Variety of national innovation systems (NIS) and alternative pathways to growth beyond the middle-income stage: Balanced, imbalanced, catching-up, and trapped NIS

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Abstract
This study uses the US patent data of 32 to 35 economies to measure, classify, and analyze the evolution and performance of their respective national innovation systems (NIS) or technology clubs, with a focus on those economies that sustained growth beyond the middle-income stage. The NIS is measured in terms of five variables, namely, knowledge localization, technological diversification, cycle time of technologies, originality, and decentralization. The cluster analysis identifies five major NIS clusters that are either balanced or imbalanced in terms of the relative values of the five NIS variables. Growth equation regressions confirm two pathways to achieve catching-up toward the high-income status. The one pathway has been identified for Ireland, Spain, Hong Kong, and Singapore, which all belong to the balanced and mixed NIS cluster and are joined recently by India and Russia, thus achieving “balanced catching-up”. The other pathway has been identified for Korea and Taiwan, which created imbalanced and catching-up clusters, and is recently joined by China. In contrast to these two groups, we have also identified the trapped NIS consisting of those economies perceived to be stuck in the middle-income trap, such as Brazil, Argentina, Chile, Mexico, South Africa, Malaysia, and Thailand. The imbalanced and catching-up NIS is characterized by short cycle time of technologies, low originality, high localization, and high diversification compared with the trapped NIS with the exactly opposite attributes. By contrast, the balanced and catching-up group is characterized by all of these NIS variables that are balanced at intermediate values.

1. Introduction

Despite the voluminous amount of research over the three-century-long history of economics, how to achieve sustained economic growth still remains underexplored and has been a longstanding topic in economics research (North, 2005: vii). Recent attention has been paid to the so-called middle-income trap (MIT), which is a situation wherein middle-income economies face decelerated growth and consequently fail to join the ranks of high-income economies. Interest in this MIT phenomenon, which was first mentioned in Gill and Kharas (2007), has increased, with this research subject having been investigated by the World Bank (2010, 2012), Eichengreen et al. (2014), and Lee (2013). Some economists have doubted the existence of such a trap, and these conflicting views seem to be due to the varying definitions of methodologies to test its existence.

Regardless of whether or not MIT exists, many countries are struggling at the middle-income stage. A study by the World Bank (2012) found that only 13 out of the 101 middle-income economies have joined the club of high-income economies since 1960. Among the group of 13 economies, 10 were reported to be upper-middle income economies, including Greece, Portugal, Spain, Ireland, Hong Kong, Israel, Japan, Mauritius, Puerto Rico, and Singapore. Only two countries were reported to be lower-middle-income economies (Korea and Taiwan), and one was an oil-exporting country (Equatorial Guinea). On the basis of this phenomenon, this study seeks to answer the question of what makes countries in the middle-income stage sustain economic
growth and reach high-income level and whether any alternative pathways exist other than those of Korea or Taiwan, as identified in Lee (2013).1

We look at the issue from a Schumpeterian perspective, given that innovation capability has been increasingly recognized as the key bottleneck and solution for an economy at the middle-income stage to sustain economic growth (Lavopa and Szirmai, 2018; World Bank, 2010: Lee and Kim, 2009; Cirera and Maloney, 2017). The critical importance of innovation capability is consistent with the earlier observation of the World Bank (2010), suggesting that middle-income economies tend to fall into MIT because they become caught between low-wage manufacturers and high-wage innovators. Accordingly, this study uses the concept of the national innovation system (NIS), which is a key theoretical framework in Schumpeterian economics. This framework goes back to Nelson (1993) and Lundvall (1992), where NIS is defined as “elements and relationships which interact in the production, diffusion and use of new, and economically useful, knowledge.” The Schumpeterian thesis suggests that the effectiveness of the NIS determines the innovation performance of nations and their economic performance.

A large of volume of the literature has measured various dimensions of NIS and analyzed the relationship between them and economic growth (Edquist, 1997; Desai et al., 2002; Fagerberg and Verspagen, 2002; Archibugi and Coco, 2004; Fagerberg and Srholec, 2008; Filippetti and Peyrache, 2011: Castellici and Natera, 2015), whereas some studies emphasize the term, technology clubs, than NIS (Castellici, 2008, 2011; Castellici and Archibugi, 2008). These studies have measured NIS or technology clubs by using numerous variables to capture the diverse aspects of an economy. These works are consistent with the view that NIS is a combination of techno-economic and socio-institutional elements (capabilities or actors) and their interactions. This paper is not about another way of measuring NIS but about sustaining growth beyond the middle-income stage, and thus adopt a narrow, patent-driven measure of NIS, specifically designed for the purpose of the research on MIT.2

A central question in this study is whether or not multiple types of NIS or technology clubs exist, which characterize the sustained economic growth beyond the middle-income stage. If such a type or club can be identified, then it can be compared with the NIS of those that are stuck in the so-called MIT, a situation wherein per capita incomes remain stagnant (20 to 40% level of the US) for long periods (World Bank, 2012: 12). The answer to the above-mentioned question from the analysis is that two distinctive types of NIS are associated with the sustained growth beyond the NIS: the one with imbalanced specialization into short-cycle technologies and the other with more balanced specialization. These two groups of economies share the common pattern of an increasing degree of knowledge localization and technological diversification, which has not been the case in the trapped economy group. A critical contribution of this research is to show that alternative pathways exist to sustain growth beyond the middle-income stage. The study verifies this idea by a combination of the cluster analyses of changing NIS types over time as well as econometric regressions linking NIS types to economic growth.

To classify countries into several types of NIS or technology clubs, we use five component variables expressing different dimensions of NIS, namely, knowledge localization (diffusion), technological diversification, innovator decentralization, originality, and cycle time of technologies (CTT). Some of these components were first proposed in Jaffe et al. (1993) and Jaffe and Trajtenberg (2002) and were used to analyze NIS in Lee (2013) and Lee and Lee (2019). As explained in detail in the Section 3, one advantage of these variables is that they can express some of the technological structures of economy that are more relevant at the middle- or high-income stage but go beyond the simple share of manufacturing or services in the GDP. These technological aspects of NIS are measured by using a single data set comprising patents filed in the US. The advantage of using such a dataset is that the data sources are homogeneous. Thus, the variables are easily collected and consistently measured for different countries over a long period. This method can also be justified given that the analysis does not focus on every spectrum of economies but only on those in the middle- or high-income stage that have filed a certain volume of patents.

In this sense, the analysis focuses on the relationship among production, diffusion and distribution of technological and scientific knowledge, and economic growth. We then demonstrate that some economies, such as Ireland, Spain, Hong Kong, and Singapore, have also created their own unique medium-cycle technology-based NIS that is different from the short-cycle-technology-based group of Korea, Taiwan, and China.3

The rest of the study is organized as follows. Section 2 discusses the record of catching-up or falling behind by diverse economies worldwide to derive some hypotheses for NIS grouping. Section 3 discusses the relevant literature on the NIS and provides a discussion of empirical methodologies and the measurement of key variables. Section 4 presents the results of cluster analysis about the variety of NIS and their dynamic evolution, and conducts a regression analysis of the growth equation. Section 5 discusses the dynamic process of transition from the middle-income to the high-income stage involving catching-up NIS compared with the trapped NIS. Section 6 concludes this study by summarizing the main results and discussing the broad implications.

2. Record of economic catching-up and stagnation and hypothesizing

Although the focus of empirical analysis is on a group of economies that have made the successful transition toward high-income status, other countries are considered together for comparison. A group of countries consists of those considered to be stuck in the MIT, and the other group comprises high-income economies. We consider 32 economies worldwide, with a minimum condition that they should have approximately 10 or more US patents filed each year.

First, we consider those regarded as having sustained growth beyond the middle-income stage (World Bank, 2012: 12): Japan, Spain, Ireland, Portugal, Greece, Israel, Hong Kong, Singapore, South Korea, Taiwan.4 Second, among the emerging economies, we included those five large economies or the so-called BRICS, namely, Brazil, Russia, India, China, and South Africa. Third, we included five

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1 Lee (2013) focused only on the successful cases of catch-up in a few East Asian economies, such as Korea, Taiwan, and China, but failed to include other economies (or the 13 economies) to seek possible alternative pathways.

2 NIS approach is flexible as it allows both narrow and broad definitions (Chaminade et al. 2018: 6-9).

3 Such results about NIS types also connect this study with the broader literature on the variety of capitalism (VoC) initiated by Soskice and Hall (2001) by providing comparisons of NIS types and types of capitalism. The literature on VoC proposed by Soskice and Hall (2001) classified economies worldwide in terms of several key institutions and identified two or three representative types of capitalism, such as liberal market economies (LMEs), coordinated market economies, and mixed market economies.

4 Mauritius, Puerto Rico, and Equatorial Guinea are among the 13 countries identified by the World Bank. But, we excluded them for various reasons; their number of patents are particularly little to be reliable, such as Puerto Rico, Mauritius, and one is an oil exporting country (Equatorial Guinea). Also, Mauritius has reached the 40% of the US income level, but discuss it only when we discuss long term growth rates as in Figure 1B.
other economies that are relatively big and at the upper middle-income stage but may belong to different NIS, if any correspondence exists between economic performance and NIS. In Fig. 1B, we turn to the other economies that are relatively big and at the upper middle-income stage but suspected to be in the MIT, namely, Brazil Argentina, Mexico, and Chile from Latin America, and South Africa in Africa. Mauritius is added to this group for comparison. The per capita GDP of all five economies have maintained stagnant since the 1960s, roughly within the 20% to 40% level of the US for more than 5 decades since the 1960s. The level of Argentina was higher than 40% in the 1960s. This trend continued to decline below the 40% level since then. Given the homogenous record of slow catching-up, these countries should belong to the same NIS, if NIS can explain their performance.

Finally, we turn to the long-term performance of Asian economies. In Fig. 1C, every economy has shown a steady (slow or fast) catch-up trend, which is in sharp contrast with the trend of the overall stagnation or even decline in Latin America. These economies, which was initially a low middle-income economy, started with their per capita income below the 20% that of the US or the threshold for upper middle-income level, except Hong Kong and Singapore whose income levels were approximately 30% that of the USA; however, their catching-up speed also has some variations. For example, the four east Asian tigers show fast catching-up, reaching more than 60% or even 100% of that of the US. Thailand and Malaysia remained within 20% to 40% range (or the so-called MIT range) for the last 50 years or until 2000s. China is the only economy with a low income level in 1960, and it has shown a rapid catch-up, reaching the 30% level by the late 2010s. Given this somewhat slow catch-up in Thailand and Malaysia and the literature on the possibility of the MIT occurring in these economies (Yusuf and Nabeshima, 2009), these two economies may belong to different NIS groups from Asian tigers and China but to the same as those of other trapped economies from Latin America. We will show later that this is the case.

The above discussion suggests the possibility of more than one or multiple groups corresponding to varying catching-up performance. Given some variations in this catching-up or stagnation record, we may assume the possibility that one or more catching-up groups and at least one trapped group are present. This phenomenon may be attributed to the fact that a group of economies is catching-up to a high level of per capita GDP close to 100% of the US and another group above the 60% level but below 90%. A third group of economies is still below 40% (MIT) or close to 40% (stagnation). Some outliers can be observed, such as Japan with a large GDP size and incomparable number of US patents and China with a huge size but rapidly catching-up since the 1980s. Given the huge and diverse heterogeneity among these economies beyond the innovation-related aspects, we will turn to the issue of how the NIS typologies would be able to explain the divergent growth performance: fast or slow catching-up, stagnation, or relative decline.

3. Diverse ways of measuring NIS and technology clubs

3.1. Literature

On the basis of the early studies on NIS (Lundvall, 1992), the OECD has conducted several studies of its own (OECD, 1999, 1997). The OECD (1997) adopted the original definition of the NIS by Lundvall, which focuses on four types of knowledge flows. Since the last decade, an increasing number of empirical studies have measured the relevant dimensions comprising the NIS. However, few studies have concentrated on the typology of the NIS through cluster analysis, with important exceptions, such as Godinho et al. (2005), Balzat and Pyka (2006), Castellacci and Archibugi (2008), Fagerberg and Srholec (2008), and Castellacci and Natera (2015), who all analyzed NIS by using factor or cluster analysis.

Godinho et al. (2005) presented one of the early pioneering studies that conducted a cluster analysis of 24 variables in 2002/2003, covering as many as 69 countries with eight NIS dimensions. Although their study identified two or six clusters depending upon the degree of aggregation, the three most important dimensions differentiating NIS types are those related to innovation, diffusion, and knowledge, whereas the factors associated with the five remaining dimensions play a much smaller role. Thus, this finding provides justification for this study to focus on dimensions related to the creation, diffusion, and use of knowledge. Meanwhile,
There are several studies that use the term, technology clubs, though they may be considered as falling broadly under the NIS literature. Notably, Castellacci and Archibugi (2008) conducted factor and cluster analyses for a large number of countries and identified three technology clubs, namely, advanced, follower, and human capital), specifically, in the upgrading transition from a low-tier to a high-tier club (Castellacci and Archibugi, 2008; Castellacci, 2011). Their analyses also underscore the importance of improving innovation capabilities and their diffusion (R&D, patents, or publication intensity) beyond technological infrastructure and absorptive capacity (telephony and electricity and human capital), specifically, in the upgrading transition from the follower club to the advance club.

While these studies also identify several countries undergoing upgrading transition, their study do not consider a considerable variety of dimensions of knowledge creation and diffusion beyond the simple measure of Internet penetration and thus do not fully provide the details of the dynamic process of upgrading or convergence. This point is where the current study aims to start, by considering new variables to represent the evolution of the technological structure of an economy, such as technological diversification, decentralization, localization, and specialization, beyond simple measures of R&D, patents, or publication intensity.

### 3.2. Current study

The current study has one or more differentiating aspects compared with each of the abovementioned studies. First, this work takes a somewhat narrow but focused measurement of NIS, focusing on knowledge flows measured by patent citation data. Despite its intrinsic limitations, it is close to the original definition of NIS by Lundvall (1992) or OECD (1997). Second, this study conducts a cluster analysis to identify diverse NIS types across country
groups rather than take pre-assumed or geographically oriented grouping. Third, compared with the research of Lee and Lee (2019), which is a straightforward regression of economic growth on a composite index of NIS and complexity, the current study links the NIS types to alternative pathways from middle- to high-income economies and to downgrading or stagnation (i.e., being stuck at the MIT).

We now briefly explain the five NIS component variables, while the details are available in Appendix 1. The first variable for NIS is knowledge localization, which is about the degree of localization.

Fig. 1. Per Capita Income as % of that of the US. Notes and Sources: Drawn using the data from the Maddison project: https://www.rug.nl/ggdc/historicaldevelopment/maddison/releases/maddison-project-database-2018.
representing intranational creation and diffusion of knowledge (Jaffe et al., 1993). This variable measures how much knowledge is domestically created by citing the patents owned by the same nationality. It refers to the degree of national-level self-citation after normalization and is thus designed to be free from the size effect (namely, a big country has a high localization ratio). If the degree of localization is large, then the domestic diffusion of knowledge is high, whereas the share of foreign patents in the citation is low. The second variable is technological diversification, which captures the degree to which a country produces patents in a wide variety of technological fields. Technological diversification is about the width of the patent portfolio of a country and may be complementary to product or export diversification.\footnote{Technological diversification is measured by the number of technological classes in which a country 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.}

The third variable is to measure technological specialization by the variable called cycle time of technologies (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 and Trajtenberg, 2002). Specifically, CTT refers to the extent to which a patent relies on recent or old technologies for the invention of new knowledge.\footnote{In our analysis, we do not have a separate variable for international reliance in knowledge sourcing because it is inversely related to knowledge localization. Specifically, the inverse of knowledge localization can be a measure of a country level of (internationally) open innovation.} Hence, 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.\footnote{In our analysis, we used relative (or normalized) CTT, which is the absolute years difference because we use the multiyear (eight-year) average values to construct NIS.} Lee (2013) reported that successful latecomer economies, such as South Korea and Taiwan, tend to focus on sectors with short CTT, such as information technology (IT) goods, during their rapid economic catch up since the mid-1980s. In contrast, advanced countries tend to specialize in sectors with relatively long CTT, such as the pharmaceutical sector.

The fourth NIS variable is about 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 fifth variable is originality, Hall et al. (2005) and Trajtenberg et al. (1997) suggested that this variable measures the degree to which a patent makes (backward) citations to patents from a wider range of technological classes rather than from a narrow field of technologies. This definition represents the rationale that the originality of a patent will be high when the technological root of the underlying knowledge or research related to the patents is broad. The synthesis of divergent ideas is possibly characteristic of research that has high originality and is thus basic in that sense (Trajtenberg et al., 1997). In this way, this variable can also be interpreted as representing the degree of knowledge convergence and combination.

The above-mentioned measures of NIS relying on patents are subject to the intrinsic limit. limitations. First, patents are subject to sectoral and cross-country heterogeneity. Accordingly, we use patents filed in the biggest economy, the US, granted and assigned to each country for empirical analysis.\footnote{While such correspondence between the three indicators and the level of economic development are desirable, they are also high-entry barrier sectors for latecomers.} In other words, we use a homogenous dataset (i.e., US patent data) to overcome the intrinsic challenge of comparing NIS using variables from a heterogeneous source, and thus this method is good for a long-term analysis of the evolution of NIS. Further, we conduct several types of robustness tests, such as omitting US and its nearby countries in the cluster analysis or growth regressions, which will be explained later. Then, a remaining issue is that patents capture codifiable/explicit knowledge only. However, tacit dimensions of knowledge are ignored, which is equally important in innovation but cannot be filed as patents. Thus, at least two additional variables can be considered, such as scientific publications and trademarks.

Trade marks protect and appropriate the value of innovations when innovations are made with the use of tacit knowledge (De Vries et al., 2017) and thus have been recognized as another proxy measure of innovation that complements patents (Mendonga et al., 2004; Sandner and Block, 2011; Fikkmka et al., 2014). Trademarks can also be regarded as a market-based IPR whereas patents are technology-based IPR (Block et al., 2014). In the context of development, Kang et al. (2020) verified two alternative modes of technological development by latecomers, namely, patent-driven and trademark-driven paths. They found from the Korean experience that at an earlier stage of development, industrial firms are domestic market-oriented and tend to file trademarks given their weak level of technological capabilities. Only at later stages do they tend to switch to file many patents, as their capabilities grow sufficiently enough to conduct hard core innovations that can turn into patents.

The academic publications represent scientific knowledge, which is different from technological knowledge represented by patents. Although generating additional scientific knowledge should be desirable, its ultimate impact on economic growth is affected by the effectiveness of an NIS in translating scientific knowledge into commercial usages. Kim and Lee (2015) showed that technological knowledge (patents) tends to have a great immediate influence on economic growth. By contrast, scientific publications do not necessarily lead to technological knowledge (patents) or actual economic growth unless a country has an effective NIS translating the former to the latter.

While the NIS is still more than something that can be reduced to the three indicators of patents, trademarks, and publication, we find some linkages between them and a production structure of a country, as reflected in simple regressions shown in Appendix 2. The analyses show that for a given level of economic development (per capita income), the number of trademarks normalized by a size of an economy tends to be positively associated with the share of manufacturing, whereas that of patents is positively associated with both the shares of manufacturing and services in GDP, trade openness. Moreover, that of publications is positively linked to trade openness and tertiary education but negatively related to the share of manufacturing.

While such correspondence between the three indicators and production structure is interesting, a deeper analysis of growth at the middle- or high-income stage would require more variables than simple production structure. Fine-grained variables, such as the share of high-tech, medium-tech or low-tech, would be better. However, such variables from the OECD are available only for a limited time span even for OECD countries. The OECD measures of the high-tech, med tech, and low tech are based on R&D intensity, which is also the key variable in a study on technology clubs (Bos et al., 2010). While having a bigger share of high R&D intensity sectors are desirable, they are also high-entry barrier sectors for latecomers.
In contrast, the short cycle technology sectors correspond to low entry barrier (quick obsolescence of existing knowledge) and high growth prospects (high frequency of new innovations), which qualifies as a good target sector for latecomers. In this sense, cycle time variables represent a useful criterion for sectoral specialization for latecomers. Also, technological diversification can be a counter-part variable of production/export diversification, whereas technological decentralization can correspond to industrial structure (like more competitive or oligopolistic). In sum, whereas traditional production structure variables have become less useful given the blurring boundary across first, secondary and tertiary industries and the share of services in the South equally high as that in the North due to premature de-industrialization, NIS variables considered here to reflect technological structure of an economy may be considered useful as an analytical tool, as shown by the next section.

4. Analyzing the variety of the NIS and its performance in economic growth

4.1. Identifying NIS clusters using the patent citation data

This part utilizes the USPTO (2017) bulk data, that is, a weekly released US patent panel dataset for the period of 1976 to 2017. This bulk data has been subject to a long process of data mining.16 Table 1 presents the recent values of the five NIS component variables in the 32 economies, that is, the average values for the period of 2008 to 2015.17 We then conduct a cluster analysis, which is also used in the literature on VoC, by using these five NIS component variables (Table 1). The cluster analysis aims to identify the degree of structural commonality among objectives (namely, countries in our case), and it accomplishes a categorization of the countries by maximizing the coherence of each group (or cluster) and the heterogeneity across different groups.18 This clustering method is applied to the five NIS variables of the countries selected in this study to identify countries in the same or different cluster.

The cluster analyses are conducted for two rounds for different sample for robustness. A smaller sample of 22 representative economies are used at the first round, and all the 32 economies are analyzed in the second round.19 Both analyses using the 22 and 32 countries produce the consistent results of identifying the four or five clusters plus two outlier countries of US and Japan.20 Fig. 2 shows the dendrogram of the results of the cluster analysis by using the data of the most recent period or average of the values for the 2008 to 2015 period.21 Given no single best rule, one may utilize a priori knowledge to select a reasonable number of clusters or groups (Godinho et al., 2005). We choose the 0.3 level of dissimilarity (box with red dotted lines in Fig. 2) to identify five groups as long as we count only those with at least three or more members, aside from the two outliers (US and Japan).

We can understand the main characteristics of these NIS clusters by reading the values of the NIS variables of each cluster in Table 2 and looking at the radial graphs of each NIS cluster in Fig. 3.22 Before we discuss the features of each group, several overriding features of the results of the cluster analysis can be examined. First, one of the important and interesting aspects of the differences of NIS between advanced versus emerging economies is that the former tends to show equally high values for all the five component variables NIS. By contrast, typical emerging economies show a bigger divergence among the five components. Accordingly, we identify two imbalanced NIS among emerging economies, the one showing successful catching-up and the other demonstrating the symptom of MIT. Among the balanced NIS in high-income economies, we can also distinguish two tiers: the first tier with a highest composite or aggregate NIS index with a larger area in the radial graph of NIS and the second tier with medium–high values of composite/aggregate NIS or a bit smaller size of the area radial graph than the first tier group. Thus, we may call the balanced and first tier NIS, and balanced and second-tier NIS countries.

First, a cluster of the major European economies consists of Germany, France, the UK, and Italy, which is additionally joined by Switzerland and Canada from the full sample. This group is the balanced and first-tier NIS cluster, corresponding to the highest value of composite NIS index. The actual values in Table 2 and graphs in Fig. 3 indicate that this group boasts the largest area with equally high values in all the five indicators. The size of the area in the radial graph can be represented by the variable called NISS (3.39) in Table 2, which is the simple summation of five component variables after normalization to make it range from zero to five. The low variation is shown by low values of coefficient of variation (0.285 in Table 2) of the 5 NIS variables. The second cluster includes Finland, Sweden, Netherlands, and Israel, and can be called the balanced and second-tier NIS because they are balanced in all the five aspects; however, their aggregate values are not as high as those of the first-tier group.23 Thus, the radial graph of this group is nested inside the boundary of the balanced and first tier NIS cluster in Fig. 3.

The third and fourth cluster include two groups from emerging economies, and both are imbalanced but with quite different spe-

20 The novelty of the database is its ability to provide full information for the entire set of patents granted in the US. We conduct data mining following the method suggested by Potter and Hatton (2013) to turn this bulk data into user-friendly forms (Lee and Lee 2019). The first step is to acquire the patent data files by manually downloading 2132 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 documents in the corpus and then catalog the patent numbers for each patent granted since 1976.

21 Patents are classified into each country according to legal assignees of each patent and into year according to its granted year.

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23 The values of the NIS variables in this radial graph are all normalized to make them range from zero to one, thus making the relative difference more visible than the absolute values presented in Table 1 or 2. For instance, the values of the A variables are transformed by using the maximum and minimum values of the A variables in the sample period: Normalized value of A = (A − minimum value of A)/ (maximum value of A − minimum value of A).

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The third group comprised of three economies in East Asia with a rapid growth or catching-up, such as China, South Korea, and Taiwan. This group is also the imbalanced NIS because it shows a much higher coefficient value of variation among the five component variables (0.685) than the two balanced clusters. The aggregate index (NIS5) of this group is the third at 2.49. The fourth group includes other typical emerging economies, namely, Argentina, Brazil, Chile, Malaysia, Mexico, South Africa, Thailand, Greece, Portugal. Sources: Author’s calculation.

<table>
<thead>
<tr>
<th>Group</th>
<th>Nations</th>
<th>1-HHI</th>
<th>Localization</th>
<th>Diversification</th>
<th>Originality</th>
<th>Relative cycle time</th>
<th>NIS5</th>
<th>Average No. of patents per year</th>
<th>Coefficient of Variation (5 NIS indicators)</th>
<th>Growth of per capita income (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Balanced and first tier NIS</td>
<td>Canada, France, Germany, Italy, Switzerland, UK</td>
<td>0.9811</td>
<td>0.0913</td>
<td>0.6979</td>
<td>0.4625</td>
<td>1.1114</td>
<td>3.3937</td>
<td>4725</td>
<td>0.285</td>
<td>0.04</td>
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<tr>
<td>Balanced and Mixed NIS</td>
<td>Denmark, Hong Kong, India, Ireland, Norway, Russia, Singapore, Spain</td>
<td>0.9641</td>
<td>0.0458</td>
<td>0.2705</td>
<td>0.4552</td>
<td>1.0423</td>
<td>2.4229</td>
<td>493</td>
<td>0.530</td>
<td>1.51</td>
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<tr>
<td>Balanced and mixed cycle Group</td>
<td>Hong Kong, Ireland, Singapore, Spain</td>
<td>0.9599</td>
<td>0.0365</td>
<td>0.2851</td>
<td>0.4498</td>
<td>1.0019</td>
<td>2.2911</td>
<td>533</td>
<td>0.580</td>
<td>1.52</td>
</tr>
<tr>
<td>Balanced and second tier NIS</td>
<td>Finland, Sweden, Israel, Netherlands</td>
<td>0.8846</td>
<td>0.0827</td>
<td>0.4816</td>
<td>0.4686</td>
<td>1.0221</td>
<td>2.6514</td>
<td>1804</td>
<td>0.221</td>
<td>0.21</td>
</tr>
<tr>
<td>Imbalanced short-cycle NIS</td>
<td>China, South Korea, Taiwan</td>
<td>0.9226</td>
<td>0.1044</td>
<td>0.6550</td>
<td>0.3595</td>
<td>0.8421</td>
<td>2.4887</td>
<td>8426</td>
<td>0.628</td>
<td>4.39</td>
</tr>
<tr>
<td>Imbalanced and long cycle NIS</td>
<td>Argentina, Brazil, Chile, Greece, Malaysia, Mexico, Portugal, South Africa, Thailand</td>
<td>0.9371</td>
<td>0.0264</td>
<td>0.0784</td>
<td>0.4336</td>
<td>1.1730</td>
<td>2.1086</td>
<td>58</td>
<td>0.714</td>
<td>0.74</td>
</tr>
<tr>
<td>Imbalanced and long-cycle Group</td>
<td>Argentina, Brazil, Chile, Malaysia, Mexico, South Africa, Thailand</td>
<td>0.9380</td>
<td>0.0289</td>
<td>0.0889</td>
<td>0.4430</td>
<td>1.1750</td>
<td>2.1730</td>
<td>67</td>
<td>0.685</td>
<td>1.51</td>
</tr>
<tr>
<td>Two special cases</td>
<td>Greece, Portugal</td>
<td>0.9340</td>
<td>0.0180</td>
<td>0.0415</td>
<td>0.4008</td>
<td>1.1661</td>
<td>1.8831</td>
<td>26</td>
<td>-1.95</td>
<td></td>
</tr>
</tbody>
</table>

Note and Sources: Author’s calculation. NIS5 index values are a summation of the 5 NIS components values after normalization. See Lee and Lee (2019) for details. All the values are average value for the 2008–2015 period. Coefficients of variations are calculated using the normalized values of the 5 NIS component variables.

The third group comprised of three economies in East Asia with a rapid growth or catching-up, such as China, South Korea, and Taiwan. This group is also the imbalanced NIS because it shows a much higher coefficient value of variation among the five component variables (0.685) than the two balanced clusters. The aggregate index (NIS5) of this group is the third at 2.49. The fourth group includes other typical emerging economies, namely, Argentina, Chile, Thailand, Malaysia, Brazil, Mexico, and South Africa. Several economies across Asia, Africa, and Latin America belong to this group despite their possible different initial conditions. The two radial graphs (panel B of Fig. 3) representing these two groups first show that both graphs are imbalanced due to the considerable differences among the values of the five NIS variables, with their coefficients of variation higher than 0.6 or even 0.7.

Portugal and Greece from the full sample were in the separate group and then classified to the trapped cluster group since 2000.
An important contrast exists between the third and fourth group; the former stays in the right side of the graph with high localization and diversification but short CTT. By contrast, the latter is in the left side with a long CTT and high originality but low localization and diversification. Specifically, these two clusters are the exact opposites of each other, except that both share a similar level of decentralization or equally higher concentration compared with the balanced NIS clusters. As will be explained later, there is some connection from short (or long) CTT to high (or low) localization and diversification. Given this, we label the third group simply as the ‘imbalanced and short cycle’ NIS, and the fourth as the ‘imbalanced and long cycle’ NIS. The gap in the aggregate NIS index (NIS5 in Table 2) of these two groups is quite substantial, namely, 2.49 (imbalanced, short cycle group) versus 2.11 (imbalanced, long cycle group), which is consistent with the divergence growth record (Fig. 1B and C).

The fifth group is somewhat mixed because it includes Ireland, Spain, Singapore, and Hong Kong, as well as Denmark, Norway, Russia, and India. This group may be named as the balanced and mixed NIS cluster. This group has a smaller NIS5 index of 2.42 than the first and second tier balanced NIS groups because the values of the five NIS variables are smaller than the corresponding values in the first-tier group. However, the variation is not that high (0.53) as those of the two imbalanced groups. We pay attention to a subset of economies in the balanced and mixed NIS clusters, namely, four economies of our interest (i.e., Hong Kong, Ireland, Singapore, and Spain), which are listed as among the 13 economies by the World Bank (2012) as those who joined the rich economy club. The radial graphs of these four economies (with an NIS5 value of 2.29 in Table 2) are still balanced and shows medium values of CTT, localization and diversification. Thus, we name this subset of the group as the balanced and medium cycle group, and their successful catching-up performance is also verified by growth regressions in Section 5.

The simple growth rates in Table 2 show that imbalanced short-cycle NIS boasts the highest rate of per capita income (4.39% per annum), followed by the balanced and medium cycle group (1.52%) and the imbalanced and long cycle group (0.74%). Actually, the growth regressions in Section 4.4 will verify the linkage from these NIS types to economic growth, differentiating those who went beyond the MIT and those stuck in MIT.

4.2. Dynamic evolution of NIS types and two pathways for Catching-up

Now, we discuss the dynamic evolution of countries changing its types of NIS cluster over time. Table 3 presents the results of the multiperiod cluster analysis of NIS values of 32 economies for a longer term, that is, 32 years from 1984 to 2015. This multiperiod cluster analysis is conducted in several ways to test the robustness of the results. Overall, we can identify several interesting patterns. An important pattern to be discussed is the imbalanced short cycle NIS cluster (group 5 in Table 3), which includes South Korea, Taiwan, and China. This cluster emerged during the second period (1992–1999) in Table 3, first by South Korea, then joined by Taiwan during the third period, and finally by China since the mid-2000s. These three economies all used to belong to the big mixed group in the earlier period but have eventually moved to the imbalanced and short cycle NIS. The identification of another pathway from the middle- to the higher-income status is important, such as the balanced and mixed NIS cluster, including Spain, Ireland, Singapore, and Hong Kong. Table 3 shows that this group is first created by Singapore during the second period, then joined by Ireland, and finally Hong Kong and Spain.

Specifically, these two groups of catching-up economies used to belong to the same big mixed group (group 1) in the early period, but each created its own unique pathway toward the high-income economy status. Given that these economies have shown rapid growth, we must determine the key driving variables to help them achieve this feat. On the one hand, simply looking at the number of patents cannot fully explain the emergence of these two groups because the average number of patents of the balanced medium cycle group (533 per annum) is considerably smaller than that of the first tier balanced NIS group (4725 per annum, Table 2). On the other hand, the other catching up group consisting of China, Korea, and Taiwan has maintained a quite imbalanced NIS and thus remained slightly different from the advanced economies. Nevertheless, these economies have been rapidly catching up in terms of the number of patents (reaching 8426 per annum).

25 The two results using the basic 22 and full 32 economies are consistent with regards the important patterns that comprise the main focus of this study. Six to nine clusters, depending on the period, are shown in Table 3. However, the patterns of the five major clusters have eventually emerged, if we exclude the clusters with only one- or two-member countries.

26 A robust result is that the balanced and first tier NIS cluster (group 7 in Table 3) always includes six economies, namely, the four major European economies plus Canada and Switzerland, throughout the entire period. This pattern of stable clustering over time is consistent with the idea of the VoC literature. However, unlike the existing VoC literature, the UK and Canada (the so-called “Anglo-Saxon economies” or LME in the VoC literature) now share the same cluster as the continental European economies and are not coupled with the US.

27 In relation to this finding, several studies on the VoC literature argue that East Asian capitalism can be considered another type of capitalism. See Storz et al. (2013) and the related special issue on East Asia in Socio-Economic Review.
Although India is not yet a high-income economy, its increasingly faster rate of economic growth but with its balanced industrial structure makes it to join the balanced medium cycle group; it is strong in both short (IT service) and long cycle (pharmaceutical) technology-based sectors (Rao and Balasubrahmanya, 2017). IT services are also short-cycle technology-based sectors with low entry barriers. Therefore, if India sustained the current economic growth beyond the middle income stage, then its path would not be that of imbalanced NIS path but of balanced NIS path. However, the possibility of such a situation is the case because this ratio is highest in the imbalanced and long cycle group (average 2.1 per year for the 2011–2015 period; Table 4), which is also because the group produces a small number of patents. This trademark to patent ratio is lowest in the imbalanced and short cycle group, thereby indicating its orientation toward a patent-driven path. Fig. 4 also shows that this ratio had dropped during the 1990s as this group produced more patents than trademarks since then, thereby realizing a switch from trademark-based to patent-driven growth. These ratios are in the middle for the two balanced groups. Table 4 and Fig. 5 suggest somewhat different patterns. This ratio to the number of patents in each country.

### 4.3. Using trademarks and publications to measure the NIS

As discussed in Section 3, measuring NIS by using patent citation data is subject to certain limitations. This subsection considers additional proxies to capture nonpatent aspects of NIS. We first consider the variable of scientific publications to reflect the strength of each country in producing scientific knowledge. We also consider the variable of trademarks to represent non-patentable or tacit knowledge. These factors represent other forms of knowledge (tacit knowledge for trademarks and scientific knowledge for publications) than is represented by patents associated with codifiable technological knowledge.

These two additional proxies of innovation can be contemplated by considering the number of publications and trademarks divided by the size of population of each country. Table 4 shows that the absolute and relative numbers (per person) of trademarks (registered in the US) and publications are lowest in imbalanced and long cycle group and highest in the first and second tier balanced group. Although the first and second tier balanced groups have on average 16.6 trademarks per million population per year (2011–2015 period), the number is only 1.0 in the case of imbalanced and long cycle group and 8.5 in the imbalanced and short cycle group. Comparative numbers for publication are 2412.0, 417.6, and 905.3. This finding implies that the relationship between these variables to economic growth might be similar to that of patents, namely the higher the numbers, the higher economic growth.

Another way to consider these two additional measures is to examine their ratios to the number of patents in each country. The ratio of trademark to patents is an attempt to reflect two alternative pathways of trademark- versus patent-driven path of technological development. When an economy is at a low level of development, it tends to produce only a small number of patents but end up relying on trademarks (Kang et al., 2020). Fig. 4 shows that such a situation is the case because this ratio is highest in the imbalanced and long cycle group (average 2.1 per year for the 2011–2015 period; Table 4), which is also because the group produces a small number of patents. This trademark to patent ratio is lowest in the imbalanced and short cycle group, thereby indicating its orientation toward a patent-driven path. Fig. 4 also shows that this ratio had dropped during the 1990s as this group produced more patents than trademarks since then, thereby realizing a switch from trademark-based to patent-driven growth. These ratios are in the middle for the two balanced groups.

The ratio of publication to patents reflects the idea that each country’s relative orientation toward either scientific versus technological knowledge may have different impacts on the economy. One might expect this ratio to be highest for high income economies, but Table 4 and Fig. 5 suggest somewhat different patterns. This ratio is highest in the countries belonging to the imbalanced and long cycle (trapped) NIS group. This reflects the simple fact that these countries produce a very small number of patents, whereas their academia still produce a certain number of publication but that is somewhat separated from industrial implementation or commercialization (Kim and Lee, 2015). The norm for this ratio for high income economies is approximately 20 (Table 4), which has been kept stable for a long period of time (Fig. 5). The

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28 India is also quite different from the trapped economies, given its high level of technological diversification. In terms of evolution of the NIS types, in the first two subperiods (before 2000), India was together with other trapped groups. Only since 2000, India, together with Ireland and China (at the same time), joined the balanced and mixed group created by Singapore. This transition coincided with the India’s rise in IT services since the 2000s. Only during the most recent period (2008–2015), this group is joined by Russia, Denmark, Spain, Norway, and Hong Kong. The per capita GDP of India has been growing at the rate of 5.1 per annum during the 2008–2017 period compared with the 32 country average of 1.1% per annum, which is rather comparable to China. India has also been rapidly increasing the number of patents, which is comparable to other countries in the balanced and catching-up group (Table 1).

29 Given that publications are those published in all SCI journals, and patents are only those granted in US, the above value of the ratio of public to patents should not be given much meanings and we thus use their relative values only for comparison across country groups.
The imbalanced short cycle group has been catching-up with this ratio picking up since the late 2000s to the level of the advanced and balanced NIS group (Fig. 5).

The above discussion may imply that the high ratios of trademark to patents and publication to patents are not necessarily a good predictor for economic growth, rather are indicative of weakness of not producing enough number of patents by emerging countries. Although not reported here, actual growth regression has verified no significant relationship between these variables to economic growth. The only interest-

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### Table 4
Patents, Trademarks and Scientific Articles in Different NIS Types.

<table>
<thead>
<tr>
<th></th>
<th>Imbalanced long-cycle</th>
<th>Balanced-mixed</th>
<th>Imbalanced-short-cycle</th>
<th>Balanced (1st &amp;2nd tier)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of trademarks</td>
<td>72.3</td>
<td>72.3</td>
<td>432.9</td>
<td>535.8</td>
</tr>
<tr>
<td>No. of publications</td>
<td>15005.8</td>
<td>30163.9</td>
<td>110661.9</td>
<td>66150.8</td>
</tr>
<tr>
<td>No. of patents</td>
<td>43.89</td>
<td>551.73</td>
<td>9830.27</td>
<td>3952.06</td>
</tr>
<tr>
<td>No. of trademark per million</td>
<td>1.0</td>
<td>8.6</td>
<td>8.5</td>
<td>16.6</td>
</tr>
<tr>
<td>No. of publications per million</td>
<td>417.6</td>
<td>1970.5</td>
<td>905.3</td>
<td>2412.0</td>
</tr>
<tr>
<td>No. of patents per million</td>
<td>1.1</td>
<td>78.5</td>
<td>239.6</td>
<td>171.2</td>
</tr>
<tr>
<td>No. of trademarks /No. of patent</td>
<td>2.1</td>
<td>0.2</td>
<td>0.0</td>
<td>0.1</td>
</tr>
<tr>
<td>No. of publications /No. of patents</td>
<td>454.4</td>
<td>96.8</td>
<td>20.2</td>
<td>20.1</td>
</tr>
</tbody>
</table>

**Notes:** The numbers refer to the annual average values of variables for the recent 5 years (2011–15).
**Sources:** the authors. Patents and trademarks are those registered in the US (US PTO); Scientific publications are extracted from the data base of the Web of Science-ESCI.

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**Fig. 4.** Trends of the ratios of Trademarks to Patents, and Publications to Patents. Part A: The Ratio of Trademarks to Patents. Part B: The Ratio of Publications to Patents.

Notes: The values in vertical axis are real values but the distance between them are not natural but reflect the log values of the real numbers. The real values are calculated using the three-year moving averaged values of patents, trademarks, and publications. 'Trapped' refers to the Trapped NIS, b-mixed refers to the balanced and mixed NIS, and i-catch-up refers to the imbalanced catching-up NIS economies, whereas ‘advanced’ include refers to the first and second tier balanced NIS economies. Each country is grouped to different categories in different years, following the classifications in Table 3.
The CTT pattern implies that, although long CTT is eventually a desirable pattern, the imbalanced short cycle group went into short CTT-based sectors first and then later turned to the long CTT. Although having a large number of publications is desirable, the imbalanced and short cycle (catching up) group greatly relied on patents and later started to catch up in publications (Figure 5). Such a nonlinear pattern or detour is not realized in the imbalanced trapped group because it shows from the beginning a high average CTT and a high ratio of publication to patents but no sign yet of catching up in patents.

4.4. Linking variety of NIS to economic growth

We now create a dummy variable for each NIS cluster and then examine its linkage with economic growth by running regressions of growth equation. We conduct estimation of growth equation in the methods of panel time-series and cross-sectional panel analysis. The former is our preferred and more reliable method and presented as the main results (Table 5A), whereas the latter results are also presented as a kind of robustness test (Table 5B). The panel time series estimation follows the method of cross-sectionally augmented distributed-lag (CS-DL) estimator proposed by Chudik et al. (2016), which can be considered a large heterogeneous panel analysis (Pesaran and Smith, 1995; Pesaran, 2015). The CS-DL estimation applies large heterogeneous approaches to an autoregressive distributed-lag (ARDL) model based on VAR specifications. This method is applied to growth equation estimation (Chudik et al., 2017), and it has certain advantages over the conventional cross-sectional panel approach. The estimators can be robust to endogenous feedback effects (i.e., the effect of lagged-dependent variables on the explanatory ones), and their error terms can be uncorrelated with explanatory variables.31

Among the models on economic growth, this study utilizes the model based on Mankiw et al. (1992) and Islam (1995) instead of the one proposed by Barro (1991). The difference between those two models is that the former directly considers the share of investment to GDP as a determinant of the growth rate. By contrast, the latter includes various institutional factors instead as the determinants of (unobservable) steady-state income level, which implicitly assumes that the rate of investment is decided accordingly. Although such a difference may not matter in a cross-sectional panel analysis, it brings in some differences in panel time-series approaches. Given that deriving the long-run level relationship from VAR model requires including the present and lagged differences of all the explanatory variables, applying Barro model means huge losses in the degree of freedom. Rather than the growth model of Barro (1991), which generally includes numerous institutional factors, such as fertility rate, government consumption share in GDP, and trade openness, the model based on Mankiw et al. (1992), which reduces the explanatory variables into one related with investment share to GDP and lagged income level, is more appropriate in applying large heterogenous panel analysis. While some technical details are in the Appendix 3, the following Eq. (4) is the bench mark regression models we estimate:

\[
\ln(y(t)) = \left(1 - e^{-\alpha} \right) \frac{\alpha}{1 - \alpha} \left[\ln(s_t) - \ln(n + 0.05)\right] + e^{-\alpha} \ln(y(t-1))
\]  

The CTT pattern implies that, although long CTT is eventually a desirable pattern, the imbalanced short cycle group went into short CTT-based sectors first and then later turned to the long CTT. Although having a large number of publications is desirable, the imbalanced and short cycle (catching up) group greatly relied on patents and later started to catch up in publications (Figure 5). Such a nonlinear pattern or detour is not realized in the imbalanced trapped group because it shows from the beginning a high average CTT and a high ratio of publication to patents but no sign yet of catching up in patents.

Chudik et al. (2016) argued that CS-DL is applicable regardless of whether dependent or explanatory variables have unit-roots or not, shows a good small sample performance when T is approximately 30 to 50 (in our analysis T is 32 years), and is robust to the misspecification of lag orders and possible serial correlations of error term.
where \( \lambda \) indicates the speed of convergence to the steady-state income level, \( t \) indicates time dimension of the panel time series, and \( y(t) \) is measured by per capita income, \( s_b \), by the share of investment to aggregate GDP, and \( n \), by population growth rate.

Then, this study analyzes the role of NIS on economic growth by additionally including NIS related variables to the above equation. This notion implies an assumption that the economic growth unexplained by physical capital investment or initial income level can be expounded by the NIS factors.\(^{32}\) We focus on three NIS clusters, namely, imbalanced and short cycle, imbalanced and long cycle, and balanced and mixed clusters, for regressions. The remaining countries served as the benchmark group, including the first and second tier balanced NIS groups. In regressions, each country is assigned to one of the four groups, and such assignment has kept changing depending on its changing NIS type (reported in Table 3) in each of the four, 8 year long, subperiods spanning 32 years from 1984 to 2015.\(^{33}\) We run regressions for these 32 countries and also for

Table 5A
NIS Types to Economic Growth: Panel Time Series Estimation.

<table>
<thead>
<tr>
<th>Dependent variable = Ln(per capita GDP)</th>
<th>(A0)</th>
<th>(A1)</th>
<th>(A2)</th>
<th>(A3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln (investment/GDP) - ln(population growth + 0.05)</td>
<td>0.173 (0.176)</td>
<td>0.125 (0.158)</td>
<td>0.349*** (0.114)</td>
<td>0.419*** (0.106)</td>
</tr>
<tr>
<td>Imbalanced long-cycle NIS dummy</td>
<td>–0.311*** (0.042)</td>
<td>–0.283*** (0.033)</td>
<td>–0.079*** (0.023)</td>
<td>–0.060*** (0.021)</td>
</tr>
<tr>
<td>Balanced med-cycle NIS dummy</td>
<td>0.052** (0.022)</td>
<td>–0.017 (0.025)</td>
<td>0.026*** (0.010)</td>
<td>0.038*** (0.008)</td>
</tr>
<tr>
<td>Imbalanced short-cycle NIS dummy</td>
<td>0.553*** (0.179)</td>
<td>0.251*** (0.014)</td>
<td>0.097*** (0.013)</td>
<td>0.093*** (0.002)</td>
</tr>
<tr>
<td>Ln(trademark/population)</td>
<td>0.126*** (0.024)</td>
<td>0.126*** (0.024)</td>
<td>0.126*** (0.024)</td>
<td>0.126*** (0.024)</td>
</tr>
<tr>
<td>Ln(publication/population)</td>
<td>0.383*** (0.066)</td>
<td>0.400*** (0.092)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant term</td>
<td>9.859*** (0.317)</td>
<td>9.875*** (0.294)</td>
<td>7.186*** (0.487)</td>
<td>6.917*** (0.628)</td>
</tr>
<tr>
<td>Observations</td>
<td>1078</td>
<td>1078</td>
<td>1067</td>
<td>1067</td>
</tr>
<tr>
<td># of Countries</td>
<td>34</td>
<td>34</td>
<td>34</td>
<td>34</td>
</tr>
</tbody>
</table>

Source: the authors;
Notes: Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01;
Included countries in Table 5A are the original sample of 32 economies minus USA plus three additional countries of Turkey, Indonesia, Philippines, some of which (eg. Turkey) is often dropped due to their missing values. In the least squares dummy variable (LSDV) model (Table 5B), there is no country and time fixed effect included, due to the collinearity with NIS dummies, which makes the estimation close to OLS. Including the time fixed effect generates the consistent results, and the US and Japan are excluded in Table 5B regressions. Each country belongs to different group dummies depending upon years in 5A regressions but belongs to a fixed group as follows in 5B regressions.

1) Balanced and 1st tier NIS: Canada, France, Germany, Italy, Switzerland, and the UK.
2) Balanced and medium cycle NIS: Hong Kong, Ireland, Singapore, and Spain.
3) Other Balanced NIS: Denmark, Finland, India, Israel, Netherlands, Norway, Russia, and Sweden
4) Imbalanced and Short cycle NIS: China, South Korea, and Taiwan.
5) Imbalanced and Long cycle NIS: Argentina, Brazil, Chile, Greece, Malaysia, Mexico, Portugal, South Africa, and Thailand.

Table 5B
NIS Types to Economic Growth: Cross-sectional Panel Estimation.

<table>
<thead>
<tr>
<th>Dependent var.: average GDP per capita growth</th>
<th>A variant of LSDV Estimation</th>
<th>GLS: Pooled estimation with dummies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient</td>
<td>t-value</td>
<td>Coefficient</td>
</tr>
<tr>
<td>Ln (Initial Per capita GDP)</td>
<td>-0.0080*** (2.75)</td>
<td>-0.0075** (2.56)</td>
</tr>
<tr>
<td>Population Growth Rate</td>
<td>-0.11 (0.40)</td>
<td>-0.063 (0.18)</td>
</tr>
<tr>
<td>Fixed Investment Rate</td>
<td>0.11** (2.40)</td>
<td>0.12** (2.66)</td>
</tr>
<tr>
<td>Secondary School Enrollment</td>
<td>-0.0018 (0.13)</td>
<td>-0.0071 (0.44)</td>
</tr>
<tr>
<td>Balanced and 1st tier NIS</td>
<td>0.077*** (2.85)</td>
<td>0.074** (2.50)</td>
</tr>
<tr>
<td>Balanced med cycle NIS</td>
<td>0.092*** (3.28)</td>
<td>0.086*** (2.68)</td>
</tr>
<tr>
<td>Other Balanced NIS</td>
<td>0.078*** (2.86)</td>
<td>0.077** (2.50)</td>
</tr>
<tr>
<td>Imbalanced short cycle NIS</td>
<td>0.11*** (3.91)</td>
<td>0.10*** (3.30)</td>
</tr>
<tr>
<td>Imbalanced and long cycle NIS</td>
<td>0.073*** (2.91)</td>
<td>0.070** (2.56)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.579*** (4.68)</td>
<td>0.076*** (4.30)</td>
</tr>
<tr>
<td>Observations</td>
<td>230</td>
<td>177</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.64</td>
<td>0.60</td>
</tr>
</tbody>
</table>

Source: the authors;
Notes: Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01;
Included countries in Table 5B are the original sample of 32 economies minus USA plus three additional countries of Turkey, Indonesia, Philippines, some of which (eg. Turkey) is often dropped due to their missing values. In the least squares dummy variable (LSDV) model (Table 5B), there is no country and time fixed effect included, due to the collinearity with NIS dummies, which makes the estimation close to OLS. Including the time fixed effect generates the consistent results, and the US and Japan are excluded in Table 5B regressions. Each country belongs to different group dummies depending upon years in 5A regressions but belongs to a fixed group as follows in 5B regressions.

32 Applying large heterogenous panel approaches based on the VAR model enables us to control possible feedback effects not only of dependent variables on explanatory variable(s) but also of one explanatory variable on other explanatory ones. In particular, controlling the feedback effects is important because the improvement in NIS can also affect the physical investment.

33 For instance, Korea gets the value of one for the trapped group for the 1984–1991 period because it belonged to that group in that period, and then obtained the value of one for the imbalanced and catching up dummy for the period since 1992. With regard to the data source, the main source is the national account data provided by the Penn World Tables 9.1 (Feenstra et al., 2015; www.ggdc.net/pwt). The per capita GDP variable is based in the constant 2011 US$. The Appendix 4 provides the descriptive statistics.
35 countries after adding three additional countries of Turkey, Philippines, and Indonesia.\textsuperscript{34}

Table 5A presents the main results. Two different sets of models with regard to adding variables for trademarks and publication show that economic growth is high in the two NIS cluster (balanced and mixed and imbalanced short cycle), as indicated in their group’s coefficients, which are positive and significant; economic growth is the highest in the imbalanced and short cycle NIS, followed by the balanced and mixed NIS group. By contrast, the imbalanced and long cycle NIS economies show a negative coefficient, thereby implying no catch-up with the benchmark group, or the gap with the high-income NIS group is rather widened.

Although the model, A0, is a benchmark estimation, the models of A1 to A3 add the number of trademarks and scientific publication per million, respectively. These alternative knowledge variables are significant, together with the NIS dummies, thereby confirming the robustness of the effects of NIS dummies even in the presence of alternative measures of knowledge other than patents.

5. Dynamics of Catching-up in diverse groups

The preceding section demonstrated the superior catching up performance of the two NIS, namely, imbalanced short cycle and balanced medium cycle, in contrast to the trapped performance of the imbalanced and long cycle NIS. The final question would be about the process by which these two, balanced and imbalanced, catching-up NIS emerged, and overcame the trapped NIS condition. In this section, we explore the dynamic paths by looking at the long-term changes in the NIS component variables.\textsuperscript{35}

First, Fig. 5A and B show the trends of technological diversification and knowledge localization. In the advanced economies belonging to the balanced and first tier NIS, the levels of technological diversification and localization have remained high for a long time or the last 40 years. This fact suggests that high levels in these variables are important indicators of technological strength and one of the core aspects of advanced or high-tier NIS. An interesting pattern is the recent downward trend of localization, which reflects the trend of increasing globalization of R&D and open innovation. These two graphs clearly show the increasing (or catching-up to the level of the mature advanced economies) trend of technological diversification and knowledge localization in the imbalanced and short cycle group consisting of China, South Korea, and Taiwan. This catching up is in contrast to the stagnation of these variables in the imbalanced and long cycle group. This contrast is the key aspect of the difference between the two catching-up vs. trapped NIS groups.

The levels of diversification and localization in the case of the balanced and catching-up group (Singapore, Ireland, Hong Kong, and Singapore) are between those of the imbalanced and catching-up and the imbalanced and trapped groups. Although the level of technological diversification of the balanced and catching-up group is 0.3 or half that of the imbalanced and catching up group, its level is more than 3 times higher than that of the trapped group. The level of localization by the balanced and catching-up group is not as high as that of the imbalanced and catching-up group. This notion implies that such a group pursues a more open innovation compared with the more closed model of innovation in the imbalanced and catching-up group.

Fig. 5C shows the trend of CTT. An interesting pattern here is that the imbalanced catching-up group (China, South Korea, and Taiwan) used to maintain a similar level of average CTT with other middle- or high-income economies in the early 1980s; however, they have substantially shortened their average CTT since the mid-1980s by specializing in short CTT-based sectors, such as IT. This finding is consistent with their innovation-based catch-up that started in the mid-1980s even though their new NIS cluster emerged in the 1990s. By contrast, the average CTT of advanced economies remained at high levels, which is consistent with their strength in long CTT-based sectors, such as pharmaceuticals, machine tools, and high-tech materials.

This change in specialization along the CTT trend seems to be the common driving force in the transition to the catching-up NIS. Korea and Taiwan shared a common takeoff with the so-called original equipment manufacturing (OEM) mode in labor-intensive sectors (Hobday, 1995) in the 1960s and 1970. In China, this situation started in the 1980s and 1990s. However, industrialization based on the OEM mode indicates that an economy cannot maintain competitiveness in the long term because its wage rates will continue to rise, which is exactly the symptom of the MIT; Korea and Taiwan used to belong to the same trapped group in the 1980s and China up to the 1990s (Table 3). Korea and Taiwan since the mid-1980s, and China since the mid-1990s broke the trap by moving into short-CTT-based sectors, such as ITs, with the help of diverse industrial policy, including the private–public joint R&D consortium (Hou and Gee, 1993; Kim, 1993; Lee, 2013, Chs. 7 & 8).

Short CTT-based patents imply citing recent patents rather than old ones, and thus such specialization indicates less need to cite the old patents owned by the incumbents. It is also a niche strategy for latecomers because short CTT areas have low entry barriers, given that the technologies are quickly outdated or disrupted (Lee, 2013). Such specialization into short CTT also helps the latecomers quickly increase their knowledge localization, because short CTT means relying less on the knowledge base of incumbent economies. If a latecomer keeps entering newly emerging technologies, then it will be technologically diversified eventually. Specialization into short CTT also implies improved growth prospects due to the frequent arrival of innovations and opening of new opportunities (Lee, 2013).

In contrast, the trapped economies have pursued specialization into extremely long CTT sectors, even longer than those in advanced economies. The reasons for the stagnation of localization and diversification can be explained using the same logic. Specifically, these countries have to keep citing and relying on the patents owned by the advanced economies because they specialized in long CTT. This reliance implies low possibility for increasing the knowledge localization, as shown by the stagnant trend of this variable in Fig. 5B (Lee, 2013). Becoming involved in long CTT also indicates that these countries are doing similar activities as the incumbent economies; hence, no niche exists (Lee, 2013). This pattern is consistent with the idea of the decoupling of academic research and industrial commercialization in Latin America, which has been pointed out as one of the weak aspects of NIS in Latin America (Katz, 2001; Kim and Lee, 2015).
By contrast, the average CTT of the balanced and catching-up group comes in between that of advanced economies and imbalanced catching-up economies, but much shorter than that of the trapped NIS group. Specifically, these economies pursued neither direction of extreme specialization. Fig. 5C shows that the balanced and catching-up group pursued specialization into short CTT-based sectors since the early 1980s into the mid-1990s and has remained at that level or close to the average value of one after this turning point of the mid-1990s. This intermediate level of CTT is also consistent with their intermediate degree of technological diversification. A detailed analysis of each country in this group indicates that each of them have experienced a steady increase of technological diversification, increasing from zero to 0.1 range in the early 1980s to the range of 0.23 to 0.33 (Spain, Singapore) in the mid-2010s (Fig. 5D). Despite some variations among these four economies, this steady increase of diversification is one of their common attributes, in contrast to the stagnation (never above 0.1) of diversification for the last four decades in the trapped economies.

The average CTT of China, South Korea, and Taiwan also stopped decreasing around the early 2000s and even reversed the past trend to show a slight increase of their CTT (Fig. 5C). This result implies the possibility of their innovation system becoming similar to that of higher tier balanced NIS in the future. In other words, the catching-up NIS economies initially went to the opposite direction from the balanced NIS by specializing in short CTT-based sectors and have now begun to move into the long CTT-based sectors. We refer to this pattern as a “detour” because these economies might eventually become similar to a mature balanced NIS via a catching-up NIS.

We have also checked the trend of decentralization of innovation or inverse of concentration. The advanced economies correspond to the highest level, thereby indicating that a wide or dispersed innovation base is a desirable pattern. The second highest value is shown by the balanced and catching-up group. The two imbalanced (trapped vs. catching-up) NIS are similar at a low level in this variable.36 Finally, we consider the trend of the originality variable, which is where the catching-up NIS group is lagging behind compared with the three other groups. The notion that the former group achieved an economic catch-up despite this gap in originality implies that this variable may not be an important variable for economic growth at least at the catching-up stage (Lee, 2013: Ch.3).

In summary, this study has identified two alternative catching-up paths associated with different NIS, as hypothesized in Section 2. The existence of two catching-up paths is analogous to the classical debate about two development strategies, namely, balanced strategy (Nurkse, 1953) versus imbalanced strategy (Hirschman, 1958). Fig. 6 illustrates these two alternative pathways. The linear path expresses the idea that many economies are at the stage of the imbalanced and trapped NIS at earlier stage, and some of them have been able to move to the balanced and catching-up NIS and might become like the higher tier balanced NIS in the future. This linear path is consistent with the idea of balanced development. By contrast, the nonlinear or detour path is the road taken by far East Asian economies with unbalanced and catching-up NIS, owing to its specializing in short-cycle technologies.

If we further broaden the discussion, another way of comparing these two pathways is through their tendency to specialize in a few niche areas or broaden its specialization to include many diverse areas, such as service sectors. Although Nurkse (1953) emphasized the need to balance agriculture and manufacturing, economies at the middle or higher income stage may need to strike some balance between manufacturing and services. Fagerberg and Verspagen (1999) indicated that manufacturing only acted as an engine of growth for developing countries but not for developed ones.37 Unbalanced strategies make sense if an economy has inherited a “heavier degree of imbalances” (Hirschman, 1958) and finds many heterogenous degrees of entry barriers among sectors. The four balanced catching-up economies started at higher levels of income (or at the upper middle income) in the early 1960s than the imbalanced and catching-up economies, which were at low or low middle-income economies (Fig. 1A and C).

A commonality of economies in the balanced and catching-up NIS is the emergence of decent, high-value-added service sectors (different from immature deindustrialization into low value-added services), such as not only IT services but also engineering and banking services. Notable cases are the IT services in Ireland and Singapore and engineering and banking services in Spain (Breznitz, 2012; Garcia-Calvo, 2016). Hong Kong is an extreme case of service and trading hub for manufacturing in mainland China (Sharif and Baark, 2008). An interesting case in Spain is elaborated as not only IT services but also engineering and banking services. Notable cases are the IT services in Ireland and Singapore and engineering and banking services in Spain (Breznitz, 2012; Garcia-Calvo, 2016). Hong Kong is an extreme case of service and trading hub for manufacturing in mainland China (Sharif and Baark, 2008). An interesting case in Spain is elaborated regarding the rise of service sectors and the fall in capital and skill-intensive manufacturing owing to the presence (or absence) of nonhierarchical but strategic coordination among economic actors (Garcia-Calvo, 2020).38

The balanced catching-up group has also managed to keep a certain size of manufacturing relative to services, with the exception of Hong Kong given its special relations to mainland China. Singapore and Ireland have kept the GDP share of manufacturing at the range of 20% to 25% until the mid 2000s according to the WDI data of World Bank (2017). In particular, Ireland featured a strong medical technology cluster, which may be considered a long CTT-based sector (Cunningham et al., 2020). Singapore has featured strong innovators in not only manufacturing, such as electronics (short CTT) and precision and transport engineering (long CTT) and service sectors.

36 This pattern may imply that reducing the degree of concentration might not matter much at catching up stage, as discussed in Lee (2013: Ch. 3). Detailed figures of the trends of decentralization and originality are available upon request.

37 This view is slightly different from that proposed by Haraguchi et al. (2017) who reported the continuing importance of manufacturing.

38 She emphasized the existence of public–private interdependencies and direct business–state interactions as an element for success. She argued such peer coordination constituted an offer of conditional, mutual support by which firms in service sectors complemented the state’s strategic planning and financial limitations in exchange for sector-specific advantages. Further, in peripheral European countries, the EU membership has a role in fostering their NIS and economic growth. Campos et al. (2019) pointed out Greece as the only country wherein the EU entry did not produce the expected positive impacts, which is consistent with our NIS cluster analysis that Greece never joined the balanced and mixed cluster.
CTT), but also knowledge-intensive business services (Wong and Singh, 2008).

In summary, these balanced and catching-up economies share a certain degree of active industrial policy broadly defined, which worked to generate indigenous business actors in various sectors of manufacturing and services out of their early reliance on FDI or MNEs (Cunningham et al., 2020; O’Malley, et al., 2008; Wong and Singh, 2008). Table 6 compares the relative productivity of services and manufacturing by using the ratio of relative productivity of services versus manufacturing where the relative productivity of each sector can be measured by the ratio of the share of services (manufacturing) in GDP to the share of services (manufacturing) in employment. If we take the ratio of the relative productivity of services to the relative productivity of manufacturing, then the ratio variables can be a simple measure of productivity of services relative to that of manufacturing. Table 6 shows that this relative productivity of services is highest (or higher than 1) in the balanced and catching NIS group, whereas it is lowest at the imbalanced and trapped group. This finding may suggest that decent service sectors may have been the engine of catching-up growth in the former group. By contrast, the latter group is less successful in promoting high valued-added services.

### 6. Summary and concluding remarks

This study uses the US patent data of 32 economies to measure, classify, and analyze the evolution and performance of their NIS with a focus on those economies that have sustained economic growth beyond the middle-income stage. The cluster analysis identifies several varieties of NIS. In the NIS of high-income or advanced economies, the values of the five NIS component variables are equally high at similar levels (and thus balanced). By contrast, the NIS values of a majority of emerging economies tend to be imbalanced, with such values being relatively uneven across the five NIS variables. Then, this study identifies two pathways for catching-up growth from the lower-middle income to high-income economies. One pathway has been identified for Ireland, Spain, Hong Kong, and Singapore, which all belong to the balanced and medium-cycle NIS, and India and Russia have recently joined this cluster. The other pathway has been identified for Korea and Taiwan, which created a cluster of imbalanced and short-cycle technology specialization, and is recently joined by China. This idea bodes well for the future of China in terms of the prospect of growing beyond the middle-income status. In contrast to these two groups, we have also identified the imbalanced and long-cycle NIS consisting of those economies perceived to be stuck in the MIT. The imbalanced and short-cycle NIS in East Asia is characterized by such imbalance of short CTT, low originality versus very high localization, and diversification compared with the long cycle or trapped NIS with the exact opposite attributes of these aspects. By contrast, the balanced and medium-cycle catching-up group is characterized by all of these NIS variables that are balanced and with modest values.

The rapid economic catch-up by the imbalanced and short cycle NIS group is attributed to these economies that have increasingly specialized in short CTT sectors, thereby increasing their levels of knowledge localization and diversification. In the meantime, the alternative pathway of the balanced and catching-up group shows that extreme specialization into either long or short CTT-based sectors is not always necessary in achieving a decent degree of diversification and decentralization. The long CTT is a desirable attribute, as shown by all long CTT specializations in advanced economies. However, it is risky at the transition stage because it also represents a sector with high entry barriers. In summary, these diverse patterns are still consistent with some correspondences among the levels of CTT, localization, and diversification in latecomer economies. Specifically, short (long) CTT specialization corresponds to high (low) localization and diversification. By contrast, medium CTT corresponds to a medium level of localization and diversification. The above findings and implications of the paper differ sharply from those of papers in the technology club literature, which focus on closing the technology gap between advanced and follower clubs (e.g., by filing more patents). The current paper also measures the gap in the technological structure, such as CTT. However, countries in the trapped group realized that their level of CTT is higher than that of advanced economies but failed to catch up in income level or economic growth. In contrast, successful catching up in per capita income occurs not by closing but by enlarging the gap (see Fig. 5C), as emerging countries in East Asia went on to specialize in short CTT technologies (eg. IT).

An important contribution of this study is that it confirms some correspondences between diverse patent-driven NIS types and catching-up/falling behind performance. The NIS clusters have turned out to be aptly matched with their diverse economic performance. India is also an interesting case because it is still a low middle-income economy but is a member of the balanced NIS, which may bode well for the future of its economy. On the basis of Table 6, India is not yet a member of the balanced NIS. However, it shows that the relative productivity of services is highest (or higher than 1) in the balanced and catching NIS group, whereas it is lowest at the imbalanced and trapped group. This finding is consistent with the literature (Cirera and Maloney, 2017), which indicates that multiple parts of the NIS are underdeveloped in the incipient NIS that is typical in developing countries.

### Table 6

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<td>0.73</td>
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<td>0.71</td>
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<td>0.89</td>
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<td>Balanced and Catching-up Group</td>
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<td>1.08</td>
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<td>1.03</td>
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<td>0.98</td>
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<td>0.95</td>
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<tr>
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<td>0.73</td>
<td>0.77</td>
<td>0.73</td>
<td>0.74</td>
</tr>
</tbody>
</table>

Notes: Ratio is defined as A/B, where A is (share of services in GDP)/(share of services in employment) and B is (share of manufacturing in GDP)/(share of manufacturing in employment).

1) Imbalanced and trapped (long-cycle) Group: Argentina, Brazil, Chile, Malaysia, Mexico, South Africa, and Thailand
2) Imbalanced and catching-up (short-cycle) Group: China, South Korea, and Taiwan
3) Balanced and catching-up (medium-cycle) Group: Hong Kong, Ireland, Singapore, and Spain
4) Balanced and first tier Group: Canada, France, Germany, Italy, Switzerland, and the UK.
5) Balanced and second tier Group: Sweden, Finland, Israel, Netherlands

Sources: Calculations using the data from the World Development Report (World Bank) as well as from the sites of the official statistics for Taiwan and China.

39 This finding is consistent with the literature (Cirera and Maloney, 2017), which indicates that multiple parts of the NIS are underdeveloped in the incipient NIS that is typical in developing countries.
of these findings, an important policy implication is that the currently trapped economies may have not just one but several alternative pathways to overcome the middle-income trap. Consistent with the Schumpeterian idea that all sectors are heterogeneous in many aspects, economies are advised to specialize in sectors with low entry barriers (or to avoid sectors with high entry barriers) associated with short (or long) CTT.

A limitation of this study is its heavy reliance on patent citation data in classifying NIS clusters although growth regressions further take the additional variables of trademarks and scientific publications into account. Considering more variables, such as fine-grained variables for production structure and university-industry linkages, may help in better understanding the process of economic development and solve the puzzle of some mismatches. Moreover, a detailed roadmap along the catching-up NIS patterns needs to be elaborated, possibly through a deep and historical analysis of each country.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix 1: Definition and Measurement of the five NIS component variables

Following Lee and Lee (2019), we present some description of the concept of the NIS variables.

The first variable is knowledge localization, which is about the source in the acquisition of knowledge and the degree of localization representing the intra-national creation and diffusion of knowledge (Jaffe et al., 1993). This variable measures how much knowledge is created domestically by citing the patents owned by inventors of the same nationality. In an effort to measure knowledge localization, the basic insight of the approach used by Jaffe et al. (1993) is that a probability (or degree) that one country’s patents citing or being cited by another country has to be compared to a similar probability defined with respect to reasonably comparable reference patents. The non-citation-conditioned probability thus serves as a baseline or reference value for comparing the proportion of citation that matches. On this basis, using the gap between the two types of probability previously discussed, knowledge localization is defined as follows:

\[
\text{Knowledge Localization}_{xt} = A - B = \frac{n_{ct}}{n_{ct}} \frac{n_{ct}}{n_{ct}}.
\]

where \(n_{ct} \) is the probability of country \(x\)’s patent citing its own patent, \(n_{ct} \) is the number of citations made to country \(x\)’s patents by its own patents granted in year \(t\), \(n_{ct} \) is the number of all citations made by country \(x\)’s patents granted in year \(t\), \(n_{ct} \) is the number of citations made to country \(x\)’s patents by all patents, except for that country’s patents, filed in year \(t\), and \(n_{ct} \) is the number of all citations made by all patents granted in year \(t\), except for country \(x\)’s patents. Thus, this variable actually refers to the degree of national-level self-citation after normalization.

If the localization is large, then the domestic diffusion of knowledge is high and the share of foreign patents in the citation is low. In our analysis, we do not have a separate variable for international reliance in knowledge sourcing, because it is inversely related to knowledge localization. Although the cross-country panel regressions in Lee (2013: Ch. 3) confirmed that this variable is positively related to economic growth in high-income economies, there is a possibility of an inverse U-shaped relationship between knowledge localization and economic growth, implying that too much reliance on domestic knowledge sources along might not be good.

The second variable for NIS is technological diversification, which captures the degree to which a country produces patents in a wide variety of technological fields. Thus, it is about width versus depth in the patent portfolio of a country. This variable is measured by the number of technological classes in which a country has registered patents divided by 438, which is the total number of three-digit patent classes in the US patent classification system in 2016. The formula for computation is given by

\[
\text{Technological Diversification}_{xt} = \left( \frac{N_x}{438} \right)_{xt},
\]

where \(N_x\) is the number of technological classes that country \(x\) has filed patents in year \(t\). If the technological diversification is large, then a country has filed patents in a large number of classes.

The third variable for NIS is the cycle time of technologies (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 application (grant) years of the citation and the cited patents (Jaffe and Trajtenberg, 2002). Specifically, it refers to the extent to which a patent relies on recent or old technologies for the invention of new knowledge. Hence, a short CCT indicates that the life span of the knowledge lasts only a few years, after which the usage declines dramatically as it soon becomes outdated or less used. Lee (2013) reported that advanced countries tend to specialize in sectors with relatively longer CTT, such as the pharmaceutical sector, whereas successful latecomer economies, such as South Korea and Taiwan tended to focus on sectors with shorter CTT, such as information technology (IT) goods, during the period of their rapid economic catch up since the mid-1980s. In our analysis, we used relative CCT, and not the absolute CCT, of all patents assigned to each country. For each patent, the absolute CTT is defined as backward citation lag, that is, the time lag between application years of the citing and cited patents (Jaffe and Trajtenberg, 2002) or the time span between the predecessor and the successor. The variable can be defined as follows:

\[
\text{CTT of patent } x = \text{Backward citation lag of patent } x \\
= \text{application (granted) year of citing patent } x \\
- \text{application (granted) year of patent } y \text{ cited by } x.
\]

40 We have outliers, such as Japan and Israel, which did not join either of the two catching up NIS. The sample of countries can also be extended to include other transition economies, such as those in Eastern Europe.
We initially calculate the average CTT of each patent using the information of all patents cited by each patent. Then, we transform it to relative CTT by dividing this by the average CTT of all patents filed in year \( t \). We finally calculate the relative average CTT of each country at year \( t \) by using the relative CTT of all patents belonging to each country.

The fourth NIS variable is about decentralization versus concentration in knowledge creation for innovators. This refers to whether or not the producers of knowledge are led by a few businesses or evenly distributed among a large number of innovators. Using the Herfindahl–Hirschman index (HHI) of concentration, the variable is defined as follows:

\[
1 - \text{HHI}_{xt} = 1 - \sum_{k=1}^{N} \left( \frac{N_{k}}{N_{x}} \right)^{2},
\]

(4)

where \( l_{i} \) is the set of assignees, \( N_{i} \) is the number of patents granted by assignee \( i \) in year \( t \), and \( N_{x} \) is the total number of patents granted by country \( x \) in year \( t \), excluding the unassigned patents. We use \( 1 - \text{HHI} \) to express the decentralization or inverse of concentration. If HHI is large, then the patents are filed by a small number of assignees. The cross-country panel regressions in Lee (2013: Ch. 3) have already proven that this variable is significantly and positively related to economic growth in the world.

The fifth variable for NIS is originality. As previously suggested by Trajtenberg et al. (1997), it measures the degree to which a patent makes (backward) citations to patents from a wider range of technological classes rather than from a narrow field of technologies. We follow the suggestions by Hall et al. (2005) and Trajtenberg et al. (1997) in defining the variable for each patent \( i \) of country \( x \) in year \( t \), as shown in the following:

\[
\text{Originality}_{xt} = \left( 1 - \sum_{k=1}^{N} \left( \frac{N_{k}}{N_{x}} \right)^{2} \right)^{2},
\]

(5)

where \( k \) is the technological class (especially US patent classification), \( N_{k} \) is the number of citations made by patent \( k \) to patents that belong to patent class \( k \), and \( N_{x} \) is the total number of citations made by patent \( i \). Using Eq. (5), we calculate the average for each country at year \( t \) for each patent. This definition represents the rationale that the broader the technological root of the underlying knowledge or research related to the patents is, the higher the originality of a patent will be. The synthesis of divergent ideas is possibly characteristic of research that has high originality and is thus basic in that sense (Trajtenberg et al., 1997). Defined this way, this variable represents the degree of knowledge convergence and combination.

The above five variables can be considered the relevant components of an effective NIS and are sufficiently comprehensive (Lee and Lee, 2019). In other words, these variables cover diverse dimensions of creation and diffusion (intra-national vs. international) of knowledge for innovation, decentralization or concentration, technological diversification (width), wide or narrow sourcing of knowledge, and longevity of knowledge in each economy. Some other dimensions, such as the university–industry interaction, can be considered highly correlated with some of these five variables; for instance, as explained in Lee and Lee (2019), if a country show a high degree of university–industry collaboration, then it may also show a high degree of local creation and diffusion of knowledge, low concentration, and/or high diversification. Lee and Lee (2019) showed that adding or omitting one or two components does not affect the considerable explanatory power of NIS in analyzing economic growth.
The growth model of Mankiw et al. (1992) and Islam (1995) is based on the following production function and capital accumulation:

\[ Y(t) = K(t)^\alpha (A(t)L(t))^{1-\alpha}, \]

\[ \dot{K}(t) = s_y y(t) - (n + g + \delta) K(t), \]

where \( y(t) \) and \( y(0) \) are the current and initial level of income, respectively; and \( L, K, \) and \( A \) stand for labor, capital, and a variable representing labor-augmenting productivity, respectively; \( k_y = K_y / (AL) \); \( y = Y_y / (AL) \); \( s_y \) is the fraction of income invested in the physical capital; \( n \) and \( g \) are growth rates of \( L(t) \) (i.e., population) and \( A(t) \), respectively; and \( \delta \) is the depreciation rate of the physical capital. Mankiw et al. (1992) calibrated \( g \) and \( \delta \) as 0.02 and 0.03, respectively. Mankiw et al. (1992) and Islam (1995) derived following empirical models on economic growth on the basis of the above:

\[ \ln(y(t)) - \ln(y(0)) = \left(1 - e^{-z}\right) \frac{z}{1 - z} \ln(s_y) - \ln(n + g + \delta) \]

\[ - \left(1 - e^{-z}\right) \ln(y(0)), \]

where \( z \) indicates the speed of convergence to the steady-state income level. In the empirical analysis, \( s_y \) is measured by the share of investment to aggregate GDP, and \( n \) is calculated by population growth rate. Considering that per capita GDP growth rates are approximated by the log-difference between the current and the initial levels of per capita GDP and using the calibrations of Mankiw et al. (1992), Eq. (3) can be rewritten as follows:

\[ \ln(y(t)) = (1 - e^{-z}) \frac{z}{1 - z} \ln(s_y) - \ln(n + 0.05) + e^{-z} \ln(y(t-1)). \]

Eq. (4) is the benchmark regression models we estimate.

### Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.worlddev.2021.105472.

### References


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### Appendix 3: On Estimation Models

The growth model of Mankiw et al. (1992) and Islam (1995) is based on the following production function and capital accumulation:


