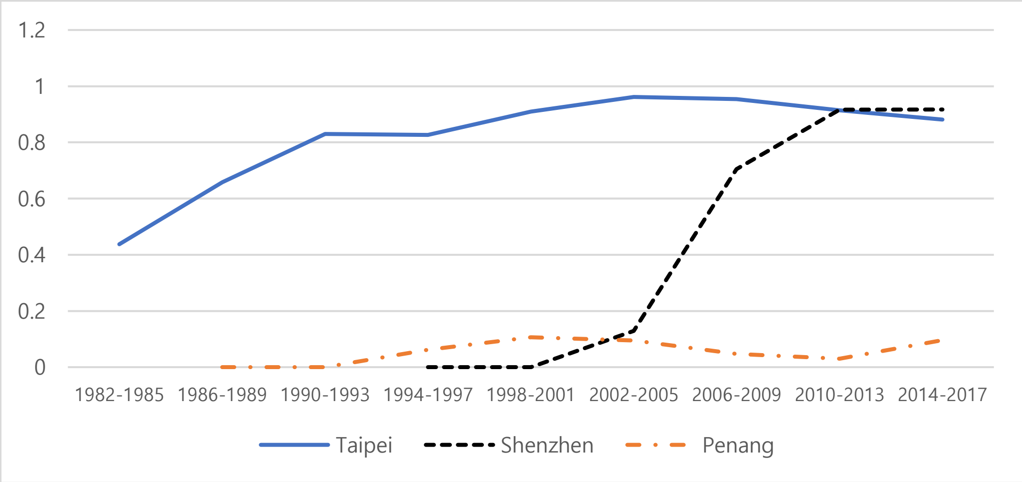
Figure 6 Composition of localization, nationalization, and internationalization



Source: Author's calculations

Figure 7 shows the time trend of the local firm ownership of the three regions. The share in Taipei reached almost 100% by the mid-2000s from about 40% in the 1980s, whereas that of Shenzhen reached the same level by the mid-2010s within a shorter period because its share was near 0% in the mid-1990s. By contrast, Penang did not report a sharp increase in its local share, which remained around 10% since the 1990s.

Figure 7 Local Ownership of Innovation

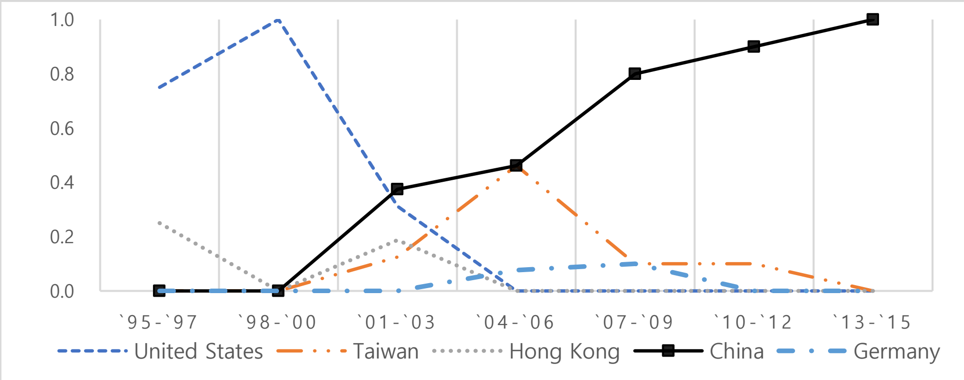


Source: Author's calculations

Figure 8 presents a more detailed picture by looking at the cross-country decomposition of the top 10 assignees in each region. The trends in Taipei confirmed the dominance of Taiwanese firms since the mid-1990s. In Shenzhen, the share of domestic or Chinese-owned firms in the top 10 assignees kept increasing since the late 1990s and reached almost 100% between 2013 and 2015. This finding echoes the decrease in the shares by the US and Taiwan. Unlike Shenzhen and Taipei, Penang remained dominated by US firms with 50% to 70% shares since the 1990s. This value echoes the decrease in the shares by Malaysian firms from 20% to 0% in the mid-2010s.

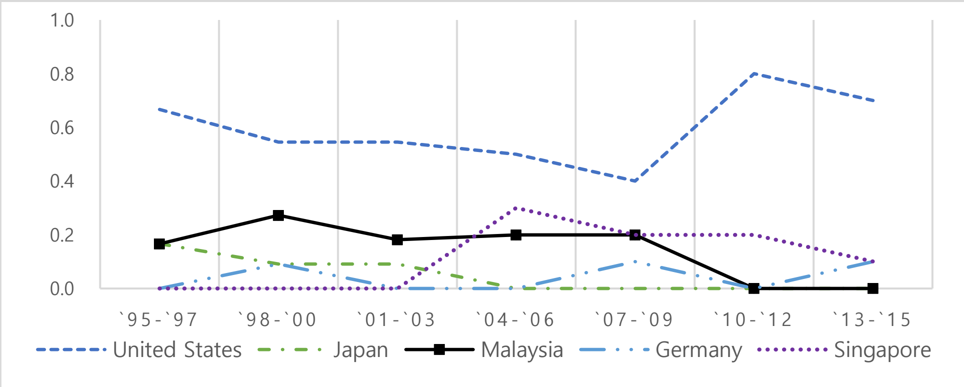
Figure 8 Shares by the Top 10 Assignees by Origin

(A) Shenzhen



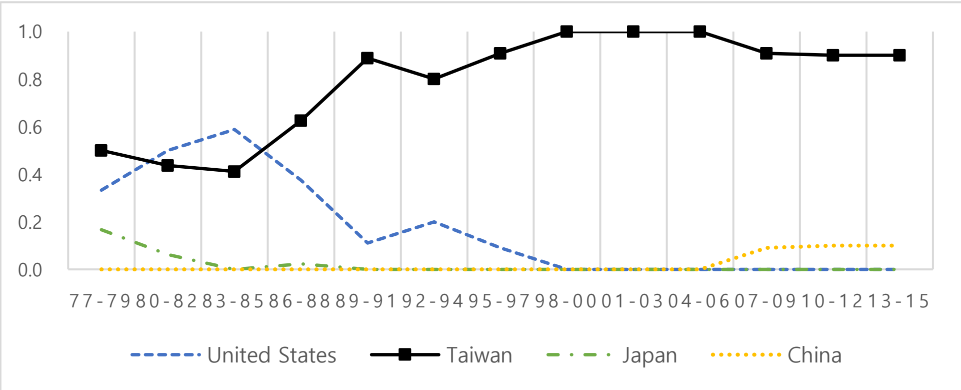
Source: Author's calculation

(B) Penang



Source: Author's calculation

(C) Taipei



Source: Author's calculation

The names of the top firms in Shenzhen and Penang since the 2000s can be found in the Appendix (A1, A2). In 2005, two Taiwanese firms, namely, Hong Hai Precision and Foxconn, ranked top 1 and 2 in Shenzhen. However, in 2011, the top

4 ranks were dominated by indigenous Chinese firms, such as Huawei, with the Taiwanese firm Hong Hai Precision ranking 5th. By 2015, all top 10 firms in Shenzhen were Chinese-owned firms, with ZTE ranking 1st followed by Huawei. The Appendix shows that US firms, including Intel, Motorola, and Altera, continue to dominate in Penang.

Taipei and Shenzhen have steadily reduced their dependency on foreign firms' knowledge, but the same cannot be said for Penang. The creation of considerable amounts of knowledge by indigenous firms in Shenzhen has enabled the region to transition from a peripheral RIS to a catching-up RIS. In addition, the increasing amount of indigenous knowledge in Taipei and Shenzhen has created a knowledge pool that can trigger an increase in their localization and nationalization of knowledge.

4. Three Models of Catching-Up: Taipei, Shenzhen, and Penang

After verifying the hypothesis, this section addresses the burning question of ”how” Shenzhen, following Taiwan, has been able to promote its locally owned firms through its interaction with and learning from foreign MNCs. By comparison, Penang is slowly catching up and remains reliant on MNCs. The question of "how" can be placed in the context of a larger question of how to sustain economic growth in emerging economies, thereby overcoming the possibility of the MIT.

As the source and solution for the MIT, previous studies, such as the ADB-sponsored study of Eichengreen et al. (2012; 2013) and Lee (2013), identified innovation capabilities as the key binding constraint for the MIT. This view is also consistent with an early statement by the World Bank, who argued that middle-income economies tend to fall in a trap because they get caught between low-wage manufacturers and high-wage innovators; their wage rates are too high to compete with low-wage exporters, and the level of their technological capability is too low to enable them to compete with advanced countries (World Bank, 2010). Therefore, the solution to the MIT is innovation. However, these diagnostics and solution do not address the issue of ownership of innovation, that is, who emerges as the carrier of innovation. By contrast, this study identifies emergence of local ownership as one of the most important and interesting aspects that differentiate the fast catching-up in Shenzhen from the slow catching-up in Penang. Subsequently, we elaborate how each region has behaved in terms of promoting local ownership and then propose the three regions as alternative models of catching-up RIS at the local–global interface.

First, the Taipei model can be characterized by a high degree of localization and the lowest degree of internationalization (Section 4). However, Taipei was also previously dominated by foreign MNCs and faced a crisis as foreign vendors switched to other lower-wage economies, such as Malaysia, for their OEM orders (Amsden & Chu, 2003: 70-79; Li et al., 2016) as the wage rates increased in Taiwan in the 1980s. This phenomenon is a typical sign of MIT. Under this situation, many engineers who used to work in a foreign-owned television factory left the firm to start their own firms in related areas (Amsden & Chu, 2003:23-24). For them, the source of technology changed from FDIs to technology licensing agreements with foreign entities, which resulted in the emergence of a more effective model that combines firm-level R&D effort with supportive industrial/innovation policy by the government, including public–private collaborations (Lebdioui et al., 2021; J.D. Lee et al., 2021; Lee, et al., 2021a).

Specifically, public research organizations, such as the Industrial Technology Research Institute (ITRI), play the role of a "new developmental state" because they develop high-tech parts and components that were formerly imported and produced by private firms (Amsden & Chu, 2003: 77). Furthermore, for an important upgrading transition from making small (analog) calculators to laptops, the ITRI led the public–private R&D consortium to develop a common machine architecture for laptops and their prototypes, which can be easily translated into a series of standardized components produced by manufacturers through mass production. This

R&D consortium represented a watershed after some previous failures, hence demonstrating its potential to establish new "fast follower" industries (Mathews, 2002). Despite collaborative relations with foreign entities for technology licensing, the acquisition of innovation (design) capability required an active learning effort from the Taiwan side. For instance, in making circuit chips, Taiwanese engineers went around the world to study large-scale integration applications. By combining their observations and knowledge gained from Japanese suppliers, they excelled at integrating a large number of parts and components being sourced globally at the lowest prices into a small space (Amsden & Chu, 2003: 28-32).

Second, the Penang model is somewhat opposite to that of Taipei in terms of the continuing dominance of foreign MNCs in production and innovation. In the past, MNCs have been attracted to the low-cost wages and tax haven status of Penang. Despite increasing income and wage rates, the share of MNCs in Penang's total investment ranged from 60% to 70% from 2014 to 2015. While this trend showed some fluctuations, no clear declining trend was observed, the local one contributed approximately 30% to 40% in the same period (Figure 5 in Lee et al., 2019). The new cycle of development is emerging, and the economy of Penang has been diversified from labor-intensified manufacturing operations to high-value-added manufacturing, including services from them, such as software, engineering design, R&D, and industrial system-based services, as well as new servicing industries, such as medical tourism, education, and shared service centers (Penang Institute, 2015: 10–15). These structural changes also respond to the rise of China as an alternative location for MNCs (Diez & Kiese, 2006).

Penang witnessed some downsizing and exit of MNC manufacturing operations and mergers and acquisitions among multinationals to rationalize their resources and reduce redundancies over the past few years.[2] However, many MNCs maintained

[2] Multinationals, such as Seagate Technology and Fairchild, are among the exit companies that may lead to a high level of employee retrenchment. From January 2015 to June 2017, a total of 6,136 employees were estimated to be affected by such exits by MNCs (Lee et al., 2019).

certain operations in Penang as they are provided with strong supply chains, which allow them to produce advanced technologies and services. Some locally owned firms have also emerged to advance their high value-added activities in Penang (Lee et al., 2019; Diez & Kiese, 2006), including Vitrox (an HP spin-off that produces automated machine inspection vision systems), Globetronics (an Intel spin-off that provides semiconductor process services), and EngTek (from a 1970 humble workshop providing services to MNCs to produce hard disk drive components and precision tools). A key driver of this positive scenario is a local institution that has enabled the training and upskilling of their local force, such as Penang Skill Development Center, a non -profit institution that provides technical knowledge and training programs to engineers within the region (Lee et al., 2019).

Third, Shenzhen lies between Taipei and Penang in terms of their levels of per capita income and their localization and internationalization of knowledge (Figures 3 and 4) although it is closer to Taipei in terms of share of local ownership of innovation (Figure 6). The leading companies in terms of number of patents are Huawei and ZTE (Appendix 1). How did these firms grow and become dominant? Similar to those in Taipei, firms in Shenzhen relied on a combination of firm-level R&D effort and supportive industrial/innovation policy by the government, including public–private collaborations (Lebdioui et al., 2021; Lee et al., 2021b; Yang, 2015).

The industrial policy in China has been termed as the “trading market for technology” (Mu & Lee, 2005), that is, the Chinese government used its huge bargaining power associated with the size of the Chinese market to require foreign joint venture firms to transfer important parts of their technologies. A famous example is the indigenous development of fixed-line telephones, which resulted from the technology transfer and diffusion from a JV, Shanghai Bell, with the Chinese side holding 60% or majority of the shares. The transferred key technologies were later diffused to the local R&D consortium to develop Chinese-owned fixed telephone switches. This consortium eventually transferred the technologies to ZTE, two other

SOEs, and one private firm (Huawei) to be in charge of the actual production. When these four indigenous Chinese firms started to compete directly with JVs, the role of the Chinese government was to provide market protection and give financial and moral incentives for the adoption and use of domestic products (Mu & Lee, 2005; Xin & Wang, 2000).[3]

Given its status as a SEZ, Shenzhen has enjoyed privileges in various policy initiatives (Yang, 2015). In the most recent case of Tencent, the help from the local government was critical to guarantee funding from venture capital and other financial investors at the initial stage of growth (Breznitz & Murphree, 2011: 175-178). To strengthen local firm ownership of knowledge, Shenzhen promoted the growth of local firms, such as Huawei and Tencent, by investing in universities and large research institutes (Breznitz & Murphree, 2011; Yang, 2015; Zhang et al., 2016). The Shenzhen municipal government also encouraged higher education and attracted advanced manpower in Shenzhen, where universities and URIs, such as the Shenzhen University in 1983, Shenzhen Polytechnic in 1993, the THU Shenzhen Tsinghua Research Institute, the research base of PKU, CAS, Chinese Academy of Engineering, and Hong Kong University of Science & Technology, were established by providing incentives or benefits (Chen & Kenney, 2007). These initiatives helped a diverse and large pool of human resources from other regions in China and other countries to come to Shenzhen. For instance, Huawei runs R&D centers in Beijing, Shanghai, Nanjing, Shenzhen, Hangzhou, and Chengdu (Li, 2009).

Shenzhen also engages in R&D collaboration with other countries. Since 1999,

[3] The Ministry of Post and Telecommunications in China (MPT) organizes conferences every year to coordinate local telephone service authorities to purchase indigenous equipment, and these conferences mark a turning point for the growth of the communication manufacturing industry in China (Xin and Wang, 2000). Encouraged by the People's Bank of China, the China Construction Bank supplied Huawei a buyer credit worth 3.85 billion RMB, which accounted for 45% of the bank's total buyer credit in 1998 (Mu and Lee, 2005).

Huawei has worked collaboratively with R&D labs in Texas Instruments, Motorola, IBM, Intel, Agere Systems, Sun Microsystems, Altera, Qualcomm, Infineon, and Microsoft, and since June 2005, the firm has established 10 joint research labs. Huawei also has global R&D centers in Bangalore (India), Moscow (Russia), Stockholm (Sweden), Silicon Valley (US), California (US), and Dallas (US) (Li, 2009). Meanwhile, ZTE has 14 R&D centers worldwide, 8 of which are located in China. The ZTE R&D centers in China work closely with 50 local research institutes (Hu & Mathews, 2008).

The above discussion suggests that Taipei and Shenzhen are more active or aggressive in their degree of public intervention compared with Penang in Malaysia, which may account for the different degrees of local ownership of innovation across three regions. While the former two cities rely on direct intervention from the public sector in specific R&D projects to help indigenous firms, the public sector in Penang focuses more on human capital development or re- or up-skilling of the workforce being utilized by foreign MNCs.

5. Concluding Remarks

This study raises the question of "why" economic performance and growth trajectories differ among Taipei, Shenzhen, and Penang in Asia. The most developed of these regions is Taipei, whereas the least developed is Penang. Specifically, this research asks why Shenzhen is catching up rapidly with Taipei while Penang is slowly catching up. From a Schumpeterian perspective, this paper answers this question by focusing on the divergent nature of RIS across these regions, specifically the local–global interface, which resulted in divergence in the degree and speed of localization of knowledge creation and ownership. This paper then develops three interrelated measures of RIS, namely, localization, nationalization, and internationalization of knowledge, and measures the degree of local ownership of patents invented in a region.

First, while Taipei has the highest level of localization and nationalization of knowledge, its level of internationalization (or degree of reliance on foreign knowledge) is low and decreasing. Shenzhen has been replicating the trajectory of Taipei more closely than Penang, which has been relying on foreign knowledge sources and slowly increasing its localization or nationalization of knowledge.

Second, the main carrier and ownership of innovation in Taipei has shifted from foreign MNCs to indigenous firms, and these trends have been closely replicated in Shenzhen since the mid-2000s. Meanwhile, Penang has increased its reliance on foreign MNCs.

These findings help identify and differentiate the catching-up RIS. In other words, a dynamically catching-up RIS or upgrading process of RIS can be characterized by a steady increase in the localized creation and diffusion of knowledge, a decrease in internationalization, and an increase in the local ownership of innovation.

This study also addresses “how” the three regions have behaved differently in achieving divergent degrees of success and then views these regions as alternative models of catching-up RIS at the local–global interface. Taipei and Shenzhen are treated as models that eventually create indigenous firms, whereas the Penang model continuously relies on MNCs. Although difficult to realize, the Shenzhen model has resulted in a faster catching-up compared with the Penang model. In terms of how to promote locally owned firms, Taipei and Shenzhen have been more active or aggressive than Penang in terms of public intervention. While the former two cities rely on the direct intervention of the public sector in specific R&D projects to help indigenous firms, the public sector in Penang focuses on human capital development for the workforce being employed by MNCs. This difference may explain the different degrees of the localization of knowledge creation and ownership across the three regions.

If a latecomer region wishes to catch up fast, then an emerging policy implication would be the paramount importance of eventually increasing the localization of innovation and its ownership beyond the initial stage of learning from foreign knowledge sources. In this regard, various policy initiatives that were adopted in Taipei and Shenzhen can be used to promote indigenous innovation out of learning from foreign MNCs. Such initiatives include policies to promote spinoff and startup by locals, technology transfer from foreign to domestic firms, public and private joint R&Ds, in-house R&D centers by local firms, and policies for attracting branches of universities, encouraging academic spinoffs, and searching for sources of financing.

The next chapter aims to generalize the stylized patterns of catching-up RIS. This case study successfully identifies and elaborates some stylizable patterns or hypotheses that can be subjected to future econometric studies that utilize larger datasets. This study performs a cluster analysis to classify as many as 30 cities around the world into several types, especially mature, fast, and slow catching-up RIS, which can be subject to regression analysis following the method of Lee et al. (2021a).

IV. Varieties of RIS and Catching-Up RIS

1. Introduction

The previous chapter presents a comparative analysis of Taipei, Shenzhen, and Penang. An economic catch-up can be either fast or slow. Shenzhen catches up fast with Taipei by increasing its indigenous knowledge with large businesses and governmental support, whereas Penang catches up slow due to its low level of indigenous knowledge. Taipei has a higher income level than both Shenzhen and Penang due to its relatively high indigenous knowledge, localization, and nationalization.

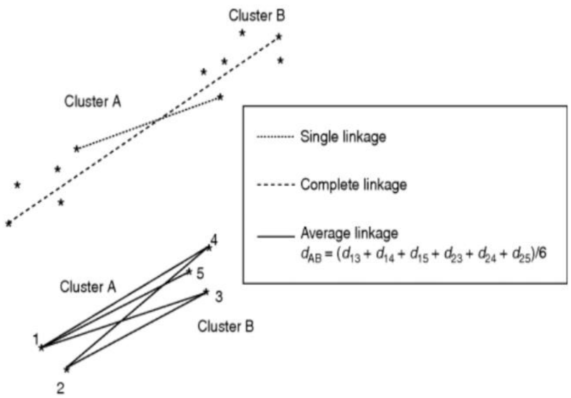
This chapter generalizes these different pathways of regional economic catching-up by broadening the extent of regions and performing a cluster analysis. Many studies have categorized NIS by income level (Castellacci, 2011; Lee, 2013: ch.3; Lee et al., 2021a). For instance, Castellacci (2011) and Lee et al. (2021a) performed a cluster analysis with variables representing the country's innovation systems. Lee (2013: ch.3) and Lee et al. (2021a) proposed five variables of NIS, namely, knowledge localization, technological diversification, technology specialization, originality, and knowledge decentralization (or concentration).

Some studies on RIS have proposed a typology of RIS in advanced countries, such as European countries (Amsden, 1992; Cooke, 1992), based on qualitative measurements. However, other studies have adopted a quantitative approach. For instance, Zabala-Iturriagagoitia et al. (2007) evaluated RIS performance in terms of technical efficiency for the case of Spain, whereas Fritsch and Slavtchev (2011) proposed alternative measures for RIS efficiency based on the concept of knowledge production function for the case of Germany. However, only few studies have proposed an RIS typology for emerging economies or a generalized typology that covers all regions in the world. To fill such gap, this study forms groups of RIS by using a patent-citation-based measurement that represents the RIS of not only advanced economies but also that of 30 regions all over the world.

2. Data and Methodology: Cluster Analysis

Data on 7 variables from 2000 to 2017 were used, namely, localization, nationalization, internationalization, technological diversification, knowledge decentralization, and technology specialization (relative cycle time). Unlike in the NIS analysis, originality was excluded from the cluster analysis due to its low importance in economic catch-up. According to Lee (2013: ch.3) and Lee et al. (2021a), despite having a low level of originality, catching-up countries can achieve a great economic catch-up, and in this sense, originality may not have a significant effect on economic growth at least at the catching-up stage. The previous chapter also shows that originality does not play an important part in the different economic catch-up rates of the three regions. Localization, nationalization, and internationalization are combined with other RIS variables in the cluster analysis. Local ownership of knowledge is also added due to its importance in economic catch-up (Mazzoleni & Nelson, 2007). The local ownership of knowledge plays a key role for Shenzhen to catch up with Taipei, which is a more advanced region, and is a key variable that differentiates fast from slow catch-up as revealed in the previous chapter.

Figure 9 Examples of three inter-cluster distance measures: single, complete and average



Everitt et al. (2011)

Cluster analysis is a method of grouping objectives by setting several criteria and showing the homogeneity within groups and the heterogeneity between groups.

Cluster analysis employs three methods, namely, average linkage, single linkage, and complete linkage, among which average linkage is the most preferred due to its less sensitivity to extremes or outliers than complete or single linkage methods (Jobson, 1992). Average linkage cluster analysis is based on Euclidean distance measurement, which is computed by averaging the proximities between all pairs of objects, with one object coming from each group (Jobson, 1992). Figure 9 presents a simple description and comparison of the three linkage methods in cluster analysis (Everitt et al., 2011).

This research covers 30 regions around the world, of which 7 are in Europe (i.e., Berlin, Munich, London, Cambridge, Stockholm, Paris, Milan, and Moscow), 4 are in the US (i.e., Silicon Valley[4] in California, Boston Area[5] in Massachusetts, and Austin[6] and Houston[7] in Texas), 13 are in Asia (i.e., Shenzhen, Beijing, and Shanghai in China, Penang in Malaysia, Osaka and Tokyo in Japan, Taipei in Taiwan, Bangalore and New Delhi[8] in India, Hong Kong, Singapore, and Seoul, Daejeon, and Gyeonggi-do in South Korea), and 3 are in South America (i.e., Santiago in Chile, Sao Paulo in Brazil, and Mexico City in Mexico).

3. Backgrounds of Economies and Hypothesis

The above regions are divided into three groups based on their per capita GRDP. The first group includes Mexico City, Santiago, Sao Paulo, Seoul, Daejeon, Gyeonggi-do, Beijing, Shanghai, Shenzhen, Penang, and Moscow (Figure 10A), whose per capita GRDP are over 20% to 40% of the US per capita GDP. The second group includes Bangalore and New Delhi, whose per capita GRDP is trapped between 20% and 40% of the US per capita GDP. The third group includes Berlin,

[4] Alameda County, San Francisco County, San Mateo County, and Santa Clara County in California are included as Silicon Valley.
[5] Middlesex County, Suffolk County in Massachusetts state are included as Boston Area
[6] Travis County in Texas is considered as Austin region.
[7] Harris County in Texas is considered as Houston region.
[8] New Delhi here is used as National Capital Territory including both Delhi and New Delhi regions.

Munich, Paris, London, Cambridge, Milan, Stockholm, Osaka, Tokyo, Austin, Houston, Silicon Valley, Boston Area, Hong Kong, Taipei, Tel Aviv, and Singapore, whose per capita GRDP is above 20% to 40% of the US per capita GDP. These regions are divided not only by their income level but also by their economic growth rate. Beijing, Shenzhen, Moscow, Bangalore, New Delhi, Santiago, Sao Paulo, Seoul, Daejeon, Gyeonggi-do, Shanghai, Penang, and Mexico City are classified as fast-growing regions whose average yearly per capita GRDP growth exceeds 5%. Given the differences in their economic backgrounds, the high-income, low-income, and fast-growing regions also show differences in their RIS characteristics.

Similar to the NIS analysis results, the high-income regions report high values for all RIS variables, including localization (equivalent to low internationalization), diversification, decentralization, and cycle time of technologies specialization (Lee 2013; Lee et al., 2021a). The results of catching-up RIS for technological diversification, decentralization, and technology specialization are similar to those of catching-up NIS, which report a low decentralization, increasing and high value of diversification, and specialization in short-cycle technologies (Lee 2013: ch.3; Lee et al., 2021a).

In case of internationalization, the catching-up economies in the NIS analysis report a lower localization compared with advanced economies but show an increasing trend. Inversely, the internationalization of catching-up economies is higher than that of advanced countries yet show decreasing trend. Meanwhile, in the RIS analysis, peripheral or immature RIS tend to heavily rely on external knowledge due to its lack of indigenous knowledge (Asheim et al., 2019: 73; Hassink, 2001; Park & Markusen, 1995; Rodríguez et al., 2014). Therefore, the localization or nationalization of regions in catching-up RIS is lower than that of high-income regions but shows an increasing trend, whereas their internationalization is higher than that of high-income regions but shows a decreasing trend.

For local ownership of knowledge, catching-up countries/regions have increasing local indigenous knowledge (Amsden & Chu, 2003; Kim & Lee, 2022; Lee, 2013; Mazzoleni & Nelson, 2007), whereas peripheral or immature RIS tends to depend on foreign knowledge due to its lack of an indigenous knowledge base and its low regional embeddedness (Asheim et al., 2019: 73; Hassink, 2001; Park & Markusen, 1995; Rodríguez et al., 2014). Therefore, catching-up regions report an increasing trend of indigenous knowledge, whereas high-income regions report a high local ownership of knowledge.

Figure 10 Ratio of GRDP per capita relative to US per capita GRDP

Figure 10A Ratio of GRDP per capita relative to US per capita GRDP: Regions in groups 1 and 2

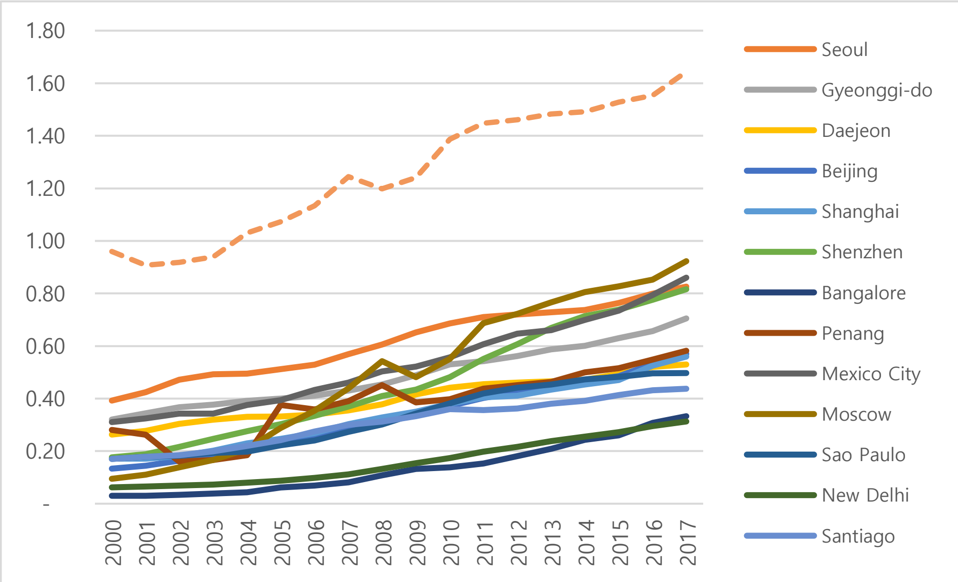
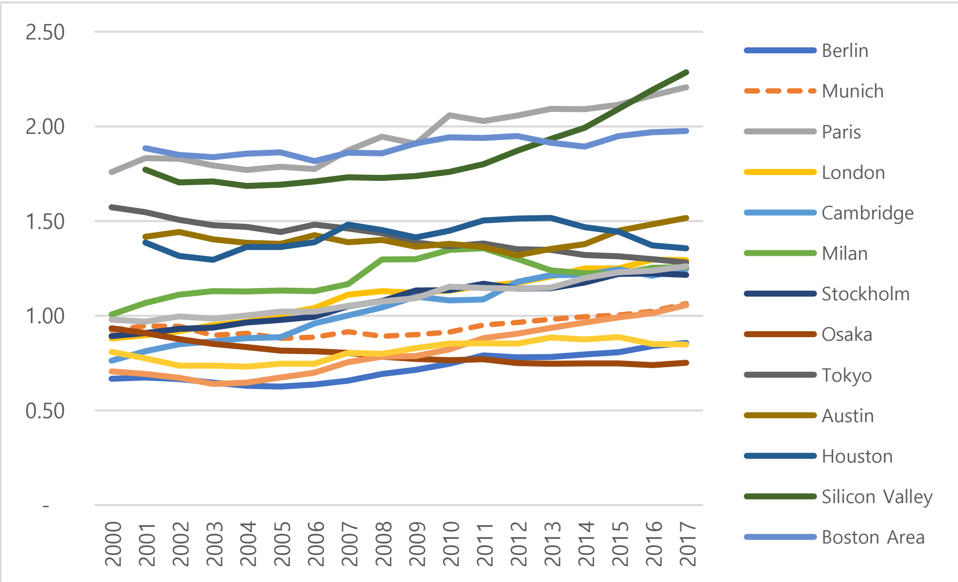


Figure 10B Ratio of GRDP per capita relative to US per capita GRDP: Regions in group 3



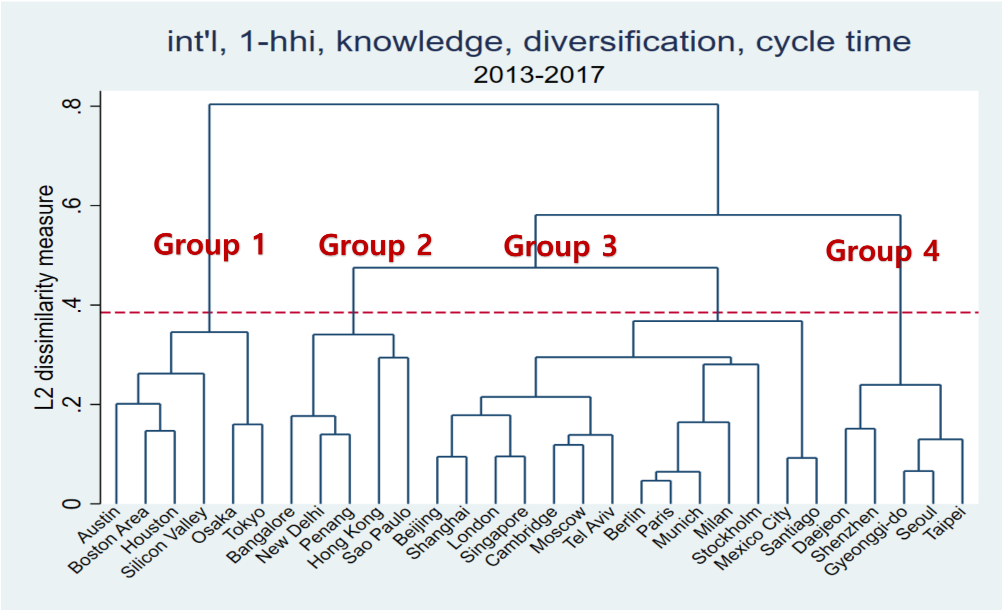
4. Identifying the Varieties of RIS

The results of the cluster analysis employing internationalization, local ownership, decentralization, diversification, and relative cycle time as variables have identified 4 groups with a 0.39 dissimilarity level (Figure 11A). These results are supported by those of another cluster analysis that employs nationalization or localization instead of internationalization as a variable (Figure 11A, 11B, 11C). Using nationalization yields the same results as those obtained using internationalization (Figure 11B). However, the cluster analysis using localization, decentralization, local ownership, diversification, and relative cycle time, results in three groups. The regions that used to be in group 1 and group 4 as a result of the cluster analysis using internationalization, decentralization, local ownership, diversification, and relative cycle time, are combined into one group.

Figure 11 Dendrogram results of cluster analysis

Figure 11A Dendrogram result of cluster analysis using the 5-year average values of 30 regions from 2013 to 2017

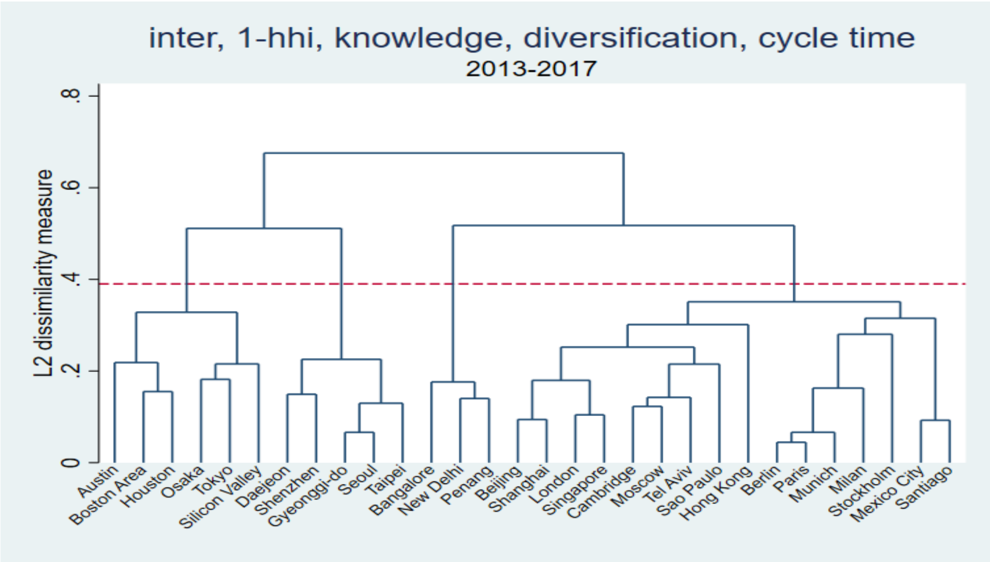
: Internationalization, decentralization, diversification, local ownership, and relative cycle time



Source: Author’s calculation

Figure 11B Dendrogram result of cluster analysis using the 5-year average values of 30 regions from 2013 to 2017

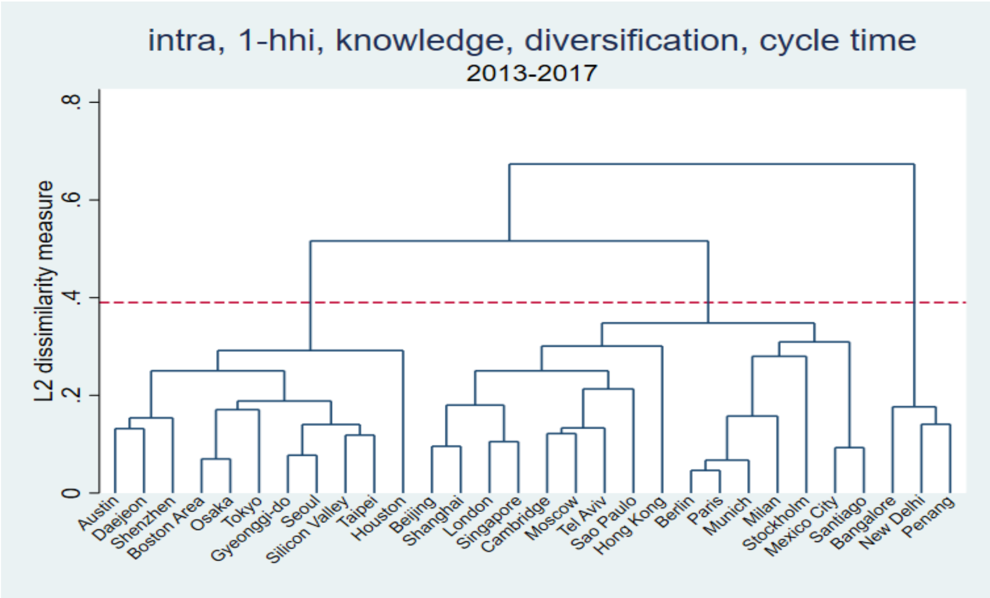
: Nationalization, decentralization, diversification, local ownership, and relative cycle



Source: Author's calculation

Figure 11C Dendrogram result of cluster analysis using the 5-year average values of 30 regions from 2013 to 2017

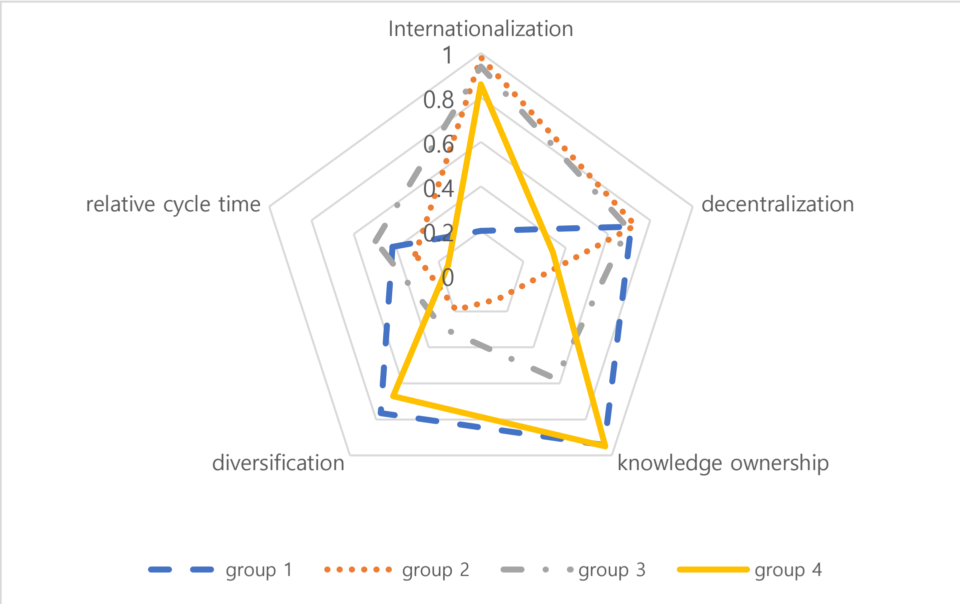
: Localization, decentralization, diversification, local ownership, and relative cycle time



Source: Author's calculation

Figure 12 presents the cluster analysis results as a radial graph to highlight the characteristics of each group. Group 1 reports high values of RIS variables except for internationalization, thereby suggesting that this group has a low dependence on foreign knowledge. These characteristics coincide with those reported in the NIS literature (Lee et al., 2021a), which reveals that advanced economies are less dependent on foreign knowledge and have high values of NIS variables. This group includes Austin, Boston Area, Houston, Silicon Valley, Osaka, and Tokyo (Table 3), whose average per capita GRDP in 2017 (2015 PPP-based USD) was US$89,242, which is the highest value among the four groups. This group was then called long cycle and high local ownership group or mature RIS group in short.

Figure 12 Radial graph for the cluster analysis results using the 5-year average values of 30 regions from 2013 to 2017



Source: Author's calculations
Note: All RIS variables are normalized between 0 and 1.

Group 2 has low diversification and local ownership, high internationalization and decentralization, and specialization in short-cycle technologies (Figure 12). Accordingly, this group was called the short cycle and weak local ownership group or catching-up 1 RIS in short. The regions in this group, namely, Bangalore, Penang, New Delhi, Sao Paulo, and Hong Kong (Table 3), reported an average per capita GRDP of US$32,493 in 2017 (2015 PPP-based USD), which is the smallest value among the four groups. In addition, these regions had an average per capita GRDP growth of 7.98% from 2013 to 2017.

Table 3 Composition of regions from the cluster analysis results

2013-2017	Group 1	Group 2	Group 3	Group 4
	Austin, Boston Area, Houston, Silicon Valley, Osaka, Tokyo,	Bangalore, Penang, New Delhi, Sao Paulo, Hong Kong	Beijing, Shanghai, Moscow, Berlin, Paris, Munich, Stockholm, Cambridge, Tel Aviv, London, Singapore, Milan, Santiago, Mexico City	Daejeon, Gyeonggi-do, Seoul, Taipei, Shenzhen

Note: The cluster analysis uses internationalization, technological diversification, knowledge decentralization, local ownership of knowledge, and technology specialization (relative cycle time) as variables.

The regions in group 3, including Beijing, Shanghai, Moscow, Berlin, Paris, Munich, Stockholm, Cambridge, Tel Aviv, London, Singapore, Milan, Santiago, and Mexico City (Table 3), specialize in long-cycle technologies and have low diversification, high internationalization and decentralization, and moderate local ownership of knowledge (Figure 12). Accordingly, this group is called the long cycle and mid local ownership group, whose average per capita GRDP in 2017 (2015 PPP-based USD) was US$ 62,517. Given that both the high and low per capita GRDP regions in this group were residual, this group is also called residual RIS group in short.

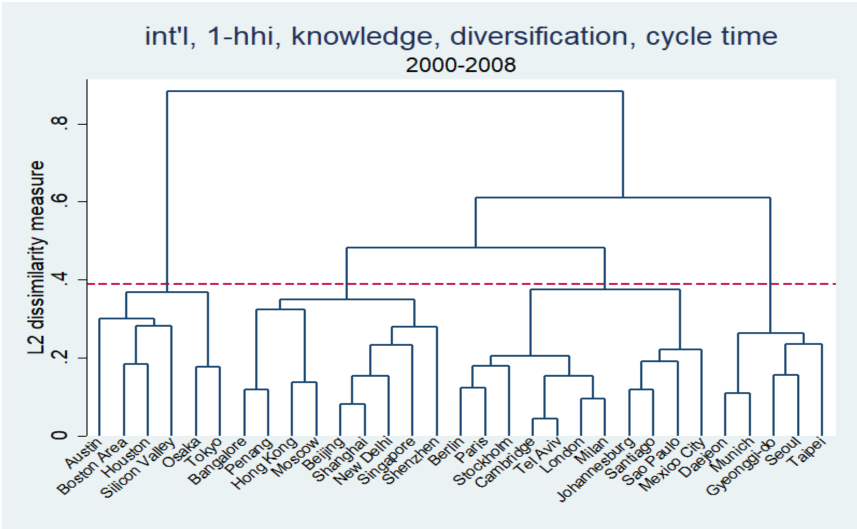
The regions in group 4 have high RIS variables, except for decentralization and technology specialization (Figure 12), and specialize in short-cycle technologies similar to group 2. This group is then labelled as the short cycle and strong local ownership group, which includes Daejeon, Gyeonggi-do, Seoul, Taipei, and Shenzhen (Table 3). There regions had an average per capita GRDP of US$48,345 in 2017 (2015 PPP-based USD), and their average per capita GRDP growth rate from

2013 to 2017 was 5.33%. Given that this group has higher per capita GRDP yet a lower per capita GRDP growth rate than group 2, this group is called catching-up 2 RIS in short.

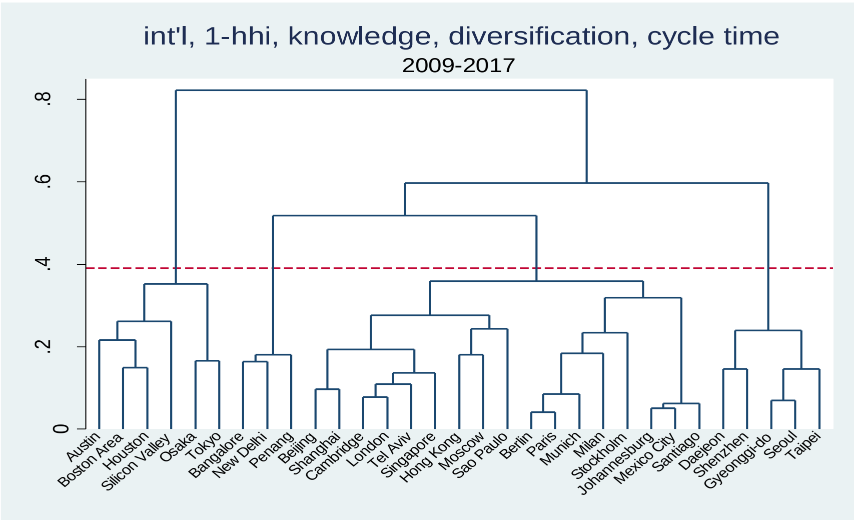
The above results are supported by the cluster analysis by dividing the entire research period into two sub-periods, namely, 2000 to 2008 and 2009 to 2017 (Figure 13). Both periods include all four groups (Figure 13), and the RIS characteristics for each group are consistent with those reported in the cluster analysis that covered the recent 5 years (2013 to 2017) (Figure 15).

Figure 13 Dendrogram results of the cluster analysis using the 9-year average values of 30 regions for 2 sub-periods

(A) First period, from 2000 to 2008



(B) Second period, from 2009 to 2017

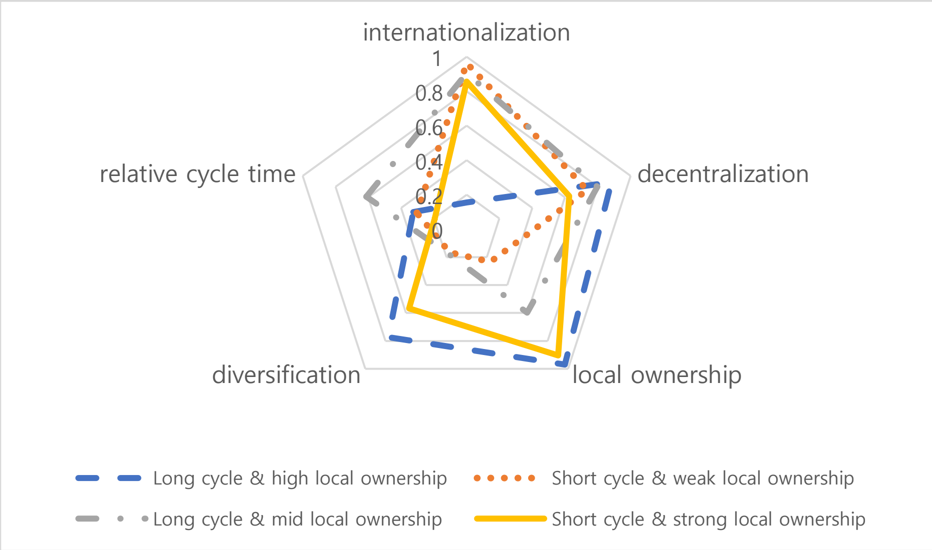


Source: Author's calculations

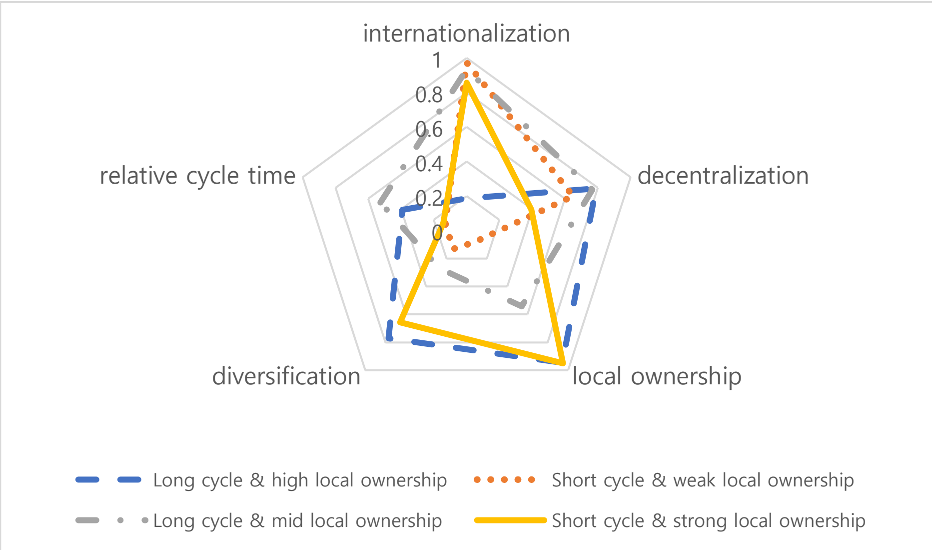
Note: Five RIS variables, namely, internationalization, decentralization, diversification, knowledge ownership, and relative cycle time, were used for the cluster analysis for each sub-period.

Figure 14 Radial graph for the cluster analysis results using the 9-year average values of 30 regions for 2 sub-periods

(A) 2000-2008



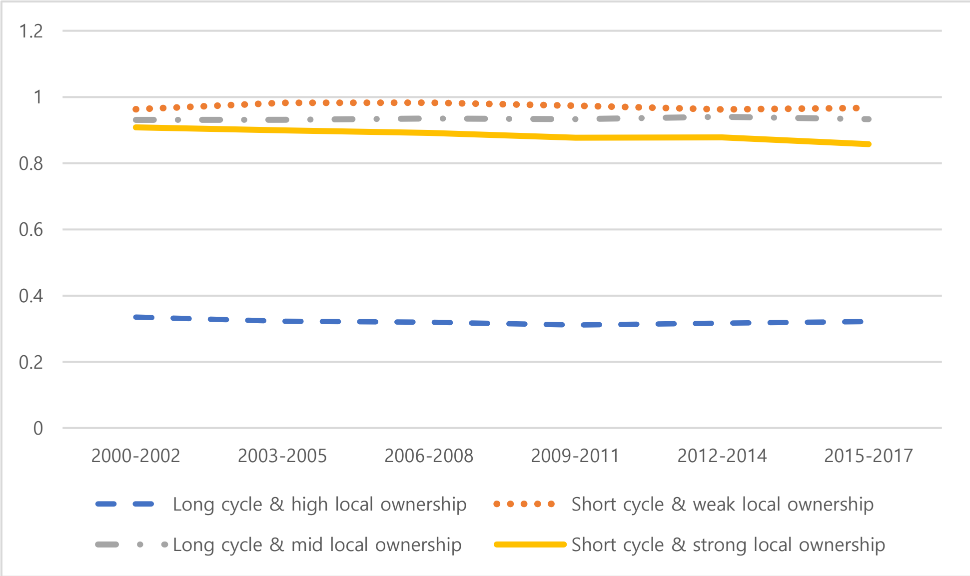
(B) 2009-2017



Source: Author's calculations
Note: All RIS values were normalized between 0 and 1.

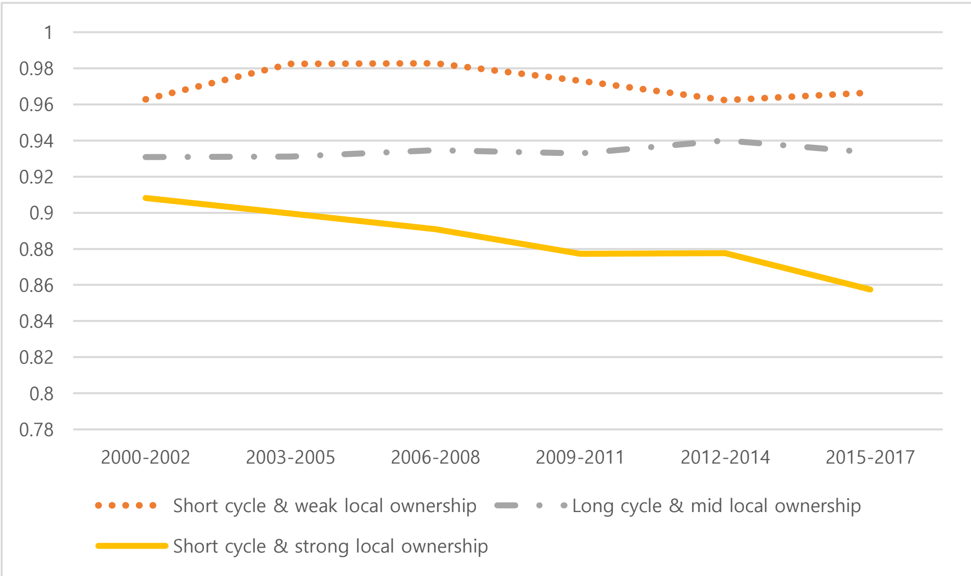
Figure 15 Dynamic trends of internationalization

(A) Four groups of trends



Source: Author's calculations

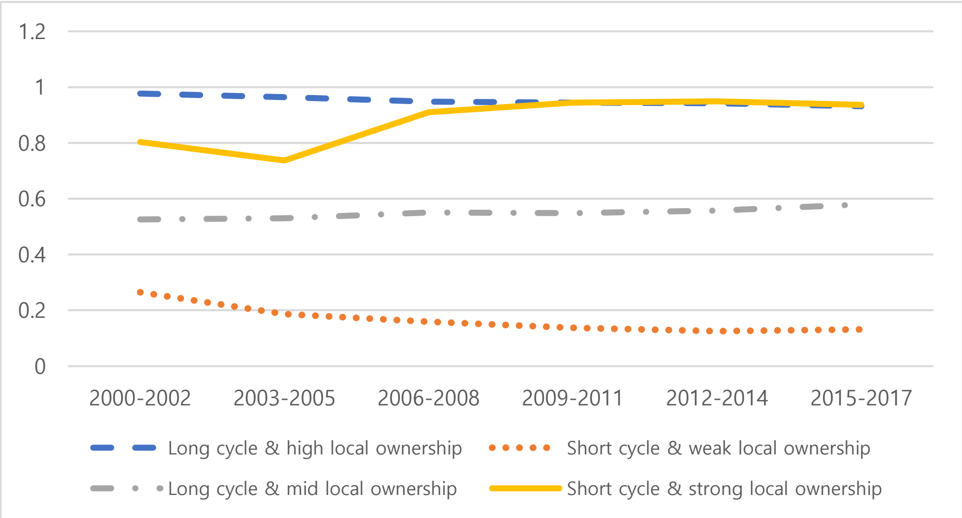
(B) Three groups of trends



Source: Author's calculations

Figure 15 illustrates the dynamics of internationalization for each group. When describing the trends of internationalization for all groups simultaneously, there seems rare dynamic change of internationalization in case of long cycle & high local ownership group, but it has the highest level in internationalization (Figure 15A). However, when describing the trends for the three other groups apart from the long cycle and high local ownership group, the trends in the short cycle and strong local ownership group were decreasing, while the other groups did not show such trends (Figure 15B).

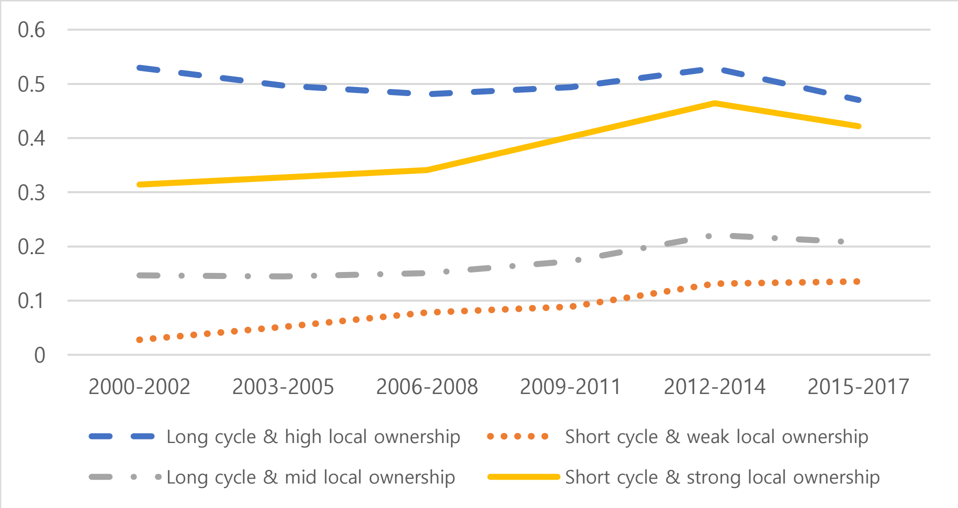
Figure 16 Dynamic trends of local ownership of knowledge ownership of knowledge



Source: Author's calculation

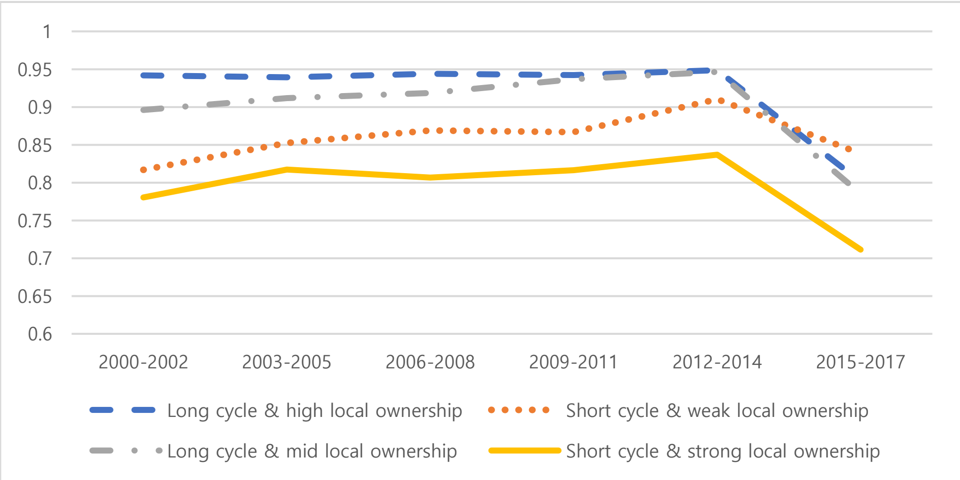
Figure 16 and Figure 18 show the dynamic trends of local ownership of knowledge and knowledge decentralization for each group, respectively. Since the early 2000s, local ownership of knowledge in the short cycle and strong local ownership group increased and reached that of the long cycle and high local ownership group. Approximately 80% of the patents invented in the short cycle and strong local ownership group between 2000 and 2002 were locally owned, and this percentage increased to 93% in the 2015–2017 period. By contrast, the short cycle and weak local ownership group equally specialized in short-cycle technologies compared with the short cycle and strong local ownership group, but the local ownership of knowledge of the former was far below that of the latter and even showed a decreasing trend. Almost 26% of the patents invented in the short cycle and weak local ownership group were owned by local firms in 2000–2002, and this percentage decreased to 13% in 2015–2017 (Figure 16).

Figure 17 Dynamic trends of technological diversification



Source: Author's calculation

Figure 18 Dynamic trends of knowledge decentralization



Source: Author's calculation

Knowledge creation became highly concentrated to only few firms in recent years, but the short cycle and strong local ownership group consistently reported the lowest level of knowledge decentralization across all research periods (Figure 18). Meanwhile, the long cycle and high local ownership group reported the highest technological diversification, which exceeded 47% across all periods, whereas the technological diversification of the short cycle and strong local ownership group increased from 31% in 2000–2002 to 42% in 2015–2017. The short cycle and weak local ownership group consistently reported the lowest technological diversification across all periods, which slightly increased from 2% in 2000–2002 to 13% in 2015–2017.

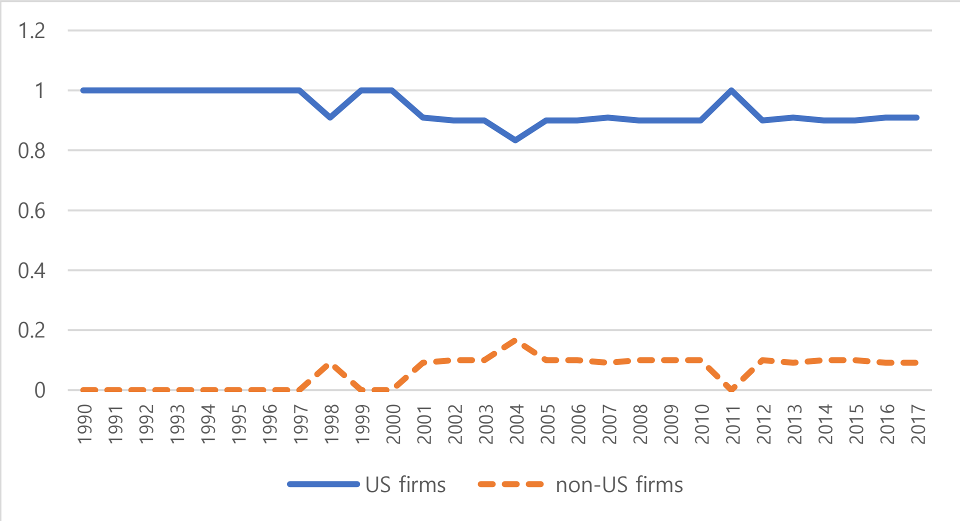
Figure 19 Radial graph for the representative regions of each group

Source: Author's calculations

Each of the four groups has a representative region. Specifically, the mature RIS group is represented by Boston Area, catching-up 1 RIS is represented by New Delhi, residual RIS is represented by Berlin, and catching-up 2 RIS is represented by Gyeonggi-do. Figure 18 shows the RIS characteristics of each region as a radial graph. Boston Area has two counties, namely, Sussex and Middlesex, which are represented by the cities of Boston and Cambridge, respectively. These cities are famous for their universities, including Harvard University, Massachusetts Institute of Technology, and Boston University. Figure 18 shows that these cities have low knowledge creation internationalization and high indigenous knowledge. This result is supported by Figure 20, which shows the nationalities of the top 10 assignees in

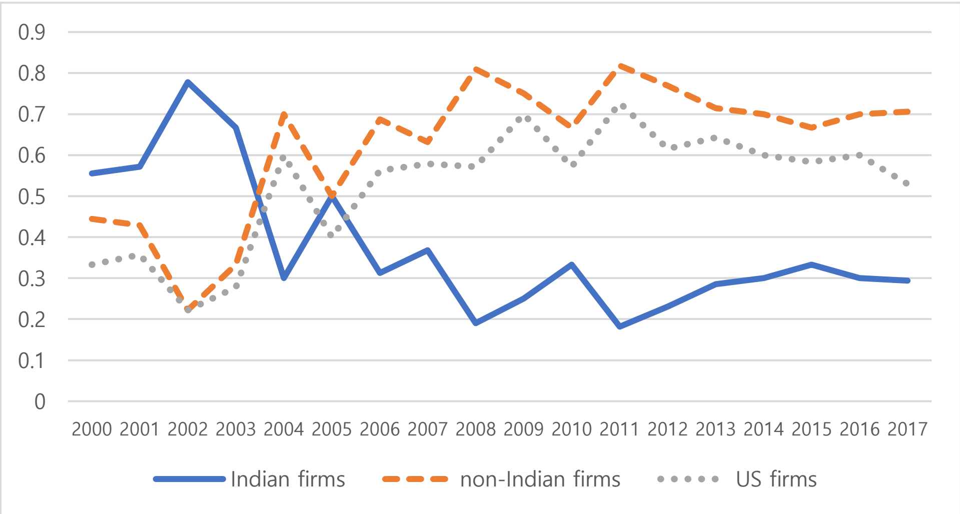
Boston Area. According to this graph, the majority of the top assignees in this region are US firms. Health care and social assistance (13.8%) and professional, scientific, and technical services (11.7%) account for the majority of employment in Boston Area, whereas manufacturing accounts for the least (3.7%).[9] Private companies or research institutes lead the knowledge creation in this region (Appendix 4).

Figure 20 Nationality of the top 10 assignees in Boston Area



Source: Author's calculations

Figure 21 Nationality of the top 10 assignees in New Delhi

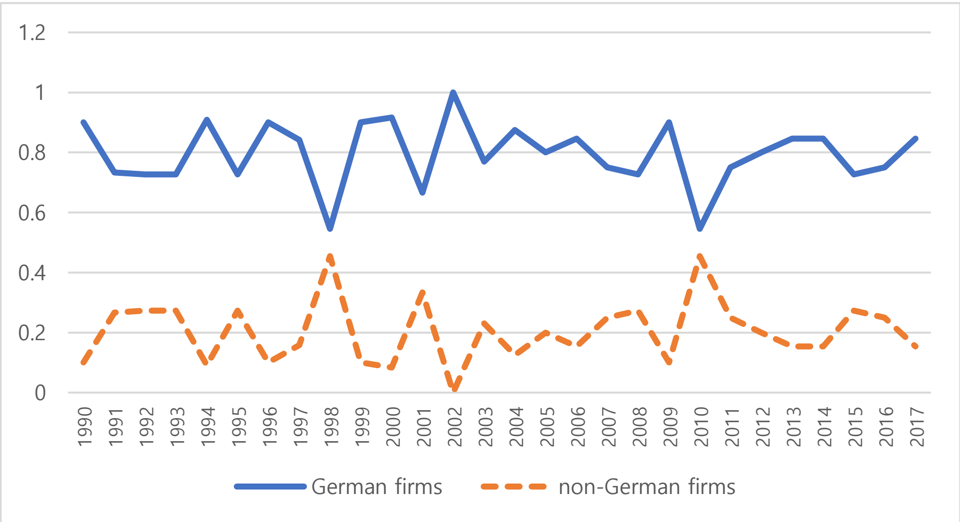


Source: Author's calculations

[9] Source: Calculated by the author using data from the US Census Bureau (EC1700BASIC).

New Delhi is a representative city for catching-up 1 RIS with high internationalization and weak indigenous knowledge. Most of the top 10 assignees in this region are non-Indian firms, of which US firms account for the majority (Figure 21). As a capital city of India, New Delhi has many prominent universities and research institutes. The region mainly relies on its tertiary industry as reflected in its percentage of gross value added.[10] Employment in the manufacturing industry is mainly concentrated in apparel, wholesale and retail and repair of motor vehicles and motorcycles, printing and reproduction of recorded media, fabricated metal products except for machinery, leather and related products, and rubber and plastic products, which altogether account for over 50% of the employment in New Delhi. Most of the firms in the top 10 assignees are related to IT services or semiconductor manufacturing (Appendix 5).

Figure 22 Nationality of the top 10 assignees in Berlin

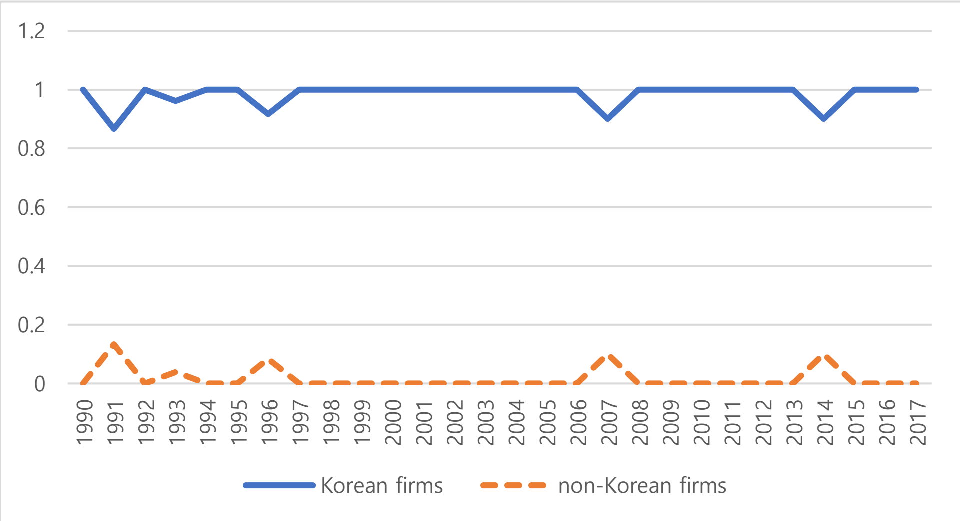


Source: Author's calculations

[10] Source: Estimates of State Domestic Product of Delhi 2015–2016, Planning Department, Government of NCT of Delhi (http://delhiplanning.nic.in/content/state-domestic-product-capital-formation).

Berlin a representative city of the residual RIS group with high internationalization and moderate indigenous knowledge. Figure 22 shows the composition of German and non-German firms among the top 10 assignees in Berlin. The majority of the firms in these top 10 assignees are domestic. The gap between domestic and foreign firms in Berlin is not as huge as that in Boston. In other words, Berlin maintains a certain combination of domestic and foreign firms for knowledge creation. Berlin is a capital city in Germany that plays a leading role in the country's energy, life sciences, information and communication technologies, optics, mobility, microsystems engineering, and clean technology industries. [11] In terms of employment, the manufacturing of electronic equipment accounts for the majority (16%), followed by food, pharmaceutical products, data processing equipment, and electric and optical products in 2016.[12]

Figure 23 Nationality of the top 10 assignees in Gyeonggi-do



Source: Author's calculations

[11] Source: State Department for Economics, Energy, and Public Enterprises (https://www.berlin.de/sen/wirtschaft/en/economics-and-technology/branches/industry/)

[12] Source: Economic and Innovation Report, 2017, State Department for Economics, Energy, and Public Enterprises (https://www.berlin.de/sen/wirtschaft/konjunktur-und-statistik/archiv/artikel.40856.php)

Gyeonggi-do is a province surrounding the capital city of Seoul in South Korea that accommodates the factories of big businesses in the country. As shown in Figure 19, Gyeonggi-do has high internationalization and strong local ownership of knowledge. Figure 23 shows that Korean domestic firms play a major role in creating knowledge in the region. Most industries in Gyeonggi-do are among the main industries in Korea, including semiconductor, displays, mobile phones, and automobiles (Monthly Economic Trends, June 2017 vol. 03). Gyeonggi-do mainly specializes in industries related to manufacturing, such as electrical and electronic devices, machinery and equipment, metal products, and chemical products, and is considered a core region of the ICT industry together with Seoul. Specifically, in 2012, the ICT industry accounted for 40% of the manufacturing in Gyeonggi-do (Gyeonggi Research Institute, 2017). Moreover, as the role of knowledge creation is concentrated to only few firms, the top 10 assignees in Gyeonggi-do include a small number of big businesses called "Chaebol," and the gap between the top 1 and 2 assignees is very large (Appendix 6).

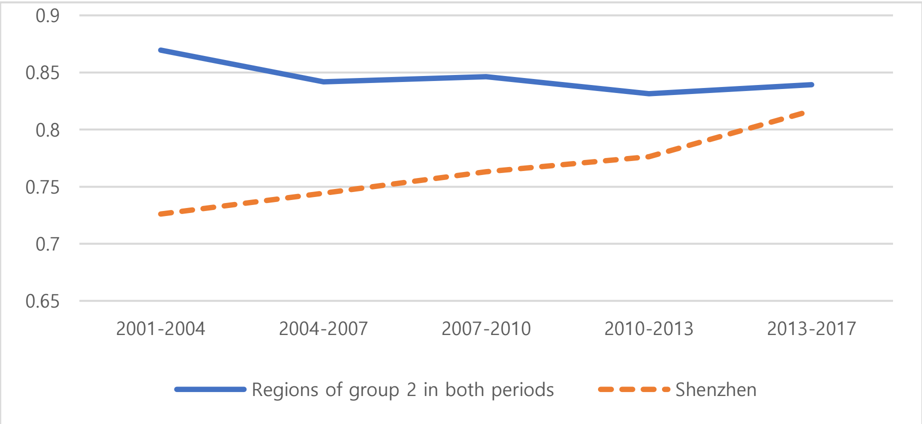
Table 4 Region composition by RIS groups

	2000–2008	2009–2017
Long cycle and high local ownership (mature RIS)	Austin, Boston Area, Houston, Silicon Valley, Tokyo, Osaka	Austin, Boston Area, Houston, Silicon Valley, Osaka, Tokyo
Long cycle and mid local ownership (residual RIS)	Berlin, Paris, Stockholm, Cambridge, Tel Aviv, London, Milan, Santiago, Sao Paulo, Mexico City	Beijing, Shanghai, Cambridge, London, Tel Aviv, Singapore, Hong Kong, Moscow, Sao Paulo, Berlin, Paris, Munich, Milan, Stockholm, Mexico City, Santiago
Short cycle and strong local ownership (catching-up 2 RIS)	Daejeon, Munich, Gyeonggi-do, Seoul, Taipei	Daejeon, Shenzhen, Gyeonggi-do, Seoul, Taipei

Short cycle and weak local ownership (catching-up 1 RIS)	Bangalore, Penang, Hong Kong, Moscow, Beijing, Shanghai, New Delhi, Singapore, Shenzhen	Bangalore, New Delhi, Penang

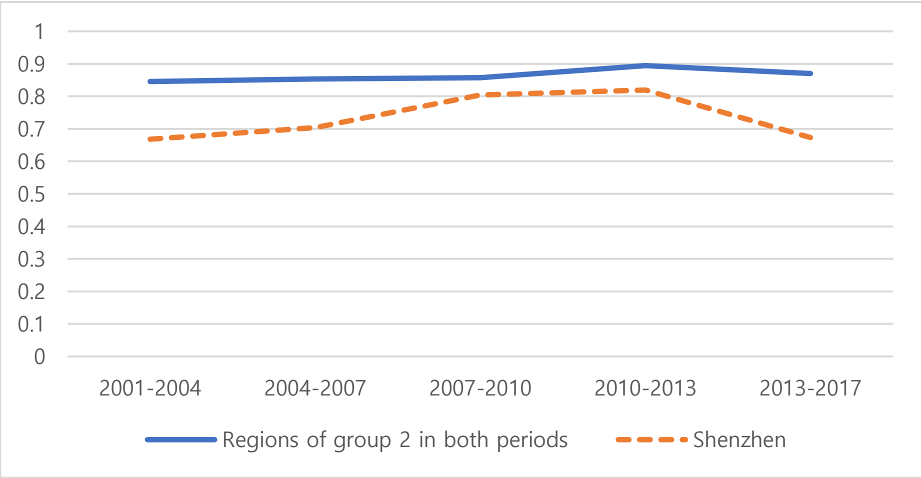
Table 4 presents the composition of regions resulting from the cluster analysis using two sub-periods. Two patterns of movement are detected among the RIS groups, namely, from catching-up 1 RIS to catching-up 2 RIS and from catching-up 1 RIS to residual RIS. First, a region moving from catching-up 1 RIS in the first period to catching-up 2 RIS in the second period (Shenzhen) and three regions staying in catching-up 1 RIS in both periods (Bangalore, Penang, New Delhi) show similar patterns in all RIS variables, except for relative cycle time and indigenous knowledge (Figures 24 to 28). The indigenous knowledge in Shenzhen has increased, whereas the average indigenous knowledge for regions staying in catching-up 1 RIS has decreased (Figure 28). While both groups specialize in short-cycle technologies, the relative cycle time in Shenzhen is increasing, whereas that of regions staying in catching-up 1 RIS is decreasing (Figure 24). Shenzhen also has low internationalization (Figure 26), highly diversified technologies (Figure 26), and knowledge creation concentrated on a few firms (Figure 25).

Figure 24 Relative cycle time (Pattern 1)



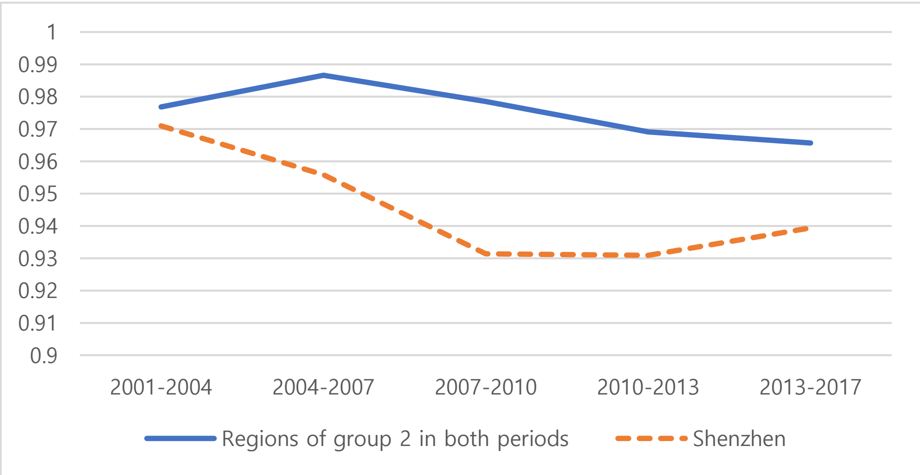
Source: Author’s calculations

Figure 25 Decentralization (Pattern 1)



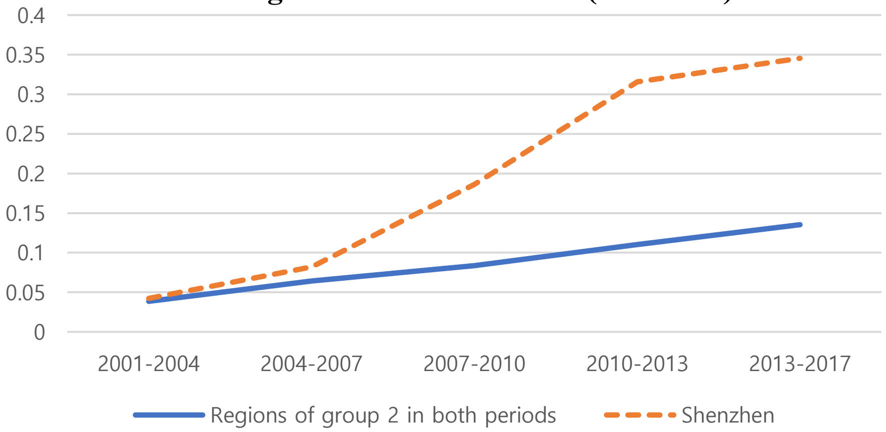
Source: Author’s calculations

Figure 26 Internationalization (Pattern 1)



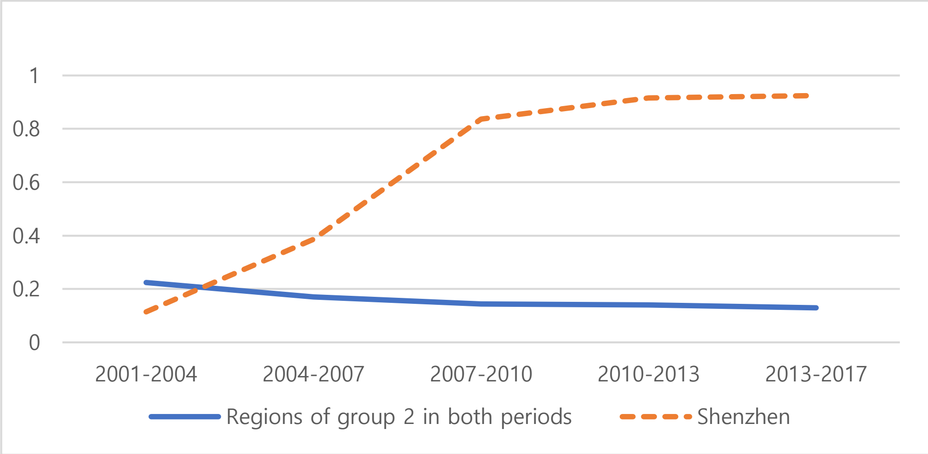
Source: Author’s calculations

Figure 27 Diversification (Pattern 1)



Source: Author’s calculations

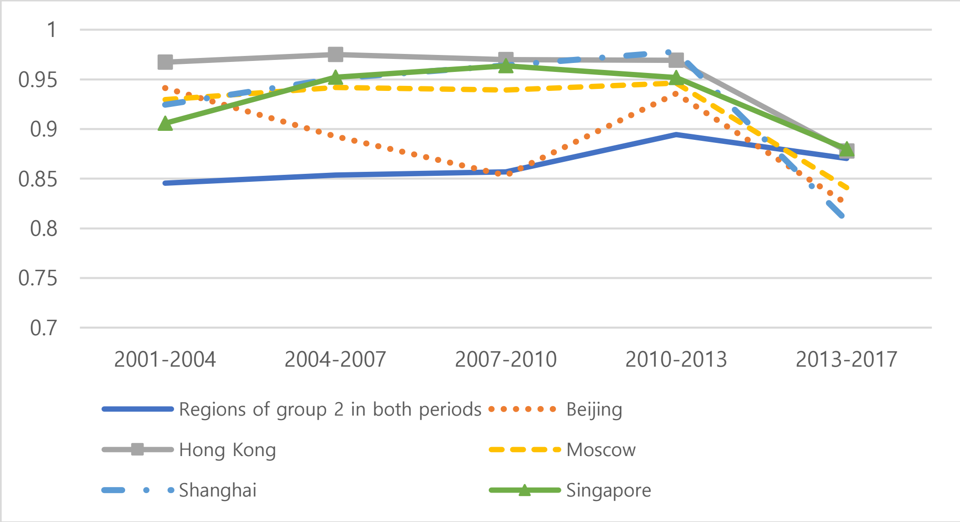
Figure 28 Local ownership of knowledge (Pattern 1)



Source: Author's calculations

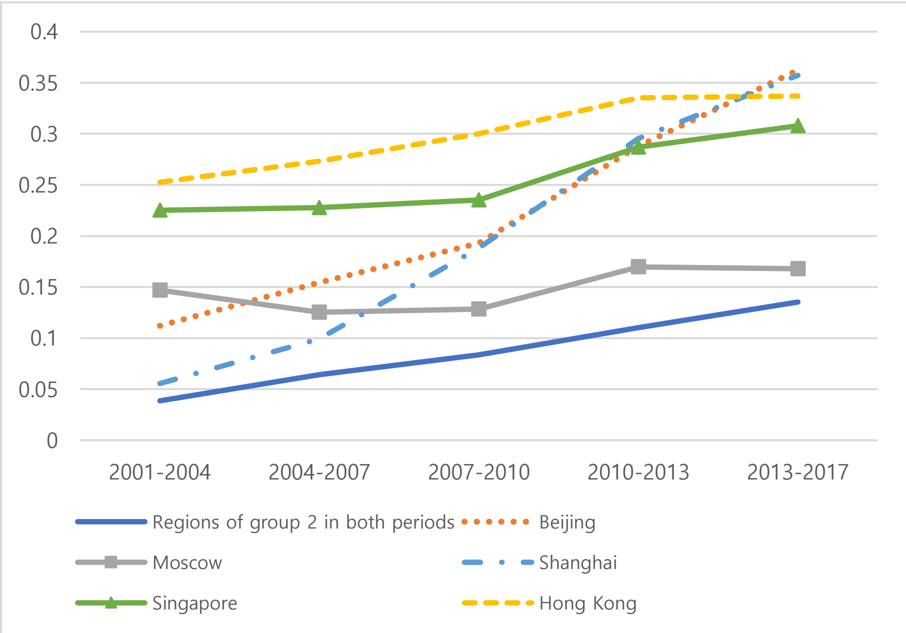
Figures 29 to 33 present the trends of each RIS variable between those regions staying in catching-up 1 RIS in both periods and those regions moving from catching-up 1 RIS to residual RIS. These two groups show similar trends in their RIS variables, except for relative cycle time and local ownership of knowledge. Internationalization decreases while diversification increases across all regions (Figures 29 and 32). For relative cycle time, some regions show a decreasing trend, whereas others (e.g., Singapore) show an increasing trend. Meanwhile, those regions staying in catching-up 1 RIS show a slight decrease in their relative cycle time (Figure 33). In case of local ownership of knowledge, the trends are similar with the trends of local ownership in pattern 1. The regions staying in catching-up 1 RIS in both periods show decreasing trend in local ownership like in pattern 1, however, regions moving to residual RIS group in the second period have an increasing trend (Figure 31).

Figure 29 Decentralization (Pattern 2)



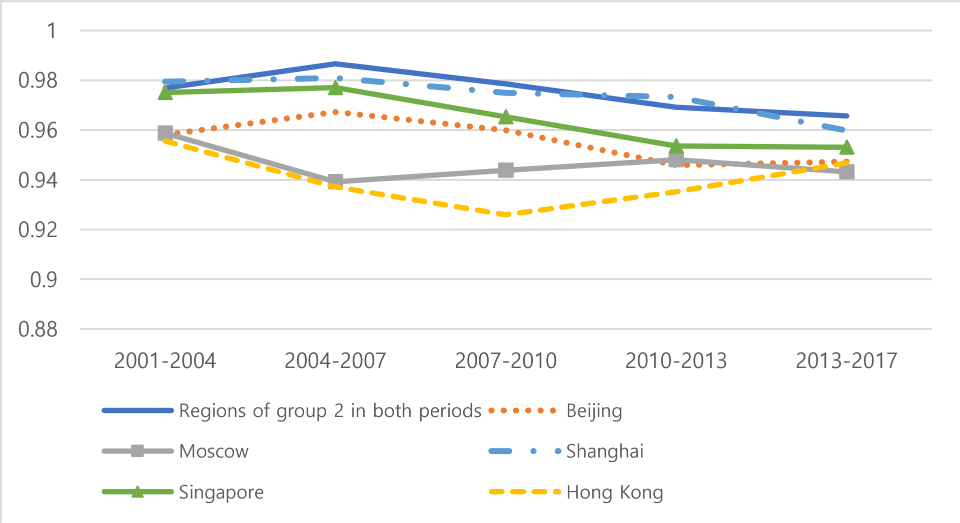
Source: Author's calculations

Figure 30 Diversification (Pattern 2)



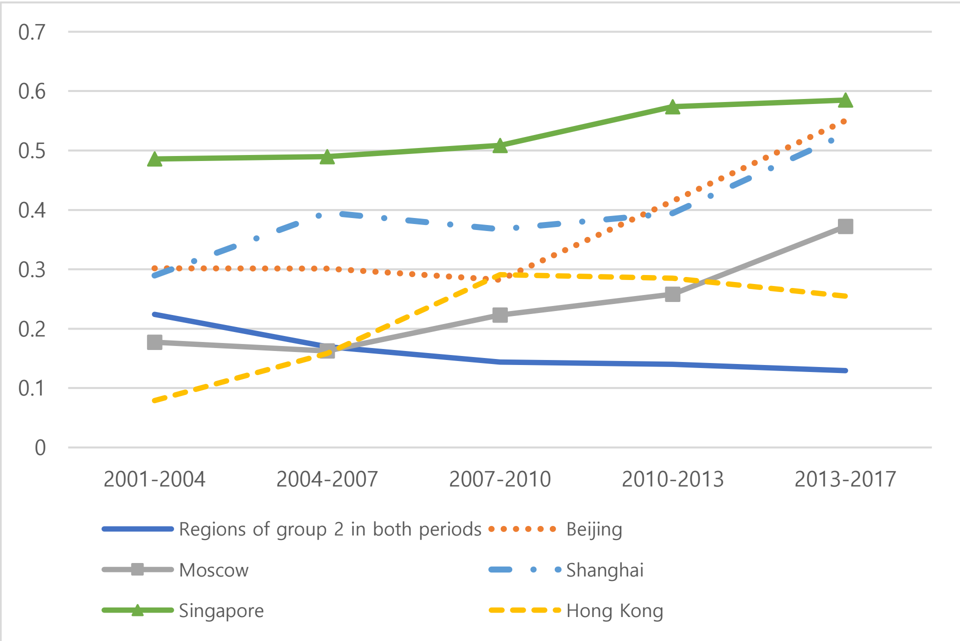
Source: Author's calculations

Figure 31 Internationalization (Pattern 2)



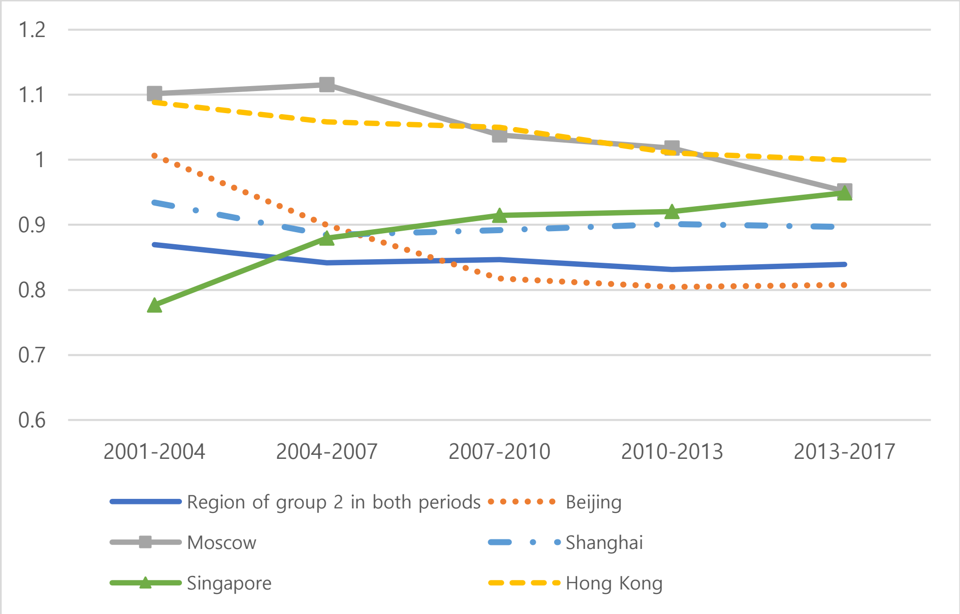
Source: Author's calculations

Figure 32 Local ownership of knowledge (Pattern 2)



Source: Author's calculations

Figure 33 Relative cycle time (Pattern 2)

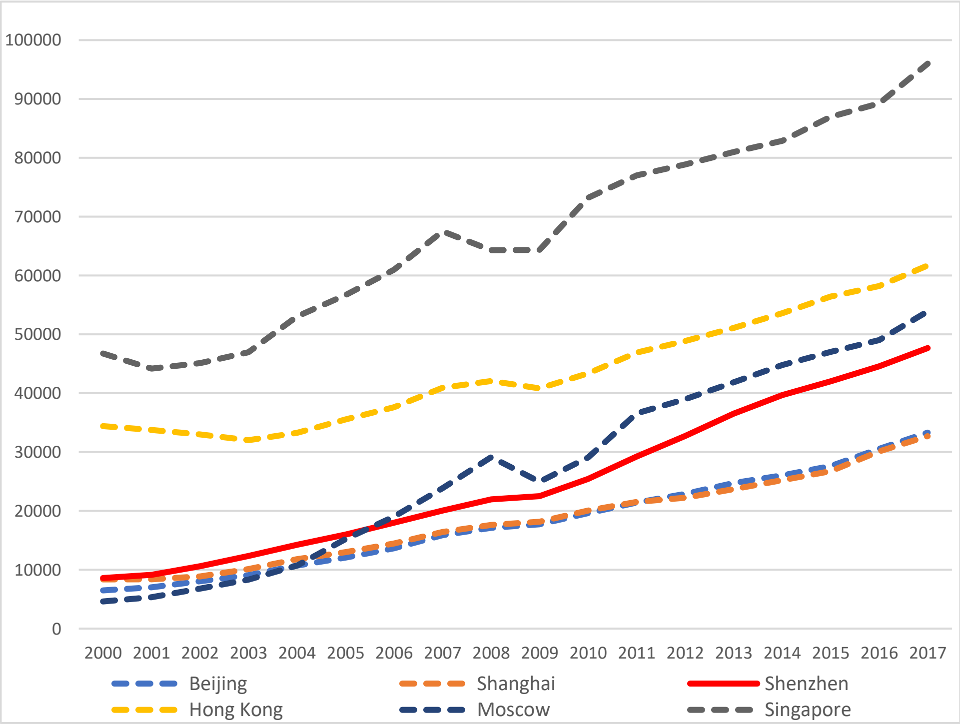


Source: Author's calculations

Two changing patterns are observed, namely, regions upgrade their RIS by increasing their indigenous knowledge and decreasing their reliance on foreign knowledge (internationalization). The differences in these patterns lie in the levels of indigenous knowledge and internationalization. Shenzhen, which moved from catching-up 1 RIS to catching-up 2 RIS, shows a high level of indigenous knowledge (0.92 in 2017) and lower level of internationalization (0.93 in 2017). However, among those regions moving to residual RIS, Singapore reports the highest level of indigenous knowledge in 2017 (0.58), and the other regions in pattern 2 report lower levels for this variable. Meanwhile, Moscow reports the lowest level of internationalization in 2017 (0.94), and the regions in pattern 2 report higher levels of internationalization.

Unlike in the NIS analysis where latecomer countries can catch up with advanced countries by specializing in short-cycle technologies, the RIS analysis shows different patterns of economic catch-up among these regions even if they all specialize in short-cycle technologies. In other words, merely specializing in short-cycle technologies is not enough to catch up with advanced regions, and this technological specialization should be accompanied by an increase in indigenous knowledge and decrease in reliance on foreign knowledge.

Figure 34 GRDP per capita (2015 PPP-based USD): Comparison between patterns 1 and 2



These results are supported by the per capita GRDP for each region. Figure 34 shows the trends of per capita GRDP for each region belonging to either pattern 1 or 2. The dotted lines represent the regions in pattern 2, whereas the solid line represents the regions in pattern 1. The per capita GRDP of Shenzhen is lower than those of Singapore, Hong Kong, and Moscow but higher than those of Beijing and Shanghai. The average yearly growth rate of Shenzhen's per capita GRDP from 2001 to 2017 was 10.67%, which is higher than those reported in Singapore (4.45%), Hong Kong (3.56%), Shanghai (8.44%), and Beijing (10.16%) yet lower than that in Moscow (16.28%). Therefore, pattern 1 has a faster regional economic growth than pattern 2.

Among the regions in pattern 2, Shanghai and Beijing can move from catching-up 1 RIS to residual RIS by increasing their indigenous knowledge and decreasing their dependence on foreign knowledge. These arguments are supported by the firm composition of the top 10 assignees (Figure 36 and Figure 36). The percentage of Chinese domestic firms in Shanghai has increased and is about to surpass the percentage of non-Chinese firms in its top 10 assignees. While similar trends have been reported in Beijing, this region arrived at its reversal point earlier than Shanghai (Figure 36). However, the growth rate of Chinese domestic firms in the top 10 assignees in Beijing is not as fast as that of Chinese domestic firms in Shenzhen (Figures 8A, Figure 36 and Figure 36), hence underscoring the differences in the RIS movement paths of Shenzhen, Beijing, and Shanghai. Among the list of top 10 assignees, Tsinghua University, one of the most prominent universities in the world, plays a leading role in knowledge creation, and since 2015, private corporations, such as Boe Technology and Huawei, have become the major creators of knowledge (Appendix 7). Moreover, Shanghai has a highly diverse set of foreign companies, including US firms and private companies, instead of merely relying on universities or governmental research institutions (Appendix 8). Specifically, the region has 626 MNCs that set up their regional headquarters and 426 foreign-funded R&D centers. Meanwhile, Beijing has over 45,000 foreign-invested enterprises and 186 MNCs that set up their regional headquarters. These facts reflect the characteristics of Beijing as the capital of China and as a trading hub with a long history.

Figure 35 Nationality of the top 10 assignees in Shanghai

Source: Author's calculations

Figure 36 Nationality of the top 10 assignees in Beijing

Source: Author's calculations

5. Conclusion

This research identifies various RIS types by performing a cluster analysis with five RIS variables. Similar to national-level studies, the regions in this study are categorized into four groups in terms of their RIS, namely, the long cycle and high local ownership group (mature RIS), short cycle and weak local ownership group (catching-up 1 RIS), long cycle and mid local ownership group (residual RIS), and short cycle and strong local ownership group (catching-up 2 RIS). While the mature RIS group has the largest average per capita GRDP among these groups, it also reports the lowest per capita GRDP growth rate. By contrast, the catching-up 1 RIS group reports the lowest average per capita GRDP and the highest per capita GRDP growth rate. Meanwhile, the average per capita GRDP of the catching-up 2 RIS group is higher than that of the catching-up 1 RIS group but lower than that of the mature RIS group, which reports a high per capita GRDP growth rate.

Although those two groups that report a high per capita GRDP growth rate both specialize in short-cycle technologies, they follow different paths of development; one has a lower per capita GRDP and low level of indigenous knowledge, whereas the other has a higher per capita GRDP and high level of indigenous knowledge. Although the NIS analysis reveals that latecomers can catch up with advanced countries by specializing in short-cycle technologies, the results of the RIS analysis suggest that merely specializing in short-cycle technologies is not enough for latecomer regions to catch up with their developed counterparts. Indigenous knowledge is as important as specializing in short-cycle technologies when latecomer regions try to leapfrog toward advanced regions. In addition, when regions create knowledge, local big firms play an important role at the catching-up stage. Therefore, to ensure a successful economic catch-up, latecomer regions should rely on local big businesses to create indigenous knowledge as a first step and then specialize in short-cycle technologies and detouring incumbents as a second step.

V. Linking RIS Groups to Economic Growth

1. Introduction

The chapter links the four RIS groups introduced in the previous chapter to economic growth. Schumpeterian scholars insist that the differences in NISs can lead to differences in innovation performance and economic growth rates. While this statement has been proven in empirical studies, this work tests its applicability in regional-based studies of innovation systems.

Many studies have explored the relationship among knowledge, innovation, and economic growth in regional bases (Andersson & Karlsson, 2007; Capello et al., 2009; Harris, 2011; Huggins & Thompson, 2015; Rodríguez-Pose & Crescenzi, 2008). For instance, Rodríguez-Pose and Crescenzi (2008) investigated the impact of innovation on regional economic performance in Europe and found that innovation systems or learning regions, which indicate the "localized structural and institutional factors that shape the innovation capacity of specific geographical context," can facilitate innovation. In this sense, the innovation system of a region affects its innovation and leads to its economic growth. However, Rodriguez-Pose and Crescenzi (2008) focused on geographies below the country level and covered both advanced and emerging regions in Europe.

This research performed a cluster analysis using five variables of RIS, namely, internationalization, local ownership of knowledge, knowledge decentralization, technological diversification, and technology specialization. On the basis of the cluster analysis results, an empirical analysis using system GMM estimation and least square dummy variable estimation is performed to confirm how the different characteristics of RIS lead to differences in economic growth.

2. Cluster analysis

The cluster analysis focused on the 5 sub-periods defined in this research and used the same 30 regions mentioned in the previous chapter. These regions were grouped into long cycle and high local ownership RIS (mature RIS), long cycle and medium local ownership RIS (residual RIS), short cycle and strong local ownership RIS (catching-up 2 RIS), and short cycle and weak local ownership (catching-up 1 RIS), whose RIS characteristics are the same as those reported in the previous chapter but remain consistent across all sub-periods. Table 5 presents the regions included in each group across the sub-periods. As shown in the table, the constitution of each group varies across each sub-period, except for that of mature RIS.

Table 5 RIS groups and their regional composition across 4-year sub-periods

	01-04	**04-07**	**07-10**	**10-13**	**13-17**
Mature RIS	Austin, Boston, Area, Houston, Silicon Valley, Osaka, Tokyo	Austin, Boston, Area, Houston, Silicon Valley, Osaka, Tokyo	Austin, Boston, Area, Houston, Silicon Valley, Osaka, Tokyo	Austin, Boston, Area, Houston, Silicon Valley, Osaka, Tokyo	Austin, Boston, Area, Houston, Silicon Valley, Osaka, Tokyo
Residual RIS	Berlin, Stockholm, Daejeon, Munich, Cambridge, Tel Aviv, London, Milan, Paris, Sao Paulo	Berlin, Paris, Stockholm, Cambridge, Tel Aviv, London, Milan, Mexico City, Santiago, Sao Paulo	Berlin, Paris, Stockholm, Milan, Cambridge, Tel Aviv, London, Shanghai, Singapore, Mexico City, Santiago	Beijing, Shanghai, Cambridge, Tel Aviv, London, Singapore, Hong Kong, Moscow, Berlin, Paris, Munich, Milan, Stockholm, Mexico City, Santiago, Sao Paulo	Beijing, Shanghai, London, Singapore, Cambridge, Moscow, Tel Aviv, Berlin, Paris, Munich, Milan, Stockholm, Mexico City, Santiago
Catching-up 2 RIS	Gyeonggi-do, Seoul, Taipei	Daejeon, Munich, Gyeonggi-do, Seoul, Taipei	Daejeon, Munich, Shenzhen, Gyeonggi-do, Seoul, Taipei	Daejeon, Shenzhen, Gyeonggi-do, Seoul, Taipei	Daejeon, Shenzhen, Gyeonggi-do, Seoul, Taipei
Catching-up 1 RIS	Bangalore, Penang, Shenzhen, Beijing, Shanghai, New Delhi, Singapore, Hong Kong, Moscow	Bangalore, Penang, Hong Kong, Moscow, Beijing, New Delhi, Shanghai, Singapore, Shenzhen	Bangalore, Penang, Beijing, New Delhi, Hong Kong, Moscow, Sao Paulo	Bangalore, New Delhi, Penang	Bangalore, New Delhi, Penang, Hong Kong, Sao Paulo

Note: Mexico City and Santiago were deleted in the first period (2001–2004) as outliers.

3. Literature Review and Hypothesis

Lee et al. (2021a) examined NIS types and national economic groups and found that different types of NIS led to differences in economic growth. They used five NIS variables, namely, localization, technological diversification, knowledge decentralization, relative cycle time, and originality, for the cluster analysis, and then classified countries into several NIS groups based on whether their levels of NIS variables are in balance and whether they are specializing in short- or long-cycle technologies (Lee et al., 2021a). They considered the imbalanced and short cycle group as the catching-up NIS group, which has low decentralization, high diversification, high localization, short-cycle technologies, and the fastest economic growth among all other NIS groups (Lee et al., 2021a).

Table 6 Descriptive Statistics

All regions for the whole period	Mean	Standard deviation	Min	Max
Per capita GRDP growth rate	0.056	0.056	-0.062	0.326
Log of initial per capita GRDP	10.402	0.856	7.310	11.646
Patent counts per 1000	0.339	0.643	0.001	4.415
Population growth rate	0.013	0.012	-0.005	0.052
N	150			
Mature RIS for the whole period				
Per capita GRDP growth rate	0.013	0.020	-0.024	0.057
Log of initial per capita GRDP	11.207	0.283	10.605	11.568
Patent counts per 1000	1.126	1.062	0.223	4.415
Population growth rate	0.011	0.009	-0.003	0.028
N	30			
Residual RIS for the whole period				
Per capita GRDP growth rate	0.047	0.030	-0.011	0.140
Log of initial per capita GRDP	10.599	0.590	9.069	11.646
Patent counts per 1000	0.120	0.210	0.001	1.161
Population growth rate	0.010	0.008	-0.003	0.041
N	61			
Catching-up 2 RIS for the whole period				
Per capita GRDP growth rate	0.052	0.026	0.003	0.129
Log of initial per capita GRDP	10.349	0.420	9.726	11.047
Patent counts per 1000	0.365	0.237	0.052	1.025
Population growth rate	0.010	0.013	-0.005	0.045
N	24			
Catching-up 1 RIS for the whole period				

Per capita GRDP growth rate	0.115	0.081	-0.062	0.326
Log of initial per capita GRDP	9.408	0.884	7.310	10.879
Patent counts per 1000	0.029	0.031	0.002	0.108
Population growth rate	0.023	0.014	0.003	0.052
N	33			

Table 6 shows the descriptive statistics of each group. These groups on average have a per capita GRDP yearly growth rate of 5.6%, with the catching-up 1 RIS and catching-up 2 RIS groups having the highest growth rates of 11.5% and 5.2%, respectively. Meanwhile, the mature RIS group has the largest initial per capita GRDP, followed by the residual RIS, catching-up 2 RIS, and catching-up 1 RIS groups. Mature RIS also has the largest number of patents per 1000, whereas catching-up 1 RIS has the smallest number.

The above descriptive statistics suggest that in the RIS analysis, different types of RIS show differences in their economic performance, while the catching-up RIS groups specializing in short-cycle technologies achieve the highest average growth rate among all groups.

4. Methodology and Model

The system GMM estimation approach proposed by Arellano and Bover (1995) and Blundell and Bond (1998) is ideal for correcting unobserved region heterogeneity, omitted variable bias, measurement errors, and potential endogeneity by using explanatory variables in a model as instrument variables. However, this approach may lead to an overidentification of instrumental variables because given that explanatory variables and their lagged versions are used as instrument variables, these instrument variables may proliferate. To address this overidentification problem, this study also performed Hansen’s test for overidentification and AR(2) test for the second order serial correlation of the residuals in a differenced equation. The least square dummy variable estimation (LSDV) was also conducted to check the consistency of the regression results. Similar to fixed effect estimation, the LSDV estimation controls for the individual effects (regional effects in this paper).

$$y_{it} = \alpha + \beta pcgdp_{it} + \gamma\{Group_{xit}\}_{x=1}^{4} + \delta X_{it} + u_i + v_{it} \quad (1)$$

Equation (1) presents a model for the regression analysis, where y_{it} is the dependent variable representing per capita GRDP growth rate expressed in 2015 PPP-based US dollars for region i at time t, $pcgdp_{it}$ is the logarithm of per capita GRDP (USD, 2015 constant PPP) at the initial year of each period for region i at time t, and $Group_{it}$ represents the dummy variables of RIS groups resulting from the cluster analysis. The mature RIS, catching-up 1 RIS, residual RIS, and catching-up 2 RIS groups are denoted by $Group_{1it}, Group_{2it}, Group_{3it},$ and $Group_{4it}$, respectively. If a region (i) belongs to each group at time t, then $Group_{xit}$ equals 1; otherwise, $Group_{xit}$ equals 0. X_{it} is a group of control variables including population growth and patents counts per 1000 persons, u_i denotes the region-specific error term, and v_{it} represents the idiosyncratic component.

5. Data

Most variables in this research, including regional GDP and population, were collected from the OECD Stat database or from the statistics department websites of each region or country. For those regions without any available GRDP data but with regional income data, a proxy was used, such as the region's relative income size compared to the per capita GDP of its country (Equation 2). Data on the number of patents were collected from the US Patent and Trademark Office. The research period was set from 2001 to 2017, which was divided into 5 sub-periods, namely, 2001 to 2004, 2004 to 2007, 2007 to 2010, 2010 to 2013, and 2013 to 2017. All variables were calculated as the average of all regions in each period. Detailed information about the sources of data can be found in Appendix 2.

$$per\ capita\ RGDP\ proxy\ = \frac{(income\ of\ a\ region)}{(income\ of\ the\ country\ where\ the\ region\ belongs)} \times (per\ capita\ GDP\ of\ the\ country) \quad (2)$$

6. Result

Table 7 presents the regression results. The first and second columns present the results from the LSDV estimation, whereas the last column presents the result of the system GMM estimation. The results across these three columns are consistent. All estimation approaches yield positive coefficients of RIS group dummy variables, which suggests that all groups achieve a faster economic growth than the mature RIS groups, which is used as the benchmark. Specifically, the coefficients for the catching-up 1 RIS, catching-up 2 RIS, and residual RIS groups are 0.116, 0.110, and 0.105, respectively. The residual RIS group demonstrates a slower growth than the two catching-up groups but a faster growth than the mature RIS group. Therefore, the regions in both catching-up RIS groups have a fast economic growth and can catch up with the mature RIS group faster than those in the residual RIS group.

Table 7 Regression results

	LSDV[1]	LSDV[2]	System GMM
Log of initial per capita GRDP	-0.00276^{**}	-0.00105^{*}	-0.0427^{*}
	(-2.54)	(-1.88)	(-1.94)
Number of patents per 1000	0.00737	0.00666^{*}	0.0354^{***}
	(1.67)	(1.79)	(4.40)
Population growth	1.056^{**}	1.136^{***}	0.270
	(2.71)	(3.73)	(0.21)
Catching-up 1 RIS	0.0966^{***}	0.0981^{***}	0.116^{***}
	(5.01)	(5.84)	(2.65)
Catching-up 2 RIS	0.0466^{***}	0.0491^{***}	0.110^{**}
	(5.19)	(8.10)	(2.04)
Residual RIS	0.0453^{***}	0.0460^{***}	0.105^{***}
	(5.15)	(7.28)	(2.65)
Constant			0.410^{*}
			(1.72)
N	150	150	150
Adjusted. R^2	0.733	0.702	
Hansen			0.648
Number of cities	30	30	30

AR(2)	0.483

Notes: The dependent variable is the average annual growth rate of per capita GDP (PPP-based USD) in each period.
Mature RIS (group 1) is used as a benchmark dummy variable.
Outliers are not shown in the regression results.
1. Time and region dummies are not included because of multicollinearity.
2. Time dummies are included but region dummies are not.

The above results confirm that different types of RIS can lead to different economic growth rates. For instance, the two catching-up RIS groups grow faster than the mature and residual RIS groups. The regions in these two catching-up RIS groups specialize in short-cycle technologies, whereas those in the residual and mature RIS groups specialize in technologies with longer cycle times. This finding is consistent with the NIS analysis results (Lee et al., 2021a). However, unlike the NIS analysis, the RIS analysis revealed two patterns of catching up, namely, specializing in short-cycle technologies with weak indigenous knowledge (catching-up 1 RIS) and specializing in short-cycle technologies with strong indigenous knowledge (catching-up 2 RIS). The first pattern achieves the fastest growth rate but has a low income level, whereas the second pattern has a slightly slower economic growth but has a higher income level. To achieve a sustainable growth, regions need to increase their capacity of indigenous knowledge, decrease their reliance on foreign knowledge, and increase their local or national knowledge usage at the same time. The mature RIS group has high indigenous knowledge, low internationalization, and higher income level compared with the catching-up RIS groups. Moreover, given that economies continue to grow and reach the frontier of technologies, the incumbents or foreign firms in the frontier are reluctant to transfer or sell their technologies to latecomers (Lebdioui et al., 2021; Lee, 2005). Therefore, merely relying on foreign-owned knowledge is not enough to sustain the catch-up at a later stage (Lebdioui et al., 2021; Lee, 2005). Despite reporting a high growth rate, the regions in the catching-up 1 RIS group may fail to sustain their growth without indigenous knowledge capacity. Therefore, RIS research that links RIS types to regional economic growth should emphasize the importance of indigenous knowledge, local or national knowledge usage, and specialization in short-cycle technologies. Specifically, achieving high indigenous knowledge and low dependence on foreign knowledge is the steppingstone for regional economic catch-up, and specializing in short-cycle time of technologies is the next step.

Table 8 Comparison of NIS and RIS groups

NIS		RIS	
Advanced NIS	**High** Localization Diversification Decentralization **Long cycle** technologies	Mature RIS	**High** Localization Nationalization Diversification Decentralization Local ownership **Low** Internationalization **Long cycle** technologies
Catching-up NIS: Balanced and medium cycle	**Med** Localization Diversification Decentralization Cycle time	Catching-up 1 RIS	**High** Internationalization Decentralization **Low** Localization Nationalization Diversification **Short cycle** technologies
Catching-up NIS: Imbalanced and short cycle	**High** Localization Diversification **Low** Decentralization **Short cycle** technologies	Catching-up 2 RIS	**High** Local ownership Diversification **(↑)** Localization Nationalization **Low** Internationalization Decentralization **Short cycle** technologies
Trapped NIS	**High** Decentralization **Low** Localization Diversification **long cycle** technologies	Residual RIS	**High** Decentralization Internationalization **Med** Local ownership **Low** Diversification **Long cycle** technologies

The NIS and RIS groups have some similarities and dissimilarities in their features (Table 8). For instance, the characteristics of NIS in advanced countries are similar to those of mature RIS in that their knowledge creation is highly localized, diversified, and decentralized and they generally specialize in long-cycle technologies. Meanwhile, the features of the catching-up 2 RIS group are similar to those of the imbalanced and short cycle catching-up NIS group. For instance, both groups specialize in short-cycle technologies and report increasing and decreasing trends of localization and internationalization, respectively. Moreover, knowledge creation is concentrated on only a few firms. However, the variables of the catching-up 1 RIS and residual RIS groups differ from those of the NIS groups.

7. Conclusion

This chapter explores the characteristics of four RIS types, namely, mature RIS, residual RIS, catching-up 1 RIS, and catching-up 2 RIS, by performing a cluster analysis covering five sub-periods and reveals that different RIS types can lead to differences in regional economic performance. The mature RIS group, which is a high-income group, shares some RIS features with the advanced NIS group in that it has high values for all RIS variables, including localization or nationalization, diversification, decentralization, technology specialization, and local ownership of knowledge. Meanwhile, the residual RIS group is catching up with the mature RIS group with its faster economic growth rate compared with the two catching-up RIS groups. The residual RIS has a decentralized knowledge creation and internationalized knowledge utilization but has less diversified technologies and lower amount of indigenous knowledge compared with the other groups. The two catching-up RIS groups show a faster regional economic growth than the other RIS groups and specialize in short-cycle technologies.

As emphasized in the NIS analysis, specializing in short-cycle technologies is a good strategy for latecomers to catch up with advanced countries. However, the RIS analysis reveals that two other factors, namely, local ownership of knowledge and local or national knowledge utilization, should be considered. At the later stage of economic catch-up for latecomers, merely relying on foreign knowledge will not sustain their economic catch-up because foreign firms or incumbents are afraid to be caught up by latecomers and are reluctant to transfer or sell their technologies or knowledge. Therefore, latecomers should secure indigenous knowledge capacity and reduce their dependence on foreign knowledge.

VI. Contributions and Limitations

1. Key Findings

Three key findings are obtained in this study.

First, Chapter 3 compares three Asian regions, namely, Taipei, Shenzhen, and Penang, in terms of their RIS. These three regions overcame the middle-income trap but show differences in their per capita GRDP and regional economic growth, with Taipei having the highest level, followed by Shenzhen and Penang. In addition, Shenzhen catches up with Taipei faster than Penang. This study analyzes these differences by using variables representing RIS and finds that the fast catch-up rate of Shenzhen can be ascribed to its high indigenous knowledge and low reliance on foreign knowledge.

Second, chapter 4 extends the sample to cover 30 regions across the world. Results of the cluster analysis identified four types of RIS. The mature RIS group specializes in long-cycle technologies and has high degrees of local ownership, localization, diversification, and decentralization. By contrast, the catching-up RIS groups specialize in short-cycle technologies. The catching-up RIS group 1 (low degree of catching-up and low per capita GDP) has a low degree of local ownership, localization of knowledge, and diversification, whereas the catching-up RIS group 2 (high degree of catching-up and per capital GDP) has high diversification and centralization due to its increasing degree of local ownership and localization of knowledge.

Third, chapter 5 links the four groups of RIS identified in chapter 4 to economic growth via a regression analysis and finds that the two catching-up RIS groups specializing in short-cycle technologies have a faster growth rate than either the mature or advanced RIS group.

In sum, for those regions that are trying to catch up, merely relying on their specialization in short-cycle technologies does not guarantee their successful economic catch-up; they should also expand their proportion of indigenous knowledge and reduce their reliance on foreign knowledge.

2. Contributions and Limitations

As a methodological contribution, this dissertation develops quantifiable measures of RIS by using a homogenous set of data (patent-citations-based indices). This study is the first to perform a qualitative RIS analysis using patent data and including diverse regions across the world. By using such RIS measurement, this study reveals that the regions located in the same nation can show differences in their RIS characteristics (e.g., Beijing and Shenzhen in China and Silicon Valley and Houston in the Unites States). Although patent data cannot reflect tacit knowledge but only include explicit knowledge, RIS reflects the degree of tacit knowledge in each region given that RIS cannot be improved without the accumulation of tacit knowledge via knowledge interaction. This paper also explores regional economic catch-up by analyzing RIS and identifies the key characteristics of catching-up RIS, which differ from those of mature RIS. The findings also confirm a relationship between RIS typology and economic growth. These findings may offer some policy implications for latecomer regions that are trying to catch up with advanced regions.

However, the borders of RIS may be ambiguous or soft because they do not exactly fit the borders of the administrative districts of a region. As this paper only includes those regions that have already jumped into some parts of the global value chain, the findings may not offer perfect guidance for those regions that are just starting at the initial stage of technology-based economic growth. Moreover, other regional indicators, including industrial structure, labor force, and openness, have not been considered in this work. Nevertheless, this study presents a new way of measuring and comparing RIS around the world.

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Appendices

A1 List of top assignees in Shenzhen, China

Appendix 1: List of top assignees in Shenzhen, China

Grant year	Assignee	Assignee's country	Patents
2002	Hon Hai Precision Industry Co., Ltd.	TW	17
2002	Foxconn Precision Components Co., Ltd.	TW	14
2002	Shenzhen STS Microelectronics Co., Ltd.	CN	4
2002	Shanghai Jiao Da Onlly Co., Ltd.	CN	1
2002	Majorank International Limited	HK	1
2002	HotTowels LLC	US	1
2002	Shenzhen Hyper Technology Inc.	CN	1
2002	Shenzhen CIMC-Tianda Airport Support Ltd.	CN	1
2005	Hon Hai Precision Industry Co., Ltd.	TW	34
2005	Huawei Technologies Co., Ltd.	CN	6
2005	Crastal Technology (Shenzhen) Co., Ltd.	CN	1
2005	Orleans Furniture, Inc.	US	1
2005	Wok & Pan Industry, Inc.	CN	1
2005	Actherm Inc.	TW	1
2005	TCL King Electronics (Shenzhen) Co., Ltd.	CN	1
2005	Shanghai Jiao Da Onlly Co., Ltd.	CN	1
2005	Molex Incorporated	US	1
2005	Shenzhen LB Battery Co., Ltd.	CN	1
2005	Emerson Network Power Co., Ltd.	CN	1
2005	Phoenixtec Power Co., Ltd.	TW	1
2005	Cool Cubes, Inc.	US	1
2005	Fih Co., Ltd.	TW	1
2005	Liming Network Systems Co., Ltd.	CN	1
2011	Hong Fu Jin Precision Industry (Shenzhen) Co., Ltd.	CN	403
2011	Huawei Technologies Co., Ltd.	CN	296
2011	Fu Zhun Precision Industry (Shenzhen) Co., Ltd.	CN	122
2011	Shenzhen Fu Tai Hong Precision Industry Co., Ltd.	CN	97
2011	Hon Hai Precision Industry Co., Ltd.	TW	59
2011	Innocom Technology (Shenzhen) Co., Ltd.	CN	51
2011	Shenzhen Mindray Bio-Medical Electronics Co., Ltd.	CN	41

2011	ZTE Corp.	CN	25
2011	BYD Co. Ltd.	CN	24
2011	Ensky Technology (Shenzhen) Co., Ltd.	CN	8
2011	FuKui Precision Component (Shenzhen) Co., Ltd.	CN	8
2015	ZTE Corp.	CN	375
2015	Huawei Technologies Co., Ltd.	CN	349
2015	Shenzhen China Star Optoelectronics Technology Co., Ltd.	CN	332
2015	Hong Fu Jin Precision Industry (Shenzhen) Co., Ltd.	CN	173
2015	Tencent Technology (Shenzhen) Co., Ltd.	CN	116
2015	Fu Tai Hua Industry (Shenzhen) Co., Ltd.	CN	102
2015	Huawei Device, Co., Ltd.	CN	69
2015	BYD Co. Ltd.	CN	29
2015	Zhongshan Innocloud Intellectual Property Services Co., Ltd.	CN	27
2015	Shenzhen Fu Tai Hong Precision Industry Co., Ltd.	CN	26

A2 List of top assignees in Penang, Malaysia

Appendix 2: List of top assignees in Penang, Malaysia

Grant year	Assignee	Assignee's country	Patents
2000	Altera Corporation	US	44
2000	Motorola, Inc.	US	42
2000	Intel Corporation	US	25
2000	Iris Corporation Berhad	MY	14
2000	Sony Corporation (JP)	JP	5
2000	Motorola Malaysia SDN BHD	MY	4
2000	Advanced Micro Devices, Inc.	US	3
2007	Avago Technologies ECBU IP (Singapore) Pte Ltd	SG	207
2007	Intel Corporation	US	152
2007	Altera Corporation	US	144
2007	Osram Opto Semiconductors (Malaysia) Sdn. Bhd.	MY	68
2007	Avago Technologies General IP (Singapore) Pte. Ltd.	SG	34
2007	Advanced Micro Devices, Inc.	US	18
2007	SilTerra Malayisa Sdn. Bhd.	MY	12
2007	Robert Bosch GmbH	DE	11

2007	Philips Lumileds Lighting Company, LLC	US	9
2007	Joinsoon Electronics Mfg. Co., Ltd.	TW	7
2007	Spansion LLC	US	7
2007	Micron Technology, Inc.	US	7
2007	Regent Medical Limited	GB	7
2010	Avago Technologies ECBU IP (Singapore) Pte Ltd	SG	185
2010	Intel Corporation	US	135
2010	Altera Corporation	US	130
2010	Fairchild Semiconductor Corporation	US	52
2010	eASIC Corporation	US	33
2010	Avago Technologies General IP (Singapore) Pte. Ltd.	SG	32
2010	Motorola, Inc.	US	28
2010	Spansion LLC	US	25
2010	Robert Bosch GmbH	DE	20
2010	Aptina Imaging Corporation	KY	20
2015	Altera Corporation	US	134
2015	Intel Corporation	US	108
2015	Avago Technologies General IP (Singapore) Pte. Ltd.	SG	89
2015	Flextronics AP, LLC	US	62
2015	Intellectual Discovery Co., Ltd.	KR	60
2015	INTELLISERV, LLC	US	42
2015	Motorola Solutions, Inc.	US	32
2015	Allegiance Corporation	US	29
2015	Robert Bosch GmbH	DE	26
2015	Spansion LLC	US	20

A3 Sources of economic indicators

	Variables	Sources	Notes
1. Berlin	GDP	OECD Stat	
	Population	OECD Stat	
	PPP	World Bank	
	Area	OECD Stat	
	GDP deflator	World Bank	
2. Munich	GDP	OECD Stat	
	Population	OECD Stat	
	PPP	World Bank	
	Area	OECD Stat	
	GDP deflator	World Bank	
3. Paris	GDP	OECD Stat	
	Population	OECD Stat	
	PPP	World Bank	
	Area	OECD Stat	
	GDP deflator	World Bank	
4. London	GDP	OECD Stat	
	Population	OECD Stat	
	PPP	World Bank	
	Area	OECD Stat	
	GDP deflator	World Bank	
5. Cambridge	GDP	Office for National Statistics, regional gross domestic product: local authorities	
	Population	Office for National Statistics, regional gross domestic product: local authorities	
	PPP	World Bank	
	Area	Mid-2013 Population Estimates: Population density of the United Kingdom; estimated resident population.	
	GDP deflator	World Bank	
6. Milan	GDP	OECD Stat	
	Population	OECD Stat	
	PPP	World Bank	
	Area	OECD Stat	
	GDP deflator	World Bank	
7. Osaka	GDP	2001–2017, OECD Stat Re-calculated 2000 GDP after calculating the growth rate of GDP using data from the Cabinet Office Policy, Prefectural	

		Economy.	
	Population	Statistics Office of Japan, e-Stat, System of Social and Demographic Statistics (SSDS), Prefectural Data	
	PPP	World Bank	
	Area	OECD Stat	
	GDP deflator	World Bank	
8. Gyeonggi-do	GDP	OECD Stat	
	Population	KOSIS	
	PPP	World Bank	
	Area	OECD Stat	
	GDP deflator	World Bank	
9. Tokyo	GDP	2001–2017, OECD Stat Re-calculated the 2000 GDP after calculating the growth rate of GDP using data from the Cabinet Office	
	Population	Statistics Office of Japan, e-Stat, System of Social and Demographic Statistics SSDS), Prefectural Data	
	PPP	World Bank	
	Area	OECD Stat	
	GDP deflator	World Bank	
10. Seoul	GDP	OECD Stat	
	Population	KOSIS	
	PPP	World Bank	
	Area	OECD Stat	
	GDP deflator	World Bank	
11. Daejeon	GDP	OECD Stat	
	Population	KOSIS	
	PPP	World Bank	
	Area	OECD Stat	
	GDP deflator	World Bank	
12. Beijing	GDP	OECD Stat	
	Population	OECD Stat	
	PPP	World Bank	
	Area	OECD Stat	
	GDP deflator	World Bank	
13. Shanghai	GDP	OECD Stat	
	Population	OECD Stat	
	PPP	World Bank	
	Area	OECD Stat	
	GDP deflator	World Bank	
14. Shenzhen	GDP	Shenzhen Statistical	

		Yearbook	
	Population	Shenzhen Statistical Yearbook	
	PPP	World Bank	
	Area	Shenzhen Statistical Yearbook Guangdong Statistical Yearbook	
	GDP deflator	World Bank	
15. Hong Kong	GDP	Census and Statistics Department, The Government of the Hong Kong Special Administrative Region	
	Population	Census and Statistics Department, The Government of the Hong Kong Special Administrative Region	
	PPP	World Bank	
	Area	World Bank	
	GDP deflator	World Bank	
16. Taipei	GDP	Use per capita income, National Statistics R.O.C. (Taiwan)	New Taipei + Taipei City
	Population	Use per capita income, National Statistics R.O.C. (Taiwan)	
	PPP	World Bank	
	Area	Taiwan Urban and Regional Development Statistics	
	GDP deflator	World Bank	
17. Bangalore	GDP	Note: Per capita income, government of Karnataka, Directorate of Economics and Statistics, 2000–2016, State and District Domestic Product of Karnataka 2017–2018, Economic survey of Karnataka 2018–2019 and 2019–2020 Note: 2017 population, GDP, per capita GDP, Directorate of Economics and Statistics, District Domestic Product of Karnataka 2016–2017 Note: 2016 population, GDP, per capita GDP, Directorate of Economics and Statistics, State and District Domestic	Bangalore urban

		Product of Karnataka 2017–2018 Note: Per capita income (India), World Bank, per capita GDP (current LCU)	
	Population	Note: population, UN Population Dynamics in Department of Economic and Social Affairs. Annual population of urban agglomerations with 300,000 inhabitants or more in 2018, by country, 1950–2035 (thousands)	
	PPP	World Bank	
	Area	2001, 2011 Karnataka Census	
	GDP deflator	World Bank	
18. Tel Aviv	GDP	OECD Stat	
	Population	OECD Stat	
	PPP	World Bank	
	Area	OECD Stat	
	GDP deflator	World Bank	
19. Penang	GDP	Department of Statistics Malaysia, National Accounts	
	Population	Department of Statistics Malaysia, Population Quick Info, Jabatan Perangkaan Malaysia, Intercensus Population Estimates Population Quick Info (stats.gov.my)	
	PPP	World Bank	
	Area	Penang Statistics Quarter 4	
	GDP deflator	World Bank	
20. Mexico City	GDP	Instituto Nacional de Estadística y Geografía (INEGI), Sistema de Cuentas Nacionales de México. Producto Interno Bruto por Entidad Federativa. Año Base 2013. Serie de 1980 a 2019. 2019 revisada	
	Population	Instituto Nacional de Estadistica y Geografia (INEGI)	
	PPP	World Bank	
	Area	OECD Stat	

	GDP deflator	World Bank	
21. Moscow	GDP	OECD	
	Population	OECD	
	PPP	World Bank	
	Area	OECD	
	GDP deflator	World Bank	
22. Sao Paulo	GDP	IBGE, ISDRA, Table 5938: Gross domestic product at current prices, taxes, net of subsidies, on products at current prices and gross added value at total current prices and by economic activity, and respective holdings - Reference 2010 (ibge.gov.br)	
	Population	IBGE, SIDRA, Table 5938: Gross domestic product at current prices, taxes, net of subsidies, on products at current prices and gross added value at total current prices and by economic activity, and respective holdings - Reference 2010 (ibge.gov.br)	
	PPP	World Bank	
	Area	IBGE	
	GDP deflator	World Bank	
23. New Delhi	GDP	Economic Survey of Delhi	NCT of Delhi
	Population	Economic Survey of Delhi	
	PPP	World Bank	
	Area	Economic Survey of Delhi	
	GDP deflator	World Bank	
24. Santiago	GDP	Banco Central Chile Statistics, Statistical Bulletins	Metropolitan of Santiago
	Population	Banco Central Chile Statistics, Statistical Bulletins	
	PPP	World Bank	
	Area	OECD Stat	
	GDP deflator	World Bank	
25. Singapore	GDP	World Bank	
	Population	World Bank	
	PPP	World Bank	
	Area	World Bank	

	GDP deflator	World Bank	
26. Boston Area	GDP	BEA county level	Middlesex county Suffolk county
	Population	BEA county level	
	PPP	World Bank	
	Area	United States Census Bureau (2010)	
	GDP deflator	World Bank	
27. Silicon Valley	GDP	BEA county level	Alameda county San Francisco county San Mateo county Santa Clara county
	Population	BEA county level	
	PPP	World Bank	
	Area	United States Census Bureau (2010)	
	GDP deflator	World Bank	
28. Houston	GDP	BEA county level	Harris county
	Population	BEA county level	
	PPP	World Bank	
	Area	United States Census Bureau (2010)	
	GDP deflator	World Bank	
29. Austin	GDP	BEA county level	Travis county
	Population	BEA county level	
	PPP	World Bank	
	Area	United States Census Bureau (2010)	
	GDP deflator	World Bank	
30. Stockholm	GDP	OECD Stat	
	Population	OECD Stat	
	PPP	World Bank	
	Area	OECD Stat	
	GDP deflator	World Bank	

A4. List of top 10 assignees in Boston Area, United States

Year	Assignee	Assignee's country	Patents
2015	Massachusetts Institute of Technology	US	163
2015	EMC Corporation	US	120
2015	Verizon Patent and Licensing Inc.	US	107
2015	International Business Machines Corporation	US	84
2015	The MathWorks, Inc.	US	72
2015	Bose Corporation	US	57
2015	President and Fellows of Harvard College	US	57
2015	Mitsubishi Electric Research Laboratories, Inc.	JP	53
2015	The General Hospital Corporation	US	47
2015	Boston Scientific Scimed, Inc.	US	38
2016	Massachusetts Institute of Technology	US	164
2016	International Business Machines Corporation	US	132
2016	EMC Corporation	US	120
2016	The General Hospital Corporation	US	57
2016	VERIZON PATENT AND LICENSING INC.	US	54
2016	The MathWorks, Inc.	US	53
2016	President and Fellows of Harvard College	US	52
2016	Boston Scientific Scimed, Inc.	US	48
2016	Mitsubishi Electric Research Laboratories, Inc.	JP	48
2016	Bose Corporation	US	42
2016	iRobot Corporation	US	42
2017	Massachusetts Institute of Technology	US	218
2017	International Business Machines Corporation	US	158
2017	EMC IP Holding Company LLC	US	99
2017	President and Fellows of Harvard College	US	78
2017	Boston Scientific Scimed, Inc.	US	58
2017	Bose Corporation	US	55
2017	VERIZON PATENT AND LICENSING INC.	US	55
2017	The General Hospital Corporation	US	54
2017	Mitsubishi Electric Research Laboratories, Inc.	JP	51
2017	Amazon Technologies, Inc.	US	43

2017	The MathWorks, Inc.	US	41

A5 List of top 10 assignees in New Delhi, India

Year	Assignee	Assignee's country	Patents
2015	International Business Machines Corporation	US	51
2015	STMicroelectronics International N.V.	CH	16
2015	FREESCALE SEMICONDUCTOR, INC.	US	12
2015	ADOBE SYSTEMS INCORPORATED	US	11
2015	National Institute of Plant Genome Research	IN	3
2015	Poly Medicure Limited	IN	3
2015	Amazon Technologies, Inc.	US	2
2015	Cadence Design Systems, Inc.	US	2
2015	COUNCIL OF SCIENTIFIC & INDUSTRIAL RESEARCH	IN	2
2015	Hewlett-Packard Development Company	US	2
2015	Hughes Systique India Private Limited	US	2
2015	Panacea Biotec Limited	IN	2
2016	International Business Machines Corporation	US	38
2016	ADOBE SYSTEMS INCORPORATED	US	19
2016	STMicroelectronics International	CH	19
2016	FREESCALE SEMICONDUCTOR, INC.	US	13
2016	POLY MEDICURE LIMITED	IN	6
2016	Ciena Corporation	US	5
2016	COUNCIL OF SCIENTIFIC & INDUSTRIAL RESEARCH	IN	5
2016	Indian Institute of Technology	IN	5
2016	Oracle International Corporation	US	5
2016	XILINX, INC.	US	4
2017	International Business Machines Corporation	US	35
2017	ADOBE SYSTEMS INCORPORATED	US	24
2017	STMicroelectronics International	CH	19
2017	COUNCIL OF SCIENTIFIC & INDUSTRIAL RESEARCH	IN	9
2017	FREESCALE SEMICONDUCTOR, INC.	US	9
2017	Amazon Technologies, Inc.	US	4

2017	Cadence Design Systems, Inc.	US	4
2017	Department of Biotechnology	IN	3
2017	NXP B.V.	NL	3
2017	ACCENTURE GLOBAL SERVICES LIMITED	IE	2
2017	BANK OF AMERICA CORPORATION	US	2
2017	Infosys Limited	IN	2
2017	POLY MEDICURE LIMITED	IN	2
2017	Rovi Guides, Inc.	US	2
2017	UOP LLC	US	2
2017	WIPRO LIMITED	IN	2
2017	XILINX, INC.	US	2

A6 List of top 10 assignees in Gyeonggi-do, Korea

Year	Assignee	Assignee's country	Patent s
2015	Samsung Electronics Co., Ltd	KR	2982
2015	Samsung Display Co., Ltd.	KR	1383
2015	LG Electronics Inc.	KR	1038
2015	SK Hynix Inc.	KR	609
2015	Samsung SDI Co., Ltd.	KR	548
2015	Hyundai Motor Company	KR	492
2015	Samsung Electro-Mechanics Co., Ltd.	KR	431
2015	LG Display Co., Ltd.	KR	346
2015	Cheil Industries Inc.	KR	50
2015	Seoul Viosys Co., Ltd.	KR	50
2015	MANDO CORPORATION	KR	48
2016	Samsung Electronics Co., Ltd	KR	3313
2016	Samsung Display Co., Ltd.	KR	1451
2016	LG ELECTRONICS INC.	KR	1117
2016	SK Hynix Inc.	KR	881
2016	Hyundai Motor Company	KR	662
2016	Samsung SDI Co., Ltd.	KR	394
2016	SAMSUNG ELECTRO-MECHANICS CO., LTD.	KR	372
2016	LG Display Co., Ltd.	KR	362
2016	HYUNDAI MOBIS CO., LTD.	KR	68

2016	MANDO CORPORATION	KR	60
2017	Samsung Electronics Co., Ltd	KR	3397
2017	Samsung Display Co., Ltd.	KR	1526
2017	LG ELECTRONICS INC.	KR	853
2017	Hyundai Motor Company	KR	814
2017	SK Hynix Inc.	KR	738
2017	Samsung SDI Co., Ltd.	KR	373
2017	LG Display Co., Ltd.	KR	332
2017	Samsung Electro-Mechanics Co., Ltd.	KR	262
2017	LSIS CO., LTD.	KR	93
2017	HYUNDAI MOBIS CO., LTD.	KR	68

A7 List of top 10 assignees in Beijing, China

Year	Assignee	Assignee's country	Patents
2006	Microsoft Corporation	US	82
2006	Tsinghua University	CN	21
2006	Winbond Electronics Corp.	TW	10
2006	China Petrochemical Corporation	CN	9
2006	International Business Machines Corporation	US	9
2006	Intel Corporation	US	8
2006	Schlumberger Technology Corporation	US	5
2006	The Procter & Gamble Company	US	5
2006	GE Medical Systems Global Technology Company, LLC	US	4
2006	Nokia Corporation	FI	4
2007	Microsoft Corp.	US	86
2007	Tsing Hua University	CN	22
2007	Intel Corporation	US	13
2007	International Business Machines Corporation	US	7
2007	Nokia Corporation	FI	6
2007	Lucent Technologies Inc.	US	4
2007	Schlumberger Technology Center	US	4
2007	Winbond Electronics Corp.	TW	4
2007	China Petroleum & Chemical Corporation	CN	3

2007	GE Medical Systems Global Technology Company, LLC	US	3
2007	Hon Hai Precision Industry Co. Ltd	TW	3
2007	Samsung Electronics Co., Ltd.	KR	3
2007	Smith International, Inc.	US	3
2008	Microsoft Corporation	US	119
2008	Tsinghua University	CN	34
2008	International Business Machines Corporation	US	20
2008	Intel Corporation	US	19
2008	China Petroleum & Chemical Corporation	CN	15
2008	Nokia Corporation	FI	12
2008	GE Medical Systems Global Technology Company, LLC	US	11
2008	Canon Kabushiki Kaisha	JP	6
2008	Nuctech Company Limited	CN	5
2008	Primax Electronics Ltd.	TW	5
2008	Samsung Electronics Co., Ltd	KR	5
2009	Microsoft Corporation	US	187
2009	Tsinghua University	CN	53
2009	International Business Machines Corporation	US	21
2009	GE Medical Systems Global Technology Company, LLC	US	12
2009	Intel Corporation	US	9
2009	Samsung Electronics Co., Ltd	KR	8
2009	Da Tang Mobile Communications Equipment Co., Ltd.	CN	7
2009	Nokia Corporation	FI	7
2009	Vimicro Corporation	CN	7
2009	Alcatel-Lucent USA Inc.	US	6
2009	Schlumberger Technology Corporation	US	6
2010	Microsoft Corporation	US	185
2010	Tsinghua University	CN	102
2010	International Business Machines Corporation	US	38
2010	Intel Corporation	US	26
2010	Nokia Corporation	FI	21
2010	Nuctech Company Limited	CN	21
2010	GE Medical Systems Global Technology Company, LLC	US	20

2010	Beijing Boe Optoelectronics Technology Co., Ltd.	CN	15
2010	China Petroleum & Chemical Corporation	CN	9
2010	Samsung Electronics Co., Ltd.	KR	9
2010	Schlumberger Technology Corporation	US	9
2010	Vimicro Corporation	CN	9
2011	Microsoft Corporation	US	149
2011	Tsinghua University	CN	103
2011	International Business Machines Corporation	US	77
2011	Beijing Boe Optoelectronics Technology Co., Ltd.	CN	33
2011	Intel Corporation	US	23
2011	Nokia Corporation	FI	19
2011	Samsung Electronics Co., Ltd	KR	16
2011	Beijing FUNATE Innovation Technology Co., Ltd.	CN	15
2011	Lenovo Limited	HK	15
2011	Nuctech Company Limited	CN	15
2012	Microsoft Corporation	US	194
2012	Tsinghua University	CN	146
2012	International Business Machines Corporation	US	125
2012	Beijing Boe Optoelectronics Technology Co., Ltd.	CN	35
2012	Intel Corporation	US	35
2012	Samsung Electronics Co., Ltd	KR	25
2012	Huawei Technologies Co., Ltd.	CN	24
2012	Beijing FUNATE Innovation Technology Co., Ltd.	CN	23
2012	Lenovo Limited	HK	23
2012	Nokia Corporation	FI	18
2013	Tsinghua University	CN	188
2013	International Business Machines Corporation	US	173
2013	Microsoft Corporation	US	160
2013	Huawei Technologies Co., Ltd.	CN	74
2013	Beijing Boe Optoelectronics Technology Co., Ltd.	CN	63
2013	Intel Corporation	US	44
2013	Thomson Licensing	FR	36
2013	Fujitsu Limited	JP	32

2013	China Academy of Telecommunications Technology	CN	31
2013	Institute of Microelectronics, Chinese Academy of Sciences	CN	31
2014	Tsinghua University	CN	229
2014	International Business Machines Corporation	US	157
2014	Microsoft Corporation	US	144
2014	Huawei Technologies Co., Ltd.	CN	119
2014	Intel Corporation	CN	56
2014	China Academy of Telecommunications Technology	CN	54
2014	Institute of Microelectronics, Chinese Academy of Sciences	US	47
2014	Beijing Boe Optoelectronics Technology Co., Ltd.	CN	44
2014	Thomson Licensing	CN	41
2014	Fujitsu Limited	CN	40
2015	Boe Technology Group Co., Ltd.	CN	265
2015	Tsinghua University	CN	171
2015	Huawei Technologies Co., Ltd.	CN	167
2015	International Business Machines Corporation	US	154
2015	Intel Corporation	US	75
2015	Microsoft Technology Licensing, LLC	US	71
2015	Beijing Boe Optoelectronics Technology Co., Ltd.	CN	44
2015	Telefonaktiebolaget L M Ericsson (publ)	SE	37
2015	Microsoft Corporation	US	35
2015	Samsung Electronics Co., Ltd.	KR	33
2016	Boe Technology Group Co., Ltd.	CN	798
2016	Huawei Technologies Co., Ltd.	CN	268
2016	International Business Machines Corporation	US	232
2016	Tsinghua University	CN	156
2016	Microsoft Technology Licensing, LLC	US	93
2016	Intel Corporation	US	86
2016	Beijing Boe Optoelectronics Technology Co., Ltd.	CN	78
2016	Beijing Lenovo Software Ltd.	CN	73
2016	Fujitsu Limited.	JP	64
2016	Nokia Technologies Oy	FI	48

2017	Boe Technology Group Co., Ltd.	CN	1342
2017	Huawei Technologies Co., Ltd.	CN	358
2017	International Business Machines Corporation	US	308
2017	Tsinghua University	CN	139
2017	Xiaomi Inc.	CN	117
2017	Lenovo Co., Ltd.	HK	109
2017	Microsoft Technology Licensing, LLC	US	87
2017	Intel Corporation	US	83
2017	Telefonaktiebolaget LM Ericsson (publ)	SE	63
2017	Nokia Technologies Oy	FI	57

A8 List of top 10 assignees in Shanghai, China

Year	Assignee	Assignee's country	Patents
2008	Intel Corporation	US	18
2008	General Electric Company	US	7
2008	Grace Semiconductor Manufacturing Corporation	CN	6
2008	Alcatel	FR	5
2008	Inventec Appliances Corp.	TW	4
2008	O2 Micro International Limited	KY	4
2008	On-Bright Electronics Co., Ltd.	TW	4
2008	Hoffman-La Roche Inc.	US	3
2008	Agere Systems Inc.	US	2
2008	China Petroleum & Chemical Corporation	CN	2
2008	E Ink Corporation	US	2
2008	Integrated Device Technology, Inc.	US	2
2008	Koninklijke Philips Electronics N.V.	NL	2
2008	Montage Technology Group Limited	KY	2
2008	Shanghai Institute of Pharmaceutical Industry	CN	2
2008	Spreadtrum Communications Corporation	US	2
2009	Semiconductor Manufacturing International Corporation	CN	29
2009	Intel Corporation	US	24
2009	Delta Electronics, Inc.	TW	10
2009	Integrated Device Technology, Inc	US	10
2009	Alcatel	FR	7

2009	SABIC Innovative Plastics IP B.V.	NL	7
2009	Alcatel Lucent	FR	5
2009	BCD Semiconductor Manufacturing Limited	KY	5
2009	General Electric Company	US	5
2009	Hoffmann-La Roche Inc.	US	5
2009	Inventec Corporation	TW	5
2010	Semiconductor Manufacturing International Corporation	CN	43
2010	Intel Corporation	US	21
2010	On-Bright Electronics Co., Ltd.	TW	13
2010	General Electric Company	US	11
2010	Integrated Device Technology, Inc.	US	10
2010	Delta Electronics, Inc.	TW	9
2010	Alcatel Lucent	FR	6
2010	Spreadtrum Communications Inc.	KY	6
2010	Agere Systems Inc.	US	5
2010	Inventec Appliances Corp.	TW	5
2010	SAP AG	DE	5
2011	Semiconductor Manufacturing International Corporation	CN	52
2011	General Electric Company	US	26
2011	Intel Corporation	US	20
2011	Integrated Device Technology, Inc.	US	14
2011	Delta Electronics, Inc.	TW	12
2011	Shanghai Ultimate Power Communications Technology Co., Ltd.	CN	10
2011	Honeywell International Inc.	US	9
2011	Inventec Corporation	TW	9
2011	BCD Semiconductor Manufacturing Limited	KY	7
2011	Cypress Semiconductor Corporation	US	6
2011	Marvell International Ltd.	BM	6
2011	On-Bright Electronics Co., Ltd.	TW	6
2012	Semiconductor Manufacturing International Corporation	CN	48
2012	Alcatel Lucent	FR	23
2012	Intel Corporation	US	23
2012	Ambit Microsystems (Shanghai) Ltd.	CN	17

2012	Huawei Technologies Co., Ltd.	CN	16
2012	Koninklijke Philips Electronics N.V.	NL	12
2012	International Business Machines Corporation	US	11
2012	Inventec Corporation	TW	11
2012	Delta Electronics, Inc.	TW	10
2012	General Electric Company	US	10
2013	Semiconductor Manufacturing International Corporation	CN	58
2013	Intel Corporation	US	37
2013	Alcatel Lucent	FR	31
2013	Huawei Technologies Co., Ltd.	CN	28
2013	International Business Machines Corporation	US	22
2013	Koninklijke Philips Electronics N.V.	NL	19
2013	On-Bright Electronics Co., Ltd.	TW	18
2013	General Electric Company	US	15
2013	Shanghai Institute of Microsystem and Information Technology, Chinese Academy of Sciences	CN	15
2013	Ambit Microsystems (Shanghai) Ltd.	CN	14
2013	Marvell International Ltd.	BM	14
2014	Semiconductor Manufacturing International Corporation	CN	74
2014	Huawei Technologies Co., Ltd.	CN	73
2014	Alcatel Lucent	FR	50
2014	Delta Electronics, Inc.	TW	49
2014	International Business Machines Corporation	US	32
2014	Inventec Corporation	TW	26
2014	Intel Corporation	US	23
2014	General Electric Company	US	22
2014	Shanghai Huali Microelectronics Corporation	CN	22
2014	Shanghai Hua Hong NEC Electronics Co., Ltd.	CN	19
2015	Huawei Technologies Co., Ltd.	CN	98
2015	Semiconductor Manufacturing International Corporation	CN	79
2015	Alcatel Lucent	FR	59
2015	Inventec Technology Corporation	TW	28
2015	International Business Machines Corporation	US	27
2015	Shanghai Tianma Micro-Electronics Co., Ltd.	CN	24

2015	Intel Corporation	US	23
2015	On-Bright Electronics Co., Ltd.	TW	23
2015	Delta Electronics Co., Ltd.	TW	22
2015	EMC Corporation	US	16
2016	Huawei Technologies Co., Ltd.	CN	142
2016	Semiconductor Manufacturing International Corporation	CN	140
2016	International Business Machines Corporation	US	52
2016	Alcatel Lucent	FR	49
2016	Shanghai Tianma Micro-Electronics Co., Ltd.	CN	48
2016	Intel Corporation	US	42
2016	General Electric Company	US	37
2016	Inventec Technology Corporation	TW	30
2016	Spreadtrum Communications Co., Ltd.	US	23
2016	SAP SE	DE	22
2017	Semiconductor Manufacturing International Corporation	CN	172
2017	Huawei Technologies Co., Ltd.	CN	151
2017	Shanghai Tianma Micro-Electronics Co., Ltd.	CN	92
2017	International Business Machines Corporation	US	43
2017	On-Bright Electronics Co., Ltd.	TW	35
2017	Tyco Electronics Co. Ltd.	CH	35
2017	Intel Corporation	US	32
2017	Alcatel Lucent	FR	29
2017	Shanghai Tianma AM-OLED Co., Ltd.	CN	28
2017	SAP SE	DE	27

국문 초록

혁신은 경제 성장과 경제 추격에 있어 중추적인 역할을 해왔다. 동아시아 국가들이 보여준 것과 같이 혁신은 중진국 함정 단계를 넘어 경제적 추격을 지속하는데 있어서, 가격이나 비용적인 요소보다 더 중요한 요인이었다. 국가의 혁신역량 혹은 혁신의 효율성을 나타내기 위해 국가혁신체제라는 개념이 고안되었는데, 이는 슘페터 경제학의 핵심적인 개념이다. 하지만 국가 단위의 연구에 초점이 맞춰진 국가혁신체제로는 국가 내 여러 지역의 이질적인 특성을 고려하여 분석할 수 없다. 그렇기 때문에 지역혁신체제라는 분석틀이 필요했고 1990년대부터 지역혁신체제의 개념이 확립되었다. 본 연구에서는 세계 주요 도시의 지역혁신체제 분석을 통해 도시/지역 간 다른 특징들을 살펴보고, 특히 빠른 경제성장을 보이는 추격형 지역들이 선진 지역들과 어떤 다른 특성을 보이는 지에 대해 알아보고자 한다.

본 연구에서는 지역혁신체제를 양적으로 측정하기 위해 7가지의 지표를 사용하는데, 지식의 지역화, 국내화, 국제화 지수를 포함해, 지식 소유권의 토착화 정도, 기술다각화, 지식분권도, 기술사이클 등이다. 국가혁신체제 연구에서는 지식을 창출할 때 국내 지식을 이용하는지 해외 지식을 이용하는지, 두 가지 차원으로만 나누어지지만, 지역 단위의 연구에서는 같은 지역의 지식을 이용하는지, 같은 국가이지만 다른 지역의 지식을 이용하는지, 그리고 다른 국가의 지식을 이용하는지 등 세 가지 차원으로 나누어지기 때문에, 새롭게 국내화 지수라는 개념이 추가되었다. 또한 본 연구에서는 토착 지식이 혁신에 있어 중요한 역할을 하는지에 대해 알아보기 위해, 토착지식을 측정할 수 있는 지식 소유의 토착화 정도 변수도 새롭게 만들어 추가하였다.

첫 번째 장에서는 아시아에서 공통적으로 중진국 함정에서 벗어나 빠른 경제성장을 보이고 있는 대만의 타이페이, 중국의 심천, 그리고 말레이시아의 페낭의 지역혁신체제에 대해 비교 연구를 하고, 심천이 타이페이를 페낭보다 더 빠르게 추격할 수 있었던 이유에 대해 지역혁신체제 관점에서 분석한다. 국가혁신체계 연구에서는 후발 국가들이 선진국들을 추격하기 위해서 단주기 기술로의 특화가 중요하게 작용한다고 하였지만, 본 연구에서는 세 지역 모두 단주기 기술에 특화했음에도 불구하고 1인당 GRDP와 경제 성장률에서 차이를 보였다. 이렇게 다른 결과를 보인 이유는 국제화 지수 (외국기술 의존도)가 타이페이와 심천지역에서 낮고, 그리고 지식 소유의 토착화 정도가 페낭보다 높게 나타나기 때문이다. 따라서, 세 지역의 비교 연구를 통해, 지역 간 경제추격에 있어 토착 지

식의 증가와 그에 따른 해외 지식에 대한 의존도 감소가 얼마나 중요하게 작용하는 지를 발견할 수 있었다.

두 번째 장에서는 앞 장에서 다루었던 타이페이, 심천, 페낭을 포함한 전 세계 30개 지역의 지역혁신 체제의 특징을 2001년에서 2017년까지의 지역혁신체제 변수를 통해 살펴보고, 클러스터 분석을 통해 어떻게 유형화가 가능한 지에 대해 연구한다. 클러스터 분석 결과, 지역이 단주기 혹은 장주기 기술에 특화하는지, 토착 지식이 큰지 작은지에 따라, 총 네 개의 지역 혁신 체계 그룹으로 분류가 된다. 첫째 유형은 선진국형으로, 국제화 정도 (해외지식 의존도)가 낮고, 높은 토착소유화, 기술다각화, 및 분권화를 보인다. 추격형 유형은 두가지로 나누어 지는데, 보다 고도화된 유형은 한국이나 대만의 도시와 같이 해외지식 의존도가 낮고, 지식의 토착소유화 정도가 높은 유형이고, 덜 고도화된 유형은 페낭이나 방갈로와 같이 해외지식 의존도가 높고, 토착소유화 정도가 낮은 유형이다.

세 번째 장에서는 두 번째 장에서 클러스터 분석을 통해 나타났던 지역혁신체제 그룹들과 경제성장률의 상관관계를 알기 위해 회귀분석을 진행하였다. 그 결과, 단주기 기술에 특화된 두 가지의 추격형 그룹들이 가장 빠른 경제 성장률을 보이며 선진 지역(장주기 기술 특화·높은 토착지식)을 빠르게 추격하는 결과를 보여준다.

세 개의 장을 종합하여 살펴보면, 지역 혁신체제 연구에서도 국가 혁신체제 연구의 결과와 마찬가지로, 후발지역들의 추격형 지역 혁신체제의 특징을 확정지울 수 있었다. 특히, 똑 같이 단주기 기술로의 특화하는 후발 지역 간에도 추격성과가 다르게 나타나는 것은, 결국 지식소유의 토착화의 제고와 해외 지식에 대한 의존도를 줄이는 것이 선결 조건임을 밝힌 것이 중요한 공헌이다.

주요어: 지역혁신체제, 지역 개발, 경제 추격, 혁신, 클러스터 분석, 지역경제성장, 지역 경제 추격

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