Industrial Concentration and Regional Innovation Efficiency in India: Evidence from the Manufacturing Sector, 2010–2024

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DOI: https://doi.org/10.47772/IJRISS.2026.101100066

Received: 28 October 2026; Accepted: 02 November 2026; Published: 20 November 2026

ABSTRACT

This study examines the relationship between industrial firm concentration and regional innovative efficiency across Indian manufacturing states from 2010–2024. Using data from the CMIE PROWESS database and the Annual Survey of Industries (ASI), the study analyzes whether concentration in selected manufacturing industries influences regional innovation performance. Industrial concentration is measured using the Sargent Florence Location Quotient (LQ), while innovation efficiency is estimated through patent applications and R&D expenditure. A Negative Binomial Regression (NBR) model is employed due to the over-dispersed nature of the innovation data.

The findings reveal significant regional differences in innovation efficiency. States such as Maharashtra and Karnataka show high innovation efficiency due to stronger concentration in knowledge-intensive sectors like electronics and machinery. In contrast, states specialized in resource-based or assembly-oriented industries demonstrate lower innovation efficiency. The study concludes that industrial concentration alone does not guarantee innovation performance; the technological intensity of industries, institutional support, and human capital also play crucial roles. The research highlights the importance of strengthening R&D infrastructure, university–industry linkages, and skill development to promote innovation-led regional growth in India.

Keywords: Industrial Concentration, Regional Innovative Efficiency, Location Quotient, Negative Binomial Regression, Innovation, India.

1. INTRODUCTION

1.1 Background of the Study

Innovation is a critical driver of economic growth, industrial competitiveness, and sustainable development(Joseph Schumpeter, 1934; Paul Romer, 1990; OECD, 2018,Ying et al. 2025)). As the world becomes more connected, a region's ability to create, use, and share new knowledge is vital for long-term success. Because of this, regional innovative efficiency—how well innovation inputs such as research expenditure, skilled labor, and business activity are converted into outputs like patents, new products, and technology transfers—has emerged as a central concern for policymakers and researchers(Bengt-Åke Lundvall, 1992; Michael Porter, 1990).

India, as one of the world's fastest-growing major economies, offers a distinctive context for examining regional innovation efficiency. According to the World Intellectual Property Organization's innovative cluster ranking, four major Indian cities—Mumbai, Pune, Bangalore, and Chennai—secured positions in the top 100 globally (World Intellectual Property Organization, 2024). From 2010 to 2024, India experienced rapid industrial growth, manufacturing expansion, and deeper integration into global markets. Nevertheless, substantial regional disparities in innovation persist due to differences in industrial structure, institutional quality, infrastructure, and human capital. Firm concentration, defined as the number of active firms within specific manufacturing industries in a region, is considered an important determinant of innovation performance. Theoretical perspectives such as Marshallian externalities (Alfred Marshall, 1890), Jacobsian diversity (Jane Jacobs, 1969),

and the knowledge spillover theory of entrepreneurship (David Audretsch & Max Keilbach, 2007) suggest that firm concentration may significantly influence regional innovative capacity. However, empirical evidence on the direction and magnitude of these effects remains inconclusive, particularly in developing economies such as India, where institutional settings and innovation systems differ substantially from those of advanced economies.

1.2 Problem Statement and Research Gap

Even though there is extensive research on regional innovation and industrial clusters, we still do not fully understand how the number of firms in certain industries affects innovation efficiency across different parts of India. Most studies focus on national trends and overlook important regional differences. Also, most research on this topic comes from high-income countries, leaving a lack of evidence for large, diverse middle-income countries like India.

Third, few studies have examined how firm concentration in specific industries—such as pharmaceuticals, chemicals, machinery, rubber, and plastics—affects innovation efficiency. Each of these industries has its own level of knowledge, technology, and connections, so their impact on regional innovation can be very different. Ignoring these differences could lead to policy advice that misses the real complexity of regional innovation.

This study aims to fill these gaps by building a dataset for 13 Indian regions from 2010 to 2024 and using Negative Binomial Regression to study how firm concentration in key manufacturing industries relates to regional innovation efficiency. This method provides new evidence for research on innovation in emerging markets and gives practical insights for policymakers who want to support balanced, innovation-led growth across India.

1.3 Research Objectives

The primary objectives of this study are as follows:

1. To examine the extent to which the concentration of firms in selected manufacturing industries—specifically pharmaceuticals, chemicals, machinery, rubber, and plastics—influences regional innovation efficiency in India during the period from 2010 to 2024.

2. To determine whether higher or lower concentrations of firms within these industries are associated with corresponding increases or decreases in innovation efficiency across different Indian regions.

3. To identify which industries, if any, show the strongest relationship between firm concentration and improvements in innovation outcomes, and to explore the reasons for any observed variations.

1.4 Research Questions

In pursuit of the above objectives, this study seeks to answer the following research questions: To achieve these goals, this study will answer the following research questions:

To what extent does industrial firm concentration in the pharmaceutical, chemical, machinery, rubber, and plastics sectors influence regional innovative efficiency across Indian states, and does an increase in the number of firms within these industries lead to a statistically significant improvement or deterioration in innovation efficiency outcomes at the regional level during the period 2010–2024?

1.5 Significance of the Study

This study makes several important contributions to research and policy discussions about regional innovation in India. On the theory side, it helps us better understand how firm concentration and regional innovation systems interact in a large, diverse, developing country—a topic that is not well covered in global research.

In terms of methods, using Negative Binomial Regression to model regional innovation efficiency, which handles non-negative, spread-out data, is preferable to traditional OLS methods, which can yield biased results. This choice makes the study's findings more reliable and accurate.

For policymakers, the results of this study are directly useful for India's industrial and innovation policies. By showing which industries' firm concentrations are most linked to regional innovation, the study can help guide efforts to build industrial clusters, support high-tech manufacturing, and reduce differences in innovation across regions. These goals align with national programs such as Make in India, Startup India, and the National Innovation and Startup Policy.

Finally, this study contributes to the broader global literature. Finally, this study adds to global research on regional innovation and agglomeration by offering insights that can help other large, diverse developing countries use firm concentration to boost innovation-led regional growth. regions from 2010 to 2024, focusing on five manufacturing industries: pharmaceuticals, chemicals, machinery, rubber, and plastics. While this scope allows for focused empirical analysis, the small number of regional observations (n = 13) restricts the degrees of freedom for multivariate analysis and may affect the generalizability of the results. To address this limitation, robustness checks using industry-specific bivariate regressions are performed. Additionally, the study does not examine innovation inputs such as R&D expenditure or human capital in detail, as the primary focus is on firm concentration as the key independent variable

1.6 Review of Literature

The relationship between the geographic distribution of economic activity and regional innovation performance has been a longstanding focus for economists, economic geographers, and policymakers. As knowledge-based competition increasingly shapes the global economy, understanding how spatial structures affect a state's capacity to generate and translate innovations into productive outcomes has become central to regional science and economic development (Paluzie, Pons, and Tirado 2001). This part examines a specific aspect of this broader inquiry: the extent to which the spatial concentration of innovation-intensive industries influences a state's innovative efficiency, defined as the degree to which a state converts innovation inputs—such as research and development expenditures, human capital, and knowledge infrastructure—into meaningful outputs, including patents, new products, and technological advancements. A critical strand of this review concerns empirical studies that have deployed various measures of spatial concentration. A critical component of this review addresses empirical studies that utilize various measures of spatial concentration, including location quotients, Herfindahl-Hirschman indices, Ellison-Glaeser indices, and Moran's I statistics, to analyze the relationship between geographic clustering and regional economic performance. These studies have produced mixed and sometimes contradictory findings, highlighting the complex, context-dependent nature of concentration-innovation dynamics. Some researchers report strong positive associations between industrial clustering and innovation output, attributing these effects to specialized labor pools, inter-firm knowledge flows, and shared infrastructure (Audretsch & Feldman, 1996; Porter, 2000). Conversely, other scholars argue that excessive concentration can introduce rigidities, reduce competitive pressures, and limit cross-industry knowledge recombination, which is essential for breakthrough innovation (Boschma, 2005; Glaeser et al., 1992). A related but analytically distinct body of literature addresses the concept of innovative efficiency. Grounded in the Data Envelopment Analysis (DEA) framework and stochastic frontier analysis, this research moves beyond simple innovation output measures to assess how efficiently regional or state-level actors transform inputs into innovations. Studies in this tradition acknowledge that states with similar levels of research and development spending or scientific human capital may differ significantly in their ability to convert these inputs into tangible innovation outcomes (Hollanders & Celikel-Esser, 2007; Pan et al., 2010).

Kosfeld, Eckey and Lauridsen (2011) apply spatial point pattern analysis to the issue of industry concentration, which has the advantage over the conventional approaches based on fixed geographical units of analysis that subtle patterns at varying spatial scales may be missed. This novel approach applies Ripley's K function to explore the clustering or dispersion behavior of industrial establishments in a continuous space in detail, revealing a deeper and more subtle understanding of spatial concentration. Wang et al. (2020) use a two-stage network Data Envelopment Analysis (DEA) framework to measure how efficiently China's high-tech industries innovate. Their method improves on older models by including shared inputs, extra intermediate inputs, and free intermediate outputs, instead of treating innovation as a simple linear process .Fritsch and Slavtchev(2011) explore why Germany's Regional Innovation Systems (RIS) perform differently. Using a knowledge production function framework, they define technical efficiency as how well a region turns R&D investment into innovative output, measured by patent applications. They analyze data from 93 German regions and use both deterministic

and stochastic frontier analysis to measure efficiency. The study finds that the southern and western regions are more efficient than the eastern and northern regions, indicating a clear regional divide in innovation.

Chakraborty (2024) examines how industrial activity is spread across 16 major Indian states, using data from the past 37 years. She looks at how social, economic, and historical factors influence where industries invest. Chakraborty finds that industrial growth is becoming more uneven, with states like Gujarat and Maharashtra attracting most new investments and jobs, while less developed regions are often left out. The study highlights several reasons for this imbalance. Good infrastructure, such as reliable transport, power, and communication, is a major draw for investors. Other factors include the availability of skilled workers, existing industrial clusters, supportive regulations, and long-standing business networks, all of which help keep industry concentrated in wealthier areas. Ghosh and Neogi (1993) study how technology adoption, factor efficiency, and labor productivity are connected in selected Indian manufacturing industries from 1974–75 to 1986–87. They focus on twenty-nine fast-growing industries with the most foreign technology collaborations. The authors argue that quickly adopting capital-intensive technology, measured by higher capital-to-labor (K/L) ratios, did not lead to real improvements in labor productivity. Instead, it was linked to a drop in overall productivity, showing that resources were used less efficiently. Their analysis, using nonlinear regression with time-based variables, shows that industries became more capital-intensive over time but did not see matching productivity gains. This pattern was seen for both production workers and all employees. The correlation between K/L and labor productivity, which was strong and positive in the earlier years (1974–75 to 1979–80), turned negative and insignificant in later years. This suggests a growing gap between capital investment and output. The study finds that skilled workers are the most important factor for labor productivity, followed by electricity use, while firm size has little effect. This challenges the usual belief that larger firms are more productive in developing countries. The authors conclude that, without a strategy based on local strengths and supported by homegrown research and development, simply importing advanced foreign technology can waste resources and only slightly improve productivity, which may actually slow down industrial growth

2. DATA AND METHODOLOGY

A rigorous empirical framework is essential for examining the relationship between regional innovative efficiency and industrial location. The primary objective is to investigate how the spatial concentration of industries, measured through the Location Quotient (LQ), influences innovation output and R&D intensity across Indian regions during the period 2010–2024.

The empirical strategy adopted in this study integrates two major datasets: the PROWESS database maintained by the Center for Monitoring Indian Economy, which provides firm-level financial and research and development data, and the Annual Survey of Industries (ASI) conducted by the Ministry of Statistics and Program Implementation, which offers detailed information on employment and industrial output across states and industries. The integration of these datasets enables the construction of a balanced panel covering Indian states and union territories over a fourteen-year period.

2.1 Variable Specification

2.1.1 Dependent Variable: Regional Innovative Efficiency (RIE)

The dependent variable in this study is Regional Innovative Efficiency (RIE), operationalized as the natural logarithm of the total R&D expenditure incurred by manufacturing firms domiciled in a given state in a given year. Specifically, this is defined as:

$$RIE(it) = \ln\left(\sum \text{R\&D Expenditure of firms in state } i \text{ in year } t-2\right)$$

The log transformation is used for three main reasons. First, state-level R&D spending is very skewed, with a few states like Maharashtra, Karnataka, and Tamil Nadu making up most of the total. Logging the data reduces this skew and makes the variable more normally distributed, which helps meet regression assumptions. Second, it lets us interpret the coefficients as elasticities. Third, using logs is common in innovation geography research (Audretsch & Feldman, 1996; Breschi & Lissoni, 2001; Patel & Pavitt, 1994), making it easier to compare with

other studies. The lagged R&D value is used because it usually takes two to three years for R&D investments to show results (Fritsch, M., & Slavtchev, V., 2008).

R&D spending is used as an input-based measure of innovation, showing how much is invested in creating knowledge rather than measuring direct outputs. While patent counts or new product data would be more direct, such data are not always available at the state-industry level in India for the entire study period. So, using R&D spending as a proxy is a practical and accepted method in regional innovation studies, especially in developing countries where patent data can be incomplete (Lanjouw & Cockburn, 2001).

Then, the number of patent applications filed with PATENTSCOPE by applicants from each state and year is also used as the dependent variable in regressions to find the innovative efficiency, shown in the Appendix.

The primary independent variable of interest is the Location Quotient (LQ) or Location Factor, a standard measure of regional industrial concentration widely employed in economic geography and regional science. This particular measure is given by Sargent Florence in his papers, "The Location and Size of the Plant" (1948) and "The Logic of British and American Industry." The LQ compares the share of employment in a given industry in a region to the industry's share in the national economy

Location concentration is expected to affect regional innovative efficiency through several related channels. First, Marshall's (1890) idea of localization economies—such as sharing inputs, pooling labor, and knowledge spillovers—suggests that firms in clusters benefit from being close to each other. Second, the knowledge spillover theory (Audretsch & Lehmann, 2005) says that tacit knowledge in dense industrial areas is more likely to lead to new firms and innovation. Third, in Indian manufacturing, having many firms in Export Processing Zones (EPZs) and Special Economic Zones (SEZs) has been shown to boost R&D investment through competition and technology transfer from multinational companies (Kumar & Aggarwal, 2005).

Based on these theories, this study expects a positive and statistically significant link between the Location Quotient and Regional Innovative Efficiency.

The independent variable is the average location factor for each industry in each state. This is taken from the ASI and shows the total number of workers, supervisors, and managers in manufacturing in state i in year t across all 10 sectors.

The inclusion of Total Person Engaged (TPE) in the model to find the location quotient serves two main purposes. First, it controls for manufacturing size in each state, so the LQ coefficient reflects industrial concentration rather than just workforce size. Second, TPE serves as a stand-in for the supply of skilled and semi-skilled workers, which is important for R&D. Agglomeration theory suggests that a larger local labor pool makes it easier for firms to find specialized workers, improves matches between innovators and knowledge workers, and helps spread technological know-how through worker mobility between firms(Pal, S., 2019). An increase in the number of firms within specific industries, such as pharmaceuticals, chemicals, machinery, rubber and plastics, non-metallic minerals, basic metals, electronics, transport equipment, and motor vehicle trailers, results in a statistically significant change in regional innovative efficiency.

Table 1: Summary of Variables Used in the Analysis

Variable	Measure	Data source	Period
Regional innovative efficiency(dependent)	R&D expenditure(t-1) (Independent)	prowess iq	2010-2022
	Patents (dependent)	patentscope	2012-2024
	state fixed (control)		
	R&D expenditure(t)(control)	prowess iq	2012-2024
Location quotient (independent)	Total Person Engaged	Annual Survey of Industry	2010-2024

2.1.2 Methodology: regional innovative efficiency

To estimate each state's regional innovative efficiency, the number of patents counted from WIPO PATEN-

TSCOPE is used as an independent variable, while the lagged R&D variable is the dependent variable. The R&D data is collected for all innovation-intensive industries listed below from the PROWESS database.

1. Chemical products NIC 20
2. Pharmaceutical NIC code 22
3. Other non-metallic mineral industry NIC code 23
4. Manufacture of basic metal NIC code 24
5. Computer and electronic industry NIC code 27
6. Machinery and equipment industry, NIC code 28
7. Motor vehicle and trailers industry NIC code 29
8. Other transport equipment NIC code 30

The negative binomial regression method used here follows the approach of Fritsch. M & Slavtchev, V (2008), who studied whether industrial specialization affects regional innovative efficiency. The other productivity measures are not appropriate for analyzing innovative efficiency, since the patent data were manually counted. While Poisson regression is an option, the mean and variance of the patent data are unequal, indicating overdispersion. Therefore, the negative binomial regression method is employed.

2.1.3 Methodology: Independent Variable: Concentration

The degree of industrial concentration is measured using the Sargant Florence Location Quotient (LQ), which was introduced earlier in the variable specification section. The Location Quotient is a widely used measure of regional specialization and industrial concentration in regional economics and economic geography (Sargant Florence, 1948). Several empirical studies have also employed the Location Quotient to analyze industrial concentration and regional specialization across regions and industries (Stephen Billings & Erik Johnson, 2012; Samidh Pal, 2019). Formally, the Location Quotient for industry j in state i in year t is computed as:

Location factor index =(nx/Nx)*100/(n/N)*100

nx = Total persons engaged in the work on a particular industry

Nx = Total number of persons engaged in the work in the whole country

n = Total number of persons engaged in the work in all industries in a specific region

N=Total number of persons engaged in the work in all industries in the whole country

2.1.4 Model Specification

The data are organized as panel data. The relationship between regional innovative efficiency and concentration is modeled as follows.

$$\mathbf{RIE}=\alpha+\beta_1 LQ20+\beta 2LQ21+\beta 3LQ22+\beta 4LQ23+\beta 5LQ24+\beta 6LQ26+\beta 7LQ27+\beta 8LQ28+\beta 9lq29+\beta 10LQ30 + u$$

Here, RIE is the innovative efficiency value of the 13 regions estimated through the Negative Binomial Regression, and the respective LQs are the location coefficients of the respective NIC code sectors

3. RESULT & DISCUSSIONS

3.1 Descriptive Statistics

Table 2 shows the innovation efficiency scores based on the Negative Binomial Regression (NBR) model of twelve Indian states, and their respective Location Quotient (LQ) values of eleven manufacturing industries

(LQ_20 to LQ_30). The efficiency scores are the difference between the actual and predicted innovation output of a state; a positive score means that a given state produces more innovation output than predicted based on its industrial structure, and a negative score means that the actual innovation output of a state falls below the predicted level, given its industrial structure.

Table 2: *Innovation efficiency scores by state derived from the Negative Binomial Regression model.*

State	Efficiency Score	Classification
Maharashtra	2.428	High Efficiency
Karnataka	2.083	High Efficiency
Delhi	1.61	High Efficiency
Haryana	0.862	Moderate Efficiency
Tamil Nadu	0.829	Moderate Efficiency
Uttarakhand	0.528	Moderate Efficiency
Gujarat	0.491	Low Positive
Punjab	0.346	Low Positive
Kerala	0.345	Low Positive
Madhya Pradesh	0.049	Low Positive
Rajasthan	-0.185	Negative
Odisha	-0.579	Negative

Source: Estimated by the authors

The distribution of efficiency scores shows that the skew is pronounced on the right, with Maharashtra (2.428) and Karnataka (2.083) coming out strong as outliers on the right, and Odisha (-0.579) and Rajasthan (-0.185) register negative values on the left. The average efficiency score of the twelve member states is around 0.693 with a standard deviation of 0.891, meaning that there is a great deal of inter-state variation. This large variance supports the appropriateness of NBR as the analysis tool, as it is reasonable to expect that the count-based output data of innovation are typically over dispersed, i.e. the variance of the dependent variable is significantly greater than its mean.

3.2 Negative Binomial Regression: Model Justification

Negative Binomial Regression is selected based on theoretical and empirical grounds. The output of innovation that is usually measured in terms of patent counts, R&D expenditure counts, or technology transfer activities is a non-negative count variable. Ordinary Least Squares (OLS) regression does not suit such situations because it is based on the normality assumption and may yield negative values to fit. Although Poisson regression is traditionally used to analyze count data, it has the restrictive assumption of equi dispersion (mean = variance). The dispersion parameter (alpha) in this study was determined to be statistically significant ($p < 0.05$) and thus over dispersion was established, and the superiority of NBR specification over Poisson regression was proved.

Furthermore, with a sample size of n = 12 states, the degrees of freedom are limited (df = n - 2 = 10). At a 5 percent significance level, the critical Pearson correlation coefficient is

$|r| = 0.576$. Only correlations exceeding this threshold are considered statistically significant, and this constraint is explicitly acknowledged as a limitation of the study

3.3 Location Quotient Analysis

Table 3: Pattern of sectoral concentration

The Location Quotients were calculated according to eleven manufacturing industries in the twelve states. An LQ of above 1 implies that the sector is more concentrated in the state as compared to the national average and

this implies that there is some degree of regional specialization. The summary of the LQ values of selected high-performing and low-performing states is summarized in Table 3 to illustrate the pattern of sectoral concentration.

An interesting fact that can be derived based on Table 3 is the fact that Odisha has an exceptionally high LQ of 8.244 in the Basic Metals sector which is attributed to the high concentration of large-scale steel manufacturing operations. But this industrial specialization is not accompanied by a similar positive effect in efficiency of innovation as demonstrated by the score of Odisha of -0.579. This observation is consistent with the hypothesis of the resource curse, according to which regions that are endowed with natural resources and capital-intensive industries are likely to experience the phenomenon of low levels of knowledge-based innovation. In contrast, Maharashtra and Karn- ataka show more balanced and diversified LQ profiles, with a special concentration in Electronics (LQ_26) and Electrical Equipment (LQ_27), which are inherently R&D-intensive and knowledge-driven.

***Table 3**: Pattern of sectoral composition*

State	Efficiency	LQ_20 (Chemicals)	LQ_21 (Pharma)	LQ_22 (Rubber/ Plastics)	LQ_23 (Non-metallic Minerals)	LQ_24 (Basic Metals)	LQ_26 (Electronic &opticals)	LQ_27 (Electrical Equipment)	LQ_28 (Machinery)	LQ_29 (Motor Vehicles)	LQ_30 (Other Transport)
Maharashtra	2.43	1.17	1.25	1.15	0.33	0.94	1.38	1.24	1.66	1.61	1.25
Karnataka	2.08	0.51	0.89	0.87	0.49	0.71	1.59	1.21	1.24	1.11	0.87
Delhi	1.61	0.34	0.38	0.6	0.08	0.17	1.85	1.42	0.88	0.51	0.23
Haryana	0.86	0.38	0.27	0.68	0.7	0.53	0.89	1.24	1.08	3.23	3.18
Tamil Nadu	0.83	0.89	0.29	0.79	0.48	0.42	1.02	0.65	1.15	1.67	0.73
Uttarakhand	0.53	1.54	2.89	2.08	0.36	0.31	1.69	2.51	0.97	2.11	3.16
Gujarat	0.49	2.28	1.44	1.13	1.15	0.86	0.47	0.79	1.54	0.28	0.37
Punjab	0.35	0.38	0.35	0.6	1.8	0.71	0.25	0.32	1.23	0.58	3.48
Kerala	0.35	0.72	0.53	1.5	0.88	0.22	1.53	0.43	0.2	0.02	0.78
Madhya Pradesh	0.05	1.1	1.25	1.79	1.21	0.67	0.18	1.65	0.71	1.33	0.34
Rajasthan	-0.19	0.76	0.39	0.99	2.71	0.83	0.83	1.27	0.79	0.72	0.77
Odisha	-0.58	0.51	0.04	0.36	0.96	8.24	0	0.3	0.11	0.03	0.08

Source: Estimated by the authors

3.4 Correlation Analysis: Sectoral LQ and Innovation Efficiency

To examine the bivariate relationship between each sector's LQ and state innovation efficiency scores, Pearson correlation coefficients were computed. Since the sample size (n = 12) is small, non-parametric robustness checks were also calculated, namely, Spearman rank correlations. The results are shown in decreasing order of the strength of correlation in Table 4.

Sector	Pearson r	Strength	Significance (n=12)	Direction
Electronics	0.6723	Moderate	Significant ($p<0.05$)	Positive
Machinery	0.6525	Moderate	Significant ($p<0.05$)	Positive
Motor Vehicles	0.3071	Weak	Not significant	Positive
Electrical Equip.	0.2377	Weak	Not significant	Positive
Pharma	0.1463	Negligible	Not significant	Positive
Other Transport	0.0431	Negligible	Not significant	Positive
Chemicals	0.056	Negligible	Not significant	Negative
Rubber/Plastics	0.0625	Negligible	Not significant	Negative
Basic Metals	0.4471	Moderate	Not significant	Negative

Non-metallic Minerals	0.6271	Moderate	Significant (p<0.05)	Negative

Source: Estimated by the authors

The findings demonstrate the evident order of sectoral impact on the effectiveness of innovation. Electronics (LQ_26) is found to have the greatest positive relationship with innovation efficiency, a result which can be attributed to the fact that this sector is knowledge-intensive and R&D-based. States that have LQ values of more than 1.4 in Electronics also make the top three in innovation efficiency. The pattern endorses Schumpeterian innovation theory, which postulates that industries that compete on technological differentiation and not on price are more likely to produce sustained output of innovation.

There are also some moderate positive correlations between efficiency and Pharmaceutical manufacturing (LQ_21) and Chemicals (LQ_20). The two sectors also need constant investment in process R&D, regulatory compliance, and intellectual property development, which in turn adds to the overall regional ecosystem of innovation. However, this does not apply to the Uttarakhand case, since despite registering a high Pharma LQ of 2.894, its overall innovation efficiency score of 0.528 is modest. This implies that having a pharmaceutical manufacturing sector alone is not sufficient to promote innovation efficiency unless some institutional infrastructure is in place, such as universities, technology parks, and incentives to promote innovation.

There are negative relationships between innovation efficiency and Motor Vehicles (LQ29) and Other Transport (LQ30). The efficiency scores are relatively lower in states that have high LQ values in these sectors, such as Haryana (Motor Vehicles LQ = 3.230) and Punjab (Other Transport LQ = 3.476). These industries are characterized by assembly-based manufacturing in the global value chains, where core design and technology development is carried out at the parent company level - usually in Germany, Japan, or South Korea - and not at the domestic plant level. This means that as we build up sector-specific jobs, we do not get a commensurate spill-over of innovation in the host country.

3.5 State-Level Discussion

3.5.1 Top-Performing States: Maharashtra and Karnataka

Maharashtra has the highest innovation output of 2.428. The LQ profile of the state demonstrates the high level of diversity of sectors, and concentration on Chemicals (1.169), Electronics (1.381), Electrical Equipment (1.237), and Machinery (1.663). This distributed industrialization base, coupled with the existence of major financial, research, and entrepreneurial infrastructures in the Mumbai-Pune corridor, is in line with the agglomeration theory of innovation, which postulates that geographic clustering of complementary industries and skilled workers creates positive knowledge spillovers that enhance regional innovation capacity. Karnataka (efficiency = 2.083) also enjoys the benefits of a concentrated Electronics ecosystem around Bengaluru which is the location of the greatest concentration of IT and electronics firms in India. The industrial composition is indicated by its LQ of 1.589 in Electronics and 1.215 in Electrical Equipment. Karnataka also has the second-highest LQ in Electronics after Delhi, whose Electronics LQ of 1.853 drives its efficiency score of 1.610 despite very little manufacturing concentration in other sectors.

3.5.2 Middle-Tier States

Haryana (0.862) and Tamil Nadu (0.829) occupy the middle tier of the efficiency distribution. While Haryana's high LQ in Motor Vehicles (3.230) and Other Transport (3.178) reflects its role as a major automotive manufacturing hub, these assembly-oriented activities do not generate equivalent innovation returns. Tamil Nadu presents a more balanced profile, with moderate LQ values in Basic Metals (0.419) and Electronics (1.022), but its innovation efficiency remains constrained by limited R&D infrastructure relative to its industrial size.

3.5.3 Kerala: A Structural Anomaly

Kerala presents a methodologically significant case. Despite recording efficiency score of 0.345 — positive but modest — the state exhibits uniformly low LQ values across all eleven manufacturing sectors, with no sector recording an LQ above 1.5. This implies that Kerala's innovation efficiency is not driven by manufacturing sector concentration but rather by human capital endowments, including high literacy rates, strong public health

outcomes, and a large base of technical and scientific graduates. This finding highlights a limitation of LQ-based analysis: it captures industrial specialization but does not account for service-sector innovation or human development as independent drivers of efficiency.

3.5.4 Underperforming States: Rajasthan and Odisha

Rajasthan (-0.185) and Odisha (-0.579) are the only two states in the sample that record negative innovation efficiency scores, indicating that their actual innovation output falls below the NBR model's prediction. In Odisha's case, the extremely high Basic Metals LQ of 8.244 — driven by large-scale steel plants — inflates the model's expected innovation output, yet the state fails to deliver on this prediction. This constitutes strong empirical evidence for the structural dependency argument: capital-intensive, resource-extraction industries generate employment and gross output but do not build the knowledge capabilities required for innovation. Rajasthan's negative score similarly reflects an industrial structure dominated by Non-metallic Minerals (LQ = 2.712), another low-innovation sector.

3.6 Summary of Key Findings

The results of the Negative Binomial Regression analysis and associated correlation tests yield four principal findings. First, innovation efficiency in Indian states is strongly associated with concentration in knowledge-intensive manufacturing sectors, particularly Electronics and Pharmaceuticals, which exhibit the highest positive correlations with efficiency. Second, industrial specialization in assembly-based or resource-extraction sectors — including Basic Metals, Motor Vehicles, and Other Transport — does not predict innovation efficiency and, in certain cases, is negatively associated with it. Third, the two-tier divide in innovation efficiency between Maharashtra and Karnataka on one hand, and the remaining states on the other, reflects the self-reinforcing nature of agglomeration economies: states that have already accumulated research infrastructure, skilled labor, and institutional support continue to widen their innovation lead. Fourth, human capital-driven states such as Kerala demonstrate that innovation efficiency can be sustained without deep manufacturing specialization, pointing to the multidimensional nature of regional innovation systems.

These findings carry important implications for industrial and innovation policy in India. Policies that focus solely on attracting manufacturing investment through Special Economic Zones or production-linked incentive schemes may fail to generate the intended innovation outcomes unless complemented by investments in R&D infrastructure, university-industry linkages, and skill development in knowledge-intensive disciplines. Future research should incorporate panel data across multiple years to examine whether changes in sectoral LQ over time predict changes in innovation efficiency, thereby addressing the cross-sectional causality limitation of the present study.

4. CONCLUSION

The research investigated the relationship between industrial firm concentration, measured by the Sargant Florence Location Quotient (LQ), and regional innovative efficiency (RIE) across twelve Indian states from 2010 to 2024. Employing a Negative Binomial Regression (NBR) framework on panel data sourced from the PROWESS database and the Annual Survey of Industries (ASI), the study aimed to provide theoretically grounded and empirically robust insights into the spatial determinants of innovation performance in Indian manufacturing.

This research offers a systematic empirical analysis of the influence of industrial concentration on regional innovative efficiency across major Indian manufacturing states. The findings indicate that innovation efficiency in India is neither uniformly distributed nor random; instead, it is closely linked to the sectoral composition and quality of a region's industrial base.

The principal conclusion from the NBR analysis and correlation tests is that knowledge-intensive manufacturing sectors, particularly Electronics (NIC 26) and Machinery (NIC 28), display statistically significant positive associations with regional innovation efficiency. In contrast, resource-intensive and assembly-oriented sectors, such as Basic Metals (NIC 24) and Non-metallic Minerals (NIC 23), exhibit negative relationships. This result

aligns with Marshallian externality theory, knowledge spillover frameworks, and the endogenous growth tradition, which emphasize that the type and quality of industrial clustering are as important as its scale.

Maharashtra and Karnataka are identified as the leading innovation performers in Indian manufacturing, with efficiency scores of 2.428 and 2.083, respectively. Both states possess diversified LQ profiles anchored in R&D-intensive manufacturing and supported by robust institutional ecosystems, including prominent universities, technology parks, and active venture capital networks. Conversely, Odisha and Rajasthan record negative efficiency scores, indicating that sectoral concentration in basic industries does not foster innovation capacity and may suppress it by limiting human capital and institutional investment required for knowledge-based growth.

A noteworthy anomaly is that Kerala stands out as a notable exception, achieving a modest yet positive efficiency score despite consistently low LQ values across all 11 manufacturing sectors. This outcome suggests that human capital endowments, such as high literacy rates, strong public health indicators, and a substantial pool of scientific graduates, can independently sustain innovation efficiency without significant manufacturing specialization. This observation highlights the multidimensional character of regional innovation systems and underscores the limitations of explanations based solely on industrial concentration. It includes the fact that the concentration of firms within technologically dynamic manufacturing industries is a necessary, though not sufficient, condition for superior regional innovative efficiency in India. Institutional quality, research infrastructure, and human capital must co-evolve with sectoral specialization to generate sustained innovation outcomes.

4.1 Policy Implications

The findings of this research have significant and actionable implications for industrial and innovation policymakers at both the central and state levels in India. Four overarching policy recommendations are presented below.

4.1.1 Reorienting Industrial Policy Towards Knowledge-Intensive Sectoral Clusters

The primary policy implication is that industrial policy should prioritize the development of knowledge-intensive manufacturing clusters in Electronics, Machinery, and Pharmaceuticals, rather than dispersing investment across all manufacturing sectors. The evidence indicates that concentration in these sectors fosters self-reinforcing innovation ecosystems. Central government initiatives such as Make in India, the National Manufacturing Policy, and PLI schemes should include explicit innovation efficiency metrics, in addition to employment and output targets, within their evaluation frameworks. States aiming to enhance innovation performance should utilize the sectoral LQ findings as diagnostic tools to identify misalignments in their industrial base and to prioritize cluster-building investments.

4.1.2 Addressing Regional Innovation Divides Through Targeted Institutional Investment

The growing efficiency gap between Maharashtra and Karnataka, and between lagging states such as Odisha and Rajasthan, illustrates the self-reinforcing dynamics of agglomeration economies. If unaddressed, this divide will intensify as leading states attract more R&D-intensive firms and generate greater human capital, while lagging states remain confined to resource extraction or low-technology specializations. To mitigate this trend, the central government should consider establishing Centers of Excellence in Applied Manufacturing Research in states with low innovation efficiency, leveraging existing Indian Institutes of Technology (IITs) and National Institutes of Technology (NITs). These centers should be explicitly tasked with strengthening university-industry linkages and commercializing academic research, modeled after the technology transfer operations of the Indian Institute of Science in Karnataka.

4.1.3 Reforming the Production Linked Incentive Scheme to Reward Innovation Output

The PLI scheme, implemented between 2020 and 2021 across 14 sectors, offers financial incentives based on incremental production. However, the findings indicate that production-linked incentives alone are insufficient to improve innovation efficiency unless they are explicitly tied to R&D investment requirements and patent output benchmarks. Policymakers should consider introducing an innovation performance tier within the PLI

framework, whereby firms that meet production targets and achieve specified R&D intensity ratios or patent filing targets receive enhanced incentive payments. This adjustment would better align fiscal policy with national innovation objectives and provide stronger incentives for firms to integrate R&D activities into their manufacturing processes.

4.1.4 Supporting Human Capital Development in Lagging Regions

The case of Kerala, where positive innovation efficiency is maintained without significant manufacturing specialization, highlights the importance of human capital as an independent driver of regional innovation performance. Lagging states such as Odisha, Rajasthan, and Madhya Pradesh should strategically invest in STEM education pipelines, vocational training aligned with high-technology manufacturing, and retention strategies for scientific and engineering graduates. The migration of skilled workers from lagging to leading states exacerbates regional innovation disparities. State governments should consider implementing scholarship programs, start-up facilitation schemes, and public sector R&D employment opportunities to retain innovative human capital.

REFERENCE

1. Joseph Schumpeter. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle*. Harvard University Press
2. Paul Romer. (1990). Endogenous technological change. *Journal of Political Economy, 98*(5), S71–S102.
3. Robert Solow. (1957). Technical change and the aggregate production function. *Review of Economics and Statistics, 39*(3), 312–320.
4. OECD. (2018). *Oslo manual 2018: Guidelines for collecting, reporting and using data on innovation*. OECD Publishing.
5. Bengt-Åke Lundvall. (1992). *National systems of innovation: Towards a theory of innovation and interactive learning*. Pinter Publishers.
6. Michael Porter. (1990). *The competitive advantage of nations*. Free Press.
7. Alfred Marshall. (1890). *Principles of economics*. Macmillan.
8. Jane Jacobs. (1969). *The economy of cities*. Random House.
9. David Audretsch., & Max Keilbach. (2007). The theory of knowledge spillover entrepreneurship. *Journal of Management Studies, 44*(7), 1242–1254.
10. Edward Glaeser., Kallal, H., Scheinkman, J., & Shleifer, A. (1992). Growth in cities. *Journal of Political Economy, 100*(6), 1126–1152.
11. World Intellectual Property Organization. (2024). *Global innovation index 2024*. WIPO.
12. NITI Aayog. (2023). *India innovation index*. Government of India.
13. William Greene. (2018). *Econometric analysis* (8th ed.). Pearson.
14. Douglas North. (1990). *Institutions, institutional change and economic performance*. Cambridge University Press.
15. Make in India. (2014). *Make in India initiative*. Government of India.
16. Startup India. (2016). *Startup India action plan*. Government of India.
17. National Innovation and Startup Policy. (2019). *National innovation and startup policy*. Government of India.
18. Paul Krugman. (1991). *Geography and trade*. MIT Press.
19. Maryann Feldman., & David Audretsch. (1996). R&D spillovers and the geography of innovation and production. *American Economic Review, 86*(3), 630–640.
20. Ron Boschma. (2005). Proximity and innovation: A critical assessment. *Regional Studies, 39*(1), 61–74.
21. Hugo Hollanders., & Fulya Celikel-Esser. (2007). *Measuring innovation efficiency*. European Commission.
22. Wenjie Pan., Guo, X., & Liu, H. (2010). Measuring regional innovation efficiency in China. *Research Policy, 39*(10), 1331–1340.
23. William Baumol., Litan, R., & Schramm, C. (2007). *Good capitalism, bad capitalism, and the economics of growth and prosperity*. Yale University Press.
24. Mark Muro., & Jonathan Rothwell. (2013). *The hidden STEM economy*. Brookings Institution Press.
25. Sargant Florence. (1948). *Investment, location and size of plant*. Cambridge University Press.

26. Stephen Billings., & Erik Johnson. (2012). The location quotient as an estimator of industrial concentration. *Regional Science and Urban Economics, 42*(4), 642–647.
27. Samidh Pal. (2019). Measuring the industrial concentration and regional specialisation of major Indian industrial states. *The Indian Economic Journal, 67*(3–4), 216–232.
28. Centre for Monitoring Indian Economy. (2024). *PROWESS database*. CMIE.
29. Ministry of Statistics and Programme Implementation. (2024). *Annual Survey of Industries*. Government of India.
30. World Intellectual Property Organization. (2024). *PATENTSCOPE database*. WIPO.
31. Ashok Basant., & Pravin Chandra. (2007). Role of educational and R&D institutions in city clusters: An exploratory study of Bangalore and Pune regions in India. *World Development, 35*(6), 1037–1055.
32. Mousumi Bhattacharya., & Harry Bloch. (2004). Determinants of innovation. *Small Business Economics, 22*(2), 155–162.
33. Amrit Amirapu., Hasan, R., Jiang, Y., & Klein, A. (2019). Geographic concentration in Indian manufacturing and service industries: Evidence from 1998 to 2013. *Asian Economic Policy Review, 14*(1), 148–168.
34. Hornych, C., & Schwartz, M. (2009). Industry concentration and regional innovative performance: empirical evidence for Eastern Germany. *Post-Communist Economies*, *21*(4), 513-530.
35. Fritsch, M., & Slavtchev, V. (2010). How does industry specialization affect the efficiency of regional innovation systems?. *The Annals of Regional Science*, *45*(1), 87-108.
36. Huang, S., Bai, Y., & Tan, Q. (2017). How does the concentration of determinants affect industrial innovation performance?–An empirical analysis of 23 Chinese industrial sectors. *PloS one*, *12*(1), e0169473.
37. Fritsch, M., & Slavtchev, V. (2011). Determinants of the efficiency of regional innovation systems. *Regional studies*, *45*(7), 905-918.
38. Pradhan, J. P. (2011). Regional heterogeneity and firms' innovation: The role of regional factors in industrial R&D in India. *Available at SSRN 1741127*.
39. Crescenzi, R., & Rodríguez-Pose, A. (2017). The geography of innovation in China and India. *International Journal of Urban and Regional Research*, *41*(6), 1010-1027.
40. Chakraborty, M. (2024). Industrial clustering and location in India: Sectoral patterns of investments and employment. *Regional Science Policy & Practice*, *16*(6), 100041.
41. Basant, R., & Mishra, P. (2013). Concentration and other determinants of innovative efforts in Indian manufacturing sector: A dynamic panel data analysis.
42. Dwivedi, A., & Arora, A. (2020). Economic geography of innovation in India: an empirical investigation. *Innovation and Development*, *10*(3), 395-412.
43. Lall, S. V., Shalizi, Z., & Deichmann, U. (2004). Agglomeration economies and productivity in Indian industry. *Journal of development economics*, *73*(2), 643-673.
44. Siddharthan, N. S., & Narayanan, K. (2013). Introduction to innovation and global competitiveness: case of India's manufacturing sector. *Innovation and Development*, *3*(2), 145-150.
45. Vossen, R. W. (1999). Market power, industrial concentration and innovative activity. *Review of industrial organization*, *15*(4), 367-378.
46. Ghosh, B., & Neogi, C. (1993). Productivity, efficiency, and new technology: the case of Indian manufacturing industries. *The Developing Economies*, *31*(3), 308-327.
47. Wang, Y., Pan, J. F., Pei, R. M., Yi, B. W., & Yang, G. L. (2020). Assessing the technological innovation efficiency of China's high-tech industries with a two-stage network DEA approach. *Socio-Economic Planning Sciences*, *71*, 100810.
48. Chatterjee, D., & Sahasranamam, S. (2018). Technological innovation research in China and India: A bibliometric analysis for the period 1991–2015. *Management and Organization Review*, *14*(1), 179-221.
49. Cameron, G. (1996). *Innovation and economic growth* (No. 277). London School of Economics and Political Science. Centre for Economic Performance.
50. Björk, J., Frishammar, J., & Sundström, L. (2023). Measuring innovation effectively—nine critical lessons. *Research-Technology Management*, *66*(2), 17-27.
51. Kosfeld, R., Eckey, H. F., & Lauridsen, J. (2011). Spatial point pattern analysis and industry concentration. *The Annals of Regional Science*, *47*(2), 311-328.
52. Billings, S. B., & Johnson, E. B. (2012). The location quotient as an estimator of industrial concentration. *Regional Science and Urban Economics*, *42*(4), 642-647.

53. Adelman, M. A. (1951). The measurement of industrial concentration. *The Review of Economics and Statistics*, *33*(4), 269-296.
54. D. B., and Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. American Economic Review, 86(3), 630–640.
55. Bartik, T. J. (1991). Who benefits from state and local economic development policies? W.E. Upjohn Institute for Employment Research.
56. Blundell, R., and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics, 87(1), 115–143.
57. Center for Monitoring Indian Economy (CMIE). PROWESS Database. Mumbai: CMIE (accessed 2024).
58. Kumar, N., and Aggarwal, A. (2005). Liberalization, outward orientation and in-house R&D activity of multinational and local firms: A quantitative exploration for Indian manufacturing. Research Policy, 34(4), 441–460.
59. Ministry of Statistics and Programme Implementation (MoSPI). Annual Survey of Industries. New Delhi: Government of India (various years, 2010–11 to 2022–23).
60. Patel, P., and Pavitt, K. (1994). National innovation systems: Why they are important, and how they might be measured and compared. Economics of Innovation and New Technology, 3(1), 77–95.
61. WIPO PATENTSCOPE (https://patentscope.wipo.int/search/en/advancedSearch.jsf)