Theoretical Economics Letters, 2022, 12, 1095-1125
https://www.scirp.org/journal/tel
ISSN Online: 2162-2086
ISSN Print: 2162-2078

Do Knowledge and Technology-Intensive Industries Spatially Concentrate in Rural and Urban Areas of India? Evidence from Economic Census Micro-Level Data

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How to cite this paper: Agarwal, S., & Behera, S. R. (2022). Do Knowledge and Technology-Intensive Industries Spatially Concentrate in Rural and Urban Areas of India? Evidence from Economic Census Micro-Level Data. *Theoretical Economics Letters, 12,* 1095-1125.
https://doi.org/10.4236/tel.2022.124060

Received: May 31, 2022
Accepted: August 16, 2022
Published: August 19, 2022

Abstract

This paper investigates the geographic concentration of knowledge and technology-intensive (KTI) industries, covering 0.43 million establishments across various districts of rural and urban areas in India. Using the spatially weighted Ellison-Glaeser index, cartogram and choropleth map results show that few KTI industries are highly geographically concentrated in urban and rural areas, specific to certain districts and a few Indian states. Within highly employable states of India, workers are employed in only a particular location of a few districts. Also, we differentiate between urban and rural concentrated and urban and rural dispersed districts within highly employable states. In addition, results validate the extent of the geographical concentration of KTI industries in rural and urban areas of highly employable Indian states. Further, results exhibit that industries spatially concentrate in only a few locations across specific districts in India, indicating natural advantages and other economic forces are pretty strong in certain areas. Besides, results suggest that the demand-based networks and push-and-pull supply chains are well established in a specific location of a few districts, incentivizing other firms to locate their business, which creates a spatial spillover effect and benefits all economic agents. Empirical results suggest that policymakers in India could unleash the resource potential of spatially concentrated districts by implementing a location-based policy and considering multi-level governance and informal and formal institutions, which could further boost regional economic growth.

Keywords

Urban-Rural, Geographic Concentration, Technology Intensity, Regional Policy

JEL Classifications

R11, R12, O32, R58

1. Introduction

The uneven geographical concentration of economic activity is a feature that is pervasive in many countries (Braunerhjelm & Johansson, 2003; Vitali et al., 2013; Crafts & Klein, 2021). In the era of globalization, innovation is at the core of competitive advantage attainment and altering the geographic landscape as knowledge clusters become the significant drivers of the prosperity of nations (Huggins, 2008). The idea of geographic concentration goes way back to Marshall (1890), arguing that the agglomeration of firms affects productivity through sharing intermediate inputs at low cost, a local labour market pooling, and the exchange of ideas between firms. Knowledge spillovers play an essential role in understanding the uneven growth patterns of regions (Glaeser et al., 1992; Henderson et al., 2001). A firm's survival depends on cutting-edge knowledge, due to which firms are dispersing their R&D activities to tap into geographic centres of excellence worldwide (Lundvall, 2007; Mudambi, 2008). It implies the importance of geographical proximity in creating and diffusing knowledge as it requires face-to-face interaction between different economic actors (Becker et al., 1999; Breschi & Lissoni, 2009; Balland et al., 2015). Under this backdrop of geographical proximity, the pivotal question is whether Knowledge and Technology-Intensive (KTI) industries spatially concentrate in rural and urban areas in India. More specifically, the question arises in the context of emerging economies like India, how KTI industries are geographically concentrated or dispersed to a different location, and whether the KTI industries have any role in regional economic growth for hiring a massive surplus labour force in India. This paper investigates this central question in the context of KTI industries in India.

The artificial intelligence revolution and innovative development have entirely transformed the global economy (Burström et al., 2021; Korinek & Stiglitz, 2021). Globally, KTI industries invest the most significant shares of their output in research and development (R&D)—contributing 11% to both US gross domestic product (GDP) ($2.3 trillion) and global GDP ($9.2 trillion) in 2019 (National Science Foundation, 2022)[1]. KTI industry's value-added output has more than doubled from $3.4 trillion in 2002 to $9 trillion in 2018. Out of global KTI output ($9 trillion) in 2018, 64% came from medium-high R&D intensive industries, while the high R&D intensive industry's output contribution is only 36% (National Science Foundation, 2020). In the case of India, value-added by KTI

[1]The classification of knowledge and technology-intensive (KTI) industries is internationally recognized in the Organization for Economic Co-operation and Development (OECD) report. KTI industries consist of high and medium-high R&D intensity industries, where R&D intensity implies the ratio of an industry's business R&D expenditures to its value-added output (National Science Foundation, 2020). For more details, see Galindo-Rueda & Verger (2016).

industries increased from $34.5 billion in 2003 to $209.2 billion in 2018[2]. Within Asia, India holds the fourth position in value addition of KTI industries, after China, Japan, and South Korea in 2018. The United States (US) and China share the top spot as the world's largest producers of total KTI output (each with a 25% global share of KTI value added in 2019) (National Science Foundation, 2020).

The previous studies show that most Indian agglomeration literature focuses on the IT cluster and its development. However, the Indian literature completely neglects the KTI industries and their contribution to regional economic growth. The KTI industries include IT and software publishing, scientific research and development, air and spacecraft, pharmaceuticals, computer, electronic and optical products, motor vehicles, medical and dental instruments, railroad, chemicals, and electrical industries. The United States and China invest heavily in the research and commercialization of artificial intelligence (AI) technologies (National Science Foundation, 2020). However, the US leads in KTI services industries, whereas China leads KTI manufacturing industries production. Moreover, US KTI production is geographically concentrated, with 15 states accounting for 76% of the total value added domestically by KTI industries. KTI manufacturing in the US is concentrated in the Midwest, along the coasts, and in a few states in the South, while KTI services are concentrated along the coasts and a few Southwestern states (National Science Foundation, 2022). US KTI industries are the principal force behind the nation's research and development (R&D) enterprises. From an economic standpoint, R&D activities constitute a critical component of US economic growth and competitiveness.

India is one of the world's largest functioning democracies and has a critical mass of English-speaking knowledge workers and free-market economic institutions. Besides, India has developed a broad and diversified Information and Communication Technology (ICT) infrastructure in recent years, reflecting its advantageous position. In his famous book "The World Is Flat: A Brief History of the Twenty-First Century", Thomas Friedman wrote that the economic playing field was levelling out for India. The best example is Bangalore, India's Silicon Valley, which comprises modern IT infrastructure and technologies backed by the top technical institute and has India's most competent engineers. The Bangalore IT cluster is the fastest-growing software cluster outside the USA (Parthasarathy, 2004; Huggins, 2008). Various studies (Parthasarathy, 2004; Khomiakova, 2007; Grondeau, 2007; Lorenzen & Mudambi, 2013) focus on the IT cluster formation and the importance of social embeddedness in decentralized network structures.

Moreover, specific to Indian industries, only a few previous studies (Lall et al., 2004; Lall & Chakravorty, 2005; Fernandes & Sharma, 2012) measure the spatial concentration of Indian manufacturing industries in their empirical studies.

[2]For detailed data source see IHS Markit, special tabulations (2019) of Comparative Industry Service.

Mukim's (2015) study finds that buyer-seller linkages and technology spillovers are the most significant factors in explaining the co-agglomeration of formal-informal manufacturing enterprises. Desmet et al. (2015) study found that agglomeration forces in service sectors still dominate dispersion forces in high-density areas, given the role played by ICT. Ghani et al. (2016) studied the spatial pattern of manufacturing and service industries in India from 2001 to 2010. Their study finds that the organized manufacturing sector moves away from urban cores to the rural periphery while services move towards the urban centres. According to the 2011 Economic Census, 72.4% of the workforce and 68.8% of the country's population exist in rural areas of India (Chand et al., 2017). Also, the rural-urban divide accounts for a large share of spatial inequality with significant differences in output per capita and access to core public services, such as electricity, roads, and education in India (Joumard et al., 2017)[3]. Regional inequality is of interest not only for equity reasons but also for economic development (Achten & Lessmann, 2020).

Nevertheless, India's gross domestic expenditure on R&D (GERD) increased from $19180.50 million in 2000 to $57825.12 million in 2018. However, India's GERD as a percentage of GDP decreased from 0.77% in 2000 to 0.66% in 2018[4]. It indicates ample opportunities for India to invest in R&D activities to enhance KTI industries' output significantly. To boost economic output and exports of products and services in the foreign market, the competitiveness and productivity of firms matter. For regional economic growth and productivity of firms, the geographic concentration of economic activities matters (Combes & Gobillon, 2015; Graham et al., 2010). This is a prerequisite to exploring the geographical concentration of KTI industries to design appropriate urban and rural policies that attract or strengthen knowledge-intensive industries. Chen's (2020) study reveals that in China, upgrading the industrial structure significantly affects poverty reduction in urban areas but not in rural areas. This indicates that differences between urban and rural areas must be considered while framing regional policies to upgrade the industrial structure.

Our study contributes to Indian agglomeration literature, particularly KTI industries, in several ways. First, this paper estimates the geographic concentration of KTI industries at a 3-digit National Industrial Classification (NIC) code, using Economic Census (2013) data at the establishment levels across various rural and urban areas in India[5]. Besides, this paper examines the spatial distribution and magnitude of spatial concentration of different KTI industries in rural and urban areas. The spatial distribution of KTI industries visualizes through the

[3]As per Census of India 2011, the definition of urban areas is defined as follows: 1) All statutory places with a municipality, corporation, cantonment board or notified town area committee, etc. 2) A place satisfying the following three criteria simultaneously: a) a minimum population of 5000; b) at least 75 percent of the male working population engaged in non-agricultural pursuits, and c) a density of population of at least 400 per sq. km. (1000 per sq. mile).

[4]The data can be accessed using the following source *UNESCO Institute for Statistics* (*UIS*).

[5]Following Economic Census (2013) data, the establishment refers to a unit in a single location predominantly busy with one kind of entrepreneurial activity.

cartogram technique, and geographical concentration is measured using a spatially weighted Ellison-Glaeser index. Second, this study measures the geographical concentration of highly concentrated KTI industries within highly employable states across urban and rural India[6]. Third, we identify the districts where excess employment concentration prevails across the highly concentrated KTI industries. More specifically, we distinguished between urban and rural concentrated and urban and rural dispersed districts within highly employable states using a choropleth map.

The remainder of the paper is organized as follows. Section 2 provides a snapshot of previous studies of the agglomeration literature. Section 3 presents the data description and methodology for computing the geographical concentration of industries. Section 4 summarizes our empirical findings, and finally, Section 5 offers concluding remarks.

2. Literature Review

Many scholars examined the spatial concentration of knowledge-intensive industries (KTI) empirically. The idea of spatial concentration of firms goes way back to Marshall's (1890) pioneering work. Marshall argued that three sources are essential for firms' geographical concentration: input sharing, labour market pooling, and knowledge spillovers[7]. However, in this study, we specifically focus on knowledge spillovers, which refer to the transfer or flow of knowledge between firms or workers close to each other. Jacobs (1969) argues that a diversity of regional economic activity nurtures innovation and growth through inter-industry knowledge spillovers rather than intra-industry spillovers. Porter (1990) supports intra-industrial spillovers but states that competition among firms incentivizes them to exchange knowledge and innovate. The seminal work of Glaeser et al. (1992) sparked a substantial volume of empirical research to examine whether agglomeration externalities matter for knowledge creation and innovation[8]. Various studies (Acs et al., 1992; Jaffe et al., 1993; Zucker et al., 2002) showed that knowledge spillovers are geographically localized and significant at a local level in the context of the USA. In their study for the USA, Audretsch and Feldman (1996) observed that industries in which knowledge spillovers are predominant tend to be more geographically concentrated compared to industries where knowledge externalities are less prevalent. Moreover, Buzard et al. (2020) and Ganguli et al. (2020) research shows that geographical proximity facilitates knowledge spillovers.

Knowledge is essential to boost competitiveness and innovation performance, form local surroundings and experience spatial clustering (Malmberg et al., 1996). Tödtling et al. (2006) study reveals that knowledge intensity has played a

[6]The highly concentrated industries are those in which the estimated values of the spatially weighted Ellison-Glaeser (hereafter EG) index are above 0.05.

[7]These sources are external to individual firms and benefits relevant to firms within the same industry known as localization economies.

[8]For literature reviews, see De Groot et al., 2016.

vital role in developing a knowledge-based economy, implying the importance of knowledge-intensive industries. Paci and Usai's (1999) study shows evidence of cross-border technological spillovers, but agglomeration effects die out with the increase in distance, implying knowledge spillovers are bounded spatially. In contrast, Li's (2014) study reveals that border and distance effects increase over time due to the strengthening of knowledge agglomeration but decrease with the age of patents. Moreover, Andersson et al. (2016) reveal that knowledge spillovers are spatially and sensitive to geographical distance. Another dimension in the knowledge spillover literature is that excessive reliance on local knowledge can prompt territorial lock-in effects, implying the importance of inter-regional linkages. A substantial body of literature (Trippl et al., 2009; Eriksson & Lengyel, 2019; Ascani et al., 2020; Balland & Boschma, 2021) shows that Interregional linkages prevent region's locked-in tendency. Besides, Mudambi and Swift (2012), Beugelsdijk and Mudambi (2014), and Lorenzen and Mudambi (2013) have done extensive research on the spatial dimension of FDI and modes of entry of Multinational enterprises (MNEs) into the host country's regional location. These studies trace the origins of research on geographic clusters and identify the seminal contributions focusing on the role of MNEs, connectivity of firms of different clusters through knowledge, R&D, innovation of new technology, etc.

In the Indian context, various studies explore the appropriate determinants of firm locational choice and productivity (Behera, 2017). Similarly, Behera (Behera et al., 2012; Behera, 2015a, 2015b) find that R&D and technology import intensity enhances the productivity of Indian manufacturing industries. Lall et al. (2004) find that urbanization economies have a significant cost-reducing effect on firms that lead to industrial clustering in metropolitan areas in India. Chakravorty et al. (2005) studied eight industrial sectors in three Indian metropolises (Mumbai, Kolkata, and Chennai) to determine whether localization economies play a substantial role in cluster formation. Mukim's (2015) study finds that buyer-seller linkages and technology spillovers are the most significant factors in explaining the co-agglomeration of formal-informal manufacturing enterprises. The literature on productivity spillover focusing on Indian industries revealed some interesting facts. Kathuria (2002) finds that local Indian firms in the manufacturing industry could reap the fruits of knowledge spillovers from foreign-owned firms only if they can decode the spilt knowledge's technicalities. In this genre, Franco and Sasidharan (2010) study the effects of export spillovers on emerging markets, particularly India, from 1994 to 2006. They have shown that in-house research efforts are the most crucial factor for grabbing the benefits of technology spillovers than any other external sources of technology.

The research on Indian IT clusters preceding 2007 mainly focuses on Bangalore. Parthasarathy (2004) reveals the importance of social embeddedness in agglomeration by analyzing how changing state-society relations shaped the software industry in Bangalore. Khomiakova (2007) studied multiple IT clusters development in India, and Grondeau (2007) examined the characteristics of ICT clusters, mainly focusing on Bangalore and Hyderabad clusters. Lorenzen and Mudambi (2013) propose that clusters linked to the global economy through decentralized network structures have the most potential for local spillovers. Their empirical study considers IT clusters in Bangalore and the Indian film entertainment cluster (Bollywood). Besides this, various research (Kerr, 2008; Sonderegger & Täube, 2010; Zaheer et al., 2009) shows diaspora (non-local network) plays a substantial role in cluster formation.

Nevertheless, to our best understanding, none of the previous literature examines the spatial concentration of KTI industries covering 0.43 million establishments across rural and urban Indian districts. Therefore, this paper bridges the research gap in the agglomeration literature by measuring the extent of the geographical concentration of KTI industries and visualizing the spatial distribution of highly concentrated KTI industries across various Indian states. Within highly employable Indian states, our empirical interest is to quantify which KTI industries are geographically concentrated using the spatially weighted Ellison-Glaeser index. This index captures neighbourhood effects and, based on our understanding, this is the first study to measure the geographical concentration of KTI industries within highly employable Indian states in rural and urban India. Besides, this study also computes the excess employment concentration in India and tries to locate the districts where agglomeration exists because of the substantial role of the centripetal forces.

3. Data and Methodology

3.1. Measuring the Geographical Concentration of Industries

A substantial literature (Rosenthal & Strange, 2001; De Dominicis et al., 2013; Lu & Tao, 2009) measures geographical concentration using the Ellison-Glaeser index[9]. This index examines the presence of localization driven by the natural advantage of specific areas and sector-specific spillovers against the localization caused by random firm-specific choices (Dauth et al., 2018). If the extent of localization is more significant than expected when firms choose their location randomly, it is concluded that the industry is geographically concentrated (Ellison & Glaeser, 1997). As spillover effects do not recognize any areal boundaries, Arbia (2001) and Lafourcade & Mion (2007) recognize simple Ellison-Glaeser (EG) index did not take into account the neighbourhood effects. Given that issue, Guimaraes et al. (2011) extend the original EG index (1997) by adding spatial dependence through a spatial weight matrix. The spatially weighted EG index is calculated below:

[9]Note that we cannot calculate Duranton and Overman's (2005) or Billings and Johnson's (2016) localization measures because these indices require the address of each plant to calculate the distance between plants. EG index is appropriate for countries where precise information about a firm's location is unavailable.

$$\gamma_i^{sw} = \frac{G_i^S - H_i\left(1 - X'\Psi X\right)}{\left(1 - H_i\right)\left(1 - X'\Psi X\right)} \tag{1}$$

where $G_i^S = (S - X)'\Psi(S - X)$ denote the spatially weighted geographical concentration (G_i), Ψ denotes a spatial weight matrix $(\Psi = W + I)$, where W is a weight matrix, and I represents the identity matrix[10]. The previous studies (Behrens & Bougna, 2015; Dauth et al., 2018; Crafts & Klein, 2021) used the spatially weighted EG index to examine the geographical concentration of industries in Canada, and Germany and the US.

3.2. Excess Employment Concentration

To formally estimate which industries are more concentrated than what would be if firms choose their business location randomly, the following steps need to be calculated:

$$G = \left(s_{jk} - p_j\right)^2 \tag{2}$$

where, $s_{jk} = \frac{x_{jk}}{x_k}$ denotes the share of K^{th} industry employment in a district (j), while x_{jk} represents total employment for K^{th} industry in region j and x_k represents total employment for K^{th} industry. Also, $p_j = \frac{x_j}{x}$ denotes the share of total employment in a district (j), in which x_j represents total employment in a spatial unit j, and x represents total employment in all spatial units (1, 2, 3, … J). Equation (2) corresponds to the geographic concentration of a particular industry in a spatial unit.

Next, we measure the expected value of the geographic concentration of a particular industry in a spatial unit when plants in an industry choose their location independently, and there are no-industry-specific natural advantages and spillovers (Ellison & Glaeser, 1997). The expected value of geographic concentration is calculated as follows:

$$E(G) = \left(1 - \sum_j x_j^2\right)H, \tag{3}$$

where Herfindahl index $(H) = \sum_k z_k^2$ denotes K^{th} plant's share of industry's employment. Subsequently, to measure the extent of localization that is greater than what would be expected when plants choose their location randomly, calculate the difference between G and $E(G)$ is shown below:

$$\text{Excess concentration} = G - E(G) \tag{4}$$

Equation (4) helps identify districts where the industry has excess employment concentration. If excess concentration has a positive value, it indicates the extent of geographic concentration is more significant than expected to arise randomly (Ellison & Glaeser, 1997). However, when excess concentration has a negative

[10]We use the queen contiguity weight matrix, where that $\omega_{rs} = 1$ where r and s are neighbours (when a polygon shares a vertex or an edge) and $\omega_{rs} = 0$ otherwise.

value, the plants are more evenly distributed than expected at random.

3.3. Choropleth and Cartogram Maps

Following the prior literature (Monmonier, 1974; Mersy, 1990), we have used the choropleth maps to evaluate the spatial distribution of workers across India's various states and union territories. The choropleth maps depict statistical data through different colour shades on pre-defined administrative areas, i.e., states and districts. The spatial distribution includes detecting hot and cold spots, global and local patterns, comparing two or more regions' estimated values and assessment of global and local heterogeneity. However, choropleth maps suffered from the area-size bias in which larger regions attract more attention than smaller regions (Dent, 1999; Speckmann & Verbeek, 2010). Therefore, to avoid bias, equal-area cartograms can be applied (Wood & Dykes, 2008; Kraak & Ormeling, 2020) to detect the spatial distribution of workers concerned with a particular location. Cartograms are a valuable and intuitive tool to visualize statistical data about administrative areas, where the size of an administrative area corresponds to a specific geographic variable (Olson, 1976; Van Kreveld & Speckmann, 2007; Sun & Li, 2010). Besides, Following Gastner and Newman's (2004) diffusion-based method for constructing density-equalizing maps, we have further computed the cartogram to evaluate the spatial concentration of workers.

3.4. Data Description

This study uses the latest Economic Census (EC) (2013) data, covering both formal and informal establishments across various districts in India[11]. It is the most acceptable micro-unit level establishment data available in the Indian context to evaluate the geographical concentration of KTI industries. Further, the EC dataset includes manufacturing and service industries' employment of workers at the district level. The EC dataset covers 71 manufacturing and 120 service industries, followed by the National Industrial Classification (NIC-2008)[12]. Although the NIC (2008) provides the sub-classification of industries up to a maximum 5-digit level, EC data are available for up to 3-digit level classification. Following the EC data, we are more confined to the 3-digit level industrial classifications analysis to measure the spatial concentration of the industries at the district level data. In the EC dataset, out of 191 industries, we select 35 KTI industries, comprising 29 manufacturing and six service sector industries in India[13].

Our study considers two spatial structures to measure the geographical con-

[11]Economic Census (EC) is a countrywide census of establishments engaged in all economic activities except crop production and plantations (Central Statistics Office, 2013). The EC data can be accessed by using this link, http://icssrdataservice.in/datarepository/index.php.

[12]The NIC (2008) classification report published by the Central Statistics Office, MOSPI. NIC is a standard classification comparable to that of International Industrial classification standards. NIC is essential to maintain and develop a database of different economic activities of industries.

[13]For detailed classifications of KTI industries, see **Table A1** in **Appendix**.

centration of industries. The first spatial structure measures industries' geographical concentration using aggregated data at a district level covering 636 districts across 34 Indian states and union territories. We have to construct the spatial weight matrix to quantify geographical concentration while accounting for neighbouring effects. It requires India's district boundaries shapefiles data, which consist of districts name, states names, geographical coordinates through latitudes and longitudes and census code[14]. For these 636 districts, we construct a queen contiguity weight matrix in Stata14 using the spmat command created by Drukker et al. (2013). For another spatial structure, we construct a queen contiguity weight matrix for the geographical concentration of industries within Indian states and union territories separately for every 29 contiguous states of India using district-level data. Moreover, **Table 1** reports that KTI industries covering 0.13 million establishments employ 1.09 million workers in rural areas while 2.9 million workers from 0.29 million establishments in urban areas. Most employment (73%) and establishments units (68%) of KTI industries are in the urban areas in India.

4. Empirical Results and Discussion

4.1. Geographical Concentration and Spatial Distribution of KTI Industries

Our empirical interest is to evaluate the geographical concentration of KTI industries using the spatially weighted Ellison-Glaeser index (EGSPAT) at a district level in India. **Table 2** and **Table 3** report the highly concentrated KTI industries in urban and rural areas. **Table 2** shows that only seven KTI industries are highly concentrated (estimated value of spatially weighted Ellison-Glaeser index above 0.05) in the urban areas of India. Out of seven highly concentrated KTI industries, five belong to the manufacturing sector, and two belong to the service sector. Nevertheless, reported results (see **Table 3**) exhibit that ten are highly concentrated KTI industries in rural areas. Among them, eight belong to the manufacturing sector, and two belong to the service sector.

Our next interest is to detect in which Indian states and union territories most of the workers of highly concentrated KTI industries are employed. As discussed, we draw a cartogram to visualize the spatial distribution of employment at the micro-unit establishment level for highly concentrated KTI industries in rural and urban India. Besides, following Jenks's (1967) Natural Breaks optimization method, we divide the total workers employed in highly concentrated KTI industries into five levels of class intervals, depicted in five colours on a choropleth map. **Figure 1(a)** shows that Andhra Pradesh and Maharashtra are the two Indian states that substantially enlarged the cartogram for urban areas[15]. Further, to explore the spatial distribution of workers within Andhra Pradesh and Maharashtra, we have drawn a choropleth map depicting the districts where more

[14]The data can be accessed through this link: http://projects.datameet.org/maps/districts. The shapefiles data will be further converted into STATA extension file format (.dta) for further analysis.

[15]In the cartogram, Andhra Pradesh has also included Telangana employment of workers' data.

Table 1. Summary of employment and establishment data in KTI industries.

Region	Employment	Percentage (%)	Establishment	Percentage (%)
Rural area	1,095,825	27	139,412	32
Urban area	2,902,847	73	292,431	68
Total	3,998,672	100	431,843	100

Source: Author's computation using India's Economic Census (2013) data. Notes: Economic Census (2013) provides data for 641 districts, but KTI industries have a presence in 616 and 627 districts of the rural and urban areas, respectively.

Table 2. Highly geographically concentrated KTI industries in urban areas of India.

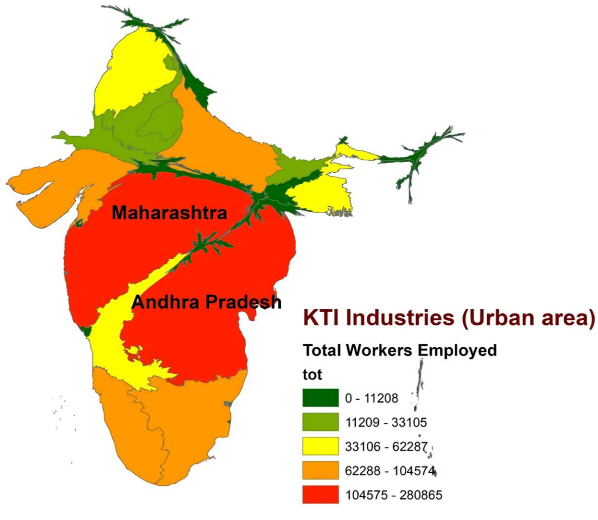
NIC	Industry Name	EGSPAT
582	Software publishing	0.297*
309	Manufacture of transport equipment n.e.c.	0.252*
303	Manufacture of air and spacecraft and related machinery	0.240*
620	Computer programming, consultancy and related activities	0.075*
302	Manufacture of railway locomotives and rolling stock	0.069*
261	Manufacture of electronic components	0.060*
201	Manufacture of basic chemicals, fertilizer and nitrogen compounds, plastics and synthetic rubber in primary forms	0.057*

Source: Author's computations. Notes: NIC and EGSPAT represent National Industrial Classification at a 3-digit and spatially weighted Ellison-Glaeser index. *Shows the estimated value of EGSPAT is statistically significant at a 5 percent level (Guimaraes et al., 2011). The results imply all industries are statistically significant at a 5 percent level. The EGSPAT index estimated value is greater than 0.05, indicating a highly concentrated industry.

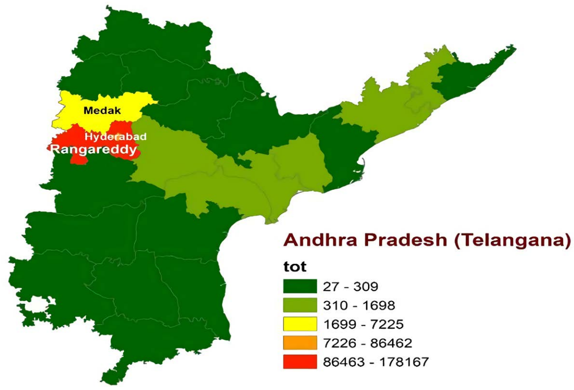
Table 3. Highly geographically concentrated KTI industries in rural areas of India.

NIC	Industry Name	EGSPAT
620	Computer programming, consultancy and related activities	0.571*
266	Manufacture of irradiation, electromedical and electrotherapeutic equipment	0.387*
722	Research and experimental development in social sciences and humanities	0.370*
304	Manufacture of military fighting vehicles	0.218*
293	Manufacture of parts and accessories for motor vehicles	0.204*
309	Manufacture of transport equipment n.e.c.	0.201*
262	Manufacture of computers and peripheral equipment	0.159*
203	Manufacture of man-made fibres	0.090*
265	Manufacture of measuring, testing, navigating and control equipment, watches and clocks	0.076*
252	Manufacture of weapons and ammunition	0.070*

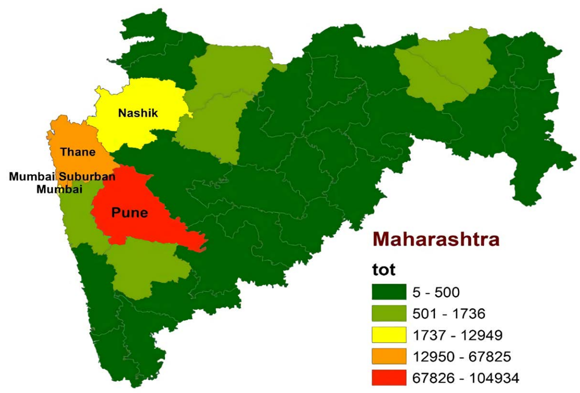
Source: Author's computations. Notes: *Shows the estimated value of EGSPAT is statistically significant at a 5 percent level. The results imply all industries are statistically significant at a 5 percent level.



(a)



(b)



(c)

Figure 1. Visualizing the employment of workers for KTI industries in urban areas of India. (a) Cartogram visualizing the KTI industries in urban areas of India. Notes: A cartogram depicts India's states and union territories region's area, which is proportional to the number of workers employed for KTI industries in rural areas. In red, Maharashtra and Andhra Pradesh enlarge the cartogram for the class interval (104,575 - 280,865). (b) Choropleth map visualizes the spatial distribution of workers within Tamil Nadu. (c) Choropleth map visualizes the spatial distribution of workers Haryana. Sources: Own computations using ArcGIS 10.6 by considering the Economic Census (2013) data.

workers are employed. More specifically, the choropleth map visualizes the spatial distribution of workers through the colour difference, indicating that the red colour shows a higher level of employment of workers. Figure 1(b) depicts that within Andhra Pradesh, the Rangareddy district employed the highest number of workers, portrayed in red, followed by Hyderabad in orange and Medak district in yellow[16]. Similarly, Figure 1(c) depicts that within Maharashtra, the Pune district employed a maximum number of workers (shown in red), followed by the Thane and Mumbai suburban district in orange and Mumbai and Nashik districts in yellow colour.

In contrast, Figure 2(a) shows that Tamil Nadu and Haryana are the two Indian states that grow larger on the cartogram for rural areas, depicted in red. However, Figure 2(b) illustrates that within Tamil Nadu, the Kancheepuram district, shown in red, employed the highest number of workers, followed by Krishnagiri, Erode, and Thiruvallur in orange colour. Besides, Figure 2(c) illustrates that within Haryana, the Gurgaon district employed a maximum number of workers, depicted in red, followed by the Rewari district in orange. Figure 1 and Figure 2 clearly show that the centripetal forces play a substantial role as highly concentrated KTI industries are confined to a particular location[17].

4.2. Geographical Concentration of Highly Concentrated KTI Industries within Indian States and Union Territories

Our subsequent empirical analysis uses district-level data to quantify KTI industries' geographical concentration within highly concentrated states of India. Table 4 reports the estimated spatially weighted EG index values of the highly concentrated KTI industries within the three highly concentrated states (Maharashtra, Andhra Pradesh, and Tamil Nadu) in urban areas of India. The estimated results in Table 4 exhibit that in the states like Maharashtra, the manufacture of transport equipment, n.e.c. (NIC-309) is found to be the most highly concentrated KTI industry (EGSPAT estimated value is 0.231). However, out of seven highly concentrated KTI industries, only five industries (NIC-309, 201, 620, 302, and 261) in Maharashtra are statistically significant at a 5 percent level[18]. In contrast, in a state like Telangana, the manufacture of air and spacecraft and related machinery (NIC-303) is the top most highly concentrated industry (estimated EGSPAT value is 1.472) than other highly concentrated KTI industries. Similarly, in Andhra Pradesh, the manufacture of transport equipment, n.e.c. (NIC-309) is a highly concentrated industry than other KTI industries.

Similarly, Table 5 reports the computed spatially weighted EG index for highly concentrated KTI industries of India's two highly concentrated states

[16]On June 2, 2014, the official separation of Telangana from the state of Andhra Pradesh took place. These three districts, namely Rangareddy, Hyderabad and Medak, are now part of Telangana state.

[17]Centripetal forces lead to agglomeration of industries like buyer-supplier linkages, labour market pooling, knowledge spillover, etc.

[18]The manufacture of air and spacecraft and related machinery (NIC-303) and Software publishing (NIC-582) industry spatially weighted EG index estimated values are insignificant at 5% level.

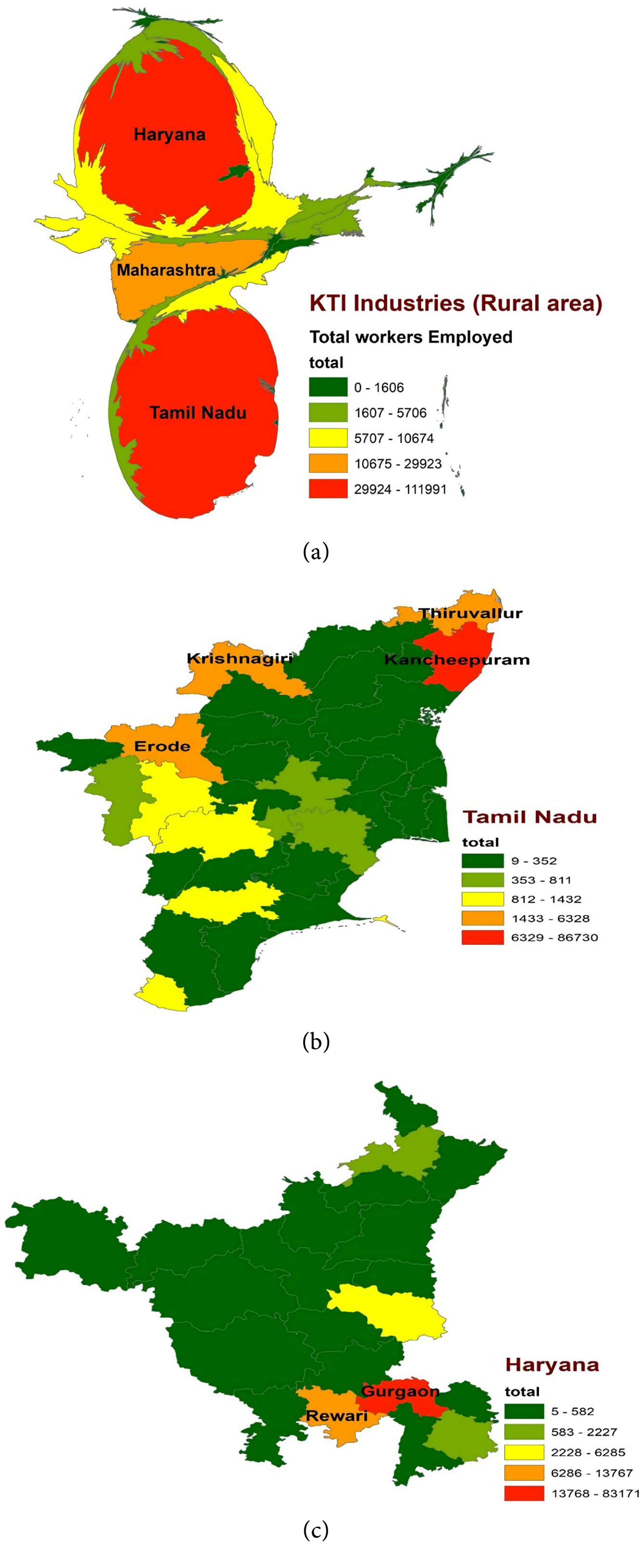


Figure 2. Visualizing the employment of workers for KTI industries in rural areas of India. (a) Cartogram visualizing the KTI industries in rural areas of India. (b) Choropleth map visualizes the spatial distribution of workers within Tamil Nadu. (c) Choropleth map visualizes the spatial distribution of workers within Haryana. Sources: Own computations using ArcGIS 10.6 by considering the Economic Census (2013) data.

Table 4. Highly concentrated KTI industry's geographical concentration in urban areas within selected states of India.

NIC3	KTI Industries	EGSPAT
Maharashtra		
309	Manufacture of transport equipment n.e.c.	0.231*
201	Manufacture of basic chemicals, fertilizer and nitrogen compounds, plastics and synthetic rubber in primary forms	0.209*
620	Computer programming, consultancy and related activities	0.177*
302	Manufacture of railway locomotives and rolling stock	0.117*
261	Manufacture of electronic components	0.056*
303	Manufacture of air and spacecraft and related machinery	0.018
582	Software publishing	−0.010
Telangana		
303	Manufacture of air and spacecraft and related machinery	1.472*
620	Computer programming, consultancy and related activities	0.277*
582	Software publishing	0.254*
302	Manufacture of railway locomotives and rolling stock	0.229*
201	Manufacture of basic chemicals, fertilizer and nitrogen compounds, plastics and synthetic rubber in primary forms	0.168*
261	Manufacture of electronic components	0.132*
309	Manufacture of transport equipment n.e.c.	−0.016
Andhra Pradesh		
309	Manufacture of transport equipment n.e.c.	0.264*
302	Manufacture of railway locomotives and rolling stock	0.147*
201	Manufacture of basic chemicals, fertilizer and nitrogen compounds, plastics and synthetic rubber in primary forms	0.124
620	Computer programming, consultancy and related activities	0.123*
261	Manufacture of electronic components	0.117*
303	Manufacture of air and spacecraft and related machinery	0.083
582	Software publishing	0.047*

Source: Own computations. Notes: NIC and EGSPAT represent National Industrial Classification at a 3-digit and spatially weighted Ellison-Glaeser index. *Shows the estimated value of EGSPAT is statistically significant at a 5 percent level (Guimaraes et al., 2011).

(Haryana and Tamil Nadu) in rural areas. The reported results exhibit that the manufacture of irradiation, electromedical and electrotherapeutic equipment (NIC-266) is the most highly concentrated KTI industry in Haryana. In contrast, computer programming, consultancy and related activities (NIC-620) is the top, most highly concentrated industry in Tamilnadu (estimated EGSPAT value of 0.782). As this industry belongs to the IT sector, facilitating the prevalence of the

Table 5. Highly concentrated KTI industries' geographical concentration in rural areas within selected states.

NIC3	KTI Industries	EGSPAT
Haryana		
266	Manufacture of irradiation, electromedical and electrotherapeutic equipment	1.257*
293	Manufacture of parts and accessories for motor vehicles	0.171*
309	Manufacture of transport equipment n.e.c.	0.165
203	Manufacture of man-made fibres	0.113
252	Manufacture of weapons and ammunition	0.095*
265	Manufacture of measuring, testing, navigating and control equipment, watches and clocks	0.070
620	Computer programming, consultancy and related activities	0.040*
722	Research and experimental development on social sciences and humanities	0.009
262	Manufacture of computers and peripheral equipment	−0.436
Tamil Nadu		
620	Computer programming, consultancy and related activities	0.782*
203	Manufacture of man-made fibres	0.253*
293	Manufacture of parts and accessories for motor vehicles	0.138*
309	Manufacture of transport equipment n.e.c.	0.124
266	Manufacture of irradiation, electromedical and electrotherapeutic equipment	0.078
722	Research and experimental development on social sciences and humanities	0.061
262	Manufacture of computers and peripheral equipment	0.046
265	Manufacture of measuring, testing, navigating and control equipment, watches and clocks	0.033
252	Manufacture of weapons and ammunition	−0.005
304	Manufacture of military fighting vehicles	−0.057

Source: Own computations. Notes: *Shows the estimated value of EGSPAT is statistically significant at a 5 percent level (Guimaraes et al., 2011).

information and Communication services industry in Tamil Nadu indicates a higher concentration of employment.

4.3. Excess Employment Concentration within Selected States of Urban and Rural Areas

After finding evidence of the geographical concentration of KTI industries within highly concentrated states across the urban areas in India, the subsequent empirical interest is to evaluate the excess employment concentration of highly concentrated KTI industries[19]. More specifically, this study explores India's urban concentrated and dispersed districts[20]. **Figure 3** depicts Maharashtra's excess employment concentration map to identify concentrated and dispersed urban districts. The results exhibit that only two districts, Pune in red and Thane depicted in yellow, have a positive value and indicate that they are urban concentrated. However, the green colour shows the plants in an industry are more evenly distributed than expected at random for the remaining districts of Maharashtra. This indicates that the extent of localization is viable for only two districts in Maharashtra[21]. Further, results suggest that natural advantages, agglomeration effect and technology spillover restrict the geographical concentration of KTI industries to only a few districts.

Similarly, **Figure 4** depicts only three urban concentrated districts of Telangana states in India (Medak in red and Hyderabad and Rangareddy in light green)[22]. The dark green patch shows seven urban dispersed districts of Telangana, indicating the establishment units in an industry are more evenly distributed than expected at random. In contrast, **Figure 5** depicts the excess employment concentration map of Andhra Pradesh, indicating that all districts are urban dispersed[23]. This suggests that centripetal forces do not play any viable role in the geographical concentration of highly concentrated KTI industries in Andhra Pradesh. Nevertheless, in this case, one plausible reason is that the cartogram depicted in **Figure 1** visualizes the spatial distribution of workers enlarges for Andhra Pradesh. However, the excess concentration map of employment for Andhra Pradesh indicates that all districts are urban dispersed (see **Figure 5**). This is possible because Telangana state employment data was merged with Andhra Pradesh before Telangana became into existence of a new state in India.

Like in an urban area, our subsequent empirical interest is to evaluate and detect the location of excess employment concentration of highly concentrated KTI industries in rural areas across the highly concentrated states in India (Haryana and Tamil Nadu)[24]. **Figure 6** depicts the excess employment concentration map of Haryana to identify rural concentrated and rural dispersed districts. The computed graph in **Figure 6** exhibits that only two districts, Ambala in red and Gurgaon in yellow, have a positive value and are concentrated in rural areas.

[19]We choose only those highly concentrated KTI industries (see **Table 4**) that are statistically significant at a 5 percent level (Guimaraes et al., 2011).

[20]Note that we have calculated the excess employment concentration of a particular industry in a district of India. The districts with a positive excess employment concentration indicate the urban concentrated districts. In contrast, a negative value indicates the urban dispersed districts where the plants in an industry are more evenly distributed than expected at random.

[21]For more details, see **Table A2** in the **Appendix** section.

[22]Note that we have selected only highly concentrated KTI industries (see **Table 4** Telangana section), which are statistically significant at a 5 percent level. For more details, see **Table A3** in the **Appendix** section.

[23]For more details, see **Table A4** in the **Appendix** section.

[24]Follwing the prior discussion, we select only highly concentrated KTI industries (see **Table 5**), where the estimated EGSPAT values are statistically significant at a 5 percent level.

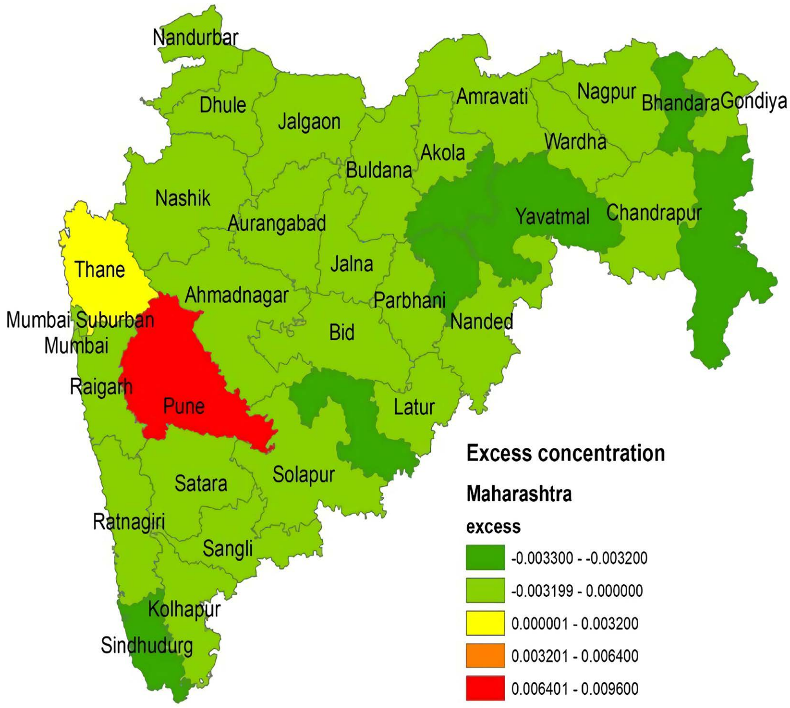


Figure 3. Choropleth map of excess employment concentration of highly concentrated KTI industries within Maharashtra urban area. Source: Own computations using ArcGIS software by considering the Economic Census (2013) data. Notes: The red and yellow patch shows positive values of excess concentration in KTI industries (indicates the urban concentrated districts). In contrast, the green patch shows negative values of excess concentration in KTI industries, demonstrating the urban dispersed districts. For the red colour, positive values lie in the range of 0.0064 to 0.0096. Similarly, for the yellow colour, values lie in the range of 0.000001 to 0.0032.

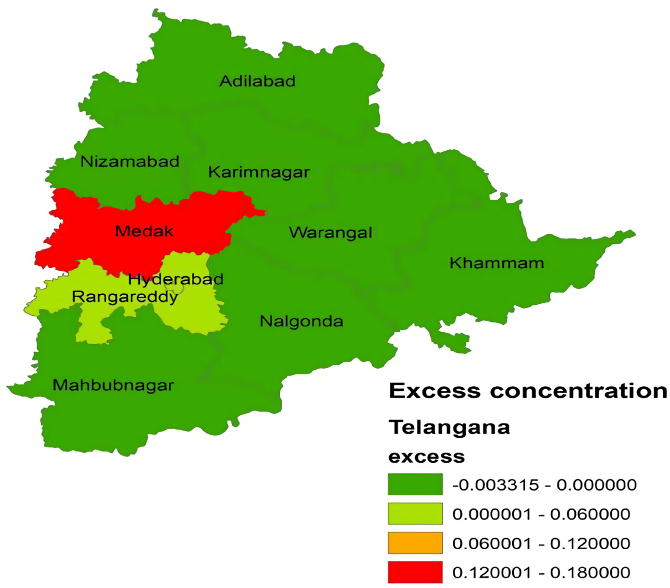


Figure 4. Choropleth map of excess employment concentration of highly concentrated KTI industries within Telangana urban area. Source: Own computations using ArcGIS software by considering the Economic Census (2013) data.

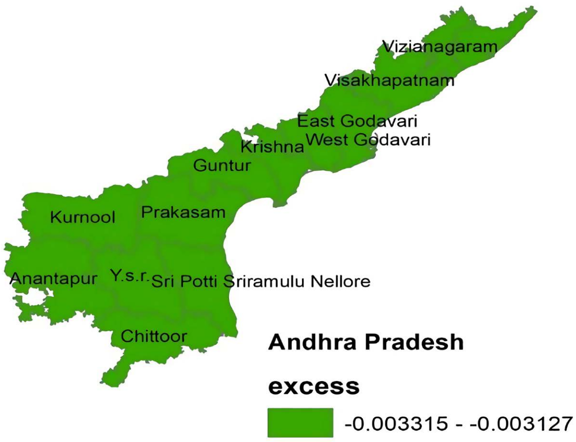


Figure 5. Choropleth map of excess employment concentration of highly concentrated KTI industries within Andhra Pradesh urban area. Source: Own computations using ArcGIS software by considering the Economic Census (2013) data.

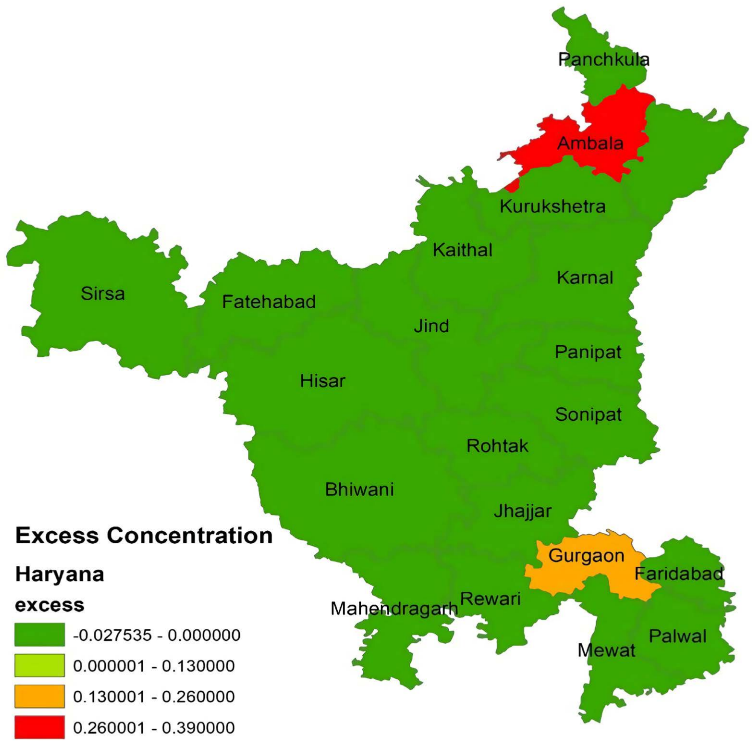


Figure 6. Choropleth map of excess employment concentration of highly concentrated KTI industries within Haryana rural area. Source: Own computations using ArcGIS software by considering the Economic Census (2013) data.

However, the dark green colour shows the plants in an industry are more evenly distributed than expected at random for the remaining districts of Haryana. Therefore, this validates that the localization effect is visible and significant in only two districts in Haryana[25]. Similarly, Figure 7 shows that two districts (Kancheepuram depicted in red and Erode in yellow) are concentrated in rural

[25]For more details, see Table A5 in the **Appendix** section.

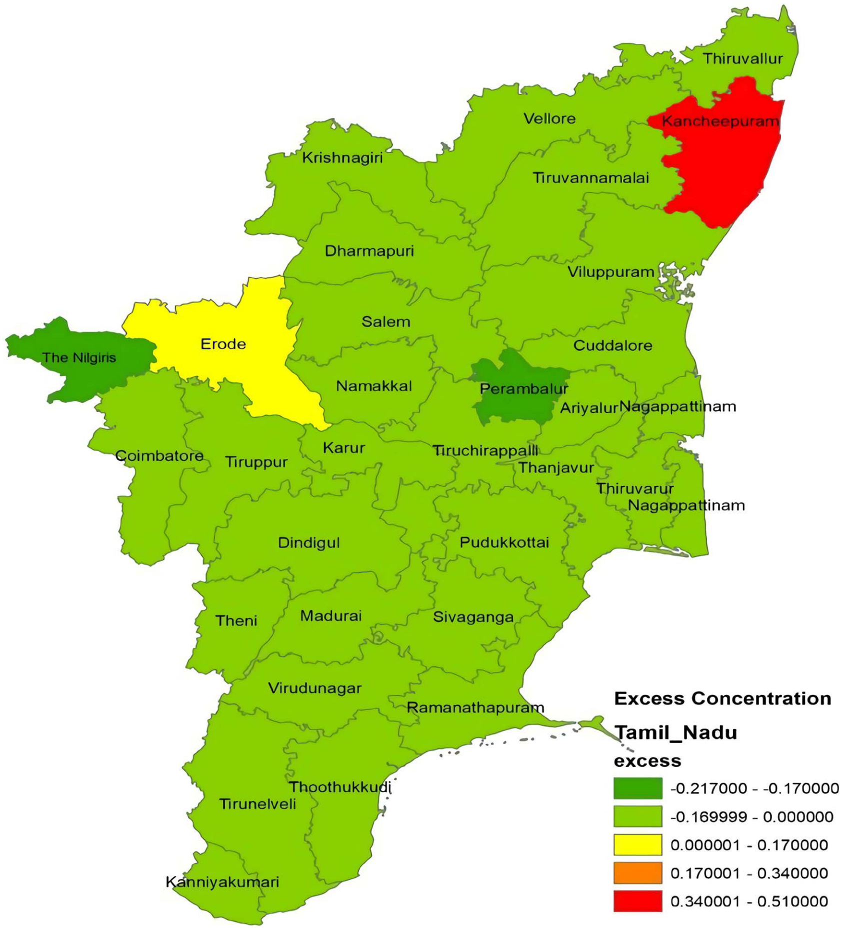


Figure 7. Choropleth map of excess employment concentration of highly concentrated KTI industries within Tamil Nadu rural area. Source: Own computations using ArcGIS software by considering the Economic Census (2013) data.

areas, indicating the effect of localization. In contrast, in Tamil Nadu, the remaining 29 districts depicted in light and dark green patches are rural-dispersed, showing the meagre impact of localization[26].

In a nutshell, our empirical findings for the spatial concentration of KTI industries are encapsulated as follows. First, we measure the geographical concentration of KTI industries in urban and rural areas using the spatially weighted Ellison-Glaeser index. The results exhibit that out of 35 KTI industries, only seven KTI industries are highly concentrated in the urban area, whereas ten KTI industries are in the rural area. Second, our subsequent empirical interest is to detect which Indian states and union territories employ a maximum number of workers in highly concentrated KTI industries. Results show that Andhra Pradesh and Maharashtra for urban areas and Tamil Nadu and Haryana for rural areas are the two Indian states that substantially employ maximum workers. Within these Indian states, only a few districts employed the highest number of workers in urban and rural areas. Third, we explore highly concentrated KTI

[26]For more details, see Table A6 in the **Appendix** section.

industries' which are more geographically concentrated within highly concentrated Indian states. The results reveal that for an urban area, within Maharashtra and Andhra Pradesh, the manufacture of transport equipment, n.e.c. (NIC-309) is a highly concentrated industry than other KTI industries. But for Telangana, the manufacture of air, spacecraft, and related machinery (NIC-303) is the top most highly concentrated KTI industry.

Similarly, for rural areas, within Haryana, irradiation, electromedical and electrotherapeutic equipment (NIC-266) is the most highly concentrated KTI industry. However, within Tamil Nadu, computer programming, consultancy and related activities (NIC-620) is the top most highly concentrated KTI industry. Finally, our subsequent empirical interest is to evaluate the excess employment concentration of highly concentrated KTI industries within highly concentrated states in urban and rural areas. Results show that in urban areas, only two districts (Pune and Thane) in Maharashtra, three districts (Medak, Hyderabad and Rangareddy) in Telangana, and no district in Andhra Pradesh shows the extent of localization. Therefore, this indicates centripetal forces play a viable role in the geographical concentration of highly concentrated KTI industries. Besides, for the rural area, only two districts (Ambala and Gurgaon) in Haryana and two districts (Kancheepuram and Erode) in Tamil Nadu are urban-concentrated. This indicates that the localization effect is more substantial and confined to specific locations in rural and urban India. In addition, the centripetal forces facilitate spatial concentration in particular locations of a few districts across the highly concentrated Indian states in the urban and rural areas.

5. Conclusion

This paper has explored the geographic concentration of knowledge and technology-intensive (KTI) industries at the district level covering 0.43 million establishments in rural and urban areas in India using the spatially weighted Ellison-Glaeser index, cartogram and choropleth map. Empirical results reveal that seven industries in urban and ten industries in rural areas are highly concentrated KTI industries in India. Further, empirical results indicate that urban areas of Andhra Pradesh and Maharashtra and rural areas of Haryana and Tamil Nadu are substantially enlarged on the cartogram, suggesting that the highly concentrated KTI industries are spatially confined to a particular location.

Moreover, results also reveal that localization is substantially more potent and geographically concentrated in particular locations of a few districts across the highly concentrated states (Andhra Pradesh and Maharashtra for the urban area; Haryana and Tamil Nadu for rural area) in India. Therefore, industries spatially concentrated in only a few locations in specific districts in India connote the effect of natural advantages or other economic forces that might increase profits for firms located near firms of the same or different industries. Successively, our results suggest that the push and pull-based supply chains and demand-based networks are pretty strong in such districts and have the potential to attract new players while entering and exploring a new market. Therefore, the policymakers may consider and emphasize highly agglomerated districts in India to boost productivity, output and employment, which would augment growth at both local and national levels. In sum, following Gertler's (2018) ideas, for effective policy implementation, Indian policymakers may also consider multi-level governance, informal (traditions, values and conventions) and formal institutions (laws, rules and regulations), to become essential socially constructed elements for different economic actors and their economic activities.

Acknowledgements

We would like to thank anonymous journal reviewers for their valuable comments and insightful suggestions, which enabled us to improve the quality of this paper to a large extent. We would also like to thank the Editors and Joy Deng, Managing Editor of the journal, for giving us a chance to revise this paper.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix

Table A1. Classification of KTI industries.

	Manufacturing	Non-Manufacturing
High R&D intensity industries	303: Air and spacecraft and related machinery	72: Scientific research and development
	21: Pharmaceuticals	582: Software publishing
	26: Computer, electronic and optical products	-
Medium-high R&D intensity industries	252: Weapons and ammunition	62 - 63: IT and other information services
	29: Motor vehicles, trailers and semi-trailers	-
	325: Medical and dental instruments	-
	28: Machinery and equipment n.e.c.	-
	20: Chemicals and chemical products	-
	27: Electrical equipment	-
	30: Railroad, military vehicles and transport n.e.c.	-

Source: Galindo-Rueda & Verger (2016). Notes: NIC-26 comprises (NIC-261, 262, 263, 264, 265, 266, 267 and 268), NIC-72 comprises (NIC-721 and 722), NIC-29 comprises (NIC-291, 292, and 293), NIC-28 comprises (NIC-281 and 282), NIC-20 comprises (NIC-201, 202, and 203), NIC-27 comprises (NIC-271, 272, 273, 274, 275, and 279), NIC-30 comprises (NIC-302, 304, and 309) and NIC-63 comprises (NIC-631 and 639).

Table A2. Urban concentrated and dispersed districts of Maharashtra for highly concentrated KTI industries.

States Name	Districts	Excess concentration
Maharashtra	Pune	0.00807
Maharashtra	Thane	0.00100
Maharashtra	Nashik	−0.00085
Maharashtra	Mumbai Suburban	−0.00135
Maharashtra	Mumbai	−0.00255
Maharashtra	Nagpur	−0.00274
Maharashtra	Raigarh	−0.00274
Maharashtra	Kolhapur	−0.00275
Maharashtra	Solapur	−0.00275
Maharashtra	Amravati	−0.00276
Maharashtra	Ahmadnagar	−0.00276
Maharashtra	Satara	−0.00276
Maharashtra	Jalgaon	−0.00276

Continued

Maharashtra	Akola	−0.00276
Maharashtra	Sangli	−0.00276
Maharashtra	Bid	−0.00276
Maharashtra	Aurangabad	−0.00276
Maharashtra	Latur	−0.00276
Maharashtra	Nanded	−0.00276
Maharashtra	Dhule	−0.00276
Maharashtra	Wardha	−0.00276
Maharashtra	Parbhani	−0.00276
Maharashtra	Ratnagiri	−0.00276
Maharashtra	Nandurbar	−0.00276
Maharashtra	Jalna	−0.00276
Maharashtra	Gondiya	−0.00276
Maharashtra	Buldana	−0.00276
Maharashtra	Chandrapur	−0.00276
Maharashtra	Yavatmal	−0.00316
Maharashtra	Bhandara	−0.00316
Maharashtra	Sindhudurg	−0.00316
Maharashtra	Osmanabad	−0.00332
Maharashtra	Washim	−0.00332
Maharashtra	Garhchiroli	−0.00332
Maharashtra	Hingoli	−0.00332

Source: Own computations.

Table A3. Urban concentrated and dispersed districts of Telangana for highly concentrated KTI industries.

States Name	Districts	Excess concentration
Telangana	Medak	0.1687
Telangana	Rangareddy	0.0435
Telangana	Hyderabad	0.0041
Telangana	Nalgonda	−0.0028
Telangana	Khammam	−0.0028
Telangana	Warangal	−0.0028
Telangana	Nizamabad	−0.0028
Telangana	Adilabad	−0.0028
Telangana	Mahbubnagar	−0.0028
Telangana	Karimnagar	−0.0033

Source: Own computations.

Table A4. Urban concentrated and dispersed districts of Andhra Pradesh for highly concentrated KTI industries.

States Name	Districts	Excess concentration
Andhra Pradesh	Srikakulam	−0.0033
Andhra Pradesh	Vizianagaram	−0.0033
Andhra Pradesh	Prakasam	−0.0033
Andhra Pradesh	Y.s.r.	−0.0032
Andhra Pradesh	West Godavari	−0.0032
Andhra Pradesh	Chittoor	−0.0032
Andhra Pradesh	Sri Potti Sriramulu Nellore	−0.0032
Andhra Pradesh	Anantapur	−0.0031
Andhra Pradesh	East Godavari	−0.0031
Andhra Pradesh	Guntur	−0.0031
Andhra Pradesh	Kurnool	−0.0031
Andhra Pradesh	Visakhapatnam	−0.0031
Andhra Pradesh	Krishna	−0.0031

Source: Own computations.

Table A5. Rural concentrated and dispersed districts of Haryana for highly concentrated KTI industries.

States Name	Districts	Excess concentration
Haryana	Ambala	0.3336
Haryana	Gurgaon	0.1792
Haryana	Rewari	−0.0053
Haryana	Sonipat	−0.0143
Haryana	Palwal	−0.0165
Haryana	Mewat	−0.0165
Haryana	Karnal	−0.0166
Haryana	Hisar	−0.0166
Haryana	Jhajjar	−0.0166
Haryana	Jind	−0.0166
Haryana	Kaithal	−0.0166
Haryana	Kurukshetra	−0.0166
Haryana	Panipat	−0.0166
Haryana	Mahendragarh	−0.0166
Haryana	Sirsa	−0.0166
Haryana	Panchkula	−0.0166
Haryana	Faridabad	−0.0166
Haryana	Fatehabad	−0.0275
Haryana	Rohtak	−0.0275
Haryana	Bhiwani	−0.0275
Haryana	Yamunanagar	−0.0275

Source: Own computations.

Table A6. Rural concentrated and dispersed districts of Tamil Nadu for highly concentrated KTI industries.

States Name	Districts	Excess concentration
Tamil Nadu	Kancheepuram	0.444
Tamil Nadu	Erode	0.053
Tamil Nadu	Kanniyakumari	−0.006
Tamil Nadu	Tiruppur	−0.01
Tamil Nadu	Thiruvallur	−0.014
Tamil Nadu	Theni	−0.015
Tamil Nadu	Thoothukkudi	−0.015
Tamil Nadu	Dharmapuri	−0.015
Tamil Nadu	Thiruvarur	−0.015
Tamil Nadu	Pudukkottai	−0.015
Tamil Nadu	Nagappattinam	−0.015
Tamil Nadu	Thanjavur	−0.015
Tamil Nadu	Madurai	−0.015
Tamil Nadu	Karur	−0.015
Tamil Nadu	Tiruchirappalli	−0.015
Tamil Nadu	Coimbatore	−0.015
Tamil Nadu	Tiruvannamalai	−0.015
Tamil Nadu	Virudunagar	−0.015
Tamil Nadu	Vellore	−0.015
Tamil Nadu	Viluppuram	−0.015
Tamil Nadu	Tirunelveli	−0.015
Tamil Nadu	Dindigul	−0.015
Tamil Nadu	Krishnagiri	−0.015
Tamil Nadu	Salem	−0.015
Tamil Nadu	Sivaganga	−0.015
Tamil Nadu	Ariyalur	−0.017
Tamil Nadu	Ramanathapuram	−0.017
Tamil Nadu	Cuddalore	−0.017
Tamil Nadu	Namakkal	−0.017
Tamil Nadu	Perambalur	−0.215
Tamil Nadu	The Nilgiris	−0.217

Source: Own computations.