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Do Neighbourhood Effects Matter for the Geographical Concentration? Evidence from the Indian Industries

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Abstract

This paper investigates the impact of neighbouring effects on the geographical concentration of manufacturing and service industries at the district level using India's Economic Census (2013) data. As empirical literature suggests, spillovers do not recognize areal boundaries, and spatial dependence among regions needs to be incorporated while quantifying the geographical concentration of industries. In this context, we employ the spatially weighted Ellison-Glaeser (EG) index to evaluate the impact of neighbourhood effect on the spatial concentration of 71 manufacturing and 120 service industries in India. Using aggregate data at the district level by covering 636 districts and 34 states and union territories in India, empirical results exhibit that the magnitude of the neighbourhood effect does not substantially impact the geographical concentration of 191 industries. More specifically, the neighbourhood effect is over-shadowed while considering an aggregate of 636 districts covering all states and union territories in India. To gain more insight into the role of neighbourhood effects and for robustness checks, we measure manufacturing and service industries' geographical concentration within India's 29 contiguous states and union territories. Our subsequent empirical evidence validates that neighbourhood effects are well captured by the spatially weighted Ellison-Glaeser index for the top three highly concentrated manufacturing and service industries. Moreover, we find that the spatially weighted EG index plays a predominant role while computing geographical concentration for the highly concentrated manufacturing and service industries across various Indian states and union territories at the district level in India.

Keywords

Spatially Weighted Ellison-Glaeser Index, Neighbouring Effect, Manufacturing Industries, Service Industries, India

1. Introduction

The geographical concentration of economic activity is a pervasive phenomenon worldwide (Vitali et al., 2013; Chica, 2016). The empirical literature (Andersson & Lööf, 2011; Gaubert, 2018; Lavoratori & Castellani, 2021) reveals that the geographical concentration of industries positively impacts employment, growth and economic output. However, the measurement of geographical concentration is one of the primary difficulties in agglomeration literature. A substantial literature (Rosenthal & Strange, 2001; Barrios et al., 2009; Alkay & Hewings, 2012) measures geographical concentration through various indices, but the Ellison-Glaeser index (EG) is widely used in the agglomeration literature. However, some studies (Arbia, 2001; Lafourcade & Mion, 2007; Guillain & Le Gallo, 2010) recognized EG index does not consider adjacent regions while quantifying geographical concentration.

The spillover effects do not recognize any areal boundaries; this issue must be appropriately addressed. Duranton and Overman (2005) and Marcon and Puech (2010) proposed geographic concentration measures based on a distance between economic agents to avoid this problem. However, these measures require detailed information about plant location and necessary geocoding. This data for most countries is not easily accessible, and India is among them where only spatially aggregated areal data is available. For areal data, Guimarães et al. (2011) extend the original EG index (1997), which includes neighbourhood effects through a spatial weight matrix. Research using aggregate spatial data where the neighbourhood effect is captured through spatially weighted EG index is still relatively scarce, but the literature is growing gradually. Behrens & Bougna (2015) reported the locational patterns of manufacturing industries in Canada, Dauth et al. (2018) examined the long-run geographical concentration of manufacturing, service, and knowledge-intensive industries in Germany, and Crafts & Klein (2021) investigated the US manufacturing industries. The previous studies suggest that the spatially weighted EG index effectively captures neighbourhood effects while measuring industries' geographical concentration. Most previous studies focus on the manufacturing sector, and only a few empirical studies (Kolko, 2010; De Dominicis et al., 2013; Koh and Riedel, 2014; De Almeida et al., 2021) look into the geographic concentration of service industries for various countries.

Moreover, specific to Indian industries, only a few previous studies (Lall et al., 2004; Lall & Chakravorty, 2005; Fernandes and Sharma, 2012) applied the Gini and Ellison-Glaeser index to measure the spatial concentration in their empirical studies. The previous studies examine the manufacturing industries' geographical concentration at a district and state level using the Gini and Ellison-Glaeser indexes. These studies do not consider neighbourhood effects across regions while measuring the geographical concentration of Indian industries. However, existing studies completely neglect to estimate the geographical concentration of Indian service industries. Desmet et al. (2015) study put the service sector in the limelight for considering the spatial development of India. Although, in 2013, the value-added from the service sector contributed to over 50% of India's GDP (Ghani et al., 2016). The service sector can provide India's growth path to a higher level (Eichengreen & Gupta, 2013). The share of manufacturing in national Gross Value-Added (GVA) increased from 17.40% in 2011-2012 to 18.36% in 2017-2018, but it dropped to 17.1% in 2019-2020 (CSO, 2021). It indicates how important it is to examine the spatial concentration of manufacturing and service industries in India. More specifically, in the Indian context, only a few studies by Amirapu et al. (2019) considered the manufacturing and service sectors simultaneously to measure the geographic concentration of Indian industries using economic census data. Further, their study considers the spatially weighted Ellison-Glaeser (2011) index to compute the geographical concentration of industries. However, their study does not examine whether neighbourhood effects play a substantial role while measuring the spatial concentration of industries at the NIC-3-digit level.

To the best of our knowledge, none of the previous studies examines whether accounting for spatial dimension matters while quantifying the geographical concentration of manufacturing and service industries at a district level in India. Therefore, this motivates us to empirically examine the spatial concentration of three highly concentrated manufacturing and service industries in two spatial structures. Our study contributes to Indian agglomeration literature in several ways. First, as spillovers do not confine to areal boundaries and spatial dependence among regions, we apply the spatially weighted Ellison-Glaeser index while measuring the spatial concentration of India's top three highly concentrated manufacturing and service industries. This index is beneficial for those countries that do not have exact location firms' data. For India, establishment location data is unavailable; therefore, by confining to areal data, the spatially weighted EG index (2011) could be applied to capture neighbourhood effects while quantifying the geographical concentration of manufacturing and service industries at a district level. Second, our study considers two spatial structures to understand the role of neighbourhood effects. One spatial structure measures the geographical concentration of industries in an aggregate sense at the district level, indicating that the district level covers India's 636 districts across 34 states and union territories. Another spatial structure is to measure an industry's geographical concentration within every 29 contiguous states of India using district-level data[1]. The assessment of capturing the neighbourhood effect while estimating the spatial concentration of 191 industries at the district level is a novel attempt. Besides, this paper tries to fill the existing gap in the Indian agglomeration literature by creating a spatial weight matrix within India's 29 contiguous states and union territories to assess the impact of the neighbourhood effect on

[1]Out of 34 states and union territories in India, we carry out our empirical analysis only for 29 Indian states and union territories. Five Indian states and union territories (Chandigarh, Daman & Diu, Dadar and Nagar Haveli, Goa, and Puducherry) are excluded because we cannot compute the spatial weight matrix due to neighbours' non-availability.

the spatial concentration of Indian Industries. Third, we use economic census data, the only Indian dataset that permits estimation of the complete establishment size distribution—across all sizes and types of establishments. The dataset is more reliable micro-unit level establishment data available in the Indian context to examine the geographical concentration of manufacturing and service industries. The dataset covers 71 manufacturing and 120 service sector industries, followed by National Industrial Classification (NIC-2008) at a 3-digit level. Regional differences within Indian states are enormous in human resources, infrastructure, and local political economy. Therefore, while exploring the geographical concentration of industries, it is guided to use the highly disaggregated data at the district level. Consequently, we have conducted the most significant micro-level analysis by covering 10.3 million manufacturing establishments with 30.1 million workers and 33.6 million service establishments with 73.8 million workers.

The remainder of the paper is organized as follows. Section 2 provides a snapshot of theoretical and empirical studies in the agglomeration literature. Section 3 presents the data description and methodology for quantifying the geographical concentration of industries. Section 4 summarizes our empirical findings, while Section 5 concludes our study with future research directions.

2. Literature Review

2.1. Theoretical Review

A substantial body of literature explains heterogeneity in the spatial distribution of economic activity (e.g. Marshall, 1890; Jacobs, 1969; Krugman, 1991; Henderson, 2003). The idea of the sources of geographic concentration of firms goes way back to Marshall's (1890) pioneering work. Marshall argued that geographical concentration leads to firm productivity through input sharing, labour market pooling, and knowledge spillovers. These sources are external to individual firms and benefits pertinent to firms within the same industry known as localization economies. Duranton and Puga (2004) study classify the micro-foundations for agglomeration economies via sharing, matching, and learning[2]. Jacobs (1969) argues that a diversity of regional economic activity nurtures innovation and growth in inter-industry rather than intra-industry spillovers. This indicates that a firm benefits from being located near other firms of other industries known as urbanization economies[3]. In explaining the uneven spatial distribution of economic activity, urban economics and new economic geography dominate recent research in economics (Brakman et al., 2009). A critical difference between these two approaches is that NEG highlights the role of spatial linkages. In urban economics, cities or regions are like freely floating islands, which imply not consi-

[2]The benefits of sharing are local infrastructure, indivisible facilities, sharing gains from specialization, matching defined are employers and employees, and learning represent new technologies, diffusion and accumulation of knowledge.

[3]It includes the availability of extensive labour with multiple specializations, easy access to complementary services (law, accounting, advertising, and banking), inter-industry assimilation of knowledge, and the availability of general infrastructure at a lower cost.

dering spatial interdependencies between regions[4]. Krugman (1991) laid the foundation of "New Economic geography" (hereafter, NEG) and created a spatial economic model to understand the mechanism of firm localization and put stress on the role of "second nature geography" (location of economic agents, i.e., workers and firms relative to one another in space).

In contrast, previous neoclassical explanations for uneven economic activity distribution across space emphasize "first-nature geography" (resource endowments, topology, and the physical geography of climate). The main building blocks of NEG are product differentiation modelled through various assumptions, increasing returns to scale, reducing transport costs, and creating pecuniary externalities in agents' location choices (Redding, 2010). When these three building blocks are combined with interregional factor (labour) mobility, they give rise to cumulative causation forces and lead to the spatial concentration of economic activity[5]. Krugman's model is based on Dixit & Stiglitz (1977) model of imperfect competition and increasing returns to scale. However, the importance of increasing returns to scale came from the Starrett (1978) "Spatial Impossibility Theorem"[6]. In Krugman's model, the firms specialize and concentrate at a particular location if there are strong internal economies of scale and low transportation costs. There are likely many reasons for the geographical concentration of industries, but two key factors influencing it are natural advantages and localized knowledge spillovers (Ellison & Glaeser, 1997)[7].

2.2. Empirical Review

The agglomeration of firms occurs due to various sources of agglomeration economies, localization economies, urbanization economies, natural advantages, market access, lower transportation costs, and other factors. Helsely and Strange (1990) showed that the searching costs of firms with differentiated labour demands and workers with differentiated skills are reduced when firms are geographically concentrated. Audretsch and Feldman (1996) find that knowledge-intensive industries are generally more agglomerated than traditional industries, implying the importance of knowledge spillovers. Ellison & Glaeser (1997) find that industries that are not localized have a lower level of productivity. Puga (2010) study reveals that the production is more clustered geographically even after controlling for comparative advantages, spatial patterns in wages and rents, and systematic variations in productivity within the urban environ-

[4]For more details, see Fujita and Mori, 2005: p. 395; Combes et al., 2005.

[5]When workers locate at a place and expenditure done by consumers incentivizes firms to locate their business activity near consumers ("home market effect"). Similarly, when firms concentrate at a place, it reduces the prices of goods and services, incentivizing workers to locate near that location ("price index effect").

[6]The Spatial Impossibility Theorem states that when homogenous space and transport cost is high, a competitive equilibrium does not exist where goods are traded between regions. Moreover, the perfect competition combined with homogenous space and high transport costs leads to each region producing for itself, i.e., backyard capitalism (Ottaviano and Thisse, 2004).

[7]The computer industry in Silicon Valley is the best example of a natural advantage in California's wine industry and knowledge spillovers.

ment. Also, the geographical concentration of activities has a positive impact on productivity. Over the last two decades, the most advanced firm and establishment-level datasets emerged that help study agglomeration economies and productivity spillovers within cities. A group of research focuses on distance-based continuous measures of geographical concentration (Duranton and Overman (2005), Marcon and Puech (2010)) for industries' agglomeration causal effect on productivity (Melo et al., 2009; Graham et al., 2010; Combes & Gobillon, 2015), and for dynamic outlooks that include firms entry and exit (Dumais et al., 2002; Glaeser et al., 2015). Besides, Mudambi and Swift (2012), Beugelsdijk and Mudambi (2014), and Lorenzen and Mudambi (2013) have done extensive research on the geographical dimension of FDI and modes of entry of 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. For instance, in India, Behera (2017) examine the productivity spillovers from FDI at the regional level using 22 manufacturing industries. He finds that firms' absorptive capacity with market concentration acts as a crucial conduit for innovation, enhancing the total factor productivity. Similarly, Behera et al. (2012) and Behera (2015a, 2015b) find that R&D and technology import intensity enhances the productivity of Indian manufacturing industries.

In the Indian context, various studies explore the appropriate determinants of firm locational choice and firm productivity. Mitra (1999) uses firm-level data to evaluate the significance of agglomeration economies in two manufacturing industries by applying a statistical stochastic frontier model. The study reveals substantial evidence of a positive association between technical efficiency and city size. But, after a certain threshold level, the size of the city works as diseconomies of scale. Lall et al. (2003) find that industrial diversity (urbanization economies) has 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. The results suggest that urbanization economies are more important for a firm's business location than localization economies. Lall and Mengistae (2005) study of manufacturing plant levels from India's major industrial centres shows significant productivity gaps across cities due to differences in agglomeration economies, market access and the local business environment. Sridhar and Wan (2010) study reveal that more labour-intensive firms tend to refrain from locating in large cities of India. However, firms established in the post-reform period tend to locate in large cities.

Moreover, the availability of inputs positively impacts firm location in India. Mukim (2015) analyze coagglomeration patterns between formal and informal manufacturing enterprises in India. The study finds that buyer-seller linkages and technology spillovers are the most significant factors that explain formal-informal manufacturing enterprises' coagglomeration. Desmet et al. (2015) focus on India's spatial development, particularly in the service sector. The study reveals that high-density clusters of economic activity continue to be India's engines of growth. Besides, given the role played by Information and Communication Technology (ICT), the study finds that agglomeration forces in service sectors still dominate dispersion forces in high-density areas. Ghani et al. (2016) studied the spatial pattern of manufacturing and service industries in India from 2001 to 2010. The main finding of their study is summarized as follows. First, the organized manufacturing sector moves away from urban cores to the rural periphery while services move towards the urban centres. Second, manufacturing industries have a stronger inclination to locate closer to larger cities in an urban area as compared to the service activity. Third, human capital matters for services while infrastructure for manufacturing output.

The measurement of geographical concentration is one of the primary difficulties in agglomeration literature. Many scholars (Krugman, 1991; Audretsch and Feldman, 1996; Brülhart, 2001) have tried to measure the degree of geographical concentration using a series of global indices such as the Locational Gini coefficient and Herfindahl Index[8]. However, the Gini index is insensitive to the spatial concentration of firms within the industry. This shortcoming is overcome by the Ellison-Glaeser index (1997) (hereafter EG index), which contains the Herfindahl index to measure plant-level employment concentration in the industry. A plethora of literature (Dumais et al., 2002; Braunerhjelm & Johansson, 2003; Devereux et al., 2004; Lu & Tao, 2009) measures geographical concentration through the EG index (1997) is applied broadly across different countries. Rosenthal and Strange (2001) use the EG index (1997) and find that labour market pooling significantly impacts industry agglomeration at all geographical scales.

The EG index (1997) has its benefits and practical applicability. However, it suffered from a "checkerboard problem" and "modifiable areal unit problem" (MAUP) (Arbia, 2001; Duranton and Overman, 2005)[9]. The MAUP problem occurs when there are pre-defined boundaries, and the researcher has to work with these units, which leads to bias in the measurement of geographical concentration[10]. However, the checkerboard problem implies that the geographic position of regions or region-relatedness is not considered while computing industries' geographical concentration. Ideally, the geographic concentration needs to be measured using distance-based continuous measures following Ripley (1977), Duranton and Overman (2005), and Marcon and Puech (2003, 2010), relying on the point pattern spatial data that requires location for each plant.

[8]The Gini index calculates the dispersion between a particular industry's regional employment and the regional distribution of overall employment.

[9]The checkerboard problem arises because the geographic position of regions or region-relatedness is not considered while quantifying industries' geographical concentration.

[10]For more details about MAUP, see Briant et al. (2010).

Nevertheless, scholars often only have access to spatially aggregated areal data and thus cannot apply the distance-based continuous measures. However, to overcome the checkerboard problem in areal data, Guimarães et al. (2011) extend the Ellison-Glaeser index (1997) by incorporating spatial dependence among regions. Their application of the spatially weighted EG index in the US context shows that it captures neighbourhood effects while quantifying geographical concentration. Behrens & Bougna (2015) study the locational patterns of manufacturing industries in Canada by applying the unweighted EG index and spatially weighted EG index. Their results reveal that Spearman's rank correlation between weighted and unweighted EG indices was around 96%. It indicates that the geographical concentrations were not extending "too much" across different regions in Canada. Similarly, Dauth et al. (2018) also applied the EG index and spatially weighted EG index in Germany from 1980 to 2010 to examine the long-run geographical concentration of manufacturing, service, and knowledge-intensive industries at the county level. In a similar line, Crafts & Klein (2021) study also applied a spatially weighted EG index to examine the geographical concentration of US manufacturing industries between 1880 and 2007.

In the Indian context, Lall et al. (2004) studied how agglomeration economies contribute to economic productivity by measuring the geographical concentration of only formal manufacturing firms using the Gini Index and Ellison-Glaeser index (1997). They use Annual Survey of Industries (ASI) data for the 1994-1995 period at the NIC two-digit level. The result suggests that improved market access significantly determines firm-level productivity. Lall & Chakravorty (2005) evaluated the relationship between industrial spatial location and spatial income equality by measuring the magnitude of industrial concentration using the Gini Index. Their study conducted empirical analysis for only eight manufacturing industries using the ASI database's plant-level data for 1998-1999[11]. Fernandes and Sharma (2012) examine the impact of industrial reforms on the geographic concentration of manufacturing industries measured by the Ellison-Glaeser index (1997) using plant-level data from ASI over the period 1980-1999. Kathuria (2016) used plant-level data for 1997-1998 to examine the geographical concentration of organized manufacturing firms in 21 Indian states using the Ellison-Glaeser index (1997). Nevertheless, to our best understanding, none of the previous literature examines the spatial dimension of neighbourhood effects factor for the geographical concentration of 71 manufacturing and 120 service industries at a district level in India. Therefore, this paper bridges the research gap in the agglomeration literature by estimating the effect of neighbourhood factors on the spatial concentration of three highly concentrated manufacturing and service industries in India using two spatial structures.

[11]ASI data is based on sample surveys which give data at a broad level, i.e., at a state level. To adequately measure industries' geographical concentration, we require a database suitable at a disaggregated level, i.e., at the district level.

3. Data and Methodology

3.1. Measuring the Geographical Concentration

The measurement of geographical concentration is one of the primary difficulties in agglomeration literature. Many scholars have tried to compute the degree of geographical concentration using a series of global indices such as the Locational Gini coefficient and Herfindahl Index (Brülhart, 2001; De Dominicis et al., 2013). The fundamental problem with the Gini index is that it is insensitive to the spatial concentration of firms within the industry (Guimarães et al., 2007). The limitations in the Gini index are overcome by the Ellison-Glaeser (EG) index (1997), as it contains the Herfindahl index to measure plant-level employment concentration in the industry. It derives from a location choice model, assuming that firms choose their location as if dartboards were thrown at a map (Dauth et al., 2018). The index for an industry (i) in a country with M regions (indexed by m) is defined as follows:

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

where G_i represents an index of geographical concentration, defined as $G_i = \left(S - X\right)'\left(S - X\right)$, the vector $S' = \left[s_1, s_2, \cdots, s_M\right]$ represents the share of industry i employment across geographical regions m and $X' = \left[x_1, x_2, \cdots, x_M\right]$ represent a vector of aggregate employment shares across geographical regions m.

Arbia (2001) and Lafourcade & Mion (2007) recognized traditional measures of geographical concentration (locational Gini coefficient and unweighted EG index) but did not take into account the spatial dependence factors. As spillover effects do not recognize any areal boundaries, so ideally, this issue has to be addressed (Guillain & Le Gallo, 2010). We cannot calculate Duranton and Overman's (2005) or Billings and Johnson's (2016) geographical concentration index because these indices require the address of each establishment to calculate the distance between them. This distance data requirement is not available in the case of India. However, Guimarães et al. (2011) extend the original EG index (1997), which includes neighbourhood effects through a spatial weight matrix to capture the neighbourhood effects. The spatially weighted Ellison-Glaeser index is suitable for countries where precise information about a firm's location is unavailable. The spatially weighted version of the Ellison-Glaeser index is calculated as follows:

$$\gamma_i^{sw} = \frac{G_i^S - H_i\left(1 - X'\Psi X\right)}{\left(1 - H_i\right)\left(1 - X'\Psi X\right)} \tag{2}$$

where $G_i^S = \left(S - X\right)'\Psi\left(S - X\right)$ represent the spatially weighted version of the geographical concentration index $\left(G_i\right)$ and Ψ is a spatial weight matrix $\left(\Psi = W + I\right)$. For $\Psi = I$, the index collapses to the standard EG measure. W is a first-order queen contiguity rule created by assuming the convention that

$\omega_{rs} = 1$ when r and s are neighbours and that $\omega_{rs} = 0$ otherwise. Each row in the binary contiguity matrix is divided by row sum to get a row standardized weight matrix ω_{rs} which is as follows:

$$\omega_{rs} = \frac{\omega_{rs}}{\sum_s \omega_{rs}} \tag{3}$$

3.2. Data Description

For empirical analysis, the study uses the latest Sixth Economic Census (EC) data of 2013-2014 compiled by the Central Statistics Office, Ministry of Statistics and Programme Implementation (MOSPI)[12]. The EC (2013) data enumerated all establishments engaged in various agricultural and non-agricultural activities, excluding crop production, plantation, public administration, defence, and compulsory social security (Central Statistics Office, 2013)[13]. Some studies (Unni & Raveendran, 2006; Manna, 2010) pointed out that EC data suffer from the under-coverage of minor establishments (i.e. number of own account establishments) compared with estimates based on follow-up surveys. Despite this caveat, EC is not censored by size or constrained to include only the formal or informal sector and thus the only Indian dataset that permits estimation of the complete establishment size distribution—across all sizes and types of establishments (Amirapu and Gechter, 2020). The Economic census (EC) dataset is more reliable micro-unit establishment data available in the Indian context to examine the geographical concentration of manufacturing and service industries. The dataset covers 71 manufacturing and 120 service sector industries, followed by NIC-2008 at a 3-digit level.

Table 1 summarizes employment and establishment data for India's manufacturing and service industries. It shows that 10.3 million manufacturing establishments employ 30.1 million workers and 33.6 million service establishments employ 73.8 million workers. The manufacturing and service sectors comprise 43.9 million establishments that employ 103.9 million workers. We need to calculate the spatial weight matrix to capture the neighbourhood effect. We require data on India's district boundaries to construct a spatial weight matrix[14]. Our study considers two spatial structures to understand the role of neighbourhood effects. First, the spatial structure measures industries' geographical concentration using data aggregated at the district level by covering 636 districts across 34 states and union territories of India. Second, the spatial structure measures an industry's geographical concentration within every 29 contiguous states of India using district-level data. We apply the queen contiguity spatial weight matrix for both spatial structures to capture the neighbourhood effect[15].

[12]The data can be accessed in the following link: http://icssrdataservice.in/datarepository/index.php

[13]Following Economic Census (2013) data, the establishment refers to a unit in a single location predominantly busy with one kind of entrepreneurial activity. Further, an establishment refers to producing at least a part of the unit's goods and services for sale, i.e., the entire product is not solely consumed.

[14]The data can be accessed by following this link: http://projects.datameet.org/maps/districts.

[15]We use spmat command created by (Drukker et al., 2013) to compute queen contiguity weight matrix in Stata14.

Table 1. Summary of employment and establishment in manufacturing and service industries.

Industry	Total employment of workers		Total establishments	
	Number	Percentage %	Number	Percentage %
Manufacturing	30,159,829	29.02	10,300,815	23.46
Service	73,775,393	70.98	33,607,260	76.54
Total	103,935,222	100	43,908,075	100

Source: Author's computation using India's Economic Census (2013) data. Notes: Economic census (2013) provides data for 34 states and union territories which comprises 642 districts, out of which we have taken data for 636 districts. We have excluded six districts due to neighbours' data non-availability. The six districts consist of Shahdara and South-East (New Delhi); Nicobar, North & Middle Andaman and South Andaman (Andaman and Nicobar Islands); and Lakshadweep.

4. Empirical Results and Discussion

4.1. Industry's Geographical Concentration Using Aggregated Data at a District Level

Our empirical interest is to evaluate the geographical concentration of manufacturing and service industries using Ellison-Glaeser (EG) indices at a district level in India. Table 2 reports the estimated weighted and unweighted EG index values for the top three highly concentrated manufacturing and service industries. According to both EG indices, the manufacture of glass and glass products (NIC-231), sports goods (NIC-323) and air and spacecraft and related machinery (NIC-303) are three highly concentrated manufacturing industries. Similarly, software publishing (NIC-582), leasing of nonfinancial intangible assets (NIC-774) and landscape care and maintenance service activities (NIC-813) are three highly concentrated service industries. The weighted and unweighted EG index estimated values for highly concentrated manufacturing and service industries seem similar. This indicates that the neighbourhood effect cannot be adequately captured across these manufacturing and service industries while we estimate spatial concentration in the aggregate data. Therefore, this suggests that the neighbourhood effect is overshadowed when estimating geographical concentration across the district level in India while considering an aggregate of 636 districts covering all states in India. Therefore, to examine the role of neighbourhood effects, we conduct a more robust check by considering another spatial structure to analyze the spatial concentration of industries within the Indian states and union territories.

4.2. Industry's Geographical Concentration within Indian States

Our subsequent empirical analysis uses district-level data to measure an industry's geographical concentration within India's 29 contiguous states and union territories. Table 3 shows the estimated weighted and unweighted EG index

Table 2. Top three geographically concentrated manufacturing and service industries in India.

NIC	Industry Name	Unweighted Measure		Weighted Measure	
		EG	Rank	EGSPAT	Rank
Manufacturing industry					
231	Manufacture of glass and glass products	0.254*	1	0.253*	1
323	Manufacture of sports goods	0.222*	2	0.221*	2
303	Manufacture of air and spacecraft and related machinery	0.211*	3	0.211*	3
Service industry					
582	Software publishing	0.256*	1	0.254*	1
774	Leasing of non-financial intangible assets	0.214*	2	0.213*	2
813	Landscape care and maintenance service activities	0.127*	3	0.125*	3

Source: Author's computations. Notes: NIC represents National Industrial Classification at a 3-digit level. EG represents the Ellison-Glaeser index, and EGSPAT represents the spatially weighted EG index. The significance of the EG and EGSPAT index is measured at the 5 percent significance level (Guimarães et al., 2011). *Denotes the estimated values are statistically significant at 5 percent level.

Table 3. India's top three geographically concentrated manufacturing industries (EG vs EGSPAT index).

States Name	Unweighted Measure		Weighted Measure	
	EG	Rank	EGSPAT	Rank
Glass and glass products (NIC-231)				
Himachal Pradesh	0.138*	8	0.228*	4
Rajasthan	0.153*	6	0.181*	5
Andhra Pradesh	0.080*	13	0.161*	6
Sports goods (NIC-323)				
Meghalaya	1.144*	1	0.707*	3
Maharashtra	0.137*	11	0.129*	12
Haryana	0.083*	14	0.125*	13
Air and spacecraft and related machinery (NIC-303)				
Jharkhand	0.261*	7	0.217*	9
Telangana	0.961*	2	1.167*	2
Kerala	0.195*	9	0.338*	7

Source: Author's computations. Notes: EG and EGSPAT represents the unweighted and spatially weighted Ellison-Glaeser index. *Denotes the estimated values are statistically significant at 5 percent level.

values for a few selected states within the three most highly concentrated manufacturing industries. Himachal Pradesh secured the eighth rank for glass and glass products (NIC-231) when we measured geographical concentration using the unweighted EG index. In contrast, it secured the fourth rank using the spatially weighted Ellison-Glaeser (EGSPAT) index. However, it reveals a difference in industry ranking within a state while measuring geographical concentration. Also, Andhra Pradesh secured thirteen positions using the unweighted EG index and the sixth position using the EGSPAT index. It exhibits that two EG indices give different results within an industry for a particular Indian state.

Similarly, for the sports goods (NIC-323) industry, Meghalaya secured the first rank when applying the unweighted EG index, while it secured the third rank using the EGSPAT index. For Haryana and Rajasthan, EG indices estimated values are different, but hierarchy-wise, both secure the same position. It implies no substantial deviation in a state while using EG and EGSPAT indexes for a particular industry. For the air, spacecraft, and related machinery (NIC-303) industry, Jharkhand secured the seventh position using the EG index and the ninth position using the EGSPAT index. It secured the ninth rank in Kerala using the EG index while securing the seventh position following the EGSPAT index. Within Telangana, the air and spacecraft and related machinery (NIC-303) industry secured the second rank according to EG and EGSPAT index. However, the estimated values seem different for both indices. Nevertheless, the estimated results in **Table 3** show that neighbourhood effects seem evident within the three highly concentrated manufacturing industries across Indian states using the district-level data.

Further, Spearman's rank correlation needs to be computed to detect the highly concentrated manufacturing industries where deviation in EG indices seems higher for particular states. **Table 4** shows Spearman's rank correlation for three highly concentrated manufacturing industries. It shows that glass and glass products (NIC-231), sports goods (NIC-323), and air and spacecraft and related machinery (NIC-303) industry have a high-rank correlation of 93.6%, 98.56% and 97.20%, respectively[16]. This indicates that glass and glass products (NIC-231) show a high deviation in ranking for a particular state and union territories compared to other highly concentrated manufacturing industries.

Nevertheless, using the district-level data, we estimate the geographical concentration of three highly concentrated service industries within 29 contiguous states and union territories. **Table 5** shows the estimated results of three highly concentrated service industries. In the case of the software publishing (NIC-582) industry, Punjab has secured the third position using the EGSPAT index and the fourth position using the unweighted EG index. Similarly, in the case of the other two states (Haryana and Orissa), results reveal a negligible difference in ranking. Besides, it seems that the estimated values of both indices are similar for the leasing of nonfinancial intangible assets (NIC-774) industry across the selected states in India.

Next, we estimate Spearsman's rank correlation between the two indices across three highly concentrated service industries in India. Spearsman's rank correlation

[16]While computing Spearman's rank correlation, we have selected only those Indian states and union territories for a particular industry which are statistically significant at the 5 percent level.

Table 4. Spearman's rank correlation for India's top three geographically concentrated manufacturing and service industries.

NIC	Industry Name	Spearsman's rank correlation
Manufacturing industries		
231	Manufacture of glass and glass products	93.60
323	Manufacture of sports goods	98.56
303	Manufacture of air and spacecraft and related machinery	97.20
Service industries		
582	Software publishing	99.38
774	Leasing of nonfinancial intangible assets	98.80
813	Landscape care and maintenance service activities	91.42

Source: Author's computations.

Table 5. India's top three geographically concentrated service industries (EG vs EGSPAT index).

States Name	Unweighted Measure		Weighted Measure	
	EG	Rank	EGSPAT	Rank
Software publishing (NIC-582)				
Punjab	0.582	4	0.602	3
Haryana	0.281	9	0.297	7
Orissa	0.155	12	0.210	11
Leasing of nonfinancial intangible assets (NIC-774)				
Madhya Pradesh	0.480	7	0.483	6
West Bengal	0.268	11	0.289	10
Jharkhand	0.150	15	0.171	14
Landscape care and maintenance service activities (NIC-813)				
Uttarakhand	0.416	2	0.560	1
Delhi	0.217	10	0.261	6
Bihar	0.232	9	0.241	7

Source: Author's computations.

results reported in Table 4 show that in the case of software publishing (NIC-582) and the leasing of nonfinancial intangible assets (NIC-774), the estimated rank correlation is 99.38% and 98.80%, respectively. However, for landscape care and maintenance service activities (NIC-813), the estimated rank correlation is 91.42%, indicating more deviation while estimating both indexes for spatial concentration. Table 5 shows that Delhi has secured the tenth and sixth positions using the EG and EGSPAT index for the landscape care and maintenance service activities (NIC-813) industry. In contrast, the estimated values validate a significant difference in the other states, like Uttarakhand and Bihar. Further, empirical results suggest that the spatial dimension is well captured using the spatially weighted Ellison-Glaeser index across the three highly concentrated service industries. Nevertheless, to get the relationship and the deviation between these two indices, our subsequent empirical interest is to plot a regression line between these two indexes.

Plotting the Regression Line between EG Indices in Highly Concentrated Manufacturing and Services Industries

The results reported in Table 3 and Table 5 exhibit a substantial deviation between the EG indexes in India's highly concentrated manufacturing and service industries. However, we plot this relationship using a familiar regression line to get more robust evidence of the relationship between the two indexes. Figures 1(a)-(f) depicts the fitted line between EG indices for the top three highly concentrated manufacturing and services industries. The x-axis represents the EG index, while the y-axis represents the spatially weighted EG index. Moreover, for the glass and glass products (NIC-231) industry, the estimated regression coefficient between spatially weighted vs unweighted EG index is close to 1 (0.996 ≈ 1), and it is significantly different from zero (see Figure 1(a))[17]. It suggests that one unit change in the unweighted factor has increased the spatial weight factor close to 1 unit. Besides, blue dots depict that for some Indian states, the EGSPAT index is greater or less than the EG index. It validates that states have secured a different position in terms of spatial concentration while we use the spatially weighted EG index. Although as regression indicates, on average, the spatially weighted index is more or less similar to its counterpart.

Similarly, Figures 1(b)-(f) plots the fitted line between EG indices for the other five highly concentrated industries. Figure 1(a), Figure 1(d) and Figure 1(e) displays that the spatially weighted index is more or less similar to its counterpart on average. Figure 1(b) depicts that, on average, the spatially weighted index is less than the unweighted EG index by 21 percent for the sports goods (NIC-323) industry. It indicates that our estimated results do not align with what Duranton and Overman (2005) find in their study by criticizing the unweighted EG index. The unweighted EG index is criticized for the checkerboard problem, leading to downwardly biased estimated values.

However, in the case of sports goods, the spatially weighted EG index is lower than the unweighted EG index. However, Figure 1(c) and Figure 1(f) suggests that the spatially weighted index is higher than the unweighted EG index by 9 and 10 percent for air and spacecraft and related machinery (NIC-303) and landscape care and maintenance service activities (NIC-813) industry. In other words, results exhibit that a one-unit change in the unweighted factor has increased the spatial weight factor by more than 1 unit. Figure 1 suggests that the

[17]We select only those Indian states where the spatially weighted Ellison-Glaeser index (EGSPAT) is statistically significant at a 5% level. For glass and glass products (NIC-231), out of 29 states and union territories of India, only 17 have the statistically significant estimated EGSPAT values. For more details, see Table A1 in the **Appendix** section.

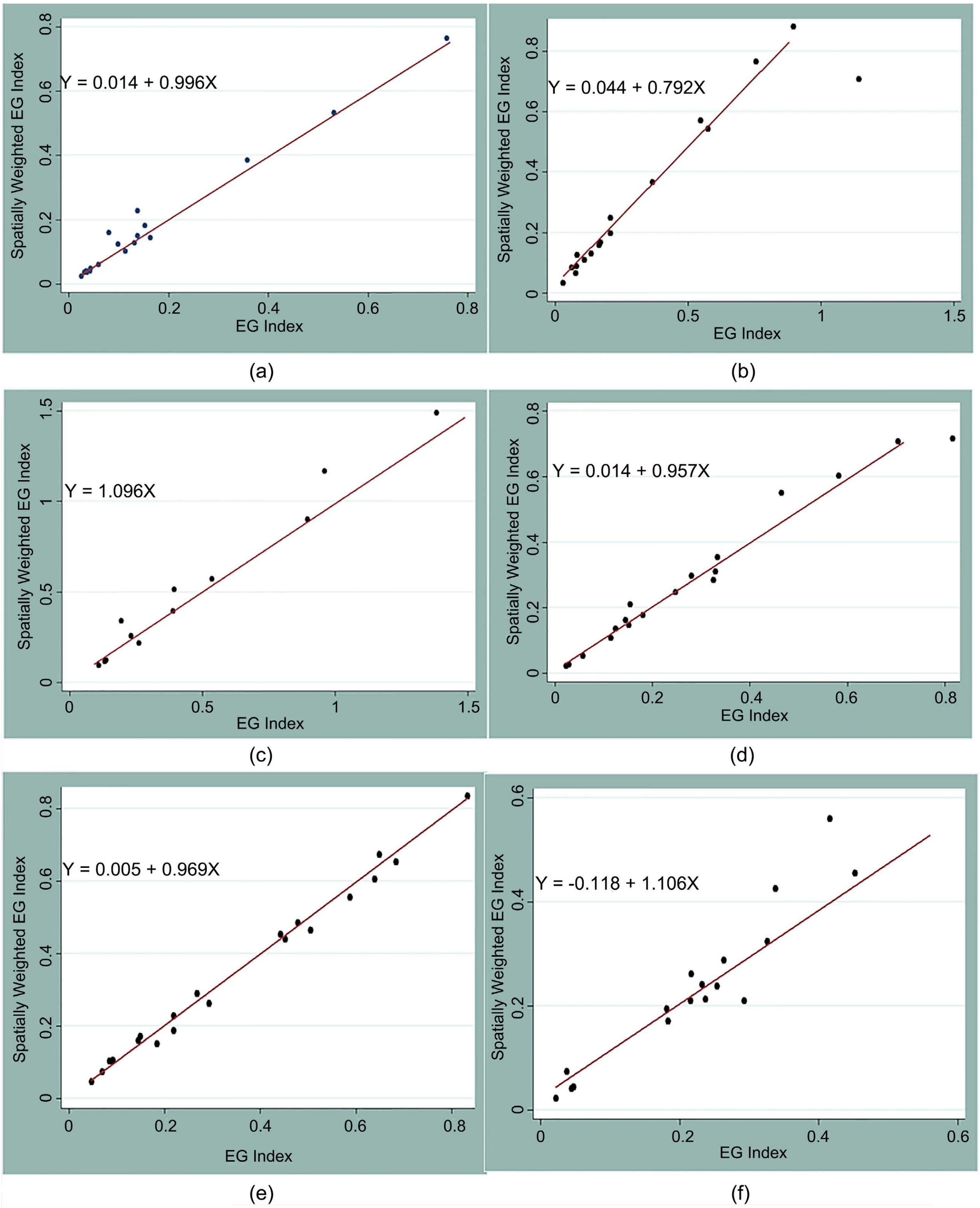

Figure 1. The fitted line between weighted and unweighted Ellison-Glaeser (EG) index (three highly concentrated manufacturing and services industries). Source: Author's computations using Stata14. Notes: We choose only those Indian states where the spatially weighted Ellison-Glaeser index is statistically significant at a 5 percent level. For more details, see **Tables A1-A6** in the **Appendix** section. (a) Glass and glass products (NIC-231); (b) Sports goods (NIC-323); (c) Air and spacecraft and related machinery (NIC-303); (d) Software publishing (NIC-582); (e) Leasing of nonfinancial intangible assets (NIC-774); (f) Landscape care and maintenance service activities (NIC-813).

spatially weighted EG index is substantial while quantifying geographical concentration for a particular state across the highly concentrated manufacturing and service industries except for the sports goods (NIC-323) industry.

5. Conclusion

This study aims to understand whether incorporating neighbourhood effects play a substantial role while quantifying the geographical concentration of manufacturing and service industries in India at a district level. As this paper stresses that spillovers do not recognize any areal boundaries, this issue was addressed by Guimarães et al. (2011) by incorporating the neighbouring effects in the original Ellison-Glaeser (EG) index (1997). To accomplish this aim, we apply the spatially weighted vs unweighted Ellison-Glaeser (EG) index to capture the spatial concentration of India's top three highly concentrated manufacturing and service industries. Our study considers two spatial structures to understand the role of neighbourhood effects. First, we measured industries' geographical concentration using aggregate data at the district level by covering 636 districts and 34 states and union territories in India. Secondly, we use district-level data to measure an industry's geographical concentration within India's 29 contiguous states and union territories. The main results of the study are summarized below.

The empirical results reveal that using aggregate data at the district level by covering 636 districts, estimated values of an unweighted EG index and spatially weighted EG index are more or less similar for three highly concentrated manufacturing and service industries. Therefore, this suggests that spatial attributes like neighbourhood effects do not substantially impact the geographical concentration of highly concentrated industries. Thus, we further measure industries' geographical concentration within India's 29 contiguous states and union territories for more robustness checks. Our subsequent empirical evidence validates that neighbourhood effects are well captured. Moreover, we find substantial evidence of neighbourhood effect across the three highly concentrated manufacturing and service industries for different Indian states using the district-level data except for the sports goods (NIC-323) industry.

In a nutshell, accounting for neighbouring effect while quantifying the spatial concentration of manufacturing and services industries improve the robustness of our empirical finding within Indian states and union territories. As the spatially weighted index shows potential, this study is a starting point for future agglomeration studies in the Indian context. Economic Census data limit the information to variables like total employment of workers and count of establishments for manufacturing and service industries. However, other variables like gross value added, number of months of firm operation, expenses on R&D, wages and salaries, operating expenses etc., are not available in the economic census data. In future work, it could be interesting to link the economic census data with another dataset like the Centre for Monitoring Indian Economy

(CMIE) based dataset "Prowess". Therefore, after linking these two datasets, it could be easier to get a piece of additional information about these parameters and variables and could provide location information about a particular establishment or firm. The precise details on firm location help in applying the Duranton and Overman (2005) or Marcon and Puech (2010) indices which measure geographical concentration based on a distance between economic agents. Therefore, we have preserved this research direction for future research work.

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Conflicts of Interest

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

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Appendix. (Industry's Geographical Concentration within Indian States)

Table A1. Computed EG and spatially weighted EG index for glass and glass products (NIC-231).

S. No.	State Names	EG	EGSPAT
1	Uttar Pradesh	0.759*	0.765*
2	Bihar	0.532*	0.5338
3	Manipur	0.358*	0.3858
4	Himachal Pradesh	0.1388	0.2288
5	Rajasthan	0.153*	0.181*
6	Andhra Pradesh	0.0808	0.1618
7	Karnataka	0.1398	0.149*
8	Telangana	0.163*	0.1448
9	Jammu & Kashmir	0.132*	0.128*
10	Uttarakhand	0.0988	0.123*
11	Punjab	0.1138	0.101*
12	Madhya Pradesh	0.0608	0.059*
13	Tamil Nadu	0.044*	0.0488
14	Jharkhand	0.0358	0.0418
15	Delhi	0.042*	0.041*
16	Kerala	0.037*	0.037*
17	West Bengal	0.032*	0.036*
18	Maharashtra	0.025*	0.025*

Source: Author's computations. Notes: NIC represents National Industrial Classification at a 3-digit level. EG represents the Ellison-Glaeser index, and EGSPAT represents the spatially weighted EG index. The significance of the EG and EGSPAT index is measured at the 5 percent significance level (Guimarães et al., 2011). *Denotes the estimated values are statistically significant at 5 percent level, the same as below.

Table A2. Computed EG and spatially weighted EG index for sports goods (NIC-323).

S. No.	State Names	EG	EGSPAT
1	Punjab	0.896*	0.881*
2	Uttar Pradesh	0.756*	0.765*
3	Meghalaya	1.144*	0.707*
4	Chhattisgarh	0.549*	0.570*
5	Madhya Pradesh	0.576*	0.544*
6	Jammu & Kashmir	0.369*	0.366*
7	Delhi	0.209*	0.248*
8	Jharkhand	0.209*	0.196*

Continued

9	Orissa	0.172*	0.166*
10	West Bengal	0.166*	0.1588
11	Tamil Nadu	0.137*	0.129*
12	Maharashtra	0.137*	0.129*
13	Haryana	0.083*	0.125*
14	Gujarat	0.111*	0.108*
15	Andhra Pradesh	0.080*	0.088*
16	Rajasthan	0.064*	0.084*
17	Telangana	0.079	0.066*
18	Bihar	0.031	0.032*

Source: Author's computations.

Table A3. Computed EG and spatially weighted EG index for air and spacecraft and related machinery (NIC-303).

S. No.	State Names	EG	EGSPAT
1	Jammu & Kashmir	1.382*	1.488*
2	Telangana	0.961*	1.167*
3	Bihar	0.897*	0.900*
4	Haryana	0.537*	0.570*
5	Delhi	0.395*	0.511*
6	Punjab	0.390*	0.394*
7	Kerala	0.195*	0.338*
8	Gujarat	0.231*	0.258*
9	Jharkhand	0.261*	0.217*
10	Madhya Pradesh	0.137*	0.121*
11	Maharashtra	0.132*	0.116*
12	West Bengal	0.111*	0.092*

Source: Author's computations.

Table A4. Computed EG index and spatially weighted EG index for software publishing (NIC-582).

S. No.	State Names	EG	EGSPAT
1	Arunachal Pradesh	0.816*	0.715*
2	Tamil Nadu	0.705*	0.708*
3	Punjab	0.582*	0.602*
4	Delhi	0.465	0.550*
5	Telangana	0.333*	0.353*
6	Jammu & Kashmir	0.330*	0.310*

Continued

7	Haryana	0.281*	0.297*
8	Jharkhand	0.325*	0.285*
9	Uttar Pradesh	0.248*	0.247*
10	Orissa	0.155*	0.210*
11	West Bengal	0.181*	0.177*
12	Kerala	0.145*	0.161*
13	Bihar	0.152*	0.146*
14	Gujarat	0.125*	0.136*
15	Andhra Pradesh	0.116*	0.107*
16	Rajasthan	0.058*	0.052*
17	Assam	0.029*	0.026*
18	Madhya Pradesh	0.024*	0.022*

Source: Author's computations. Notes: The estimated value of the EG index for Delhi is not statistically significant at the 5 percent level.

Table A5. Computed EG index and spatially weighted EG index for leasing nonfinancial intangible assets (NIC-774).

S. No.	State Names	EG	EGSPAT
1	Andhra Pradesh	0.833*	0.833*
2	Jammu & Kashmir	0.650*	0.673*
3	Gujarat	0.684*	0.653*
4	Punjab	0.640*	0.605*
5	Haryana	0.588*	0.554*
6	Madhya Pradesh	0.480*	0.483*
7	Himachal Pradesh	0.506*	0.465*
8	Orissa	0.443*	0.452*
9	Manipur	0.453*	0.439*
10	West Bengal	0.268*	0.289*
11	Chhattisgarh	0.294*	0.262*
12	Tamil Nadu	0.219*	0.228*
13	Kerala	0.220*	0.187*
14	Jharkhand	0.150*	0.171*
15	Telangana	0.145*	0.159*
16	Rajasthan	0.185*	0.151*
17	Assam	0.092*	0.106*
18	Maharashtra	0.086*	0.103*
19	Bihar	0.071*	0.072*
20	Uttar Pradesh	0.047*	0.047*

Source: Author's computations.

Table A6. Computed EG and spatially weighted EG index for landscape care and maintenance service activities (NIC-813).

S. No.	State Names	EG	EGSPAT
1	Uttarakhand	0.416*	0.560*
2	Maharashtra	0.452*	0.455*
3	Jammu & Kashmir	0.338*	0.426*
4	Gujarat	0.326*	0.323*
5	Uttar Pradesh	0.264*	0.287*
6	Delhi	0.2178	0.261*
7	Bihar	0.232*	0.241*
8	West Bengal	0.254*	0.237*
9	Jharkhand	0.237*	0.212*
10	Rajasthan	0.216*	0.210*
11	Haryana	0.293*	0.208*
12	Madhya Pradesh	0.181*	0.193*
13	Chhattisgarh	0.183*	0.170*
14	Andhra Pradesh	0.038*	0.073*
15	Kerala	0.048*	0.043*
16	Telangana	0.045*	0.041*
17	Orissa	0.022*	0.022*

Source: Author's computations.