

Schumpeterian Innovation and Regional Mobility in Paraná: A Markov Chain Analysis (2006–2021)

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ABSTRACT

Innovation is unevenly distributed across regions, shaping long-term development trajectories. This article analyzes the evolution of innovation dynamics in Paraná from 2006 to 2021, with the objective of identifying persistence and mobility among municipalities. Using a first-order Markov chain applied to employment in knowledge-intensive activities and intellectual property registrations, the study reveals strong innovation persistence and limited upward mobility. High- and low-innovation groups remain largely stable, reinforcing technological disparities. The findings offer empirical evidence to support policies aimed at reducing territorial inequalities and strengthening local innovation capacity.

KEYWORDS: Innovation Dynamics; Markov Chains; Technological Mobility; Regional Development.

1. INTRODUCTION

Schumpeter was a pioneer in emphasizing the impact of innovation on the economic development of countries, which should be understood as a process of creative destruction that drives growth through technical progress [1]. In this perspective, new technologies and processes generate cycles of economic transformation, strengthening competitive advantages, especially for small and medium-sized enterprises. To achieve innovation, many companies rely on tax incentives and technical support from institutions that encourage research and innovation development [2,3].

Despite its recognized importance, innovation is not evenly distributed across territories. In Brazil, regional inequalities persist in access to knowledge, technology, and infrastructure, which directly affect the ability of local economies to innovate. The state of Paraná, for instance, presents a strong concentration of innovative activities in consolidated urban poles such as Curitiba and Londrina. At the same time, other municipalities show limited technological capacity, reflecting spatial asymmetries that hinder the diffusion of innovation and the formation of balanced innovation ecosystems [4–6].

Considering this context, the present study aims to analyze the dynamics of innovation in Paraná between 2006 and 2021, focusing on the evolution and persistence of municipalities according to their levels of innovation intensity. To achieve this goal, a non-spatial Markov chain approach is applied to identify transitions and technological mobility among municipalities classified into low, medium, and high innovation groups over time.

The analysis of the temporal dynamics of innovation is justified by its relevance for understanding regional development patterns. Identifying whether innovation remains concentrated in a few municipalities or diffuses throughout the territory provides insights for public policy aimed at promoting technological convergence and reducing inequalities. Moreover, the study contributes to the empirical literature on innovation dynamics in emerging economies, particularly at the subnational level, where longitudinal evidence remains limited.

2. THEORETICAL FRAMEWORK

2.1. INNOVATION SYSTEMS AND REGIONAL DEVELOPMENT

Innovation has become a central element in discussions on long-term economic development, particularly as regions attempt to adapt to global technological change and increasing competitive pressures. Rather than emerging randomly or being driven solely by firm-level capabilities, innovation is shaped by the broader environment in which firms, institutions, and actors interact. This perspective forms the foundation of the innovation systems approach, which emphasizes that knowledge generation and learning processes occur within territorially embedded structures that connect firms, universities, research

centers, and public agencies. In this sense, regional development becomes closely tied to the capacity of territories to create, diffuse, and appropriate knowledge.

Regional innovation systems provide the institutional and organizational conditions that support learning, experimentation, and cooperation [7]. Regions differ substantially in their ability to coordinate actors and foster knowledge exchange, which helps explain persistent disparities in technological performance. Innovation systems operate through localized routines of interaction that allow territories to accumulate capabilities and develop distinctive technological paths [8]. These interactions reinforce cumulative advantages, enabling some regions to sustain long-term innovation trajectories while others struggle to overcome structural constraints.

The spatial dimension of innovation has gained increasing relevance in the literature, especially in efforts to understand why technological activities tend to cluster. Proximity (whether cognitive, institutional, social, or geographical) facilitates knowledge transfer by reducing coordination costs and allowing more frequent exchanges among actors [9]. Regions that combine dense social networks with diversified economic structures often show stronger innovative performance because they can more easily integrate external knowledge and recombine it with existing capabilities. This interplay between openness and embeddedness is essential for understanding regional development dynamics.

Institutional quality also plays a fundamental role in shaping regional innovation outcomes. Territories with transparent governance, stable regulatory environments, and effective public institutions create a more favorable context for investment and technological upgrading [10]. Such environments encourage firms to engage in long-term strategies and support the formation of research collaborations and innovative partnerships. In contrast, regions with fragmented governance structures tend to experience weaker coordination among actors, limiting their ability to sustain innovation-driven growth.

The heterogeneity in regional innovation systems becomes particularly visible in emerging economies, where historical development patterns have produced uneven access to infrastructure, qualified labor, and technological assets. Regions with early industrialization trajectories accumulate advantages over time, leading to persistent spatial gaps in innovation capacity [11]. Peripheral territories often face constraints related to limited absorptive capacity, shortages of skilled workers, and dependence on external knowledge sources [12]. These conditions reduce their ability to participate in innovation networks and hinder the diffusion of technological benefits.

Taken together, the literature suggests that innovation systems play a decisive role in shaping regional development paths. Territories that combine strong institutional environments, diversified economic bases, and dense knowledge networks tend to perform better and sustain innovation over time. In contrast, structurally weaker regions experience difficulties in mobilizing resources and coordinating actors, reinforcing long-term spatial inequalities in technological capacity.

This understanding provides the foundation for analyzing regional innovation dynamics in Paraná and for examining how differences in local structures shape the persistence and mobility of innovative activities.

2.2. SPATIAL AND INSTITUTIONAL DETERMINANTS OF INNOVATION INEQUALITY

Innovation does not emerge uniformly across space because territories differ in their structural, institutional, and socioeconomic characteristics. Regions accumulate distinct development trajectories that influence their ability to absorb, recombine, and apply knowledge. As a result, spatial inequalities persist, reinforcing uneven patterns of technological progress and limiting the diffusion of innovation across regions.

Spatial structure plays a fundamental role in shaping these disparities. Territories with diversified productive bases provide fertile ground for interaction among sectors, which stimulates learning and fosters new technological opportunities [13]. Diversified regions benefit from cross-sector spillovers and greater exposure to new ideas, while specialized or isolated territories may become vulnerable to technological stagnation. Complex regional economies accumulate higher innovation potential because they contain complementary industries that promote knowledge recombination [14].

The geography of innovation is also strongly influenced by agglomeration forces. Dense urban areas tend to concentrate skilled labor, advanced services, and research institutions that jointly support technological activity. Agglomeration promotes frequent face-to-face interaction, which is vital for sharing tacit knowledge [15]. Smaller municipalities often lack the density required to generate such interactions, resulting in lower absorptive capacity and weaker innovation systems.

Institutional quality represents another critical determinant. Regions with transparent governance, stable regulations, and effective public administration are better equipped to attract investment, support research collaborations, and sustain innovation-oriented policies. Institutional strength enhances firms' willingness to engage in long-term technological strategies [16]. Conversely, fragmented governance structures and bureaucratic inefficiencies limit cooperation among public and private actors, hindering the development of local innovation ecosystems.

Human capital also contributes to persistent territorial inequalities. Regions with strong educational infrastructure and access to skilled labor experience cumulative advantages in knowledge-intensive activities [17]. When highly skilled workers

cluster in specific areas, innovation capacity becomes increasingly concentrated, leaving peripheral territories dependent on external knowledge sources. This self-reinforcing mechanism contributes to long-term polarization in innovation outcomes.

Geographical distance further shapes regional disparities. Knowledge flows weaken as distance increases, even in an era of digital communication [18]. Complex knowledge still requires intensive interaction, trust, and shared norms, all of which are more easily developed in proximate environments. Peripheral territories often face higher coordination costs and weaker access to knowledge networks, limiting their participation in innovation processes.

Infrastructure also plays a decisive role. Transport networks, digital connectivity, research universities, and laboratories influence the intensity and quality of local knowledge creation. Insufficient infrastructure reduces firms' ability to adopt advanced technologies and engage in collaborative projects [19]. Regions with robust research institutions show consistently higher innovation performance compared to structurally weaker areas [20].

Historical development paths further shape long-term spatial inequalities. Early-industrialized regions accumulate capabilities that persist over generations [21]. Innovation disparities often emerge from institutional lock-in, where territories struggle to break away from low-technology trajectories [22].

Taken together, these spatial and institutional elements reinforce long-standing patterns of inequality in regional innovation systems. Understanding these mechanisms is essential for interpreting the persistent gaps observed in Paraná, where innovation remains heavily concentrated in a few technologically advanced municipalities.

2.3. TECHNOLOGICAL PERSISTENCE AND MOBILITY IN REGIONAL ECONOMIES

Technological development in regional economies rarely follows linear or uniform trajectories. Instead, territories tend to exhibit persistent patterns in their innovation capacity, shaped by accumulated knowledge, institutional structures, and long-term development paths. This persistence reflects the idea that regions build capabilities gradually, relying on historical legacies and localized learning processes. Over time, these mechanisms influence whether municipalities remain in high- or low-innovation groups or transition between them.

The concept of technological persistence is closely associated with path dependence. Early investments in human capital, infrastructure, and technological capabilities create self-reinforcing mechanisms that lock regions into specific development trajectories [23]. Once a region establishes an innovative base, it tends to attract further investment and skilled labor, reinforcing its advantages. Conversely, territories that start with limited technological capacity often face difficulties in developing new capabilities due to institutional and structural barriers.

Research on regional development confirms that these persistent patterns contribute to long-term inequalities. Regions with strong historical ties to knowledge-intensive sectors maintain advantages through accumulated expertise and dense networks of collaboration [24]. In contrast, territories with weaker initial conditions struggle to engage in innovative activities and remain dependent on external knowledge sources. This dynamic constrains local learning processes and reduces the likelihood of upward technological mobility.

Technological mobility refers to the extent to which regions can shift from low- to high-innovation groups over time. Studies indicate that mobility tends to be limited, especially in emerging economies. Regional transitions require substantial institutional coordination, investment in education, and the development of specialized infrastructure [25]. Without these elements, municipalities find it difficult to break away from low-innovation trajectories. Upward mobility is more likely when regions simultaneously expand research capacity and strengthen ties with innovative centers [26].

Institutional quality plays an essential role in shaping both persistence and mobility. Coordinated governance structures and effective public policies enhance the ability of peripheral regions to upgrade technologically [27]. In contrast, institutional fragmentation and weak public management reinforce dependence on more advanced territories. Regions with strong governance structures benefit from better resource allocation, more effective innovation policies, and stronger support for collaborative networks.

Human capital also contributes significantly to mobility. Regions with access to skilled labor are more likely to transition into higher innovation groups because human capital fosters absorptive capacity, enabling territories to assimilate external knowledge and adapt it to local contexts [28]. Areas with limited educational resources tend to remain in low-innovation clusters, reinforcing persistent inequalities.

Infrastructural conditions further shape these dynamics. Transport networks, digital connectivity, and research facilities create the physical foundation for knowledge circulation [29]. Regions lacking such infrastructure experience delays in technological upgrading, even when they possess potential for industrial growth. These limitations hinder interactions among firms, universities, and institutions, which are essential for sustained innovation.

Another important dimension is the structure of regional knowledge networks. Regions embedded in dense collaborative networks exhibit greater resilience and adaptability [30]. These networks facilitate access to external knowledge

and enable firms to integrate new technologies more rapidly. In contrast, isolated territories struggle to participate in interregional innovation flows, reducing their chances of transitioning into more advanced technological trajectories.

Altogether, the literature suggests that technological persistence and limited mobility are deeply rooted in structural characteristics, institutional quality, human capital endowments, and network connectivity. These mechanisms operate cumulatively, reinforcing existing regional disparities. Understanding how these forces shape long-term innovation trajectories is crucial for assessing the dynamics observed in Paraná and for identifying opportunities to promote greater technological mobility among its municipalities.

2.4. MARKOV MODELS AND THEIR APPLICATIONS IN INNOVATION ANALYSIS

Markov chain models have become an important tool for examining how regions transition between different states of technological development over time. These models capture the probability that a municipality will remain in its current innovation category or move to a higher or lower state. Because they treat regional trajectories as stochastic processes, Markov chains offer a structured way to measure persistence, mobility, and long-term equilibrium patterns in innovation dynamics.

Markov chains are particularly useful for studying path dependency because they allow researchers to identify whether territories tend to remain locked into specific development states. When transition probabilities show strong diagonal dominance, this indicates persistence and low mobility among groups. Conversely, higher off-diagonal probabilities signal greater chances of movement between innovation categories [31]. This framework is especially relevant for emerging economies where structural constraints frequently limit upward transitions.

In regional studies, Markov models have been applied to analyze spatial disparities and long-term technological trajectories. Markov chains can reveal stable technological clusters and persistent regional inequalities [32]. Regions with stronger institutional environments and more diversified economic structures tend to exhibit higher probabilities of upward movement. Markov processes also help assess how macroeconomic shocks or policy interventions alter regional development paths [33].

Markov models are also used to examine technological capabilities. Transitions in innovation performance reflect cumulative learning and absorptive capacity [34]. Regions that invest in human capital, research infrastructure, and institutional coordination are more likely to move upward, while those lacking these foundations stagnate. Innovation mobility depends on the alignment between local capabilities and external knowledge flows [35].

A growing literature integrates Markov chains with spatial analysis. Spatially augmented Markov approaches demonstrate that neighboring regions influence each other's mobility patterns, reinforcing regional clusters and persistence effects [36]. Spatial dependence can reveal whether territories trapped in low-innovation states are influenced by neighbors with similar structural conditions [37].

In innovation policy research, Markov models have been used to evaluate the effectiveness of regional strategies. National innovation programs affect technological upgrading in peripheral areas, but infrastructure alone is insufficient without institutional support [38]. Markov chains also help assess the evolution of regional competitiveness, emphasizing that upward transitions require long-term investments in research capacity and collaboration networks [39].

Markov models contribute to forecasting technological trajectories. Multi-step transition matrices allow the estimation of long-term equilibrium distributions, helping anticipate future technological polarization [40]. Similarly, Markov processes can predict shifts in industrial structure and assess whether regional disparities are likely to narrow or widen over time [41].

Overall, Markov chain models provide a powerful framework for analyzing innovation dynamics because they combine temporal structure, probabilistic transitions, and long-term equilibrium analysis. Their versatility allows researchers to model persistence, mobility, convergence, and divergence in regional technological performance. This analytical perspective is essential for understanding the patterns observed in Paraná, where innovation clusters demonstrate strong persistence and limited upward mobility.

3. METHODOLOGY

The study adopts a quantitative and empirical strategy to examine the evolution of innovation across the 399 municipalities of the state of Paraná between 2006 and 2021. The database was constructed from official administrative sources, combining information on employment in knowledge-intensive activities (KIA) and intellectual property registrations (PI). The period of analysis reflects the availability and consistency of municipal records, allowing the observation of structural changes in local innovative capacity over sixteen years [42-44].

The variable KIA captures the municipal participation in knowledge-intensive activities, including industries and services that rely on advanced skills, research, and technological development. Following international classifications [42,45], KIA was computed from RAIS data by aggregating all formal employment relationships identified under the OECD codes for

knowledge-intensive sectors. This total was divided by the municipal population, resulting in a standardized indicator of employment density in technological activities.

The PI variable represents the number of patent registrations per municipality, obtained from the National Institute of Industrial Property (INPI). Patent data constitute an established proxy for local innovative effort and technological output, reflecting a municipality's capacity to generate, absorb, and disseminate new knowledge [46,47]. Together, KIA and PI provide complementary dimensions of municipal innovation, capturing both structural inputs and measurable outcomes.

To analyze the temporal behavior of municipal innovation, a discrete-time, first-order Markov chain model was employed. Markov models are appropriate for characterizing dynamic processes in which future states depend only on present conditions [33,48].

Formally, let $\{X_t\}$ be a stochastic process taking values in a finite set of innovation states

$$S = \{1, 2, 3\}$$

The process satisfies the first-order Markov property when:

$$P(X_{t+1} = j | X_t = i, X_{t-1}, \dots, X_0) = P(X_{t+1} = j | X_t = i) \quad (1)$$

The transition probabilities are organized in the matrix:

$$P = \begin{pmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{pmatrix} \quad (2)$$

Diagonal elements p_{ii} indicate the persistence of municipalities within the same innovation category, while off-diagonal elements capture upward or downward mobility. The classification of municipalities into low-, medium-, and high-innovation groups was based on terciles of the standardized mean of KIA and PI, ensuring comparability over time and enabling the detection of structural transitions.

To evaluate long-term dynamics, the stationary distribution of the chain was computed. A stationary vector π satisfies:

$$\pi = \pi P \quad (3)$$

subject to

$$\sum_{i=1}^3 \pi_i = 1$$

The stationary distribution indicates the equilibrium proportions of municipalities expected in each innovation category if the transition dynamics observed in the period remain unchanged. A distribution concentrated in the lowest state signals persistent technological dependence, whereas greater mass in higher states reflects potential convergence toward more advanced innovation structures.

In addition to the stationary distribution, mobility was assessed using a probabilistic measure that summarizes the expected degree of movement across states. The Bartholomew mobility index was applied, defined as:

$$B = \sum_{i=1}^n \sum_{j=1}^n \pi_i p_{ij} |i - j| \quad (4)$$

Higher values of B indicate greater dynamism and transitions among innovation levels, while lower values reflect structural inertia.

Finally, a set of diagnostic tests was conducted to verify the adequacy of the Markov specification, including assessments of time homogeneity, the appropriateness of the first-order structure, and the ergodicity of the chain. These procedures ensure that the model consistently captures the evolution of municipal innovation and provides a robust foundation for interpreting long-term technological trajectories.

4. RESULTS AND DISCUSSION

The Markov model applied to innovation levels in Paraná (2006–2021) allows the evaluation of the temporal dynamics and persistence of regional innovative capacity. By analyzing the transition probabilities, it is possible to assess the stability of innovation categories and the likelihood of mobility among municipalities over time.

Table 1: Transition Probability Matrix of Innovation Levels in Paraná (2006–2021).

From / To	High	Medium	Low
High	0.823	0.170	0.008
Medium	0.172	0.652	0.176
Low	0.006	0.178	0.816

Source: Authors' elaboration based on dataset (2006–2021).

The transition matrix indicates that municipalities classified as high or low innovation tend to remain in the same category, with persistence rates of 0.823 and 0.816, respectively. This stability suggests strong path dependence, typical of regional innovation systems where accumulated capabilities, infrastructure, and institutional structures reinforce existing disparities [46,49]. The medium category shows slightly more fluidity (0.652), representing municipalities with potential to move upward or downward in the innovation hierarchy.

The Bartholomew Mobility Index (−0.645) reveals very low intertemporal mobility, reinforcing the dominance of persistence and regional lock-in effects. This limited movement implies that municipalities rarely transition between innovation strata, confirming the structural rigidity of the system. The immobility chi-square test ($p < 0.001$) rejects the hypothesis of perfect stability, suggesting that although the process is highly persistent, it is not completely static. These combined results portray a slow and path-dependent innovation trajectory, with minor changes concentrated in intermediate regions.

Table 2: Summary of Statistical Tests Applied to the Markov Chain (2006–2021).

Test	Statistic	p-value	Interpretation
Homogeneity (χ^2)	2.43	0.657	No significant change across periods
Order (1st vs 2nd)	–	1.000	1st order process adequate
Ergodicity	–	–	Chain is ergodic (unique equilibrium)
Bartholomew Index	-0.645	–	Very low innovation mobility
Immobility (χ^2)	∞	<0.001	Rejects the perfect stability hypothesis

Source: Authors' elaboration based on R computations. Tests confirm stability and persistence in innovation dynamics.

The robustness tests confirm that the model captures an ergodic and stationary process, meaning that innovation patterns converge toward a single equilibrium distribution over time. However, this equilibrium reproduces the same structural asymmetries observed in the transition matrix, indicating that technological concentration persists despite minor changes.

Such persistence aligns with the concept of cumulative causation in regional innovation, where dominant centers maintain their competitive advantages through continuous accumulation of knowledge, infrastructure, and institutional networks [9,50].

Table 3: Adjusted Results Summary after Statistical Validation (2006–2021).

Indicator	Initial Value	Adjusted Value	Interpretation
Persistence (High)	0.823	0.823	Very strong persistence in high innovation
Persistence (Low)	0.816	0.816	Persistent technological lag
Mobility Index	-0.645	-0.645	Extremely low mobility
Ergodic Equilibrium (π)	0.333	0.333	Uniform stationary distribution
Validation (p -value)	–	<0.001	Model statistically consistent

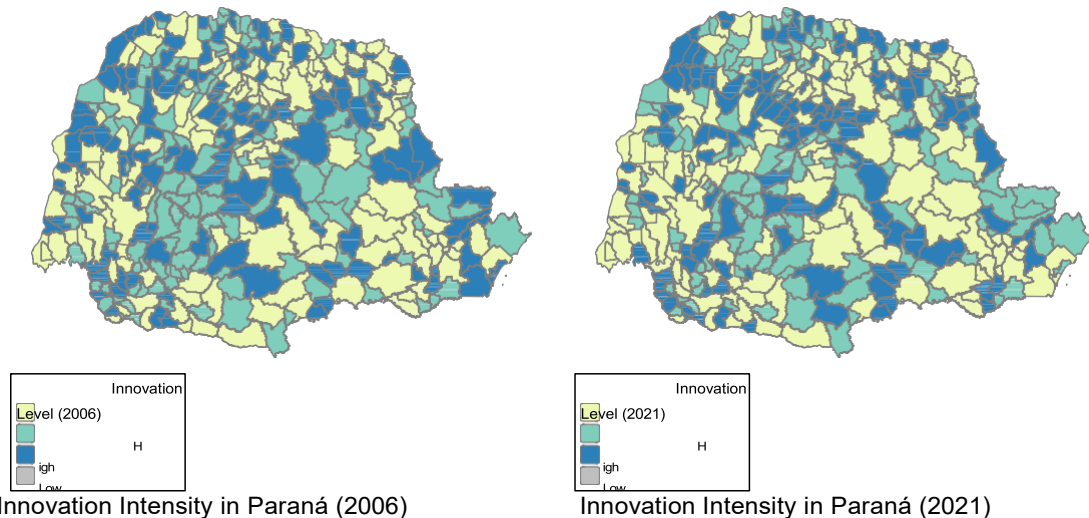
Source: Authors' elaboration based on validated Markov chain results. Adjusted values reflect confirmed robustness after all tests.

From a theoretical perspective, the persistence of innovation in Paraná's main urban poles (Curitiba, Londrina, and Maringá) illustrates the Schumpeterian notion of creative accumulation rather than creative destruction [1].

In these cities, established firms and research institutions consolidate innovation, while peripheral regions remain constrained by limited absorptive capacity and weaker institutional networks. This spatial pattern exemplifies the evolutionary

nature of innovation, in which economic growth results from cumulative learning processes and localized feedback mechanisms [51,52].

Figure 1: Spatial Distribution of Innovative Efficiency in Paraná (2006–2021).



Note: Map produced by the authors.

The figure shows the spatial heterogeneity of innovation intensity across the municipalities of Paraná, highlighting a higher concentration of innovation in the metropolitan areas of Curitiba, Londrina, and Maringá.

This spatial configuration confirms the persistence of regional disparities already captured in the transition matrix, revealing that innovation capacity remains highly localized in dynamic urban centers. Such evidence reinforces the path-dependent nature of technological development and supports the interpretation that policy interventions aimed at decentralizing innovation are essential to promote balanced and sustainable economic growth across the state.

5. CONCLUSION

The analysis of innovation dynamics in Paraná between 2006 and 2021 reveals strong persistence in technological activities, mainly concentrated in consolidated urban poles such as Curitiba, Londrina, and Maringá. The results of the Markov chain indicate high stability and low intertemporal mobility, reflecting structural asymmetries and path-dependent dynamics that limit the diffusion of innovation toward peripheral municipalities.

These findings highlight the need for public policies that promote the decentralization of knowledge and the expansion of local innovation ecosystems, especially through investments in education, research infrastructure, and technological training. By strengthening local capacities, such measures can contribute to a more balanced and integrated innovation network across the state.

This study presents some limitations, mainly related to the use of secondary data and the exclusive reliance on quantitative indicators. Future research should incorporate spatial econometric models and qualitative approaches to capture institutional, cultural, and network dimensions that influence the trajectory of innovation in regional contexts.

CONFLICT OF INTEREST

None.

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