Varieties of Regional Innovation Systems around the World and Catch-up by Latecomers

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Abstract

This study identifies the characteristics and types of the regional innovation systems (RIS) of regions and cities in emerging economies in comparison to those in advanced economies. It uses the citation data of the US patents filed by 30 regions. Some RIS variables are newly developed, and they include intra-regional, inter-regional, and inter-national sourcing of knowledge and local ownership of innovation. The cluster analysis of these variables enables us to identify four major types of RIS around the world and link them to regional economic performance. The four types are, in the descending order of their per capita income levels, as follows: large, mature RIS characterized by a combination of long cycle technology specialization and high local ownership (Group 1), mixed RIS characterized by a long cycle and low local ownership (Group 2), "strong catch-up" characterized by short cycle and high local ownership (Group 3), and "weak catch-up" characterized by short cycle and low local ownership (Group 4). Groups 3 and 4 include only the regions in emerging world. They similarly specialize in the same short cycle time of technologies (CTT)-based sectors but show different records of economic performance. The key differentiating variable is the degree of local ownership of knowledge, which can be a basis for increasing domestic sourcing of knowledge and sustained catching up. Another important variable is decentralization, of which the level is lower in the strong catch-up group than in the weak catch-up group. In this Group 3, catching up is led by big businesses. Several cities experiencing upgrading, like Moscow, Beijing, and Shanghai, also show an increasing trend of local ownership and centralization.

Keywords: regional innovation systems, innovation, patents, economic growth, economic catch-up
JEL code: C23, O31, O32, O33, O50, R11, R58

1. Introduction

Innovation systems has become a key concept in Schumpeterian economics since they were first proposed by Freeman (1987) and later at national levels by Lundvall (1992) and Nelson (1993). Lundvall (1992) defines national innovation systems (NIS) as “elements and relationships which interact in the production, diffusion and use of knowledge rooted inside the borders of a nation state.” Various dimensions of NIS have been introduced to analyze their relationship with economic growth (Archibugi & Coco, 2004; Castellacci, 2008, 2011; Edquist, 1997; Fagerberg & Srholec, 2018; Fagerberg & Verspagen, 2002; Lee & Lee, 2019). The concept of innovation systems has also been applied at the regional level, given the uneven distribution of innovations even in the same nation (Asheim et al., 2019). The regional innovation system (RIS) approach explains the heterogeneous distribution of innovation in the territory and aids in constructing policies enhancing the innovation capability of regional economies (Isaksen et al., 2018).

Cooke et al. (1998: 1581) define 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 studies have been conducted on the relationship between knowledge, innovation, and economic growth in regional bases (Andersson & Karlsson, 2007; Capello et al., 2009; Harris, 2011; Huggins & Thompson, 2015; Rodríguez-Pose & Crescenzi, 2008). In particular, Rodríguez-Pose and Crescenzi (2008) analyze the impact of innovation on regional economic performance in Europe to find the importance of localized structural and institutional factors that shape the innovation capacity of a specific geographical context.

Furthermore, various RIS studies have explained a typology and dynamic change of RIS and show a variety of criteria and perspectives on the RIS (Asheim et al., 2019; Asheim & Gertler, 2006; Asheim, 1998; Cooke, 2001, 1998, 2005). Quantitative approaches have also been used to study the efficiency of different kinds of RIS (Fritsch & Slavtchev, 2011; Zabala-Iturriagagoitia et al., 2007). However, these studies are mostly for the regions in advanced countries; especially quantitative ones, involving latecomer regions are insufficient. In the literature, “peripheral or immature” RIS rely highly on foreign knowledge because of the lack of the indigenous knowledge or regional embeddedness and low level of regional embeddedness (Asheim et al., 2019; Hassink, 2001; Park & Markusen, 1995; Rodríguez et al., 2014).

Latecomers’ reliance on foreign knowledge is unsurprising considering that 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). Any process of catching up a region in emerging economies may involve reduced reliance on foreign knowledge and increased consolidation of local knowledge bases. Taking this reasoning as an initial motivation, we find out how different RIS of catching-up regions have been compared with those of advanced regions. This study is an attempt at quantitative analysis of RIS of 30 regions/cities around the world to identify the differentiating characteristics of catching-up RIS from the emerging world, using patent-citation-based measurements of diverse aspects of RIS. One of the key questions is what are the several types and pathways for catching-up development by latecomer regions.

Some studies discuss the typology of RIS although majority of them are about regions in advanced countries (Cooke, 1992) or use qualitative analyses. Some quantitative studies include Zabala-Iturriagagoitia et al. (2007), which evaluates RIS performance in terms of technical efficiency for Spanish case, and Fritsch and Slavtchev (2011), which suggests alternative measures for the efficiency of RIS based on the concept of a knowledge production function for German case. Nonetheless, quantitative analysis of RIS typology for emerging economies remains lacking, especially global analysis involving cities in both developed and developing world using a consistent framework and methodology.

In the meantime, empirical studies of NIS in both developed and developing countries have blossomed in the last decades. Some of them have focused on categorizing several types of the NIS by income level (Castellacci, 2011; Lee, 2013; Lee et al., 2021). Castellacci (2011) and Lee et al. (2021) use cluster analysis with variables representing the country's innovation systems. Using the five variables proposed in Lee (2013, Chapter 3) to measure the NIS, namely, knowledge localization, technological diversification, specialization in terms of CTT, originality, and knowledge decentralization (or concentration), Lee et al. (2021) make an interesting typology of NIS. The typology identifies several types of NIS, such as balanced and mature NIS, imbalanced and catching-up NIS specializing in short CTT-based sectors, and imbalanced and trapped NIS specializing in long CTT-based sectors. We adopt and further modify this empirical methodology for a region-level analysis.

Some case studies of RIS in several cities/regions have already used the similarly developed methodology. Although some of the above variables were first introduced in the early works of Jaffe et al. (1993) and Jaffe and Trajtenberg (2002), they were first utilized for the analyses of RIS in Wong and Lee (2021) for South Korea and Taiwan; Kim and Lee (2022) for Taipei, Penang, and Shenzhen; and Wong et al., (2022) for Singapore, Dublin and Penang. One of the methodological contributions of these RIS analyses is to decompose the national-level localization of knowledge creation and diffusion into the two components of intra-regional knowledge localization and inter-regional knowledge localization, where the latter refers to a region's innovation sourcing knowledge from other regions in the same nation. Furthermore, Kim and Lee (2022) introduce the variable of local ownership (of innovations) into RIS analysis and confirm its importance as a key determinant of long-term innovation performance of regions.

Kim and Lee (2022) differentiate two pathways of catching-up regions, namely, fast catch-up in Shenzhen, China and slow catch-up as in Penang, Malaysia. The explanation focusing on local ownership is that Shenzhen's faster catch-up is due to its increasing local ownership of knowledge with the rise of locally owned big businesses. By contrast, Penang's slower catch-up has to do with its continued reliance on MNCs but failing to promote local ownership of knowledge at the hand of locally owned companies. The analysis in this paper intends to see if these findings from related case studies of several regions' RIS can be generalized by analyzing a larger data set of RIS involving 30 cities around the world.

An analysis with a larger data set of RIS also enables us to identify varieties of RIS around world, differentiating regions in advanced economies from those in emerging economies. In particular, we can identify two types of RIS in the emerging world, with different degrees of local ownership corresponding to different levels of per capita GDP (gross regional domestic product or GRDP). In terms of empirical methods, we use cluster analysis to classify the 30 regions into different clusters in terms of several RIS variables. We then create a dummy for each of these clusters and use these dummies in growth regressions to match each to different speeds of economic growth.

In what follows, Section 2 discusses the literature and derives key hypotheses for empirical analysis. Section 3 discusses methodological issues, data, and measurement. Section 4 provides the results of the cluster analysis about RIS varieties and their changes over time and presents the regression analysis about the relationship between RIS types and economic growth. Section 5 focuses on several regions that have experienced changes in types and upgrading over time to reveal the dynamics and pathways for upgrading and catching up. The last section concludes the paper with a summary and remarks.

2. Literature Review, Theoretical Issues, and Hypotheses

Various RIS studies explain a typology and dynamic change of RIS and show a variety of criteria and perspectives on the RIS (Asheim et al., 2019; Asheim & Gertler, 2006; Asheim, 1998; Cooke, 2001, 1998, 2005). Asheim (1998) proposes three types of RIS, such as territorially embedded RIS, territorially networked RIS, and regionalized NIS. Cooke (2001) propose two types, namely, entrepreneurial and institutional RIS. Others propose a place-based leadership approach (Beer & Clower, 2014; Benneworth et al., 2017). Research on RIS typology for emerging economies as well as generalized typology covering various regions over the world is lacking, yet effort has been exerted to conceptualize RIS in emerging economies.

Localization of Knowledge Sourcing

The concept of peripheral or immature RIS focuses on its high reliance on foreign knowledge and lack of the indigenous knowledge (Asheim et al., 2019; Hassink, 2001; Park & Markusen, 1995; Rodríguez et al., 2014). 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). This pattern indicates that latecomer regions show a low level of patenting and localization at early stages and more citations to foreign patents than indigenously owned patents even after they start to conduct their own R&D and file patents. We then hypothesize that catching-up regions show an increasing trend of local knowledge bases and regional embeddedness in creating and diffusing knowledge and, at the same time, a decreasing trend of their reliance on foreign knowledge bases.

Such a characterization of upgrading in the RIS of emerging economies is consistent with the theoretical arguments and evidence at the national-level studies of upgrading and catching up of emerging economies. Lee (2013) and Lee et al. (2021) confirm the trend of increasing localization of knowledge creation and diffusion, which is measured by national-level self-citation of a nation and how much knowledge is domestically created by citing the patents owned by the same nationality (Jaffe et al., 1993).[1] Therefore, one of the first tasks in this study is verifying such an upgrading at the level of regions or cities. However, a regional-level analysis needs modification. First, because a region may interact with other regions in the same nation, we have to decompose the national-level localization into intra-regional and inter-regional localization. The former may be called intra-region sourcing of knowledge, whereas the latter may be called inter-regional sourcing of knowledge. The remaining source is the international or foreign sourcing of knowledge.

The share of these three types of knowledge creation and diffusion, namely, intra-region, inter-region, and inter-national (foreign) sourcing of knowledge, should be summed up to one because a patent from a region cites a patent from the same or different region in the same nation or a patent from other nations. Following Kim and Lee (2022), we define the three measures as follows:[2]

$$Intra-regionalization_{xt} = \frac{n_{xxt}}{n_{xt}}, \quad (1\text{-A})$$

$$Inter-regionalization_{xt} = \frac{n_{xx't}}{n_{xt}}, \quad (1\text{- B})$$

$$Internationalization_{xt} = \frac{n_{xdt}}{n_{xt}}, \quad (1\text{- C})$$

Where n_{xt} is the common denominator representing the total number of citations made by all patents

[1] It refers to the degree of national-level self-citation after normalization and is thus designed to be free from the size effect (i.e., a big country has a high localization ratio). If the degree of localization is large, then the domestic diffusion of knowledge is high, but the share of foreign patents in the citation is low.

[2] Given that the three measures are summed up to be one, for the purpose of the analysis, normalization needed in national-level analysis using the concept of control patents proposed to control the size effect is unnecessary (Jaffe et al., 1993).

invented in a region x' granted in year t. In Equation (1-A), n_{xxt} is the total number of citations to the patents invented in a region x made by the patents invented by region x and granted in year *t*. In Equation (1-B) $n_{xx't}$ is the total number of citations made to the patents invented in other regions (x') in the same nation made by all the patents from a region *x*. In Equation (1-C), n_{xdt} is the number of citations made to the patents invented in foreign nations (d) made by region x's patents granted in year t.

We now use the patent data of 30 cities around the world to measure the above three measures of knowledge sourcing so as to verify the hypotheses that regions and cities in advanced countries show a high level of intra- or inter-regional sourcing of knowledge, whereas cities in emerging world show a low level of intra- or inter-regional sourcing of knowledge. Additionally, any catching up or upgrading of RIS in the emerging world should show an increasing tendency of intra- or inter-regional sourcing of knowledge, combined with a decreasing tendency of foreign sourcing.

The above hypotheses have already been confirmed by some scholars who have conducted comparative case studies of RIS in emerging economies, but they have yet to be generalized to a bigger data set. Wong and Lee (2021) confirm the increases in intra-region localization and decreases in reliance on foreign knowledge in the rapidly catching-up regions in Asia, namely, Hsinchu with its core firm of TSMC and Suwon with its core firm of Samsung. Kim and Lee (2022) confirm that Shenzhen has shown a faster increase of intra-region sourcing of knowledge than Penang, which is one of the reasons for the two cities' different speed of catching up, with Taipei as a reference city that has already achieved a status of a high-income economy.

Local Ownership of Knowledge and Innovation

One puzzle arising from the comparative analyses of three information technology (IT) clusters in Asia, namely, Taipei, Shenzhen, and Penang, is how come Shenzhen and Penang correspond to different speeds of catching up, although they share the common origin of takeoff relying on FDI in the same industrial specialization into IT manufacturing. The above question is a puzzle in the sense that some existing works on technological catch-up, such as Park and Lee (2006) and Lee (2013), argue that latecomers achieve a fast catch-up if they specialize in short CTT-based and thus low entry barrier sectors, such as IT-based manufacturing. Prime examples are the past Korea and Taiwan and recent mainland China. Then, a question arises, that is, how can the different speeds of catch-up in the same short CTT specialized clusters across different economies.

The answer suggested by Kim and Lee (2022) is the different degrees of the rise in local ownership as learned from MNCs and after both regions, Shenzhen and Penang. Local ownership of innovation made inside a region is important because some innovations (patents) are filed by an inventor in a region, but this inventor may be hired by a foreign MNC located in the region. Local ownership is high if there are more spinoff and spillover from the MNC and is an important indicator of technological catch-up. The share of local ownership in Taipei reached almost 100% by the mid-2000s from about 40% in the 1980s (Kim & Lee, 2022). The share of the local ownership in Shenzhen reached the similar level by the mid-2010 within a shorter period because the share used to be close to zero in the mid-1990s. By contrast, the local share in Penang did not show such a sharp increase, but it has remained around 10% since the 1990s.

In the above study, the variable of the local ownership of innovation measures the share of patents owned by indigenous firms out of all the patents invented in a region (with inventors' address in the same region) assigned to firms of all kinds of ownership. It can be defined as follows:

$$Local\ ownership = \frac{N_{cxt}}{N_{xt}} \qquad (2),$$

where N_{cxt} is the number of patents invented in a region x and assigned to a firm with its nationality in the host country c, and N_{xt} is the total number of patents assigned to any firm and invented in a region (with the first inventor address located in region x) granted in time t.

We use the same variable to measure the degree of local ownership of 30 regions around the world and see if the differences in local ownership can explain the different performances in economic growth and upgrading of RIS. Cities in emerging economies can be really divided into two types, namely, the one with strong local ownership corresponding to a higher per capita income, and the other with low local ownership corresponding to a lower level of per capita income. Given that both groups show similarly short level of average CTT but are lower than cities in advanced economies, they can be named as "short CTT and strong local ownership" and "short CTT and weak local ownership" RIS.

Other Dimensions of RIS

The preceding subsection has discussed the key hypothesis of this study, which is localization of knowledge creation and ownership. These aspects of localization complement and reinforce each other such that a high degree of local ownership facilitates further the increases in localization of knowledge sourcing. This is unsurprising because MNCs feel less need to conduct R&D in host countries and cities in the emerging world.

The current sub-section turns to other aspects of RIS that are addressed in empirical analysis. In this regard, we also consider several variables suggested in the NIS study of Lee et al. (2021) but can also be measured and analyzed at a region level. Thus, the RIS analysis in this study uses the following three component variables: technological diversification, CTT, and innovation decentralization.[3] We briefly explain these NIS component variables, which are measured at the level of regions or cities. The details are available in Appendix 1.

The first variable for RIS analysis is technological diversification, which captures the degree to which a country or a region produces patents in a wide variety of technological fields. Technological diversification is about the width of the patent portfolio of a region/country and may be complementary to product or export diversification.[4] The second RIS variable is technological decentralization in knowledge creation across innovators. This variable refers to whether or not the producers of knowledge are led by a few big businesses or evenly distributed among a large number of innovators. We measure this degree of decentralization as 1 minus the HHI of concentration.

The third variable is to measure technological specialization by the variable called CTT, which is related to the question of whether countries specialize in sectors with rapid or slow obsolescence of knowledge. It refers to the average time lag between the grant years of the citing patents and that of the cited patents (Jaffe & Trajtenberg, 2002). Specifically, CTT refers to the extent to which a patent relies on recent or old technologies for the invention of new knowledge.[5] A short CTT indicates that the life span of the knowledge lasts only a few years, after which the usage dramatically declines as it soon becomes outdated or less used. In this sense, short CTT-based sectors correspond to low technological entry barriers against late entrants. Lee (2013) and Lee et al. (2021) find that successful latecomer economies, such as South Korea and Taiwan, tend to focus on sectors with short CTT, such as IT goods, during their rapid economic catch-up since the mid-1980s. By contrast, advanced countries tend to specialize in sectors with relatively long CTT, such as the pharmaceutical sector.

In the NIS literature, different characteristics of NIS are noted between advanced and catching-up countries (Lee, 2013; Lee et al., 2021). NIS in advanced countries tend to have all equally high values in all NIS variables, such as diversification, decentralization, and average CTT; in comparison, NIS in emerging economies tend to have low values in NIS component variables. We apply similar logics from

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[3] Our analysis of RIS omits the originality variable, which is shown to be less significant in the literature, such as Lee (2013, Chapter 3), thus suggesting that originality may not have a significant effect to economic growth at least at the catching-up stage. In Kim and Lee (2022), originality also does not play an important role in explaining different speeds of economic catch-up between the three regions.

[4] Technological diversification is measured by the number of technological classes in which a country/region has registered patents divided by the maximum number of three-digit patent classes in the patent classification system (this number was 438 in 2016, and we use this number for every year). Although a Herfindahl–Hirschman index (HHI) is an alternative, this measurement has a more direct and easy-to-interpret meaning and many variations across the country.

[5] In our analysis, we use relative (or normalized) CTT, which is the absolute years of the CTT divided by the average CTT of all patents granted in the same year. We use the average values of the relative CTT of all patents assigned to each country for analysis.

the NIS literature to the RIS analysis and thereby try to differentiate RIS in emerging economies from that in advanced economies. Specifically, we hypothesize that RIS in high-income region group have high values in all RIS variables, such as high diversification, high decentralization, and long CTT specialization, in addition to high degree of local ownership and local sourcing of knowledge (= low foreign sourcing). By contrast, RIS in emerging economies are characterized as either all low values, such as low diversification and decentralization and short CTT, or imbalances, like low diversification but very long CTT or vice versa.[6]

3. Measurement, Data, and Methodology

Methodological Issues

If we summarize the discussion in the preceding section, our measurement of RIS consists of seven variables, some of which are newly suggested, whereas others are adoption of those used to measure NIS. The former includes the three variables representing intra-region, inter-region, and inter-national sourcing of knowledge, plus local ownership of innovation. The latter includes technological diversification, decentralization, and CTT. These variables are measured using a single data set comprising patents filed in the US. The advantage of using such a data set is that the data sources are homogenous; thus, the variables are easily collected and measured consistently for different cities around the world. Such a method can also be justified given that the focus of analysis is not every spectrum of cities but only those located in the middle- or higher-income economies but tend to show varying degrees of innovation capabilities that can be measured by patent data.

Our empirical analysis utilizes the USPTO bulk data, i.e., a weekly released US patent panel data set containing a large number of information for the period of 1976–2017. To turn this bulk data into user-friendly forms, we follow Lee et al. (2021) to conduct data mining using the method of Potter and Hatton (2013).[7] After this process, we measure the seven RIS component variables. We identify patents

[6] Lee et al. (2021) categorize the NIS in four groups i.e., balanced and mature NIS, balanced and medium-cycle NIS, imbalanced, short-cycle, and catching-up NIS, and imbalanced, long-cycle, and trapped NIS. Among these four, the two imbalanced NIS groups are relevant for emerging economies. In imbalanced and short-cycle NIS, knowledge creation is highly localized, technologies are highly diversified, and economies in this group specialize in short-cycle technologies, and this group tends to correspond to a faster catching up compared with imbalanced and long-cycle NIS. The imbalanced and long-cycle NIS group has features of low localization and diversification and specializes in long-cycle technologies. This group includes those countries that face growth slow-down and thus are stuck in the middle-income trap.

[7] The first step is to acquire the patent data files by manually downloading 2,132 separate files. The second step is to decompress the downloaded data and begin parsing the corpus and converting it to SAS data sets. The third step is to use SAS programming to create a program that can parse all

for each city in terms of the address of the first inventor of a patent.

One issue may be whether these seven variables are comprehensive enough to represent the diverse dimension of innovation activities of a region. There is a tradeoff between comprehensiveness associated with a large number of variables versus parsimoniousness associated with less burden on data requirements. Some of existing studies on NIS or RIS tend to use many and diverse indicators for different research orientations.[8] Our choice of these knowledge-related variables is close to the original definition of innovation systems, which is a mechanism to generate, diffuse, and utilize knowledge (see Lundvall's definition above and OECD, 1997). Another justification in using only these variables is Lee and Lee (2019), who develop a composite NIS index using these variables and show that it is a comprehensive enough predictor of economic growth and more robust than or equally robust as the index of economic complexity (Hausmann et al., 2014). In addition, Lee et al. (2021) conduct a cluster analysis of NIS typologies and show that the identified types of NIS explain well the different economic performances.

Sample of 30 Cities

The data set in this study covers 30 regions and cities around the world, and Appendix Table 1 lists them, together with other basic information, such as the number of US patents, per capita GDP (GRDP), population, and so on. In Appendix Table 1, all variables are calculated as the yearly average value of each variable in the most recent period, 2013–2017. Given our focus on emerging economies and their regions, our criteria to select cities is a combination of innovation intensity measured by patent counts and representativeness of economies where the cities are located. For instance, in Asia, two giant economies, China and India, are considered first, so their innovation-intensive cities are included in the sample. Japan and the four east Asian tigers (Singapore, Hong Kong, Taiwan, and South Korea) are considered, and their innovation intense cities are chosen in consideration of patent counts. This is why Gyeong-gi province where Samsung is located as well as Daejeon, which is a hub city for many government research institutes, are included in the sample, in addition to Seoul.

We thus include 13 Asian regions, namely, Tokyo, Gyeonggi province in South Korea, Seoul, Osaka, Taipei, Beijing, Shenzhen, Daejeon in South Korea, Shanghai, Bangalore, Singapore, Hong Kong, New Delhi, and Penang, in the order of the patents. The sample include three regions in Latin

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documents in the corpus and then catalog the patent numbers for each patent granted since 1976.

[8] For instance, the empirical literature on NIS uses many variables to capture diverse aspects of an economy, ranging from techno-economic to political institutional dimensions and IT-related infrastructure, and even openness and financial systems. Although the broad scope may be a merit, such breadth blurs the boundaries between innovation and other areas of the economy, often leading to NIS groupings that are difficult to interpret. See Lee et al. (2021) for a detailed discussion of this point.

America, such as Sao Paulo in Brazil, Santiago in Chile, and Mexico City in Mexico. These cities are the top 3 cities in Latin America in terms of the patent counts.

Cities in advanced countries serve as a benchmark for emerging economy cities. First, for European cities, they are basically chosen to represent the four large economies of Germany, France, UK, and Italy, plus one Nordic country of Sweden. Therefore, we include seven European regions, which are Munich, Paris, Berlin, Cambridge (the UK), London, Stockholm, and Milan, in the descending order of the number of patents. Moscow is in Europe but is treated as an emerging country city as Russia belongs to the BRICS group and its per capita income is about 50% of that of the US. Similarly, Tel Aviv is located in middle east Asia but is treated as a city in advanced economy, given the uniqueness and high income status of Israel.

So far, patents are classified into different cities defined by their official administrative boundary and the address of the first inventor. For US regions and cities, different administrative practices require to merge several counties to define a bigger area. For instance, there is no such city as Silicon Valley, so we merge several counties into one unit called Silicon Valley. A similar practice is applied for other regions in the US (details are in Appendix 2). In terms of their patenting activities, the data set include four areas in the United States, namely, Silicon Valley area, Boston–Cambridge area (later referred to as Boston for simplicity), Austin area, and Houston area, in the descending order of the number of patents.

Basically, most variables such as the regional GDP and population, are resourced from the Regional Economy in OECD.Stat database; otherwise, from each city, region, or country's statistics department website. The detailed information about the data resource is explained in Appendix 3.

Cluster Analysis and Growth Regressions

We apply cluster analysis to these RIS component variables to classify the RIS of cities into several types. Cluster analysis is a method of grouping objectives by a pre-determined set of their attribute variables, revealing homogeneity of within-group and heterogeneity of between-groups. In cluster analysis, there are three methods of average linkage, single linkage, and complete linkage. We adopt the average linkage method, which is preferable to the single linkage or complete linkage methods because of their relative sensitivity to extremes or outliers (Jobson, 1992). The average linkage cluster analysis is based on Euclidean distance measurement, and this is determined by averaging the proximities between all pairs of objects, one object for each group (Jobson, 1992).

Using the results of cluster analysis, we create a dummy for each cluster and conduct growth regressions to match these cluster dummies to economic growth. We conduct regression analysis to adopt the method of system GMM estimation proposed by Arellano and Bover (1995) and Blundell and Bond (1998). This estimation is supposed to handle unobserved region heterogeneity, omitted variable bias, measurement error, and potential endogeneity by using explanatory variables as instrument variables. There is a possibility of overidentification of instrumental variables because explanatory variables and their lagged variables are used as instrument variables. Therefore, we conduct Hansen test for overidentification and AR(2) test for the second-order serial correlation of the residuals in differenced equation. In addition to the system GMM estimation, we conduct the least square dummy variable (LSDV) estimation to check the consistency of the regression results. The LSDV estimation is similar with the fixed effect estimation and controls the individual fixed effects (here, region-specific effects).

4. Varieties of RIS and their Linkages to Economic Growth

Key RIS Variables and Cluster Analysis Leading to Four Types

Table 1 presents the basic innovation profiles of 30 cities and regions in terms of the values of the seven RIS component variables as annual averages for the 2013–2017 period. Paris is at the top with its highest GDP per capita, whereas Bangalore in India comes last. We have the annual values of these seven variables for the 18 year period of 2000–2017. We then conduct cluster analysis to classify the 30 cities into several types. For this, we divide the whole period into two sub-periods, 2000–2008 and 2009–2017 as well as into five sub-periods to check robustness and show dynamics over time. In the 5 sub-period division, the first period is from 2001 to 2004, the second period is from 2004 to 2007, the third period is from 2007 to 2010, the fourth period is from 2010 to 2013, and the fifth period is from 2013 to 2017.

[Table 1 and Figure 1]

Figure 1 shows the dendrogram for the results of the cluster analysis for the recent nine-year sub-period, and Table 2 shows the results for the two sub-periods and the five sub-periods. In both results, we identify four major groups, although the member cities show variations over time or sub-periods. Table 2 presents the four groups in the descending order of the average per capita income of the constituent cities.

If we read the recent nine-year period results in Table 2A, Group 1 includes 6 cities in large, high income economies, such as four from the US (Austin, Boston, Houston, and Silicon Valley) and two from Japan (Osaka and Tokyo). Group 2 can be called a mixed group in that it includes not only eight cities from advanced economies (Berlin, Paris, Munich, Stockholm, Milan, Cambridge, Tel Aviv, and London) but also another eight cities from emerging economies (Moscow, Hong Kong, Shanghai, Singapore, Beijing, Sao Paulo, Mexico City, and Santiago).

The next two groups, Groups 3 and 4, include cities in emerging economies only, although income levels and innovation performances vary. Group 3 corresponds to a higher per capita income than

Group 4, and it includes Taipei, Seoul, Shenzhen, Gyeonggi-do (S. Korea), and Daejeon (S. Korea). Group 4 includes Penang, New Delhi, and Bangalore, which are all in Asia. The above classification results from the recent nine years is exactly the same as the results from the recent five years, except that Hong Kong and Sao Paulo belong to Group 4 in the recent five-year results as opposed to Group 2 in the recent nine-year results.

Table 3 summarizes the defining characteristics of each group in terms of the average values for the seven RIS variables, beside per capita income. First, the outstanding feature of Group 1 is the highest value of inter-regional sourcing (0.52), which seems to reflect that these cities are all located in a large economy with enough scope and diversity within a nation. We may call this group as "large, mature economy cities" or large mature RIS for simplicity. This group also boasts the highest intra-regional sourcing (0.14) of knowledge, indicating a high degree of local embeddedness of its innovation activities, represented by Silicon Valley (0.24 in Table 1). In addition, it shows the lowest degree of international sourcing of knowledge, reflecting its less dependence on foreign knowledge, which is matched by the highest ratio of local ownership (0.94) of innovations. Moreover, this group boasts a high degree of technological diversification, decentralization, and long CTT.

Group 4, corresponding to the lowest per capita GDP, seems to be exactly opposite to the Group 1 in that it features the lowest intra- and inter-regional sourcing (0.02 and 0.01, respectively) but the highest reliance on foreign knowledge (0.97) and lowest degree of local ownership (0.13). Its technological specialization is in short CTT (0.84 : shortest among the four groups). As discussed in Section 2, short CTT specialization has not resulted in strong catching up in living standards of Group 4 cities, which seems to be attributable to its lowest degree of local ownership. This group seems to be consistent with the idea of the immature or peripheral RIS. They may thus be termed as "weak catch-up," featuring a combination of short CTT and low local ownership.

In comparison, Group 3 corresponds to "strong catch-up" shown by its per capita income, which is more than two times higher than Group 4. Despite the similar specialization into short CTT, a differentiating factor is the high local ownership (0.94), which is as equally high as that of Group 1. Consistent with high local ownership, its dependence of foreign knowledge is the second lowest, after Group 1 (0.87), and its intra-regional sourcing of knowledge is the second highest (0.07).

Group 2 includes diverse cities around the world, and its per capita income and intra-regional sourcing are in between those of Groups 1 and 3. It shows the longest CTT. It also shows an equally high reliance on foreign knowledge and an equally low inter-regional sourcing, compared with Group 4. Although this group comprise cities from developed and emerging economies, two sub-groups of cities are not much different in terms of the values of RIS variables (see Table 3 for each sub-group cities from developed vs. emerging economies). Therefore, the average values of the whole Group 2 is not merely an average of heterogeneous cities but reflects well the characteristics of cities from both developed and emerging economies.

One simple way to characterize these four groups is a 2×2 combination of CTT and ownership. CTT is an important variable suggested in the NIS literature and in the RIS analysis. That both of the top two RIS group specialize in long CTT-based sector is interesting to note. By contrast, two RIS groups comprising cities in emerging economies only correspond to short CTT specialization. Figure 2A shows the trend of CTT in these four groups, indicating clearly that the top two lines correspond to Groups 1 and 2, whereas the bottom two graphs correspond to Groups 3 and 4.

Groups 1 and 2 correspond to higher incomes and long CTT, but Group 1 is a combination of long CTT and high local ownership, whereas Group 2 is a combination of long CTT and low ownership. By contrast, Groups 3 and 4 comprise emerging economy cities only and specialize commonly in short CTT. However, Group 3 features short CTT and high local ownership and boasts strong catch-up, whereas Group 4 features short CTT but low local ownership and corresponds to weak catch-up. Hence, we name Group 3 as short CTT and high local ownership; Group 4, short CTT and low local ownership.

Figure 2B shows the trend of local ownership in four groups, indicating clearly that only Group 3 (strong catch-up) caught up with Group 1. In addition, only Group 3 shows the decreasing trend of inter-national sourcing of knowledge and increasing sourcing of intra- and inter-regional sourcing of knowledge (Figure 2C, 2D, 2E) and technological diversification (Figure 2F). In terms of technological diversification, long cycle and high local ownership group (Group 1) is the most diversified among the groups with above 47% for all periods. Group 3 (short cycle and high local ownership) started from 31% in 2000–2002 period and increased to 42% in 2015–2017, which is close to the level of Group 1. Group 4 (short cycle and low local ownership) has the lowest level of ownership in all periods, although it shows some increasing trend and follows other groups.

[Figure 2, Table 2]

Linking the RIS Groups to Economic Growth

For growth regression analysis, we use the result of the cluster analysis using the five sub-period average values to generate more observations. Figure 2 describes what regions belongs to which group by sub-periods.

The members of the mature RIS are the most stable to include always the six cities of four from the US (Austin, Boston, Houston, and Silicon Valley) and two from Japan (Osaka and Tokyo). Group 2 (mixed) tends to include for both of the recent two sub-periods eight cities from advanced economies (Berlin, Paris, Singapore, Stockholm, Milan, Cambridge, Tel Aviv, and London) and six emerging cities (Moscow, Beijing, Shanghai, Singapore, Mexico City, and Santiago). Moscow, Beijing and Shanghai joined this group from the third or fourth sub-period, which can be regarded as indication of their upgrading from Group 4, which is further discussed in the next section. Although Munich joined this group from the fourth period, it used to belong to either Group 2 or 3 during the first three sub-periods.

Group 3 (strong catch-up: short cycle and high local ownership) also tends to be somewhat consistent to include five cities in Asia for the recent three sub-periods, such as four from either South Korea or Taiwan (Seoul, Taipei, Daejeon, and Gyeonggi-do) and one from mainland China (Shenzhen). Shenzhen's entry into this group since the third period can be considered as a reflection of its upgrading from Group 4, which is further discussed in the following section.

Group 4 (weak catch-up: short cycle and low local ownership) has Bangalore, New Delhi and Penang as its core and stable members. Hong Kong may also be considered as a stable member of this group as it belonged to this group during four sub-periods out of five. Moscow, Shenzhen, Beijing, and Shanghai used to belong to this group during the first two sub-periods before they upgraded and moved to either Group 2 (mixed group) or Group 3 (strong catch-up group). By contrast, San Paulo has been somewhat instable, going between Groups 4 and 2 depending on a sub-period. It has moved back to Group 4 during the most recent sub-periods.

Using the results of cluster analyses over the five sub-periods, we generate the four dummy variables that take different cities as its members depending on the sub-periods. The four dummies represent four groups (1, 2, 3, and 4), with each representing the long cycle and high local ownership RIS (large, mature RIS), longer cycle and medium local ownership RIS (mixed RIS), short cycle and high local ownership RIS (strong catch-up), and short cycle and low local ownership (weak catch-up). We subsequently conduct growth regressions to link these dummies to economic growth measured by the growth rates of per capita GDP (GRDP). Equation (1) is a model for the regression analysis.

$$y_{it} = \alpha + \beta pcgdp_{it} + \gamma\{Group_{xit}\}_{x=1}^{3} + \delta X_{it} + u_i + v_{it} \quad (1),$$

where y_{it} is a dependent variable, representing the growth rate of per capita GRDP in 2015 PPP based US dollars for region i at time t, and $pcgdp_{it}$ refers to the logarithm of per capita GRDP (USD, 2015 constant PPP) at the initial year of each period for region i at time t. $Group_{it}$ represents the dummy variables of RIS groups, and there are three group dummies: $Group_{1it}, Group_{2it}, and\ Group_{3it}$, stands for weak catch-up, strong catch-up, and mixed RIS group, respectively. If a region (i) belongs to a certain group at time t, then $Group_{xit}$ equals 1; otherwise, 0. X_{it} is a group of control variables, including population growth and average intellectual capital represented by patents counts per 1,000 person, u_i stands for the region-specific error term, and v_{it} represents idiosyncratic component.

Table 4 shows the results of regression, and the descriptive statistics are available in Appendix Table 2 for the whole and group samples. The first and second columns of Table 4 presents the results from the LSDV estimation, and the last column presents the result of system GMM estimation. The results are consistent. In all methods of estimation, the coefficients of RIS group dummy variables are positive, which means that this grouping is meaningful and that all groups achieve the faster economic growth than the large, mature RIS group, which is used as a benchmark and thus not shown as any dummy. The size of the coefficient for each group might appear to be of different magnitudes but all turn out to be indifferent according to statistical tests.

The above results show that both groups of strong and weak catch-up RIS grow faster than mature RIS, and they have the common technological specialization into short CTT. This part is similar with the result in NIS analysis (Lee et al., 2021). However, we come across somewhat new and different findings. Compared with the NIS analysis, we find two patterns of catching-up with short CTT specialization. The first pattern is specializing in short cycle technologies with weak indigenous knowledge (Group 4), and the second pattern is specializing in short cycle technologies with strong indigenous knowledge (Group 3). The first pattern corresponds to low income level; the second pattern corresponds to a higher income level than the first pattern. This difference implies that for the sustainable growth to reach a high income status, regions eventually need to increase the contribution of indigenous knowledge, decrease the reliance on foreign knowledge, and increase the local or national knowledge bases.

[Table 3, 4, and 5]

5. Pathways for Upgrading and Catching Up

The preceding section focuses on typologies of RIS and their linkage to economic growth. This section focuses on the pathways for upgrading from one type to other types.

Two Pathways for Upgrading

As mentioned in the preceding section, several cities changed their RIS types over time (Table 2).We note two patterns of upgrading between the RIS groups. The first one is a move from weak catch-up RIS (Group 4) to strong catch-up RIS (Group 3), and the second one is a move from a weak catch-up RIS (Group 4) to the mixed group RIS (Group 2). The first pattern includes Shenzhen, whereas the second pattern include Beijing, Shanghai, and Moscow (the names of these cities are all marked as bold in Table 2B.

If we compare Shenzhen to the core three cities (Bangalore, Penang, and New Delhi) in Group 4 that remained in Group 4 for the whole period, the main differentiating factor is the different trends in local ownership, followed by inter-national sourcing of knowledge, and diversification. Figure 3A, figure 3B, and figure 3C depicts this. The degree of local ownership in Shenzhen increased very fast, from less than 20% to close to 90%, whereas the average value of the local ownership for the core three cities in Group 4 remained below 20% for decades (Table 3A). In Shenzhen, the inter-national sourcing of knowledge decreased from 97% to 93%, but the corresponding figures for the three cities did not decrease much or stayed around the level of 97% (Table 3B). By contrast, we see no differentiating trend in decentralization or CTT. The average CTT of Shenzhen remained shorter than the compared group, with some rather increasing trend to get close to the level of Group 4's average. Its level of decentralization remained lower than the average of Group 4, reflecting the rise of big businesses in Shenzhen.

[Figure 3]

For the cases of upgrading from weak catch-up (Group 4) to the mixed group (Group 2), the differentiating factors are again local ownership (increasing), followed by inter-national sourcing of knowledge (decreasing) and diversification (increasing). We see no differentiating trend in decentralization or CTT. The values of CTT of the three upgrading cities remained above or similar to the average CTT of Group 4. Although Moscow and Beijing showed some decreasing trend, Shanghai showed no change at all, remaining similar to the average of Group 4.

In sum, the two pathways for upgrading feature in common the trend of increasing local ownership, diversification, and decreasing reliance on foreign knowledge (internationalization). CTT and decentralization do not show any clear-cut trend. This implies importantly that increasing local sourcing and decreasing foreign sourcing of knowledge should be the most important factors for upgrading, whereas short CTT specialization does not automatically guarantee this to happen. Rather, short CTT specialization needs to be combined with increasing local ownership. A right combination of short CTT and local ownership is required, and that is the main defining characteristics of the strong catch-up group.

Decentralization versus Centralization for Catch-up

Another issue in the pathways for upgrading is whether a latecomer city should pursue decentralized way of innovation distribution or centralization into the hands of a few number of big businesses. If we look at the trend of decentralization in Figure 2G, we note that the strong catch-up group corresponds to the lowest degree of decentralization or highest centralization and does not show a clear-cut trend of further decentralization. By contrast, Groups 2 and 4 present a noticeable decentralizing trend. This divergence implies different modes of upgrading and catching up.

Given that Group 3 include cities in South Korea and Taiwan as well as Shenzhen, it is unsurprising that these cities represent upgrading led by big businesses that are also locally owned matched by the decreasing trend of inter-national sourcing of knowledge. Although Beijing, Shanghai, and Moscow has recently joined Group 2, they have also most recently increased the degree of centralization (Figure 3D), in parallel with increasing local ownership during the most recent period and rapid diversification. If such trends continue in the future, these three cities can be expected to move beyond the current Group (2) to join Group 3 (strong catch-up).

Mixed RIS as Another Pathway

One remaining issue may be a viability of the mixed RIS as a possible model for catching up by latecomer cities. The average values of RIS variables for cities from emerging economies in this group is quite similar to those for cities in the same group but from advanced economies. This interesting homogeneity in RIS raises an important question of why then per capita income levels remain so different between these two sub-groups, for instance, \$32,749 vs. \$69,561 (Table 3). Their income level (\$32,749) is also much lower than the average of the strong catch-up group (\$43,748). The persistent difference in income level despite the similar RIS values implies that such a difference may not be sufficiently explained by region-level factors. One answer may be the role of national-level (or NIS) factors affecting performance of cities within a nation in addition to other regional variables not considered here. We will answer this question in future studies, where we will explore in detail how the interaction of RIS and NIS variables affect the performance of cities.

Another possibility is that the current states of cities from emerging world is not an end-state equilibrium but only a transitory state. Some of them may increase further the local ownership from the current values of 50%–60% or so to more than 80% or close to the level of strong catch-up group. Shenzhen is an example of upgrading to Group 3 (strong catch-up group) via this pathway. The degree of local ownership used to be less than 40% in the mid-2000s but reached more than 90% by the mid-2010s.

6. Summary and Concluding Remarks

We attempt to identify quantitatively the characteristics and types of RIS of regions and cities in emerging economies in comparison to those in advanced economies. We adopt and modify the Schumpeterian framework and methodology of innovation systems, which was originally developed at national level. We measure seven variables expressing the diverse aspects of a region's innovation systems, using the citation data of the US patents filed by 30 regions and cities around the world. Among the seven RIS variables, four are newly developed, namely, intra-regional, inter-regional, and inter-national sourcing of knowledge and local ownership of innovation. The other three are used in the recent literature, and they are CTT, technological diversification, and decentralization. The cluster analysis of these variables enable us to identify four major types of RIS around the world and link them to regional economic performance.

The four types are, in the descending order of their per capita income levels, as follow: large, mature RIS characterized by a combination of long cycle technology specialization and high local ownership (Group 1), mixed RIS characterized by a long cycle and low local ownership (Group 2), "strong catch-up" characterized by short cycle and high local ownership (Group 3), and "weak catch-up" characterized by short cycle and low local ownership (Group 4). Consistent with the findings from the NIS literature, Group 1 tends to boast equally high values in all of the six variables and the lowest value in inter-national sourcing. In particular, it has higher values in inter-regional sourcing, which reflect the size of national economy the cities belong to. In sharp contrast, Group 4 is in the opposite spectrum tend to show low values in all of the six variables and the highest value in inter-national sourcing of knowledge, which is expected from an immature or peripheral RIS with lack of indigenous knowledge base and embeddedness. Growth regressions confirm that Groups, 2, 3, and 4 correspond to faster rates of growth compared with the benchmark group, Group 1.

An interesting and contributing finding is that Groups 3 and 4 include only the regions in emerging world and thus similarly specialize in the same short CTT-based sectors. However, they show somewhat different records of economic catch-up and income levels. The key differentiating variable is the degree of local ownership of knowledge and innovation, which can be a basis for increasing domestic sourcing of knowledge and sustained catching up to a high income level. Several cities, such as Shenzhen, Moscow, Beijing. and Shanghai, which experienced the pathways of upgrading from Group 4 in the earlier period to either Group 3 or 2 in later periods, also show a rapid or steady increase of local ownership, followed by increasing domestic sourcing and decreasing inter-national sourcing.

Another important variable is decentralization, which is associated with the fact that the level of decentralization in the strong catch-up group is lower than that in the weak catch-up group, whereas Group 1 boasts the highest level of decentralization associated with more dispersed and diverse sources of innovation. Such a pattern in Group 3 implies that catching up has been led a small number of big businesses rather than a large number of SMEs. This pattern is consistent with the experiences of South Korea, Taiwan, and mainland China, which all generate some of the Global 500 Fortune class firms. Several cities experiencing upgrading, like Moscow, Beijing, and Shanghai, also show a decreasing trend of decentralization. This point of catching up led by big businesses is actually consistent with the finding from the NIS literature, like Lee (2013) and Lee et al. (2021). It is called a detour path, meaning that they will be eventually more decentralized at later stage of development.

Overall, some of the findings are consistent with those of NIS literature, but others are new and distinctive. One source of difference between the NIS and RIS analyses for emerging economies is that although some cities and regions in our sample are located in the middle-income trap countries, their own income level is already quite high compared with the national average of the affiliated nations.

This study has a number of contributions. First, this research makes a methodological contribution of developing quantifiable measures of RIS using a homogenous set of data (patent-citations based indices). This is one of the first quantitative RIS analysis using patent data and covering many and diverse regions across worlds. Second, it contributes to the field by identifying characteristics of RIS of catching-up regions, different from mature cities in advanced economies and linking them to economic growth. Third, it identifies a common mechanism of RIS upgrading, which is led by locally owned big businesses exploring more of domestic sourcing of knowledge while reducing reliance on foreign knowledge. The findings can be useful to derive policy implications for latecomer regions in their effort to catch up with advanced regions.

However, several limitations can be noted. First, there is a possibility of ambiguity or softness of the borders of RIS because the borders of RIS do not fit to that of the administrative districts of the region. We only include the regions already achieving some innovation output or integrated into certain parts of the global value chain; thus, this study is limited in deriving implications for regions starting the early stage of innovation and economic growth. Besides, we do not use much of other, especially tacit knowledge, indicators of regions, such as industry and trade structure, labor market institutions, and government–business relations.

Nevertheless, this study shows a new and useful way of measuring and comparing RIS around the world. Analyses of this kind are still at early stage of progress. The current stage is mostly for generating more stylized facts and identifying new regularities. A more rigorous analysis for general causality will be done in future studies. Other topics for future studies are the role of national institutions and other variables on growth of cities and their RIS and the manner in which the interaction between the RIS and NIS variables affect the performance of a region.

Appendix

Appendix 1: Additional RIS variables

First, technological diversification refers to the number of diverse fields of technologies a region/nation has filed a patent for and can be defined as follows (Lee et al. 2021; Lee, 2013):

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

where N_i refers to the total number of technological classes that patents from region i are registered (i.e., in how many diverse fields a region has filed the patents). The total number of classes in the patent systems can be determined at several levels, such as three or four digits. The number in the US patent classification system was 473 classes at the three-digit level in 2019.

Second, decentralization or concentration of innovation measures the degree of even or uneven distribution of innovators (patent assignees and legal owners of patents), i.e., whether innovation is conducted by a large number of firms or dominated by a few large firms. Thus, Herschman–Herfindahl index (HHI) can be measured with the following formula (Lee, 2013):

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

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 unassigned patents. We then use the formula of $(1 - HHI_{xt})$ to define the variable of the decentralization of innovation over assignees in region x in time *t* (Lee et al., 2021).

Third, the variable of cycle time of technologies (CTT) is first proposed in Jaffe and Trajtenberg (2002) and used in Lee (2013). Its definition is as follows:

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

This absolute value of CCT keeps increasing over time, so defining whether the technology is changing rapidly or slowly is difficult. In this sense, this value is normalized around 1, which is named as relative (or normalized) CTT. The formula for relative CTT is

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

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

Appendix 2: Definition of the regions in the US

In the analysis, Boston–Cambridge area (hereafter referred to as Boston), Silicon Valley, Houston area, and Austin area are defined as follows. In the US, the minimum administrative level for regional data is county level, which often include cities inside it. Hence, we define the above areas as a sum of several related counties or a county itself that include cities. The Boston area includes two counties, Middlesex county where Boston city belongs to and Suffolk county where Cambridge city and Somerville belong to. The Houston area is basically the Harris county, and the Austin area is the Travis county. In these cases, each county includes the cities within its administrative boundary.

Silicon Valley started with San Jose in Santa Clara county as its core area. The region expanded to include several neighboring counties (Mann & Luo 2010). According to Guzman and Stern (2015), Silicon Valley comprises as many as 35 cities belonging to several counties. There is no formal definition, and Silicon Valley is broadly considered to include areas surrounding San Francisco Bay. In our study, we consider Silicon Valley as the four counties surrounding the bay, which are Alameda county, San Francisco county, San Mateo county, and Santa Clara county.

Appendix 3: Sources of economic indicators

The biggest source for the data on gross regional domestic product (GRDP) and population are from the data set called Regional Economy in the OECD database. Data on the purchasing power parity are from World Bank. In the case such data are unavailable for some regions, we resort to the sites of the government of each country or region. Specific details follow.

In case of the regions in the US, we use county-level data available from the US Bureau of Economic Analysis. For Cambridge in the UK, data on its GRDP and population are from the official website of the government and its Office for National Statistics:
https://www.ons.gov.uk/economy/grossdomesticproductgdp/data sets/regionalgrossdomesticproductlocalauthorities;
https://www.ons.gov.uk/economy/grossdomesticproductgdp/data sets/regionalgrossdomesticproductlocalauthorities.

For data on Osaka and Tokyo in Japan, the System of Social and Demographic Statistics in the Statistics of Japan provides prefecture level for population for each region in Japan. As OECD provides the GRDP data from 2001 to 2017 for the two regions in Japan, we use the growth rate of GRDP from the Prefectural Economy in Cabinet Office Policy to re-calculate each region's GRDP in 2000. Regarding the population data for the regions in Korea such as Gyeonggi-do, Seoul, and Daejeon, we use Korean Statistical Information Service: https://kosis.kr/index/index.do#none.

In China, each regional government provides its own statistical yearbook. OECD provides the GRDP and population data for Beijing and Shanghai. For Shenzhen, the necessary data of GRDP and population are from the Shenzhen Statistical Yearbook. The Census and Statistics Department of the

Government of the Hong Kong Special Administrative Region provides GRDP and population data for Hong Kong. In this study, Taipei region includes New Taipei and Taipei City. The statistics department of Taiwan does not provide the gross regional domestic product but provides regional per capita income and population.

In this case and others, including Bangalore, we estimate per capita GRDP by multiplying the ratio of per capita income of a region to national average by per capita GDP of a country to which a city belong. GRDP data for Bangalore are not provided, but per capita income data are provided by Directorate of Economics and Statistics in the Government of Karnataka. Data on per capita income from 2000 to 2016 are from State and District Domestic Product of Karnataka 2017–2018 and data on regional per capita income from 2017 to 2018 are from the Economic Survey of Karnataka 2018–2019 and 2019–2020. The data on population, GRDP, and per capita GRDP in 2017 are from District Domestic Product of Karnataka 2016–2017 provided by Directorate of Economics and Statistics. GRDP and population data for New Delhi are from Economic Survey of Delhi.

In Malaysia, National Accounts of Department of Statistics provides the gross regional domestic product and population of Penang. Mexico City data on GDP and population are from National Institute of Statistic and Geography (Instituto Nacional de Estadística y Geografía, INEGI). They provide GRDP in 2013-based price, so we transform GRDP in 2015-based USD using GDP deflator and PPP provided by World Bank. Brazilian Institute of Geography and Statistics provides GRDP and population for Sao Paulo (https://sidra.ibge.gov.br/home/pmc/brasil). In case of Santiago, we consider the Metropolitan of Santiago as Santiago and use data of GRDP and population provided from Statistical Bulletin in Banco Central Chile. We use GDP and population data for Singapore from World Bank.

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Table 1 Average values of RIS Variables by region (annual average for 2013-2017)

	Localization	Nationalization	Internationalization	Knowledge own	Relative cycle time	Diversification	Decentralization
Paris	0.0518	0.0724	0.8758	0.7524	1.075	0.277	0.8912
Silicon Valley	0.2432	0.5183	0.2385	0.894	0.8736	0.5869	0.8251
Boston Area	0.0905	0.6268	0.2827	0.9405	0.9921	0.4719	0.8738
Singapore	0.0472	0	0.9528	0.5849	0.9491	0.3078	0.8799
Austin	0.0711	0.6802	0.2487	0.9133	0.9079	0.3577	0.8053
Houston	0.186	0.5668	0.2472	0.9524	1.1215	0.4123	0.8944
Tokyo	0.1488	0.3154	0.5358	0.9528	0.9694	0.6283	0.9384
London	0.0009	0.0411	0.958	0.5721	1.003	0.2304	0.8833
Milan	0.0341	0.0358	0.9301	0.6235	1.1449	0.2199	0.924
Cambridge	0.0242	0.0381	0.9377	0.465	1	0.1962	0.8887
Taipei	0.1027	0.07	0.8273	0.8522	0.8511	0.4989	0.8325
Stockholm	0.0253	0.0691	0.9056	0.7603	0.8791	0.1543	0.7859
Munich	0.0253	0.0894	0.8853	0.7329	1.0305	0.3133	0.9148
Hong Kong	0.0436	0.0096	0.9468	0.255	0.9996	0.337	0.8779
Tel Aviv	0.0289	0.0728	0.8983	0.4977	0.893	0.1721	0.8364
Moscow	0.0519	0.005	0.9432	0.3721	0.9518	0.1679	0.8409
Berlin	0.0375	0.0734	0.8891	0.7151	1.0798	0.2778	0.9148
Seoul	0.0656	0.0881	0.8463	0.9678	0.8529	0.482	0.8173
Mexico City	0.0131	0.008	0.9789	0.6077	1.2113	0.0592	0.8152
Osaka	0.1045	0.3863	0.5092	0.9628	0.9881	0.5129	0.8305
Shenzhen	0.0408	0.0208	0.9385	0.9247	0.8165	0.3455	0.673
Gyeonggi-do	0.1154	0.0642	0.8205	0.9794	0.822	0.5243	0.7888
Penang	0.0341	0.0096	0.9563	0.0838	0.9031	0.0854	0.8329
Beijing	0.0448	0.009	0.9462	0.5504	0.8076	0.3624	0.8248
Daejeon	0.0467	0.0586	0.8947	0.9876	0.9426	0.3552	0.7033
Shanghai	0.0258	0.0154	0.9588	0.5277	0.897	0.3573	0.8077
Sao Paulo	0.0131	0.0058	0.9812	0.3685	1.1164	0.0968	0.8444
Santiago	0.0242	0.0019	0.9739	0.693	1.2377	0.0613	0.7915
New Delhi	0.0146	0.0209	0.9646	0.1962	0.8279	0.1053	0.8609
Bangalore	0.0136	0.0115	0.9749	0.1082	0.787	0.2152	0.9171
Average	0.0590	0.1328	0.8082	0.6598	0.9644	0.3058	0.8438

Table 2. Results of the Cluster Analysis - localization, nationalization, internationalization, decentralization, knowledge ownership, diversification, cycle time

Part A

	2000-2008	**2009-2017**
Group 1	Silicon Valley, Boston Area, Austin, Houston, Tokyo, Osaka	Silicon Valley, Boston Area, Austin, Houston, Tokyo, Osaka
Group 2	Paris, London, Milan, Cambridge, Stockholm, Tel Aviv, Berlin, Mexico City, Santiago, Sao Paulo	Paris, Singapore, Milan, London, Cambridge, Stockholm, Munich, Hong Kong, Tel Aviv, Berlin, Moscow, Mexico City, Beijing, Shanghai, Sao Paulo, Santiago
Group 3	Taipei, Munich, Seoul, Gyeonggi-do, Daejeon	Taipei, Seoul, Shenzhen, Gyeonggi-do, Daejeon
Group 4	Singapore, Hong Kong, Penang, Shenzhen, Moscow, Shanghai, Beijing, New Delhi, Bangalore	Penang, New Delhi, Bangalore

Part B

	2001-2004	**2004-2007**	**2007-2010**	**2010-2013**	**2013-2017**
Group 1	Silicon Valley Boston Area Austin Houston Tokyo, Osaka	Silicon Valley Boston Area Austin Houston Tokyo, Osaka	Silicon Valley Boston Area Austin Houston Tokyo, Osaka	Silicon Valley Boston Area Austin Houston Tokyo, Osaka	Silicon Valley Boston Area Austin Houston Tokyo, Osaka
Group 2	Paris, London Milan Cambridge Stockholm Munich Tel Aviv Berlin, Daejeon	Paris, London Milan Cambridge Stockholm Tel Aviv Berlin Mexico City Sao Paulo Santiago	Paris, Singapore London, Milan Cambridge Stockholm Tel Aviv, Berlin Mexico City **Shanghai** Santiago	Paris, Singapore London, Milan Cambridge Stockholm Munich, Hong Kong, Tel Aviv **Moscow**, Berlin Mexico City **Beijing, Shanghai**, Sao Paulo, Santiago	Paris, Singapore London, Milan Cambridge Stockholm Munich, Tel Aviv **Moscow**, Berlin Mexico City **Beijing, Shanghai** Santiago
Group 3	Taipei Seoul Gyeonggi-do	Taipei, Munich Seoul Gyeonggi-do Daejeon	Taipei, Munich Seoul, **Shenzhen** Gyeonggi-do Daejeon	Taipei Seoul **Shenzhen** Gyeonggi-do Daejeon	Taipei Seoul **Shenzhen** Gyeonggi-do Daejeon
Group 4	Singapore, Hong Kong **Moscow**, **Shenzhen**, Penang, **Beijing, Shanghai**, Sao Paulo, New Delhi Bangalore	Singapore, Hong Kong **Moscow** **Shenzhen** Penang, **Beijing** **Shanghai,** New Delhi, Bangalore	Hong Kong Moscow Penang **Beijing** Sao Paulo New Delhi Bangalore	Penang New Delhi Bangalore	Hong Kong Penang Sao Paulo New Delhi Bangalore
Group 5	Mexico City, Santiago				

note: dissimilarity measure level is 0.47

Table 3 Average values of RIS variables by group: average for 2013 to 2017

2013-2017	Cities	Intra-regional	Inter-regional	Inter-national	Local ownership, knowledge	Knowledge decentral'n	Tech. diversif'n	Relative cycle time	per capita GRDP (USD, 2015 PPP-based)	Growth of per capita GRDP (%)
Group 1 (Large, Mature RIS)	Silicon Valley, Boston Area, Austin, Houston, Tokyo, Osaka	0.14	0.52	0.34	0.94	0.86	0.49	0.98	84592.68	2.27
Group 2 (Mixed RIS)	Total 18 cities in this group	0.03	0.03	0.94	0.57	0.86	0.22	1.02	55756.56	4.40
	[sub-group A] Paris, Singapore, London, Milan, Cambridge, Stockholm, Munich, Berlin, Hong Kong, Tel Aviv	0.03	0.05	0.92	0.60	0.88	0.25	1.01	69561.14	3.06
	[sub-group B] Moscow, Mexico City, Beijing, Shanghai, SaoPaulo, Santiago	0.03	0.01	0.96	0.52	0.82	0.18	1.04	32748.92	6.62
Group 3 (Weak Catchup RIS)	Taipei, Seoul, Shenzhen, Gyeonggi-do, Daejeon	0.07	0.06	0.87	0.94	0.76	0.44	0.86	43748.19	5.33
Group 4 (Strong Catchup RIS)	Penang, New Delhi, Bangalore	0.02	0.01	0.97	0.13	0.87	0.14	0.84	20173.93	10.36
Average		0.06	0.13	0.81	0.66	0.84	0.31	0.96	55964.13	4.72

note: cluster analysis using internationalization, technological diversification, knowledge decentralization, local ownership of knowledge, and technology specialization (relative cycle time).

Table 4 Linking RIS to Economic Growth: 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)
No. 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)
Weak Catch-up RIS	0.0966***	0.0981***	0.116***
	(5.01)	(5.84)	(2.65)
Strong Catch-up RIS	0.0466***	0.0491***	0.110**
	(5.19)	(8.10)	(2.04)
Mixed 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
no. of cities	30	30	30
AR(2)			0.483

Note: Dependent variables is average annual growth rate of per capita GDP.
Mature RIS (group 1) is used as a benchmark.
Coefficients for Outlier dummies are not shown here.
1. Time dummies and regions dummies are not included because of multicollinearity.
2. Time dummies are included but region dummies are not included.

Appendix Table 1 Average Values from 2013 to 2017 (order by per capita GRDP)

	Average growth rate of per capita GRDP	Average per capita GRDP	population	patents	patents per 10,000
Paris	3.02	120,803.05	12,775,109	584.2	0.46
Silicon Valley	5.74	118,983.42	5,155,804	22,779.0	44.18
Boston Area	1.89	109,832.16	2,366,265	4,066.8	17.19
Singapore	4.02	87,213.21	5,524,685	942.0	1.71
Austin	4.46	81,342.80	1,177,602	2,386.4	20.26
Houston	-0.59	80,899.69	4,529,792	2,070.4	4.57
Tokyo	0.52	74,242.84	9,272,390	11,446.2	12.34
London	3.59	71,311.04	12,084,662	390.8	0.32
Milan	0.92	70,127.41	4,905,173	253.6	0.52
Cambridge	2.77	69,436.76	372,801	432.8	11.61
Taipei	3.62	68,817.73	6,666,178	3,972.8	5.96
Stockholm	2.86	67,727.17	2,185,874	294.8	1.35
Munich	3.62	57,396.88	2,806,039	787.0	2.80
Hong Kong	4.78	56,203.47	7,312,740	625.0	0.85
Tel Aviv	1.50	49,168.32	1,351,360	402.0	2.97
Moscow	6.72	47,320.05	12,199,240	261.0	0.21
Berlin	3.52	46,224.14	5,073,591	500.6	0.99
Seoul	4.44	43,665.01	9,903,047	4,681.6	4.73
Mexico City	7.55	42,521.07	8,853,550	42.4	0.05
Osaka	1.62	42,255.16	2,692,969	4,060.2	15.08
Shenzhen	7.82	42,098.20	11,444,640	2,296.4	2.01
Gyeonggi-do	6.32	36,045.33	12,443,481	9,302.2	7.48
Penang	6.90	29,587.08	1,700,120	98.6	0.58
Beijing	7.82	28,452.85	21,561,000	3,085.4	1.43
Daejeon	4.46	28,114.70	1,540,854	1,578.0	10.24
Shanghai	8.07	27,699.63	24,188,260	1,420.8	0.59
Sao Paulo	4.06	27,213.24	11,966,137	79.2	0.07
Santiago	5.53	23,286.69	7,228,440	43.6	0.06
New Delhi	9.34	15,573.05	18,520,200	153.0	0.08
Bangalore	14.84	15,361.66	10,157,455	1,103.6	1.09
Average	4.72	55,964.13	7,931,982	2,671.35	5.73

Appendix Table 2: Descriptive Statistics

All regions for whole period	mean	standard deviation	min	max
growth rate of per capita GRDP	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 whole period				
growth rate of per capita GRDP	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			
Mixed RIS for whole period				
growth rate of per capita GRDP	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			
Strong Catch-up RIS for whole period				
growth rate of per capita GRDP	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			
Weak Catchup RIS for whole period				
growth rate of per capita GRDP	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			

Figure 1 Dendrogram of cluster analysis using 7 RIS variables

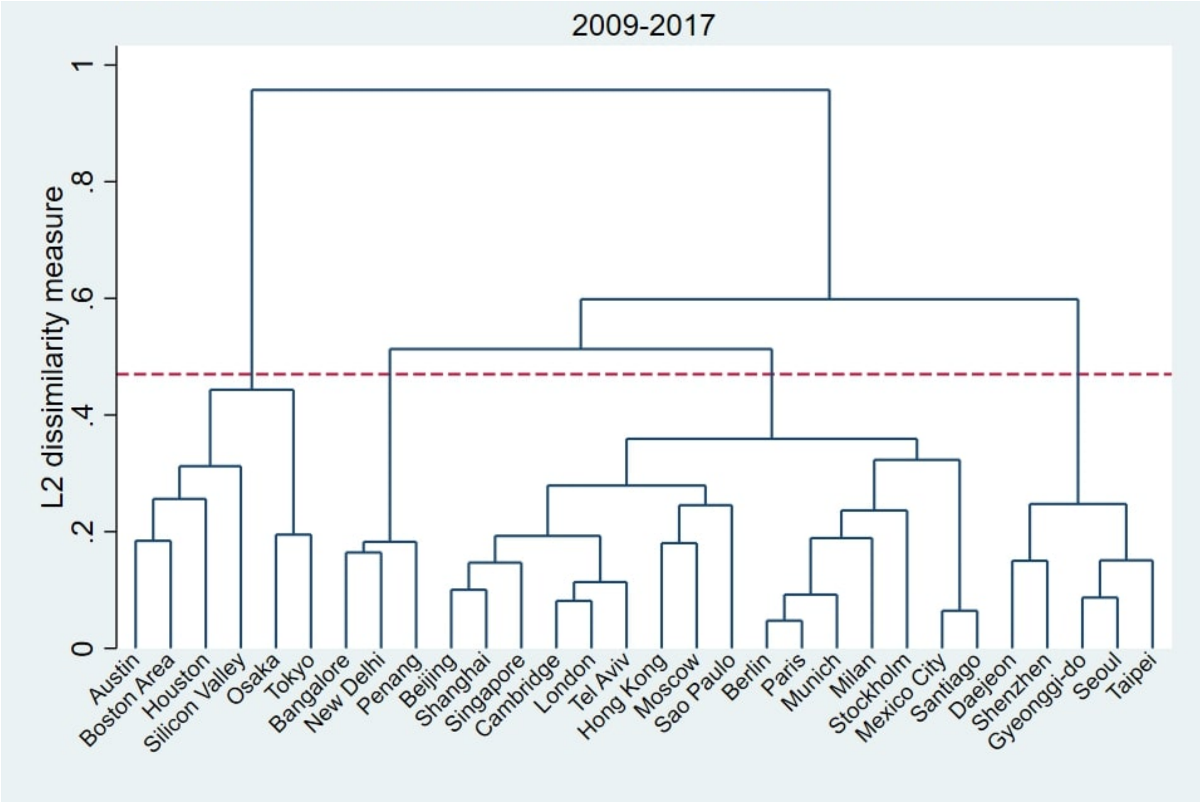
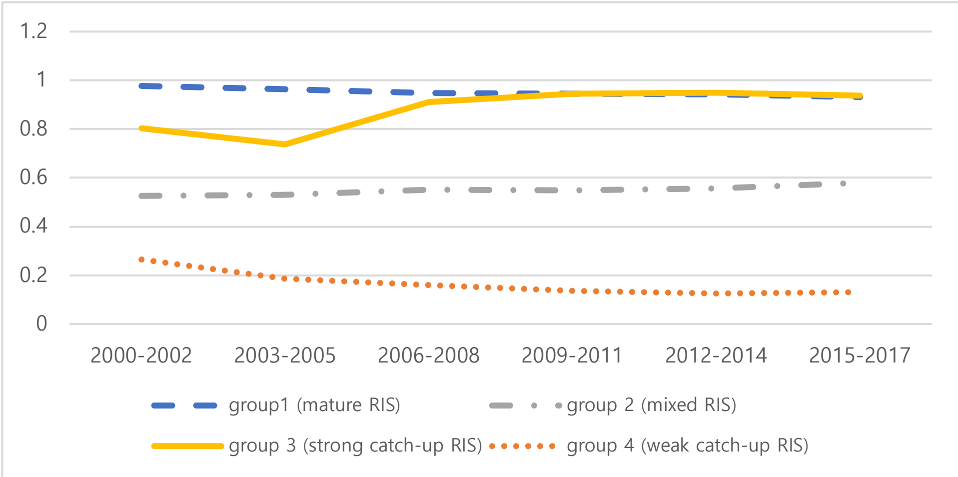
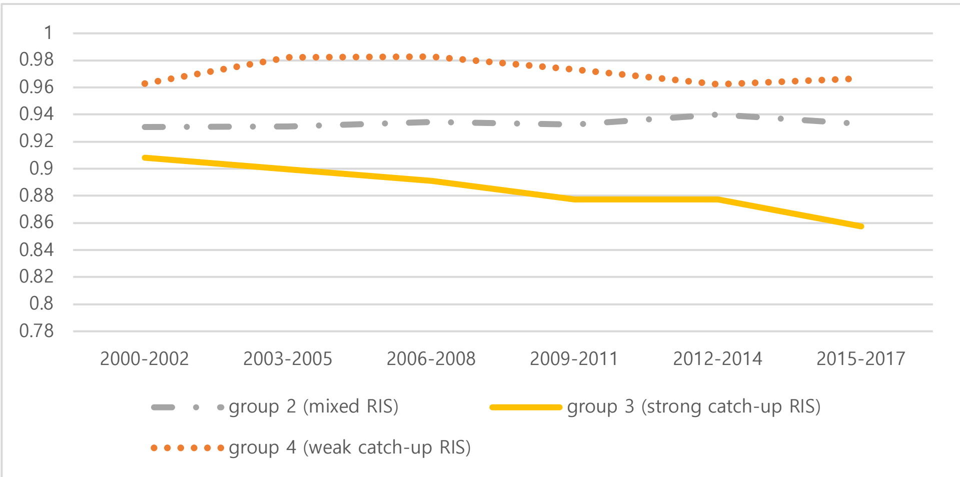


Figure 2B Trends of Local ownership of knowledge



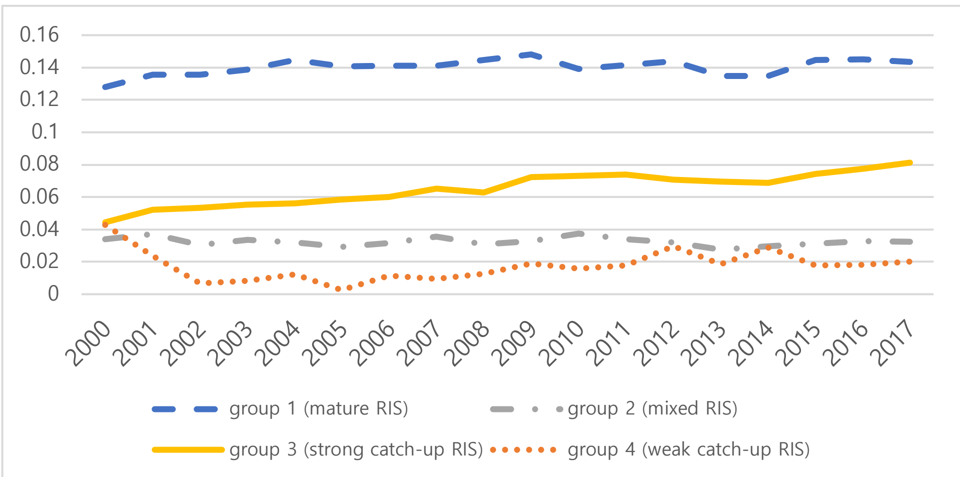
Source: Author's calculation

Figure 2C Trends of International Sourcing



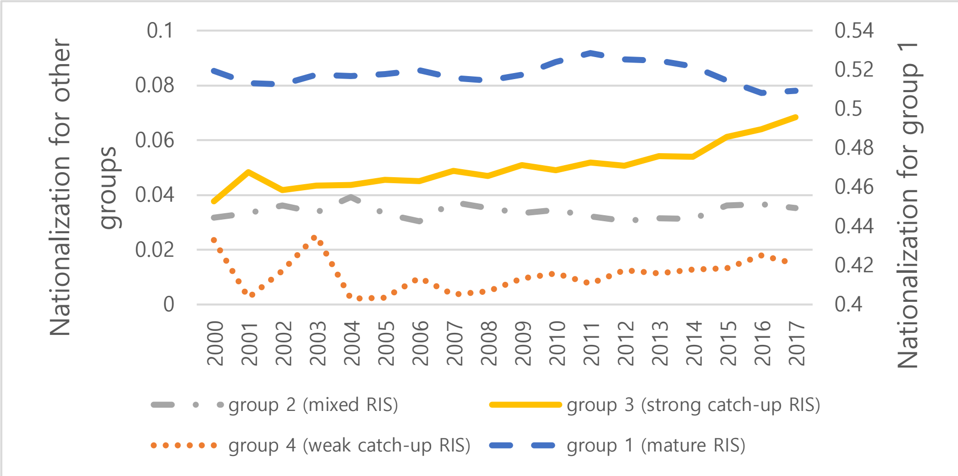
Source: Author's calculation
Note: Values for Group 1 (mature) are all below 40%, and not shown here.

Figure 2D Trends of Intra-regional Sourcing by group



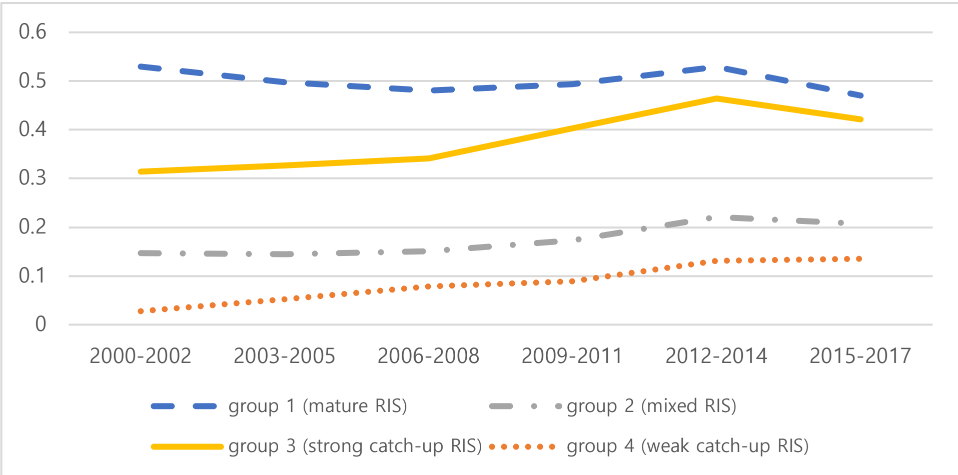
Source: Author's calculation

Figure 2E Trends of Inter-regional Sourcing by group



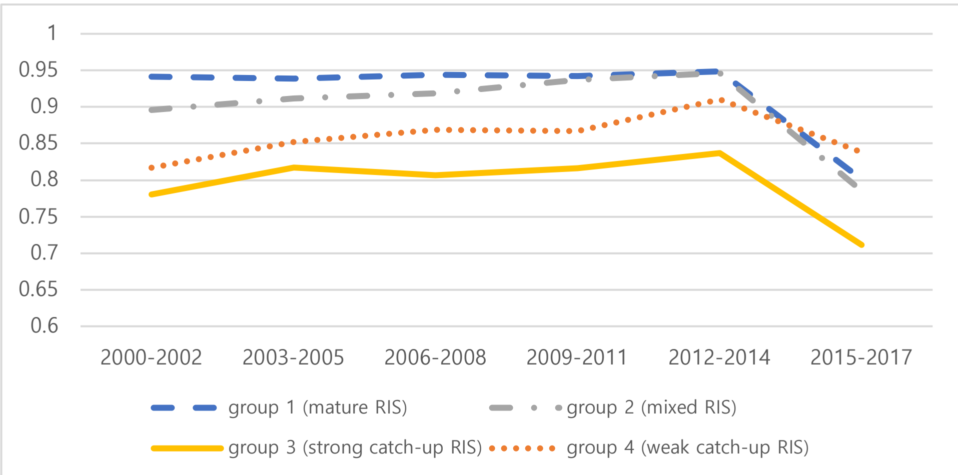
Source: Author's calculation

Figure 2F Trends of Technological diversification



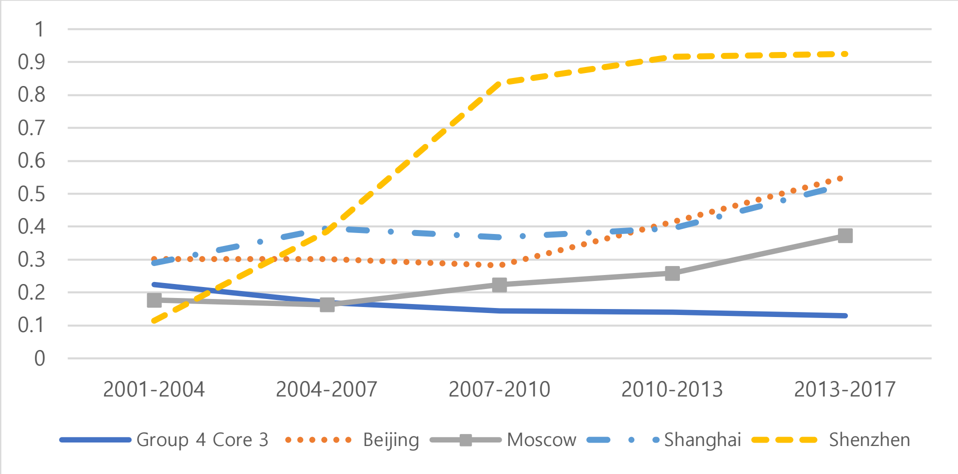
Source: Author's calculation

Figure 2G Trends of Knowledge decentralization



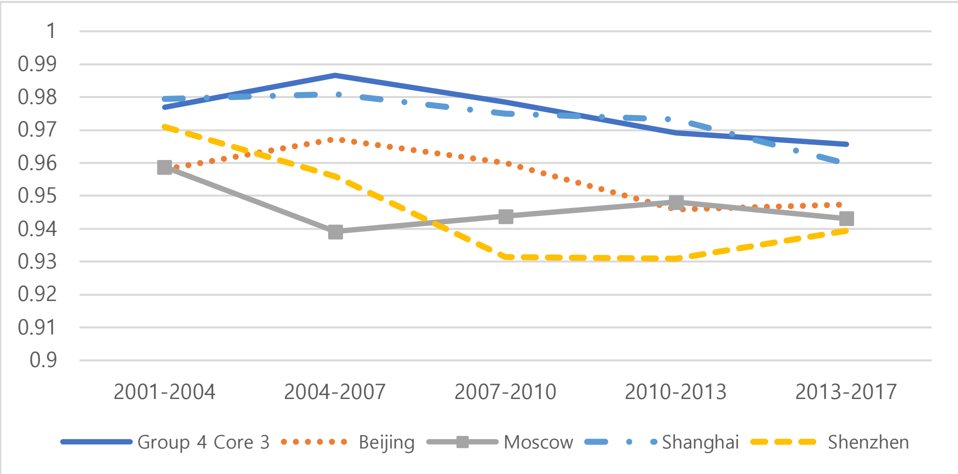
Source: Author's calculation

Figure 3A Local ownership of knowledge



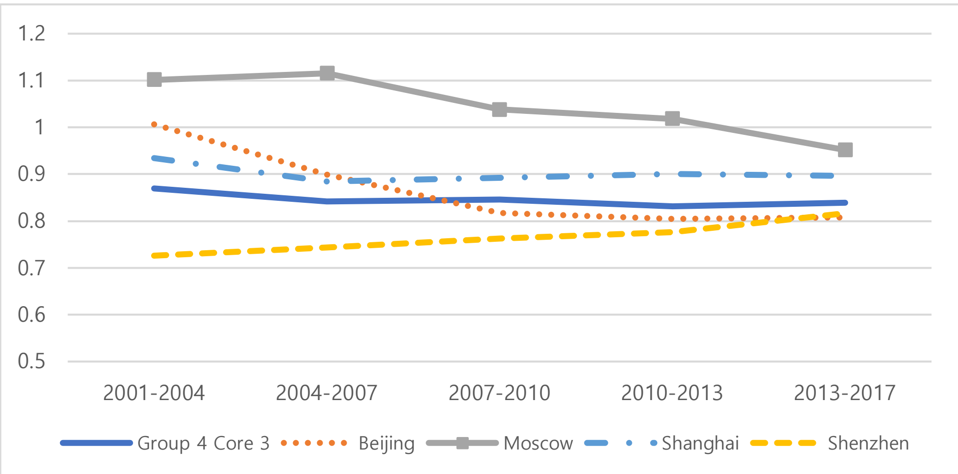
Source: Author's calculation
Note: Core 3 include Bangalore, New Delhi, and Penang

Figure 3B International Sourcing



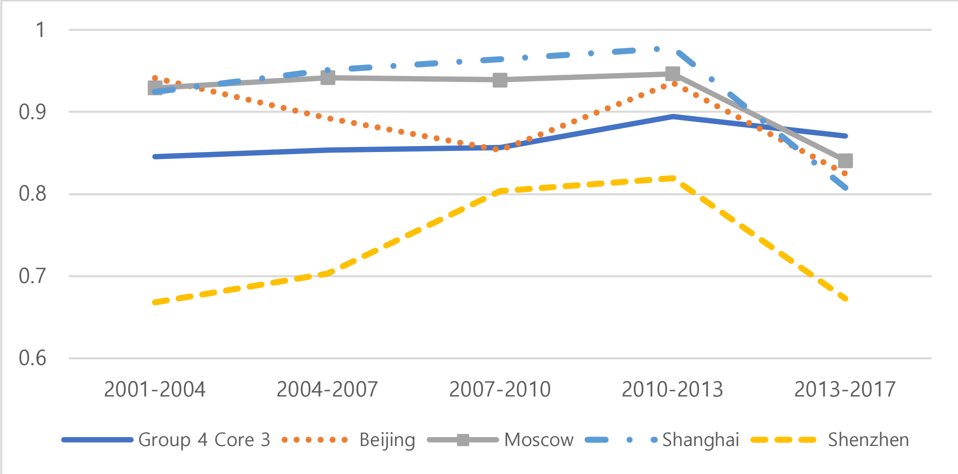
Source: Author's calculation
Note: Core 3 include Bangalore, New Delhi, and Penang

Figure 3C Relative cycle time



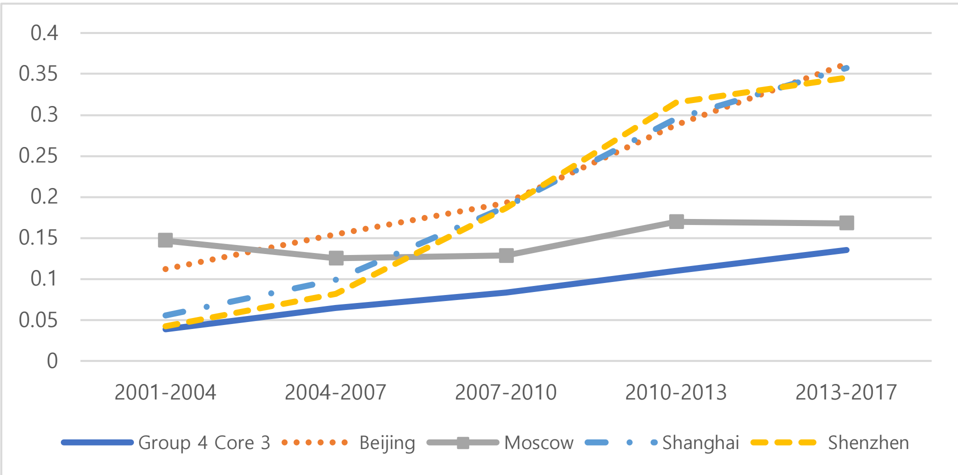
Source: Author's calculation
Note: Core 3 include Bangalore, New Delhi, and Penang

Figure 3D Decentralization



Source: Author's calculation
Note: Core 3 include Bangalore, New Delhi, and Penang

Figure 3E Diversification



Source: Author's calculation
Note: Core 3 include Bangalore, New Delhi, and Penang

Figure1x Trends of Inter-regional Sourcing – Beijing, Shanghai, Shenzhen, Bangalore, New Delhi, and Group 1