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Distributional dynamics of patenting across states in Mexico: A spatial Markov chain approach

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Abstract

This investigation aims to analyze the distributional dynamics of patenting across Mexican states. Our main results suggest, by means of implementing a spatially conditioned Markov chain framework, the regional context is relevant to understand the evolution of the state patenting patterns of distribution over time and across space in Mexico. In this regard, additional evidence suggests top-innovators states interacting with neighboring states sharing similar levels of regional patenting may benefit from positive spatial externalities, while those states positioned in lower levels of the patenting distribution would experience difficulties in accessing top-innovators' technological knowledge that may impede their upward transition to higher classes within the patenting distribution.

Keywords: innovation, patenting, spatial Markov chains, Mexico.
JEL classification: O31, R10, CO2.

Dinámica distributiva del patentamiento en los

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Abstract

Estados de México: Un enfoque de cadenas de Markov espaciales

El objetivo de esta investigación es analizar la dinámica distributiva del patentamiento realizado en los estados mexicanos. Nuestros principales resultados sugieren, mediante la aplicación de un enfoque de cadenas Markovianas condicionadas espacialmente, que el contexto regional es relevante para comprender la evolución de los patrones distributivos del patentamiento estatal a través del tiempo en México. En tal sentido, evidencia adicional sugiere que los estados más innovadores en interacción con estados geográficamente cercanos que comparten niveles similares de patentamiento se beneficiarían de la presencia de externalidades espaciales positivas, mientras que los estados con los menores niveles en la distribución de patentamiento estatal experimentarían dificultades para acceder al conocimiento tecnológico de los estados más innovadores que pudieran obstruir su transición hacia mayores niveles de patentamiento.

Palabras clave: innovación, patentamiento, cadenas de Markov espaciales, México.

Clasificación JEL: O31, R10, CO2.

Introduction

In the space-time distributional evolution of regional innovation, the geographical proximity fulfills a determinant role because it tends to disseminate the ideas and knowledge among nearest regions faster. Consequently, and as in a chain of effects, it also contributes improving the regional productivity. Innovation means inventive capacity of one economy besides improved designs and process that reduce costs of production and raise benefits. Commonly, high levels of innovation are compromised also with high rates of investment in R&D, and this last input is in turn correlated with high level of knowledge. Thus, innovation-knowledge-R&D are widely interrelated, but they need adequate channels that easily spread the spillovers effects positively impacting the productivity. In this game of correlated forces, the role played by the proximity has attracted much attention, lately.

It has been widely recognized the feature of multidimensionality that own the proximity. For example, some types of proximity are geographic, cognitive, social, institutional, and organizational, but also it is accepted that the geographical one facilitates the innovation and reinforces other types of proximity (Boschma, 2005). Some recent studies have found in the geographic clustering important potential conduits of technology transfer and knowledge creation (Attfield *et al.,* 2000, Inoue *et al.,* 2019), others highlight the technological catch-up faster (Griffith *et al.,* 2009). This outcome is especially clear in regional contexts where clusters of firms and industrial districts tend to be geographically concentrated producing important spillovers on the neighboring. In addition, the transfer of technology obtained through geographic connectivity is usually the solution to the R&D financing problems that the most economically lagging regions generally suffer.

Indeed, in our days, productivity significantly seems to be based on some of the many ways materializing the innovation, such as technology (Griffith *et al.,* 2009, Alexopoulos and Cohen, 2019, Ardito *et al.,* 2019, Chen, 2020), creation of patents (Bilir, 2014, Guo, 2015), and the protection to the property rights (Alvi *et al.,* 2007, Sweet and Eterovic, 2019, Chu *et al.,* 2020). All these factors are mainly highlighted among developed economies, for who the internal investment on R&D is essential, a condition that not always can be satisfied in the less developed world, due to problems of financing. However, the stock of investment on R&D is jealously monitored by developed countries. Economies with higher R&D also tend to exhibit more growth (Attfield *et al.,* 2000, Ulku, 2004, Agénor and Neanidis, 2015) because the technological progress from R&D displaces the productive capacity and, this way, higher rates of growth are possible.

The market failure on R&D investment can be replaced from public financing. However, deviation of resources to increase the expenditure on R&D is costly, and especially prohibitive for less developed countries, therefore, business relationship is fundamental among countries. With this end, the connectivity is also vital. More connected countries can take advantage from technological advances and improve their productivity. In this process, proximity becomes very important, because the closer one economy is to another that has created innovation, the easier and faster is to absorb this new progress. Economic activity spatially concentrated is benefited from the knowledge spillovers. Short distances facilitate the knowledge dissemination, while large distances difficult it.

As regions becomes more interconnected, they will be able to expand its stock of knowledge, improving their productivity, without necessarily increasing their internal investment in R&D. Conversely, remaining isolated will not be influenced by the technology and knowledge being created abroad, so improved productivity only will be possible augmenting the internal investment in R&D, a mechanism that not necessarily guarantees improvement of its inventive capacity because innovation constitutes, for sectors and industries, a process of maturation that takes some time. In change, the process of linking through any of the previous channels speeds the acquisition of inventions, making possible the knowledge stock that allows stimulating productivity.

In this respect, as occurs with the spatial distribution of economic activity performance, the localized nature of innovation (Capello and Camilla, 2013) and knowledge diffusion sensibility to distance (Varga *et al.,* 2005) render innovation to be unevenly spatially distributed across countries and regions. Whereas this latter is an acknowledged feature of innovation activity (Egger and Loumeau, 2018), what has remained largely unexplored are its dynamical distributional characteristics over space. Investigating this latter issue is of relevance, first, because it may help elucidate the relationship between income/growth inequality and technological innovation, a topic which has recently gained interest (Foellmi and Zweimüller, 2017; Acemoglu, 1998); and second, uncovering distributional properties such as the more likely technological transition path over both short and long run horizons, or what the role of geographical proximity could be in shaping these paths, provide a standpoint not only to reevaluate the national and regional innovation policy efforts, but also it may help to their re-elaboration.

This investigation addresses the case of Mexico, a developing country which although its efforts to increase the investments made on R&D by public and private sectors, it appears to be insufficient to boost technological innovation and therefore economic growth. The country has devoted in recent years just 0.3% share of its GDP to R&D expenditure, whereas its patent production has averaged about 7% in its growth rate during the last fifteen years. In addition, at regional level, some states have witnessed a renewed interest about promoting local innovation whereas, at the same time, not all the states seem to encompass these initiatives, and thus giving rise to a heterogeneous spatial distribution of regional technological innovation (Germán-Soto *et al.,* 2009, Torres-Preciado *et al.,* 2014). However, due to the changing feature of the regional distribution of innovation, it is not clear whether states' uneven spatial distribution of innovation tend to reduce or to amplify over time; or how likely states would advance (or retrocede) towards higher (or lower) levels of innovation activity, and moreover, whether the spatial interaction mediated by geographical proximity among states significantly accounts for the underlying distributional evolution of regional innovation in Mexico.

In this context, this research aims to contribute to empirical studies on technological innovation by investigating both the short-term and long-term features of the distributional evolution of patents counts across the Mexican states and how these distributional features might change by accounting for the spatial dimension. In this regard, we intend to particularly answer the following questions: What features are descriptive of the distributional evolution of patenting across states in Mexico? Does the evolution of the patenting distribution over time show a convergence or divergence pattern across states? Does spatial interaction matter in shaping the distributional evolution of patenting across states in Mexico? If so, to what extent the geographical context influences the evolution of the patenting distribution in Mexico? We provide answers to these questions by implementing a spatially augmented Markovian chain framework proposed by Rey (2001) which allows to investigate distribution dynamics when spatial dependence between geographical units features spatial systems.

The reminder of this article is organized as follows. Section 1 reviews recent literature on innovation and economic inequality. Section 2 describes the methodology to study the spatiotemporal dynamics of patenting across states in Mexico. Section 3 discusses the empirical findings and finally concludes.

1. Literature review

This review focuses on the lines in which technological knowledge and innovation take place in the space or territory. Within the several theories and approaches in this branch, the geographical proximity is specially debated due to its importance in increasing the probability of knowledge spillovers and supporting the innovative activities. Most concentrates on the mechanisms on how the knowledge and innovation take place in space (Capello, 2007) with a fruitful literature examining from a knowledge production function, as Fritsch (2002), who compares qualities of regional innovation systems, or as Parent (2012), who analyze the spatiotemporal regional spillovers. In Fornahl and Brenner (2009) innovation results by the relationship between industrial agglomeration and local knowledge production. Antonelli and Colombelli (2017) find that access to external knowledge has positive effects on productivity of firms. Capello (2007) highlights spatial elements playing important role that widely explain the regional growth differentials. In regional growth, the geographic proximity is increasingly taking much importance (Parent and LeSage, 2008). For example, Boschma (2005) indicates that proximity facilitates interactive learning, although it may also have negative effects on innovation, while Griffith *et al.* (2009) find that proximity to frontier firms makes catch-up faster in terms of productivity growth.

The analysis of the effects of globalization on multinationals by Toulemonde (2008) finds that proximity –in this case firms agglomerate their production in a single plant– involves reductions of trade costs. Other works seek explanations in the space-time (Parent and LeSage, 2012) that can be simplified through estimates from Markov chains, viewing how the geographic space can be considered as key factor explaining the heterogeneous association between innovation and inequality (Tselios, 2011). Advances on technology have their own space-time development path forming frontiers on knowledge and skills that constraint the movement to other places, creating path-dependent time geographies (Oinas and Malecki, 2002).

Ozman (2009) and Oinas and Malecki (2002) sustain that local interaction networks are very important for innovation and technological change but our understanding on this branch remains still few explored. Pierrakis and Saridakis (2019) examine the social networks and find that public funds of capital have higher volumes of interactions. Although strategic alliances are necessary to build a well-connected infrastructure network (Yao, Li and Weng, 2018).

Regarding the knowledge spillovers, the geographical proximity is not the unique element to consider, in fact exist many other types of proximity as cognitive, organizational, social, institutional (Boschma, 2005 and Mattes, 2012), and personal proximity (Leszczyńska and Khachlouf, 2018), all they influencing the interactive learning and innovation, but such as is highlighted by Boschma (2005), from a dynamic approach, geographical proximity can reinforce other dimensions of proximity.

Briefly, cognitive proximity is referred at the level of capabilities owned by firms or showed by a region in the objective to absorb the knowledge portrayed in new technologies. To the extent that knowledge cannot be considered completely as public good, economic agents should have a minimum level of knowledge in order to communicate and learn from each other. If knowledge-level is not sufficient, costs to treat with a particular technology will increase too much. Thus, regions showing cognitive proximity may improve the productivity. Nevertheless, levels above to certain umbral can be detrimental for innovation (Boschma, 2005).

Organizational proximity means capacity to coordinate and to manage the stock of knowledge in organizations. Particularly, creation of networks, market organization, appropriability, governance, among others, tend to differ and, as consequence, the distance will be not the same. Thus, this form of proximity can represent a relevant argue of the productivity differences among regions.

Social proximity is a property more identified in relations at the micro-level. It seeks explanation on the dependence of the regions from social ties or relations to reach suitable economic outcomes. The idea is that social relations developed by workers of different firms can help to reinforce the ties of friendship making more effective interactions that, finally, will derive from this brainstorming favoring the productivity. Advances in telecommunications and connectivity from very diverse mechanisms as cellphones, platforms as WhatsApp, Facebook, Twitter, etc., will lead to reductions in the social distance, favoring the productive process.

Institutional proximity can be understood at the macroeconomic level of the social proximity (Boschma, 2005). In this case, institutional structures as laws, rules, democracy, even the culture, can support the innovation. To the extent that stronger institutions exist, more easily will be the transition toward innovation and improved productivity. Therefore, the institutional frame results influential.

Additionally, Leszczyńska and Khachlouf (2018) propose separate the personal traits from the social proximity because individual characteristics differently impact the innovation. This notion refers specific personality traits that can facilitates collaborations and, this way, improves the access on innovation and influences the productivity level.

Empirical findings treating with these types of proximity have been diverse. In Feldman (1994) and Aw and Palangkaraya (2004) geographical proximity supports innovative activities and raise the probability of knowledge spillovers. Carbonara and Giannoccaro (2011) define a concept of proximity based on four of the above notions and evaluate the influence of proximity in the competitiveness of the Industrial Districts. Although results are in the direction that proximity favors the competitiveness, they also highlight that much proximity is detrimental. Mattes (2012) investigates the differences between concepts of proximity and suggests that the knowledge nature significantly acts for the types of proximity, so they complement and substitute each other. Marrocu *et al.* (2013) find that technological proximity outperforms the geographic one in European regions. They also highlight a limited role from social and organizational networks. Martinus and Sigler (2018) use a concept of global city clusters to explain the linkages observed from the different notions of proximity in Australia. Some of the results identify a strong role of the geographical proximity in shaping regional networks. Harris *et al.* (2019) report differentiated effects of the spatial proximity on productivity by firm size of the UK economy. Effects were positive only for larger plants, a result attributable to the absorptive capacity characterizing this size of firms. Lee and Kim (2020) study the neighboring effects between low-income and high-income regions of South Korea. They find that negative effects from spatial proximity are greater than the positive in the economic growth of the low-income regions. Cappellano and Makkonen (2020) assess the role of the proximity in the economic interaction of cross-border in a US-Canadian region. The results and conclusions on the role of the cognitive proximity are not clear because in a first stage they are high, but in a second one the region presents a low level of interactions.

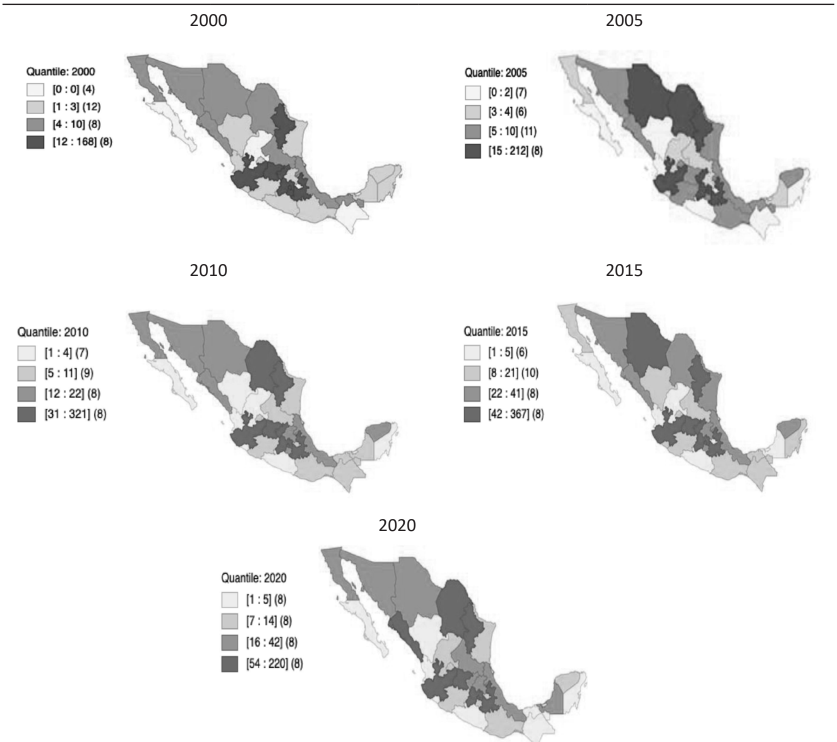
All notions of proximity provide different ways to assess the impact of the distance on innovation, and as consequence, in productivity. It is possible that some of them are more important than others in affect the innovation, depending of the level of development, the maturation degree of the productive process, specific sectors or the interest shown in some objective. In the present exercise our interest is the exam of the Mexican regions, with the geographical proximity as the main hypothesis to be tested. Some research in this area discus the distribution of the FDI conditioned to spatial interaction effects across Mexican states (Torres *et al.,* 2017), others investigate proximity effects using Markov chain models when a set of regions transit to higher levels of manufacturing industry (Flores-Segovia and Castellanos-Sosa, 2021). However, studies on the spatial interaction effects of the innovation are scarce, despite spatial interaction effects seem to be present in the economies and that this avenue of research enjoys a longer tradition in developed countries.

Finally, as technology constantly changes then evolution of the innovation is characterized as path dependent and so it is affected by technological change (Mokyr, 1990). In addition, depending of the phase of a major innovation, proximity can have a positive or negative impact on innovation. At the end, the inventive process portrayed in a patent can differ greatly across regions and over time, therefore, a suitable tool of analysis is to see this dynamic from Markov chains, from which it makes possible to infer about the evolution of the spatial distribution of patenting.

2. Spatial distribution of regional patenting in Mexico: an exploratory insight

An overall look at the spatial distribution of regional patenting in Figure 1 shows it is unevenly configured across the entire territory in Mexico with most of the northern states, and some center-located states, featuring high levels of patenting that contrast those of southern states mostly positioned at lower levels of the quantile classes. This spatial configuration, however, evolutes over time according to transition dynamics specific to each state. In this regard, for example, the state of Baja California although located at northern Mexico exhibits a transition to the lower levels of the quantile distribution before returning to the upper levels in the next years. The states of Jalisco, Nuevo León, Estado de Mexico, and Ciudad de Mexico have shown, in contrast, fewer fluctuating dynamics of transition that locate them within the highest quantile class of patenting levels on a permanent basis. This mixture of spatial transitions across the quantile classes also unveils the evolution in the formation of spatial clustering between states of similar patenting levels and its alteration into geographical patterns showing proximate states sharing dissimilar patenting levels which speak about how spatial interaction evolve.

Figure 1
Spatial distribution of patents in Mexico 2000-2020
(Quantiles)



Source: own elaboration.

Additional insight can be gained regarding the predominant sort of spatial interaction between a specific state and its geographic neighbors that is likely to expect by means of implementing a Markovian version of the local indicators of spatial association statistics which classify, in four types, its relative spatial transitions over time towards four possible classes (See Table A1 in Annex). Accordingly, a type 0 transition from class HH(t) towards class HH(t+1) representing the joint spatial transition between a specific state and its neighbors sharing the characteristic of having high (above average) patenting levels shows a high probability, ranging from 0.74 to 0.80 across the four displayed subperiods, indicating the next year they will likely remain within the same class (table 1). However, joint spatial transitions between the state-neighbor pair from class LL(t) towards class LL(t+1) stand as the highest transition probability across the four subperiods suggesting, therefore, spatial clustering of low patenting levels might persist over time. It is also worth noticing the remaining two spatial transitions of type 0 also exhibit high probabilities, particularly that from class LH(t) towards class LH(t+1), which grows slightly across the subperiods. In correspondence, the remaining pairwise of spatial transitions within the fourth-type classification system exhibit lower probability levels, though type-I movements from class H(t)L(t) towards L(t)L(t) tend to display non-negligible probabilities which suggests some states holding high levels of patenting might equate its neighbors' lower patenting levels. In this regard, the higher probability of witnessing a spatial transition of type 0 seems to attribute spatial stability to the regional patenting dynamics over the short run. From a long run perspective, however, the corresponding spatial transition probabilities within the steady-state vector in Table 1 shows consistently, across the four subperiods, both the formation of spatial clusters of low patenting activity between the state-neighbor pair and the spatial association between low-patenting states surrounded by high-patenting neighbor states, as more likely forms of spatial interaction.

Table 1
Local indicator of spatial association (LISA) probability transition matrix of regional patenting in Mexico

2005					
Quadrants	HH(t+1)	HL(t+1)	LH(t+1)	LL(t+1)	Steady state
HH(t)	0.80	0.00	0.20	0.00	0.18
HL(t)	0.14	0.71	0.07	0.07	0.12
LH(t)	0.05	0.05	0.83	0.07	0.40
LL(t)	0.00	0.05	0.08	0.87	0.30
2010					
Quadrants	HH(t+1)	HL(t+1)	LH(t+1)	LL(t+1)	Steady state
HH(t)	0.75	0.08	0.17	0.00	0.09
HL(t)	0.06	0.72	0.06	0.16	0.13
LH(t)	0.04	0.03	0.85	0.07	0.37
LL(t)	0.00	0.04	0.07	0.88	0.41
2015					
Quadrants	HH(t+1)	HL(t+1)	LH(t+1)	LL(t+1)	Steady state
HH(t)	0.74	0.08	0.18	0.00	0.09
HL(t)	0.07	0.76	0.03	0.14	0.15
LH(t)	0.04	0.04	0.86	0.06	0.33
LL(t)	0.00	0.04	0.06	0.90	0.42
2020					
Quadrants	HH(t+1)	HL(t+1)	LH(t+1)	LL(t+1)	Steady state
HH(t)	0.80	0.07	0.13	0.00	0.10
HL(t)	0.07	0.75	0.02	0.15	0.16
LH(t)	0.03	0.03	0.88	0.06	0.31
LL(t)	0.00	0.05	0.05	0.89	0.42

Note: Each subperiod for which the spatial LISA statistics were calculated initiates in 2000 and respectively ends in the indicated year.
Source: own calculations.

Additional summary measures corroborate that spatial stability would likely be the predominant feature of the short run spatial dynamics of patenting as the probability of witnessing a type 0 spatial transition, in which the state-neighbor pair prevails the next period within the same class, stands as the higher among the remaining probability transitions over the four subperiods (table 2). Moreover, a measure of the flux or instability in the spatial system involving transitions of types I and II altogether show lower and even slightly decreasing probabilities across the four investigated subperiods, thus reinforcing spatial stability as key characteristic of the dynamics in the patenting distribution. A noteworthy additional feature of the short run spatial dynamics is its highly cohesive behavior which, as implied by the spatial cohesion measure involving transitions of types 0 and IIIA, suggests the state-neighbor pair will likely preserve its relative spatial relation whether they remain or not within the same class[1].

Table 2
Transition probabilities in the spatial dynamics of patenting in Mexico according to a fourth-type classification system

		2005			
Type 0	I	II	IIIA	IIIB	Cohesion
0.84	0.06	0.08	0.0	0.02	0.84
Ascend	0.039	0.055	0.000	0.016	Flux
Descend	0.023	0.023	0.000	0.008	0.14
		2010			
Type 0	I	II	IIIA	IIIB	Cohesion
0.84	0.07	0.07	0.00	0.02	0.84
Ascend	0.035	0.042	0.000	0.010	Flux
Descend	0.031	0.031	0.000	0.007	0.14
		2015			
Type 0	I	II	IIIA	IIIB	Cohesion
0.85	0.07	0.06	0.00	0.02	0.85
Ascend	0.033	0.036	0.000	0.011	Flux
Descend	0.033	0.027	0.000	0.004	0.13
		2020			
Type 0	I	II	IIIA	IIIB	Cohesion
0.86	0.07	0.06	0.00	0.01	0.86
Ascend	0.035	0.033	0.000	0.010	Flux
Descend	0.033	0.026	0.000	0.003	0.13

Note: The probabilities associated to each type of the spatial transitions were calculated as their corresponding relative frequency with respect to the total number of possible transitions for each year. Under a similar calculation, the cohesion measure involved transitions of types 0 and IIIA altogether, and the flux measure included only transitions of types I and II.
Source: own calculations.

[1] It is worth to notice, however, the spatial transitions of type IIIA have nil probabilities across the four investigated subperiods which explains that the cohesion index reflects type 0 transitions, only.

3. Methodological framework

Although the exploratory analysis in the previous section provided useful insights regarding the kind of spatial interaction and spatial transitions that likely characterize the spatial-temporal dynamics of patenting in Mexico, it offers, however, limited information concerning the evolution of the patenting distribution as LISA Markov statistics are constructed only upon 2 quantile classes and, furthermore, it does not take into consideration how spatial interaction may condition the spatial transitions across the patenting distribution. To overcome these limitations, the analysis of the evolution of the patenting distribution is proposed to be conducted using Rey's (2001) spatial Markov approach which explicitly considers geographical proximity.

The Markovian approach, in this regard, provides an adequate framework for the purpose of our research due to its methodological advantages over different alternatives which are often implemented in the economic literature[2]. In this regard, this framework can provide a more accurate understanding of the underlying evolution of regional distributions as it informs about the entire sample distribution over time (Quah, 1996b; Rey, 2001). In addition, the Markovian framework is sufficiently flexible a methodological tool that can be extended as to explicitly include potential spatial interaction effects thus providing a fully integration of the regional context into the analysis of distribution patterns (Rey, 2001) and, moreover, based on some of its mathematical properties, it can also account for the long-run features in regional distributions.

In this respect, consider a stochastic process has the Markovian property if its distribution in the next state or class depends on the

[2] In the economic literature two empirical approaches to investigate the evolution of regional distributions have predominated. One, trough the calculation of statistical measures of dispersion such as the sample variance across countries, regions or states; and second, by means of so-called absolute (or conditional) convergence models where cross country/regional growth rates are regressed against initial income levels and some other conditional regressors. In the first case, changes in the dispersion over time may inform about a convergence or divergence process, but not whether this process is leading to higher or lower classes. The second approach has been criticized because it is based only on two separate points in time, and not the entire sample, to infer about the underlying cross-country/regional distributional process which may also be sensitive to changes in the timeframe. See Quah (1993b) for a thorough examination of both types of approaches.

previous state or class and not on its entire past. A Markov process consists of two objects: a probabilistic transition matrix with dimension recording the probability of moving from class i to class j in the next period and a vector with dimension comprising the probabilities at initial stage. In this regard, the elements of the transition matrix can be formally described as a stochastic matrix according to the expression:

$$P_{ij} = \Pr ob\left(x_{t+1} = e_j \mid x_t = e_i\right) \quad (1)$$

The transition probability matrix thus provides useful information for analyzing the evolution of the regional patenting distribution based on several of its properties. In this regard, based on the assumption of time invariant probabilities which reads as $P_{t,ij} = P_{t+b,ij}$, it is possible to approximate the average time to move from class i to j, and owing to the ergodicity property, the limiting distribution of the probability transition matrix converges to a steady-state vector that also provides information regarding the long run features of the distribution. Notwithstanding, as noted by Rey (2001), a proper treatment of regional distributions would require explicit consideration of spatial proximity as spatial spillovers may potentially condition its time evolution, and thus, he proposes an extension of the Markov process described in expression (1).

In this respect, for ease of clarity, Table 3 exemplifies the arrangement of the elements for the spatially conditioned transitional stochastic matrix. The entire matrix dimension is nxnxn where the column labeled as spatial lag represents the contiguous state neighbors to a specific region i which is distributed in three different states or classes: low, medium, and high. Thus, by positioning in the low-class spatial lag column, the element informs about the probability a region i interacting with contiguous neighbors characterized for having a low patenting level remains in a low level of patenting the next period. Similarly, expresses the conditional probability that a region i improves its innovativeness by moving from low to medium regional patenting the next period once spatial interaction with low-patenting neighboring states has been accounted.

Table 3
Example of a NxNxN spatially conditioned stochastic transition matrix

Spatial lag (neighbors)	Class	Low	Medium	High
Low	Low	PLL|L	PLM|L	PLH|L
	Medium	PML|L	PMM|L	PMH|L
	High	PHL|L	PHM|L	PHH|L
Medium	Low	PLL|M	PLM|M	PLH|M
	Medium	PML|M	PMM|M	PMH|M
	High	PHL|M	PHM|M	PHH|M
High	Low	PLL|H	PLM|H	PLH|L
	Medium	PML|H	PMM|H	PMH|L
	High	PHL|H	PHM|H	PHH|H

Source: own elaboration.

As noticed by Bickenbach and Bode (2003), however, if spatial proximity may indeed condition the distributional evolution over time, then, the property of spatial independence would not hold, and consequently, the estimated limiting distribution of the transition probabilities from the spatially unconditioned matrix may provide misguided inference regarding the long run distribution. Moreover, a similar issue arises in presence of time inhomogeneity which imply that one or more structural changes are part of the regional distribution dynamics thus violating the assumption of stationary or time invariant transitions probabilities within the Markov matrix. The potential violation of the assumptions underlying the Markov chain approach thus led Bickenbach and Bode (2003) to develop a set of statistical tests based on the Pearson (Q) and Likelihood Ratio (LR) statistics, which are implemented below, to help discern under the null whether the Markov process sketched in (1) is accurate to describe the evolution of the patenting distribution across states against the alternate, which otherwise suggest the distribution dynamics is not stationary along the time dimension and spatially dependent, respectively. In particular, the time homogeneity tests are performed by splitting, first, the transitions from the entire period into

M=4 subperiods, and then, comparing each patenting transition matrix from each subperiod with the transition matrix of the entire sample period. The spatial independence tests required to form distribution classes based on patenting levels in neighboring regions, and then, each spatially conditioned transition matrix compared against the transition matrix from the total sample. The Q and LR statistics thus described follows a distribution with degrees of freedom (d.f.).

3.1. Database and spatial structure

The statistical data consist of the number of patent counts from 2000 to 2020 for the thirty-two Mexican states and were obtained from the Mexican Institute for the Industrial Property (IMPI by its acronym in Spanish). Some previous transformations were applied to the raw data to perform Markov chain calculations. First, a relative measure of the number of patents was calculated for each state as a deviation from its mean over the entire period which, in turn, was used to calculate terciles over the pooled data. Using terciles to represent the transition state space is useful to investigate mobility of the 32 states between low, medium, and high levels of patenting across the sample time span[3].

The spatial interaction was modelled using a spatial weight matrix W with size 32x32 designed according to a queen-type criterion. In this respect, a state i may show spatial dependence with its neighboring states j when touching a border or vortex, where j = 1, . . ., N assuming $0 \leq wij \leq 1$ and $i \neq j$ with wij = 0 when i = j. Additionally, the spatial weight matrix W has been standardized thus $\sum wij = 1$, which defines the spatial lag as a weighted average of neighboring states.

4. Empirical results

An examination of our calculations in Table 4, which summarizes the transition probabilities across the patenting distribution without accounting for geographic proximity between states, show high probability values at its diagonal indicating that states would feature high persistence over time. In specific, states initially located at the high class, for example, have a 0.88 probability of prevailing within this same

[3] In addition, from a technical point of view, choosing only terciles allowed us to avoid sparsity in the stochastic matrices of transition.

class the next period, while states located at the bottom class exhibit a 0.74 probability of prevailing as low patenting states. Furthermore, states within the bottom class also show a significant probability of advancing towards the medium class. Moreover, the steady state vector of probabilities which describes the evolution of the patenting distribution in the long run exhibits slight differences between their magnitudes suggesting a convergence process towards the high patenting class would be underway. In addition, Table A3 in Appendix shows the mean recurrence time and mean first passage time which respectively describe the number of years a state would spend in returning to one of the three classes and in moving between two different classes for the first time[4]. In this regard, a state located at the low class would spend 3.4 years in moving towards the medium class for the first time, while it would require 16.4 years in arriving at the high class. Conversely, the implied number of years that a state located at the high patenting class would require in moving towards the bottom and medium classes for the first time are, respectively, 18.1 and 8.9 in average. Consequently, the high persistence characterizing the global probability transition matrix at its diagonal thus implies the states would spend fewer years when returning to their initial class location. This feature is also summarized by the Shorrocks' mobility index which underlines a rather low mobility between classes (table A4 in Appendix).

Table 4

Global probability transition matrix of the state patenting distribution in Mexico

Class	Low	Med	High	Steady state
	Prob.	Prob.	Prob.	
Low	0.74	0.26	0.00	0.30
Med	0.24	0.62	0.14	0.33
High	0.00	0.12	0.88	0.37

Source: own calculations and Table A2 in Appendix.

In assessing whether the global probability transition matrix in Table 4 would accurately describe the distribution dynamics of patenting

[4] The mean first passage time from state to state is calculated according to the expression $m_{ij}=(z_{jj}-z_{ij}/s_j)$ which elements corresponds, respectively, to matrices $Z=(I-P+S)^{-1}$ and S representing the fundamental matrix, Z, the identity matrix, I, the probability transition matrix, P, and the steady state probability matrix, S.

across states, we performed both the time homogeneity and spatial independence tests as proposed by Kang and Rey (2018) and Bickenbach and Bode (2003). The statistical tests results based on both the Q and LR statistics shown in Table A5 in Appendix suggests non-rejection of the null stipulating the global probability transition matrices for the entire and subsample periods are not statistically different, thus indicating the distribution dynamics of patenting can be considered homogeneous across the complete sample period and, therefore, may be accurately described by its associated global probability transition matrix. Regarding the spatial independency test which stablishes that the global probability transition matrix in Table 4 equals each spatially conditioned probability transition matrix in Table 5, the obtained results based both on the likelihood ratio (LR) and Q statistics show rejection of the null which strongly suggests geographical proximity is relevant to understand the evolution of patenting distribution across states in Mexico (table A8 in appendix).

In this regard, according to the spatially conditioned probabilities of transition in Table 5, spatial stability would remain as a likely overall feature of the spatial patenting system in Mexico. However, particularities in our results indicate that low patenting states in interaction with low patenting neighboring states show a significant low persistence, amounting to a probability of 0.68, in prevailing at the low patenting class which contrasts the higher persistence implied by the 0.74 probability in the global probability transition matrix (table 4). Moreover, states located at the medium patenting class which interacts with low patenting neighboring states showed a slight increase in its measured persistence with respect to transition probabilities in the global matrix, though their probability of moving towards a low patenting class increased notably thus suggesting states at the medium class of the patenting distribution may be negatively affected by its geographic proximity to low patenting states. Our calculations suggest, notwithstanding, that states located at the high patenting class would be less affected by its geographic proximity to low patenting states.

In addition, probability figures in Table 5 show that spatial interaction with neighboring states located at the medium class would be less beneficial for states located at the low patenting class as it is demonstrated by a higher probability of prevailing in the low class of the patenting distribution than the corresponding transition probabilities in the global and the spatially-conditioned-to-low-patenting-neighbors matrices, which suggests strong barriers to cross border diffusion of technological knowledge may be present. Notwithstanding, geographic proximity with neighboring states at the medium class of the patenting distribution might facilitate the transition from the medium class towards the high class of patenting as suggested by the corresponding probability amounting to 0.35 which surpasses its probabilities counterparts within the global and the spatially-conditioned-to-low-patenting-neighbors matrices estimated in 0.14 and 0.07, respectively.

According to our calculations, however, spatial stability would accentuate across the patenting distribution when spatial interaction occurs with high patenting neighboring states. In this respect, as evinced by a probability amounting to 0.91, states located at the high patenting class showed the highest persistence when compared against the global probability matrix as well as among states interacting with neighbors within any part of the distribution, thus suggesting geographic proximity may enforce the innovative performance of high patenting states through cross border diffusion of technological knowledge. Although, accentuation of the spatial stability also implies increased persistence in states located at the low and medium classes and, therefore, a smaller probability of moving upward in distribution of the Mexican patenting system (table 5).

Table 5
Spatially conditioned probability transition matrix of patenting across states in Mexico

Spatial lag	Class	Low	Med	High
Low	Low	0.68	0.33	0.00
	Med	0.30	0.63	0.07
	High	0.00	0.14	0.86
Med	Low	0.78	0.22	0.00
	Med	0.18	0.47	0.35
	High	0.00	0.15	0.85
High	Low	0.79	0.22	0.00
	Med	0.21	0.71	0.07
	High	0.00	0.09	0.91

Source: own calculations.

Moreover, in Table 6 calculated steady state transition probabilities highlights several key features regarding the long run distribution of patenting in Mexico, for example, spatial interaction with low patenting states would render a convergence process towards the medium class of the patenting distribution. Additionally, in concordance with our calculated probabilities of transition in Table 5, spatial interaction with medium patenting neighboring states shows a convergence process towards the high class in the long run which corroborates that positive spatial externalities arising from low barriers to technological knowledge diffusion would be present. Geographic proximity with high patenting states, however, would render a divergence process characterized by a bimodal distribution towards the low and medium classes of the patenting distribution which may derive from high barriers to cross border diffusion of technological knowledge.

Table 6
Spatially conditioned steady state probability transition matrix of patenting across states in Mexico

Spatial lag/Class	Low	Med	High
Low	0.37	0.41	0.22
Med	0.20	0.24	0.56
High	0.35	0.36	0.29

Source: own calculations.

Additional insight can be obtained by examining the mean recurrence time and mean first passage time statistics in Table 7 which suggest that low patenting states in interaction with low patenting neighbors would spend 3.1 years in arriving to the medium class for the first time, while, in concordance with transition probabilities in Table 5, medium patenting states would spend 5.2 years in arriving to the low patenting class; geographic proximity with medium patenting neighbors, however, would imply 4.5 years for low patenting states moving upwards to the medium class of the distribution, while medium states would require 5.3 years in achieving the high patenting class, for the first time, and high patenting states would experience 1.8 years, the lowest calculated magnitude, in returning to the high class of the patenting distribution. Interaction with high patenting states, however, would require that low patenting states spend more than three decades in moving towards the high patenting class which demonstrates that barriers to cross border technological knowledge diffusion would be present.

Table 7
Mean recurrence time and mean first passage time of the spatially conditioned probability transition matrix of patenting across states in Mexico (years)

Spatial lag	Class	Low	Med	High
Low	Low	2.7	3.1	28.9
	Med	5.2	2.5	25.9
	High	12.6	7.4	4.5
Med	Low	5.0	4.5	9.8
	Med	18.4	4.2	5.3
	High	25.3	6.8	1.8
High	Low	2.8	4.6	32.7
	Med	8.8	2.8	28.0
	High	19.8	11.3	3.5

Source: own calculations.

These results conform with the calculations for the Shorrocks' summary measures of mobility in Table A9 in Appendix, which clearly suggest those states interacting with low or medium patent-producers display higher mobility, whereas those interacting with high patenting neighbors show relatively less mobility.

Conclusions

The present investigation seeks to contribute to the empirical literature on the economics of innovation by focusing on the spatiotemporal evolution of innovation activity in a developing country. Our main results suggest regional context is relevant to understand the evolution of patenting distribution across states in Mexico. Moreover, evidence based on a spatial Markov framework suggests top-innovators states interacting with alike neighboring states may benefit from positive spatial externalities, whereas is apparent that lower innovators experience significant difficulties in gaining access to top-innovators' technological knowledge stock. Additionally, bottommost-patenting-states interacting with alike neighboring states may benefit poorly from spatial positive externalities thus unveiling a situation that helps explain the low-patenting efforts characterizing most southern states. In contrast, states interacting with medium-class neighboring states may significantly benefit from positive spatial externalities.

The aforesaid results help elucidate some implications for technology policy design and implementation. Accordingly, the national technology policy should pursue a regional perspective that considers the heterogenous spatial distribution of technology development and the apparent difficulties some states are facing acceding to regional technological knowledge. In particular, the results call for the need of designing and implementing regional technology policies aiming the creation and diffusion of innovation in southern states and promoting interregional cooperation mechanisms that help facilitating access to top-innovators' technological knowledge stock. These sort of regional technology policies would open the possibility of changing the observed long-run patterns from a multimodal to a unimodal one.

Finally, future empirical analysis can be extended in several ways, for example, focusing on the spatiotemporal distribution of technological innovation among countries, sectors or quality-differenced innovations; also, empirically and theoretically assessing the factors behind the observed spatial-time dynamics of innovation and how the observed distributional dynamics relates to growth dynamics among countries or regions.

Disclosure statement

No potential conflict of interest is reported by the authors

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Appendix

Table A1
Classification of the spatial transitions

Quadrants	HH(t+1)	HL(t+1)	LH(t+1)	LL(t+1)
HH(t)	0	II	I	IIIA
HL(t)	II	0	IIIB	I
LH(t)	I	IIIB	0	II
LL(t)	IIIA	I	II	0

Note: Type 0 spatial transitions describes transitions in which the state-neighbor pair keeps the next period within the same class; spatial transitions of types I and II describe, respectively, a movement of only the state and only the neighbors; spatial transitions of type IIIA and IIIB describe a simultaneous movement of both a state and its neighbors in the same and opposite directions respectively.
Source: Own elaboration based on Rey (2001).

Table A2
Global transition matrix of state patenting in Mexico

Class	Low	Med	High
Low	153	54	0
Med	48	124	28
High	0	25	176

Source: own calculations.

Table A3
Mean recurrence time and mean first passage time for the global transition matrix of state patenting in Mexico (years)

Class	Low	Med	High
	Years	Years	Years
Low	3.3	3.8	17.6
Med	8.9	3.0	13.7
High	16.9	8.1	2.7

Source: own calculations.

Table A4
Shorrocks' mobility index for the global probability transition matrix

n	3
tr(P)	2.24
n-1	2
m	0.38

Source: own calculations.

Table A5
Time homogeneity test

Subperiod	d.f.	Q	LR
2000-2020	6	19.04	8.24
2000-2005	4	4.15	1.60
2005-2010	4	11.12	5.25
2010-2015	4	1.58	0.82
2015-2020	4	2.20	0.57

Source: own calculations based on Tables A6 and A7.

Table A6
Summands of the Pearson test statistic for testing time homogeneity for each subperiod

		Subperiod 2000-2005			
Class at t-1	Observations	Low	Med	High	Sum
Low	45	0.05	0.01	0.00	0.05
Med	41	0.48	0.10	2.43	3.01
High	42	0.00	0.95	0.13	1.09
		Sum			4.15
		Subperiod 2005-2010			
Class at t-1	Observations	Low	Med	High	Sum
Low	44	0.38	1.08	0.00	1.46
Med	43	5.72	2.81	0.16	8.69
High	41	0.00	0.85	0.12	0.98
		Sum			**11.12**
		Subperiod 2010-2015			
Class at t-1	Observations	Low	Med	High	Sum
Low	46	0.12	0.34	0.00	0.45
Med	40	0.70	0.06	0.35	1.11
High	42	0.00	0.01	0.00	0.01
		Sum			1.58
		Subperiod 2015-2020			
Class at t-1	Observations	Low	Med	High	Sum
Low	43	0.16	0.44	0.00	0.60
Med	44	0.23	0.00	0.55	0.78
High	41	0.00	0.72	0.10	0.82
		Sum			2.20

Source: own calculations.

Table A7
Summands of the Likelihood Ratio (LR) test statistic for testing time homogeneity for each subperiod

Subperiod 2000-2005

Class at t-1	Observations	Low	Med	High	Sum
Low	45	-1.24	0.27	0.00	-0.96
Med	41	2.39	1.65	-2.10	1.94
High	42	0.00	-1.67	2.29	0.62
		Sum			1.60

Subperiod 2005-2010

Class at t-1	Observations	Low	Med	High	Sum
Low	44	-3.32	4.01	0.00	0.69
Med	43	10.01	-7.07	1.06	4.00
High	41	0.00	-1.58	2.14	0.56
		Sum			5.25

Subperiod 2010-2015

Class at t-1	Observations	Low	Med	High	Sum
Low	46	2.06	-1.83	0.00	0.24
Med	40	-2.21	1.23	1.56	0.58
High	42	0.00	-0.20	0.21	0.00
		Sum			0.82

Subperiod 2015-2020

Class at t-1	Observations	Low	Med	High	Sum
Low	43	0.12	0.09	0.00	0.22
Med	44	0.05	0.00	0.10	0.15
High	41	0.00	0.12	0.08	0.21
		Sum			0.57

Source: own calculations.

Table A8
Markov spatial independency test

Number of classes:		**3**	
Number of transitions:		**608**	
Number of regimes:		**3**	
Test	Likelihood ratio	Chi-2	
Statistic	25.59	28.82	
Degree of freedom	8	8	
P-value	0.001	0.000	
P(H0)	**Low**	**Med**	**High**
Low	0.74	0.26	0.00
Med	0.24	0.62	0.14
High	0.00	0.12	0.88

Source: own calculations.

Table A9
Shorrocks' mobility index for the spatially conditioned probability transition matrix

n	3
tr(P)	2.17
n-1	2
m	0.42
tr(P)	2.10
n-1	2
m	0.45
tr(P)	2.41
n-1	2
m	0.29

Source: own calculations.