THE DIFFUSION OF INNOVATION: A SPATIAL ECONOMETRIC APPROACH

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SUMMARY

The present paper highlights a critical aspect of endogenous growth theory to unravel the pivotal theme of knowledge production and innovation activities. This research draws inspiration from seminal works by Griliches (1979), Romer and Jones (1990-1995), which laid the foundation for the Knowledge Production Function (KPF) with patent flow as a primary output indicator. The versatility of forms of innovation ranging from tangible to intangible allows its mobility across economic agents, carrying substantial implications at both local and international scales. By estimating the spatial panel data model across a sample of 20 countries affiliated with the OECD organization over a 20-year period from 1995 to 2015, our examination identified a beneficial spatial interdependence in the production of innovation among countries. Also, a positive direct impact of innovation stock was observed within a country, both internally and in neighboring nations. Additionally, our analysis unveiled a significant negative indirect influence of Research and Development (RD) stock on innovation production in adjacent countries.

Keywords: Endogenous growth theory, Innovation, Knowledge Production Function, Spatial econometrics.

JEL CODES CLASSIFICATION : C23, C33.

DIFFUSION DE L'INNOVATION : UNE APPROCHE PAR L'ECONOMETRIE SPATIAL

RÉSUMÉ

Le présent article met en lumière un aspect critique de la théorie de la croissance endogène, centré sur le thème central de la production de connaissances et de l'activité d'innovation. S'inspirant des travaux fondateurs de Griliches (1979), Romer et Jones (1990-1995), qui ont jeté les bases de la fonction de production de connaissances (KPF) avec le flux de brevets comme principal indicateur de résultat. La polyvalence des formes d'innovation entre le matériel et l'immatériel permet sa mobilité entre les agents économiques, ce qui entraîne des implications substantielles à l'échelle locale et internationale. En estimant le modèle de panel spatial sur un échantillon de 20 pays affiliés à l'OCDE sur une période de 20 ans allant de 1995 à 2015. Notre examen a d'abord identifié une interdépendance spatiale bénéfique dans la production d'innovation entre les pays. En outre, un impact direct positif du stock d'innovation a été observé au sein d'un pays, tant à l'intérieur que dans les pays voisins. De plus, notre analyse a révélé une influence indirecte négative significative du stock de recherche et développement (RD) sur la production d'innovation dans les pays adjacents.

Mots-clés : Innovation, Fonction de production de connaissances, économétrie spatiale, théorie de la croissance endogène.

إنتشار الابتكار :بإستعمال منهجية الإقتصادي المكاني

ملخص

تسلط هذه الورقة الضوء على جانب حاسم من نظرية النمو الداخلي، مع التركيز على الموضوع المحوري المتمثل في إنتاج المعرفة ونشاط الابتكار. مستوحى من الأعمال الأساسية لجرليتشي (1979 ، ورومر وجونز (1990-1995، التي أرست

.للمخرجات رئيسي كمؤشر الاختراع براءات تدفق مع المعرفة إنتاج لوظيفة الأساس العوامل عبر بتنقله يسمح الملموس وغير الملموس بين الابتكار أشكال تنوع إن تقدير خلال من .والدولي المحلي المستويين على كبيرة آثاراً يحمل مما الاقتصادية، والتنمية الاقتصادي التعاون لمنظمة تابعة دولة 20 من عينة عبر المكانية اللوحة نموذج فحصنا حدد البداية، في .2015 عام إلى 1995 عام من عاما عشرين مدى على إيجابي تأثير وجود لوحظ كما .البلدان بين الابتكار إنتاج في المفيد المكاني الترابط الدول في أو الداخلي المستوى على سواء الدولة، داخل الابتكار لمخزون مباشر لمخزون كبير مباشر غير سلبي تأثير عن تحليلنا كشف ذلك، إلى بالإضافة .المجاورة المجاورة البلدان في الابتكار إنتاج على والتطوير البحث

كلمات المفتاحية: الابتكار، دالة إنتاج المعرفة، الاقتصاد القياسي المكاني، نظرية النمو الداخلي

INTRODUCTION

The diffusion of innovation explores how new ideas, technologies, and practices spread across geographical regions and impact economies of both international and local markets. This phenomenon plays a crucial role in shaping the development and growth patterns of societies, as it involves understanding how innovations diffuse from their origin to different locations, and how their adoption influences local economies.

Understanding the patterns and determinants of innovation spread can inform policymakers on effective strategies to promote technology adoption, enhance productivity, and bolster regional competitiveness. Moreover, such research aids in identifying potential knowledge hubs and innovation clusters, which are crucial drivers of economic agglomeration and knowledge spillovers.

Innovation is considered to be one of the most important factors in growth theory (Solow model, 1956). In this context and due to the broad range of concepts of innovation, our paper will review the concept of innovation exclusively through the framework of this theory.

Starting from the conclusions that were drawn from Solow's models' work, Solow's residuals are defined as the rest of an economy's output growth that cannot be interpreted as the accumulation of capital and labor. This element is often described as a measure of productivity growth yield from technological innovation and is equally referred to as: Total Factor Productivity (TFP).

The endogenous growth models came to illustrate: (i) what knowledge is? (ii) how knowledge is generated? and how knowledge is transferred into the production field in the form of goods and services? Thus, it becomes clear that knowledge has the main key role in this theory, and this is what was found in the innovation-based theory of Romer (1990), which recognizes that intellectual capital is distinct from physical capital and that innovation causes productivity growth by creating new varieties of products but not necessarily improved. This statement leads us to investigate the difference between innovation and knowledge!

The term "innovation" has two distinct meanings: it can refer to "novelty," or an "act or process of creating or introducing something new". Thus, innovation is referred to as new knowledge, or it can indicate the process of creating new knowledge as a product. (as, for example, in Porter and Stern (2000), and the as a description of the process of creation of new knowledge (e.g.: Freire-Seren (2001))

The historical Knowledge Production Function (KPF) was introduced for the first time by Griliches in 1979. The latter measured innovation activity by using patent flow as an output and the expenditures on research and development as an input, based on the data of 121 U.S. firms over 13 years. In accordance with Cobb-Douglas function outputs, the KPF function highlighted a positive relationship between the input of research expenditures and the output, opening the door for the scientific community to focus their work on different inputs and add new factors into this function as done by Romer & Jones (1990-1995). Recently, Michael A. Verba's model (R&D-based KPF 2020) extended the Romer & Jones KPF by adding new elements to the existing body of knowledge (innovation stock) the number of scientists and engineers in the R&D sector, and the R&D-based KPF, which provided a better approximation of true knowledge dynamics than either Romer-Jones or Griliches's knowledge production function did.

On the other hand, divergence rises concerning the definition of innovation under its tangible (food or goods) and intangible (production process or management methods) forms, which leads researchers to highlight the question of innovation diffusion in different markets and gain more insight on the question concerning which channel has the most dominant role in innovation.

The three previous points, and the emergence of the new economic geography (see Henderson and Thisse, 2004), help us to study the existing externalities between local and foreign returns of innovation. Indeed, several studies on this topic have been conducted, starting with

Jaffe (1989), who was the first to analyze the spatial dependencies of innovation outside the context of the firm.

In this context, our present study will focus on the country-level dependencies since we consider that the diffusion of innovation can be achieved through many channels, such as international trade (FDI or export and import), workers' career and mobility, academic-business collaboration, or knowledge-intensive business services. The study will also follow the Spatial Elhorst methodology that focuses on the analysis of spatial data with panel structures. It combines spatial econometrics and panel data techniques to study the interplay between space and time in economic phenomena. Key elements of the methodology include the use of spatial autoregressive models to capture spatial dependencies and spillover effects among neighboring observations. The methodology has practical applications in regional economics, urban planning, and environmental studies, offering valuable tools to understand spatially dependent data.

Accordingly, Dirk Frantzen (2000) concluded that in the panel of OECD countries, the average influence of international innovation diffusion is substantially stronger than that of domestic researcher and development (R&D). However, in the case of large economies, the influence of the latter is found to be more important. These findings, along with the aforementioned elements, such as the KFP framework and the new geographic economy, build a kind of curiosity about how we can use all of those elements to measure innovation diffusion at a country’s level, and this paper attempts to propose satisfactory answers to this questioning.

1. LITERATURE REVIEW

To demystify the innovation concept, it is necessary to start with a listing of the most relevant definitions: novelty and/or . act or process of creating or introducing something new. The two definitions are used in different articles, and each of them carries a certain amount of theoretical depth: The first one defines innovation as a unit of measure of knowledge (Porter and Stern, 2000), and the second one defines it as a description of the process of new knowledge creation (Freire-Seren, 2001).

According to the Oxford dictionary, the term “knowledge” refers to a theoretical or practical understanding of a subject. It can be implicit (as with practical skill or expertise) or explicit (as with the theoretical understanding of a subject); formal or informal; systematic or particular (website). “Technical change” (Griliches, 1988), “Technological change” (Verspagen, 1995), and “Invention” (Griliches, 1979) represent different works that dealt this concept of innovation in various ways. The accumulative character of knowledge over time forms a stock, forms a stock, a concept that comes under the label of “Technology” (Benhabib and Spiegel, 2005; Los and Verspagen, 2000). Also based on “Oslo Manual”, 3rd edition, 2005, an innovation is referred to as the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations.

The complexity of the meaning of innovation appears through the previous definitions for a variety of reasons. Besides, it is necessary to highlight the central role of innovation (technical change) in growth theory. Starting from Solow (1956-1957) in the model of aggregate production, where it acts as a key input, alongside with capital and labor. The main role of innovation is crucial in the endogenous growth theory. This role is shown in growth models with their three development phases. In the first so-called phase, the AK models hypothesized that high rates of growth depend upon thrift, some of which finances a higher rate of technological progress, resulting in higher growth; no explicit distinction was made, however, between technological progress and capital accumulation in these models (Romer, 1987; Rebelo, 1991). In the second phase, "innovation-based" models posit that innovation causes productivity growth by creating new varieties of intermediate goods. Here, innovations do not necessarily generate better intermediate products, just more of them. The increased use of these goods is associated with their greater supply and variety, leading to higher growth (Romer, 1990). Finally, in the third phase, the innovation-based theory took a Schumpeterian approach. According to Schumpeter, innovation involves the introduction of new combinations of various elements in the production process, such as technology, resources, and organizational methods. He first presented these ideas in his seminal work "The Theory of Economic Development," which was initially published in 1911. Later, Schumpeter expanded on his innovation theory and the concept of creative destruction in his book "Capitalism, Socialism and Democracy," published in 1942.

Aghion and Howitt (1992, 1998), for instance, developed a model in which a version of Schumpeter's process of creative destruction generates vertical innovations that drive the development of technological knowledge, increasing productivity and fueling economic growth. Innovations in this model are the result of deliberate investment in research processes. Although, newly developed intermediate goods render existing ones obsolete, the expectation of future spending on research acts as a brake on current research spending where firms must balance the costs and benefits of such spending.

Drawing on what have been discussed so far, the next step of the research on the innovation topic will be directed to answer the question of how can we measure knowledge production and what are the most significant factors of this production process?

Following Griliches's works, Romer (1990) added a new dimension to the knowledge production function by first including the innovation stock as a factor in the process of knowledge production since he assumed that a linear relationship exists between new innovation and the stock of the innovation that already exists and secondly by adding the number of researchers and workers in the R&D department as a new factor alongside the R&D expenditures.

The main findings of Romer's model indicate that the amount of research labor should increase the spillovers in knowledge production. Jones (1995) tested the validity of this prediction by appealing to data on total factor productivity growth (as an innovation activity output). As well as scientists and engineers working in R&D (in the place of research labor). This leads to the conclusion that in the U.S., the number of R&D scientists and engineers has increased significantly over the postwar period while total factor productivity (TFP) growth has been characterized by relative constancy. We found other models with the same objective to study the KPF by changing the output and adding new factors, but we will stop at the three previous models because they cover our theoretical needs in this article.

As a summary of the previous debate around the definitions and models of the KPF, we have tried to cover the notions of the innovation form, new production procedures, as well as production machines, which are both considered innovations in spite of the fact that the first invention was intangible while the second one was tangible. When researchers attempt to measure the innovation activity or the innovation stock, the nature of the innovation forms creates complicated cases (Griliches, 1979).

The debate on innovation forms by focusing on the basic example already mentioned below (Process or machine of production). Those innovations can be shared between producers at the local market level, and with globalization and international links, this capability of innovation to be diffused at this level for many reasons should be investigated.

Two hypotheses are made in relation to the innovation diffusion through this channel: the first one is that an increase in imports can intensify competition in the market, reduce profit margins of native firms, and thus encourage the firms to innovate in order to enhance their efficiency and secure their market share. This hypothesis has been proven theoretically (Jacquemin 1982; Caves 1985) and empirically (Pugel 1978, 1980; Turner 1980; Levinsohn 1991). And the second one argues that the effect of inward FDI is even greater than that of imports because of FDI's higher costs, time-consumption, and irrevocability in terms of sunk costs (Bertschek, 1995).

In fact, the diffusion of innovation through international trade constitutes the larger segment of study, but there are other interesting bridges of innovation that are related to the factor of knowledge production that can participate in the innovation transfer in the international market, such as human capital mobility, especially in skillful workers (i.e., doctors and researchers). By taking a look at the literature, two approaches can be found; one based on the movement of the most skillful people according to the advantages offered by each country to capture the maximum number of researchers or innovative people; and the second one is related to the FDI or import approach, where, for instance, foreign companies will, upon entering the local market, provide more and better training for the staff of the local company and train the employees to increase average labor productivity in the host state. The same logic applies to importing sophisticated production machines and training local staff; all can be considered innovation diffusion.

The accessibility of innovation to the producers in the local or international markets is not a simple matter since not all the innovators (individuals, countries, or companies) are willing to share their findings without any compensation. Thus, procedures and authorizations, as well as a good intellectual property (IP) system, become essential to solve this market issue and ensure a fair competitive environment. A good implementation of such mechanisms has a great impact on innovation productivity by incentivizing innovators to give the best products and services in the market. On the other hand, if such protection issues are not sufficiently considered the innovation may lose its competitive advantage and be ousted from the market.

Intellectual property (IP) encompasses various categories that safeguard different forms of creations and innovations; (1) patents offer exclusive rights to inventors for their novel technologies and processes,(2) copyrights protect original works of authorship, such as books, music, and artwork, (3) trademarks distinguish brands and logos, enabling businesses to build brand recognition and loyalty, (4) trade secrets keep confidential business information secure, providing a competitive edge, (5) Industrial designs shield the visual appearance of products, ensuring their uniqueness in the market and (6) geographical indications connect products to specific regions, highlighting their distinct characteristics and origins. These IP categories collectively promote creativity, innovation, and fair competition in the global economy.

After removing the ambiguity from the most critical element of our subject as well as the innovation concept and its forms, the innovation diffusion with the main channels, and the IP elements, we are able to illustrate the two KPF models:

1. Griliches's knowledge production function represents the first methodological approach to study innovation and technical change by measuring the contribution of R&D in knowledge spillovers. Based on the Cobb-Douglas production function as a framework, the basic formula is:

Innovation activity = f (R&D input).

In this equation, innovation activity is the output of new knowledge, and R&D input is input into knowledge discovery effort by way of R&D expenditure.

2. The Romer-Jones knowledge production function represents the most valuable approach in the endogenous growth model because the knowledge sector takes on focal importance since the growth rate of knowledge determines the growth rates of all other variables in the system.

The basic relationship in Romer-Jones' KPF is:

Innovation activity = f (knowledge stock, labor employed in the R&D sector).

The choice of these two previous approaches is based on their background theories and on their respective definitions of knowledge formation. Both approaches in the literature on returns to R&D take knowledge production as synonymous with research effort (Hall, Mairesse, and Mohnen, 2010). In endogenous growth theory too, new technologically relevant ideas involve research effort, but the arrival rate of innovations is also conditioned by the stock of previously accumulated knowledge (Romer, 1990; Aghion and Howitt, 1992; Jones, 1995), and here lies the main difference between the two functions.

Combining the KPF models with the new concept of innovation in economic geography (Anselin, Varga, and ACS, 1997) basically indicates that knowledge and technology can move in an increasingly rapid way across borders. This approach motivates the researchers to focus on the spatial KPF model based on the econometric approach with the aim of detecting the spatial interactions between the innovation activity and its factors. In other words, the neighborhood regions can impact the local innovation activity or the opposite. This is what was confirmed in some empirical studies such as Chun-Yu Ho and Wei Wang, Jihai Yu, (2018) who based their study on a sample of 30 countries over the period ranging between 1975 to 2010. The latter found that there is a positive spillover effect of innovation from one country to its trade partners through bilateral import flows. The spillover effect accounts for approximately 1.3 to 3.6% of the total effect of R&D input on innovation output over time.

This example encourages us to dive deeper by combining Romer's KPF with the spatial econometric approach on a sample of 20 countries belonging to the OECD over a time frame of 20 years (1995-2015).

2. EMPIRICAL ESTIMATION AND RESULTS

2.1. Spatial Econometric Approach Overview

The dynamic nature of economic phenomena, coupled with the huge development in international economic relationships (virtually erasing boundaries between countries), especially in the area of commercial exchanges, has had a tremendous impact on the econometric field characterized by the extension of the classical panel data approach and The consideration of the spatial correlation between the countries. This phenomenon has been reflected in the fast-growing spatial econometrics literature since the turn of this century.

Historically the term "spatial econometrics" was introduced for the first time by the Belgian economist Jean Paelinck (universally recognized as the father of the discipline) in the general address he delivered to the annual meeting of the Dutch Statistical Association in May 1974 (Paelinck and Klaassen, 1979). In our study we will follow Elhorst's methodology based upon the foundation of spatial econometrics, which integrates spatial relationships into traditional econometric models. (Figure N 01)

The Durbin spatial model (Elhorst, Spatial Econometrics,2012) is presented in the following equation:

$$\boldsymbol{Y_{it}} = \boldsymbol{\delta W Y_{it}} + \boldsymbol{X_{it}\beta} + \boldsymbol{W X_{it}\theta} + \mathcal{E}_{\boldsymbol{it}}$$

The equation presents respectively the space-time model for a panel of **N** observations over **T** time periods is obtained by adding a subscript **t**, which runs from **1** to **T.**

$\boldsymbol{Y_{it}}$: Dependent variable.

$\boldsymbol{\delta}$: Spatial autoregressive coefficient.

$\boldsymbol{X_{it}}$: Independent variable.

$\boldsymbol{\beta}$: Coefficient independent variable.

$\boldsymbol{\theta}$: Spatial autocorrelation coefficient of independent variables.

$\boldsymbol{Wij}$: Standardized spatial weighted row matrix.

Wij is the element of an (N × N), in this paper, we employed a contiguity matrix to indicate 1 whether spatial units share a boundary or 0 where not, we normalize the matrix according to row.

$$\boldsymbol{W_{ij}} = \begin{cases} \mathbf{1}, & \boldsymbol{i \neq j, \dots, N; j = 1, \dots, N;} \\ \mathbf{0}, & \boldsymbol{i = j, \dots, N; j = 1, \dots, N;} \end{cases}$$

$\boldsymbol{\varepsilon_{it}}$: Model's error.

In a spatial econometric model, three different types of interaction effects can be distinguished: endogenous interaction effects among (**Y**), the dependent variable, exogenous interaction effects among (**X**), the independent variables and interaction effects among (Ɛ) the error terms. Elhorst (2012) considers the following models to be the basic three models used in spatial correlation:

The first model is the spatial lag model (SLM).

$$\boldsymbol{Y_{it} = \rho \sum_{j=1}^{N} W_{ij} Y_{jt} + \beta X_{it} + \mu_i + \eta_t + \varepsilon_{it}, i = 1, \dots, N, t =, \dots, T}$$

The second spatial error model (SEM).

$$\boldsymbol{Y_{it} = \beta X_{it} + \mu_i + \eta_t + \phi_{it}}$$

$$\boldsymbol{\phi_{it} = \lambda \sum_{j=1}^{N} W_{ij} \phi_{jt} + \varepsilon_{it}}$$

The third one is spatial Durbin model (SDM).

$$\boldsymbol{Y_{it} = \rho \sum_{j=1}^{N} W_{ij} Y_{jt} + \beta X_{it} + \sum_{j=1}^{N} W_{ij} X_{jt} \gamma + \mu_i + \eta_t + \varepsilon_{it}}$$

2.2. Model specification

In this paper, we will work with the compact R&D-based KPF with the accumulated knowledge stocks as a factor in knowledge production and research and development efforts:

$$\dot{A}it = \mathbf{F(Rit, Ait)}$$

Spatial Durbin Model (SDM):

$$\dot{A}_{it} = \rho \sum_{j=1}^{N} W_{ij}\dot{A}_{jt} + \beta X_{it} + \sum_{j=1}^{N} W_{ij}X_{jt}\gamma + \mu_i + \eta_t + \varepsilon_{it}$$

$\dot{A}$ is the patent flow (the total number of patents held by residents and non-residents), and **X** is the matrix of the independent variables. **A** is the accumulated stock of a patent, **R** is the accumulated stock of research and development (measured by the total expenditures in the sector of R&D), and **ε** is the standard error term. The treatment of accumulation in knowledge or R&D stock can be defined technically as the sum of all additions to knowledge or adjusted R&D with a depreciation rate, which in our case is 10%, and we use the log function on both sides of the model.

2.2.1 Data and Model Description

On a total of 20 countries (N=20), the yearly data from 1996 to 2015 (T=20) was obtained from the World Bank website. The countries included are as follows: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Hungary, Japan, Mexico, Norway, Portugal, Poland, Russian Federation, Slovak Republic, Spain, Sweden, Turkey, United Kingdom and United States. The specific description of the variables used in this paper is shown below:

Table 1: Details of Variables

Variables name	Definition
Patent flow	Patent applications (residents and non-residents) are measured in numbers
Patent stock	Based on the patent flow are measured in numbers
Research and development expenditures	Research and development expenditures are measured in millions of dollars

Source: Researcher own preparation.

2.3. Testing Methodology and Model selection:

To decide which spatial econometric model is best to fit the data, we will follow the testing methodology of Elhorst (2012) ((see Appendix, Figure N01).

First, we start by estimating non-spatial panel models, and then by examining the previous models' results based on classic LM tests, we can investigate the existence of spatial correlation. Hence, we can determine which type of spatial panel model is the best fit for our data.

The estimation results of non-spatial panel data models are shown in **Table 2**. The likelihood ratio test is employed to explore the joint significance of spatial fixed effects and time-period fixed effects.

The null hypothesis that the spatial fixed effects are jointly significant is rejected at a 1% significance level (45.4043, with 20 degrees of freedom, $P < 0.01$). Besides, the null hypothesis that the time-period fixed effects are jointly significant is also rejected at a 1% significance level (409.7247, with 20 degrees of freedom, $P < 0.01$). These test results justify the extension of the model with spatial and time-period fixed effects, which is also known as the two-way fixed effects model (Baltagi 2005).

The classical LM tests and robust LM tests are conducted to investigate the spatial dependence by using the next testing mythology. In the classic LM tests, both the hypothesis of no spatially lagged dependent variable and the hypothesis of no spatially autocorrelated error term must be rejected at 5 % significance. In the robust LM tests, the hypothesis of no spatially autocorrelated error term must still be rejected at 5 % as well as at 1 % significance.

Referring to the results of classical LM tests, the null hypothesis of no spatially lagged dependent variable and the null hypothesis of no spatially auto-correlated error term are strongly rejected at a 1% significance level for the pooled OLS model. Besides, the hypothesis of no spatially auto-correlated error term is rejected at a 1% significance level when the spatial fixed-effects are included.

Table 2: Estimation results of innovation diffusion: panel data models without spatial interaction effects

Determinants	**(1)**	**(2)**	**(3)**	**(4)**
	Pooled OLS	**Spatial Fixed Effects**	**Time-period Fixed Effects**	**Spatial and time-period Fixed Effects**
Log (Ait)	1.024 ***	0.991 ***	1.220***	1.222 ***
Log (RDit)	0.035 **	0.079 ***	-0.173 ***	-0.141***
Intercept	1.328 ***			
σ2	0.029	0.026	0.010	
R2	0.960	0.965	0.658	0.676
LogL	138.862	163.487	345.647	0.009
LM test no spatial lag	8.092 ***	0.443	0.944	0.892
Robust LM test no spatial lag	5.778 **	2.272	6.794***	8.252***
LM test no spatial error	84.728***	109.706 ***	1.377	2.512

Robust LM test no spatial error	82.414***	111.535 ***	7.227***	9.872 ***

Source: MATLAB V-2019 software output

Note. *, **, *** indicates significance at 10%, 5%, and 1% levels, respectively.

After examining the robust LM tests, both of the hypotheses are rejected for the time-period effects specification. The hypothesis of no spatially lagged dependent variable is rejected at a 1% significance level except when the Spatial Fixed Effects are included. Besides, the hypothesis of no spatially auto-correlated error term is rejected at a 1% significance level for all the models. These results show that there is spatial correlation among the data. Spatial panel models are better than the non-spatial interaction effects of traditional mixed panel data models.

The results of the spatial Durbin model with two-way fixed effects are shown in **Table 3** (see Appendix)**.,** and now we can start examining these results to determine which is the best spatial model.

To further determine which spatial econometric model fits better with the test results, we estimated the spatial Durbin model with two-way fixed effects (the results are shown in **Table 3**). According to the results of the Wald test and LR test, both of the null hypotheses are rejected at the 1% significance level. These results imply that the SDM model is more appropriate than the SLM model and SEM model (Elhorst, 'Matlab Software for Spatial Panels', 2014).

The estimated value of the Hausman test statistic (10.771) suggests that there might be some evidence of endogeneity in the model. However, the p-value associated with the test (0.056) is greater than the chosen significance level (e.g., 0.05), indicating that we do not have enough evidence to reject the null hypothesis of exogeneity. This means that there is no strong indication that the spatially lagged dependent variable is endogenous in this particular model. In addition to the Hausman test, we have to estimate the "phi" parameter.

According to Baltagi (2005), If “phi” parameter equals 0, the random-effects model converges to its fixed-effects counterpart (Elhorst, 2010). This parameter is reported in **Table 3**. We find that $\phi = 0.0433$ and is significant at a one percent level, which corroborates the Hausman test and suggests that the fixed effects assumption is the appropriate specification given the data.

In summary, the "phi" parameter in the random-effects model is a critical factor in assessing the exogeneity assumption. If "phi" is close to 0, it implies that the random-effects model is effectively addressing endogeneity and converges to the fixed-effects model in terms of parameter estimates. The random-effects model, on the other hand, allows for heterogeneity in the individual-specific effects, treating them as random variables with a specific distribution. However, when "phi" equals 0, it means that the individual-specific effects do not contribute to the variation in the dependent variable. In this scenario, the random-effects model effectively becomes equivalent to the fixed-effects model. Therefore, the value of the "phi" parameter plays a crucial role in determining the extent of endogeneity in the random-effects model. A value of "phi" close to 0 suggests that the random-effects model effectively addresses the endogeneity concerns, while a higher value of "phi" may indicate the presence of endogeneity and call for further investigation or alternative model specifications.

Since the diagnostic results suggest that the spatial Durbin model with fixed-effects is the best fitting model, one will limit the interpretation of coefficients estimated on the second column of bias-corrected in **Table 3**.

By using the results of the bias-corrected two-way fixed effects model, the coefficients for spatial autocorrelation (Rho) are significantly positive ($p < 0.01$) and for spatial autocorrelation, they differ significantly from zero, indicating that a change in a single region associated with any given explanatory variable affects the province itself and potentially affects other countries indirectly.

The spatial auto-regression coefficient is 0.437; it passes the 1% level significance test, indicating that the innovation flow ($\dot{A}$ **it**) of adjacent countries has a positive impact on the local country. A decrease of one unity in ($\dot{A}$ **it**) in adjacent countries results in a decrease in ($\dot{A}$ **it**) in the local country by 0.437 unity, thus confirming what we highlighted in the literature review that innovation can be transferred between countries in several channels:

First, there is foreign direct investment (**FDI**), which makes it possible to access new technologies in the local market by using new machines or a new process of training offered by foreign companies (see Ozawa 1992, pp.27–54). Second, through international cooperation (see Hobday 1995, pp. 72–80). And finally, international trade.

Since the significance of each coefficient estimated in the nonspatial model is not the same as in the spatial econometric model, the coefficient in **Table 2** cannot be compared with **Table 3**. LeSage and Pace (2009) believe that direct and indirect effects explain the true spatial spillover effect of each variable. Therefore, this paper decomposes the direct and indirect effects of explanatory variables. The results are shown in **Table 4** (see Appendix).

The direct effect refers to explanatory variables' impact on innovation within a country. And the indirect effect, or spatial spillover effect, refers to the impact of explanatory variables' impact on other countries' innovation; the total effect combines both direct and indirect effects.

Firstly, the direct effect of innovation stock (**Ait**) is positive and passed the significance test at 1%, indicating that the increase in innovation stock with one unity will significantly increase innovation production with 0.44 unity within the country itself and in adjacent countries. On the other hand, the indirect effect of innovation stock is positive but has not passed the significance test at 1%, which means the positive effect of innovation stock on innovation in the adjacent countries is not obvious.

Secondly, the direct effect of RD stock (**Rit**) is negative but has not passed the significance test at 1%, which means the negative effect of RD stock on innovation is not obvious in (local or adjacent) countries. However, the indirect effect of RD stock (**Rit**) is negative and passed the significance test at 1%, indicating that the increase in RD stock with one unit will significantly decrease the innovation production in adjacent countries with 2.9 units.

CONCLUSION

In conclusion, our study attempted to make a significant contribution to the understanding of international innovation diffusion using a spatial econometric approach. By investigating the dependencies and interactions between regions or countries, our research has sheds light on the nuanced dynamics of innovation transfer at the global level. In contrast to earlier research endeavors that predominantly concentrated on the determination of whether innovation can be disseminated as a final output, our current investigation has adopted a more nuanced approach. Specifically, we have delved deeper into the intricate dynamics of innovation diffusion by exploring whether this diffusion is exclusively confined to the final outcomes of innovative processes or extends to encompass the underlying factors contributing to innovation production. By adopting this comprehensive perspective, our study contributes to the existing literature on innovation diffusion, offering a more intricate analysis that goes beyond conventional assessments of innovation as a static, and-state phenomenon.

The empirical findings reveal compelling evidence of spatial autocorrelation in innovation activity among OECD member countries, indicating a positive and statistically significant relationship. This supports the notion, as discussed in the literature review, that innovation transcends national borders and can be effectively transferred internationally through diverse channels. The spatial auto-regression coefficient of 0.437 underscores the robustness of this result, indicating its significance at the 1% level. In this respect, our study may add to the existing body of knowledge by employing varied methods, data sources, and approaches. It reinforces also the argument that international trade, foreign direct investment (FDI), and human capital mobility particularly among researchers and highly technical workers are avenues through which innovation is shared globally.

Furthermore, our analysis has uncovered a noteworthy negative indirect effect of Research and Development (RD) stock on innovation production in neighboring countries. Specifically, an increase in RD stock in one country corresponds to a substantial decrease in innovation production in adjacent countries which highlights the presence of innovation spillovers. This finding aligns with prior research on the implications of innovation spillovers for regional and global economic growth, as documented by Breschi & Lissoni (2003) and Czarnitzki & Toole (2014).

The complexities surrounding innovation diffusion are accentuated by the disparities in countries' innovation capacities and the rapid sharing of knowledge in real-time. Our study recognizes the multifaceted nature of this phenomenon, where countries allocate significant budgets to innovation production through initiatives such as enhancing university quality, investing in research laboratories, and providing financial support to workers in the field. Moreover, both government and private sector entities play pivotal roles in fostering innovation through investments in research and development, technology adoption, worker training, and novel management practices. This comprehensive exploration contributes to the originality of our article and advances the discourse on the intricate dynamics of global innovation diffusion.

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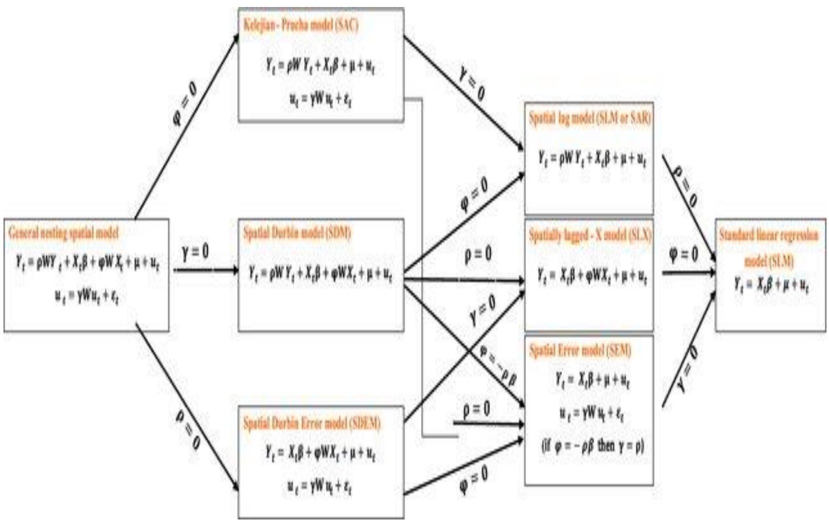
Appendix:

Figure N01: Elhorst spatial methodology.



Source: Elhorst, Spatial Econometrics,2012.

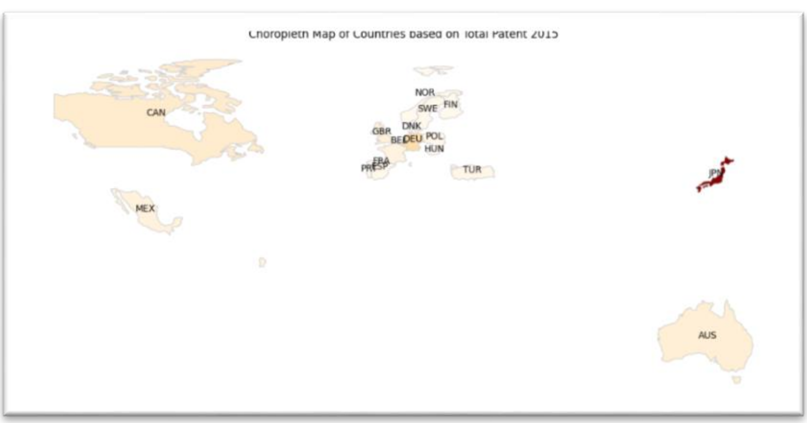


Figure N02: The choropleth map of countries based on the total patent.
Source: Researcher own preparation.

Table 3: Estimation results of innovation diffusion: spatial Durbin model specification with spatial and time-period specific effects

Determinants	**(1)**	**(2)**	**(3)**
	Spatial and time period fixed effects	**Spatial and time-period fixed effects bias-corrected**	**Random spatial effects, Fixed time-period effects**
W*Log (C)			
Log(**Ait**)	0.438657 ***	0.445931 ***	0.425422 ***
Log(**RDit**)	-0.007228	0.026588	-0.081944
W*Log(**Ait**)	-0.074114	-0.118485	0.151238 **
W*Log(**RDit**)	-2.190391 ***	-2.110142 ***	-1.816446 ***
W*dep.var.	0.199443 ***	0.310813 ***	0.130453 *
Phi			0.043312 ***
σ2	0.0095	0.0104	0.0102
R2	0.9852	0.9854	0.9841
Corrected R2	0.3141	0.3140	0.5781
LogL	361.13011	361.13011	285.6543
Wald test spatial lag	45.3626 ***	38.3738 ***	37.0215 ***
LR test spatial lag	42.3742 ***	42.3742 ***	32.1512 ***
Wald test spatial lag	50.4175 ***	43.5173 ***	44.6180 ***
LR test spatial lag	40.2120 ***	40.2120 ***	34.5548 ***

Source: MATLAB V-2019 software output

Note. ∗, ∗∗, ∗∗∗ indicates significance at 10%, 5%, and 1% levels, respectively.

Table 4: Direct and indirect effect estimation

Effect	Direct	Indirect	Total
log Ait	0.447252***	0.034373	0.481625 ***
log RDit	0.136623	-2.889453 ***	-3.026076 ***

Source: MATLAB V-2019 software output

Note. ∗, ∗∗, ∗∗∗ indicates significance at 10%, 5%, and 1% levels, respectively.