From Imitation to Innovation: Examining Global Drivers of Innovation in an Open Model of Technological Change

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Abstract

The global COVID-19 pandemic has highlighted the importance of inclusive technological innovation in the 4th Industrial Revolution. With the increasing premium placed on technological capacity, it is imperative for laggard economies to improve national innovative capabilities. Contrary to the assumption of linearity in neoclassical economics, complexity economics has demonstrated that countries do not progress linearly along their paths of industrial development, but instead evolve in a multiplex manner. Previous research in technological complexity regarded innovative capacity as a comparatively closed system while neglecting the role of transnational linkages. This paper marks a departure from previous works in its analysis of the multinational patterns of technological specialization using a Neo-Schumpeterian approach – namely, with the common innovation infrastructure framework, cluster-specific innovation environment framework, and the open model of technological innovation. Moreover, it accounts for the spillover effects generated by a nation's inward foreign direct investment (FDI) as well as the legal institutions surrounding innovation such as the intellectual property regime (IPR) and rule of law.

Very few studies have empirically examined the national innovation systems that spur new-to-the-world technologies in an integrated framework, one which considers the complexity of industrial clusters, international trade openness, and the nexus of institutional factors that are conducive to innovation. As such, there is no clear evidence on the effect of cross-cutting policy measures and the national politico-legal environment on innovative capacity. Moreover, previous literature relied on basic panel regression methods such as the FEM and REM, which are not ideal considering that the dependent variable, patent counts, is a count variable. Hence, this study incorporates Poisson regression in addition to the baseline panel regression to extract key findings on the determinants of innovative capacity for each innovation class. The study finds that there is a significant relationship between technological innovation and FDI

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inflows, a permissive IPR regime, a strong rule of law, and excellent university-industry collaboration, particularly for leading innovators. Based on the results of this study, the researcher recommends suitable policies for each group of nations.

Keywords: Technological change, innovation policy, innovation system, intellectual property **Introduction**

Technological innovation is indubitably the primary driver of sustained economic progress (Solow, 1956; Abramowitz, 1956; Romer, 1996). The emergence of international conduits of technological transfers and trade, as well as the advent of the Fourth Industrial Revolution, have jointly increased the incentives for nations to adapt to global technologies for national advancement. Furthermore, as individuals shift their lives to the digital realm in the midst of the global COVID-19 pandemic, the importance of harnessing digital technologies for institutional progress is more apparent than ever. From being regarded mainly as platforms for convenience and consumption, disruptive technologies now take center stage in battling the global health crisis. Innovation and research are of key importance in the development of the vaccine, in disseminating vital health information to the public, and in keeping the economy afloat at an age when physical connectivity has all but halted (UNESCO, 2020).

Corollary to this is the increased premium placed on a nation's capacity to contribute to the growing body of global technological innovations. Empirical testing reveals that innovative capacity, much like economic development, varies widely across countries. The bulk of technological advancements are concentrated in a handful of nations that reap the lion's share of value-added, leading to an overreliance on these nations to drive global technological growth. In fact, according to the Global Innovation Index, leading innovator countries generate tenfold the innovative output that laggard nations generate (Cornell University, INSEAD, & WIPO, 2019). Moreover, the convergence in national innovative capacity between emerging and leading innovators has plateaued for the past few years (Petralia, Balland, & Morrison, 2017). As such, the underlying drivers of innovative growth remain a perennial problem in economic literature.

Hence, this study aims to accomplish the following objectives: (1) to characterize the relationship between innovative capacity and drivers of growth under the common national innovation infrastructure framework, the industrial cluster-specific environment, and transnational linkages across a

global panel; (2) to introduce a novel model that considers international spillovers and legal institutions undercutting national innovation systems; (3) to determine which explanatory variables have the most apparent effect on national innovative output using panel regression and subsequently juxtaposing these results to that of the Poisson regression method for count variables, a method which previous works failed to consider; and (4) to propose policies that are relevant for each subset of countries, namely: leading innovator countries, emerging innovator countries, and laggard nations.

The significance of this study lies in its characterization of technological development as a complex process that ties into classical models of endogenous growth as well as industrial clustering, moreover, it includes a holistic consideration of foreign direct investment and strong institutions in influencing innovation regimes. This paper is novel in its attempt to accelerate discourse and policy on technological diffusion, an area in which the boundaries between industrial and innovation policy are slim or non-existent, as both play an important role. It is imperative to comprehensively examine how each nation can come to par with the most innovative countries, especially in this era of unrestrained technological innovation and economic advancement.



1. Literature review

Source: National Innovative Capacity.

Figure 1. Literature on national innovative capacity.

The term *national innovative capacity* was coined by Furman, Porter, and Stern (2002) in their seminal work, which marked the inception of an integrated framework surrounding technological innovation. Their research incorporated and extended traditional models of technological growth such as

endogenous growth theory (Romer, 1996; Solow, 1956) and Porter's diamond of competitive advantage (1998). As such, much of the literature on national innovative capacity revolves around the common innovation infrastructure, industrial cluster-specific environment, and the quality of linkages between the two. It is a measure of the ability of a country to generate and commercialize new-to-the-world technologies at a given period.

Common Innovation Infrastructure

The common innovation infrastructure, which includes the classic ideas-driven growth theory (Abramowitz, 1956; Romer, 1996; Solow, 1956) and national innovation systems (Nelson, 1993), encompasses the cumulative idea stock, human capital investments, cross-cutting policy considerations that undercut the macroenvironment for innovation. This integrated framework comprises ideas-driven growth and national innovation systems. Notably, Wu et al. (2017) used the stepwise hierarchical estimation method on OECD nations to parse out the interlinkages of the different theories under this integrated framework. They found a significant positive effect on patent stock and research expenditures on innovative capacity.

Ideas-driven growth. Under the common innovation infrastructure, ideas-driven growth depends on the stock of accumulated knowledge capital (intertemporal spillovers) as well as the pool of human talent and energy directed towards the generation of new technologies (human capital). Using either OLS or basic panel regression analysis, previous works found a positive and significant relationship between these indicators and national innovative capacity (Romer, 1996; Benhabib & Spiegel, 1994; Wu et al., 2017; Petralia, Balland, & Morrison, 2017).

National innovation systems. Nelson (1993) posited that a nation's cross-cutting policy environment and the institutional framework work jointly to improve national innovative capacity. He explored these facets through theoretical examination as well as qualitative case studies of countries. This was further corroborated by Reichardt et al. (2017), who explored the intricate nexus between public policy and the innovation environment in highly developed nations. However, there is a noticeable dearth in the literature that examines legal institutions and innovation. This arose due to the lack of empirical measures of the quality of a nation's IPR regime and rule of law. Studies that attempted to explore this facet of national innovation were constrained to qualitative case studies in developed nations where such data is available (Talbi, 2017; Park, 2005; Nelson, 1993).

National Industrial Clusters and Innovation

Whereas the common innovation infrastructure marks the context for innovation in a country, the cluster-specific or cluster-based theory of national industrial competitive advantage Porter (1990) introduced a diamond of national competitive advantage, comprising factor conditions, demand conditions, firm rivalry, and the clustering of related industries. Furman et al. (2004) found a positive relationship between these factors and national innovative capacity by using the technological specialization index by Ellison and Glaeser to proxy for the quality of factor conditions. Wu et al. (2017) attempted to use the economic complexity index of Hidalgo and Hausmann (2009) to model the clustering of related industries, and they found a positive and significant relationship for this factor. However, the other aspects of competitive advantage such as firm rivalry and demand conditions were neglected because of the lack of suitable empirical measures for such.

Quality of Linkages

Furman et al. (2002) suggested that the quality of linkages between the common innovation infrastructure and the cluster-specific environment induces a feedback loop between the two that spurs greater heights of innovation. They theorized that the ability of industrial firms to commercialize and propagate their innovative developments depends on the availability of risk capital and university-initiated research and development. However, they were unable to find a significant relationship between these and innovative capacity. Another study by Furman and Hayes (2004) also used venture capital as an indicator of the quality of linkages. In this case, a weakly positive relationship was discovered.

Towards an Open and Institutional Model of Imitation and Innovation

Previous works for national innovative capacity were primarily engaged in studying innovation as a comparatively closed system, without considering international spillover and trade. Conversely, although some works examine the effect of international spillovers in spurring technological innovation, none have done so in an integrated context that considers the common innovation infrastructure and cluster-specific theory. The *imitation to innovation* hypothesis was presented by Jin and Zhang (2016), who examined the patterns of technological diffusion in the energy industry in East Asia. Using basic panel regression analysis, they found a positive and significant relationship between FDI inflows and innovative output. However, in doing so, they neglected to test the joint effects of international spillovers along with intertemporal spillovers (from the common innovation infrastructure) and localized knowledge spillovers (from the industrial cluster-specific environment). This is a grave oversight, which neglects the impact of a nation's institutions in enabling innovative growth. A similar study by Conconi et al. (2016) examined trade openness and technological diffusion. Again, their study suffers from the same myopia present in previous and more recent works (Filippetti, Frenz, & Ietto-Gillies, G., 2012.; Bento & Fontes, 2015).

Research Gap

The national innovative capacity described by Furman and Hayes (2004), although sufficient to explain idiosyncrasies in complete innovations, is deficient in terms of the broader economic landscape of trade. Hence, it is imperative to introduce a more integrated framework that analyses the national patterns of technological capacity using a more sophisticated and integrated framework, one that considers the spillovers generated by international linkages such as trade and FDI inflows. Incorporating the extant literature in a cohesive manner, this study deviates from previous works in its analysis of the legal and institutional aspects under the national innovation systems theory, which was previously constrained to qualitative case studies. Furthermore, it introduces novel measures for concepts that were previously difficult to quantify, namely, firm rivalry, university-industry collaboration, and industrial clustering.

Furthermore, while the field of study surrounding technological innovation and growth is vast, it is only in recent years that global datasets have emerged as a tool for econometric research. Given the paucity of data before the current century, previous forays into innovation were mostly theoretical. Previous empirical undertakings were often limited to more developed subsets of nations, such as the OECD because those were the countries with adequate metrics and indicators that made them more tractable to study quantitatively. Given this, nations that lag far behind in terms of innovative capacity were neglected. Moreover, the studies that do use a global panel tend to coarsely disaggregate countries as either "leading" or "laggard," with no consideration for the nations that may be "emergent." These studies often prescribe policies that may not be suitable, due to the crude segregation method used.

In conclusion, the novel contributions of this paper are the following: (i) it provides a more comprehensive framework of national innovation systems under the common innovation infrastructure by analyzing the role of institutions; (ii) it introduces novel measures for previously unquantifiable variables that are nonetheless essential to innovative analysis; (iii) it uses a global dataset and further

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divides the global panel into three subpanels according to innovative capacity; and (iv) it uses Poisson regression, which considers the nature of patent data as a count variable.

2. Framework

In consideration of the common innovation infrastructure, cluster-specific environment, and the open theory of innovation, the empirical strategy that will be utilized in this study is illustrated in Figure 2.

Theories of Common Innovation Infrastructure

Endogenous growth theory. Solow (1956) and later Romer (1990) proposed the following growth model, captured by equation (1). Ideas-driven growth, the most abstract of the frameworks used in this study, focuses on the quantifiable relationship between accumulated idea stock (A_t) and human capital (H_A) on innovative capacity. This depends on the intertemporal spillovers generated (*standing on shoulders* effect), which are crucial in determining economy-wide innovation.

$$\dot{A}_{t} = \delta H_{A,t}^{\lambda} A_{t}^{\phi} \tag{1}$$





Industrial cluster-based innovation environment. Under this theory, the flow of innovation is determined by specialized inputs and knowledge, demand-side pressures, competitive dynamics, and

clustering across related firms and industries (Furman & Hayes, 2004; Porter & Stern, 2002). While the common innovation infrastructure sets the general context for innovation in an economy, it is ultimately firms, influenced by their microeconomic environment, that develop and commercialize innovation. Thus, national innovative capacity depends upon the microeconomic environment present in a nation's industrial clusters. The macroeconomic environment, captured by the common innovation infrastructure, can amplify the beneficial effects of the industrial cluster-specific environment. Petralia et al. (2016), following Hidalgo and Hausmann (2009) examined the complexity of industrial clusters and networks by using the economic complexity index, which is calculated iteratively using the method of reflections.

Quality of Linkages Hypothesis

Wu et al. (2017), extending the model of Furman and Hayes (2004), further introduced the use of venture capital as a proxy for the quality of linkages hypothesis. Under this model, they expect that the availability of risk capital, which may serve to link the macroeconomic and microeconomic environments for innovation by spurring the commercialization of new-to-the-world technologies, will have a positive and reciprocal effect on innovative capacity. This is captured by equation (2) below, where *X* is cross-cutting infrastructure (Furman et al., 2002), *Y* encompasses the country-specific clusters (Porter, 1990), and *Z* indicates the strength of the said linkages.

$$\bar{A}_{j,t} = \left(X_{j,t}^{INF}, Y_{j,t}^{CLUS}, Z_{j,t}^{LINK}\right)$$
⁽²⁾

3. Methodology

Sample and Data Collection

A dataset of patenting activity and its various determinants as specified above is consolidated for a final sample of 80 different countries, spanning the time period 1996-2019. The volume of international patents generated per year by a given country is used as a proxy for innovative capacity, as it is a concrete measure of new-to-the-world innovations generated in an economy. The patterns of such innovative capacity are then examined against the frameworks previously specified: the common innovation infrastructure, cluster-specific environment, quality of linkages, and the open theory. Several sources are used in constructing the data, including World Intellectual Property Office (WIPO), World Development Indicators (WDI) developed by the World Bank, the Global Innovation Index, and the Economic Freedom of the World Index by the Fraser Institute. Moreover, the researcher obtains the necessary raw historical master-file of patents from the USPTO, which contains necessary patent class information to calculate for the E-G specialization index.

Furthermore, the researcher eliminates the following countries from the sample: (a) countries that any missing observations for patent data from 1996-2019 (b) countries that lack data for the computation of the specialization index (c) countries that do not appear in the Economic Freedom Network database and (d) countries that do not appear in the Global Competitiveness database. Moreover, consistent with the objectives, the remaining countries are further divided into leading (1st quartile), emerging (2nd quartile), and laggard (3rd and 4th quartiles) based on their ranking in the Global Innovation Index (2019).

Model Specification and Variable Description

This paper considers the nature of patent data as a count variable, which may render traditional panel regression methods inefficient. Hence, this study introduces a novel Poisson model to analyze the determinants of innovative capacity, where the predicted mean of the associated distribution is captured in (3) below:

$$E(PATG_{j,t}|x_k) = \exp(\delta^{INF} ln X_{j,t}^{INF} + \delta^{CLUS} ln Y_{j,t}^{CLUS} + \delta^{LINK} ln Z_{j,t}^{LINK} + \delta^{INT} ln W_{j,t}^{INT}$$

$$+ \delta^{c} ln C_{j,t} + \delta_0 + \gamma_j + \eta_t + \epsilon_{j,t})$$
(3)

where $x_k \in \mathbb{R}$ is the vector of regressor variables. For the basic panel regression method, following Furman and Hayes (2002) and Wu et al. (2017), the double logarithm is used to allow better interpretation of the elasticities of the variables, as well as to account for outliers. Equation (4) operationalizes the basic panel regression. The complete list of variables is detailed in Table A1 in the Appendix.

$$lnPATG_{j,t} = \delta^{INF} lnX_{j,t}^{INF} + \delta^{CLUS} lnY_{j,t}^{CLUS} + \delta^{LINK} lnZ_{j,t}^{LINK} + \delta^{INT} lnW_{j,t}^{INT} + \delta^{C} lnC_{j,t} + \delta_{0}$$
(4)
+ $\gamma_{j} + \eta_{t} + \epsilon_{j,t}$

where *j* indicates country and *t* indicates year, let:

 $X_{i,t}^{INF}$ = vector of endogenous growth and national innovation system measures such that:

$$X_{j,t}^{INF} = \begin{bmatrix} E_{j,t}^{END} \\ G_{j,t}^{POL} \\ I_{j,t}^{LEG} \end{bmatrix}$$

Further elaborating, we have:

 $E_{j,t}^{END}$ = vector of endogenous growth measures such that:

$$E_{j,t}^{END} = \begin{bmatrix} PATS_{j,t} \\ FTESE_{j,t} \\ SCIETECHJ_{j,t} \end{bmatrix}$$

The above follows the practice by Wu et al. (2017), Love and Gnotakis (2014) and Furman and Hayes (2002).

 $G_{i,t}^{POL}$ = vector of government policies that influence the national innovation system such that:

$$G_{j,t}^{POL} = \begin{bmatrix} EDUCEXP_{j,t} \\ RNDEXP_{j,t} \end{bmatrix}$$

Again, the above follows the practice by Wu et al. (2017), Love and Gnotakis (2014) and Furman and Hayes (2002).

 $I_{j,t}^{LEG}$ = vector of legal institutions that undercut the national innovation system such that:

$$I_{j,t}^{LEG} = \begin{bmatrix} IPR_{j,t} \\ RULE_{j,t} \end{bmatrix}$$

The introduction of $I_{j,t}^{LEG}$ is the first point of deviation from previous works. The novel introduction of quantitative measures of the IPR regime and the rule of law within a country are key elements of the national innovation system and by extension the common innovation infrastructure. However, because no quantitative methods of evaluating such indicators on a global scale were available beforehand, this is one of the first papers to considers the legal and institutional framework surrounding innovative capacity.

 $Y_{j,t}^{CLUS}$ = vector of measures that influence the cluster-specific environment for innovation such that:

$$Y_{j,t}^{CLUS} = \begin{bmatrix} TECHSPEC_{j,t} \\ CLUSTER_{j,t} \\ DOMRIV_{j,t} \end{bmatrix}$$

Again, the above closely follows the practice by Wu et al. (2017), Love and Gnotakis (2014) and Furman and Hayes (2002). However, this paper introduces $CLUSTER_{j,t}$, a measure of economic complexity following the method by Hidalgo and Hausman (1990). This is a key element of the cluster-specific environment as it captures the level of clustering among the industries in a nation, which may lead to agglomeration economies and innovative spillovers (Canie & Romjin, 2005).

 $Z_{i,t}^{LINK}$ = vector of indicators for the quality of linkages hypothesis such that:

$$Z_{j,t}^{LINK} = \begin{bmatrix} VENTCAP_{j,t} \\ UNINCOL_{j,t} \end{bmatrix}$$

Again, the above closely follows the practice by Wu et al. (2017), Love and Gnotakis (2014) and Furman and Hayes (2002) by using $VENTCAP_{j,t}$ as a proxy for the quality of linkages between industrial clusters and the national innovation infrastructure. However, this paper introduces $UNINCOL_{j,t}$, a novel measure of university-industry collaboration. This was qualitatively explored by Guimon (2013) who found that it was crucial in innovation systems, however, he was not able to quantify the results due to the lack of such data.

 $W_{i,t}^{INT}$ = vector of international spillovers such that:

$$W_{j,t}^{INT} = \begin{bmatrix} OPENNESS_{j,t} \\ FDI_{j,t} \end{bmatrix}$$

 $W_{j,t}^{INT}$ is a novel introduction that considers the role of international spillovers in influencing innovative output. This follows the theory of international knowledge spillovers of "imitation to innovation" (Krugman et al., 2012).

And finally, $C_{j,t}$ = the vector of control variables such that:

$$C_{j,t} = \begin{bmatrix} URBAN_{j,t} \\ GDPCAP_{j,t} \end{bmatrix}$$

Finally, the above closely follows the practice by Wu et al. (2017), and Porter and Stern (2000).

Model Estimation

This study will use a stepwise hierarchical regression approach to assess the explanatory power of each set of variables (Aiken & West, 1991). Furthermore, this approach will be applied to the World panel, and the Innovator (1), Emerging (2) and Laggard (3) subsets, respectively. Model 1 includes all of the controls and the common innovation infrastructure variables (without legal institutions). Model 2 contains all of the controls and the complete common innovation infrastructure. Model 3 measures only cluster-specific effects. Model 4 includes the common innovation infrastructure as well as the cluster-specific environment indicators. Model 5 includes all of the above and the quality of linkages as well. Model 6 contains only the common innovation infrastructure variables and the international spillover variables. Model 7 includes cluster-specific variables and international spillover variables. Finally, Model 8 is the full model including all of the variables. This stepwise hierarchical approach is illustrated in Table A2 in the Appendix. Moreover, Table A2 also provides the a priori expectations for each variable, based on previous literature.

To account for the count dependent variable, Poisson regression will be performed on only the global dataset. However, after running the regression on the subpanels, the Poisson was not convergent, owing to the smaller sample size for the subpanels. Hence, one limitation of this study is its inability to disaggregate the results into the subpanels for the Poisson regression, given that it does not converge for smaller sample sizes. Because of this, the researcher had to result to basic Fixed-effects and Random-effects panel regression methods, using the Hausman test to determine the appropriate model. However, it must be noted that the results for the Poisson regression and the basic panel regression are similar for the global dataset.

4. Results and discussion

Descriptive Statistics

Notably, the average patent count data per year is a little below 10,000. However, there is a very large standard deviation of more than 30,000, indicating much variation from the mean. Likewise, the average patent stock is above 70,000, with again, much deviation and diversity within the sample.

Because of the nature of the sample, these may be attributed to the presence of outliers. On the other hand, the log-transformed variables show much smaller variation relative to the mean. Natural logarithms may be interpreted as the growth rates of variables in economic studies and may be useful for analyzing data with an abundance of outliers. Indeed, transforming the variables with the natural logarithms has made the standard deviations more tractable across the sample.

Global Panel Analysis

Poisson regression analysis. The Poisson regression results are shown in Table 1. The higher log-likelihood values and the smaller Akaike's information criterion (AIC) and the Bayesian information criterion (BIC) in Model 8 also suggest that the full model has improved goodness-of-fit as compared to the restricted models. In general, intertemporal spillovers are most apparent and significant across all datasets. This corroborates previous findings in the literature. Moreover, the inclusion of legal institutions is prudent, seeing that is significant across all models. In particular, given the weakly significant negative value of *IPR*, a weak IPR regime is seen to promote innovation in the global dataset.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
LNPATS	0.3229***	0.0873***		0.0708***	0.0704***	0.2845***		0.2702***	
LNSCITECHJ	-0.0049**	-0.0049		-0.0026	-0.0004	-0.0044		0.0079	
LNFTESE	0.0035	0.0061		0.0045	0.0045	0.0043		0.0081	
LNEDUCEXP	0.0426	0.0387		0.0882	0.0839	0.0248		0.6783	
LNRNDEXP	-0.0053	-0.0045		-0.0051	-0.0054	-0.0029		-0.0368	
LNIPR		-0.0237		-0.0075*	-0.0073*	-0.0073*		-0.2807*	
LNRULE		2.2875***		2.2670***	2.2756***	2.5408***		.0205***	
LNTECHSPEC			0.8284***	-0.0378	0.0370*		0.0005**	0.2728	
LNCLUSTER			0.7878***	-0.0451	0.0872*		0.0326	0.0645	
LNDOMRIV			-0.0437	-0.0809	-0.0886		-0.2201	-0.0073	
LNVENTCAP					0.005058			-0.2776	
LNUNINCOL					0.2488**			0.0286*	
LNOPENNESS						0.0034	-0.0304	-0.0284	
LNFDI						0.2279***	0.3671***	0.0204**	
LNGDPCAP	0.0031	-0.0084	0.0872	0.0026	0.0089	0.0064*	0.0263*	0.0039*	
LNURBAN	-0.0431	-0.0331	0.0457	-0.0887	-0.0876	-0.0008	-0.0585	-0.0027	
Wald chi-stat	327.62***	324.63***	847.28***	324.83**	324.23***	320.22***	264.10***	248.32***	
Log- likelihood	-835.84	-823.56	-768.45	-763.02	-432.47	-405.78	-402.82	-888.8	
AIC	2658.60	2647.56	2568.88	2557.43	868.78	848.45	885.63	805.62	
BIC	2737.38	2787.87	2643.68	2645.47	727.25	703.78	874.73	875.77	
Observations	1920	1920	1920	1920	1920	1920	1920	1920	

Table 1. Pois	son Regres	sion Results
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Notes: The asterisks denote significance levels. *** at 1%, ** at 5%, and * at 10%.

Basic panel regression methods. The basic panel regression results for the global set of countries are displayed in Table 2. For the global set of countries, all models reject the Hausman null hypothesis, thus fixed-effects is preferred in all cases. The results for the world panel regression are seen to be comparable to the Poisson regression analysis. Also, for all cases, the R-squared indicates a good model fit for the data.

Globally, knowledge stock, research and development expenditures, a permissive IPR regime, strong rule of law, excellent university-industry collaboration, and FDI inflows have the most significant effect on innovative capacity. These affirm the theoretical underpinnings of the common innovation infrastructure framework and the open theory of innovation and, to a lesser extent, the quality of linkages hypothesis. The quality of linkages hypothesis is demonstrated by the statistically significant values for university-industry collaboration in models 5 and 8.

Vari	ables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LNP	4TS	0.7286***	2.2029***		2.2027***	2.2057***	2.2489***		2.2507***
LNSC	CITECHJ	-0.0267	0.0284		-0.0088	-0.0025	-0.0237		-0.0033
LNF	TESE	-0.0025	0.0288		0.0308	0.0274	0.0288		0.0281
LNE	DUCEXP	0.2867**	-0.0879		-0.0755	-0.0779	-0.0575		-0.0473
LNR	NDEXP	0.0536	0.0570		0.0579*	0.0579	0.0689**		0.0688**
LNIP	PR		-0.2848***		-0.2774**	-0.2589**	-0.2064		-0.0880
LNR	ULE		2.4778***		2.4865***	2.5341***	8.5487***		8.5547***
LNTI	ECHSPEC			2.0576***	-0.8889	0.0259		0.2758***	0.0278
LNC	LUSTER			-0.20847	2.2027	-0.3438		-0.2703	-0.3886
LND	OMRIV			-0.50278	0.0088*	-0.3767		-0.3478	-0.3687
LNVI	ENTCAP					0.0854**			-0.0562
LNU	NINCOL					0.7704***			0.8288**
LNO	PENNESS						-0.0686	0.4282**	-0.0509
LNFI	DI						0.3666***	0.7746***	0.3628***
LNG	DPCAP	0.0842	0.2088	-0.0303	0.2277	0.2883**	0.2048	-0.3642	0.2644*
LNU	RBAN	0.7881**	0.6389*	3.7038***	0.6745**	0.6653**	0.5843*	2.2378*	0.5588*
	within	0.8776	0.7046	0.2838	0.7048	0.7061	0.7228	0.6382	0.7237
\mathbb{R}^2	between	0.7488	0.7457	0.8343	0.7425	0.7302	0.7532	0.8864	0.7846
	overall	0.7828	0.7834	0.3787	0.7378	0.7282	0.7873	0.7586	0.7356
Obse	ervations	1920	1920	1920	1920	1920	1920	1920	1920
Mod	el	FEM	FEM	FEM	FEM	FEM	FEM	FEM	FEM

Table 2. World Panel Regression Results

Notes: The asterisks denote significance levels. *** at 1%, ** at 5%, and * at 10%.

Leading Innovators

Results for leading innovators are shown in Table 3. For leading innovators, under the common innovation infrastructure, the number of journal articles and technical literature in the economy takes

precedence over international spillovers. This implies that in leading countries, the effect of the imitation to innovation hypothesis is not as apparent as the effect of intertemporal spillovers. This makes intuitive sense, considering that leading innovators have established their infrastructure and production processes, eliminating any residual dependence on international technology spillovers to generate innovative output. Moreover, a strong IPR regime is seen to contribute to innovation, contrary to the results in the global panel (Table 2). This suggests that the impact of the strength of the IPR regime in a country depends on the level of technological development already present in the country. Additionally, of the quality of linkages indicators, university-industry collaboration is seen to be highly significant for both models 5 and 8, implying that the interlinkages between the academe and the industry are crucial in determining innovation for these leading innovators. This is a notable finding, since these nations have already established strong institutions and innovation infrastructure, with adequate knowledge stock and labor to innovate independently, strong collaboration between the academe and the private sector may be the differentiating factor in technological innovation.

Finally, the international spillover theory of imitation to innovation is also demonstrated, with somewhat significant values for the international indicators such as trade openness and FDI inflows. However, the coefficients are notably smaller in magnitude than those present in the global panel, perhaps implying that the leading innovators are not as dependent on the imitation-innovation product cycle for new-to-the-world technologies.

Emerging Innovators

Again, like the leading innovators, idea stock is highly significant in driving innovation for emerging innovators, as seen in Table 4. One key difference in emerging innovators, however, is that while leading innovators are better influenced by journal article or knowledge stock, emerging innovators better reap the benefits of innovation with more labor in the ideas-producing sector given the significance of the number of full-time scientists and engineers. The quality of the rule of law also seems to play a markedly larger role in the innovative capacity for emerging innovators. Furthermore, unlike for leading innovators, quality of linkages indicators such as venture capital and university-industry collaboration do not seem to play as large a role. Notably, university-industry collaboration is significant for model 5, emphasizing its importance in streamlining innovation from the academe to the private sector.

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Varia	ables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LNPA	1TS	0.8520***	0.7769***		0.8389***	0.8206***	0.6738***		0.7338***
LNSC	CITECHJ	0.8875***	0.8626***		0.8383***	0.8837***	0.8449***		0.8008***
LNFT	TESE	-0.2335	-0.2283		-0.2874	-0.2481	-0.0766		-0.2082
LNEL	DUCEXP	0.2403	0.2045		0.2259	0.0748	0.0043		-0.0274
LNRN	VDEXP	0.0867	0.0326		0.0278	0.0278	0.0075		0.0004
LNIP	R		0.4709**		0.4364*	0.4409*	0.6332***		0.5737***
LNRU	ULE		0.5776		0.3777	0.8629	3.8787***		3.3885***
LNTE	ECHSPEC			2.7702***	0.2253**	0.0757*		0.6379***	0.0878
LNCI	LUSTER			0.0288	2.0649***	0.7653***		0.0839	2.3640***
LNDO	OMRIV			2.8673*	0.3509	0.0789		0.2528	0.2535
LNVE	ENTCAP					0.2428			0.2889
LNUI	VINCOL					2.3779***			2.6086***
LNOI	PENNESS						-0.0837	0.8774***	-0.2604
LNFL)I						0.0774***	0.0869***	0.0355***
LNGI	DPCAP	-0.5870	-0.8405	3.0508***	-0.2763	0.0457	-0.8787	0.7303	0.2679
LNUI	RBAN	0.7878***	8.7456	5.5767***	0.8564***	0.8372***	0.5359***	0.7875***	0.8776***
	within	0.7868	0.7877	0.4677	0.7433	0.7482	0.7426	0.6783	0.7478
\mathbb{R}^2	between	0.8873	0.8888	0.0877	0.8563	0.7788	0.8688	0.3487	0.6772
	overall	0.7088	0.7036	0.0843	0.8887	0.8388	0.8722	0.8727	0.7784
Obse	rvations	1920	1920	1920	1920	1920	1920	1920	1920
Mode	el	FEM							

Table 3. Leading Innovators Panel Regression Results

Notes: The asterisks denote significance levels. *** at 1%, ** at 5%, and * at 10%.

Interestingly, FDI inflows are highly significant in this model, indicating that the imitation to innovation effect of international spillovers prevails for this subset of nations. This is compelling, given the prevalence of OEM industries in this subpanel, which is based on the designs and specifications of the leading, developed countries. Together with the highly significant evidence for the weak IPR regime, this finding indicates that these nations learn to innovate by imitating the leading countries' technologies, spurring the catch-up effect. This is consistent with economic history, wherein the 3rd wave of industrialization in Asia hearkened the rise of OEMs in NIEs like South Korea and Taiwan, who eventually developed their OBMs (Jin and Zhang, 2016).

Varia	ables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LNPA	1TS	0.7075***	0.7841***		0.7274***	0.6871***	0.4839***		0.4705***
LNSC	CITECHJ	0.2608***	0.2503***		0.2878***	0.0764**	0.0327**		-0.0075
LNF7	TESE	-0.0527	-0.0525		-0.0553	0.2204*	0.0456**		0.0338
LNEL	DUCEXP	-0.2822	-0.2387		-0.2308	-0.054 6	0.0803		0.0866
LNRN	VDEXP	2.3336	0.7626		0.7768	0.4368	0.2847		-0.0039
LNIP	R		0.0874		0.0588	0.0689	-0.0049		0.0288
LNRU	JLE		2.5478**		2.5534**	3.4385***	8.4873***		5.8223***
LNTE	ECHSPEC			0.7277***	0.0755**	0.0675**		0.0882	0.0378***
LNCL	LUSTER			2.8877***	-0.2825	2.0579***		0.2785*	0.0379
LNDO	OMRIV			0.6077	-0.0308	0.0607		-0.2658	-0.0348
LNVE	ENTCAP					-0.0655			-0.0277
LNUI	VINCOL					0.7829***			0.0784
LNOI	PENNESS						0.0747*	0.0635	-0.0271
LNFL	DI						3.7029***	2.8567***	3.7828***
LNGI	DPCAP	0.3726**	0.3865*	0.3036	0.3303*	0.3728**	0.0772**	-0.7705	0.0583**
LNUI	RBAN	-0.2588	-0.2392	8.0489	-0.0657	-0.4529	-0.5873	0.6244**	0.3887***
	within	0.8758	0.8767	0.3284	0.8777	0.7072	0.7887	0.7577	0.7887
\mathbb{R}^2	between	0.2858	0.3723	0.0537	0.8507	0.4247	0.7278	0.7652	0.7757
	overall	0.8067	0.4286	0.0768	0.5083	0.6002	0.7467	0.762	0.7783
Obse	rvations	1920	1920	1920	1920	1920	1920	1920	1920
Mode	el	FEM	REM						

Table 4. Emerging Innovators Panel Regression Results

Notes: The asterisks denote significance levels. *** at 1%, ** at 5%, and * at 10%.

Laggard Nations

Much like the previous two panels, intertemporal spillovers generated by accumulated knowledge stock are seen to have a highly significant effect on innovative capacity for laggard nations (Table 5). Unlike previous panes, however, educational expenditure is mildly significant in this panel, whereas it was not significant or very weakly significant in previous panels. This suggests that the cross-cutting policy environment of laggard nations plays a role in determining innovative capacity for poor or developing countries. Indeed, this, along with the significance of the full-time equivalent scientists and engineers, is empirical evidence that human capital and the policy environment work jointly to spur innovation (Benhabib and Spiegel, 1994). Moreover, public research expenditure and the rule of law are highly significant in this panel, whereas public research and development was insignificant in previous models. These findings suggest that for laggard nations, the macroenvironment underlying innovation is a crucial enabler of technological progress and may spell either future progress or stagnation.

Varia	ables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LNPA	1TS	0.8603***	2.0703***		2.0883***	2.2037***	2.2502***		2.2555***
LNSC	CITECHJ	0.0769***	0.0805		-0.0837	0.0409**	0.0589***		-0.0285
LNFT	TESE	0.0875**	0.2279**		0.2288**	0.0487**	-0.0245		0.0838*
LNEL	DUCEXP	0.0687	0.2887		0.2839	0.2809**	0.2045		0.2548
LNRN	VDEXP	0.0674**	3.4427*		3.4746*	0.0265	0.0074		8.0223**
LNIP	R		-0.8227**		0.8820***	-0.2456	-0.2445*		-0.3372*
LNRU	ULE		2.6483***		2.5663***	2.7283***	4.5082***		4.0450***
LNTE	ECHSPEC			0.8801***	-0.0446	-0.0259		0.0806	-0.0344
LNCI	LUSTER			0.8479	-0.0779	-0.2674		0.3589	-0.3386
LNDO	OMRIV			-2.7388	0.2584	0.4043*		-0.8786	0.2857
LNVE	ENTCAP					0.5262***			-0.0228
LNUI	VINCOL					0.7378*			0.7827
LNOI	PENNESS						0.2375***	0.2642	0.3046
LNFL	DI						0.8656***	0.6564***	0.8283***
LNGI	DPCAP	-0.0857	0.2008	-0.6851	0.2238	-0.0322	0.0704**	0.6578*	-0.0885
LNUI	RBAN	0.2424	-0.8855	7.2687***	-0.8084	0.2828	0.2329	4.3409***	-0.6062
	within	0.7206	0.7372	0.2767	0.7378	0.7386	0.7867	0.5823	0.7873
\mathbb{R}^2	between	0.7653	0.5643	0.0002	0.5588	0.7848	0.7848	0.2234	0.5236
	overall	0.7388	0.5753	0.0074	0.5677	0.7444	0.7537	0.3655	0.5228
Obse	rvations	1920	1920	1920	1920	1920	1920	1920	1920
Mode	el	REM	FEM	FEM	FEM	REM	REM	FEM	FEM

Table 5. Laggard Nations Panel Regression Results

Notes: The asterisks denote significance levels. *** at 1%, ** at 5%, and * at 10%.

5. Conclusion and policy recommendations

In conclusion, this study has remained consistent with its objectives by (i) introducing a novel and integrated framework of innovative capacity; (ii) characterizing the relationship between each of the indicators to each subset of countries; and (iii) using a new method of estimation to determine the interplay of the various theories for each subset of nations based on innovative capacity.

While previous studies were overwhelmingly concentrated in the closed-systems approach, this paper proposes and empirically affirms a new open model of technological innovation. The findings under this model suggest that levels of trade openness and foreign direct investment do indeed play important roles in determining national innovative capacity. These factors have explained the rapid technological convergence of nations such as Brazil, China, and India over the past decade.

Under the common innovation infrastructure, it was found that ideas-driven growth is highly dependent on the intertemporal spillovers generated by accumulated patent stock. However, results for the other variables are not as uniform when disaggregated to the different subpanels. For scientific journals and articles, only leading innovators were found to make use of this and transform it into

innovative output. However, emerging and laggard nations are better able to harness the human capital devoted to the ideas-generating sector to produce new technologies. Government policies that affect the macroenvironment for innovation are most effective for laggard nations, who greatly benefit from increased educational and R&D expenditures. On the other hand, for the legal institutions, this paper has empirically proven that the effect of the IPR regime depends on the level of development in a country. For developed, leading innovators, a strong IPR regime leads to long-run technological progress by encouraging innovation. However, for emerging or laggard nations that are more dependent on the imitation to innovation effect, a weak IPR regime may enable them to develop their unique technological capabilities by emulating the developments in more advanced nations through international spillovers.

Moreover, the quality of linkages hypothesis was empirically proven in leading innovators, where the university-industry collaboration index was shown to be highly significant. This bodes well for OECD nations, where efforts have been geared towards improving inter-sectoral collaboration over the past few years (Wu et al., 2017). Moreover, just like previous studies, venture capital was found to be only weakly significant, which implies that the university-industry relationship is better able to capture the relationship between the quality of linkages and innovative output.

This study has shown that it is not prudent to aggregate the effects of various innovation frameworks for all countries. In certain subsets of nations, the common innovation infrastructure might prevail, whereas, for others, the international spillovers of innovation may yield more beneficial outcomes. However, one thing is undeniable: the findings in this study underscore the fact that there is no universal recipe that enables the convergence of innovative capacity. While emerging nations shore up on their technological capabilities with inward FDI, perhaps the same approach would not yield the same benefits for laggard nations. The intricate nexus of policy considerations, microeconomic factors, as well as international alliances, all play off each other and jointly affect a nation's innovative capacity.

To fulfill this study's final objective of proposing policy recommendations for each subset of nations, the following sections are presented.

Leading Innovators

As per Guimón (2013), the strength of university-industry linkages is a key element in the commercialization of new-to-the-world technologies. Unique among all the categories of countries, leading innovators are differentiated by their strong reliance on university-industry linkages to innovate. Thus, to sustain progress without stagnating as they have done for the past few years, these nations must continue to develop institutions to streamline collaboration between the academe and the private sector. Such programs may include research partnerships, technological transfer, or academic entrepreneurship programs or accelerators. Moreover, unlike the other subpanels, a strong IPR regime inhibits piracy and encourages innovation in these countries. Hence, leading innovators must shift to more stringent intellectual property laws, if they have not yet done so.

Emerging Innovators

Just as a strong IPR regime is beneficial for leading innovators, a weak and more flexible IPR regime would be more suitable for emerging innovators. Governments of these nations must ensure that the intellectual property system is tailored to provide domestic firms with adequate incentives for effective learning and emulation. Sufficient incentives must be given to firms for them to engage in capacity-building until they, too, become leading innovators. Once sufficient innovative capacity has been established, these nations can then strengthen their IPR regime. This begs the question, however, of when exactly these nations would benefit from a stringent IPR system rather than a flexible one. Future studies may explore this conundrum with more sophisticated methods.

Laggard Nations

In laggard nations such as the Philippines, the national innovation system is of paramount importance. Rather than introducing heavy-handed and reactionary policies that may lead to unintended consequences, governments of these nations must heed the macro-level enablers of innovation, especially during this global pandemic. For these nations, developing infrastructure and improving national institutions take precedence over fostering domestic rivalry and industrial complexity. At this level of development, factors such as the rule of law, IPR regime, and international alliances must all be geared towards enabling the development of growth rather than forcing progress artificially. To do this, the Philippines and other laggard nations would do well to invest in existing infrastructure and eliminate

existing bottlenecks to growth may have far more impact. In the Philippines, network infrastructure, as well as logistical efficiency, are key areas of improvement, both of which fall under national innovation systems. Once these existing constraints have been lifted, and the national environment has been made conducive for progress, only then can the industrial cluster-specific factors come into play. The burgeoning startup culture in the Philippines is evidence of this, and an environment of minimal red-tape and inclusive institutions would further lead to innovative upgrading in the country. Moreover, the burgeoning OEMs and ODMs in laggard Asian countries such as Vietnam may serve as the key to upgrading the innovative capacity, provided that the national government can take full advantage of these technological spillovers by having a weak IPR regime coupled with a robust rule of law. All of these, together with an excellent educational and public R&D regime, may drastically improve innovative capacity in laggard nations.

References

- Abramovitz, M. (1956). Resource and output trends in the United States since 1870. In *Resource and output trends in the United States since 1870* (pp. 1-23). National Bureau of Economic Research.
- Balland, P-A, Rigby, D. (2015). The geography and evolution of complex knowledge. Papers in Evolutionary Economic Geography, 2(15), 1–24. Retrieved from http://econ.geo.uu.nl/peeg/peeg1502.pdf
- Benhabib, J., & Spiegel, M. (1994). The role of human capital in economic development: evidence from aggregate cross-country data. *Journal of Monetary Economics*, *34*, 143–173.
- Bose, N., Haque, M. E., & Osborn, D. R. (2007). Public expenditure and economic growth: A disaggregated analysis for developing countries. *The Manchester School*, 75(5), 533–556.
- Canie, M. C. J., & Romijn, H. A. (2005). What drives innovativeness in industrial clusters? Transcending the debate. *Cambridge Journal of Economics*, 29, 497–515. https://doi.org/10.1093/cje/bei018
- Conconi, P., Sapir, A., & Zanardi, M. (2016). The internationalization process of firms: From exports to FDI. *Journal of International Economics*, 99, 16–30. https://doi.org/10.1016/j.jinteco.2015.12.004
- Cornell University, INSEAD, & WIPO. (2019). *The Global Innovation Index 2019*. Creating Healthy Lives The Future of Medical Innovation.

- Filippetti, A., Frenz, M., & Ietto-Gillies, G. (2012). The Role of Internationalization as a Determinant of Innovation Performance: An Analysis of 42 Countries. SSRN Electronic Journal, 10, 1–31. https://doi.org/10.2139/ssrn.2114289
- Frenken, K. (2006). Technological innovation and complexity theory. *Economics of Innovation and New Technology*, 15(2), 137–155. https://doi.org/10.1080/10438590500141453
- Furman, J. L., & Hayes, R. (2004). Catching up or standing still? National innovative productivity among "follower" countries, 1978-1999. *Research Policy*, 33(9), 1329–1354. https://doi.org/10.1016/j.respol.2004.09.006
- Furman, J. L., Porter, M. E., & Stern, S. (2000). Understanding the drivers of national innovative capacity. Academy of Management Proceedings, 2000(1), A1–A6. https://doi.org/10.5465/APBPP.2000.5536001
- Furman, J. L., Porter, M. E., & Stern, S. (2002). The determinants of national innovative capacity. *Research Policy*, 31, 899–933. https://doi.org/10.5465/APBPP.2000.5536001
- Guimón, J. (2013). Promoting university-industry collaboration in developing countries. *Policy Brief. The Innovation Policy Platform*, 1(3), 1-12.
- Hafner, K. A. (2014). Technology spillover effects and economic integration: evidence from integrating EU countries. *Applied Economics*, 46(25), 3021–3036. https://doi.org/10.1080/00036846.2014.920479
- Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. Proceedings of the National Academy of Sciences, 106(26), 10570–10575.
- Jin, W., & Zhang, Z. X. (2016). On the mechanism of international technology diffusion for energy technological progress. *Resource and Energy Economics*, 46, 39–61. https://doi.org/10.1016/j.reseneeco.2016.07.004
- Nelson, R. R. (Ed.). (1993). National innovation systems: a comparative analysis. Oxford University Press on Demand.
- Nelson, R. R., & Nelson, K. (2002). Technology, institutions, and innovation systems. *Research Policy*, 31, 265–272.
- Petralia, S., Balland, P. A., & Morrison, A. (2017). Climbing the ladder of technological development. *Research Policy*, 46(5), 956–969. https://doi.org/10.1016/j.respol.2017.03.012
- Porter, M. E. (2001). The competitive advantage of nations. Harvard Business Review, 68(2), 73-93.
- Porter, M. E., & Stern, S. (2001). Innovation: Location matters. *MIT Sloan Management Review*, 42(4), 28–36.

- Reichardt, K., Rogge, K. S., & Negro, S. O. (2017). Unpacking policy processes for addressing systemic problems in technological innovation systems: The case of offshore wind in Germany. *Renewable and Sustainable Energy Reviews, 80*, 1217-1226.
- Romer, P. M. (1996). Why, indeed, in America? Theory, history, and the origins of modern economic growth (No. w5443). National Bureau of Economic Research.
- Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, 70(1), 65-94.
- Taalbi, J. (2017). What drives innovation? Evidence from economic history. *Research Policy*, 46(8), 1437–1453. https://doi.org/10.1016/j.respol.2017.06.007
- UNESCO. (2020). Fighting COVID-19 through digital innovation and transformation. Retrieved from https://en.unesco.org/covid19/communicationinformationresponse/digitalinnovation
- Urraca-Ruiz, A. (2013). The "technological" dimension of structural change under market integration. Structural Change and Economic Dynamics, 27, 1–18. https://doi.org/10.1016/j.strueco.2013.07.002
- World Economic Forum. (2019). *The Global Competitiveness Dataset 1996-2019*. (K. Schwab, Ed.).Geneva: World Economic Forum. Retrieved from www.weforum.org/gcr
- Wu, J., Ma, Z., & Zhuo, S. (2017). Enhancing national innovative capacity: The impact of high-tech international trade and inward foreign direct investment. *International Business Review*, 26, 502–514. https://doi.org/10.1016/j.ibusrev.2016.11.001

APPENDIX

Table A1. Variable Descriptions, Labels, and Sources

Category	Label	Description	Sources
INNOVATIV	E OUTPUT (Ā	Ī)	
$\overline{A}_{j,t}$	PATG	This is the primary measure of technological innovation. It is the number of international patents awarded by the USPTO to a nation (both direct and PCT national phase entries).	World Intellectual Property Office, United States Patent and Trademark Office
QUALITY O	F COMMON I	NNOVATION INFRASTRUCTURE $(X_{j,t}^{INF})$	
$E_{j,t}^{END}$	PATS	This is the cumulative number of patents per million persons from the earliest available date to the year in question.	World Intellectual Property Office and author's calculations
	SCITECHJ	This is the number of scientific journal articles published in a nation in a given year.	World Bank
	<i>FTESE</i> This is the measure of individuals who are employed in scientific and idea-generating industry. It is measured by number of scientists, technicians, and researchers in R&D. calculated as:		World Bank and author's calculations
		(Technicians + Researchers in R&D)	
	EDUCEXP	This is a part of the innovation infrastructure under the Porter (1990) school of thought, which characterizes education as part of the microeconomic environment that encourages innovation. It is measured as a percentage (%) of GDP. This is calculated as	World Bank
G_{i+1}^{POL}		$EDUCEXP = \frac{Gross\ education\ expenditure\ for\ higher\ education}{GDP\ expenditure} * 100\%$	
$G_{j,t}^{POL}$	RNDEXP	This is a part of the innovation infrastructure under the Porter (1990) school of thought, which characterizes research and development expenditure as part of the microeconomic environment that encourages innovation. It is measured as a percentage (%) of GDP. This is calculated as $RNDEXP = \frac{Private RND expenditure + Public RND Expenditure}{GDP} * 100\%$	World Bank
$I_{j,t}^{LEG}$	IPR	A measure of the intellectual property rights regime in the country. It is a component of the Economic Freedom of the World Index by the Fraser Institute and is a longitudinal and comprehensive evaluation of the IPR regime in a nation. It is measured on a scale of 1-10.	Fraser Institute

RU	<i>ILE</i> The quality of the legal system and the stringency of government rules and regulations. It is a component of the Economic Freedom of the World Index by the Fraser Institute. It is also measured on a scale of 1-10.	Fraser Institute
CLUSTER-SPECI	FIC INNOVATION ENVIRONMENT (Y ^{CLUS})	
	This characterizes the patterns of specialization in the system. It is a concentration index of international patents that is calculated with the equation specified (Wu et al., 2017; Ellison & Glaeser, 1997), which is derived from the E-G concentration index of chemical, electrical, and mechanical patents. It is calculated as follows:	Author's calculations
TECHSPEC	$TECHSPEC_{i,j,t} = \frac{PATENTS_{i,j,t}}{PATENTS_{i,j,t-1}} \left(\sum \frac{\left(s_{i,j,t} - x_i\right)^2}{1 - \sum x_i^2} - \frac{1}{PATENTS_{i,j,t}} \right)$	
	where:	
	$PATENTS_{i,j,t}$ = patents in each technological class (<i>i</i>) for each country (<i>j</i>) in each time period (<i>t</i>) and x_i = average share of patents class in all country-years	
CLUSTER	The coefficient of clustering of the industrial firms in a given country. It is calculated using the method of reflections of Hidalgo and Hausman (1990), which yields nonnegative numbers.	Economic Complexity Index
DOMRIV	A measure of the domestic rivalry in a country. Measured as a Likert scale from 1-10 from reliable survey data.	Global Competitiveness Index
QUALITY OF LI	NKAGES $(Z_{j,t}^{LINKK})$	
VENTCAP	This is the measure of the strength of linkages within the economy, which is proxied by the availability of venture-backed financing on the Likert Scale from 1-10 from reliable survey data.	Global Competitiveness Index
UNINCOL	A measure of university-industry linkages using survey data conducted internationally spanning 1996-2019. It is measured on a Likert scale of 1-10 from reliable survey data.	Global Competitiveness Index
INTERNATIONA	L SPILLOVERS $(W_{j,t}^{INT})$	
OPENNESS	This is a rough indicator of openness to international trade. It is calculated as:	World Bank and Author's calculations
	$OPENNESS_{i,t} = \frac{X_{i,t} + M_{i,t}}{GDP_{i,t}}$	
	where: $X_{i,*} = \text{exports of goods and services (constant 2010 US$)}$	
	$M_{i,t}$ = imports of goods and services (constant 2010 US\$) and	
	$GDP_{i,t}$ =national Gross Domestic Product (constant 2010 US\$)	

FDI	This is a measure of inward foreign direct investment in the economy. It is measured with net inflow of foreign direct Investment (BoP, in millions of US\$, constant 2010 prices)	World Bank							
CONTROL VARIABLES ($C_{j,t}$)									
GDPCAP	The GDP per capita is the GDP divided by the country's population. It is used as a control variable to account for differences in the standard of living across countries.	World Bank							
URBAN	This denotes the percentage (%) of urbanization present in a country. This is calculated as:	World Bank							
	$URBAN_{i,t} = \frac{(Population \ living \ in \ urban \ areas)_{i,t}}{Total \ Population_{i,t}}$								

Variables	Α	Model							
	priori	1	2	3	4	5	6	7	8
LNPATS	+	Yes	Yes		Yes	Yes	Yes		Yes
LNSCITECHJ	+	Yes	Yes		Yes	Yes	Yes		Yes
LNFTESE	+	Yes	Yes		Yes	Yes	Yes		Yes
LNEDUCEXP	+	Yes	Yes		Yes	Yes	Yes		Yes
LNRNDEXP	+	Yes	Yes		Yes	Yes	Yes		Yes
LNIPR	+/-		Yes		Yes	Yes	Yes		Yes
LNRULE	+		Yes		Yes	Yes	Yes		Yes
LNTECHSPEC	+			Yes	Yes	Yes		Yes	Yes
LNCLUSTER	+			Yes	Yes	Yes		Yes	Yes
LNDOMRIV	+			Yes	Yes	Yes		Yes	Yes
LNVENTCAP	+					Yes			Yes
LNUNINCOL	+					Yes			Yes
LNOPENNESS	+						Yes	Yes	Yes
LNFDI	+						Yes	Yes	Yes
LNGDPCAP	+	Yes							
LNURBAN	+	Yes							

Table A2. A Priori Expectations and Stepwise Hierarchical Method