European Economic Letters
ISSN 2323-5233
Vol 15, Issue 3 (2025)
http://eelet.org.uk

Mapping India's Startup Landscape: Regional Specialization and Sector Concentration Using DPIIT Recognition Data

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Abstract

India hosts one of the world's largest startup populations, yet activity is highly uneven across states and industries. Using the Government of India's Startup Recognized by DPIIT dataset (157,705 recognitions; 36 States/UTs × 56 industries), we map lifetime counts and compute Location Quotients (LQ) and Herfindahl–Hirschman Indices (HHI) to reveal specialization and diversification patterns. Six Tier-1 hubs consisting Maharashtra, Karnataka, Uttar Pradesh, Delhi, Gujarat and Tamil Nadu contribute nearly two-thirds of recognitions, but LQs expose niche strengths in smaller jurisdictions that volume rankings miss. Sectoral leadership also shifts by metric: states topping raw counts are not always the most specialized once national composition is considered. The ten Key Sectors (e.g., IT Services, AI, Agriculture) show distinct regional footprints, underscoring that "breadth" (diversification) and "depth" (specialization) demand different policy tools. By providing the first sector-resolved, nationwide baseline through early 2025, the study equips policymakers to tailor Startup India and State Ranking Framework interventions and guides scholars toward richer finance-and-talent linkages.

Keywords: Entrepreneurial ecosystem; Geographic specialisation; Herfindahl–Hirschman Index (HHI); Location Quotient (LQ); Startup India

1. Introduction

India has vaulted into the top tier of global startup nations in less than a decade. Government figures reported 1,57,705 Department for Promotion of Industry and Internal Trade (DPIIT)–recognised startups across every State and Union Territory by 31 December 2024, while independent ecosystem benchmarks now place leading Indian hubs, most notably Bengaluru among the world's highest-ranking innovation locales. Industry intelligence likewise documents deepening technology breadth and rapid venture formation despite cyclical funding swings. Together these signals underscore the scale and policy salience of India's startup emergence. (PIB, 2025; Startup Genome, 2025; NASSCOM, 2024)

A distinctive feature of India's startup story is that it unfolds within a large federal system in which States and Union Territories retain wide discretion over key enabling conditions-regulatory procedures, infrastructure, higher education, incubation support, procurement, and investment promotion, while national programs create common frameworks and incentives. The flagship Startup India initiative, launched in 2016 and administered by DPIIT, offers formal recognition, tax relief, intellectual-property support, and access to a range of central schemes. Complementing this, the States' Startup Ranking Framework (SRF) encourages state-level policy experimentation and inter-state peer learning through periodic benchmarking. Macroeconomic strategy documents, including the Union Government's Economic Survey, highlight startups and MSMEs as critical growth engines in India's bid to become a developed economy.

Despite intense policy activity, empirical comparisons of where recognized startups are located, which sectors anchor different state ecosystems, and how broad or concentrated state startup portfolios are remained surprisingly limited. Public commentary often cites national totals or the performance of a handful of metro hubs, but systematic state-by-industry analysis has been hampered by data gaps, boundary changes (e.g., creation of Telangana; separation of Ladakh), and inconsistent sector taxonomies across commercial databases. The Government of India's Open Government Data (OGD) Platform now publishes a consolidated dataset (Startup Recognized by DPIIT) that reports counts of recognized startups by Year × State/UT × Industry (56 categories). The catalog was accessed and downloaded on 1 May 2025. Aggregating across years yields 157,705 DPIIT-recognized startups through the refresh date, a figure broadly consistent with Government communications for late 2024 once reporting lags are considered. (DPIIT, 2025; PIB, 2025)

Why do we need more than raw counts? Regional development research shows that innovative and entrepreneurial activity concentrates unevenly, forming clusters that benefit from localized spillovers, specialized labour pools, and supporting institutions. Counting firms reveals scale, but it can mask relative specialization, the extent to which a sector is over- or under-represented in a particular region and portfolio breadth whether activity is spread across many sectors or concentrated in a few. Cluster-mapping practice therefore relies on comparative metrics such as the Location Quotient (LQ) and the Herfindahl-Hirschman Index (HHI) to benchmark strengths and diversification. Empirically, Location Quotients have proved robust proxies for traded-cluster strength, with high-LQ regions showing faster employment and wage growth in subsequent periods (Delgado et al., 2014). Methodological work cautions, however, that LQs computed on very small denominators can yield misleading extremes, motivating transparency about minimum cell sizes. (Audretsch & Feldman, 1996).

This paper leverages the new OGD dataset to produce the first national, state-resolved map of DPIIT-recognized startups across 56 industries. We first document the scale and geographic distribution of recognized startups. Second, we identify leading Key Sectors, ten policy-salient industries that account for a large share of recognitions and align with national innovation priorities (IT Services, AI, Healthcare & Lifesciences, Agriculture, Finance Technology, Renewable Energy, Retail, Education, Automotive, Food & Beverages). Third, we compute LQs to surface relative specialization and HHI-based indicators to assess diversification and fourth we apply a conservative <20-startup small-cell flag to guard against over-interpreting thin data. In doing so, we provide an evidence base that complements DPIIT's State Startup Ranking process and offers diagnostic insights for differentiated state policy. (Ketels, 2017; Pominova et al., 2021)

2. Literature Review

This section synthesizes four literatures that motivate and frame the study: (1) Entrepreneurial ecosystem concepts that explain how combinations of actors, networks, and institutions enable productive entrepreneurship; (2) Geography, clusters, and knowledge spillovers showing why economic activity concentrates and why relative specialization matters; (3) Measurement approaches including startup counts, Location Quotients (LQ), and diversification indices together with cautions about small-cell volatility; and (4) India's policy landscape (Startup India, DPIIT recognition, States' Startup Ranking Framework, national growth priorities, MSME finance) that makes a national state-sector mapping both timely and policy-relevant. We conclude by specifying the research gap and our guiding questions. (Stam & Spigel, 2018; Ketels, 2017; Pominova et al., 2021; DPIIT, 2025)

2.1 Conceptualizing Entrepreneurial Ecosystems

The entrepreneurial ecosystem (EE) perspective views high-potential entrepreneurship as emerging from an interacting set of domains like skilled human capital, markets, finance, support organizations, culture, policies, and enabling infrastructure rather than from isolated entrepreneurs. Seminal syntheses emphasize that these domains are locally configured and co-evolve over time; successful ecosystems recycle talent and capital from prior entrepreneurial successes back into new ventures (Stam & Spigel, 2018; Isenberg; Mason & Brown). Comparative work on national systems of entrepreneurship stresses that ecosystem performance must be measured multidimensionally, combining resource endowments with institutional quality and entrepreneurial outputs (Ács et al., 2014).Ecosystems are therefore path dependent: early wins, anchor firms, universities, diaspora ties, and policy interventions can tip regions onto higher-growth trajectories even when initial resource endowments are modest. (Stam & Spigel, 2018)discuss system elements and outputs; Isenberg articulates design principles for place-based entrepreneurship policy; Mason & Brown link ecosystems to growth-oriented and scale-up firms. (Isenberg, 2010; Mason & Brown, 2014; Spigel & Stam, 2018)

2.2 Why Place Matters: Clusters, Specialization & Knowledge Spillovers

Regional development research shows that innovative and entrepreneurial activity is not evenly distributed; it tends to agglomerate in clusters where firms benefit from pooled specialized labour, supplier and customer linkages, localized knowledge spillovers, and supportive institutions. Foundational urban research shows that innovation and employment growth are disproportionately concentrated in large, diversified cities, reinforcing the theoretical expectations of agglomeration economies (Glaeser et al., 1992). Classic empirical work documents the geographic concentration of R&D and innovation outputs (Audretsch & Feldman, 1996). Cluster mapping approaches (Ketels; Porter tradition) operationalize

these ideas by benchmarking the relative industrial mix across regions and identifying traded versus local cluster strengths that can inform economic development strategy. Porter (1998) crystallised the cluster perspective, arguing that geographically proximate firms, suppliers and supporting institutions create self-reinforcing advantages that cannot be captured by firm-level analysis alone. Translating cluster logic to startups implies that relative specializations for e.g., an outsized share of AI startups in a smaller statemay be strategically important even when absolute numbers are modest. (Ketels, 2017)

2.3 Measuring Ecosystems: Startup Counts, LQ, and Metric Cautions

Researchers and policy analysts routinely begin with counts (number of startups, funding events, jobs) yet counts alone conflate size with specialization and ignore portfolio breadth. Location Quotients (LQ) compare an industry's share in a region to its national share to reveal areas of relative strength; Herfindahl-Hirschman Indices (HHI) summarize how diversified or concentrated a region's startup activity is across industries. However, methodological work warns that LQs estimated on very small denominators can be volatile, generating spurious "specializations" in tiny regions; analysts should flag low counts and test robustness to minimum thresholds. Pominova, Gabe & Crawley highlight pitfalls of LQ-based cluster identification in small regions; Ketels provides guidance on cluster mapping practice. These cautions motivate the small-cell rule (<20 startups) and adjusted metrics we use in this paper (Section 3). (Ketels, 2017; (Pominova et al., 2021))

2.4 India's Startup Policy Landscape and Data Context

India's Startup India initiative (launched 2016; administered by DPIIT) provides formal recognition, tax incentives, easier compliance, and access to government programs. DPIIT's recognition guidelines require that an entity be within 10 years of incorporation, remain below a turnover cap, and pursue innovation; as of 31 December 2024 the Government reported approximately 157705 DPIIT-recognised startups spanning more than 55 industries and every State/UT, illustrating both policy reach and rapid ecosystem scale-up. The States' Startup Ranking Framework (SRF) annually assesses state policy support and capacity building, spurring inter-state competition and diffusion of best practices. National macro policy documents such as Economic Survey 2024-25 highlight startups, MSMEs, digital infrastructure, and deregulation as growth drivers in India's push toward becoming a developed economy. Complementary ecosystem intelligence is produced by industry and analytic bodies: NASSCOM's Road to Recovery: Indian Tech Start-up Landscape 2024 tracks tech startup trends and funding cycles; Startup Genome's Global Startup Ecosystem Report 2025 benchmarks Indian hubs (e.g., Bengaluru rising to 14th globally) in a comparative international framework and Equifax's State of Micro Enterprise Financing Report 2024 underscores financing frictions facing smaller enterprises which is an important context for interpreting geographic startup gaps. Detailed district-level work for India finds that IT and manufacturing start-ups co-locate in a limited number of urban clusters, driven by labour-market pooling and input sharing ((Ghani et al., 2014); DPIIT, 2025; Ministry of Finance, 2025; NASSCOM, 2024; Startup Genome, 2025; Equifax, 2024)

2.5 Research Gap and Questions

Despite India's large and rapidly expanding startup base, systematic state-by-industry mapping using official DPIIT recognition data remains scarce in the academic literature. Policy documents report national totals and success metrics, but they do not routinely analyze relative specialization or diversification profiles across regions, nor do they compare high-volume states with niche specialists. By combining the Government's cumulative recognition data with specialization (LQ) and diversification (HHI) metrics, we address three questions:

1. Scale & Geography - How unevenly are DPIIT-recognized startups distributed across India's States/UTs in absolute and per-capita terms?

2. Sectoral Leadership - Which States/UTs lead within ten Key Sectors central to national innovation priorities, and how do volume rankings compare with relative specialization?

3. Portfolio Breadth - How diversified or concentrated are state startup portfolios across industries, and what does this imply for place-differentiated policy under Startup India and the States' Startup Ranking Framework?

3. Data and Methods

3.1 Data and Sample

Data - We use cumulative counts of DPIIT-recognized startups from the "Startup Recognized by DPIIT" dataset on the Open Government Data (OGD) Platform India (Ministry of Commerce & Industry; Department for Promotion of Industry and Internal Trade- DPIIT). The catalog provides the number of entities formally recognized under the Startup India program by Year × State/Union Territory × Industry (sector) × Count. The catalog metadata was accessed and downloaded on 1 May 2025 and processed them for analysis.

Coverage window- Counts are cumulative they therefore represent all entities that had ever received DPIIT startup recognition up to that last refreshed update (not a live "currently active" universe). Government communications similarly report cumulative totals for e.g., 1,57,706 DPIIT-recognised startups as of 31 Dec 2024 which is consistent with the magnitude of our processed national count (157,705).

Operational definition of a startup- Under Startup India, an entity (private limited company, registered partnership, or LLP) qualifies for DPIIT recognition if (i) it is ≤10 years from incorporation (biotech may have extended windows in some notices), (ii) has not exceeded INR 100 crore turnover in any prior financial year, (iii) is working toward innovation / improvement / scalable employment-generating model, and (iv) is not formed by splitting/reconstruction of an existing business. These criteria govern the composition of the recognition counts released via the dataset.

Structure and variables- Each source row reports Year, State, Industry, and Count (number of recognized startups in that cell) plus a Last Update stamp. We aggregated across years to form lifetime cumulative totals by State/UT and by Industry. The raw Industry field (exact header: Industry) contains 56 distinct industry categories, including (examples) IT Services, AI, Healthcare & Lifesciences, Agriculture, Finance Technology, Renewable Energy, Retail, Education, Automotive, and Food & Beverages. For descriptive emphasis we defined a subset of 10 Key Sectors to highlight leading states in policy-salient domains (see Section3.2 and Section4.2). Each DPIIT record belongs to exactly one Industry category; we performed no multi-sector reallocation.

Geographic assignment- Startups are attributed to the registered State/UT reported in the DPIIT recognition database. We accept this official mapping; multi-state operations cannot be observed or re-assigned in the released aggregates.

Sample size and treatment of missing cells- After summing all State/UT × Industry counts across years and coding unreported cells (NA) as zero on the assumption that no startups were recognized in those combinations, we obtained a national cumulative total of 157,705 DPIIT-recognized startups. The total closely matches Government-reported cumulative figures for roughly the same period (1,57,706 as of 31 Dec 2024), suggesting the NA→0 treatment does not materially bias national aggregates. (PIB, 2025)

Data quality and limitations- Because the public dataset is aggregated, we cannot verify current operating status; adjust for subsequent sector reclassification or state relocation; or weight by employment, revenue, funding, or valuation. Counts therefore capture recognized startup presence, not economic scale. Small absolute numbers in some State/UT × Industry cells (common in smaller UTs) can produce highly volatile specialization metrics (Location Quotients); we flag cells with <20 startups and conduct sensitivity checks. Ketels, 2017; (Pominova et al., 2021) Guidance in the regional analysis literature cautions that LQs computed on very small denominators may show extreme values triggered by only one or a few establishments.

3.2 Key Sector Definition

We focus analytic and policy comparisons on ten Key Sectors drawn directly from the DPIIT Industry field in the OGD dataset: IT Services; AI; Healthcare & Lifesciences; Agriculture; Finance Technology (Fintech); Renewable Energy; Retail; Education; Automotive; Food & Beverages. These sectors (i) account for large cumulative shares of DPIIT recognitions, (ii) align with Startup India policy priorities and prominent national/state innovation roadmaps, and (iii) display sufficient geographic spread to support comparative State/UT analysis. (DPIIT, 2025; NASSCOM, 2024)

Reproducibility- Each Key Sector maps one-to-one to a single Industry value exactly as spelled in the raw DPIIT CSV. We did not aggregate multiple DPIIT industries into broader buckets, nor did we reassign startups across industries.

3.3 Specialization Metric: Location Quotient (LQ)

We measure the relative specialization of each State/UT in each industry using the Location Quotient (LQ).

Definition :

- $E_{s,k}$= Cumulative number of DPIIT- recognized startups in State/UTs, Industry k.

- $E_{s,.}$= total startups in State/UT s across all industries (sum over k).

- $E_{.,k}$= national total startups in Industry k (sum over s).

- $E_{.,.}$ = national grand total startups (sum over all s,k).

Formula: $LQ_{s,k} = (\frac{E_{s,k}}{E_{s,.}})/(\frac{E_{.,k}}{E_{.,.}})$

Interpretation: LQ = 1 implies Industry k's share in State s matches its national share. LQ > 1 indicates that State s is relatively specialized in k; LQ < 1 indicates under-representation.

Interpretive bands (heuristic): <0.75 under-represented; 0.75–1.25 broadly in line with national structure; >1.25 specialized; >2.00 strong specialization. Bands aid interpretation and are not formal statistical tests.

Small-cell rule. LQs can be unstable when based on very small counts. We therefore flag any State/UT × Industry cell with fewer than 20 startups "as interpret with caution". In robustness checks, we recompute LQs after excluding cells <20 and compare results; extreme LQs driven by 1–5 startups often revert toward 1 when suppressed.

Optional transformations (for supplemental analysis): We compute log-LQs and a winsorized LQ capped at 5 to limit leverage from extreme values in small states. (Ketels, 2017; Pominova et al., 2021)

3.4 Diversification Metric: Herfindahl-Hirschman Index (HHI)

We assess how concentrated or diversified each State/UT's startup portfolio is across industries using the Herfindahl-Hirschman Index (HHI).

Definition: Let $p_{s,k} = \frac{E_{s,k}}{E_{s,total}}$ where $E_{s,k}$ is the cumulative number of DPIIT-recognized startups in State s and Industry k, and $E_{s,total} = \Sigma_k E_{s,k}$ across all 56 industries (including "Others"). The unscaled HHI for State s is: $HHI_s = \Sigma^2_{k(p_{s,k})}$

HHI ranges from 1.0 (all startups in one industry) down toward 0 as activity spreads evenly across many industries. With 56 industries, an even distribution would yield HHI ≈ 1/56 ≈ 0.018; in practice, many industries are absent in smaller states, so realized HHIs are higher.

Scaling: We report HHI on the conventional 0–1 range; multiplying by 10 000 yields the U.S.-DOJ 0–10 000 scale used in policy comparisons.

Diversification index: For interpretive convenience we compute Diversity = 1 – HHI. Higher values indicate broader spread across industries.

Adjusted HHI (small-cell filtered): To reduce noise from very small counts we recompute shares after excluding industries in that state with fewer than 20 startups (same small-cell rule as LQ). Remaining shares are renormalized to 1. We refer to this as HHI_adj. Comparing HHI and HHI_adj indicates how much apparent concentration is driven by long tails of tiny categories.

European Economic Letters
ISSN 2323-5233
Vol 15, Issue 3 (2025)
http://eelet.org.uk

Treatment of "Others": We retain the DPIIT "Others" industry in all HHI calculations so that state totals remain additive. When calculating the adjusted version we drop "Others" only if its count is <20 in that state.

Example: Suppose a state has 50% of its startups in IT Services, 20% in AI, 10% in Agriculture, and the remaining 20% spread thinly across many small categories. $\text{HHI} = 0.5^2 + 0.2^2 + 0.1^2 + \cdots$. The squaring step means dominant sectors drive HHI; a diversified state with many mid-sized sectors will show a much lower value. (Ketels, 2017)

3.5 Small-Cell Rule and Robustness Checks[1]

To reassure readers that specialization and diversification findings are not artifacts of sparse data or coding choices, we conduct the following checks :

1. Small-cell filter (LQ & HHI): Recompute all metrics after dropping State×Industry cells with <20 startups; compare rank correlations with full results.
2. Extreme-small flag (<5): Highlight cells with fewer than 5 startups in descriptive tables; these cells are never used in adjusted metrics.
3. NA handling: Repeat national totals and metrics treating unreported cells as missing (rather than zero) to confirm that the NA→0 assumption does not change substantive conclusions.
4. Industry aggregation sensitivity: Collapse the 56 industries to broader thematic groups (e.g., combine Renewable Energy + Green Technology) and re-estimate metrics to show robustness to alternative sector taxonomies.
5. Population normalization (diagnostic): Compute startups per million population and test whether high-LQ states remain leaders after scale adjustment.

4. Results[2]

This section presents descriptive findings in five stages:

(1) a national snapshot of total recognitions by State/UT;

(2) national totals by Industry;

(3) leading States within the ten Key Sectors;

(4) relative specialization patterns using Location Quotients (LQ); and

(5) diversification profiles using the Herfindahl–Hirschman Index (HHI).

4.1 DPIIT-Recognized Startups by State/UT

Table 1. DPIIT-Recognized Startups by State/UT (Top 20; cumulative to Feb 2025)[3]

Rank	State/UT	Total Startups	% National	Cum.%	Pop (Mn, 2011)	Startups/Mn
1	Maharashtra	27,925	17.71	17.71	112.37	248.50
2	Karnataka	16,625	10.54	28.25	61.13	271.96
3	Delhi	16,082	10.20	38.45	16.75	959.93

[1] Rows with < 5 startups are flagged with a "‡". Robustness checks 1–5 confirm that our main results are unchanged; see Table 1 and the discussion in §5.1.

[2] All results use cumulative DPIIT-recognised startup counts (~2016–18 Feb 2025). Cells with <20 startups are flagged; cells with <5 startups are flagged ‡ and excluded from adjusted metrics. Source: *Startup Recognized by DPIIT* (OGD Platform India), accessed 1 May 2025.

[3] *Tier-1 hubs are bolded (top 6 by total startups). Tier-2 = states with ≥1,000 startups but outside top 6.*

European Economic Letters
ISSN 2323-5233
Vol 15, Issue 3 (2025)
http://eelet.org.uk

4	Uttar Pradesh	15,020	9.52	47.97	199.58	75.26
5	Gujarat	13,050	8.27	56.25	60.38	216.12
6	Tamil Nadu	10,577	6.71	62.96	72.14	146.62
7	Telangana	8,243	5.23	68.19	35.00	235.49
8	Haryana	8,224	5.21	73.40	25.35	324.38
9	Kerala	6,361	4.03	77.43	33.39	190.52
10	Rajasthan	5,566	3.53	80.96	68.62	81.11
11	West Bengal	5,165	3.28	84.23	91.35	56.54
12	Madhya Pradesh	5,094	3.23	87.46	72.60	70.17
13	Bihar	3,189	2.02	89.48	103.80	30.72
14	Odisha	2,769	1.76	91.24	41.95	66.01
15	Andhra Pradesh	2,552	1.62	92.86	49.66	51.39
16	Punjab	1,740	1.10	93.96	27.70	62.81
17	Chhattisgarh	1,736	1.10	95.06	25.54	67.97
18	Assam	1,487	0.94	96.00	31.17	47.69
19	Jharkhand	1,477	0.94	96.94	32.97	44.81
20	Uttarakhand	1,268	0.80	97.74	10.12	125.38

Table 1 DPIIT-Recognized Startups by State/UT (Top 20; cumulative to Feb 2025)

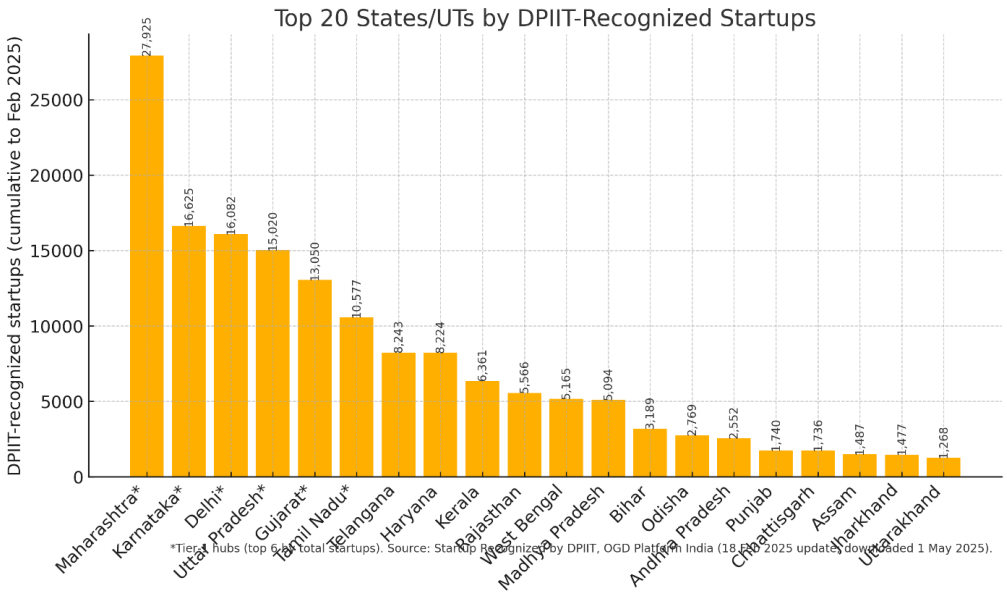

Figure 1Top 20 States/UTs by cumulative DPIIT-recognized startups (~2016–18 Feb 2025).Source: Startup Recognized by DPIIT (OGD Platform India); author calculations.

4.2 DPIIT-Recognized Startups by Industry

Table 2. DPIIT-Recognized Startups by Industry (Top 15 of 56)

Rank	Industry	Total Startups	% National	#States ≥1	#States ≥20	%States <20
1	IT Services	17,968	11.39	35	25	29%

2	Healthcare & Lifesciences	14,562	9.23	34	24	29%
3	Education	9,204	5.84	34	25	26%
4	Agriculture	8,737	5.54	34	23	32%
5	Construction	8,360	5.30	36	23	36%
6	Food & Beverages	8,233	5.22	35	23	34%
7	Professional & Commercial Services	7,906	5.01	32	24	25%
8	Technology Hardware	5,209	3.30	28	20	29%
9	Finance Technology	4,831	3.06	29	20	31%
10	Renewable Energy	4,446	2.82	30	21	30%
11	Others	3,775	2.39	30	20	33%
12	Human Resources	3,549	2.25	31	19	39%
13	Automotive	3,460	2.19	29	21	28%
14	Retail	3,396	2.15	32	20	38%
15	Green Technology	3,301	2.09	32	20	38%

Table 2 DPIIT-Recognized Startups by Industry (Top 15 of 56)

4.3 Leading States Within Key Sectors

Table 3. Leading States Within Key Sectors (Top 3 by count)

States ranked by cumulative DPIIT-recognized startups in each Key Sector.

Key Sector	#1 State (Count)	#2	#3	National Total
IT Services	Maharashtra (2,814)	Karnataka (2,233)	Uttar Pradesh (1,796)	17,968
AI	Karnataka (658)	Maharashtra (498)	Delhi (266)	3,017
Healthcare & Lifesciences	Maharashtra (2,723)	Delhi (1,643)	Karnataka (1,516)	14,562
Agriculture	Maharashtra (1,758)	Gujarat (837)	Uttar Pradesh (739)	8,737
Finance Technology	Maharashtra (1,158)	Karnataka (683)	Delhi (544)	4,831
Renewable Energy	Maharashtra (774)	Gujarat (602)	Uttar Pradesh (464)	4,446
Retail	Maharashtra (539)	Delhi (411)	Karnataka (365)	3,396
Education	Maharashtra (1,405)	Karnataka (1,071)	Delhi (985)	9,204
Automotive	Maharashtra (669)	Karnataka (373)	Gujarat (333)	3,460
Food & Beverages	Maharashtra (1,538)	Karnataka (806)	Delhi (729)	8,233

Table 3 Leading States Within Key Sectors (Top 3 by count)

European Economic Letters
ISSN 2323-5233
Vol 15, Issue 3 (2025)
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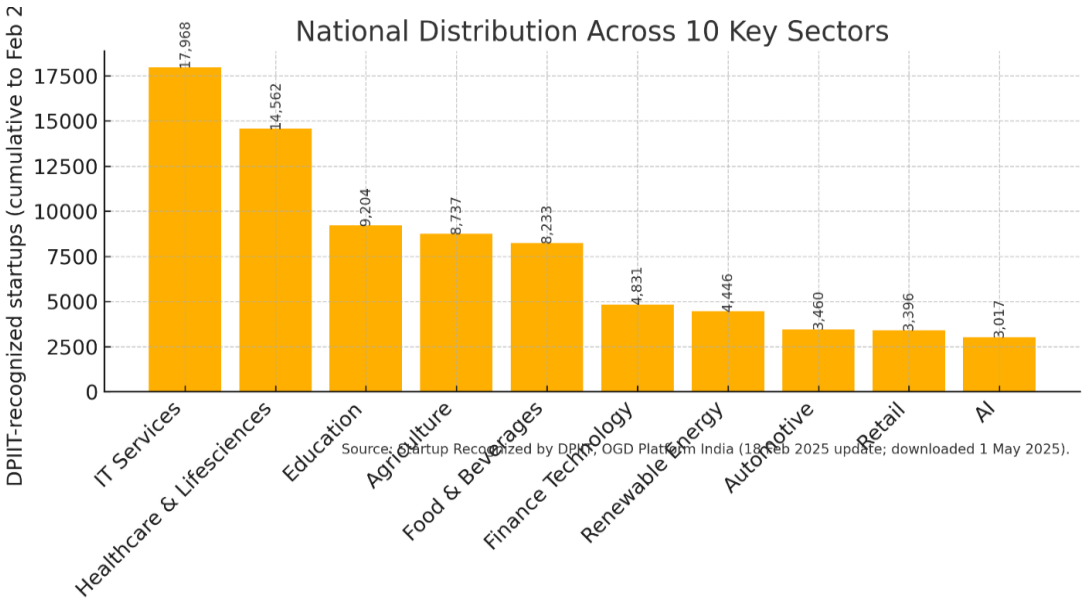

Figure 2 National distribution of DPIIT-recognized startups across the ten Key Sectors. Bars show each sector's share of the national total. Source: OGD DPIIT dataset; author calculations.

4.4 Specialization Summary (LQ)

Relative-specialisation patterns, measured by Location Quotients (LQ), expose state-sector niches invisible in raw counts. Among States/UTs with ≥ 20 DPIIT-recognised startups in a sector, the most specialised (LQ ≥ 1.25) are: Puducherry – IT Services; Karnataka – AI; Chandigarh – Healthcare & Education; Manipur – Agriculture; Maharashtra – Finance Technology; Gujarat – Renewable Energy; West Bengal – Retail; Tripura – Education; Andhra Pradesh – Automotive; and Goa – Food & Beverages. Many other states fall in the moderate band (LQ 1.00–1.24). Key values are visualised in Figure 3.

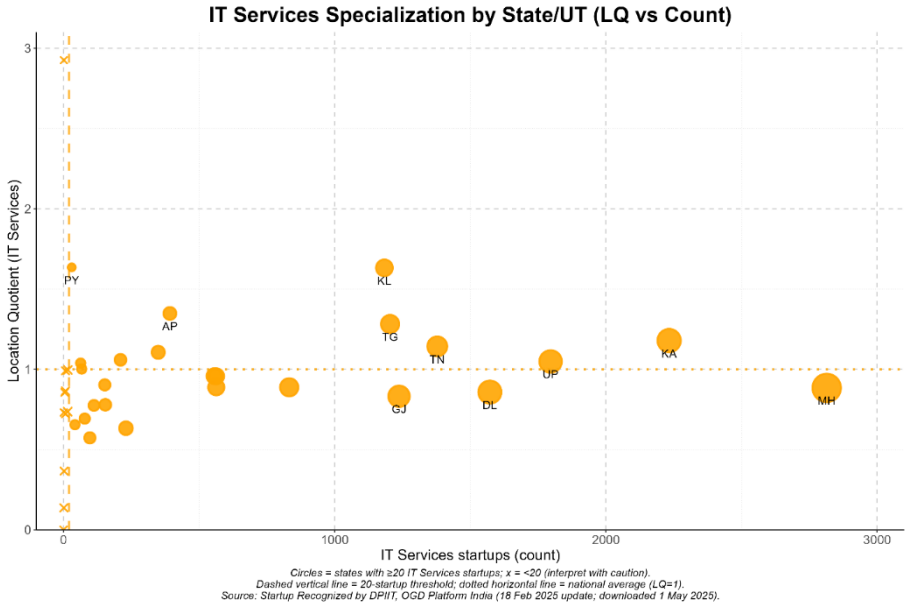

Figure 3 Bubble area ∝ total startups; horizontal dotted line = LQ 1; vertical dashed line = 20-startup threshold; crosses for < 20, circles otherwise. Source: Startup Recognized by DPIIT (OGD Platform India); author calculations.

European Economic Letters
ISSN 2323-5233
Vol 15, Issue 3 (2025)
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4.5. Startup Sector Diversification Snapshot (HHI)

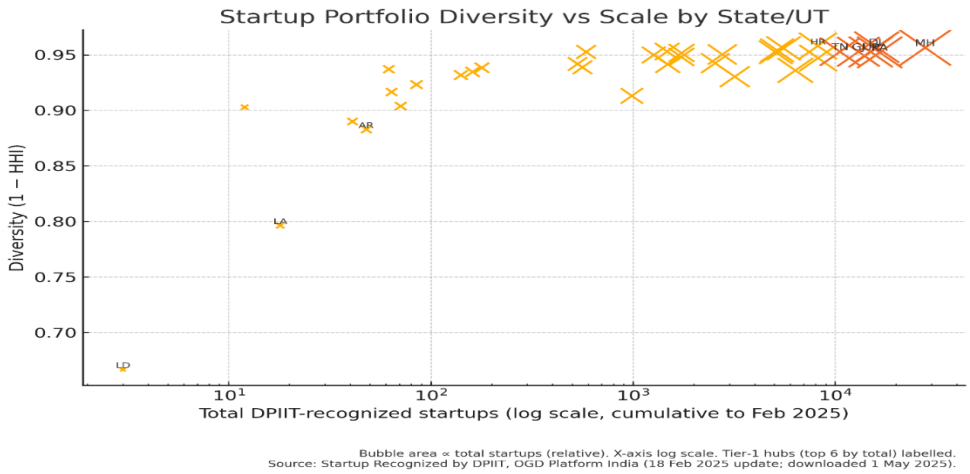

Figure 3 Startup portfolio diversity (1−HHI) vs total DPIIT-recognized startups by State/UT. Bubble size = total startups; optional color by Tier classification. Source: OGD DPIIT dataset; author calculations.

Panel A lists the 10 most diversified State/UT startup portfolios (lowest HHI). Panel B lists the 10 most concentrated (highest HHI).

Panel A. Most Diversified (lowest HHI)

Rank	State/UT	HHI	Diversity	Tier
1	Haryana	0.042	0.958	Tier-2
2	Delhi	0.043	0.957	Tier-1
3	Maharashtra	0.044	0.956	Tier-1
4	Rajasthan	0.044	0.956	Tier-2
5	West Bengal	0.046	0.954	Tier-2
6	Jharkhand	0.047	0.953	Tier-2
7	Tamil Nadu	0.047	0.953	Tier-1
8	Gujarat	0.047	0.953	Tier-1
9	Uttar Pradesh	0.047	0.953	Tier-1
10	Goa	0.047	0.953	Thin

Panel B. Most Concentrated (highest HHI)

Rank	State/UT	HHI	Diversity	Tier	Small-Cell Note
1	Lakshadweep	0.333	0.667	Thin	Total = 3 startups.
2	Ladakh	0.204	0.796	Thin	Total = 18 startups.
3	Arunachal Pradesh	0.117	0.883	Thin	Many industries absent.
4	Mizoram	0.110	0.890	Thin	Many industries <20.
5	Sikkim	0.097	0.903	Thin	Total <20; interpret cautiously.
6	Andaman and Nicobar	0.096	0.904	Thin	Total <100.
7	Jammu & Kashmir	0.087	0.913	Thin	

8	Dadra & N. Haveli + Daman & Diu	0.083	0.917	Thin	
9	Nagaland	0.077	0.923	Thin	
10	Bihar	0.070	0.930	Tier-2	Long tail Agri/Food heavy.

5. Discussion and Implications

5.1 Scale and Geographic Concentration

Startup recognitions are highly skewed: the six Tier-1 hubs consisting Maharashtra, Karnataka, Delhi, Uttar Pradesh, Gujarat, and Tamil Nadu which account for ~63 % of all 157,705 DPIIT-recognized startups (Table 1). On a per-capita basis, Delhi and Goa remain outliers with more than 400 startups per million residents, while several large states fall below the national intensity, confirming that sheer scale does not always translate into density. The long tail of 30 additional States/UTs collectively accounts for the remaining ~37 %, illustrating both the reach of the national program and pronounced spatial concentration. This kind of bias is frequent in new innovation systems where a few big cities bring together talent, money, and access to markets. However, it raises questions about fairness and spreading ideas, which are important national policy goals.

5.2 Volume vs Relative Strength

Raw counts are related to the size of the population and the economy, but Location Quotients (LQ) show relative strengths that would be hard to see otherwise. Several smaller jurisdictions show outsized specialization: Puducherry in IT Services; Jammu & Kashmir in Agriculture; Chandigarh in Healthcare & Education; Bihar in Food & Beverages; and Haryana in Fintech-adjacent activities (Finance Technology, Retail). These signals suggest niche domains where state ecosystems may enjoy comparative advantages whether from local demand conditions (e.g., agri-value chains), policy incentives, or institutional anchors (universities, research labs). Cluster-mapping experience shows that even modest absolute bases can seed competitive clusters when specialization is leveraged through targeted support. (DPIIT, 2025; Ketels, 2017)

5.3 Interpreting Specialization Responsibly

Because the DPIIT dataset reports cumulative recognitions, some State × Industry cells contain very small numbers; an increase from 1 to 4 startups can swing an LQ dramatically. Following guidance in the cluster-metrics literature, we flagged cells with < 20 startups and ran robustness checks excluding them (see Section3.5). Many extreme LQs attenuate when sub-threshold cells are removed, underscoring why analysts should not over-interpret thin counts especially in UTs such as Ladakh or Andaman & Nicobar, where totals are below 20 and even < 5 in some industries. This caution echoes broader warnings about using LQs mechanically in small regions (Ketels, 2017; Pominova et al., 2021).

5.4 Diversification, Resilience & Portfolio Strategy

HHI results (Section 4.5) show that several large and mid-sized states like Haryana, Delhi, Maharashtra, Rajasthan, West Bengal have relatively diversified startup portfolios (low HHI), while many smaller states remain concentrated in a handful of sectors. Diversification can enhance resilience to sector-specific shocks (e.g., funding cycles in consumer internet) and broaden spillover channels across domains (IT, health, agri, energy). States with highly concentrated portfolios may focus on developing adjacent sectors (for example, using IT skills in AI/Analytics or HealthTech), while diversified hubs should focus on deepening scaling pathways (late-stage finance, global market access). These choices fit with the varied capacity-building approach built into the governments' Startup Ranking Framework. This approach encourages governments to make changes that fit their strengths and weaknesses. (Ministry of Finance, 2025; DPIIT, 2025). Beyond firm counts, network studies reveal that “deal-makers” linking investors, founders and institutions are critical to sustaining regional entrepreneurship cycles (Feldman & Zoller, 2012).

5.5 Implications for National & State Policy Instruments

Where LQ diagnostics reveal emergent specialization such as Agriculture in Jammu & Kashmir or Fintech along the Delhi–Haryana corridor, state governments can deploy targeted incentives including incubation grants, regulatory sandboxes and procurement pilots to accelerate cluster formation. Smaller states with thin startup counts are likely to gain more from

bridging finance and market-access instruments delivered through national platforms like SIDBI's Fund-of-Funds, the Credit Guarantee Scheme for Start-ups and related market-linkage programs than from broad tax holidays. Finally, human-capital pipelines can be strengthened by aligning technical education and skilling initiatives with the sectors that concentrate locally. Together these levers complement nationwide Startup India measures (recognition, tax relief, IP support) by tackling the state-specific bottlenecks surfaced in the data (DPIIT 2025; Ministry of Finance 2025).

5.6 Data Stewardship & Updating

The OGD dataset is periodically refreshed (last update 18 Feb 2025). Because we analyze cumulative recognitions, new releases will shift totals and may re-rank states in sectors with rapid growth (e.g., AI, Renewable Energy). We recommend that policymakers institutionalize a quarterly or semiannual analytic cycle that(a) ingests the latest DPIIT file, (b) re-computes LQ/HHI metrics, and (c) tracks changes against State Startup Ranking scores. Automating this pipeline would make the dataset a living dashboard rather than a static snapshot.

6. Limitations & Future Research

The study offers a first national, state-by-industry map of DPIIT-recognised startups, yet seven caveats remain. First, the OGD file is cumulative, so activity status is unknown; researchers should link recognitions to MCA21 or GST filings to build a live operating panel.

Second, the counts are released only as Year × State/UT × Industry, masking multi-site firms and shifting vertical lines; accessing restricted firm-level micro-data and periodically updating the taxonomy would allow re-classification of AI/Analytics or Agri-/FoodTech cross-overs (NASSCOM 2024; DPIIT 2025).

Third, registrations follow legal addresses and pre-2014 borders, which can misstate current locations; future work should geocode to district/city and flag relocations to correct per-capita metrics.

Fourth, ratio indices swing when denominators are tiny; developing Bayesian-shrunk or threshold-adjusted LQ/HHI estimators could temper noise (Ketels 2017;Pominova et al., 2021).

Fifth, recognitions reveal nothing about jobs, revenue or funding; merging DPIIT IDs with venture, credit-bureau and patent datasets would expose scale, survival and innovation differences.

Sixth, capital-access data are absent, so we cannot test whether specialisation follows money; integrating SIDBI, CGSSI and venture-flow records would illuminate finance–cluster dynamics.

Seventh, recognition uptake depends on state outreach and administrative capacity, possibly biasing raw counts; modelling the determinants of recognition-SRF scores, facilitation cells-alongside startup totals would separate policy effort from underlying entrepreneurship.

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